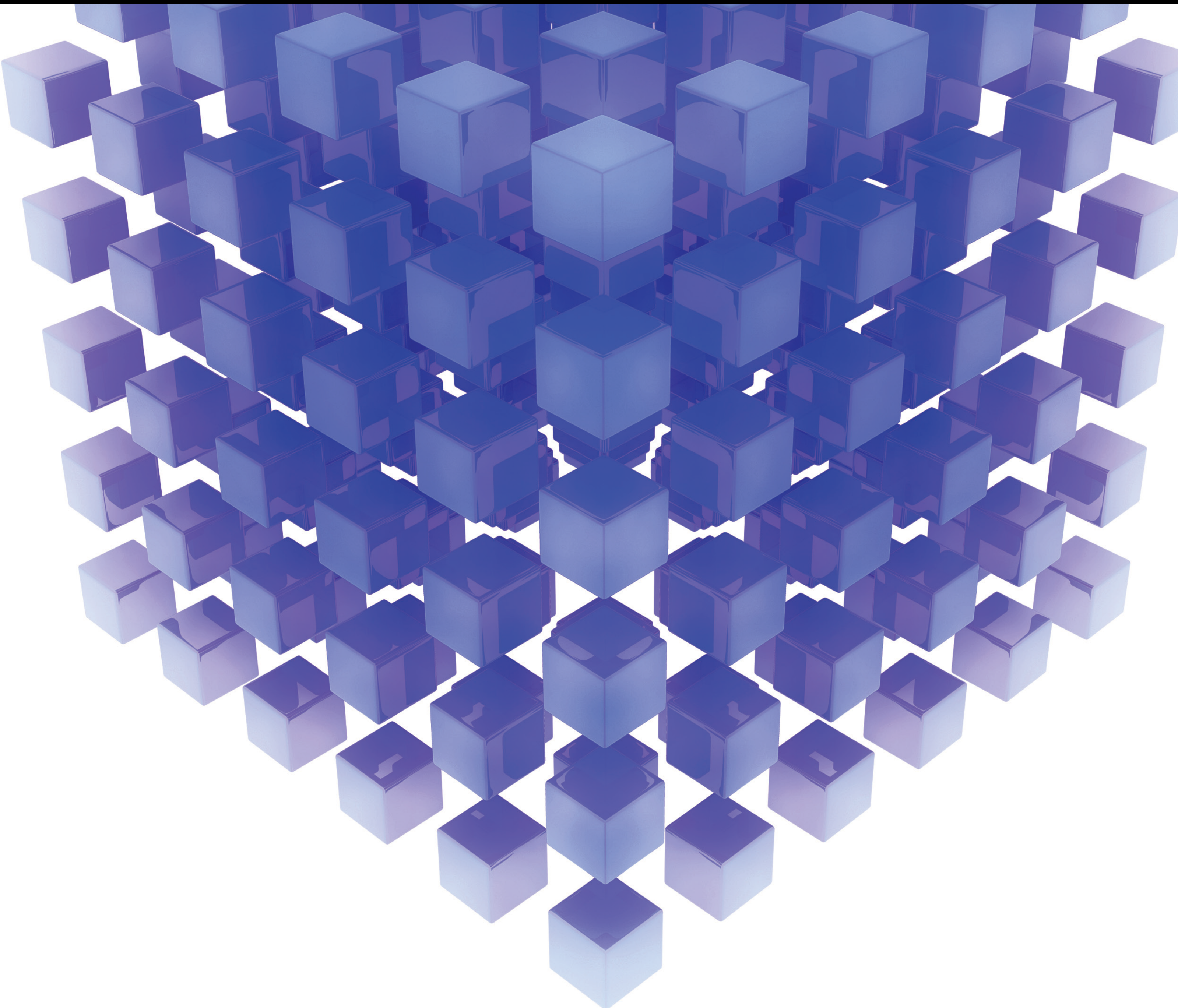
Mathematical Problems in Engineering

Artificial Intelligence in Internet of Vehicles for Autonomous Vehicles

Lead Guest Editor: Haruna Chiroma
Guest Editors: Ibrahim Abaker Targio Hashem and Muhammad Imran



Artificial Intelligence in Internet of Vehicles for Autonomous Vehicles

Mathematical Problems in Engineering

Artificial Intelligence in Internet of Vehicles for Autonomous Vehicles

Lead Guest Editor: Haruna Chiroma
Guest Editors: Ibrahim Abaker Targio Hashem and Muhammad Imran

Copyright © 2022 Hindawi Limited. All rights reserved.

This is a special issue published in "Mathematical Problems in Engineering." All articles are open access articles distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Chief Editor

Guangming Xie, China

Academic Editors

Kumaravel A, India
Waqas Abbasi, Pakistan
Mohamed Abd El Aziz, Egypt
Mahmoud Abdel-Aty, Egypt
Mohammed S. Abdo, Yemen
Mohammad Yaghoub Abdollahzadeh Jamalabadi, Republic of Korea
Rahib Abiyev, Turkey
Leonardo Acho, Spain
Daniela Addessi, Italy
Arooj Adeel, Pakistan
Waleed Adel, Egypt
Ramesh Agarwal, USA
Francesco Aggogeri, Italy
Ricardo Aguilar-Lopez, Mexico
Afaq Ahmad, Pakistan
Naveed Ahmed, Pakistan
Elias Aifantis, USA
Akif Akgul, Turkey
Tareq Al-shami, Yemen
Guido Ala, Italy
Andrea Alaimo, Italy
Reza Alam, USA
Osamah Albahri, Malaysia
Nicholas Alexander, United Kingdom
Salvatore Alfonzetti, Italy
Ghous Ali, Pakistan
Nouman Ali, Pakistan
Mohammad D. Aliyu, Canada
Juan A. Almendral, Spain
A.K. Alomari, Jordan
José Domingo Álvarez, Spain
Cláudio Alves, Portugal
Juan P. Amezquita-Sanchez, Mexico
Mukherjee Amitava, India
Lionel Amodeo, France
Sebastian Anita, Romania
Costanza Arico, Italy
Sabri Arik, Turkey
Fausto Arpino, Italy
Rashad Asharabi, Saudi Arabia
Farhad Aslani, Australia
Mohsen Asle Zaeem, USA
Andrea Avanzini, Italy
Richard I. Avery, USA
Viktor Avrutin, Germany
Mohammed A. Awadallah, Malaysia
Francesco Aymerich, Italy
Sajad Azizi, Belgium
Michele Bacciocchi, Italy
Seungik Baek, USA
Khaled Bahlali, France
M.V.A Raju Bahubalendruni, India
Pedro Balaguer, Spain
P. Balasubramaniam, India
Stefan Balint, Romania
Ines Tejado Balsera, Spain
Alfonso Banos, Spain
Jerzy Baranowski, Poland
Tudor Barbu, Romania
Andrzej Bartoszewicz, Poland
Sergio Baselga, Spain
S. Caglar Baslamisli, Turkey
David Bassir, France
Chiara Bedon, Italy
Azeddine Beghdadi, France
Andriette Bekker, South Africa
Francisco Beltran-Carbajal, Mexico
Abdellatif Ben Makhlouf, Saudi Arabia
Denis Benasciutti, Italy
Ivano Benedetti, Italy
Rosa M. Benito, Spain
Elena Benvenuti, Italy
Giovanni Berselli, Italy
Michele Betti, Italy
Pietro Bia, Italy
Carlo Bianca, France
Simone Bianco, Italy
Vincenzo Bianco, Italy
Vittorio Bianco, Italy
David Bigaud, France
Sardar Muhammad Bilal, Pakistan
Antonio Bilotta, Italy
Sylvio R. Bistafa, Brazil
Chiara Boccaletti, Italy
Rodolfo Bontempo, Italy
Alberto Borboni, Italy
Marco Bortolini, Italy

Paolo Boscariol, Italy
Daniela Boso, Italy
Guillermo Botella-Juan, Spain
Abdesselem Boulkroune, Algeria
Boulaïd Boulkroune, Belgium
Fabio Bovenga, Italy
Francesco Braghin, Italy
Ricardo Branco, Portugal
Julien Bruchon, France
Matteo Bruggi, Italy
Michele Brun, Italy
Maria Elena Bruni, Italy
Maria Angela Butturi, Italy
Bartłomiej Błachowski, Poland
Dhanamjayulu C, India
Raquel Caballero-Águila, Spain
Filippo Cacace, Italy
Salvatore Caddemi, Italy
Zuowei Cai, China
Roberto Caldelli, Italy
Francesco Cannizzaro, Italy
Maosen Cao, China
Ana Carpio, Spain
Rodrigo Carvajal, Chile
Caterina Casavola, Italy
Sara Casciati, Italy
Federica Caselli, Italy
Carmen Castillo, Spain
Inmaculada T. Castro, Spain
Miguel Castro, Portugal
Giuseppe Catalanotti, United Kingdom
Alberto Cavallo, Italy
Gabriele Cazzulani, Italy
Fatih Vehbi Celebi, Turkey
Miguel Cerrolaza, Venezuela
Gregory Chagnon, France
Ching-Ter Chang, Taiwan
Kuei-Lun Chang, Taiwan
Qing Chang, USA
Xiaoheng Chang, China
Prasenjit Chatterjee, Lithuania
Kacem Chehdi, France
Peter N. Cheimets, USA
Chih-Chiang Chen, Taiwan
He Chen, China
Kebing Chen, China
Mengxin Chen, China
Shyi-Ming Chen, Taiwan
Xizhong Chen, Ireland
Xue-Bo Chen, China
Zhiwen Chen, China
Qiang Cheng, USA
Zeyang Cheng, China
Luca Chiapponi, Italy
Francisco Chicano, Spain
Tirivanhu Chinyoka, South Africa
Adrian Chmielewski, Poland
Seongim Choi, USA
Gautam Choubey, India
Hung-Yuan Chung, Taiwan
Yusheng Ci, China
Simone Cinquemani, Italy
Roberto G. Citarella, Italy
Joaquim Ciurana, Spain
John D. Clayton, USA
Piero Colajanni, Italy
Giuseppina Colicchio, Italy
Vassilios Constantoudis, Greece
Enrico Conte, Italy
Alessandro Contento, USA
Mario Cools, Belgium
Gino Cortellessa, Italy
Carlo Cosentino, Italy
Paolo Crippa, Italy
Erik Cuevas, Mexico
Guozeng Cui, China
Mehmet Cunkas, Turkey
Giuseppe D'Aniello, Italy
Peter Dabnichki, Australia
Weizhong Dai, USA
Zhifeng Dai, China
Purushothaman Damodaran, USA
Sergey Dashkovskiy, Germany
Adiel T. De Almeida-Filho, Brazil
Fabio De Angelis, Italy
Samuele De Bartolo, Italy
Stefano De Miranda, Italy
Filippo De Monte, Italy

José António Fonseca De Oliveira Correia, Portugal
Jose Renato De Sousa, Brazil
Michael Defoort, France
Alessandro Della Corte, Italy
Laurent Dewasme, Belgium
Sanku Dey, India
Gianpaolo Di Bona, Italy
Roberta Di Pace, Italy
Francesca Di Puccio, Italy
Ramón I. Diego, Spain
Yannis Dimakopoulos, Greece
Hasan Dinçer, Turkey
José M. Domínguez, Spain
Georgios Dounias, Greece
Bo Du, China
Emil Dumic, Croatia
Madalina Dumitriu, United Kingdom
Premraj Durairaj, India
Saeed Eftekhar Azam, USA
Said El Kafhali, Morocco
Antonio Elipe, Spain
R. Emre Erkmen, Canada
John Escobar, Colombia
Leandro F. F. Miguel, Brazil
FRANCESCO FOTI, Italy
Andrea L. Facci, Italy
Shahla Faisal, Pakistan
Giovanni Falsone, Italy
Hua Fan, China
Jianguang Fang, Australia
Nicholas Fantuzzi, Italy
Muhammad Shahid Farid, Pakistan
Hamed Faroqi, Iran
Yann Favennec, France
Fiorenzo A. Fazzolari, United Kingdom
Giuseppe Fedele, Italy
Roberto Fedele, Italy
Baowei Feng, China
Mohammad Ferdows, Bangladesh
Arturo J. Fernández, Spain
Jesus M. Fernandez Oro, Spain
Francesco Ferrise, Italy
Eric Feulvarch, France
Thierry Floquet, France
Eric Florentin, France
Gerardo Flores, Mexico
Antonio Forcina, Italy
Alessandro Formisano, Italy
Francesco Franco, Italy
Elisa Francomano, Italy
Juan Frausto-Solis, Mexico
Shujun Fu, China
Juan C. G. Prada, Spain
HECTOR GOMEZ, Chile
Matteo Gaeta, Italy
Mauro Gaggero, Italy
Zoran Gajic, USA
Jaime Gallardo-Alvarado, Mexico
Mosè Gallo, Italy
Akemi Gálvez, Spain
Maria L. Gandarias, Spain
Hao Gao, Hong Kong
Xingbao Gao, China
Yan Gao, China
Zhiwei Gao, United Kingdom
Giovanni Garcea, Italy
José García, Chile
Harish Garg, India
Alessandro Gasparetto, Italy
Stylianos Georgantzinos, Greece
Fotios Georgiades, India
Parviz Ghadimi, Iran
Ştefan Cristian Gherghina, Romania
Georgios I. Giannopoulos, Greece
Agathoklis Giaralis, United Kingdom
Anna M. Gil-Lafuente, Spain
Ivan Giorgio, Italy
Gaetano Giunta, Luxembourg
Jefferson L.M.A. Gomes, United Kingdom
Emilio Gómez-Déniz, Spain
Antonio M. Gonçalves de Lima, Brazil
Qunxi Gong, China
Chris Goodrich, USA
Rama S. R. Gorla, USA
Veena Goswami, India
Xunjie Gou, Spain
Jakub Grabski, Poland

Antoine Grall, France
George A. Gravvanis, Greece
Fabrizio Greco, Italy
David Greiner, Spain
Jason Gu, Canada
Federico Guarracino, Italy
Michele Guida, Italy
Muhammet Gul, Turkey
Dong-Sheng Guo, China
Hu Guo, China
Zhaoxia Guo, China
Yusuf Gurefe, Turkey
Salim HEDDAM, Algeria
ABID HUSSANAN, China
Quang Phuc Ha, Australia
Li Haitao, China
Petr Hájek, Czech Republic
Mohamed Hamdy, Egypt
Muhammad Hamid, United Kingdom
Renke Han, United Kingdom
Weimin Han, USA
Xingsi Han, China
Zhen-Lai Han, China
Thomas Hanne, Switzerland
Xinan Hao, China
Mohammad A. Hariri-Ardebili, USA
Khalid Hattaf, Morocco
Defeng He, China
Xiao-Qiao He, China
Yanchao He, China
Yu-Ling He, China
Ramdane Hedjar, Saudi Arabia
Jude Hemanth, India
Reza Hemmati, Iran
Nicolae Herisanu, Romania
Alfredo G. Hernández-Diaz, Spain
M.I. Herreros, Spain
Eckhard Hitzer, Japan
Paul Honeine, France
Jaromir Horacek, Czech Republic
Lei Hou, China
Yingkun Hou, China
Yu-Chen Hu, Taiwan
Yunfeng Hu, China
Can Huang, China
Gordon Huang, Canada
Linsheng Huo, China
Sajid Hussain, Canada
Asier Ibeas, Spain
Orest V. Iftime, The Netherlands
Przemyslaw Ignaciuk, Poland
Giacomo Innocenti, Italy
Emilio Insfran Pelozo, Spain
Azeem Irshad, Pakistan
Alessio Ishizaka, France
Benjamin Ivorra, Spain
Breno Jacob, Brazil
Reema Jain, India
Tushar Jain, India
Amin Jajarmi, Iran
Chiranjibe Jana, India
Łukasz Jankowski, Poland
Samuel N. Jator, USA
Juan Carlos Jáuregui-Correa, Mexico
Kandasamy Jayakrishna, India
Reza Jazar, Australia
Khalide Jbilou, France
Isabel S. Jesus, Portugal
Chao Ji, China
Qing-Chao Jiang, China
Peng-fei Jiao, China
Ricardo Fabricio Escobar Jiménez, Mexico
Emilio Jiménez Macías, Spain
Maolin Jin, Republic of Korea
Zhuo Jin, Australia
Ramash Kumar K, India
BHABEN KALITA, USA
MOHAMMAD REZA KHEDMATI, Iran
Viacheslav Kalashnikov, Mexico
Mathiyalagan Kalidass, India
Tamas Kalmar-Nagy, Hungary
Rajesh Kaluri, India
Jyotheeswara Reddy Kalvakurthi, India
Zhao Kang, China
Ramani Kannan, Malaysia
Tomasz Kapitaniak, Poland
Julius Kaplunov, United Kingdom
Konstantinos Karamanos, Belgium
Michal Kawulok, Poland

Irfan Kaymaz, Turkey
Vahid Kayvanfar, Qatar
Krzysztof Kecik, Poland
Mohamed Khader, Egypt
Chaudry M. Khalique, South Africa
Mukhtaj Khan, Pakistan
Shahid Khan, Pakistan
Nam-Il Kim, Republic of Korea
Philipp V. Kiryukhantsev-Korneev, Russia
P.V.V Kishore, India
Jan Koci, Czech Republic
Ioannis Kostavelis, Greece
Sotiris B. Kotsiantis, Greece
Frederic Kratz, France
Vamsi Krishna, India
Edyta Kucharska, Poland
Krzysztof S. Kulpa, Poland
Kamal Kumar, India
Prof. Ashwani Kumar, India
Michal Kunicki, Poland
Cedrick A. K. Kwuimy, USA
Kyandoghere Kyamakya, Austria
Ivan Kyrchei, Ukraine
Márcio J. Lacerda, Brazil
Eduardo Lalla, The Netherlands
Giovanni Lancioni, Italy
Jaroslaw Latalski, Poland
Hervé Laurent, France
Agostino Lauria, Italy
Aimé Lay-Ekuakille, Italy
Nicolas J. Leconte, France
Kun-Chou Lee, Taiwan
Dimitri Lefebvre, France
Eric Lefevre, France
Marek Lefik, Poland
Yaguo Lei, China
Kauko Leiviskä, Finland
Ervin Lenzi, Brazil
ChenFeng Li, China
Jian Li, USA
Jun Li, China
Yueyang Li, China
Zhao Li, China
Zhen Li, China
En-Qiang Lin, USA
Jian Lin, China
Qibin Lin, China
Yao-Jin Lin, China
Zhiyun Lin, China
Bin Liu, China
Bo Liu, China
Heng Liu, China
Jianxu Liu, Thailand
Lei Liu, China
Sixin Liu, China
Wanquan Liu, China
Yu Liu, China
Yuanchang Liu, United Kingdom
Bonifacio Llamazares, Spain
Alessandro Lo Schiavo, Italy
Jean Jacques Loiseau, France
Francesco Lolli, Italy
Paolo Lonetti, Italy
António M. Lopes, Portugal
Sebastian López, Spain
Luis M. López-Ochoa, Spain
Vassilios C. Loukopoulos, Greece
Gabriele Maria Lozito, Italy
Zhiguo Luo, China
Gabriel Luque, Spain
Valentin Lychagin, Norway
YUE MEI, China
Junwei Ma, China
Xuanlong Ma, China
Antonio Madeo, Italy
Alessandro Magnani, Belgium
Toqeer Mahmood, Pakistan
Fazal M. Mahomed, South Africa
Arunava Majumder, India
Sarfraz Nawaz Malik, Pakistan
Paolo Manfredi, Italy
Adnan Maqsood, Pakistan
Muazzam Maqsood, Pakistan
Giuseppe Carlo Marano, Italy
Damijan Markovic, France
Filipe J. Marques, Portugal
Luca Martinelli, Italy
Denizar Cruz Martins, Brazil

Francisco J. Martos, Spain
Elio Masciari, Italy
Paolo Massioni, France
Alessandro Mauro, Italy
Jonathan Mayo-Maldonado, Mexico
Pier Luigi Mazzeo, Italy
Laura Mazzola, Italy
Driss Mehdi, France
Zahid Mehmood, Pakistan
Roderick Melnik, Canada
Xiangyu Meng, USA
Jose Merodio, Spain
Alessio Merola, Italy
Mahmoud Mesbah, Iran
Luciano Mescia, Italy
Laurent Mevel, France
Constantine Michailides, Cyprus
Mariusz Michta, Poland
Prankul Middha, Norway
Aki Mikkola, Finland
Giovanni Minafò, Italy
Edmondo Minisci, United Kingdom
Hiroyuki Mino, Japan
Dimitrios Mitsotakis, New Zealand
Ardashir Mohammadzadeh, Iran
Francisco J. Montáns, Spain
Francesco Montefusco, Italy
Gisele Mophou, France
Rafael Morales, Spain
Marco Morandini, Italy
Javier Moreno-Valenzuela, Mexico
Simone Morganti, Italy
Caroline Mota, Brazil
Aziz Moukrim, France
Shen Mouquan, China
Dimitris Mourtzis, Greece
Emiliano Mucchi, Italy
Taseer Muhammad, Saudi Arabia
Ghulam Muhiuddin, Saudi Arabia
Amitava Mukherjee, India
Josefa Mula, Spain
Jose J. Muñoz, Spain
Giuseppe Muscolino, Italy
Marco Mussetta, Italy
Hariharan Muthusamy, India
Alessandro Naddeo, Italy
Raj Nandkeolyar, India
Keivan Navaie, United Kingdom
Soumya Nayak, India
Adrian Neagu, USA
Erivelton Geraldo Nepomuceno, Brazil
AMA Neves, Portugal
Ha Quang Thinh Ngo, Vietnam
Nhon Nguyen-Thanh, Singapore
Papakostas Nikolaos, Ireland
Jelena Nikolic, Serbia
Tatsushi Nishi, Japan
Shanzhou Niu, China
Ben T. Nohara, Japan
Mohammed Nouari, France
Mustapha Nourelfath, Canada
Kazem Nouri, Iran
Ciro Núñez-Gutiérrez, Mexico
Wlodzimierz Ogryczak, Poland
Roger Ohayon, France
Krzysztof Okarma, Poland
Mitsuhiro Okayasu, Japan
Murat Olgun, Turkey
Diego Oliva, Mexico
Alberto Olivares, Spain
Enrique Onieva, Spain
Calogero Orlando, Italy
Susana Ortega-Cisneros, Mexico
Sergio Ortobelli, Italy
Naohisa Otsuka, Japan
Sid Ahmed Ould Ahmed Mahmoud, Saudi Arabia
Taoreed Owolabi, Nigeria
EUGENIA PETROPOULOU, Greece
Arturo Pagano, Italy
Madhumangal Pal, India
Pasquale Palumbo, Italy
Dragan Pamučar, Serbia
Weifeng Pan, China
Chandan Pandey, India
Rui Pang, United Kingdom
Jürgen Pannek, Germany
Elena Panteley, France
Achille Paolone, Italy

George A. Papakostas, Greece
Xosé M. Pardo, Spain
You-Jin Park, Taiwan
Manuel Pastor, Spain
Pubudu N. Pathirana, Australia
Surajit Kumar Paul, India
Luis Payá, Spain
Igor Pažanin, Croatia
Libor Pekař, Czech Republic
Francesco Pellicano, Italy
Marcello Pellicciari, Italy
Jian Peng, China
Mingshu Peng, China
Xiang Peng, China
Xindong Peng, China
Yuexing Peng, China
Marzio Pennisi, Italy
Maria Patrizia Pera, Italy
Matjaz Perc, Slovenia
A. M. Bastos Pereira, Portugal
Wesley Peres, Brazil
F. Javier Pérez-Pinal, Mexico
Michele Perrella, Italy
Francesco Pesavento, Italy
Francesco Petrini, Italy
Hoang Vu Phan, Republic of Korea
Lukasz Pieczonka, Poland
Dario Piga, Switzerland
Marco Pizzarelli, Italy
Javier Plaza, Spain
Goutam Pohit, India
Dragan Poljak, Croatia
Jorge Pomares, Spain
Hiram Ponce, Mexico
Sébastien Poncet, Canada
Volodymyr Ponomaryov, Mexico
Jean-Christophe Ponsart, France
Mauro Pontani, Italy
Sivakumar Poruran, India
Francesc Pozo, Spain
Aditya Rio Prabowo, Indonesia
Anchasa Pramuanjaroenkij, Thailand
Leonardo Primavera, Italy
B Rajanarayan Prusty, India
Krzysztof Puszynski, Poland
Chuan Qin, China
Dongdong Qin, China
Jianlong Qiu, China
Giuseppe Quaranta, Italy
DR. RITU RAJ, India
Vitomir Racic, Italy
Carlo Rainieri, Italy
Kumbakonam Ramamani Rajagopal, USA
Ali Ramazani, USA
Angel Manuel Ramos, Spain
Higinio Ramos, Spain
Muhammad Afzal Rana, Pakistan
Muhammad Rashid, Saudi Arabia
Manoj Rastogi, India
Alessandro Rasulo, Italy
S.S. Ravindran, USA
Abdolrahman Razani, Iran
Alessandro Reali, Italy
Jose A. Reinoso, Spain
Oscar Reinoso, Spain
Haijun Ren, China
Carlo Renno, Italy
Fabrizio Renno, Italy
Shahram Rezapour, Iran
Ricardo Riaza, Spain
Francesco Riganti-Fulginei, Italy
Gerasimos Rigatos, Greece
Francesco Ripamonti, Italy
Jorge Rivera, Mexico
Eugenio Roanes-Lozano, Spain
Ana Maria A. C. Rocha, Portugal
Luigi Rodino, Italy
Francisco Rodríguez, Spain
Rosana Rodríguez López, Spain
Francisco Rossomando, Argentina
Jose de Jesus Rubio, Mexico
Weiguo Rui, China
Rubén Ruiz, Spain
Ivan D. Rukhlenko, Australia
Dr. Eswaramoorthi S., India
Weichao SHI, United Kingdom
Chaman Lal Sabharwal, USA
Andrés Sáez, Spain

Bekir Sahin, Turkey
Laxminarayan Sahoo, India
John S. Sakellariou, Greece
Michael Sakellariou, Greece
Salvatore Salamone, USA
Jose Vicente Salcedo, Spain
Alejandro Salcido, Mexico
Alejandro Salcido, Mexico
Nunzio Salerno, Italy
Rohit Salgotra, India
Miguel A. Salido, Spain
Sinan Salih, Iraq
Alessandro Salvini, Italy
Abdus Samad, India
Sovan Samanta, India
Nikolaos Samaras, Greece
Ramon Sancibrian, Spain
Giuseppe Sanfilippo, Italy
Omar-Jacobo Santos, Mexico
J Santos-Reyes, Mexico
José A. Sanz-Herrera, Spain
Musavarah Sarwar, Pakistan
Shahzad Sarwar, Saudi Arabia
Marcelo A. Savi, Brazil
Andrey V. Savkin, Australia
Tadeusz Sawik, Poland
Roberta Sburlati, Italy
Gustavo Scaglia, Argentina
Thomas Schuster, Germany
Hamid M. Sedighi, Iran
Mijanur Rahaman Seikh, India
Tapan Senapati, China
Lotfi Senhadji, France
Junwon Seo, USA
Michele Serpilli, Italy
Silvestar Šesnić, Croatia
Gerardo Severino, Italy
Ruben Sevilla, United Kingdom
Stefano Sfarra, Italy
Dr. Ismail Shah, Pakistan
Leonid Shaikhet, Israel
Vimal Shanmuganathan, India
Prayas Sharma, India
Bo Shen, Germany
Hang Shen, China
Xin Pu Shen, China
Dimitri O. Shepelsky, Ukraine
Jian Shi, China
Amin Shokrollahi, Australia
Suzanne M. Shontz, USA
Babak Shotorban, USA
Zhan Shu, Canada
Angelo Sifaleras, Greece
Nuno Simões, Portugal
Mehakpreet Singh, Ireland
Piyush Pratap Singh, India
Rajiv Singh, India
Seralathan Sivamani, India
S. Sivasankaran, Malaysia
Christos H. Skiadas, Greece
Konstantina Skouri, Greece
Neale R. Smith, Mexico
Bogdan Smolka, Poland
Delfim Soares Jr., Brazil
Alba Sofi, Italy
Francesco Soldovieri, Italy
Raffaele Solimene, Italy
Yang Song, Norway
Jussi Sopanen, Finland
Marco Spadini, Italy
Paolo Spagnolo, Italy
Ruben Specogna, Italy
Vasilios Spitas, Greece
Ivanka Stamova, USA
Rafał Stanisławski, Poland
Miladin Stefanović, Serbia
Salvatore Strano, Italy
Yakov Strelniker, Israel
Kangkang Sun, China
Qiuqin Sun, China
Shuaishuai Sun, Australia
Yanchao Sun, China
Zong-Yao Sun, China
Kumarasamy Suresh, India
Sergey A. Suslov, Australia
D.L. Suthar, Ethiopia
D.L. Suthar, Ethiopia
Andrzej Swierniak, Poland
Andras Szekrenyes, Hungary
Kumar K. Tamma, USA

Yong (Aaron) Tan, United Kingdom
Marco Antonio Taneco-Hernández, Mexico
Lu Tang, China
Tianyou Tao, China
Hafez Tari, USA
Alessandro Tasora, Italy
Sergio Teggi, Italy
Adriana del Carmen Téllez-Anguiano, Mexico
Ana C. Teodoro, Portugal
Efstathios E. Theotokoglou, Greece
Jing-Feng Tian, China
Alexander Timokha, Norway
Stefania Tomasiello, Italy
Gisella Tomasini, Italy
Isabella Torcicollo, Italy
Francesco Tornabene, Italy
Mariano Torrisi, Italy
Thang nguyen Trung, Vietnam
George Tsiatas, Greece
Le Anh Tuan, Vietnam
Nerio Tullini, Italy
Emilio Turco, Italy
Ilhan Tuzcu, USA
Efstratios Tzirtzilakis, Greece
FRANCISCO UREÑA, Spain
Filippo Ubertini, Italy
Mohammad Uddin, Australia
Mohammad Safi Ullah, Bangladesh
Serdar Ulubeyli, Turkey
Mati Ur Rahman, Pakistan
Panayiotis Vafeas, Greece
Giuseppe Vairo, Italy
Jesus Valdez-Resendiz, Mexico
Eusebio Valero, Spain
Stefano Valvano, Italy
Carlos-Renato Vázquez, Mexico
Martin Velasco Villa, Mexico
Franck J. Vernerey, USA
Georgios Veronis, USA
Vincenzo Vespri, Italy
Renato Vidoni, Italy
Venkatesh Vijayaraghavan, Australia
Anna Vila, Spain
Francisco R. Villatoro, Spain
Francesca Vipiana, Italy
Stanislav Vítek, Czech Republic
Jan Vorel, Czech Republic
Michael Vynnycky, Sweden
Mohammad W. Alomari, Jordan
Roman Wan-Wendner, Austria
Bingchang Wang, China
C. H. Wang, Taiwan
Dagang Wang, China
Guoqiang Wang, China
Huaiyu Wang, China
Hui Wang, China
J.G. Wang, China
Ji Wang, China
Kang-Jia Wang, China
Lei Wang, China
Qiang Wang, China
Qingling Wang, China
Weiwei Wang, China
Xinyu Wang, China
Yong Wang, China
Yung-Chung Wang, Taiwan
Zhenbo Wang, USA
Zhibo Wang, China
Waldemar T. Wójcik, Poland
Chi Wu, Australia
Qiuhong Wu, China
Yuqiang Wu, China
Zhibin Wu, China
Zhizheng Wu, China
Michalis Xenos, Greece
Hao Xiao, China
Xiao Ping Xie, China
Qingzheng Xu, China
Binghan Xue, China
Yi Xue, China
Joseph J. Yame, France
Chuanliang Yan, China
Xinggang Yan, United Kingdom
Hongtai Yang, China
Jixiang Yang, China
Mijia Yang, USA
Ray-Yeng Yang, Taiwan

Zaoli Yang, China
Jun Ye, China
Min Ye, China
Luis J. Yebra, Spain
Peng-Yeng Yin, Taiwan
Muhammad Haroon Yousaf, Pakistan
Yuan Yuan, United Kingdom
Qin Yuming, China
Elena Zaitseva, Slovakia
Arkadiusz Zak, Poland
Mohammad Zakwan, India
Ernesto Zambrano-Serrano, Mexico
Francesco Zammori, Italy
Jessica Zangari, Italy
Rafal Zdunek, Poland
Ibrahim Zeid, USA
Nianyin Zeng, China
Junyong Zhai, China
Hao Zhang, China
Haopeng Zhang, USA
Jian Zhang, China
Kai Zhang, China
Lingfan Zhang, China
Mingjie Zhang, Norway
Qian Zhang, China
Tianwei Zhang, China
Tongqian Zhang, China
Wenyu Zhang, China
Xianming Zhang, Australia
Xuping Zhang, Denmark
Yinyan Zhang, China
Yifan Zhao, United Kingdom
Debao Zhou, USA
Heng Zhou, China
Jian G. Zhou, United Kingdom
Junyong Zhou, China
Xueqian Zhou, United Kingdom
Zhe Zhou, China
Wu-Le Zhu, China
Gaetano Zizzo, Italy
Mingcheng Zuo, China

Contents

Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 8151805, 13 pages
https://doi.org/10.1155/2022/8151805

Research Article

Research on 3D Point Cloud Object Detection Algorithm for Autonomous Driving

Haiyang Jiang,[1] **Yuanyao Lu**,[2] **and Shengnan Chen**[2]

[1]*School of Electrical and Control Engineering, North China University of Technology, Beijing, China*
[2]*School of Information Science and Technology, North China University of Technology, Beijing, China*

Correspondence should be addressed to Yuanyao Lu; luyy@ncut.edu.cn

Received 4 January 2022; Revised 22 January 2022; Accepted 25 January 2022; Published 17 February 2022

Academic Editor: Haruna Chiroma

Copyright © 2022 Haiyang Jiang et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In autonomous driving, lidar has become the main vehicle sensor due to its advantages such as long-range measurement and high accuracy. However, the collected point cloud data is sparse and unevenly distributed, and it lacks characterization capabilities when facing objects with missing or similar shapes, so that the detection accuracy is low while detecting long-distance small targets with similar shapes and a small number of point clouds. In order to improve the detection accuracy of small targets represented by point clouds, this paper adopts a method that fuses point cloud and RGB image to construct a 3D object detection network architecture based on two-stage complementary fusion. In the first stage of the fusion, we use the FPS method to select some points from the raw point cloud data as key points. Then, we voxelize the raw point cloud and use the 3D sparse convolutional neural network to extract multi-scale points cloud features, which would fuse features of different scales with key points. In the second stage of fusion, a 2D object detector is used to obtain the 2D bounding box and category information of the target in the image and take the camera as the origin to extend along the direction of the 2D bounding box to form a frustum; then the point cloud and target category information within the frustum are fused into the key points. This paper uses key points as a bridge to effectively combine the semantic information of the image such as texture and color with the point cloud features. The experimental results show that the network proposed in this paper has excellent performance on small objects.

1. Introduction

Deep learning, as a major artificial intelligence technology, has been widely used in computer vision, speech recognition, and natural language processing; more notably, the application of deep learning to 2D object detection [1–6] and semantic segmentation [7–10] techniques in computer vision has led to the rapid development of both in the past 10 years. However, with the rapid development of autonomous driving and mobile robots, only 2D object detection can no longer satisfy all the information required for environment perception. In the urban scenario of autonomous driving, a single sensor cannot accurately sense the complex and changing road traffic environment, so fusing data collected by multiple sensors is the preferred solution for current autonomous driving perception systems. LiDAR and camera are the two most commonly used sensors in current autonomous vehicles. Since the 3D point cloud generated by LiDAR has accurate depth and reflection intensity information, but due to its disadvantages such as sparse and uneven density, when facing objects with missing shape or similar shape, its representation ability is insufficient. Therefore, it often leads to missed or false detection when detecting small long-range targets with similar shape and small number of point clouds. While the 2D images generated by camera sensors are rich in semantic information such as texture and color, which can delineate targets and scenes in detail, but cause the loss of depth information by perspective projection, there is no way to guarantee the accuracy of depth estimation by either monocular [11, 12] or stereo binocular [13, 14] based algorithms, which makes it difficult to achieve high-precision 3D localization. Therefore, how to effectively combine the respective advantages of 2D images and 3D point clouds to achieve accurate and robust

3D object detection in urban road scenarios of autonomous driving is the main focus of this paper. The contributions of this paper include the following three main points.

(1) We designed a 3D object detection network architecture based on two-stage complementary fusion. The architecture uses key points as a bridge to successfully combine Point-based, Voxel-based, and Image-based methods. In this way, the complementary fusion of the geometric information collected by the lidar and the semantic information collected by the camera is realized.

(2) The innovation of this paper is proposing a Feature Fusion Model, which fuses features from voxels, original point cloud features, BEV features, and RGB image features, and conducts experimental analysis on the contribution of each part of the features to the accuracy of the network model, and the results show that, after adding RGB image features, the accuracy of point cloud object detection in 3D space is significantly improved on small targets, and objects with similar structures are also substantially improved.

(3) In order to solve the problem of overreliance on the detection performance of 2D detectors in point cloud and image fusion, this paper proposes a method for assigning the foreground point features and background point features within the cone according to the confidence score and fusing them with the point cloud features by applying parallel processing to the first and second stages to use the features provided by the images as auxiliary features.

2. Related Work

At present, most existing 3D object detection methods based on point cloud representation are mainly divided into two categories, namely, LiDAR + Image fusion method and Only LiDAR method. In the LiDAR + Image fusion method [15], it, respectively, fuses the top view and front view of the point cloud and the RGB image features with the candidate area generated in the top view, thereby achieving the data-level fusion between the point cloud and the image. However, a large amount of data processed in this method requires a lot of computing resources and communication bandwidth, and it also generates a large amount of redundant information. The 2D driving 3D method [16] is used to extract the point cloud of corresponding area to estimate the 3D bounding box, but the disadvantage of this type of method is that it relies too much on the accuracy of the 2D detection. The research work [17] uses the camera at the first stage, and it only processes the lidar point cloud at the second stage. The disadvantage of this method is that although two sensors are used, the data of the two sensors is not fused; thus it is very difficult to use this method to detect long distance and obscured objects. In Only LiDAR method, it is divided into Voxel-based method and Point-based method. Voxel-based methods usually convert the point cloud into a Bird's Eye View (BEV) [18–24] or voxelize it [25–29] at first, then use the 3D sparse convolutional neural network to extract the features. The advantage of this method is that it not only has high convolution efficiency but also can produce high-quality proposal. The disadvantage is that the loss of information in the voxelization process reduces the accuracy of location when locating the target frame. The Point-based method [30–35] directly extracts features from the raw point cloud to detect 3D objects. Although this method can get a larger receptive field, the calculation cost has also increased. Thereby, this paper combines the advantages of Voxel-based, Point-based, and Image-based methods to propose a 3D object detection network architecture based on two-stage complementary fusion. This architecture is based on 3D sparse convolutional neural network combined with mature 2D object detector, and the key points are utilized as a bridge, so that a series of precise and guided fusion methods can be designed to accurately predict the categories, 3D positions, and other information of the objects in the surrounding environment. Figure 1 shows some classic 3D object detection algorithms based on point cloud representation.

3. System Design

In order to fully combine the target object's geometric information collected by the lidar and the semantic information collected by the camera, this paper proposed a 3D object detection network structure based on two-stage complementary fusion. This structure uses key points as a bridge to combine Point-based, Voxel-based, and Image-based methods, which fully integrates and utilizes the geometric information of the point cloud and the semantic information of the image.

3.1. Fusion of Voxel-Based Feature. In the first stage of feature fusion, the Voxel-based method is used to conduct the irregular raw point cloud data voxelization. Then, we use the 3D sparse convolutional neural network [36, 37] as the backbone network for feature extraction. The output feature from the feature extraction network uses a two-layer Multilayer Perceptron (MPL) network to ascend the dimension of voxel features; then we convert its height information to channel feature to generate BEV. Secondly, 2048 points are sampled as key points from the raw point cloud data with the Farthest Point Sampling (FPS) method, and then the voxel features are fused to the key points. In the process of fusing voxel features to key points, we propose a Feature Fusion Module, which uses the set abstraction operation method [32] to aggregate voxel-wise feature volumes, at which time the voxels around the key points are regular voxels with multiscale semantic features encoded by a multilayer 3D voxel CNN. The set of all voxel feature vectors in the kth layer of the 3D voxel CNN is denoted by $\mathscr{F}^{(l_k)} = \left\{f_1^{(l_k)}, \ldots, f_{N_k}^{(l_k)}\right\}$, and $\mathscr{V}^{(l_k)} = \left\{v_1^{(l_k)}, \ldots, v_{N_k}^{(l_k)}\right\}$ denotes the set of 3D coordinates of all voxels computed from the voxel index of the kth layer and the actual voxel size, where N_k is the number of nonempty voxels in the kth layer. For each key point p_i, we first determine the number of

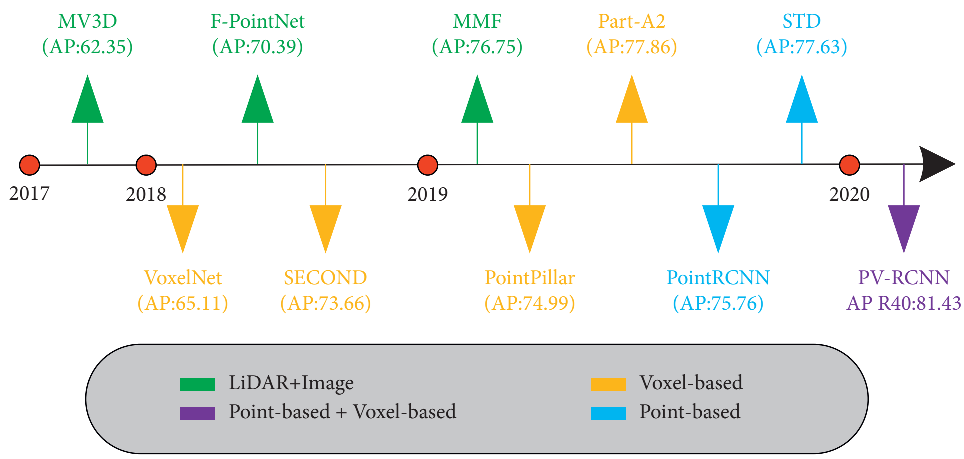


Figure 1: The development process of 3D object detection algorithm based on point cloud representation.

nonempty voxels within the radius r_k in the kth layer of the 3D voxel CNN to retrieve the set of feature vectors of valid voxels in the neighborhood of the key point r_k:

$$S_i^{(l_k)} = \left\{ \left[f_j^{(l_k)}; v_j^{(l_k)} - p_i \right]^T \middle| \begin{array}{c} \| v_j^{(l_k)} - p_i \|^2 < r_k \\ \forall v_j^{(l_k)} \in \mathcal{V}^{(l_k)} \\ \forall f_j^{(l_k)} \in \mathcal{F}^{(l_k)} \end{array} \right\}, \tag{1}$$

where $v_j^{(l_k)} - p_i$ is the local relative coordinate of the voxel and the key point, which represents the relative position of the voxel feature $f_j^{(l_k)}$. Then, the voxel features within $S_i^{(l_k)}$ are transformed using PointNetblock [31] to generate the features of key point p_i as

$$f_i^{(pv_k)} = \max\left\{ G\left(\mathcal{M}\left(S_i^{(l_k)} \right) \right) \right\}, \tag{2}$$

where $\mathcal{M}(\cdot)$ denotes the random sampling of up to $T_k = 16$ voxels from the set $S_i^{(l_k)}$ to save computational cost, and $G(\cdot)$ denotes the use of a multilayer perceptual network to encode the features and relative positions of each voxel. We perform the above strategy on different convolutional layers of the 3D voxel CNN to stitch the features aggregated in different convolutional layers to generate multiscale semantic features of key point p_i. Also, to compensate for the information loss caused by the voxelization process, we use a Point-based approach to extend the key point features by fusing the raw point cloud features $f_i^{(\text{raw})}$ and the BEV features $f_i^{(BEV)}$ to the key points, and the process of fusing the raw point cloud features to the key points is given in Figure 2.

3.2. Fusion of Image-Based and Point-Based Feature. In the second stage of network fusion, RGB images are used as input data, and yolov5 [38] is employed as a 2D object detector to classify and locate the target objects in the image data, so as to obtain the class of target objects and the location information of 2D bounding box. Through the known camera projection matrix, we project each 2D bounding box into the 3D point cloud data to form a frustum candidate area. Then, for the points in the frustum, we use the Point-based method to fuse the features into the key points, so that the effective fusion of Voxel-based, Point-based, and Image-based methods can be realized. In this way, the search range of the point cloud can be greatly narrowed down, and the operating efficiency of the network can be improved. 3D point cloud object detection by 2D-driven 3D is presented in [16]; the final detection result of the whole network tends to be overly dependent on the detection accuracy of the 2D detector. To solve this problem, this paper proposes a method to assign the foreground point features and background point features within the frustum according to the confidence score value, by using parallel processing for the first and second stages to fuse the features provided by the image as auxiliary features with the point cloud features. The 2D detector parameters are kept fixed during the entire training period of the network model since the 2D detector network model parameters are pretrained.

The specific implementation of the method of assigning the foreground point features and background point features in the frustum according to the confidence is that the point cloud in the frustum is extracted using the Point-based method [31], where the point cloud in the frustum has the point cloud data of the target object framed by the 2D bounding box, which we call foreground points, and other points that are not the target object, which we call background points. Therefore, the foreground point features in the frustum should contribute more to the network model, and the background point features should contribute less to the network model. The weight values of the internal and external point cloud features of the bounding box are assigned by the confidence provided by the 2D object detector.

$$f_i^{(RGB)} = C \cdot f_i^{(fg)} + (1 - C) f_i^{(bg)}, \tag{3}$$

where C is the confidence of the target object provided by the 2D detector, f^{fg} is the front point feature within the frustum, f^{bg} is the background point feature within the frustum, and the final key point feature is

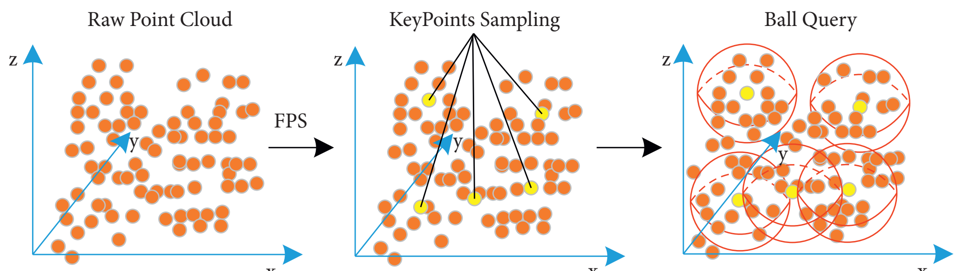


Figure 2: Process diagram of fusion of raw point cloud data to key points.

$$f_i^{(p)} = f_i^{(pv)} + f_i^{(\text{raw})} + f_i^{(BEV)} + f_i^{(RGB)}. \quad (4)$$

The overall structure of the network model is shown in Figure 3.

Generally, we compress the height of voxels from top to bottom directly in the process of generating BV, and the method of forced compression tends to miss a lot of features. In order to solve this problem, height features information of voxels will be converted to channel feature. The process of generating BEV based on the voxel method is shown in Figure 4. For instance, we assume that the voxel feature size output by the feature extraction network is $3 \times 3 \times 3 \times \text{N}$, where $3 \times 3 \times 3$ is the length, width, and height of the voxel and N is number of feature channels. Then, the size of converted feature map is $3 \times 3 \times 1 \times 3\text{N}$, which is utilized to generate BEV.

4. Projection Transformation of the Point Cloud

The 2D object detector detects the 2D bounding box of the target object from the image and then takes the camera as the origin and extends along the direction of the bounding box to form a frustum. In order to make the generated frustum area more accurate, the first thing we have to do is to use the projection transformation method to project the point cloud in 3D space onto the RGB image, so as to obtain the intersection area between the point cloud and the image plane.

4.1. Converting Image Plane Coordinate System to Pixel Coordinate System. When a point on the target object in 3D place is projected onto the image plane, it does not directly correspond to the point observed in the digital image. Therefore, we need to project each point from the image plane to the digital image.

As shown in Figure 5, o is the center of camera and the coordinate system is i, j, k, where k points to the image plane. Then, point c intersecting with the k axis is recorded as the main point, which represents the center of the image plane. Right-hand plane coordinates which take the principal point as the origin $c - xy$ are used as the image plane coordinate system. Therefore, the first step to take after projecting the point $\overrightarrow{P}$ in space to the image plane is to subtract the principal point coordinates so that the discrete image has its own coordinate system.

For converting metric coordinates (m) to pixel coordinates, this paper uses parameters k and l provided by calibration procedure, which can be utilized to convert meter to pixel and easily inherit it into the equation as is shown in

$$\overrightarrow{P} \longrightarrow \overrightarrow{P}'(x, y, z)^T \longrightarrow \left(f \cdot k \cdot \frac{x}{z} + c_x, f \cdot l \cdot \frac{y}{z} + c_y\right), \quad (5)$$

where $f \cdot k$ is called α and $f \cdot l$ is called β in the conversion matrix. Therefore, the conversion equation for converting points in 3D space to 2D image pixels is

$$\overrightarrow{P} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} \longrightarrow \overrightarrow{P}' = \begin{bmatrix} \alpha x/z + c_x \\ \beta y/z + c_y \end{bmatrix}. \quad (6)$$

For the points in the point cloud, we need to move each of them from the position of the lidar to the position of the camera through rotation and translation operations. As shown in formula above, the projection equation is related to the division of z, which makes the conversion nonlinear so that equation is difficult to be transformed. Therefore, we convert the original Euclidean coordinate system to a homogeneous coordinate system so that the projection transformation is converted from nonlinear to linear and the transformation equation can be transformed into matrix-vector multiplication. Equation (7) is the conversion formula from Euclidean coordinates to homogeneous coordinates:

$$(x, y) \longrightarrow \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \cdot (x, y, z) \longrightarrow \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}. \quad (7)$$

With the help of homogeneous coordinate system, the projection equation expressed in matrix vector is

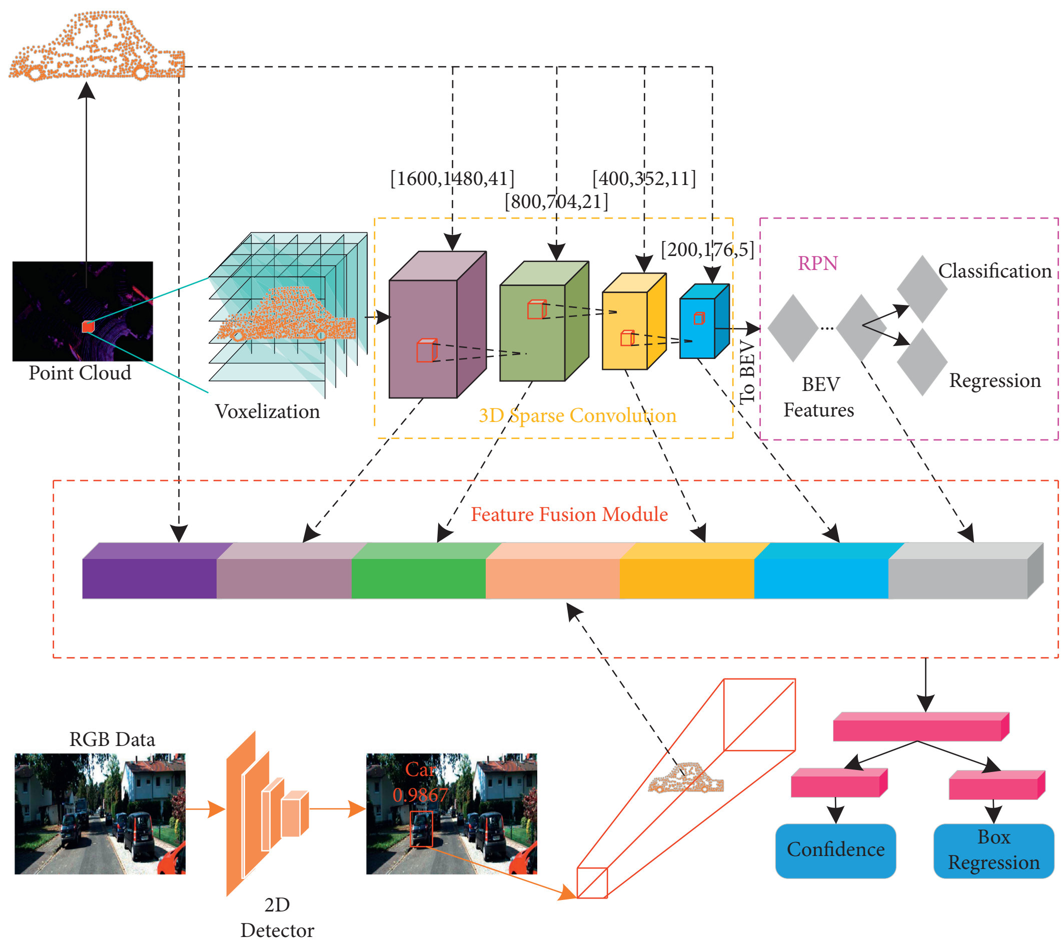


FIGURE 3: Network structure diagram of point cloud object detection.

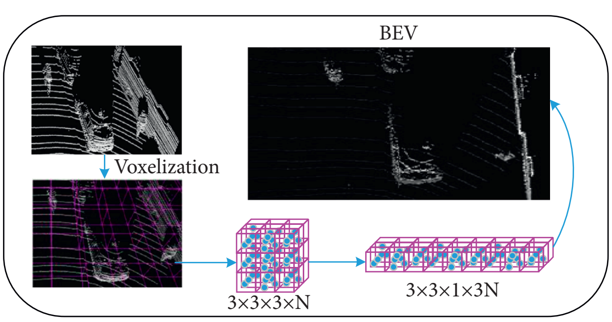


FIGURE 4: Process diagram of BEV generation.

$$\vec{P}_h' = \begin{bmatrix} \alpha \cdot x + c_x \cdot z \\ \beta \cdot y + c_y \cdot z \\ z \end{bmatrix} = \begin{bmatrix} \alpha & 0 & c_x & 0 \\ 0 & \beta & c_y & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}. \quad (8)$$

We realized the mapping from the point $\vec{P}$ in 3D space in camera coordinate system to the point $\vec{P}'$ in 2D pixel plane through (8).

4.2. Point Cloud Projection on the Image Plane. To project the points measured in lidar coordinate system to camera coordinate system, extra conversion needs to be added to the operation of projection so that we can associate points in the vehicle coordinate system to the camera coordinate system. Generally, projection operation can be divided into three parts: translation, scaling, and rotation.

4.2.1. Translation. As is shown in Figure 6, the $\vec{P}$ point is linearly translated to $\vec{P}'$ by adding translation vector t.

We can get the translation formula as follows through Figure 6:

$$\vec{P}' = \vec{P} + t = \begin{bmatrix} x + t_x \\ y + t_y \end{bmatrix}. \quad (9)$$

In the homogeneous coordinate system, the translation (10) is obtained:

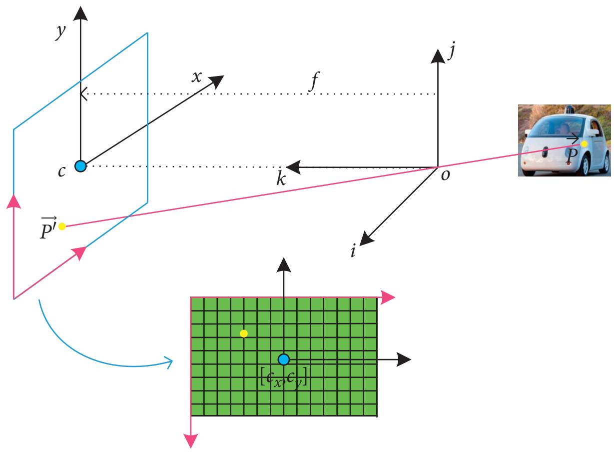


Figure 5: Process diagram of point in space projected onto image.

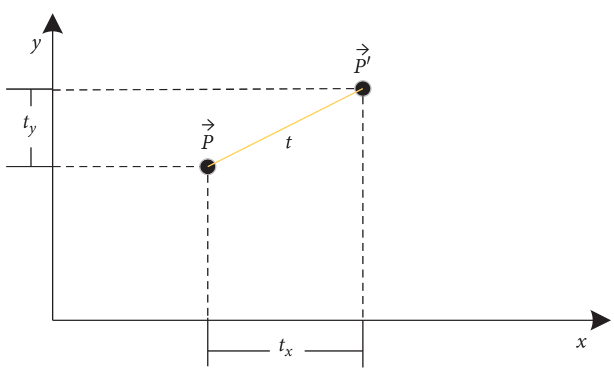


Figure 6: Point translation coordinate map.

$$\vec{P}_h' = \begin{bmatrix} x+t_x \\ y+t_y \\ 1 \end{bmatrix} = \begin{bmatrix} I & t \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}, \tag{10}$$

where I is a unit vector which is size of 2×2 and t is the coordinate increment t_x, t_y.

4.2.2. Scaling. We multiply the original vector by a scale vector to achieve scaling transformation. And the scaling formula is as follows:

$$\vec{P}_h' \longrightarrow \begin{bmatrix} s_x x \\ s_y y \\ 1 \end{bmatrix} = \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = s \cdot \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}. \tag{11}$$

4.2.3. Rotation. Figure 7 shows the process diagram of the vector $\vec{P}\,(x, y)$ after rotating θ counterclockwise to reach the vector $\vec{P}'\,(x', y')$.

We can get the following rotation matrix from Figure 7:

$$\begin{aligned} x' &= \cos\theta x - \sin\theta y, \\ y' &= \cos\theta y + \sin\theta x, \\ \vec{P}' &= \begin{bmatrix} x' \\ y' \end{bmatrix} \\ &= \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \\ &= R \cdot \vec{P}, \end{aligned} \tag{12}$$

where R is called the rotation matrix. In 3D space, the rotation of point P is realized around the three axes of x, y, and z. Therefore, the rotation matrix in 3D space is

$$\begin{gathered} R_x = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta_x & -\sin\theta_x \\ 0 & \sin\theta_x & \cos\theta_x \end{bmatrix}, \\ R_y = \begin{bmatrix} \cos\theta_y & 0 & \sin\theta_y \\ 0 & 1 & 0 \\ -\sin\theta_y & 0 & \cos\theta_y \end{bmatrix}, \\ R_z = \begin{bmatrix} \cos\theta_z & -\sin\theta_z & 0 \\ \sin\theta_z & \cos\theta_z & 0 \\ 0 & 0 & 1 \end{bmatrix}. \end{gathered} \tag{13}$$

We can obtain projection matrix that projects 3D point cloud onto 2D image plane by cascading translation matrix and rotation matrix, which is shown in

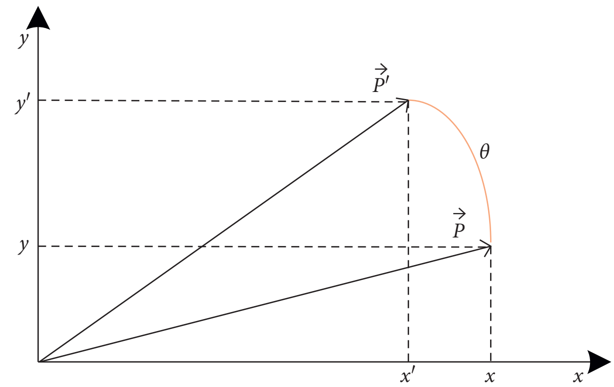


Figure 7: Point rotation coordinate map.

$$\vec{P}' = \begin{bmatrix} 1 & 0 & x_0 \\ 0 & 1 & y_0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} t_x & 0 & 0 \\ 0 & t_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} 1 & \frac{s}{t_x} & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \times [I|t] \times \begin{bmatrix} R & 0 \\ 0 & 1 \end{bmatrix} \cdot \vec{P}. \quad (14)$$

Using (14) we can then project the point cloud data in 3D space onto a 2D image, and the simulation diagram of the projection result is shown in Figure 8.

By fusing the raw data from both sensors, the point cloud can correspond to the image, so that the object detected in 2D can find the corresponding point cloud in the frustum area formed in 3D.

5. Experiment

5.1. Introduction to Training Dataset. The dataset used in this article is the KITTI [41] dataset, which was jointly developed by the Karlsruhe Institute of Technology in Germany and the Toyota American Institute of Technology. It is a computer vision algorithm evaluation dataset in autonomous driving scenes which is widely used all over the world. KITTI contains real image data collected from scenes ranged from urban areas, villages to highways. Each image can contain up to 15 cars and 30 pedestrians with various degrees of masking and truncation. The entire dataset consists of 389 pairs of stereo images, optical flow diagrams, 39.2 km visual ranging sequence, and more than 200k 3D annotated object images, which are sampled and synchronized at a frequency of 10 Hz. The original dataset is classified as 'Road,' 'City,' 'Residential,' 'Campus,' and 'Person.' For 3D object detection, label is subdivided into car, van, truck, pedestrian, pedestrian (sitting), cyclist, tram, and misc. In this section, we visualized part of the image data and point cloud data of the 2D and 3D labeled objects in the KITTI dataset, and the visualization results are shown in Figure 9.

5.2. Training Parameter Settings. When training the network model with KITTI dataset, the position of the lidar on the point cloud collection vehicle is used as the origin of the coordinates. The valid data range of point cloud length is [0,70.4] m, the valid data range of point cloud width is [-40,40] m, and the valid data range of point cloud height is [-3,1] m. After point cloud voxelization, the length, width, and height of each voxel are, respectively, 0.05 m, 0.05 m, and 0.1 m. The batch-size used during training is 2, and the learning rate is 0.01.

In this section, we trained and verified our network model with the KITTI dataset and compared it with the current state-of-the-art 3D point cloud object detection algorithms such as F-PointNet, AVOD-FPN, ContFuse, and MV3D. The software and hardware configuration and version models used in the experiment are shown in Table 1.

5.3. Algorithm Performance Evaluation. In the field of object detection, the quality of an algorithm is mainly evaluated in two ways: qualitative and quantitative evaluation. Qualitative evaluation is mainly based on observation, which is a subjective evaluation mechanism. Quantitative evaluation uses mathematical statistics to quantify algorithm performance based on specific evaluation indexes. Compared with qualitative evaluation methods, quantitative evaluation can compare the differences between different algorithms more scientifically, fairly, and accurately.

As a very important evaluation index in the object detection algorithm, recall rate mainly reflects the algorithm's ability to cover positive examples. Its mathematical expression is

$$\text{Recall} = \frac{TP}{TP + FN}. \quad (15)$$

In the formula, TP (True Positive) means "the number of positive cases that are correctly detected as positive cases," and FN (False Negative) means "the number of positive cases that are falsely detected as negative cases." Precision reflects the accuracy of the algorithm in predicting positive examples. The mathematical expression is

$$\text{precision} = \frac{TP}{TP + FP}. \quad (16)$$

In the formula, FP (False Positive) means "the number of negative cases that are falsely detected as positive cases."

The two evaluation indicators, recall rate and accuracy, show the performance of the algorithm from two different perspectives, but they are a pair of contradictory measures. Both affect each other and show a negative correlation trend. In order to balance them, we introduce the Precision-Recall (P-R) curve.

As shown in Figure 10, the P-R curve represents the corresponding recall rate (horizontal axis) and accuracy (vertical axis) when different IOU and confidence thresholds are picked. Generally, the more the P-R curve goes to the upper right corner, the better the result is. Take Figure 10 as an example; curve A is better than curve B.

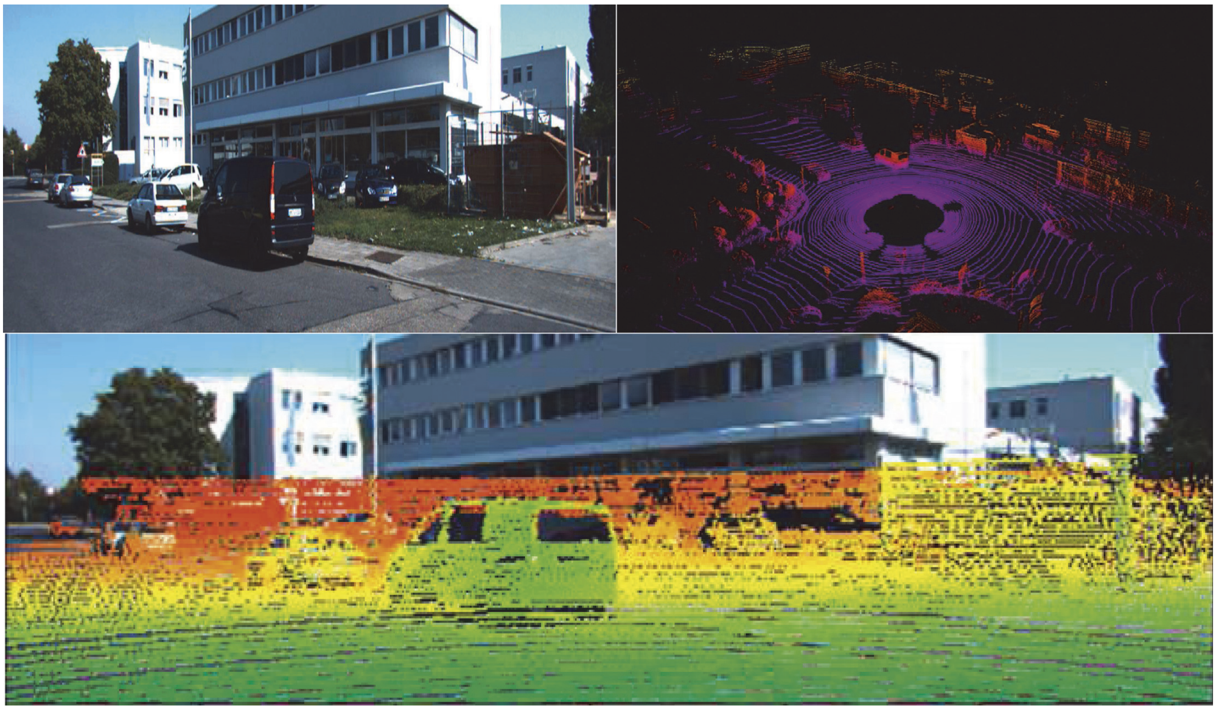


Figure 8: A simulation diagram of the point cloud projected onto the image.

Figure 9: KITTI visualization data.

The average accuracy is derived from the P-R curve. For a continuous P-R curve, the calculation of AP is shown in (17). In the formula, p represents precision, r represents recall, and p is a function which takes r as a parameter. The calculation of the discrete P-R curve AP is shown in (18), where N represents the number of samples, $p(k)$ represents the accuracy when k samples are detected, and $\cdot r(k)$ represents the change in recall rate when the number of detected samples is changed from $k-1$ to k. Mean average precision (mAP) is to average AP of multiple categories and measure

Table 1: Experimental environment used for training and testing.

Software and hardware configuration	Version of the model
Processor	Intel Xeon(R) W-2135 CPU @3.70 GHz
Graphics card	GeForce RTX 2080 Ti
RAM	32G
Operating system	Ubuntu 16.04
Frame	Pytorch 1.3.1、 TensorFlow
Programming language	*Python* 3.7、 *C++*
CUDA/CUDNN	CUDA 10.1/CUDNN v7.6

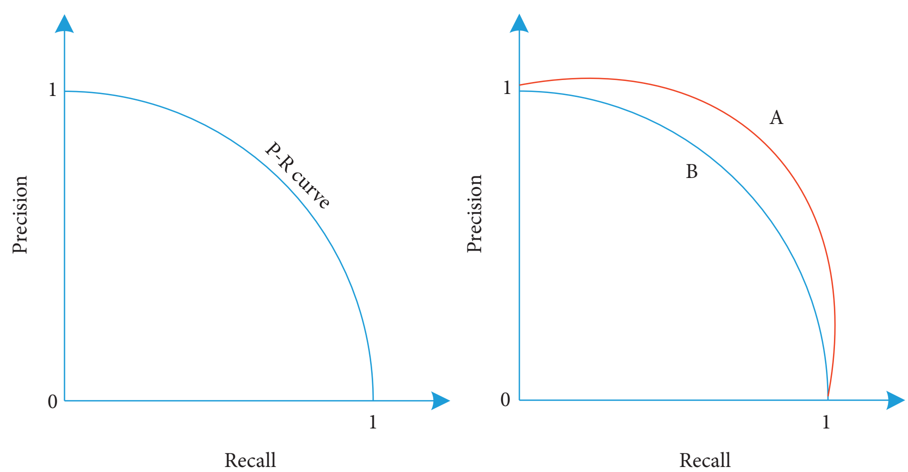


Figure 10: P-R curve diagram.

Table 2: Comparison of algorithm performance at a moderate level.

Class	Method	Modality	3DmAP
Car	F-PointNet [16]	RGB + LiDAR	70.92%
	AVOD-FPN [18]		74.44%
	ContFuse [20]		73.25%
	MV3D [15]		62.68%
	Ours		**75.02%**
Pedestrian	F-PointNet [16]	RGB + LiDAR	61.32%
	AVOD-FPN [18]		58.8%
	ContFuse [20]		—
	MV3D [15]		—
	Ours		**62.51%**
Cyclist	F-PointNet [16]	RGB + LiDAR	56.49%
	AVOD-FPN [18]		49.7%
	ContFuse [20]		—
	MV3D [15]		—
	Ours		**57.26%**

the accuracy of the algorithm in all categories. The calculation formula is shown in (19), where C is the number of categories.

$$AP = \int_0^1 p(r)d(r), \tag{17}$$

$$AP = \sum_{k=1}^{N} p(k)\cdot r(k), \tag{18}$$

$$mAP = \frac{\left(\sum_{i=1}^{C} AP_i\right)}{C}. \tag{19}$$

In this paper, AP and mAP are used as evaluation indexes to measure the performance of the model. In the following tables, the test results of all algorithms participating in the comparison are the results published by the authors of the algorithm in their articles, and those undisclosed or unavailable experimental results are indicated

Table 3: Comparison of 3D positioning performance between our algorithm and the state-of-the-art algorithm.

Method	Modality	Car			Pedestrian			Cyclist		
		Easy	Moderate	Hard	Easy	Moderate	Hard	Easy	Moderate	Hard
PointPillars [22]	Only LiDAR	90.07	86.56	**82.81**	57.60	48.64	45.78	79.90	62.73	55.58
PointRCNN [33]		92.13	87.39	82.72	54.77	48.13	42.84	82.56	67.24	60.28
Part-A^2 [29]		94.07	85.35	75.88	59.04	49.81	45.92	83.43	68.73	61.85
PV-RCNN [39]		90.25	81.43	76.82	52.17	43.29	40.29	78.60	63.71	57.65
SE-SSD [40]		91.49	82.54	77.15	-	-	-	-	-	-
AVOD-FPN [18]	RGB + LiDAR	90.99	84.82	79.62	58.49	50.32	46.98	69.39	57.12	51.09
F-PointNet [16]		91.17	84.67	74.77	70.00	61.32	53.59	77.26	61.37	53.78
ContFuse [20]		94.07	85.35	75.88	—	—	—	—	—	—
MV3D [15]		86.62	78.93	69.80	—	—	—	—	—	—
Ours		**95.01**	**88.32**	80.57	**79.67**	**66.89**	**56.36**	**90.12**	**72.41**	**63.21**

Table 4: The detection result diagram of the network model.

Feature	Pedestrian			Runtime (s)
	Easy	Moderate	Hard	
Voxel feature only	70.87%	58.50%	50.13%	0.04
+Raw point cloud feature	+1.91%	+1.37%	+0.22%	0.02
+BEV feature	+2.82%	**+3.73%**	+2.75%	0.00
+RGB feature	**+4.07%**	+3.29%	**+3.26%**	0.04
Full model	**79.67%**	**66.89%**	**56.36%**	**0.10**

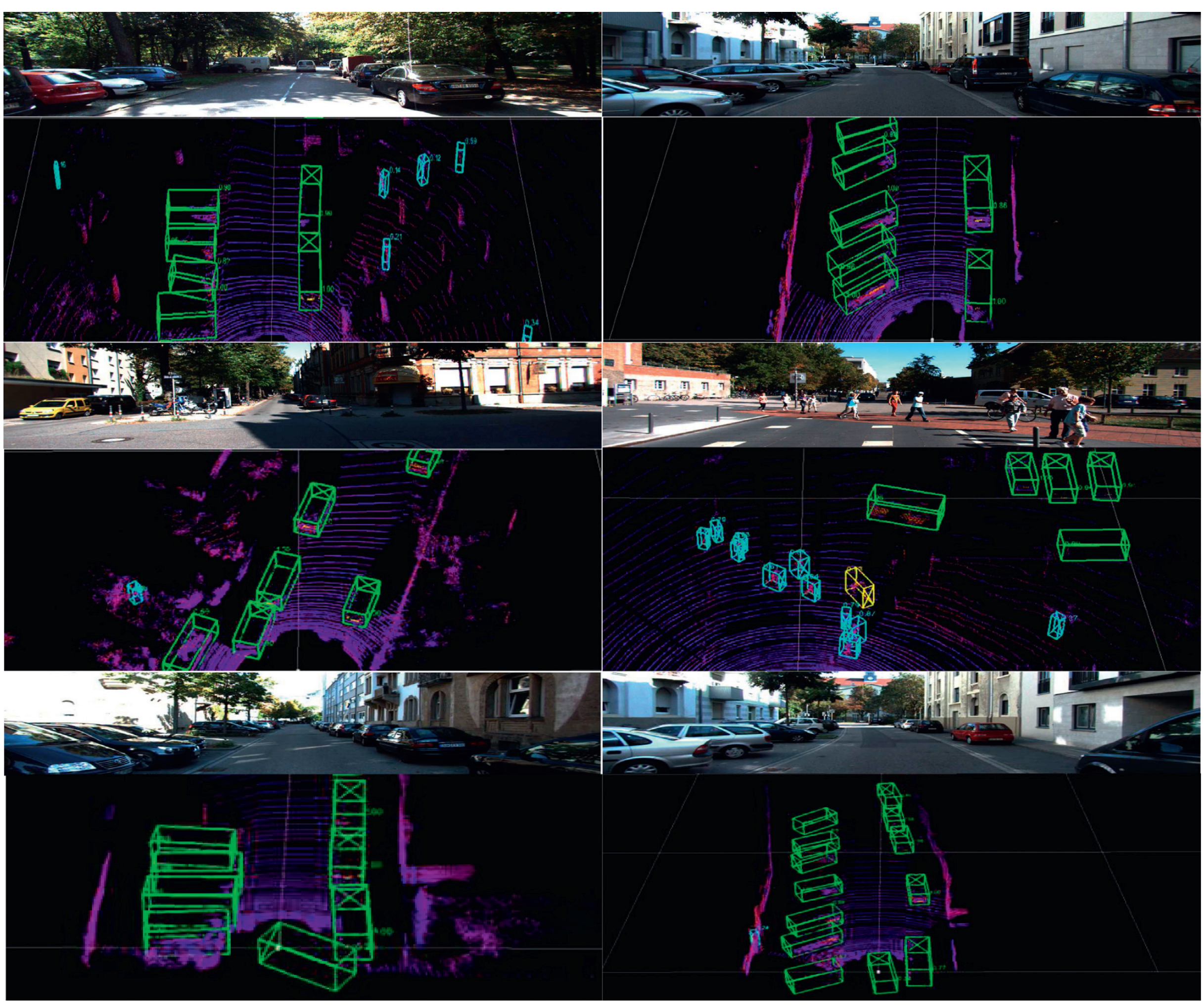


Figure 11: The detection result diagram of the network model.

by “-” or not included in the comparison. The optimal value of each test is shown in bold. The results of comparing our work comparing with current state-of-the-art fusion algorithms are shown in Tables 2 and 3.

Table 2 shows that, among all the fusion methods of LiDAR and RGB images, our method has a significant improvement in mAP in the detection of pedestrians and cyclists. The main reason is that there are less data for pedestrians and cyclists in the pure point cloud data; thus it is difficult to detect. By adding the semantic information of the image, we can determine the boundary box of the target object in the image and then project it into the point cloud, which ensures that the projected frustum definitely contains a certain type of object. In this way, the detection accuracy of pedestrians and cyclists with less point cloud data can be increased.

In Table 3, we show the comparison results of the 3D positioning accuracy AP(BEV)% comparing with some state-of-the-art algorithms.

It can be found from Table 3 that the location results of our algorithm are comparable to the state-of-the-art algorithms, and the performance is more obvious in the easy category of pedestrians and cyclists. The result proves that when our algorithm generates BEV, using redundant information for compression helps information loss.

To verify whether the semantic information of RGB images we added improves the network model, we, respectively, trained the network model only extracts voxel features, the network model with raw point cloud features added, the network model with BEV features added, and the network model with image information added, and the contribution of adding different feature information to the network model is shown in Table 4.

Through Table 4 we can see that the detection accuracy of the network model is improved due to the inclusion of image semantic features. Since the network uses parallel processing, the detection accuracy of the network model depends mainly on the voxel features of the point cloud, and the RGB image features are only used as auxiliary features to improve the detection accuracy of the algorithm, so the overall performance of the algorithm does not depend too much on the detection accuracy of the 2D detector. Finally, at the end of the paper, we give a set of final results of our algorithm as shown in Figure 11.

6. Conclusion

In order to integrate point cloud data and image data better, this article proposed a 3D object detection network architecture based on two-stage complementary fusion. The architecture uses key points as the connection bridge and successfully combines Point-based, Voxel-based, and Image-based methods. Detecting through 3D point cloud targets driven by 2D detectors further improved the detection result of pedestrians and cyclists, which have a small amount of point cloud data. The disadvantage is that there is redundant information between extracting features using Point-based methods for point cloud data within a frustum and using Point-based methods for the raw point cloud, which increases the running time of the network model. In the future we plan to introduce point cloud feature alignment methods, so that we can apply feature similarity alignment to the global features from the original point cloud and the local features from the point cloud inside the frustum. For the two features with high similarity, we discard the global features in the original point cloud and keep the point cloud features in the frustum and the target class and 2D bounding box information provided by the 2D detector, so that the retained features can participate in the subsequent calculation. In this way, we can reduce the redundancy of information and improve the efficiency of the network.

Data Availability

All data and program included in this study are available upon request by contact with the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was supported by the National Natural Science Foundation of China (61971007 and 61571013).

References

[1] Z. Dai, B. Cai, Y. Lin, and J. Chen, “UP-DETR: unsupervised pre-training for object detection with transformers,” in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020.

[2] K. J. Joseph, S. Khan, F. S. Khan, and V. N. Balasubramanian, “Towards open world object detection,” in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, Nashville, TN, USA, June 2021.

[3] Q. Chen, Y. Wang, T. Yang, X. Zhang, J. Cheng, and J. Sun, “You only look one-level feature,” in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, Nashville, TN, USA, June 2021.

[4] C. Yang, Z. Wu, B. Zhou, and S. Lin, “Instance localization for self-supervised detection pretraining,” in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, Nashville, TN, USA, June 2021.

[5] T. Liang, Y. Wang, Z. Tang, G. Hu, and H. O. P. A. N. A. S. Ling, “One-shot path aggregation network architecture search for object detection,” in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, Nashville, TN, USA, June 2021.

[6] V. S. Vibashan, P. Oza, V. A. Sindagi, V. Gupta, and V. M. Patel, “MeGA-CAD: memory guided attention for category-aware unsupervised domain adaptive object detection,” in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, Nashville, TN, USA, June 2021.

[7] M. Fan, S. Lai, J. Huang, and X. Wei, “Rethinking BiSeNet for real-time semantic segmentation,” in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, Nashville, TN, USA, June 2021.

[8] B. Sun, B. Li, S. Cai, Y Yuan, and C Zhang, “FSCE: few-shot object detection via contrastive proposal encoding,” in

Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR), Nashville, TN, USA, June 2021.

[9] S. Zheng, J. Lu, and H. Zhao, X Zhu, Z Luo, Y Wang et al., Rethinking semantic segmentation from a sequence-to-sequence perspective with transformers," in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, Nashville, TN, USA, June 2020.

[10] Y. Li, H. Zhao, X. Qi et al., "Fully convolutional networks for panoptic segmentation," in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.

[11] X. Chen, D. K. Ku, and Z. Zhang, "Monocular 3d object detection for autonomous driving," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2147–2156, Las Vegas, NV, USA, June 2016.

[12] T. He and S. Soatto, "Mono3D++: monocular 3D vehicle detection with two-scale 3D hypotheses and task priors," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, pp. 8409–8416, Honolulu, HI, USA, 2019.

[13] X. Chen, D. K. Ku, and Y. Zhu, "3d object proposals using stereo imagery for accurate object class detection[J]," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 40, no. 5, pp. 1259–1272, 2017.

[14] H. Hu, T. T. Zhao, and Q. Wang, "R-CNN based 3D object detection for autonomous driving," in *Proceedings of the International Conference of Transportation Professionals*, Xi'an, China, August 2020.

[15] X. Chen, H. M. Ma, J. Wan, B. Li, and T. Xia, "Multi-view 3d object detection network for autonomous driving," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, USA, July 2017.

[16] R. Qi, W. Liu, C. Wu, H. Su, and L. Guibas, "Frustum pointnets for 3d object detection from rgb-d data," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Salt Lake City, UT, USA, June 2018.

[17] X. X. Du, M. H. Ang, S. Karaman, and D. Rus, "A General Pipeline for 3d Detection of Vehicles," in *Proceedings of the International Conference on Robotics and Automation (ICRA)*, Brisbane, QLD, Australia, May 2018.

[18] J. Ku, M. Mozifian, J. Lee, H. Harakeh, and S. Waslander, "Joint 3d Proposal Generation and Object Detection from View Aggregation," in *Proceedings of the International Conference on Intelligent Robots and Systems (IROS)*, Madrid, Spain, October 2018.

[19] B. Yang, W. J. Luo, and R. Urtasun, "PIXOR: real-time 3d object detection from point clouds," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*, pp. 7652–7660, Salt Lake City, UT, USA, June 2018.

[20] M. Liang, L. Yang, S. H. Wang, and R. Urtasun, "Deep Continuous Fusion for Multi-Sensor 3d Object Detection," in *Proceedings of the European Conference on Computer Vision*, Munich, Germany, September 2018.

[21] B. Yang, M. Liang, and R. H. Urtasun, "HDNET: exploiting hd maps for 3d object detection," in *Proceedings of the 2nd Conference on Robot Learning (CoRL)*, Zürich, Switzerland, October 2018.

[22] A. H. Lang, S. Vora, H. Caesar, L. B. Zhang, J. Yang, and O. P. Beijbom, "PointPillars: fast Encoders for Object Detection from point Clouds," in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, Long Beach, CA, USA, June 2019.

[23] M. Liang, B. Yang, Y. Chen, R. Hu, and R. Urtasun, "Multi-task Multi-Sensor Fusion for 3d Object Detection," in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, Long Beach, CA, USA, June 2019.

[24] H. W. Yi, S. S. Shi, M. Y. Ding et al., "Segvoxelnet: exploring semantic context and depthaware features for 3d vehicle detection from point cloud," in *Proceedings of the IEEE International Conference on Robotics and Automation*, Paris, France, August 2020.

[25] S. R. Song and J. X. Xiao, "Deep sliding shapes for amodal 3d object detection in rgb-d images," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 808–816, Las Vegas, NV, USA, June 2016.

[26] Y. Zhou and O. Tuzel, "Voxelnet: end-to-end learning for point cloud based 3d object detection," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*, pp. 4490–4499, Salt Lake City, UT, USA, June 2018.

[27] Y. Yan, Y. Mao, and B. Li, "Second: sparsely embedded convolutional detection," *Sensors*, vol. 18, no. 10, p. 3337, 2018.

[28] Y. L. Chen, S. Liu, X. Y. Shen, and J. Y. Jia, "Fast point r-cnn," in *Proceedings of the IEEE international conference on computer vision (ICCV)*, Seoul, Korea (South), November 2019.

[29] S. S. Shi, Z. Wang, J. P. Shi, X. G. Wang, and H. S. Li, "From points to parts: 3d object detection from point cloud with part-aware and part-aggregation network," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 43, 2020.

[30] J. Q. Ngiam, B. Caine, W. Han et al., "Starnet: targeted computation for object detection in point clouds," https://arxiv.org/abs/1908.11069.

[31] R. Qi, H. Su, K. C. Mo, and L. P. Guibas, "PointNet: Deep learning on point sets for 3d classification and segmentation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 652–660, Honolulu, HI, USA, June 2017.

[32] R. Qi, H. Su, K. C. Mo, and L. P. Guibas, "PointNet plus plus: deep hierarchical feature learning on point sets in a metric space," in *Proceedings of the Advances in Neural Information Processing Systems*, pp. 5099–5108, Long Beach, CA, USA, December 2017.

[33] S. S. Shi, X. G. Wang, and H. S. Li, "Pointrcnn: 3d object proposal generation and detection from point cloud," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*, pp. 770–779, Long Beach, CA, USA, June 2019.

[34] Z. X. Wang and K. Jia, "Frustum Convnet: Sliding Frustums to Aggregate Local point-wise Features for Amodal 3d Object Detection," in *Proceedings of the International Conference on Intelligent Robots and Systems (IROS)*, Macau, China, November 2019.

[35] Z. T. Yang, Y. N. Sun, S. Liu, X. Y. Shen, and J. Y. Jia, "STD: Sparse-To-Dense 3d Object Detector for point Cloud," in *Proceedings of the International Conference on Computer Vision (ICCV)*, Seoul, Korea (South), November 2019.

[36] B. Graham, M. Engelcke, and V. Laurens, "3D semantic segmentation with submanifold sparse convolutional networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*, Salt Lake City, UT, USA, June 2018.

[37] B. Graham and L Maaten, "Submanifold Sparse Convolutional Networks," in *Proceedings of the CoRR*, June 2017.

[38] G. Jocher, yolov5, https://github.com/ultralytics/yolov5, 2021.

[39] S. S. Shi, C. X. Guo, L. Jiang et al., "PV-RCNN: point-voxel feature set abstraction for 3D object detection," in *Proceedings of the CVPR*, pp. 10529–10538, 2020.

[40] W. Zheng, W. Tang, and J. L. Se-Ssd, "SE-SSD: self-Ensembling Single-Stage Object Detector From Point Cloud et al," in *Proceedings of the CVPR*, 2021.

[41] A. Geiger, P. Lenz, and R. Urtasun, "Are we ready for autonomous driving? The KITTI vision benchmark suite," in *Proceedings of the IEEE Conference on Computer Vision & Pattern Recognition*, Providence, RI, USA, June 2012.

Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 6855435, 27 pages
https://doi.org/10.1155/2022/6855435

Research Article

Deep Learning-Based Solutions for 5G Network and 5G-Enabled Internet of Vehicles: Advances, Meta-Data Analysis, and Future Direction

Mubarak S. Almutairi

College of Computer Science and Engineering, University of Hafr Albatin, Hafar Al-Batin, Saudi Arabia

Correspondence should be addressed to Mubarak S. Almutairi; almutairi@uhb.edu.sa

Received 28 September 2021; Revised 22 November 2021; Accepted 18 December 2021; Published 18 January 2022

Academic Editor: Akif Akgul

Copyright © 2022 Mubarak S. Almutairi. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The advent of the 5G mobile network has brought a lot of benefits. However, it prompted new challenges on the 5G network cybersecurity defense system, resource management, energy, cache, and mobile network, therefore making the existing approaches obsolete to tackle the new challenges. As a result of that, research studies were conducted to investigate deep learning approaches in solving problems in 5G network and 5G powered Internet of Vehicles (IoVs). In this article, we present a survey on the applications of deep learning algorithms for solving problems in 5G mobile network and 5G powered IoV. The survey pointed out the recent advances on the adoption of deep learning variants in solving the challenges of 5G mobile network and 5G powered IoV. The deep learning algorithm solutions for security, energy, resource management, 5G-enabled IoV, and mobile network in 5G communication systems were presented including several other applications. New comprehensive taxonomies were created, and new comprehensive taxonomies were suggested, analysed, and presented. The challenges of the approaches are already discussed in the literature, and new perspective for solving the challenges was outlined and discussed. We believed that this article can stimulate new interest in practical applications of deep learning in 5G network and provide clear direction for novel approaches to expert researchers.

1. Introduction

The unprecedented quest for rapid mobile traffic calls opens the way for emerging mobile communication systems [1, 2]. The emerging wireless mobile networks are projected to provide sufficient support for high rate of data transfer [3] and applications that need innovative wireless radio technology paradigm [4]. In addition, it provides satellite communication for delivering enhanced broadband [5]. The diverse requirement of the emerging wireless mobile network can be satisfied through radio in intelligent adaptive learning and decision making [4]. The 5G wireless mobile network [6, 7] is expected to stimulate interest in new fundamental innovations [8, 9] that have an impact on video surveillance, monitoring services for processing stream at reliable high speed, high bandwidth, and network connectivity that is highly secured [10], and Internet of Vehicles (IoVs) forming 5G-enabled IoV [11]. The emerging 5G mobile wireless network has the potentials for ultrahigh bandwidth and communication latency that is ultralow [12]. The 5G mobile wireless network aims to provide reliable connectivity ubiquitously [13]. The 5G wireless mobile network offers 1000 times increased in Internet traffic and is expected to give support to the industries and the Internet of Things technology. The 5G wireless mobile networks have more complications in design compared with the existing mobile communication technology and its diverse applications [14]. Therefore, it requires advance artificial intelligent techniques to solve problems in the 5G wireless mobile networks.

As pointed out in [2], a lot of research and development on 5G has been conducted before it is commercialized in the year 2020. The resurfacing of artificial intelligence with full force can bring an alternative methodology in solving 5G problems with likely better performance compared with the traditional methods [14]. The increased complexity of the cellular mobile network indicated that machine learning, a subset of artificial intelligence, has the potential to effectively improve the technologies of 5G wireless mobile networks [15]. In machine learning, the new generation artificial neural networks-deep learning algorithms have been applied in different domains and found to produce remarkable output comparable to human experts [16]. Xu et al. [17] argued that in the era of the 5G, the generation of large-scale data as a result of activities emanating from mobile task requires the new generation artificial neural networks-deep learning algorithms for the data processing, especially in the area of speech recognition and computer vision. Klautau et al. [15] pointed out that the performance of the deep learning algorithms increases as the amount of data scales up. This characteristic of the deep learning algorithms makes them fit to solve large-scale problems in 5G wireless mobile networks.

The dissemination of the data in traditional networks is susceptible to limitations such as high latency, significant drop in packets, and network congestion as a result of increasing number of connected vehicles on the road. Thus, the combination of the intelligent transportation and the Internet of Things is motivated to develop the IoV that basically allows exchange of data with its surrounding environment: vehicles-to-vehicles, vehicles-to-infrastructure, vehicles-to-roadside units, vehicles-to-sensors, and vehicles-to-personal devices via wireless communication networks [18] which could be called vehicle-to-everything and autonomous vehicle applications [19].

Different architectures of the deep learning algorithms [20] such as the convolutional neural network (CNN), generative adversarial network (GAN), dense neural network (DDNN), deep reinforcement learning (DRL), long short-term memory (LSTM), autoencoder (AE), and deep recurrent neural network (DRNN) were applied in 5G to solve problems in cybersecurity defense system, resource management, energy, mobile networks, and 5G-enabled IoV.

This paper intends to conduct an in-depth literature review on the progress made by deep learning algorithms in developing solutions to different aspects of 5G wireless mobile networks and 5G-enabled IoV.

The paper intends to answer the following research questions:

(i) What are the deep learning architectures applied for solving problems in 5G mobile network?

(ii) How is the publication trend for the applications of deep learning algorithms in 5G networks?

(iii) What taxonomies can be created for the deep learning algorithms in 5G networks?

(iv) What is the extend of applying deep learning algorithms in 5G-enabled IoV?

(v) What are the challenges identified in the existing approaches of solving problems in 5G wireless mobile networks?

(vi) What are the promising directions as new perspective for solving the identified challenges?

The other sections of the paper are structured as follows. Section 2 presents the previous reviews conducted and outlines the differences with the current review. Section 3 provides the basic information about the deep learning algorithms frequently applied in 5G wireless mobile networks. Section 4 presents 5G wireless mobile network domains and classification of papers accordingly. Section 5 presents meta-data analysis. Section 6 points out challenges and future direction for research work before. Conclusions are presented in Section 7.

2. Previous Surveys and Motivation

In the literature, there are a number of reviews on the applications of deep learning in 5G wireless mobile network. As such, the paper dedicated this section to present the reviews and point out the differences with the current review. For example, Aldweesh et al. [21] conducted a survey on the applications of deep learning algorithms in detecting anomaly. It mainly focused on the cyber security defense system for the 5G wireless mobile network. In another survey, Restuccia and Melodia [22] were motivated by the fact that the 5G wireless mobile networks are based heavily on millimeter wave (mmWave) and the ultrawideband communications. Therefore, it focuses on the physical layer of the wireless mobile networks. The paper discusses the significance of real time deep learning algorithms at the physical layer. Similarly, Huang et al. [23] presented survey focusing on deep learning algorithm-based physical layer, mainly on the nonorthogonal multiple access (NOMA), massive MIMO, and mmWave. The existing surveys mainly focus on the physical layers and cyber security defense. However, a lot of topics remain unexplored in the previous surveys. In addition, the earlier surveys focus on a particular aspect of the 5G wireless mobile networks denying readers to see a broad view of the deep learning solutions in 5G wireless mobile network. A comprehensive taxonomy connecting different deep learning architectures with different tasks in 5G wireless mobile network is missing from the already published surveys. The current review covers all aspects of deep learning algorithm-based 5G wireless mobile network solutions to give the reader a broad view of the 5G wireless mobile networks research area on the applicability of different architectures of the deep learning algorithms. Another major issue with the previous survey is that no comprehensive taxonomy on the 5G wireless mobile network domains. In view of the limitations in the previous surveys conducted, this paper proposes a comprehensive taxonomy showing different deep learning architectures and tasks in 5G wireless mobile networks. Zhang et al. [24] presented a survey on the applications of deep learning algorithms in the general area of mobile and wireless networks unlike our proposal that mainly focuses on 5G wireless mobile networks.

2.1. The Adoption of Deep Learning Architecture in 5G Wireless Mobile Network. In this section, for unification of the research area, a taxonomy as shown in Figure 1 on the

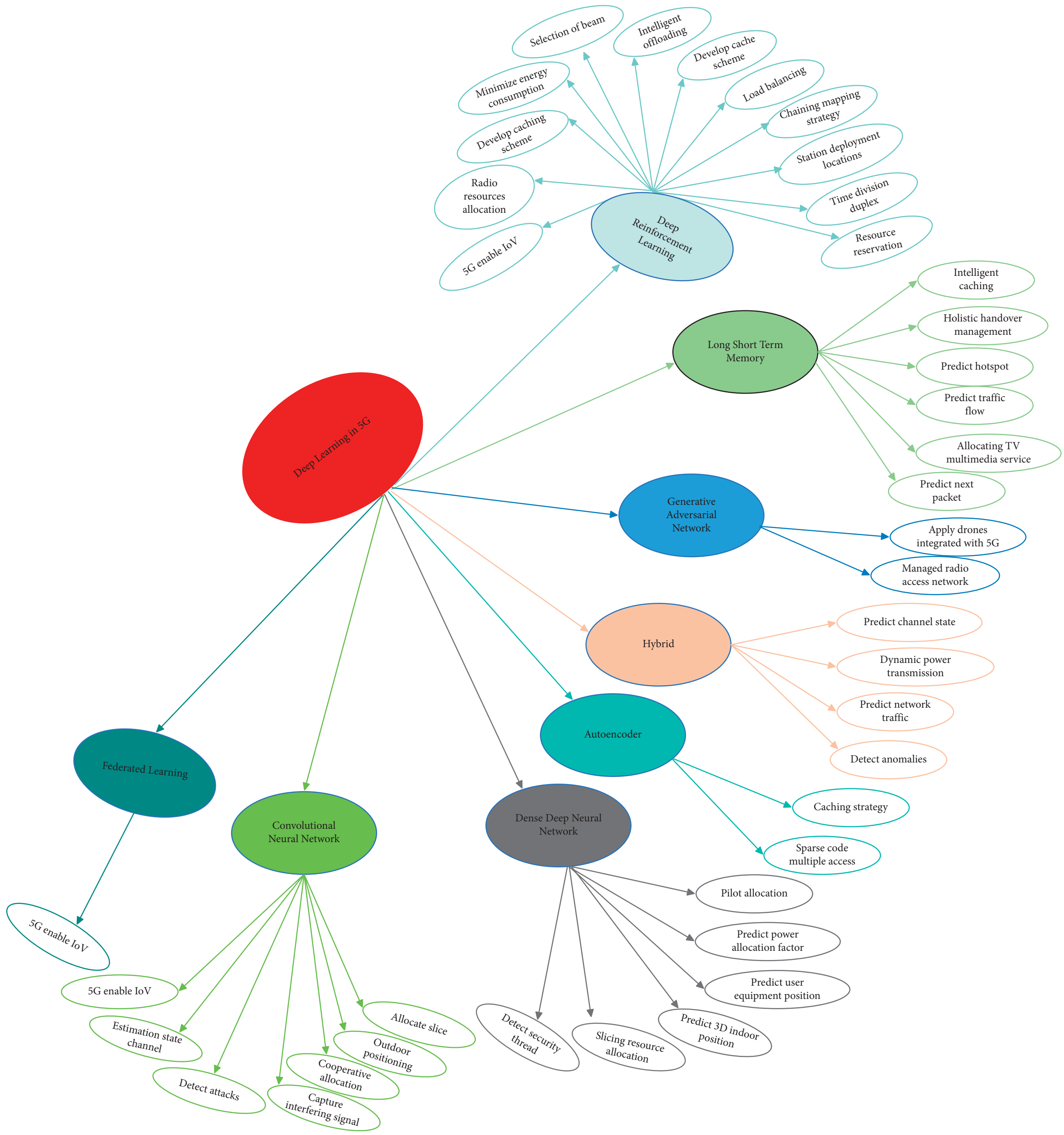


Figure 1: Taxonomy of the applications of deep learning in 5G wireless mobile networks.

adoption of deep learning architectures in performing different tasks in 5G wireless mobile networks is proposed. The taxonomy classified papers that applied deep learning algorithms in solving machine learning problems in 5G wireless mobile networks. The deep learning architectures together with the task associated to each of the deep learning architecture were extracted from different papers that used deep learning in 5G wireless mobile networks. The taxonomy can serve as a basis for the creation of deep learning-based 5G wireless mobile network framework that is holistic to be applied in 5G wireless mobile networks. The taxonomy is used as the foundation for extracting and classifying the different deep learning architectures available in the literature used for a particular task in the 5G wireless mobile networks. The deep learning architectures found to be applied in the 5G wireless mobile networks include CNN, DDNN, AE, GAN, LSTM, DRNN, hybrid deep learning, and DRL. The basic theory of each of the deep learning architecture is presented before summarizing the papers that applied it in 5G wireless mobile networks. The basic theories are presented to give readers understanding of how different deep learning architectures operate to achieve desired goal.

This can make the paper self-contained especially for new readers having the intention of starting a research career in this field.

2.2. Convolutional Neural Network. This section presents the background information about CNN and the studies that applied the CNN in 5G wireless mobile network to develop solution. The CNN is a type of feed forward neural network mostly used in image processing and pattern recognition. It is characterized by a simple structure, adaptability, and few training parameters [25]. The structure of a CNN consists of different layers including input layer, convolution layer, pooling layer, and the output layer. The convolution layer receives an input image and performs the convolution process by applying a filter to extract feature map. The pooling layer receives feature maps from the convolution layer and downsamples the feature maps. During the pooling process, n neighbouring pixels become a single pixel by adding a bias $bx+1$, scalar weighing $Wx+1$, and applying activation function, and a narrow feature map is produced. A major advantage of CNN is its parallel learning ability that helps in reducing the network's complexity. Again, it improved robustness, and scaling can be achieved by applying the subsampling process. The processing of output at the layers of CNN can be expressed by the following equations [25]:

$$O_{x,y}^{(l,k)} = \tanh\left(\sum_{t=0}^{f-1}\sum_{r=0}^{K_h}\sum_{c=0}^{K_w} W_{(r,c)}^{(k,t)} O_{(x+r,x+c)}^{(l-1,t)} + \text{Bias}^{(i,k)}\right), \quad (1)$$

where $O_{x,y}^{(l,k)}$ is the output of neuron at convolution layer l, feature pattern k, row x, and column y and f denotes the number of convolution cores in a given feature pattern. At the subsampling stage, the output of neuron at the lth subsampling layer, kth feature pattern, row x, and column y is expressed as follows:

$$O_{x,y}^{(l,k)} = \tanh\left(W^{(k)}\sum_{r=0}^{S_h}\sum_{c=0}^{S_w} O_{(x\times S_h+r,y\times S_w+c)}^{(l-1,t)} + \text{Bias}^{(i,k)}\right). \quad (2)$$

At the lth hidden layer H, the output of neuron j is given as follows:

$$O_{(l,j)} = \tanh\left(\sum_{k=0}^{s-1}\sum_{x=0}^{S_h}\sum_{y=0}^{S_w} W_{(x,y)}^{(j,k)} O_{(x,y)}^{(l-1,t)} + \text{Bias}^{(i,j)}\right), \quad (3)$$

where s denotes the number of feature patterns in the subsampling layer.

At the output layer, the output of neuron i at the lth output layer is expressed by the following equation:

$$O_{(l,i)} = \tanh\left(\sum_{j=0}^{H} O_{(l-1,j)} W_{(i,j)}^{l} + \text{Bias}^{(i,j)}\right). \quad (4)$$

2.2.1. The Studies That Applied Convolutional Neural Network in 5G Wireless Mobile Network. Bega et al. [26] developed a DeepCog based on 3D CNN for resource management in 5G mobile networks. In the 5G technology network, infrastructure is divided into slice. The DeepCog is designed to allocate each slice it is own required resources. The DeepCog is evaluated in the real world scenario, and it is found to be effective. Gante et al. [27] proposed temporal CNN for outdoor positioning of mmWave in 5G mobile wireless networks. The temporal CNN achieved baseline accuracy for the non-line-of-sight mmWave outdoor positions with 1.78 meters as the average error while maintaining moderate bandwidth, sample of binary data, and single anchor. Huang et al. [28] presented deep learning for the allocation of co-operative resources based on channel conditions in 5G mobile wireless networks. The study generated CNN by applying channel information and the resource allocation intended for optimization. The generated CNN can assist in making the full scale channel information in place of the traditional resource optimal utilization especially in a dynamic channel environment. The method is found to be effective in reducing the complexity of the optimization, reducing computational time, and producing satisfactory performance.

He et al. [29] proposed CNN to capture the characteristics of interfering signal to suppress the interfering signal. The proposed CNN-based multiuser multiple-input multiple-output (MU-MIMO) for 5G can be applied to suppress the influence of interference that is correlated with a reduced computational complexity and improve the performance of the CNN-based MU-MIMO. Hussain et al. [30] proposed CNN for the development of framework to detect distributed denial-of-service attack prompted by botnet that control devices that are malicious over 5G network. These attack mainly target the cyber physical system. The framework is found to have an accuracy of over 90% in detecting attacks.

Doan and Zhang [34] proposed CNN for anomaly detection in 5G mobile wireless networks. The CNN is found to be a good algorithm for the detection of intrusion while reducing the impact of latency.

Ahmed et al. [35] applied CNN to solve problem in spectrum access for 5G/B5G cognitive radio network of IoT. The intelligent CNN-based model learns to locate spectrum holes for users with over 90% accuracy. Cheng et al. [36] proposed an enhanced CNN with attention for modeling mmWave for the 5G network communications. The image data captured and locality feature extraction were performed using convolution while the attention enhances the use of the global information. The proposed scheme was found to be better than the classical methods. Guan et al. [37] proposed CNN transfer learning for the classification of network traffic in a dataset constrain scenario in 5G IoT. The model is trained by weight transferring and ANN finetuning. The CNN transfer learning was able to predict the network traffic with comparative performance to the classical methods. Xu et al. [38] proposed RGB stream and spatial rich model noise stream for differentiating between adversarial and clean examples. The CNN is used to detect adversarial image, and it achieved over 90% accuracy for the detection rate.

2.3. Deep Reinforcement Learning. The reinforcement learning (RL) falls among the top real time methods for decision making. It learns by interacting with the environment through action and recognition [39]. At every stage of interaction, depending on the environment's state, the agent selects an action that adjusts the state of the environment. A reward or punishment is given to the agent for every action taken depending on whether the action is beneficial or not.

The concept of RL is expressed as a Markov Decision Process (MDP) tuple given as (S, A, R, P), with S as the environment's state, A as action, R as reward, and P as the probability of state transition. The aim of RL is always to learn the best policy and maximize the sum of discounted reward of each state expressed as follows [39]:

$$J_{\pi^*} = \max_{\pi} J_{\pi} = \max_{\pi} E_{\pi}\left[\sum_{t=0}^{\infty} \gamma^t r_t\right], \tag{5}$$

where π^* and π denote the optimal policy and policy, respectively, J_π denotes total expected reward, $E_\pi[.]$ is the expectation based on the policy π and the transition probabilities, and γ is the discount factor in the range $[0, 1)$. The agent becomes opportunistic about the present reward when $\gamma = 0$ and strives for long-term great reward when $\gamma = 1$. r_t denotes the reward at time t.

The achievable return for execution of an action a in a state s is represented by the value function $Q(s, a)$. This can be updated according to each state-action pair till a given threshold turns out to be greater than the highest change in the value:

$$Q(s, a) \leftarrow \sum_{s'} p(s' \mid s, a)\left[r(s, a, s') + \gamma \max_{a} Q(s', a')\right], \tag{6}$$

where $p(s' \mid s, a)$ denote the transition probability from state s to state s' when action a has been executed, and the reward is denoted by $r(s, a, s')$. Following the convergence of the algorithm, the optimal policy is achieved by taking a greedy action on each state s. This is expressed as follows:

$$a^* = \arg\max_{a} Q^*(s, a), (\forall s \varepsilon S). \tag{7}$$

In situations where the system does not have prior knowledge about the environment, optimal policies can be achieved by a type of the RL algorithm known as Q-learning. Given α_t as the learning rate such that when $\alpha_t = 0$, the agent becomes incapable of learning, and when $\alpha_t = 1$, the agent only considers the most recent information. The updating rule of Q-learning is given as follows:

$$Q(s_t, a_t) = (1 - \alpha_t) Q(s_t, a_t) + \alpha_t\left(r_{t+1} + \gamma \max_{a} Q(s_{t+1}, a')\right). \tag{8}$$

This implies at time step t, state s_t is observed by the agent and an action a_t is chosen. Reward r_{t+1} is received by the agent for execution of the action a_t. Q-learning always tries to choose the optimal action by considering the state-action pair with the best Q-value. RL algorithms are very good in solving various problems especially problems relating to messaging and mobile network [39].

2.3.1. The Applications of the Deep Reinforcement Learning in 5G Wireless Mobile Network. The studies that applied DRL in solving machine learning problems are discussed in this section. Dai et al. [40] applied deep reinforcement learning (DRL) to develop caching scheme in 5G mobile network and beyond. Numerical results indicated that the DRL caching scheme is effective in maximizing caching resource utility. Dong et al. [41] proposed DRL to minimize normalize energy consumption for hybrid 5G mobile network technology in edge computing systems. Digital twin from the real network environment is used for the training of the DRL at central server offline. It was found that the proposed approach minimizes normalized energy consumption with less computational complexity better than the existing approaches.

Pradhan and Das [48] proposed RL for resource reservation in ultrareliable low latency communication for 5G network. It is found that the RL performs better than the baseline method in terms of the packet drop probability and resource utilization. Zhao et al. [49] proposed the application of RL for dynamic scheme of the network slice resources to improve quality of service in 5G network-enabled smart grid. The algorithm is able to change the demand of network at a fast rate of response for processing resource allocation. Ho et al. [50] proposed the application of DQN-based 5G-V2X for the optimization of 5G-based station allocation for platooning vehicles. It attempted to provide solution to the base station allocation problem. Xie et al. [51] applied DQN to develop an adaptive decision scheme for initial window in 5G MEC. The scheme is able to optimize the flow completion while minimizing the congestion. Comparison with baseline algorithms shows that the proposed scheme converges fast with stability. Supervised learning is introduced to improve the responsiveness and efficiency of the initial window decision.

Li and Zhang [52] applied DRL which is used in the 5G network to optimize the tradeoff between the quality of service and enhanced broadband and low latency communications. It is found that the quality of the service is achieved with the tradeoff between the enhanced mobile broadband and ultrareliable low latency communications. Yu et al. [53] proposed DRL for cloud radio access networks to maximize energy efficiency, service quality, and connectivity of remote radio heads. The proposed algorithm is found to effectively meet user requirement and handle cell outage compensation. Mismar et al. [54] used greedy nature DQN for the estimation of voice bearers and data bearer in sub-6 GHz mmWave band. The performance of the signal to interference plus noise ratio and sum-rate capacity has been improved. Saeidian et al. [55] proposed DQN downlink power control in 5G. It is found that the power control approach proposed in Saeidian et al. [55] improved data rate at the edge and reduced power transmitted compared with the baseline approaches. Abiko et al. [56] proposed DRL for the allocation of radio resources in 5G that satisfied service requirement notwithstanding the number of slices.

Giannopoulos et al. [57] applied DQN for the improvement of energy efficiency in multichannel transmission for 5G cognitive in decentralized, centralized, and transfer learning. Results indicated that the DQN model can enhance network energy efficiency. Gu et al. [58] developed the DRL knowledge-based assisted algorithm for the design of wireless schedulers for 5G networks with time sensitivity in traffic. The proposal improved quality of service and reduced convergence time. Yu et al. [53] designed DRL time scale consisting of fast and slow timescales learning process for optimizing resource allocation, computation offload, and caching placement. For protecting the edge device data privacy, federated learning is applied for training the DRL in a distributed approach. Experiment shows that the proposed approach reduces convergence time with over 30%. Dinh et al. [59] applied DQN for self-optimization of access point selection based on local network state knowledge. It was found that the proposed scheme enhances throughput and improves quality of service compared with the classical methods.

2.4. Autoencoder Architecture. The AEs are unsupervised learning algorithms capable of learning automatically from input data. The algorithms use simple learning circuits to convert input to output without significant alteration. The unsupervised training of AE takes a bottom-up fashion after which the supervised learning stage is employed for the training of the top layer and fine-tuning the whole architecture [60].

The framework of an $n/p/n$ autoencoder is expressed as a tuple $n, p, m, \mathbb{F}, \mathbb{G}, \mathscr{A}, \mathscr{B}, \mathscr{X}, \Delta$. In this case, $\mathscr{F}$ and $\mathbb{G}$ are sets, n and p are positive integers with $0 < p < n$, and $\mathscr{B}$ denotes class of functions from $\mathbb{G}^p$ to $\mathbb{F}^n$. $\mathscr{X} = \{x_1, \ldots, x_m\}$ is a set of m training vectors in $\mathbb{F}^n$. In the cases where external targets exist, the equivalent set of target vectors in $\mathbb{F}^n$ is represented by $\mathscr{Y} = \{y_1, \ldots, y_m\}$. Δ signifies the alteration function over $\mathbb{F}^n$. $\mathscr{A}$ denotes class of functions from $\mathbb{G}^p$ to $\mathbb{F}^n$. For each $A \in \mathscr{A}$ and any $B \in \mathscr{B}$, autoencoder transforms received vector $x \in \mathbb{F}^n$ into an output vector $A^\circ B(x) \in \mathbb{F}^n$. The aim is to achieve $A \in \mathscr{A}$ and $B \in \mathscr{B}$ that minimize the entire alteration function by this equation:

$$\min E(A, B) = \min_{A,B} \sum_{t=1}^{m} E(x_t) = \min_{A,B} \sum_{t=1}^{m} \Delta(A^\circ B(x_t), x_t). \tag{9}$$

In nonautoassociative situations where external targets y_t are given, the distortion minimization is defined as follows:

$$\min E(A, B) = \min_{A,B} \sum_{t=1}^{m} E(x_t, y_t) = \min_{A,B} \sum_{t=1}^{m} \Delta(A^\circ B(x_t), y_t), \tag{10}$$

$p < n$ occurs in cases where the autoencoder tries to apply a kind of feature extraction or compression. Different combinations of transformation classes $\mathscr{A}$ and $\mathscr{B}$, $\mathscr{F}$ and $\mathbb{G}$ sets, and distortion function Δ along with some additional constraints can be used to produce various architectures of autoencoders.

2.4.1. The Autoencoder Architecture Applications in 5G Wireless Mobile Network. The papers that applied AE in solving problem in 5G wireless mobile network are discussed in this section. For example, Lei et al. [61] proposed caching strategy based on Stacked Sparse AE (SSAE) in Evolved Packet Core of the 5G mobile wireless networks. The network functions virtual (NFV)/software defined network (SDN) is used for the development of the virtual distributed deep learning on the SSAE. Subsequently, the SSAE predicted the content popularity. The caching strategy is generated by SDN controller based on the predicted result and then synchronizing to each node of the cache via the flow table for the strategy execution. The deep learning-based strategy is found to improve the performance of the cache better than the baseline methods. Kim et al. [62] presented deep autoencoder sparse code multiple access (Deep-SCMA) for 5G mobile wireless networks. The Deep-SCMA codebook reduces the bit error rate by adaptive construction and deep autoencoder-based decoding and encoding. Results indicated that the Deep-SCMA scheme achieved lower bit error rate and fast computational time better than the conventional scheme.

2.5. Hybrid Deep Learning Algorithm. The purpose of hybridizing intelligent algorithms is to explore the strength of the individual algorithms [63, 64]. Some of the studies combined different deep learning architectures to form the hybrid algorithm. Before dueling into the hybrid architectures, brief discussion about the hybrid algorithm is presented. The hybrid intelligent algorithm is typically robust and efficient because it combined the complimentary features to deviate from the weakness of the constituent algorithms. Algorithms are hybridized because of performance improvement, multitask applications, and achieving multiple functions. The degree of interaction between the modules in hybrid models varies; it can be loosely coupled, tight coupled, fully coupled, and transformational [65]. The hybridization of the algorithms strengthens synergetic effects to the algorithms as individual algorithm limitation is overcome. The hybridization of the intelligent algorithms has brought a lot of new intelligent algorithms design [66].

2.5.1. Applications of Hybrid Deep Learning Architecture in 5G Wireless Mobile Network. Some of the studies combined different architectures of the deep learning to form hybrid architecture while others combined deep learning and shallow algorithm to form the hybrid. This section presents the papers that design hybrid deep learning for solving machine learning problem in 5G wireless mobile network. Luo et al. [67] employed the hybrid of CNN and LSTM (CNN-LSTM) to predict channel state information in a 5G wireless mobile network. Two outdoor and two indoor scenarios were used for the evaluation of the proposed scheme. The result indicated that the CNN-LSTM predicts channel state information in 5G network with the average different ratio of 2.650%–3.457% within very fast convergence time. Similarly, Huang et al. [68] proposed a combination of CNN and LSTM (CNN-LSTM)-based multitasking for the prediction of 5G mobile network traffic loads. The CNN-LSTM model is found to successfully extract geographical and temporal features. The CNN-LSTM can predict the minimum, maximum, and average traffic loads in the 5G mobile network, and it performs better than the baseline algorithms. Luo et al. [69] proposed combination of CNN and deep Q-learning (CNN–DQL) scheme for dynamic transmission power control to improve the performance of the non-line-of-sight transmission in 5G network. The CNN is used to predict the q-function offline before conducting online deep q-learning to search for the control strategy. The approach is found to maximize power transmission and quality of service.

Simulation result shows that the proposed CNN-LSTM detected the altered biometrics.

The DBN and the LSTM-based anomaly detection scheme inspect the network traffic flow in real time. The first level in the scheme executed the DBN on each RAN very fast. Subsequently, it detected the anomalous symptoms on the network traffic flow. The anomalous symptoms collected served as inputs to LSTM where the LSTM identified pattern of the cyber-attacks. The work has been extended in [77] with more extensive and comprehensive results.

2.6. Long Short-Term Memory. The LSTM solves a major problem of vanishing gradient or exploding gradient associated with the recurrent neural networks (RNNs). The error posed by the vanishing gradient problem prevents RNNs from learning in situations where the time lag between the input events and the target signals is above 5–10 distinct time steps. The LSTM on the other side is capable of linking minimum time-lags up to 1000 distinct time steps. It does this through special units termed as cells which comprise of constant error carousels (CECs) that impose constant error flow [80]. Access to the cells is granted by multiplicative gate units.

The hidden layer of a standard LSTM network consists of the memory blocks. A memory block has some memory cells and a pair of multiplicative gate units that allow flow of input and output to and from all the cells in the given block. A memory cell contains the CEC which handles the vanishing gradient error problem by keeping its local backflow error constant (without vanishing or exploding) when the cell is not receiving new input or error signals. The pair of gating units: input and output gates shield the CEC from both forward and backward error flow, respectively. The activation of the CEC determines the state of the cell. The activation of the input gate y^{in} and the activation of the output gate y^{out} given discrete time steps $t = 1, 2, \ldots, A$ can be computed by the following [80]:

$$\begin{aligned}
\text{net}_{\text{out}_j}(t) &= \sum_m w_{\text{out}_j m} y^m(t-1),\ y^{\text{out}_j}(t) = f_{\text{out}_j}\left(\text{net}_{\text{out}_j}(t)\right),\\
\text{net}_{\text{in}_j}(t) &= \sum_m w_{\text{in}_j m} y^m(t-1),\ y^{\text{in}_j}(t) = f_{\text{in}_j}\left(\text{net}_{\text{in}_j}(t)\right),
\end{aligned} \tag{11}$$

where j denotes memory block, f denotes the logistic sigmoid in the range $[0, 1]$, and w_{l_m} denotes the connection weight from the unit m to the unit l.

To compute the internal state of a given memory cell $S_c(t)$, the squashed gate input at $(t-1)$ where $(t > 0)$ can be added as follows:

$$\begin{aligned}
\text{net}_{c_j^v}(t) &= \sum_m w_{c_j^v m} y^m(t-1),\\
S_{c_j^v}(t) &= S_{c_j^v}(t-1) + y^{in_j}(t) g\left(\text{net}_{c_j^v}(t)\right),
\end{aligned} \tag{12}$$

where c_j^v denotes cell v of memory block j, squashing of the cell input is done by g, and $S_{c_j^v}(0) = 0$. To determine the output of a cell y^c, the internal state S_c is squashed using an output squashing function h and gating it with the activation of the output gate y^{out} expressed as follows:

$$y^{c_j^v}(t) = y^{\text{out}_j}(t) h\left(S_{c_j^v}(t)\right), \tag{13}$$

where h denotes a centered sigmoid in the range $[-1, 1]$.

The output units K of a network with layered topology consisting of hidden layer with memory blocks, standard input, and output layer can be defined by the equation as follows:

$$\begin{aligned}
\text{net}_k(t) &= \sum_m w_{km} y^m(t-1),\\
y^k(t) &= f_k\left(\text{net}_k(t)\right),
\end{aligned} \tag{14}$$

where f_k denotes the squashing function with logistic sigmoid in the range $[0, 1]$ and m ranges over all input units and the cells in the hidden layer. The LSTM is capable of solving tasks with complex long time-lags that was never solved by RNN.

2.6.1. Exploring Long Short-Term Memory in 5G Wireless Mobile Network. The LSTM has been explored in finding solution to machine learning problem in 5G wireless mobile network.

Yu et al. [9] studied resource allocation of TV multimedia service for 5G wireless cloud network random access network. The study proposes a deep learning framework for resource allocation. The DRL is integrated with bandwidth of the users and power resource allocation. Subsequently, the LSTM is applied for the construction of traffic multicast service, and it improves energy efficiency. Liu et al. [82] proposed LSTM to predict hotspot for potential formation of virtual small cell in 5G wireless network. The LSTM is found to predict the hotspot with accuracy and low latency and improve energy efficiency compared with the traditional approaches. Chen et al. [83] applied LSTM for the prediction of traffic flow in 5G mobile wireless network. The LSTM is combined with the broad learning system to improve the performance of the LSTM. Subsequently, the LSTM is used to predict the traffic flow in 5G wireless network and predict with accuracy while maintaining low complexity and convergence time. Memon et al. [84] predicted next packet time based on traffic trace using LSTM. The LSTM predicts the dynamic sleep time in discontinuous reception in 5G wireless mobile networks. It is found to improve power savings.

Gumaei et al. [85] combined blockchain and DRNN for edge computing 5G-enabled drone identification. Dataset was collected from raw radio frequency signals taken from many drones under several flight modes for the training of the DRNN model. The DRNN is applied to detect drones from radio frequency signals. Ullah et al. [86] used hybrid of control flow graph and DRNN for securing smart services rendered by 5G-enabled IoT. The DRNN is applied to predict clone applications. Results show that the approach recorded over 90% accuracy for cloned applications predictions from android application stores.

2.7. Generative Adversarial Networks. The GANs are deep learning models consisting of both supervised and unsupervised learning methods [87]. It basically uses two models, namely, generative and discriminative models as shown in Figure 2. The generative model acts as an image synthesizer and is capable of forging images that are analogous to real images. The discriminative model on the other side serves as an expert that isolates real images from forged images. Both the discriminative and the generative model compete against each other and are trained in parallel [88]. The discriminator gets access to images by interacting with the generator. An error signal sent to the discriminator guides it in identifying forged images, and generator uses the same error signal to forge more qualitative images. The two models are deployed in form of multilayer network having convolution and fully connected layers.

$$\max_{g} \min_{f} V(f, g) \equiv E_{x\sim\mathscr{P}X}[-\log f(x)] + E_{x\sim\mathscr{P}z} \cdot [-\log(1 - f(g(z)))]. \tag{15}$$

Given that x is a natural image obtained from a certain distribution $\mathscr{P}X$, and given z as random vector in $\mathbb{R}^d$ that comes from a uniform distribution in the range $[-1, 1]^d$; however, other normal distributions like the multivariate distribution can also be applied. Let the generative and discriminative models be denoted by g and f, respectively. The generative model receives z as an input image and forges an image $g(z)$ as output having the same form as x. Let $\mathscr{P}G$ denote the distribution of $g(z)$. The probability that an input image is obtained from $\mathscr{P}X$ is calculated by the discriminative model. Note that $f(x) = 1$ if $x \sim \mathscr{P}X$ and $f(x) = 0$ if $x \sim \mathscr{P}G$. The generative and the discriminative models of the GAN can be simultaneously trained by the following equations [87].

The equation given can be solved by alternating the two steps of updating gradient given as follows:

$$\begin{aligned} \text{1st step} &: \theta_f^{t+1} = \theta_f^t - \lambda^t \nabla_{\theta_f} V\left(f^t, g^t\right), \\ \text{2nd step} &: \theta_g^{t+1} = \theta_g^t - \lambda^t \nabla_{\theta_g} V\left(f^{t+1}, g^t\right), \end{aligned} \tag{16}$$

with θ_f and θ_g denote the parameters of f and g, respectively, t denotes iteration number, and λ denotes the learning rate x'.

2.8. Dense Deep Neural Network. The DDNN sometimes referred to as multilayer perceptrons (MLPs) or simply feedforward neural networks with multiple hidden layers is essential deep learning models with the goal of evaluating a function f^*. For instance, a classifier $y = f^*(x)$ maps an input x to a category y, and feedforward network works by defining a mapping $y = f(x; \theta)$ at the same time understands which values of θ give the excellent function approximation. The models are termed as feedforward because data pass from x through the function under evaluation via the intermediate computation that defines f and lastly to y which is the output. Feedforward neural networks are named networks because they are composed of multiple different functions. The functions are arranged in a form of a directed and acyclic graph. For instance, functions $f^{(1)}$, $f^{(2)}$, and $f^{(3)}$, linked together form a chain:

$$f(x) = f^{(3)}\left(f^{(2)}\left(f^{(1)}(x)\right)\right). \tag{17}$$

Generally, these forms of chain structures are the most applied structures for neural networks. $f^{(1)}$ is known as the first layer, $f^{(2)}$ being the second layer of the network and other layers follow the same pattern. The depth of a model is defined by the entire length of the chain. The last layer of the network is the output layer. At the training stage, $f(x)$ is derived to match f^*. Noisy and estimated examples of $f^*(x)$ evaluated at varying training points are provided by training data. This implies that for every example x, there is a label $y \approx f^*(x)$ attached to it. The essence of the training example is to clearly point out that at each point x, the output layer is expected to produce a value close to y. However, the training data do not specify the behavior of other layers instead the learning algorithm takes decision on how to exploit those layers to arrive at $\approx f^*(x)$. The layers are called hidden layers. Each hidden layer is a form of vector, and the dimension of the layers defines the model's width [91].

2.8.1. Exploring Dense Deep Neural Network in 5G Wireless Mobile Network. Butt et al. [95] proposed DNN for RF fingerprint for user equipment positioning in 5G mobile network. The DNN framework is able to predict the user equipment positioning in 5G network. Sim et al. [96] proposed DDNN for the selection of beam that is compatible with 5G new radio. The DDNN is able to select the mmWave beam, and it reduced the beam sweeping overhead. El Boudani et al. [97] proposed deep learning-based cooperative architecture in 5G network for 3D indoor positioning. The proposed approach is applied to predict 3D location of a mobile station, and it is found to perform better than the baseline algorithms. Thantharate et al. [98] used DDNN to detect and eliminate security thread before attacking 5G core wireless network. The proposed model has the ability to sell network slice as a service to service different services on single infrastructure that is reliable and highly secured. Chergui and Verikoukis [99] proposed deep learning for slicing resource allocation based on the service level agreement for 5G network reliability and end-end slicing. The gated RNN is used for the prediction of slices traffic while at every virtual network the DDNN is used to estimate the needed resources.

Ali et al. [100] proposed DNN for resource allocation to meet the requirement of the 5G network. The DNN achieved solutions for the resource allocation and remote radio head problems in the C-RAN. Rathore et al. [101] proposed DNN with blockchain for empowering security scheme for intelligent 5G IoT. The framework operated across the four layers of the emerging cloud computing architectures. The simulation of the proposed framework demonstrated efficiency and effectiveness in securing the 5G-enabled IoT systems.

2.9. The 5G Wireless Mobile Network Technology and 5G Powered Internet of Vehicle. This section presents the 5G technologies mostly targeted by the researchers for solution based on deep learning algorithms. The discussion includes the applicability of the 5G technologies in IoV. Few papers were found to apply deep learning algorithms to solve machine learning problems in 5G powered IoV. Chiroma et al. [102] argued that the deep learning algorithms are anticipated to drive the data analytics in IoV for better understanding and improvement of the IoV because large-scale data are predictable to be collected from the IoV as a result of vehicles mobility in the IoV environment.

The network slicing isolates the network functions logically and resources that are meant for the vertical market on a common infrastructure of a network. The network slicing can expand all the 5G network domains across the core network and radio access network segments [103]. The mmWave communications in the 5G significantly improve the amount of bandwidth [27]. The sparse code multiple access is a code-based nonorthogonal multiple accesses that improve spectral efficiency and connectivity that meet the standard of the 5G wireless mobile network [62]. Other 5G technologies are presented in Table 1. The 5G technologies in Table 1 are extracted from the papers analyzed in Section 3.

The 5G wireless mobile network was predicted to eliminate the challenges of the IoV by providing fast connection and low latency and offering a reliable connection for the IoV applications [105]. For example, the 5G network slicing can cope with variant use cases and different demands by many tenants over the 5G infrastructure in vehicle-to-everything communications ecosystem [103]. The 5G wireless mobile network can be used for guaranteeing security in IoV [19].

Insufficient spectrum motivated interest on enabling 5G vehicular communications at mmWave band. The mmWave band is the technology that offers very rich spectrum to support the flow of very large volume of data at high speed. It is crucial especially for the development of vehicular applications in view of the fact that the modern vehicles are embedded with a lot of sensors, as such it generates a lot of large-scale amount of data [106]. The 5G-based IoV embedded with SDN, Cloud, and Fog is developed by Benalia et al. [18]; the cloud and the fog enhance the processing and computing capability for controlling traffic. On the other hand, the flexibility, scalability, ease of programming, and global knowledge of the network are provided by the SDN. It uses the 5G MIMO and beamforming to get the high speed communication. The 5G-based IoV has the capacity of disseminating data efficiently with flexibility. The 5G slice for the vehicular infotainment application is anticipated to apply multiple radio access technology for the purpose of having high throughput as well as to cloud content remotely or near a node. The diagnosis and management of the vehicles are performed remotely via the slice configured to support the bidirectional flow of small amount of data with low frequency between vehicles and remote servers outside the core network [107].

2.9.1. Deep Learning Algorithms in 5G Wireless Mobile Network Powered Internet of Vehicles. In the 5G-based IoV, the network selection is performed by the Fuzzy CNN (FCNN). The vehicle-to-vehicle pairs were selected using the jellyfish optimization algorithm. The dynamic Q-learning and FCNN are applied to develop vertical handover decision that combined 5G mmWave, LTE, and DSRC in IoV. The performance of the Fuzzy CNN (FCNN) is evaluated using the following metrics: handover failure, handover success probability, redundant handover, throughput, packet loss, and delay [108]. Scarcity of the intensive study on data security and privacy preservation prompted the investigation of vehicular crowd sensing. A blockchain-enabled vehicular crowd sensing based on DRL is applied for the protection of user privacy and security safety in 5G powered IoV. The DRL is used for the selection of active miners and transactions, thus minimizing latency and maximizing security of blockchain. The nonorthogonal multiple access subchannels are allocated by the two-sided matching algorithm. The scheme is found to protect against common attacks, provide maximum security, and preserve privacy and integrity [109]. Similarly, privacy risk regarding centralized training of the model motivated the application of federated learning to develop a scheme based on federated learning in 5G powered IoV for recognition of license plate. The data for the modeling were harness in individual mobile phone in place of the server. It was found that the federated learning scheme preserved privacy and has high accuracy as well as effective communication cost (see Kong et al. [110]).

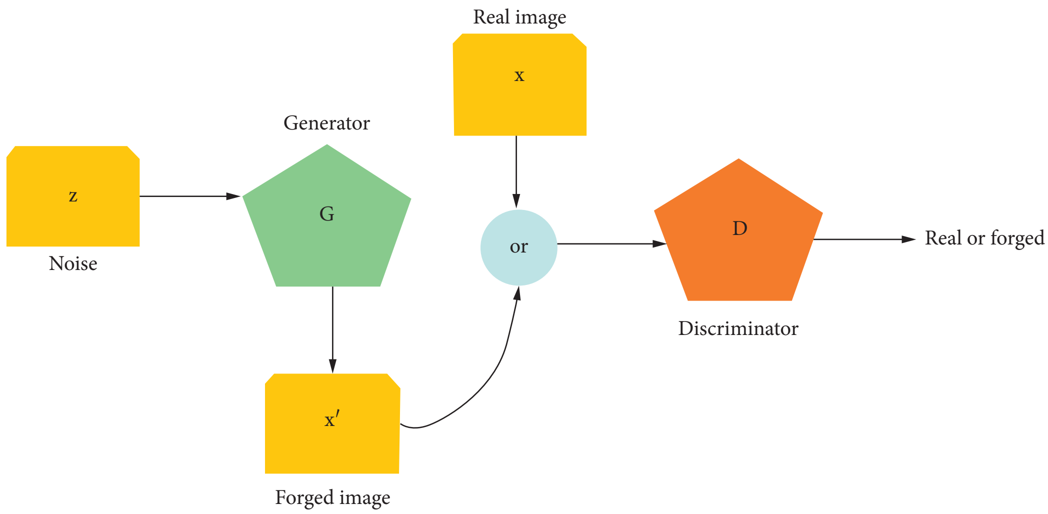


FIGURE 2: Typical architecture of generative adversarial network.

3. The 5G Wireless Mobile Network Domain

Figure 3 presents the taxonomy of the domain of applications in 5G wireless mobile technology. The taxonomy clearly indicated that a lot of domain in 5G witnessed the adoption of deep learning architectures for solving problems. The domain of applications includes cyber security defense system, resource management, signal, mobility, energy, networking, 5G-enabled vehicular network, and mobile network. The taxonomy revealed that different aspects of resource management and mobile network received tremendous attention from the researchers.

3.1. Resource Management. This section provides the applications of the deep learning algorithms in resource allocation in the 5G technology. Bega et al. [26] developed a DeepCog based on 3D CNN for resource management in 5G mobile network. In 5G technology, network infrastructure is divided into slice. The DeepCog is designed to allocate each slice it is own needed resources. The DeepCog is evaluated in the real-world scenario, and it is found to be very effective. Huang et al. [28] presented deep learning for the allocation of co-operative resources based on channel conditions in 5G mobile wireless network. The study generated CNN by applying channel information and the resource allocation intended for optimization. The generated CNN can assist in making the full scale channel information in place of the traditional resource optimal utilization especially in a dynamic channel environment. The method is found to be effective in reducing the complexity of optimization, reducing computational time, and producing satisfactory performance.

Chergui and Verikoukis [99] proposed deep learning for slicing resource allocation based on the service level agreement for 5G network reliability and end-end slicing. The gated recurrent neural network is used for the prediction of slices traffic while at every virtual network the DDNN is used to estimate the needed resources. Abbas et al. [90] proposed a network slicing scheme that can slice and effectively manage radio access network and core network resource. Subsequently, GAN is deployed to manage the network resources, and it is found to perform better in terms of bandwidth and latency. 5G-enabled TV multimedia allocation was studied by Yu et al. [9], and a deep learning framework was proposed. DRL is integrated with bandwidth of the users and power resource allocation. Subsequently, the LSTM is applied for the construction of traffic multicast service, and it improves energy efficiency.

Abiko et al. [56] proposed DRL for the allocation of radio resources in 5G that satisfied service requirement notwithstanding the number of slices. Ho et al. [50] proposed the application of DQN-based 5G-V2X for the optimization of 5G-based station allocation for platooning vehicles. It attempts to provide solution to the base station allocation problem. Zhao et al. [49] proposed the application of RL for dynamic scheme of the network slice resources to improve quality of service in 5G network-enabled smart grid. The algorithm is able to change the demand of network at a fast rate of response in the processing of resource allocation. Pradhan and Das [48] proposed RL for resource reservation in ultrareliable low-latency communication for 5G network. It is found that RL performs better than the baseline method in terms of the f packet drop probability and resource utilization.

Tang et al. [47] proposed DQN uplink/downlink resource allocation 5G heterogeneous network. The features of the complex network information were extracted using deep belief network. The Q-value based on the DQN with the reply is applied to change the time division duplex up/down link ratio based on the reward mechanism. The proposed DQN-based time division duplex is able to improve network performance based on throughput and packet loss rate compared with the resource allocation based on the traditional time division duplex. Li et al. [44] applied adaptive DQN for on-demand service function chaining mapping strategies in 5G. In the proposed approach, an agent makes decision from the heuristic service function chaining mapping algorithm with low complexity to meet the users' need. The proposal is found to enhance the entire system recourses efficiently by scheduling two heuristics effectively after learning from the episode.

Abidi et al. [70] hybridized glowworm swarm optimization and deer hunting optimization algorithm to optimize the structure of hybrid DBN and ANN for 5G network slicing. The proposed model is found to accurately provide 5G network slicing. Ahmed et al. [35] applied CNN to solve problem in spectrum access for 5G/B5G cognitive radio network of IoT. The intelligent CNN-based model learns to locate spectrum holes for users with over 90% accuracy. Ali et al. [100] proposed DNN for resource allocation to meet the requirement of the 5G network. The DNN achieved solutions for the resource allocation and remote radio head problems in the C-RAN.

3.2. Energy/Power Transmission. Energy/power transmission [111] is an issue in 5G wireless mobile network, as such many researchers applied deep learning algorithms for solving problem of energy efficiency [112] in the 5G network. Dong et al. [41] proposed DRL to minimize normalized energy consumption for hybrid 5G mobile network technology in edge computing systems. Digital twin from the real network environment is used for the training of the DRL at central server offline. It was found that the proposed approach minimizes normalized energy consumption with less computational complexity better than the existing approaches. Luo et al. [69] proposed combination of CNN and deep Q-learning (CNN-DQL) scheme for dynamic transmission power control to improve the performance of the non-line-of-sight transmission in 5G network. The CNN is used to predict the q-function offline before conducting online deep q-learning to search for the control strategy. The approach is found to maximize power transmission and quality of service. Saetan et al. [93] deviated from the impact of imperfect successive interference cancellation under the fairness perspective for downlink nonorthogonal multiple access. The DDNN is applied to predict the power allocation factor. Result indicates that the performance DDNN is in comparable to the exhaustive search. A similar study was carried out by Saetan and Thipchaksurat [94], but the focus was on sum-rate maximization. Liu et al. [82] proposed LSTM to predict hotspot for potential formation of virtual small cell in 5G wireless network. The LSTM is found to predict the hotspot with accuracy and low latency and improve energy efficiency compared with the traditional approaches.

Saeidian et al. [55] proposed DQN downlink power control in 5G. It is found that the power control approach proposed by Saeidian et al. [55] improves data rate at the edge and reduces power transmitted compared with baseline approaches. Yu et al. [46] proposed DRL for Cloud Radio Access Networks to maximize energy efficiency, service quality, and connectivity of remote radio heads. The proposed algorithm is found to effectively meet user requirement and handle cell outage compensation. Xia et al. [45] proposed the DQN-based offloading algorithm for 5G multicell MEC to obtain optimal offloading policy by the mobile phone users. It is found the proposed algorithm is able to outperform the baseline algorithm by significantly reducing the energy cost of the mobile device and the delay experience by the users of the mobile devices. Giannopoulos et al. [57] applied DQN for the improvement of energy efficiency in multichannel transmission for 5G cognitive in decentralized, centralized, and transfer learning. Results indicated that the DQN model can enhance network energy efficiency.

3.3. Cybersecurity Defense Systems. The 5G wireless mobile network requires protection from cyber-attacks [113]. Therefore, mechanism and protocol as basis for the protection of the 5G network are needed to address the security challenges [114]. Ravi [115] argued that it is highly necessary to proffer effective and efficient security breach detection mechanism using intelligent systems. Maimó et al. [76] proposed deep learning anomaly detection scheme for network flows to effectively and efficiently search for attacks in 5G mobile wireless network. The DBN and the LSTM-based anomaly detection scheme inspect the network traffic flow in real time. The first level in the scheme executes the DBN on each RAN very fast. Subsequently, it detects anomalous symptoms on the network traffic flow. The anomalous symptoms collected served as inputs to LSTM where the LSTM identified pattern of cyber-attacks. The work has been extended in [77] with more extensive and comprehensive results. Maimó et al. [78] extended the work in [77] by integrating mobile edge computing (MEC) architecture in the management of 5G wireless network anomaly detection autonomously in real time based on policies. The policies provide the effective, efficient, and dynamic management of the computing resources used during the process of the anomaly detection in 5G network traffic flow. Sundqvist et al. [79] proposed Adaboosted ensemble LSTM for the detection of anomalies in 5G radio access network. The proposed ensemble method is used to detect anomalies in 5G random access network. The Adaboosted ensemble LSTM is able to detect the anomalies in random access network very fast with reliability.

Thantharate et al. [98] used DDNN to detect and eliminate security thread before attacking 5G core wireless network. The proposed model has the ability to sell network slice as a service to service different services on single infrastructure that is reliable and highly secured. Doan and Zhang [34] proposed CNN for anomaly detection in 5G mobile wireless network. The CNN is found to be good algorithm for the detection of intrusion while reducing the impact of latency. Hussain et al. [30] proposed CNN for the development of framework to detect distributed denial-of-service attack over 5G network prompted by botnet that control devices that are malicious. These attack mainly target the cyber physical system. The framework is found to have an accuracy of over 90% in detecting attacks.

Table 1: 5G wireless mobile technology mostly applied deep learning algorithm.

References	5G technology
Bega et al. [26]; Thantharate et al. [98]; Abiko et al. [56]; Zhao et al. [49]; Abidi et al. [70]; Khan et al. [72]	Slice
Dai et al. [40]	Caching scheme
Dong et al. [41]	Hybrid 5G service
Gante et al. [27]; Yu et al. [104]; Cheng et al. [36]; Kaya and Viswanathan [73]; Zhang et al. [74]	mmWave
Huang et al. [68]	Traffic loads
Huang et al. [28]	Channel information
Kim et al. [92]	Massive MIMO
Kim et al. [62]	Sparse code multiple access
Klautau et al. [15]	Beam
Lei et al. [61]; Yu et al. [53]	Cache
Luo et al. [67]	Channel state information
Luo et al. [69]	Power transmission
Maimó et al. [76]; Doan and Zhang [34]; Chen et al. [83]; Maimó et al. [78]	Traffic flow
Ning et al. [42]; Ahmed et al. [35]	Spectrum
Ozturk et al. [81]; Klus et al. [32]	Handover
Pang et al. [12]	Intelligent cache scheme
Razaak et al. [89]	5G fixed wireless
Sadeghi et al. [43]	Scalable cache
Shahriari et al. [39]	Load balancing
Sundqvist et al. [79]; Abbas et al. [90]; Ali et al. [100]	Random access network
He et al. [29]	MU-MIMO
Li et al. [44]	Chaining
Xia et al. [45]	Multicell MEC
Saetan et al. [93]	Nonorthogonal multiple access
Pradhan and Das [48]; Li and Zhang [52]	Ultrareliable low-latency
Ho et al. [50]	5G-V2X
Tang et al. [47]; Xu et al. [38]	5G heterogeneous network
Chergui and Verikoukis [99]	Service level agreement
El Boudani et al. [97]; Guan et al. [37]; Rathore et al. [101]; Ullah et al. [86]	5G IoT network
Xie et al. [51]	5G MEC
Hussain et al. [30]	5G cyber physical system
Butt et al. [95]	User equipment positioning in 5G
Godala et al. [31]	5G new radio
Yu et al. [104]; Yu et al. [9]	Cloud radio access network
Liu et al. [82]	Virtual small cell
Mismar et al. [54]	Joint beamforming
Sim et al. [96]	New radio
Memon et al. [84]	Discontinue reception
Saeidian et al. [55]	Downlink power control
Alhazmi et al. [33]; Ahmed et al. [10]; Gumaei et al. [85]	5G signal
Clement et al. [71]	Modulation for 5G
Giannopoulos et al. [57]	5G cognitive
Gu et al. [58]; Dinh et al. [59]	Quality of service

Liu et al. [116] proposed federated learning framework for securing federated learning in 5G wireless network. Blockchain is embedded to protect the system against poisoning attacks. Performance analysis of the proposed framework indicated that the 5G-enabled federated learning framework is promising and robust. Ahmed et al. [10] proposed framework that uses 5G infrastructure based on pretrained CNN variants model with a transfer learning for multiple people tracking. The detection is performed by YOLOv3, and tracking is performed by the deep SORT algorithm. Experiment result indicated that it improves the transfer learning detection and tracking accuracy of the multiple people. Rathore et al. [101] proposed DNN with blockchain for empowering security scheme for intelligent 5G IoT. The framework operated across the four layers of the emerging cloud computing architectures. The simulation of the proposed framework demonstrated efficiency and effectiveness in securing the 5G-enabled IoT systems. Ullah et al. [86] used hybrid of control flow graph and DRNN for securing smart services rendered by 5G-enabled IoT. The DRNN is applied to predict clone applications. Results show that the approach recorded over 90% accuracy for cloned applications predictions from android application stores. Xu et al. [38] proposed RGB stream and spatial rich model noise stream for differentiating between adversarial and clean examples. The CNN is used to detect adversarial image, and

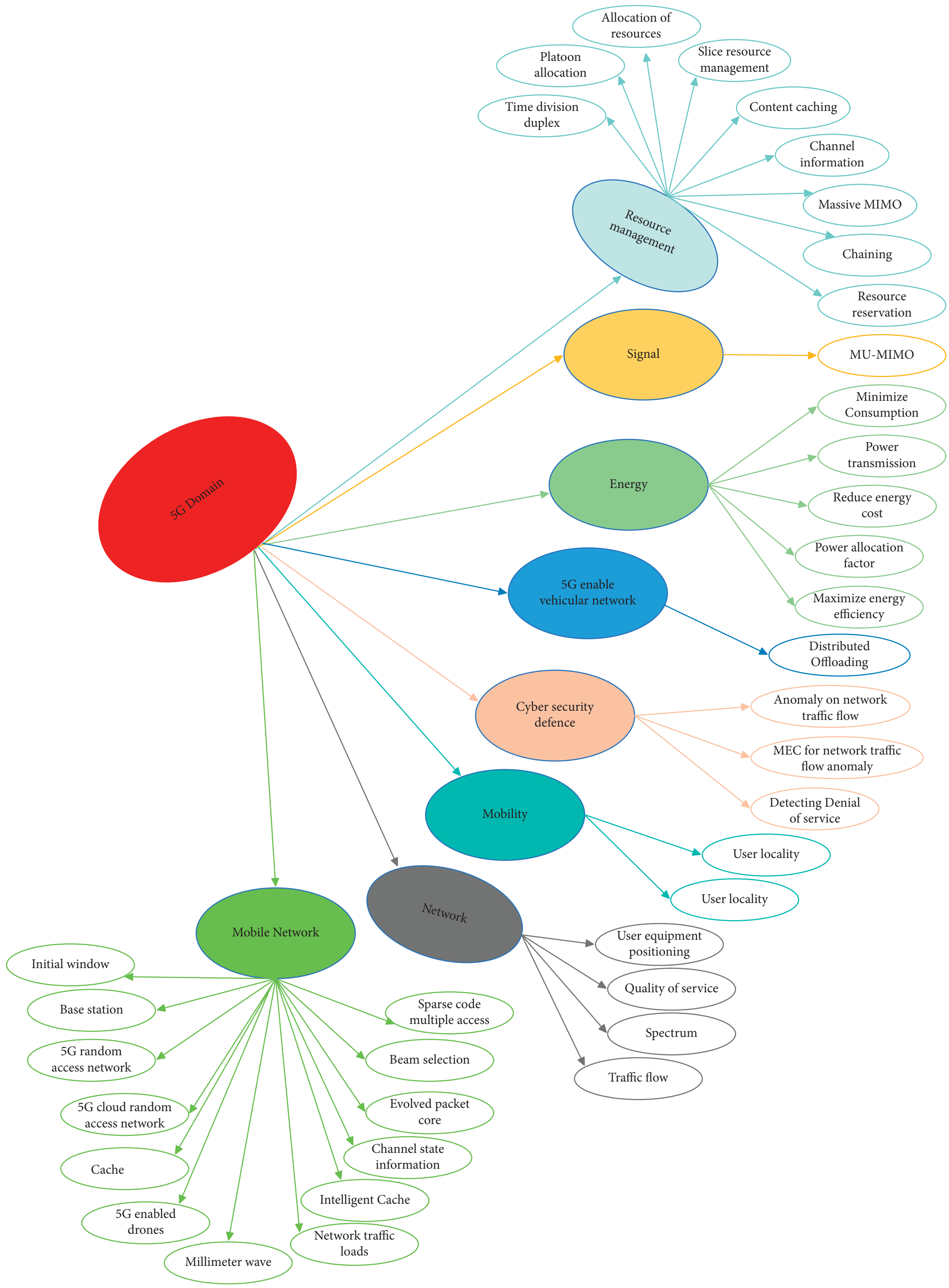


FIGURE 3: Taxonomy of the domain of applications in 5G wireless network.

it achieved over 90% accurate detection rate. Sedik et al. [75] used combination of CNN-LSTM for the detection of fake biometrics in 5G-based smart cities. The CNN-LSTM computes the 3-tier probability for the tempered biometric. Simulation result shows the proposed CNN-LSTM detects the altered biometrics.

3.4. Mobile Network. Ning et al. [42] developed an intelligent offloading framework based on DRL 5G-enabled vehicular networks that uses the combination of license spectrum and unlicensed spectrum channels. Distributed DRL-based approach is developed to significantly improve the communication between macrocell and vehicles. It was found to minimize offloading cost and maintain user latency constrain simultaneously. Lastly, the approach greatly simplifies distributed offloading traffic. Klautau et al. [15] proposed Deep Q-Learning (DQN) algorithm for the selection of beam based on 5G mobile network MIMO data. The channel realization with transceivers and objects that represent the 5G scenario is generated by combining vehicle traffic and ray tracing simulators. The mobility and channel were modeled. Gante et al. [27] proposed temporal CNN for outdoor positioning of millimeter wave in 5G mobile network. The temporal CNN achieved baseline accuracy for the non-line-of-sight millimeter wave outdoor positions with 1.78 meters as the average error while maintaining moderate bandwidth, sample of binary data, and single anchor. Dai et al. [40] applied deep reinforcement learning (DRL) to develop caching scheme in 5G mobile network and beyond. Numerical results indicated that the deep reinforcement learning caching scheme is effective in maximizing caching resource utility. Shahriari et al. [39] proposed the generic online learning system based on DRL for 5G cloud random access network load-balancer. The proposed approach is subsequently deployed for load balancing in the 5G cloud random access network. It was found that the communication load and caches misses are reduced with limited system overhead.

Kim et al. [62] presented deep autoencoder sparse code multiple access (Deep-SCMA) for 5G mobile wireless network. The Deep-SCMA codebook reduces the bit error rate by adaptive construction and deep autoencoder-based decoding and encoding. Results indicated that the Deep-SCMA scheme achieved lower bit error rate and fast computational time better than the conventional scheme. Luo et al. [67] employed the hybrid of CNN and LSTM (CNN-LSTM) to predict channel state information in a 5G wireless mobile network. Two outdoor and two indoor scenarios were used for the evaluation of the proposed scheme. The result indicated that the CNN-LSTM predicts channel state information in 5G network with the average different ratio of 2.650%–3.457% within very fast convergence time.

Huang et al. [68] proposed a combination of CNN and LSTM (CNN-LSTM)-based multitasking for the prediction of 5G mobile network traffic loads. The CNN-LSTM model is found to successfully extract geographical and temporal features. The CNN-LSTM can predict the minimum, maximum, and average traffic loads in the 5G mobile network, and it performs better than the baseline algorithms. Ozturk et al. [81] proposed the stacked LSTM model for cost evaluation of holistic handover that combined signaling overhead, latency, call dropping, and wastage of radio resource that focuses on control/data separation architecture. Analysis of the framework indicated that the stacked LSM has the potential for holistic handover management for 5G wireless network.

El Boudani et al. [97] proposed deep learning-based cooperative architecture in 5G network for 3D indoor positioning. The proposed approach is applied to predict 3D location of a mobile station, and it is found to perform better than the baseline algorithms. Sim et al. [96] proposed DDNN for the selection of beam that is compatible with 5G new radio. The DDNN is able to select the mmWave beam, and it reduced the beam sweeping overhead. Butt et al. [95] proposed DNN for RF fingerprint for user equipment positioning in 5G mobile network. The DNN framework is able to predict the user equipment positioning in 5G network. Memon et al. [84] predicted next packet time based on traffic trace using LSTM. The LSTM predicts the dynamic sleep time in discontinuous reception in 5G networks. It is found to improve power savings. Chen et al. [83] applied LSTM for the prediction of traffic flow in 5G mobile wireless network. The LSTM is combined with the broad learning system to improve the performance of the LSTM. Subsequently, the LSTM is used to predict the traffic flow in 5G wireless network and predict with accuracy while maintaining low complexity and convergence time. Mismar et al. [54] used greedy nature DQN for the estimation for voice bearers and data bearer in sub-6 GHz mmWave band. The performance of the signal to interference plus noise ratio and sum-rate capacity has been improved.

Li and Zhang [52] applied DRL in 5G network to achieve tradeoff between quality of service between enhanced mobile broad band and ultra-reliable low latency communications. It is found that the quality of the service is achieved with the tradeoff between the enhanced mobile broadband and ultra-reliable low latency communications. Xie et al. [51] applied DQN to develop an adaptive decision scheme for initial window in 5G MEC. The scheme is able to optimize the flow completion while minimizing the congestion. Comparison with baseline algorithms shows that the proposed scheme converges fast with stability. Supervised learning is introduced to improve the responsiveness and efficiency of the initial window decision.

Yu et al. [53] proposed DQN for the 3D aerial station-based station location for sudden traffic in 5G mmWave wireless network. Findings indicate that the DQN location scheme can search for the optimal deployment locations with very low convergence speed. Alhazmi et al. [33] proposed LeNet-5 a variant of CNN for the identification of signals in a cellular system environment. The LeNet-5 is able to successfully identify 5G signal, 3G, and long-term evolution in the environment. Klus et al. [32] proposed CNN for the prediction of user location. The model is first trained for the setting of the weights before reducing the unnecessary number of handovers at the same time sustaining high-quality connection at the second stage. The CNN model predicts user location and reduces number handover without affecting the throughput of the system. Godala et al. [31] proposed CNN for the estimation of state channel information in 5G mobile network new radio. It is found that the proposed framework enhances the spectral efficiency performance compared with the traditional methods.

Cheng et al. [36] proposed an enhanced CNN with attention for modeling mmWave for 5G network communications. The image data capture and locality feature extraction were performed using convolution while the attention enhances the use of global information. The proposed scheme was found to be better than the classical methods. Clement et al. [71] combined CNN, DDNN, and

LSTM to create hybrid deep architecture for the modulation classification of 5G and beyond wireless communications. Principal component analysis is used for dimension reduction. The proposed framework classified the modulation, and results show that it outperforms the constituent algorithms. Gu et al. [58] developed the DRL knowledge-based assisted algorithm for the design of wireless schedulers 5G networks with time sensitivity in traffic. The proposal improved quality of service and reduced convergence time. Guan et al. [37] proposed CNN transfer learning for the classification of network traffic in a dataset constrain scenario in 5G IoT. The model is trained by weight transferred and ANN fine-tuning. The CNN transfer learning was able to predict the network traffic with comparative performance compared with the classical methods. Gumaei et al. [85] combined blockchain and DRNN for edge computing 5G-enabled drone identification. Dataset was collected from raw radio frequency signals taken from many drones under several flight modes for the training of the DRNN model. The DRNN is applied to detect drones from radio frequency signals. Dinh et al. [59] applied DQN for self-optimization of access point selection based on local network state knowledge. It was found that the proposed scheme enhances throughput and improves quality of service compared with the classical methods.

Khan et al. [72] proposed of LSTM and SVM for reliable and efficient congestion control mechanism in 5G/6G wireless network. The simulation was conducted for data collected for multiple unknown devices, failure of slice, and overloading. Results show improvement in congestion control in 5G/6G network. Kaya and Viswanathan [73] applied LSTM and AE (LSTM-AE) for the prediction of beam in 5G mmWave. The proposed approach reduces blockage and handover by switching user to new beams or cells. The method reduces overhead and enhances signal-to-noise ratio. Zhang et al. [74] proposed DRL-LSTM for resource allocation in mmWave 5G network based on column generation. The DRL-LSTM addresses the routing and link scheduling for 5G network mmWawe.

3.5. Caching. Pang et al. [12] applied MEC to improve caching in 5G mobile network based on LSTM framework that expedites the smart-based intelligent caching instead of the commonly used frequency and time based for replacing the strategies as well as cooperation within the base stations. The LSTM intelligent-based cache framework detects the individual pattern request for individual based-station to take a decision based on the intelligent cache. The intelligent LSTM-based cache framework reduces transmission delay by at least 14%, and the backhaul data traffic saves up to 23%. Sadeghi et al. [43] proposed DRL-based cache scheme that employs Q-learning for the implementation of the best policy in online manner, thereby enabling the cache control unit of the base station to learn, monitor, and adjust to the environment dynamics. To embed the algorithm with scalability, the Q-learning linear function estimation is introduced which provides fast computational time and reduces complexity and requirement for memory. Lei et al. [61] proposed caching strategy based on Stacked Sparse AutoEncoder (SSAE) in Evolved Packet Core of the 5G mobile wireless network. The network functions virtual (NFV)/software defined network (SDN) is used for the development of the virtual distributed deep learning statement on SSAE. Subsequently, the SSAE predicted the content popularity. The caching strategy is generated by SDN controller based on the predicted result and then synchronizing to each node of the cache via the flow table for the strategy execution. The deep learning-based strategy is found to improve the performance of the cache better than the baseline methods.

3.6. Multiple-Input Multiple-Output. Kim et al. [92] developed DDNN-based pilot allocation scheme for 5G massive multiple-input multiple-output (MIMO) that used large number of antenna for multitude end users. It is found that the proposed approach improved the performance of the 5G network. The scheme recorded 99.38% accuracy with low complexity and convergence times. He et al. [29] proposed CNN to capture the characteristics of interfering signal to suppress the interfering signal. The proposed CNN-based multiuser multiple-input multiple-output (MU-MIMO) for 5G can be applied to suppress the influence of interference that is correlated with a reduced computational complexity and improve the performance of the CNN-based MU-MIMO.

3.7. Other Domain. Razaak et al. [89] applied GAN for precision farming. The GAN-based image analysis framework is developed for 5G wireless mobile network. The GAN-based unmanned aerial vehicle image processing framework indicated that precision farming can significantly benefit from the combination of 5G wireless network technology, unmanned aerial vehicle, and intelligent algorithm. It has been demonstrated that the intelligent framework has the potential of applying drones integrated with 5G and cameras for the monitoring of farm lands to reduce human intervention. Different deep learning algorithms in different 5G domains are presented in Table 2 where it shows the domain, deep learning architecture, and corresponding references for each of the architecture. Yu et al. [53] designed DRL time scale consisting of fast and slow timescales learning process for optimizing resource allocation, computation offload, and caching placement. For protecting the edge device data privacy, federated learning is applied for training the DRL in a distributed approach. Experiment shows that the proposed approach reduces convergence time with over 30%.

The main contributions found in each of the study, type of deep learning architecture adopted, and mobility level are summarized in Table 3 for easy outlook of the studies.

The deep learning architecture was extracted to show suitability of each architecture as well as the applicability in 5G wireless mobile network. The different deep learning architectures found in the literature used in the 5G wireless mobile network are summarized in Table 4 indicating the corresponding applications in 5G.

4. Discussion on the Deep Learning in 5G Network and 5G-Enabled IoV

4.1. General Overview. The deep learning algorithms found to be frequently used in the 5G wireless network and 5G-enabled IoV are as follows: GAN, DRL, CNN, LSTM, DRNN, DDNN, and hybrid of the deep learning algorithm. The basic theories of the different architectures are presented for the readers to understand how they operate to achieve their goal.

The review has indicated that it is possible to apply deep learning algorithms in solving machine learning problems in 5G wireless mobile network and 5G powered IoV. The deep learning algorithms have shown to perform better than the shallow machine learning algorithms/techniques as well as conventional approaches. The applications of different deep learning architecture in 5G wireless mobile network and 5G powered IoV are presented in the review. It is found that most of the works are on the applications of deep learning in 5G. On the other hand, the applications of deep learning in 5G powered IoV are limited with few number of recent papers.

Different taxonomies were created based on the 5G papers analyzed. The taxonomy created is as follows: 5G domains and deep learning algorithm connecting the 5G machine learning task and learning paradigm. The taxonomies clearly showed the gap that is existing, the area that attracted a lot of attention, and those with little attention in the 5G wireless mobile network. It is found that the DRL architecture received the highest number of applications in 5G wireless mobile network. On the issue of mobility, it is found that the mobility level is mostly outdoor. Resource management and mobile network in 5G wireless mobile network received tremendous attention from the research community. The learning paradigm showed that the reinforcement learning has the highest number of applications in 5G. Federated learning has limited applications; very few studies attempted to solve machine learning problem in 5G wireless mobile network that applied the federated learning.

The review indicated that there is a lot of interest from the research community for the synergy between the communications engineering and artificial intelligence research community fostering collaborations from the two communities. It is hoping that this collaboration will continue into the future because of the interest it has currently generated. In addition, the race to 6G has already begun though in an early stage as evident in Wu et al. [117]. As a result of that we believe that in the future, the collaboration between the communications engineering and artificial intelligence research communities will continue because of the advent of 6G wireless mobile communication that will open up new challenges requiring new machine learning solutions for improving the entire 6G wireless communication systems.

The applications of deep learning in 5G wireless mobile network were used in different technological aspects of the 5G. The technologies are tabulated in Table 1 with the corresponding references where the 5G technology was considered for a research. The technology of the 5G wireless network technology that received remarkable attention from the research community is the 5G network slicing.

The 5G technologies were found to be used to develop the 5G-enabled IoV to improve the performance of the IoV. The 5G technologies used for the improvement of the IoV are as follows: 5G network slicing, 5G mmWave, 5G MIMO, and beamforming. In conjunction with deep learning algorithms, the 5G-enabled IoV is improved on the area of security and privacy and network selection. The deep learning algorithms established to solve problems in 5G-enabled IoV include CNN, DRL, and federated learning leaving the greater percentage of the deep learning algorithms without exploring them in the 5G wireless mobile network.

4.2. Publication Trend. Figure 4 presents the publications of papers that applied deep learning algorithms in developing cyber defense systems for the 5G wireless mobile network. The publications start appearing in 2017 up to 2021. The publication trend indicated growing number of papers in the area as the papers keep on increasing from 2017 to date. This is practically showing growing interest in developing cyber defense system for the 5G wireless mobile network.

The publications of papers that applied deep learning algorithms in improving energy efficiency in 5G wireless mobile network are presented in Figure 5. Similar to cyber defense systems, the publications in this domain are growing up to 2020 before dropping in 2021. On the other hand, in the field of cyber security defense system, the publications went up in 2020 and dropped in 2021. Though they dropped in 2021, they are still much higher than the domain of 5G energy. Meaning is that there are more interest on the cyber security defense system compared with energy. The deep learning models are found to be effective, efficient, and robust in managing energy in 5G mobile network technology though not absolute as it is found in Falkenberg et al. [118] that random forest is better than the deep learning model in predicting power transmission used for the transmission of data in 5G wireless mobile network.

Figure 6 depicts the publication trend of the applications of deep learning algorithms in mobile network domain. The publications showed raising interest in mobile network domain of the 5G wireless communications because the papers keep increasing from 2017 to 2021. The number of the publications is more than that of energy/power transmission and cyber security defense systems. The interest in mobile network is more compared with the energy/power transmission and cyber security defense systems.

Figure 7 shows the applications of the deep learning algorithms in solving machine learning problems in managing resource in 5G. It shows growing number of publications on yearly basis. The longest bar indicated the most recent publications. This signifies that in recent times, there is a lot of interest in the resource management of the 5G wireless mobile network. However, it shows that the bar diminishes in 2021 indicating dropped in the number of publications.

Figure 8 is showing the overall publications in the application of deep learning algorithms in 5G wireless communications. The papers steadily increase from 2017 to 2020 before it suddenly dropped in 2021. In general, the interest in the adoption of deep learning in 5G wireless communications is increasing drastically based on paper published in the last 3 years as shown in Figure 8.

4.3. Learning Paradigm. Figure 9 is a taxonomy created from the data collected from the papers analyzed. The review article only used the data found in the applications of deep learning in 5G wireless communications. The learning paradigm for the 5G wireless communication is shown in Figure 8 forming taxonomy of the learning paradigm and the deep learning algorithms architecture associated with each learning paradigm. Variants of deep learning architecture such as CNN, GAN, AE, LSTM, DRL, hybrid deep learning, and DDNN are used for different learning paradigms.

It is indicated that the supervised learning has the highest number of deep learning variants which found to be applied in solving machine learning problems in 5G wireless communications showing that researchers heavily depend on the supervised learning for solving problems in 5G wireless network using different architectures of the deep learning algorithms. This is likely because of the availability of 5G wireless communications data having input and outputs. The multitasking learning received the lowest attention from the researchers likely because of limited need for multitasking learning in 5G wireless communications. Though multitask learning is not needed for 5G [119], it is needed in 6G-enabled MEC [120]. A lot of intensive work on multitasking in 5G wireless communications is required because of the limited number of publications found in the literature.

5. Challenges and Future Perspective

Despite the tremendous successes achieved in adopting deep learning architecture to solve problems in different domains of 5G wireless mobile network, yet, there are unresolved challenges. In this section, the challenges are discussed and alternative approaches to solve the challenges in the future are suggested.

5.1. Lack of Freely Available Large-Scale Data. In machine learning especially data analytic involving deep learning algorithms, large-scale dataset is key component. The performance of the deep learning algorithms in data analytic heavily depends on the scale of the available datasets. However, it is found that at present, there are no publicly available 5G large-scale data for benchmarking deep learning algorithms in 5G [15]. This is a challenge to the research community as it will definitely limit the number of research studies to be conducted by researchers and limit the study due lack of sufficient data. The lack of benchmark data set for 5G can hinder the basic foundation of proposing and evaluating new deep learning approach in solving problem related to large-scale learning in 5G wireless mobile network domain. In [30, 121], limited amount of data hindered large-scale study. Therefore, we propose research studies to develop a reliable repository for 5G large-scale data set to be available to researchers freely.

5.2. Complexity Constrain. In practice, machine learning mainly involved two stages, namely, training and testing. High complexity typically arises from the training phase of the machine learning compared with the testing phase of the machine learning process. In mobile terminal, there is the challenge of energy constrain and computational complexity constrain. Therefore, in this situation, deploying both the training and testing phase of the machine learning to the mobile terminal will result in high complexity in addition to the mobile terminal energy constrain which will further compound the challenge. As such, it is recommended for researchers to deploy only the testing phase of the machine learning systems to the shirt-pocket-sized mobile terminals [4].

5.3. Comparative Study. It is found that researchers mainly used single deep learning framework for implementing solutions, therefore limiting the study to the performance of a particular framework without subjecting comparative performance evaluation of the available deep learning frameworks. For instance, Maimó et al. [76] evaluated only Tensorflow without the comparative study of different deep learning frameworks. To determine the optimum suited deep learning framework, it is required to perform a comparative study to find the best deep learning framework with the highest performance in terms of processing [76].

5.4. Obsolete Security Protection Mechanism. The cybersecurity defense system of the 5G technology comes with new challenges as the current approaches used in protecting the mobile technology will become absolute because of the new advance features that 5G comes with. Typically, the 5G has added features of technology, and pattern of the intrusion by the hackers will change as a result of the 5G technological development. It is recommended that the existing cybersecurity defense be adapted to accommodate the new features of the 5G technology to keep protecting the system [76].

5.5. High Volume of Data. One of the main component of the 5G technology is the mmWave frequency communication. It delivers large-scale data at high rate for accommodating the uncompressed 4K UHD video as well as different consumer electronic devices that requires high throughput [122]. The data rates in 5G are 1000 times more than those in 4G [123]. The high volume of data means increasing space for data storage, processing, analytics, and mining which in turn increases hardware cost. This has automatically rendered shallow machine learning algorithms absolute. Now, it is

Table 2: Summary of different deep algorithms in different aspects of 5G wireless network.

Domain	CNN	DRL	DDNN	GAN	Autoencoder	LSTM/ DRNN	Hybrid algorithm
Resource management	Bega et al. [26]; Huang et al. [28]; Godala et al. [31]	Dai et al. [40]; Li et al. [44]; Pradhan and Das [48]; Zhao et al. [49]; Ho et al. [50]; Tang et al. [47]; Abiko et al. [56]	Kim et al. [92]; Chergui and Verikoukis [99]; El Boudani et al. [97]; Ali et al. [100]	Abbas et al. [90]			Abidi et al. [70]
Energy/ power transmission		Dong et al. [41]; Xia et al. [45]; Saeidian et al. [55]; Yu et al. [104]; Giannopoulos et al. [57]	Saetan et al. [93]			Liu et al. [82]; Memon et al. [84]	Luo et al. [69]
Network	Gante et al. [27]; Klus et al. [32]; Alhazmi et al. [33]; Guan et al. [37]	Klautau et al. [15]; Ning et al. [42]; Sadeghi et al. [43]; Shahriari et al. [39]; Yu et al. [9]; Xie et al. [51]; Li and Zhang [52]; Mismar et al. [54]; Cheng et al. [36]; Gu et al. [58]	Butt et al. [95]; Sim et al. [96]	Razaak et al. [89]	Kim et al. [62]; Lei et al. [61]	Ozturk et al. [81]; Pang et al. [12]; Yu et al. [9]; Chen et al. [83]; Gumaei et al. [85]	Huang et al. [68]; Luo et al. [67]; Sundqvist et al. [79]; Clement et al. [71]; Kaya and Viswanathan [73]; Khan et al. [72]; Dinh et al. [59]; Zhang et al. [74]
Cyber security system	Hussain et al. [30]; Doan and Zhang [34]; Xu et al. [38]		Thantharate et al. [98]; Rathore et al. [101]			Ullah et al. [86]	Maimó et al. [76]; Maimó et al. [78]; Liu et al. [116]; Sedik et al. [75]
Signal	He et al. [29]						

suggested that the deep learning algorithm with improve training speed should be considered in the future for processing data generated from 5G technology.

5.6. 5G Cybersecurity Defense System Is Vulnerable. The cybersecurity defense system for the 5G wireless mobile network heavily relied on machine learning for the development of the 5G cyber defense system. However, machine learning models are at safety risk. Developing the cyber defense system based on machine learning models is susceptible to vulnerabilities. The vulnerability of the learning system outlined by Pitropakis et al. [124] is as follows: the data for the training are prompt to poisonous injection by inserting Trojan horse into the machine learning model. The learning system is prompt to evasion attack at the testing phase to produce erroneous security alarm. The defense mechanism can be attacked by bypassing it to increase false negative or at the same time increase false positive and false negatives. Ftaimi and Mazri [125] pointed out that the deep learning models are vulnerable to adversarial attacks. We suggest that the future cybersecurity defense system for 5G wireless mobile network should be made to be robust by integrating with the mechanism to detect a possible backdoor attack on the learning systems and detect adversarial attacks on the cyber security defense system. The activation clustering methodology proposed by Chen et al. [126] can be applied to remove backdoor in the cybersecurity learning system for 5G wireless mobile network.

5.7. Restriction in 5G-Enabled Application. The development of the 5G-enabled applications like the vehicular network is restricted by cellular spectrum and energy constraints in the vehicular networks [42]. Massive and rigorous research studies are required to unravel the restrictions in the 5G-enabled applications.

5.8. 5G Ecosystem. The directional accuracy for a secured 5G ecosystem is yet to attain optimum. AS such, room for improvement still exists requiring further research to close the gap by developing secured 5G into mobile edge computing, core slicing, and radio access network. It is recommended to include traffic behavior learning in training the learning system in real time based on reinforcement learning and recurrent learning [98]. It should be extended to 6G [127].

5.9. Privacy. Collecting system logs from the live 5G wireless communication system can be difficult because of the issue of privacy, network disturbance, and repeated scenarios (see Sundqvist et al. [79]). The live data on the 5G wireless mobile network contain user data that are confidential in nature, in which not all users may like to expose it to third party. The systematic deep learning approach to conceal data confidentiality while processing the live 5G wireless network data remains an open challenge. Therefore, we have this research question for researchers: *What is the systematic deep learning approach to conceal data confidentiality before, during, and after modeling?*

Table 3: Summary of the contributions of the applications of deep learning 5G.

References	Mobility level	Deep learning architecture	Main contribution
Dong et al. [41]	Mobile edge	DRL	Minimizes normalized energy consumption with less complexity
Gante et al. [27]	Outdoor	Temporal CNN	Reduces the error of non-line-of-sight millimeter wave outdoor positions
Huang et al. [68]	Outdoor	CNN-LSTM	Improves traffic loads forecasting accuracy over baseline algorithms
Huang et al. [28]	User group	CNN	Reduces complexity of optimization and reduce computational time
Kim et al. [92]	User group	DDNN	Improves performance of cellular network while reducing computational time and complexity
Kim et al. [62]	Individual	Autoencoder	Deep-SCMA scheme performs better than conventional methods in terms of bit error rate and computational time
Klautau et al. [15]	Outdoor	DQL	Model channel and mobility
Lei et al. [61]	Individual	SSAE	Improves the performance of cache
Luo et al. [67]	Outdoor and indoor	CNN-LSTM	Converges fast in predicting channel information
Luo et al. [69]	User group	CNN-DQL	Maximizes power transmission
Maimó et al. [76]	Outdoor	DBN-LSTM	Detects symptoms on traffic flow
Maimó et al. [78]	Outdoor	DBN-LSTM	Integrates MEC in traffic flow for 5G
Ning et al. [42]	Vehicular network	DRL	Minimizes offloading cost and maintains user latency constrain simultaneously
Ozturk et al. [81]	Outdoor	Stacked LSTM	Potential for holistic handover management for 5G wireless network
Pang et al. [12]	Individual	LSTM	The intelligent framework reduces transmission delay
Razaak et al. [89]	Outdoor	GAN	Reduces efforts of human intervention
Sadeghi et al. [43]	User group	DRQL	Provides fast computational time and reduces complexity and requirement for memory
Shahriari et al. [39]	Outdoor	DRL	It was found that the communication load and caches misses are reduced with limited system overhead
Sundqvist et al. [79]	Individual	Adaboosted ensemble LSTM	Detects anomalies in random access network very fast
He et al. [29]	Outdoor	CNN	Detecting of signal interference with less computational complexity
Li et al. [44]	User group	DQN	Effective chaining
Xia et al. [45]	User group	DQN	Reduces energy cost and delay experience by users
Saetan et al. [93]	Outdoor	DDNN	Predicts power factor
Pradhan and Das [48]	Individual	RL	Provides packet drop probability and better resource utilization
Zhao et al. [49]	Outdoor	RL	Fast response to network demand
Ho et al. [50]	Outdoor	DQN	Solves the problem of base station allocation
Yu et al. [46]	Outdoor	DQN	Searches for optimal deployment location with high speed
Tang et al. [47]	Outdoor	DQN	Improved network performance based on throughput and packet drop rate
Chergui and Verikoukis [99]	Outdoor	DDNN	Estimates slices resources
El Boudani et al. [97]	Outdoor	DDNN	Predicts 3D position of mobile station
Xie et al. [51]	Outdoor	DQN	Improves efficiency of initial window decision
Hussain et al. [30]	Outdoor	CNN	Detects denial of service with high accuracy
Butt et al. [95]	Outdoor	DDN	Estimating user equipment positioning
Godala et al. [31]	Outdoor	CNN	Estimates channel state information
Li and Zhang [52]	Outdoor	DRL	Improves quality of service
Yu et al. [53]	Outdoor	DRL	Improves energy efficiency
Yu et al. [9]	Outdoor	LSTM	Resource allocation in TV broadband services
Liu et al. [82]	Outdoor	LSTM	Predicts hotspot for small virtual cell
Mismar et al. [54]	Outdoor	DQN	Signal to interference plus noise ratio improvement
Sim et al. [96]	Outdoor	DDNN	Selection of beam
Doan and Zhang [34]	Outdoor	CNN	Detects anomaly in 5G network
Memon et al. [84]	Outdoor	LSTM	Improves power savings and predicts discontinue reception
Klus et al. [32]	Localization	CNN	Predicts user localization and reduces unnecessary handover
Saeidian et al. [55]	Outdoor	DQN	Improves data rate at the edge and reduces power transmitted
Thantharate et al. [98]	Outdoor	DDNN	Detects security thread

Table 3: Continued.

References	Mobility level	Deep learning architecture	Main contribution
Abbas et al. [90]	Outdoor	GAN	Manages slice
Abiko et al. [56]	Outdoor	DRL	Allocates radio resource without change in the number of slices
Alhazmi et al. [33]	Outdoor	LeNet-5	Detects 5G signal from cellular system environment
Chen et al. [83]	Outdoor	LSTM	Predicts traffic flow while maintaining low complexity and running time
Abidi et al. [70]	Outdoor	Metaheuristic-based DBN + ANN	Provides 5G network slicing
Liu et al. [116]	Outdoor	YOLOv3 + deep SORT	Improves multiple people detection and monitoring
Ahmed et al. [35]	Outdoor	CNN	Improves efficiency in spectrum allocation
Ali et al. [100]	Outdoor	DNN	Efficient resource allocation
Cheng et al. [36]	Outdoor	CNN	Models mmWave for 5G communications
Clement et al. [71]	Outdoor	CNN + DDNN + LSTM	Modulation classification in 5G wireless network
Giannopoulos et al. [57]	Outdoor	DQN	Enhances energy efficiency in 5G cognitive
Gu et al. [58]	Outdoor	DNR	Improves quality of service and shortens convergence time
Guan et al. [37]	Outdoor	CNN	Predicts network traffic flow with limited dataset
Gumaei et al. [85]	Outdoor	DRNN	Detects drones from radio frequency signals
Rathore et al. [101]	Outdoor	DNN	Enhances security of intelligent 5G-enabled IoT
Ullah et al. [86]	Outdoor	DRNN	Predicts clone applications from android and application stores
Xu et al. [38]	Outdoor	CNN	Detects adversarial attacks in 5G-based CNN
Yu et al [53]	Outdoor	DRN	Reduces time required to execute computational offloading, resource allocation, and caching placement
Dinh et al. [59]	Outdoor	DQN	Improves quality of service and enhances throughput
Khan et al. [72]	Outdoor	LSTM-SVM	Improves congestion control in 5G/6G network
Kaya and Viswanathan [73]	Outdoor	LSTM-AE	LSTM-AE reduces overhead and enhances signal-to-noise ratio
Zhang et al. [74]	Outdoor	DRL-LSTM	The DRL-LSTM addresses the routing and link scheduling in mmWawe
Sedik et al. [75]	Outdoor	CNN-LSTM	Detects altered biometrics

Table 4: The summary of deep learning algorithm characteristics and learning suitability in 5G.

Deep learning algorithm	Learning suitability	Application in 5G
DRL	Reinforcement	Energy consumption minimization, beam selection, load balancing scheme, distributed offloading framework, service function chaining mapping, packet drop probability and resource utilization, network slicing scheme; vehicles platooning management, optimal locations deployment, time division duplex resource allocation; initial window decision policy, quality of service, maximizing energy efficiency, signal to interference plus noise ratio, improve data rate at the edge and reduces power transmitted
CNN	Supervised	Millimeter wave positioning, channel estimation, scalable caching scheme, signal interference detector, denial-of-service detector scheme, predict user location, detecting 5G signal
DDNN	Supervised learning	Pilot assignment in massive MIMO, power factor allocator, slices resources predictor, 3D base station positioning system, beam selector, authentication scheme
Hybrid algorithm	Supervised/unsupervised	Mobile network traffic loads forecasting, channel state information prediction, power transmission, cyber security system
Autoencoder	Unsupervised/semisupervised	Deep-SCMA scheme, cache scheme
LSTM	Supervised	Holistic handover management, intelligent cache scheme; TV broadband allocation, hotspot virtual small cell allocator, discontinue reception prediction, predict traffic flow
GAN	Semisupervised and unsupervised learning	5G-enabled drone monitoring system; slice resource management

5.10. Complexity. The complexity of the cost values of the reflection for anticipatory resources orchestration increases as it moves towards the edge. The ratio of 3 to 1 has been quantified between the operational expenses at the cloud radio access network with respect to the core [26].

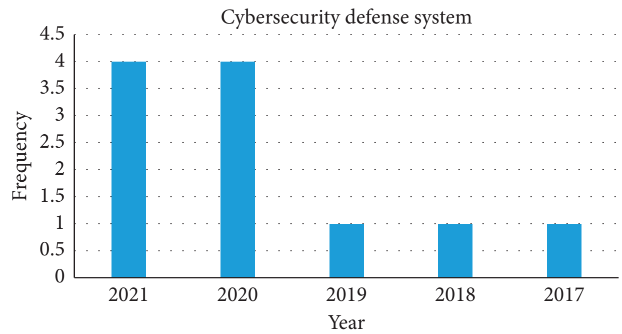


Figure 4: Trend of publication in the cyber security defense system (2017–2021).

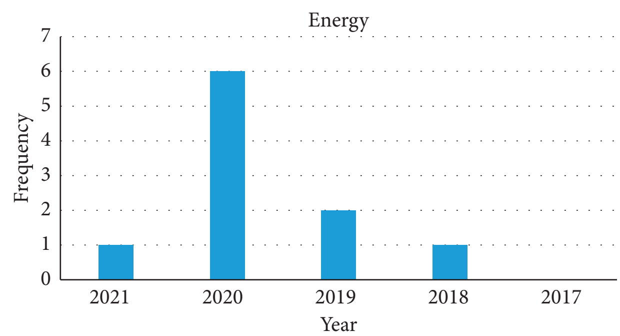


Figure 5: Trend of publication in energy/power transmission in 5G (2017 to 2021).

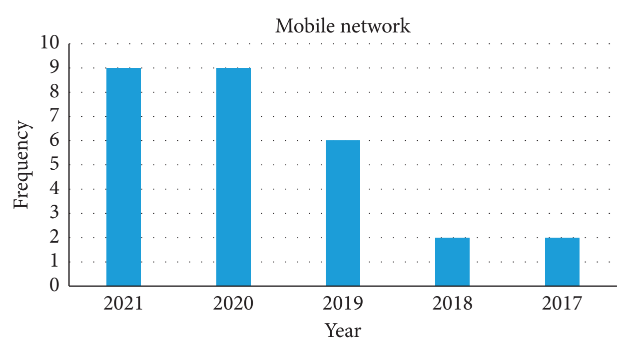


Figure 6: Publication trend for the mobile network (2017–2021).

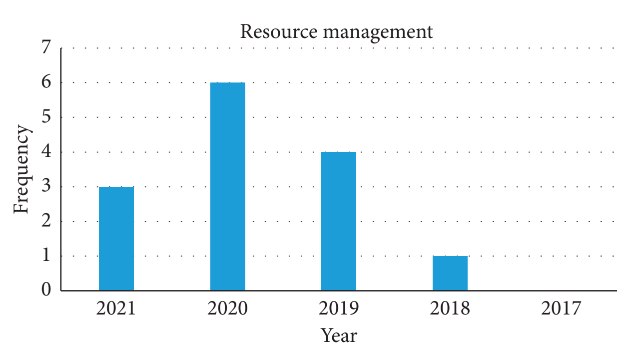


Figure 7: The trend of publication in resource management (2017 to 2021).

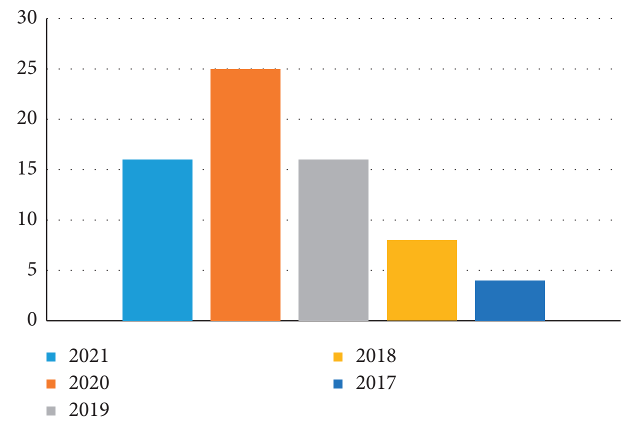


Figure 8: Overall trend of publications in deep learning adoption in 5G wireless network.

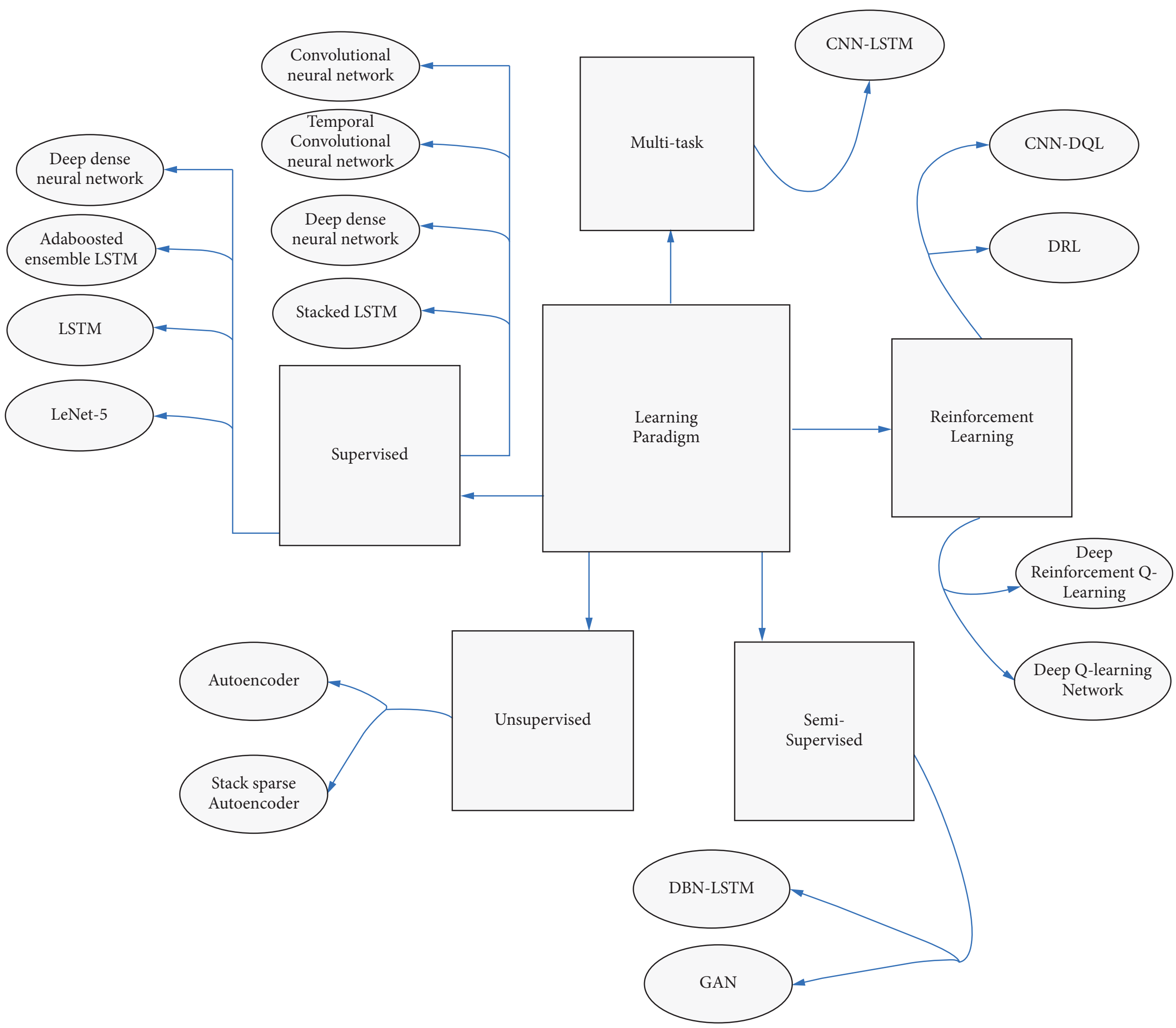


Figure 9: Taxonomy of learning paradigm applied in 5G wireless communication.

6. Conclusions

In this paper, we present review article on the adoption of deep learning architecture to solve machine learning problems in 5G wireless communications and 5G-enabled IoV. The advances made on the applications of deep learning in 5G network are presented in a concise form. Different deep learning architectures used in solving problems in the 5G wireless communications were unrevealed such the CNN, LSTM, DRL, GAN, DDNN, and hybrid deep learning. The publication trend shows that the research area is attracting attention with the highest number of publications in the last three years. Taxonomies were created for the deep learning in 5G network and the domain of applications. Deep learning algorithms have started making inroad in 5G-enabled IoV especially federated learning. The challenges in the existing approaches for solving problem in 5G network based on deep learning algorithms and promising directions as new perspective for solving the identified challenges are presented in the article. The article can be used by new researchers as an initial reading material, and established researchers can use the article to easily identify area that requires further development of the research area that will lead to the real-world practical application of deep learning solutions for 5G wireless network [128–130].

Data Availability

No data were used to support this study.

Disclosure

The leading guest editor of the special issue is author's collaborator in recent times.

Conflicts of Interest

The author declares that there are no conflicts of interest.

References

[1] M. Bagaa, T. Taleb, A. Laghrissi, A. Ksentini, and H. Flinck, "Coalitional game for the creation of efficient virtual core network slices in 5G mobile systems," *IEEE Journal on Selected Areas in Communications*, vol. 36, no. 3, pp. 469–484, 2018.

[2] M. Sakai, K. Kamohara, H. Iura et al., "Experimental field trials on MU-MIMO transmissions for high SHF wide-band massive MIMO in 5G," *IEEE Transactions on Wireless Communications*, vol. 19, no. 4, pp. 2196–2207, 2020.

[3] A. A. A. El-Latif, B. Abd-El-Atty, W. Mazurczyk, C. Fung, and S. E. Venegas-Andraca, "Secure data encryption based on quantum walks for 5G Internet of Things scenario," *IEEE Transactions on Network and Service Management*, vol. 17, no. 1, pp. 118–131, 2020.

[4] C. Jiang, H. Zhang, Y. Ren, Z. Han, K. C. Chen, and L. Hanzo, "Machine learning paradigms for next-generation wireless networks," *IEEE Wireless Communications*, vol. 24, no. 2, pp. 98–105, 2016.

[5] C. Ge, N. Wang, I. Selinis et al., "QoE-assured live streaming via satellite backhaul in 5G networks," *IEEE Transactions on Broadcasting*, vol. 65, no. 2, pp. 381–391, 2019.

[6] M. Agiwal, A. Roy, and N. Saxena, "Next generation 5G wireless networks: a comprehensive survey," *IEEE Communications Surveys and Tutorials*, vol. 18, no. 3, pp. 1617–1655, 2016.

[7] D. Sattar and A. Matrawy, "Optimal slice allocation in 5G core networks," *IEEE Networking Letters*, vol. 1, no. 2, pp. 48–51, 2019.

[8] W. Guo, "Partially explainable big data driven deep reinforcement learning for green 5G UAV," in *Proceedings of the ICC 2020-2020 IEEE International Conference on Communications (ICC)*, pp. 1–7, IEEE, Dublin, Ireland, June 2020.

[9] P. Yu, F. Zhou, X. Zhang, X. Qiu, M. Kadoch, and M. Cheriet, "Deep learning-based resource allocation for 5G broadband TV service," *IEEE Transactions on Broadcasting*, vol. 66, no. 4, pp. 800–813, 2020.

[10] I. Ahmed, M. Ahmad, A. Ahmad, and G. Jeon, "Top view multiple people tracking by detection using deep SORT and YOLOv3 with transfer learning: within 5G infrastructure," *International Journal of Machine Learning and Cybernetics*, vol. 12, pp. 1–15, 2020a.

[11] M. Khayyat, I. A. Elgendy, A. Muthanna, A. S. Alshahrani, S. Alharbi, and A. Koucheryavy, "Advanced deep learning-based computational offloading for multilevel vehicular edge-cloud computing networks," *IEEE Access*, vol. 8, pp. 137052–137062, 2020.

[12] H. Pang, J. Liu, X. Fan, and L. Sun, "Toward smart and cooperative edge caching for 5g networks: a deep learning based approach," in *Proceedings of the 2018 IEEE/ACM 26th International Symposium on Quality of Service (IWQoS)*, pp. 1–6, IEEE, Banff, Alberta, Canada, June 2018.

[13] D. Wang, D. Chen, B. Song, N. Guizani, X. Yu, and X. Du, "From IoT to 5G I-IoT: the next generation IoT-based intelligent algorithms and 5G technologies," *IEEE Communications Magazine*, vol. 56, no. 10, pp. 114–120, 2018.

[14] X. You, C. Zhang, X. Tan, S. Jin, and H. Wu, "AI for 5G: research directions and paradigms," *Science China Information Sciences*, vol. 62, no. 2, Article ID 21301, 2019.

[15] A. Klautau, P. Batista, N. González-Prelcic, Y. Wang, and R. W. Heath, "5G MIMO data for machine learning: application to beam-selection using deep learning," in *Proceedings of the 2018 Information Theory and Applications Workshop (ITA)*, pp. 1–9, IEEE, San Diego, CA, USA, February 2018.

[16] C.-X. Wang, J. Bian, J. Sun, W. Zhang, and M. Zhang, "A survey of 5G channel measurements and models," *IEEE Communications Surveys and Tutorials*, vol. 20, no. 4, pp. 3142–3168, 2018.

[17] X. Xu, D. Li, Z. Dai, S. Li, and X. Chen, "A heuristic offloading method for deep learning edge services in 5G networks," *IEEE Access*, vol. 7, pp. 67734–67744, 2019.

[18] E. Benalia, S. Bitam, and A. Mellouk, "Data dissemination for Internet of vehicle based on 5G communications: a survey," *Transactions on Emerging Telecommunications Technologies*, vol. 31, no. 5, Article ID e3881, 2020.

[19] C. R. Storck and F. Duarte-Figueiredo, "A survey of 5G technology evolution, standards, and infrastructure associated with vehicle-to-everything communications by internet of vehicles," *IEEE Access*, vol. 8, pp. 117593–117614, 2020.

[20] M. Hammad, A. M. Iliyasu, A. Subasi, E. S. Ho, and A. A. Abd El-Latif, "A multitier deep learning model for arrhythmia detection," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–9, 2020.

[21] A. Aldweesh, A. Derhab, and A. Z. Emam, "Deep learning approaches for anomaly-based intrusion detection systems: a survey, taxonomy, and open issues," *Knowledge-Based Systems*, vol. 189, Article ID 105124, 2020.

[22] F. Restuccia and T. Melodia, “Deep learning at the physical layer: system challenges and applications to 5G and beyond,” *IEEE Communications Magazine*, vol. 58, no. 10, pp. 58–64, 2020.

[23] H. Huang, S. Guo, G. Gui et al., “Deep learning for physical-layer 5G wireless techniques: opportunities, challenges and solutions,” *IEEE Wireless Communications*, vol. 27, no. 1, pp. 214–222, 2019.

[24] C. Zhang, P. Patras, and H. Haddadi, “Deep learning in mobile and wireless networking: a survey,” *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2224–2287, 2019.

[25] T. Liu, S. Fang, Y. Zhao, P. Wang, and J. Zhang, “Implementation of training convolutional neural networks,” 2015, https://arxiv.org/abs/1506.01195.

[26] D. Bega, M. Gramaglia, M. Fiore, A. Banchs, and X. Costa-Perez, “DeepCog: cognitive network management in sliced 5G networks with deep learning,” in *Proceedings of the IEEE INFOCOM 2019-IEEE Conference on Computer Communications*, pp. 280–288, IEEE, Paris, France, July 2019.

[27] J. Gante, G. Falcão, and L. Sousa, “Deep learning architectures for accurate millimeter wave positioning in 5G,” *Neural Processing Letters*, vol. 51, no. 1, pp. 487–514, 2020.

[28] D. Huang, Y. Gao, Y. Li et al., “Deep learning based cooperative resource allocation in 5G wireless networks,” *Mobile Networks and Applications*, pp. 1–8, 2018.

[29] K. He, Z. Wang, D. Li, F. Zhu, and L. Fan, “Ultra-reliable MU-MIMO detector based on deep learning for 5G/B5G-enabled IoT,” *Physical Communication*, vol. 43, Article ID 101181, 2020.

[30] B. Hussain, Q. Du, B. Sun, and Z. Han, “Deep learning-based DDoS-attack detection for cyber–physical system over 5G network,” *IEEE Transactions on Industrial Informatics*, vol. 17, no. 2, pp. 860–870, 2020.

[31] A. R. Godala, S. Kadambar, A. K. R. Chavva, and V. S. Tijoriwala, “A deep learning based approach for 5G NR CSI estimation,” in *Proceedings of the 2020 IEEE 3rd 5G World Forum (5GWF)*, pp. 59–62, IEEE, Bangalore, India, September 2020.

[32] R. Klus, L. Klus, D. Solomitckii, M. Valkama, and J. Talvitie, “Deep learning based localization and HO optimization in 5G NR networks,” in *Proceedings of the 2020 International Conference on Localization and GNSS (ICL-GNSS)*, pp. 1–6, IEEE, Tampere, Finland, June 2020.

[33] M. H. Alhazmi, M. Alymani, H. Alhazmi, A. Almarhabi, A. Samarkandi, and Y.-D. Yao, “5G signal identification using deep learning,” in *Proceedings of the 2020 29th Wireless and Optical Communications Conference (WOCC)*, pp. 1–5, IEEE, Newark, New Jersey, USA, May 2020.

[34] M. Doan and Z. Zhang, “Deep learning in 5G wireless networks - anomaly detections,” in *Proceedings of the 2020 29th Wireless and Optical Communications Conference (WOCC)*, pp. 1–6, IEEE, Newark, NJ, USA, May 2020.

[35] R. Ahmed, Y. Chen, and B. Hassan, “Deep learning-driven opportunistic spectrum access (OSA) framework for cognitive 5G and beyond 5G (B5G) networks,” *Ad Hoc Networks*, vol. 123, Article ID 102632, 2021.

[36] H. Cheng, S. Ma, H. Lee, and M. Cho, “Millimeter wave path loss modeling for 5G communications using deep learning with dilated convolution and attention,” *IEEE Access*, vol. 9, pp. 62867–62879, 2021.

[37] J. Guan, J. Cai, H. Bai, and I. You, “Deep transfer learning-based network traffic classification for scarce dataset in 5G IoT systems,” *International Journal of Machine Learning and Cybernetics*, vol. 12, no. 11, pp. 3351–3365, 2021.

[38] G. Xu, G. Feng, L. Jiao, M. Feng, X. Zheng, and J. Liu, “FNet: a two-stream model for detecting adversarial attacks against 5G-based deep learning services,” *Security and Communication Networks*, vol. 2021, pp. 1–10, 2021.

[39] B. Shahriari, M. Moh, and T. S. Moh, “Generic online learning for partial visible dynamic environment with delayed feedback: online learning for 5G C-RAN load-balancer,” in *Proceedings of the 2017 International Conference on High Performance Computing & Simulation (HPCS)*, pp. 176–185, IEEE, Genoa, Italy, July 2017.

[40] Y. Dai, D. Xu, S. Maharjan, Z. Chen, Q. He, and Y. Zhang, “Blockchain and deep reinforcement learning empowered intelligent 5G beyond,” *IEEE Network*, vol. 33, no. 3, pp. 10–17, 2019.

[41] R. Dong, C. She, W. Hardjawana, Y. Li, and B. Vucetic, “Deep learning for hybrid 5G services in mobile edge computing systems: learn from a digital twin,” *IEEE Transactions on Wireless Communications*, vol. 18, no. 10, pp. 4692–4707, 2019.

[42] Z. Ning, P. Dong, X. Wang et al., “When deep reinforcement learning meets 5G-enabled vehicular networks: a distributed offloading framework for traffic big data,” *IEEE Transactions on Industrial Informatics*, vol. 16, no. 2, pp. 1352–1361, 2019.

[43] A. Sadeghi, F. Sheikholeslami, and G. B. Giannakis, “Optimal and scalable caching for 5G using reinforcement learning of space-time popularities,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 180–190, 2017.

[44] G. Li, B. Feng, H. Zhou, Y. Zhang, K. Sood, and S. Yu, “Adaptive service function chaining mappings in 5G using deep Q-learning,” *Computer Communications*, vol. 152, pp. 305–315, 2020.

[45] Q. Xia, Z. Lou, W. Xu, and Z. Xu, “Near-optimal and learning-driven task offloading in a 5G multi-cell mobile edge cloud,” *Computer Networks*, vol. 176, Article ID 107276, 2020.

[46] A. Yu, B. Yu, H. Yang, Q. Yao, J. Zhang, and M. Cheriet, “Deep reinforcement learning based time synchronization routing optimization for C-RoFN in beyond 5G,” in *Proceedings of the 2020 International Wireless Communications and Mobile Computing (IWCMC)*, pp. 865–867, IEEE, Limassol, Cyprus, June 2020.

[47] F. Tang, Y. Zhou, and N. Kato, “Deep reinforcement learning for dynamic uplink/downlink resource allocation in high mobility 5G HetNet,” *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 12, pp. 2773–2782, 2020.

[48] A. Pradhan and S. Das, “Reinforcement learning-based resource allocation for adaptive transmission and retransmission scheme for URLLC in 5G,” in *Advances in Machine Learning and Computational Intelligence*Springer, Singapore, 2020.

[49] G. Zhao, M. Wen, J. Hao, and T. Hai, “Application of dynamic management of 5G network slice resource based on reinforcement Learning in Smart Grid,” in *International Conference on Computer Engineering and Networks*, pp. 1485–1492, Springer, Singapore, 2020.

[50] C. C. Ho, B. H. Huang, M. T. Wu, and T. Y. Wu, “Optimized base station allocation for platooning vehicles underway by using deep learning algorithm based on 5G-V2X,” in *Proceedings of the 2019 IEEE 8th Global Conference on Consumer Electronics (GCCE)*, pp. 1-2, IEEE, Osaka, Japan, October 2019.

[51] R. Xie, X. Jia, and K. Wu, "Adaptive online decision method for initial congestion window in 5G mobile edge computing using deep reinforcement learning," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 2, pp. 389–403, 2019.

[52] J. Li and X. Zhang, "Deep reinforcement learning-based joint scheduling of eMBB and URLLC in 5G networks," *IEEE Wireless Communications Letters*, vol. 9, no. 9, pp. 1543–1546, 2020.

[53] P. Yu, J. Guo, Y. Huo, X. Shi, J. Wu, and Y. Ding, "Three-dimensional aerial base station location for sudden traffic with deep reinforcement learning in 5G mmWave networks," *International Journal of Distributed Sensor Networks*, vol. 16, no. 5, Article ID 1550147720926374, 2020.

[54] F. B. Mismar, B. L. Evans, and A. Alkhateeb, "Deep reinforcement learning for 5G networks: joint beamforming, power control, and interference coordination," *IEEE Transactions on Communications*, vol. 68, no. 3, pp. 1581–1592, 2019.

[55] S. Saeidian, S. Tayamon, and E. Ghadimi, "Downlink power control in dense 5G radio access networks through deep reinforcement learning," in *Proceedings of the ICC 2020-2020 IEEE International Conference on Communications (ICC)*, pp. 1–6, IEEE, Dublin, Ireland, June 2020.

[56] Y. Abiko, D. Mochizuki, T. Saito, D. Ikeda, T. Mizuno, and H. Mineno, "Proposal of allocating radio resources to multiple slices in 5G using deep reinforcement learning," in *Proceedings of the 2019 IEEE 8th Global Conference on Consumer Electronics (GCCE)*, pp. 1-2, IEEE, Osaka, Japan, October 2019.

[57] A. Giannopoulos, S. Spantideas, N. Kapsalis, P. Karkazis, and P. Trakadas, "Deep reinforcement learning for energy-efficient multi-channel transmissions in 5G cognitive HetNets: centralized, decentralized and transfer learning based solutions," *IEEE Access*, vol. 9, pp. 129358–129374, 2021.

[58] Z. Gu, C. She, W. Hardjawana et al., "Knowledge-assisted deep reinforcement learning in 5G scheduler design: from theoretical framework to implementation," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 7, pp. 2014–2028, 2021.

[59] T. H. L. Dinh, M. Kaneko, K. Wakao et al., "Distributed user-to-multiple access points association through deep learning for beyond 5G," *Computer Networks*, vol. 197, Article ID 108258, 2021.

[60] P. Baldi, "Autoencoders , unsupervised learning , and deep architectures," in *Proceedings of the ICML Workshop on Unsupervised and Transfer Learning*, pp. 37–50, Edinburgh, Scotland, June 2012.

[61] F. Lei, Q. Dai, J. Cai, H. Zhao, X. Liu, and Y. Liu, "A proactive caching strategy based on deep Learning in EPC of 5G," in *Proceedings of the International Conference on Brain Inspired Cognitive Systems*, pp. 738–747, Shenyang, China, July 2018.

[62] M. Kim, N.-I. Kim, W. Lee, and D.-H. Cho, "Deep learning-aided SCMA," *IEEE Communications Letters*, vol. 22, no. 4, pp. 720–723, 2018.

[63] S. Li, "The development of a hybrid intelligent system for developing marketing strategy," *Decision Support Systems*, vol. 27, no. 4, pp. 395–409, 2000.

[64] M. Seera and C. P. Lim, "A hybrid intelligent system for medical data classification," *Expert Systems with Applications*, vol. 41, no. 5, pp. 2239–2249, 2014.

[65] A. Bahrammirzaee, "A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems," *Neural Computing and Applications*, vol. 19, no. 8, pp. 1165–1195, 2010.

[66] A. Abraham, E. Corchado, and J. M. Corchado, "Hybrid learning machines," *Neurocomputing*, vol. 72, no. 13-15, pp. 2729-2730, 2009.

[67] C. Luo, J. Ji, Q. Wang, X. Chen, and P. Li, "Channel state information prediction for 5G wireless communications: a deep learning approach," *IEEE Transactions on Network Science and Engineering*, vol. 7, no. 1, pp. 227–236, 2020.

[68] C. W. Huang, C. T. Chiang, and Q. Li, "A study of deep learning networks on mobile traffic forecasting," in *Proceedings of the 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pp. 1–6, IEEE, Montreal, QC, Canada, October 2017.

[69] C. Luo, J. Ji, Q. Wang, L. Yu, and P. Li, "Online power control for 5G wireless communications: a deep Q-network approach," in *Proceedings of the 2018 IEEE International Conference on Communications (ICC)*, pp. 1–6, IEEE, Kansas, MO, USA, May 2018.

[70] M. H. Abidi, H. Alkhalefah, K. Moiduddin et al., "Optimal 5G network slicing using machine learning and deep learning concepts," *Computer Standards & Interfaces*, vol. 76, Article ID 103518, 2021.

[71] J. C. Clement, N. Indira, P. Vijayakumar, and R. Nandakumar, "Deep learning based modulation classification for 5G and beyond wireless systems," *Peer-to-Peer Networking and Applications*, vol. 14, no. 1, pp. 319–332, 2021.

[72] S. Khan, A. Hussain, S. Nazir, F. Khan, A. Oad, and M. D. Alshehri, "Efficient and reliable hybrid deep learning-enabled model for congestion control in 5G/6G networks," *Computer Communications*, vol. 182, pp. 31–40, 2022.

[73] A. O. Kaya and H. Viswanathan, "Deep Learning-based predictive beam management for 5G mmwave systems," in *Proceedings of the 2021 IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1–7, IEEE, Nanjing, China, April 2021.

[74] B. Zhang, F. Devoti, I. Filippini, and D. De Donno, "Resource allocation in mmWave 5G IAB networks: a reinforcement learning approach based on column generation," *Computer Networks*, vol. 196, Article ID 108248, 2021.

[75] A. Sedik, L. A. Tawalbeh, M. Hammad et al., "Deep learning modalities for biometric alteration detection in 5G networks-based secure smart cities," *IEEE Access*, vol. 9, pp. 94780–94788, 2021.

[76] L. F. Maimó, F. J. G. Clemente, M. G. Pérez, and G. M. Pérez, "On the performance of a deep learning-based anomaly detection system for 5G networks," in *Proceedings of the 2017 IEEE SmartWorld, Ubiquitous Intelligence and Computing, Advanced and Trusted Computed, Scalable Computing & Communications, Cloud and Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, pp. 1–8, IEEE, San Francisco, CA, USA, August 2017.

[77] L. Fernandez Maimo, A. L. Perales Gomez, F. J. Garcia Clemente, M. Gil Perez, and G. Martinez Perez, "A self-adaptive deep learning-based system for anomaly detection in 5G networks," *IEEE Access*, vol. 6, pp. 7700–7712, 2018.

[78] L. Fernández Maimó, A. Huertas Celdrán, M. Gil Pérez, F. J. García Clemente, and G. Martínez Pérez, "Dynamic management of a deep learning-based anomaly detection system for 5G networks," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 8, pp. 3083–3097, 2019.

[79] T. Sundqvist, M. H. Bhuyan, J. Forsman, and E. Elmroth, "Boosted ensemble learning for anomaly detection in 5G RAN," in *IFIP International Conference on Artificial Intelligence Applications and Innovations*, pp. 15–30, Springer, Cham, Switzerland, 2020.

[80] F. A. Gers, J. Schmidhuber, and F. Cummins, "Learning to forget: continual prediction with LSTM," *Neural Computation*, vol. 12, no. 10, pp. 2451–2471, 2000.

[81] M. Ozturk, M. Gogate, O. Onireti, A. Adeel, A. Hussain, and M. A. Imran, "A novel deep learning driven, low-cost mobility prediction approach for 5G cellular networks: the case of the Control/Data Separation Architecture (CDSA)," *Neurocomputing*, vol. 358, pp. 479–489, 2019.

[82] Y. Liu, X. Wang, G. Boudreau, A. B. Sediq, and H. Abou-zeid, "Deep learning based hotspot prediction and beam management for adaptive virtual small cell in 5G networks," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 4, no. 1, pp. 83–94, 2020.

[83] M. Chen, X. Wei, Y. Gao, L. Huang, M. Chen, and B. Kang, "Deep-broad learning system for traffic flow prediction toward 5G cellular wireless network," in *Proceedings of the 2020 International Wireless Communications and Mobile Computing (IWCMC)*, pp. 940–945, IEEE, Limassol, Cyprus, June 2020.

[84] M. L. Memon, M. K. Maheshwari, D. R. Shin, A. Roy, and N. Saxena, "Deep-DRX: a framework for deep learning-based discontinuous reception in 5G wireless networks," *Transactions on Emerging Telecommunications Technologies*, vol. 30, no. 3, Article ID e3579, 2019.

[85] A. Gumaei, M. Al-Rakhami, M. M. Hassan et al., "Deep learning and blockchain with edge computing for 5G-enabled drone identification and flight mode detection," *IEEE Network*, vol. 35, no. 1, pp. 94–100, 2021.

[86] F. Ullah, M. R. Naeem, L. Mostarda, and S. A. Shah, "Clone detection in 5G-enabled social IoT system using graph semantics and deep learning model," *International Journal of Machine Learning and Cybernetics*, vol. 12, no. 11, pp. 3115–3127, 2021.

[87] M. Liu and O. Tuzel, "Coupled generative adversarial networks," in *Proceedings of the 30th Conference on Neural Information Processing Systems (NIPS 2016)*, pp. 1–9, Barcelona, Spain, December 2016.

[88] A. Creswell, T. White, V. Dumoulin, K. Arulkumaran, B. Sengupta, and A. A. Bharath, "Generative adversarial networks: an overview," *IEEE Signal Processing Magazine*, vol. 35, no. 1, pp. 53–65, 2018.

[89] M. Razaak, H. Kerdegari, E. Davies et al., "An integrated precision farming application based on 5G, UAV and deep learning technologies," in *International Conference on Computer Analysis of Images and Patterns*, pp. 109–119, Springer, Cham, Switzerland, 2019.

[90] K. Abbas, M. Afaq, T. A. Khan, A. Mehmood, and W.-C. Song, "IBNSlicing: intent-based network slicing framework for 5G networks using deep learning," in *Proceedings of the 2020 21st Asia-Pacific Network Operations and Management Symposium (APNOMS)*, pp. 19–24, IEEE, Daegu, Republic of Korea, September 2020.

[91] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, Cambridge, MA, USA, 2016.

[92] K. Kim, J. Lee, and J. Choi, "Deep learning based pilot allocation scheme (DL-PAS) for 5G massive MIMO system," *IEEE Communications Letters*, vol. 22, no. 4, pp. 828–831, 2018.

[93] W. Saetan and S. Thipchaksurat, "Application of deep learning to fairness-based power allocation for 5G NOMA system with imperfect SIC," in *International Conference on Computing and Information Technology*, pp. 199–207, Springer, Cham, Switzerland, 2020.

[94] W. Saetan and S. Thipchaksurat, "Power allocation for sum rate maximization in 5G NOMA system with imperfect SIC: a deep learning approach," in *Proceedings of the 2019 4th International Conference on Information Technology (InCIT)*, pp. 195–198, IEEE, Bangkok, Thailand, October 2019.

[95] M. M. Butt, A. Rao, and D. Yoon, "RF fingerprinting and deep learning assisted UE positioning in 5G," in *Proceedings of the 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*, pp. 1–7, IEEE, Antwerp, Belgium, May 2020.

[96] M. S. Sim, Y.-G. Lim, S. H. Park, L. Dai, and C.-B. Chae, "Deep learning-based mmWave beam selection for 5G NR/6G with sub-6 GHz channel information: algorithms and prototype validation," *IEEE Access*, vol. 8, pp. 51634–51646, 2020.

[97] B. El Boudani, L. Kanaris, A. Kokkinis et al., "Implementing deep learning techniques in 5G IoT networks for 3D indoor positioning: DELTA (DeEp Learning-Based Co-operaTive Architecture)," *Sensors*, vol. 20, no. 19, p. 5495, 2020.

[98] A. Thantharate, R. Paropkari, V. Walunj, C. Beard, and P. Kankariya, "Secure5G: a deep learning framework towards a secure network slicing in 5G and beyond," in *Proceedings of the 2020 10th Annual Computing and Communication Workshop and Conference (CCWC)*, pp. 0852–0857, IEEE, Las Vegas, NV, USA, January 2020.

[99] H. Chergui and C. Verikoukis, "Offline SLA-constrained deep learning for 5G networks reliable and dynamic end-to-end slicing," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 2, pp. 350–360, 2019.

[100] S. Ali, A. Haider, M. Rahman, M. Sohail, and Y. B. Zikria, "Deep Learning (DL) based joint resource allocation and RRH Association in 5G-Multi-Tier Networks," *IEEE Access*, vol. 9, pp. 118357–118366, 2021.

[101] S. Rathore, J. H. Park, and H. Chang, "Deep learning and blockchain-empowered security framework for intelligent 5G-enabled IoT," *IEEE Access*, vol. 9, pp. 90075–90083, 2021.

[102] H. Chiroma, S. I. M. Abdulhamid, I. A. T. Hashem et al., "Deep learning-based big data analytics for internet of vehicles: taxonomy, challenges, and research directions," *Mathematical Problems in Engineering*, vol. 2021, Article ID 9022558, 20 pages, 2021.

[103] A. Patil and H. K. Sawant, "Technical specification group services and system aspects IP multimedia subsystem (IMS)," *International Journal of Electronics, Communications and Computer Engineering*, vol. 3, no. 2, pp. 234–238, 2012.

[104] P. Yu, X. Yang, F. Zhou et al., "Deep reinforcement learning aided cell outage compensation framework in 5G cloud radio access networks," *Mobile Networks and Applications*, vol. 25, no. 5, pp. 1644–1654, 2020.

[105] L. Nkenyereye, C. H. Liu, and J. Song, "Towards secure and privacy preserving collision avoidance system in 5G fog based Internet of Vehicles," *Future Generation Computer Systems*, vol. 95, pp. 488–499, 2019.

[106] R. He, C. Schneider, B. Ai et al., "Propagation channels of 5G millimeter-wave vehicle-to-vehicle communications: recent advances and future challenges," *IEEE Vehicular Technology Magazine*, vol. 15, no. 1, pp. 16–26, 2019.

[107] C. Campolo, A. Molinaro, A. Iera, and F. Menichella, "5G network slicing for vehicle-to-everything services," *IEEE Wireless Communications*, vol. 24, no. 6, pp. 38–45, 2017.

[108] S. M. Hussain, K. M. Yusof, and K. M. Yusof, "Dynamic Q-learning and Fuzzy CNN based vertical handover decision for integration of DSRC, mmWave 5G and LTE in Internet of Vehicles (IoV)," *Journal of Communications*, vol. 16, no. 5, pp. 155–166, 2021.

[109] S. Wang, S. Sun, X. Wang, Z. Ning, and J. J. Rodrigues, "Secure crowdsensing in 5G internet of vehicles: when deep reinforcement learning meets blockchain," *IEEE Consumer Electronics Magazine*, vol. 10, no. 5, pp. 72–81, 2020.

[110] X. Kong, K. Wang, M. Hou et al., "A federated learning-based license plate recognition scheme for 5G-enabled internet of vehicles," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 12, pp. 8523–8530, 2021.

[111] A. Chaaf, M. Saleh Ali Muthanna, A. Muthanna et al., "Energy-efficient relay-based void hole prevention and repair in clustered multi-AUV underwater wireless sensor network," *Security and Communication Networks*, vol. 2021, Article ID 9969605, 20 pages, 2021.

[112] A. Rafiq, W. Ping, W. Min, and M. S. A. Muthanna, "Fog Assisted 6TiSCH tri-layer network architecture for adaptive scheduling and energy-efficient offloading using rank-based Q-learning in smart industries," *IEEE Sensors Journal*, vol. 21, no. 22, pp. 25489–25507, 2021.

[113] W. Z. Zhang, I. A. Elgendy, M. Hammad et al., "Secure and optimized load balancing for multitier IoT and edge-cloud computing systems," *IEEE Internet of Things Journal*, vol. 8, no. 10, pp. 8119–8132, 2020.

[114] A. A. A. EL-Latif, B. Abd-El-Atty, S. E. Venegas-Andraca, and W. Mazurczyk, "Efficient quantum-based security protocols for information sharing and data protection in 5G networks," *Future Generation Computer Systems*, vol. 100, pp. 893–906, 2019.

[115] N. Ravi, P. V. Rani, and S. M. Shalinie, "Secure deep neural (SeDeN) framework for 5G wireless networks," in *Proceedings of the 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, pp. 1–6, IEEE, Kanpur, India, July 2019.

[116] Y. Liu, J. Peng, J. Kang, A. M. Iliyasu, D. Niyato, and A. A. A. El-Latif, "A secure federated learning framework for 5G networks," *IEEE Wireless Communications*, vol. 27, no. 4, pp. 24–31, 2020.

[117] Y. Wu, S. Singh, T. Taleb et al., *6G Mobile Wireless Networks*, Springer, Berlin, Germany, 2021.

[118] R. Falkenberg, B. Sliwa, N. Piatkowski, and C. Wietfeld, "Machine learning based uplink transmission power prediction for LTE and upcoming 5G networks using passive downlink indicators," in *Proceedings of the 2018 IEEE 88th Vehicular Technology Conference (VTC-Fall)*, pp. 1–7, IEEE, Chicago, IL, USA, August 2018.

[119] I. A. Elgendy, W.-Z. Zhang, H. He, B. B. Gupta, and A. A. Abd El-Latif, "Joint computation offloading and task caching for multi-user and multi-task MEC systems: reinforcement learning-based algorithms," *Wireless Networks*, vol. 27, no. 3, pp. 2023–2038, 2021.

[120] A. Al-Ansi, A. M. Al-Ansi, A. Muthanna, I. A. Elgendy, and A. Koucheryavy, "Survey on intelligence edge computing in 6G: characteristics, challenges, potential use cases, and market drivers," *Future Internet*, vol. 13, no. 5, p. 118, 2021.

[121] Q. Guo, R. Gu, Z. Wang et al., "Proactive dynamic network slicing with deep learning based short-term traffic prediction for 5G transport network," in *Proceedings of the 2019 Optical Fiber Communications Conference and Exhibition (OFC)*, pp. 1–3, IEEE, San Diego, CA, USA, March 2019.

[122] W. Na, B. Bae, S. Cho, and N. Kim, "Deep-learning based adaptive beam management technique for mobile high-speed 5G mmWave networks," in *Proceedings of the 2019 IEEE 9th International Conference on Consumer Electronics (ICCE-Berlin)*, pp. 149–151, IEEE, Berlin, Germany, September 2019.

[123] K. F. Shamna, C. I. Siyad, S. Tamilselven, and M. K. Manoj, "Deep learning aided NOMA for user fairness in 5G," in *Proceedings of the 2020 7th International Conference on Smart Structures and Systems (ICSSS)*, pp. 1–6, IEEE, Chennai, India, July 2020.

[124] N. Pitropakis, E. Panaousis, T. Giannetsos, E. Anastasiadis, and G. Loukas, "A taxonomy and survey of attacks against machine learning," *Computer Science Review*, vol. 34, Article ID 100199, 2019.

[125] A. Ftaimi and T. Mazri, "Security of deep learning models in 5G networks: proposition of security assessment process," in *Proceedings of the Networking, Intelligent Systems and Security*, pp. 393–407, Springer, Singapore, April 2022.

[126] B. Chen, W. Carvalho, N. Baracaldo et al., "Detecting backdoor attacks on deep neural networks by activation clustering," 2018, https://arxiv.org/abs/1811.03728.

[127] A. Salh, L. Audah, Q. Abdullah et al., "Development of a fully data-driven artificial intelligence and deep learning for URLLC application in 6g wireless systems: a survey," 2021, https://arxiv.org/abs/2108.10076.

[128] M. K. Hasan, N. T. Le, M. Shahjalal, M. Z. Chowdhury, and Y. M. Jang, "Simultaneous data transmission using multilevel LED in hybrid OCC/LiFi system: concept and demonstration," *IEEE Communications Letters*, vol. 23, no. 12, pp. 2296–2300, 2019.

[129] M. K. Hasan, M. Shahjalal, M. M. Islam, M. M. Alam, M. F. Ahmed, and Y. M. Jang, "The role of deep learning in NOMA for 5G and beyond communications," in *Proceedings of the 2020 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, pp. 303–307, IEEE, Fukuoka, Japan, February 2020.

[130] F. Jameel, M. A. Jamshed, Z. Chang, R. Jäntti, and H. Pervaiz, "Low latency ambient backscatter communications with deep Q-learning for beyond 5G applications," in *Proceedings of the 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*, pp. 1–6, IEEE, Antwerp, Belgium, May 2020.

Hindawi
Mathematical Problems in Engineering
Volume 2021, Article ID 9022558, 20 pages
https://doi.org/10.1155/2021/9022558

Review Article

Deep Learning-Based Big Data Analytics for Internet of Vehicles: Taxonomy, Challenges, and Research Directions

Haruna Chiroma [1,2] Shafi'i M. Abdulhamid [3] Ibrahim A. T. Hashem [4] Kayode S. Adewole [5] Absalom E. Ezugwu [6] Saidu Abubakar [7] and Liyana Shuib [8]

[1] *National Yunlin University of Science and Technology, Yunlin, Douliu, Taiwan*
[2] *Federal College of Education (Technical), Gombe, Nigeria*
[3] *Department of Cyber Security, Federal University of Technology Minna, Minna, Nigeria*
[4] *College of Computing and Informatics, Department of Computer Science, University of Sharjah, Sharjah 27272, UAE*
[5] *Faculty of Communication and Information Sciences, University of Ilorin, Ilorin, Nigeria*
[6] *School of Mathematics, Statistics, and Computer Science, University of KwaZulu-Natal, King Edward Avenue, Pietermaritzburg Campus, Pietermaritzburg 3201, KwaZulu-Natal, South Africa*
[7] *Department of Mathematical Sciences, Abubakar Tafawa Balewa University, Bauchi, Nigeria*
[8] *University of Malaya, Kuala Lumpur, Malaysia*

Correspondence should be addressed to Ibrahim A. T. Hashem; ihashem@sharjah.ac.ae and Liyana Shuib; liyanashuib@um.edu.my

Received 18 June 2021; Revised 15 September 2021; Accepted 23 October 2021; Published 10 November 2021

Academic Editor: Mohammad Yaghoub Abdollahzadeh Jamalabadi

Copyright © 2021 Haruna Chiroma et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The Internet of Vehicles (IoV) is a developing technology attracting attention from the industry and the academia. Hundreds of millions of vehicles are projected to be connected within the IoV environments by 2035. Each vehicle in the environment is expected to generate massive amounts of data. Currently, surveys on leveraging deep learning (DL) in the IoV within the context of big data analytics (BDA) are scarce. In this paper, we present a survey and explore the theoretical perspective of the role of DL in the IoV within the context of BDA. The study has unveiled substantial research opportunities that cut across DL, IoV, and BDA. Exploring DL in the IoV within BDA is an infant research area requiring active attention from researchers to fully understand the emerging concept. The survey proposes a model of IoV environment integrated into the cloud equipped with a high-performance computing server, DL architecture, and Apache Spark for data analytics. The current developments, challenges, and opportunities for future research are presented. This study can guide expert and novice researchers on further development of the application of DL in the IoV within the context of BDA.

1. Introduction

By 2025, the massive ecosystem of the Internet of Things (IoT) is projected to pave a smooth way for 100 billion connections. Thus, the IoT can revolutionize future industries [1]. The IoT has been extended to the Internet of Vehicles (IoV) [2] due to incorporation of intelligent transportation systems for enhanced services [3]. The IoV allows vehicles to communicate with their internal and external environments. The communications of vehicles in sharing information can be in a different form. For example, the vehicles can communicate with sensors, road infrastructure, vehicles, and the Internet [4]. The building blocks of the IoV are the connected vehicles. The IoV evolution is driven by the dynamic mobile communication system with capabilities of gathering, sharing, processing, computing, and securing the release of information [5].

Over 90% of road accidents are caused by human errors. This finding has prompted the emergence of autonomous vehicles to eliminate drunk driving, sleeping while driving, and human errors. As next-generation vehicles that usher in a new frontier of vehicle revolution worldwide, autonomous vehicles can reduce traffic congestion and improve energy efficiency. Different vehicle manufacturing companies, such as Volkswagen, Waymo, Tesla, Hyundai, Mercedes Benz, Baidu, BMW, and Ford, conduct test runs of autonomous vehicles. These autonomous vehicles will be merged into the IoV. Autonomous vehicles need to communicate with the internal and external environments for safety and smooth driving. These vehicles have attracted the attention of the academia and the industry because of their positive impact on the society [6]. Reference [7] argued that the autonomous vehicle market is presently growing and is expected to hit USD 131.9 billion in 2019.

Autonomous vehicles are expected to flood European public roads by 2021 [2]. In China, 8.6 million autonomous vehicles are anticipated to hit public roads by 2035. Out of the 8.6 million vehicles, 3.4 million will be fully autonomous while the others will remain semiautonomous [8]. In USA, hundreds of autonomous vehicles are expected to start operating on public roads in the near future. 25% of the global automobile market between 2015 and 2040 is estimated to be dominated by autonomous vehicles [8] equipped with sensors for communications to realize the IoV experience. Reference [9] pointed out that 200 sensors are projected to be embedded in each vehicle in 2020 to cope with the increasing communications with the environments.

These sensors are expected to generate massive amounts of data. Reference [10] estimated that in 2021, 380 million connected vehicles will be running on public roads, and each was projected to generate 25 GB of data every hour. Reference [5] argued that the IoV will generate information more than the telecommunication industry. For instance, the smart processes of collecting, processing, and releasing dynamic traffic information emanating from various sources within a city will require a petabyte-scale system. Therefore, the IoV ushers in the big data arena.

Deep learning (DL) plays a critical role in big data analytics (BDA) because of its capacity to process big data to uncover knowledge from the complex system [11]. DL searches for the network elements or features in respect of input data by mimicking how human brain operates to generate the best solution [12]. Different from conventional techniques, DL can deal with raw natural data [13]. Deep neural networks have won multiple awards in pattern recognition competitions [14]. In machine learning, DL is the most active theme in current times [15]. DL is expected to record more number of successes in the near future because its architecture requires minimal human effort in engineering [13].

Despite the success of DL in different domains and the unprecedented attention it currently receives from researchers, the empirical exploration of DL in the IoV within the context of BDA is highly limited in the literature. We believe that exploring DL in the IoV within the context of BDA can improve the effectiveness and efficiency of the IoV as a key component in decision making. The IoV is an emerging concept in its early stage. Therefore, a theoretic viewpoint is required to guide the effective empirical applications of DL in the IoV within the context of big data.

We present a survey and theoretical perspective leverage of DL in the IoV within the context of BDA. The intention is to stimulate the research community to focus on exploring DL in the IoV within the context of BDA. This approach can unveil valuable knowledge from the large-scale data expected to be generated from the IoV. Exploring the theoretical aspect of big data is crucial [16] for it is empirical application.

The remainder of this paper is organized as follows. Section 2 presents the rudiments of DL. Section 3 presents the concept and new taxonomy of the IoV. Section 4 emphasizes the case studies of the IoV. Section 5 introduces the BDA platform that supports DL in the IoV. The role of DL in the IoV in the context of BDA is presented in Section 6. Section 7 presents the proposed model of the IoV integrated into the cloud equipped with a high-performance computing server, DL models, and Apache Spark. Section 8 outlines the research challenges and future research opportunities. Lastly, the concluding remarks are presented in Section 9.

2. Deep Learning Architecture and Applications

In this section, we provide a brief description of the DL and some major DL architectures and their variants given the limited scope of this study. The main application domain of DL architecture is outlined. A simple taxonomy of the architecture and applications of DL is presented in Figure 1. The major DL architecture discussed is as follows: deep belief network (DBN), generative adversarial network (GAN), and convolutional neural network (ConvNet).

DL is the branch of machine learning that allows the computers to learn from experience and comprehend the hierarchy of a concept in the world [17]. DL includes computational models that permit the composition of multiple layers of processing elements to learn the representation in datasets with multiple levels of abstraction. DL uses the backpropagation algorithm to uncover complex structure in large-scale datasets. The DL algorithms and their architecture newly proposed in the literature are geared toward minimal human effort in engineering [13].

2.1. Deep Belief Network. The DBN architecture (Figure 2) is a deep ANN that comprises a sequential arrangement of the unsupervised restricted Boltzmann machine (RBM). We discuss the basic concepts of the RBM for easy understanding of the DBN and how it works to achieve its goal. The RBM is the major building block of the DBN. The RBM is a stochastic two-layered ANN that has hidden and visible layers, as shown in Figure 3. It is restricted because the connection between neurons on the same layer is restricted. The data representation in the RBM occurs in the visible units, and the learning that represents features capturing the higher-order correlation in the experimental data occurs in the hidden layer. The visible and hidden layers are connected by a matrix of asymmetric weight W connections [18].

The computation of the weights in the RBM assumes that the probability of the distribution of input vector (x) can be expressed as follows:

$$p(xw)| \frac{1}{Z(W)\ell(x;W)} E, \tag{1}$$

where $Z(W)\ \ell(x;W)$ is the normalized constant. In the architecture of the DBN, the hidden layer of the RBM is

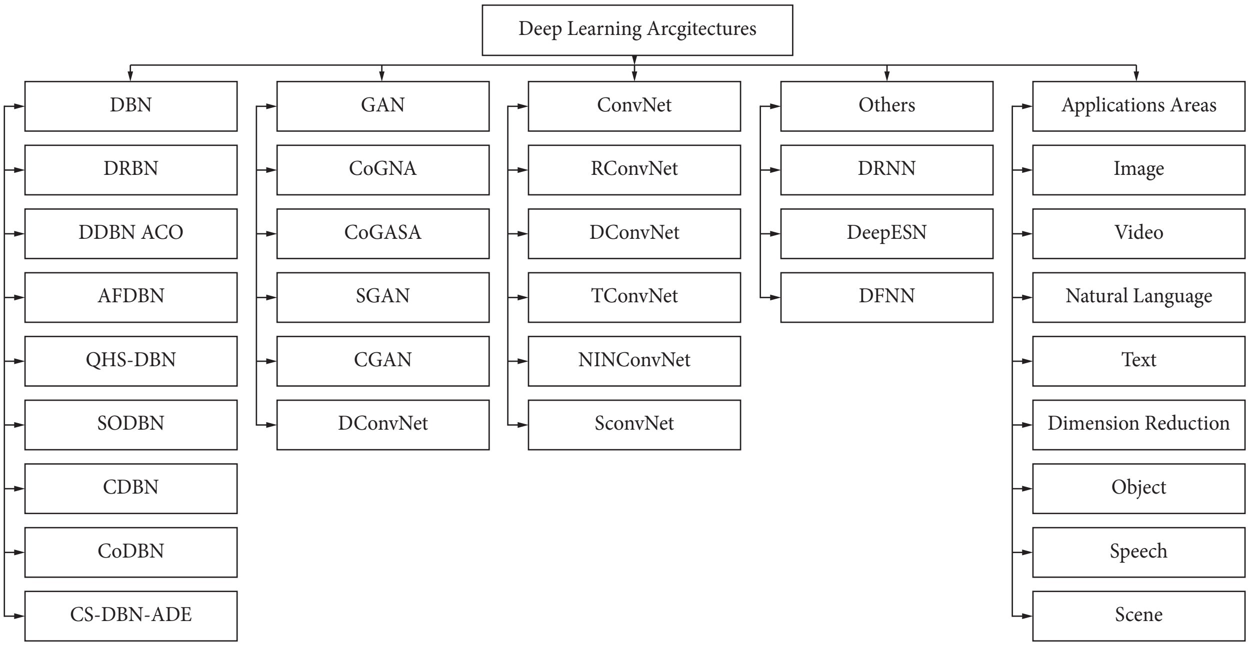


Figure 1: Taxonomy for DL architectures and their application areas.

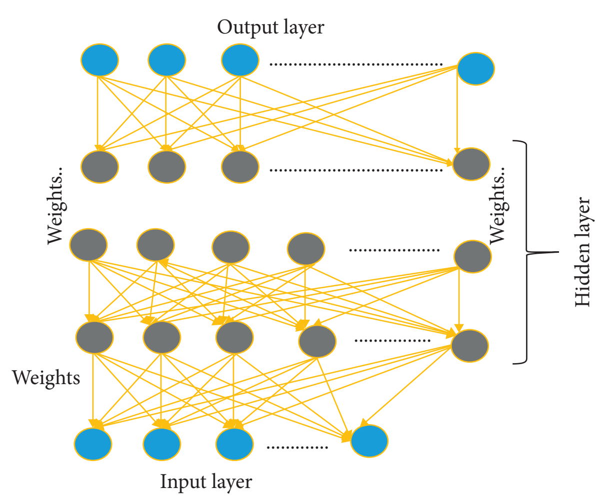


Figure 2: Architecture of the DBN.

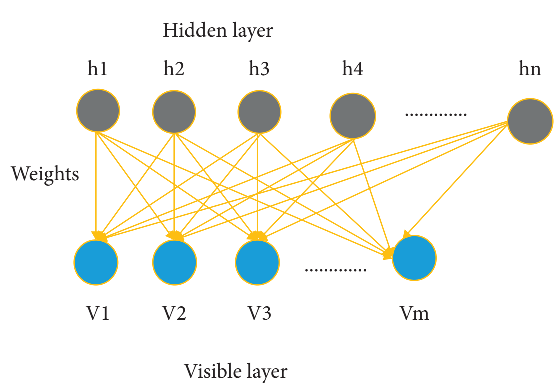


Figure 3: Restricted Boltzmann machine architecture.

visible to the subsequent RBM [19]. The main idea of the DBN is that the DBN weight W is learned by the RBM that is defined by $p(v|h,W)$ and the predistribution over the hidden vectors $p(h|W)$. Accordingly, the probability of generating v can be expressed as follows:

$$p(v) = \sum hp(h \mid W)p(v \mid h, W). \quad (2)$$

When W is learned, $p(v|h,W)$ is maintained. However, $p(h|W)$ is substituted by a superior model with better performance of the aggregated posterior over the hidden vectors [18].

The weights of the DBN are learned using the contrastive divergence approach to avoid being stuck in local minima and to improve the speed of the convergence contrary to the typical Markov Chain Monte Carlo approach [20]. The training of the DBN involves two phases, namely, unsupervised and supervised. Unsupervised training is performed by the contrastive divergence algorithm to determine the initial weights using sample input data, whereas supervised training is performed by the backpropagation algorithm to obtain the final and optimal weights [21, 22]. The DBN can be used to reduce high-dimensional data to low-dimensional data without losing accuracy [23].

2.1.1. Deep Recurrent Belief Network. The DBN vanishing gradient with increase in delay causes long delays when learning. A deep recurrent belief network (DRBN) with distributed time delay is proposed to avoid this problem. A Gaussian network is applied to initialize the weights of every hidden neuron. Markov Chain Monte Carlo is used to evolve the dynamic Gaussian Bayesian network over the training samples to initialize the weights of the hidden neurons [19].

2.1.2. Discriminative Deep Belief Network with Ant Colony Optimization. The DBN and the discriminative (D) feature of backpropagation are combined to produce DDBN. The optimum parameter of the DDBN is selected automatically without human intervention through ant colony optimization (ACO) to avoid the laborious trial and error in DDBN parameter selection. The resulting algorithm is the combination of DBN, D, and ACO to obtain DDBN-ACO [24].

2.1.3. Adaptive Fractional Deep Belief Network. Adaptive fractional DBN (AFDBN) is another variant of the DBN. In this variant, fractional calculus is used to generate the learning weights to obtain an optimal weight suitable for yielding optimum results. Learning by fractional theory is conducted by derivative theory [25].

2.1.4. Quaternion-Improved Harmony Search Deep Belief Network. Quaternion-improved harmony search (QHS) is applied to fine-tune the parameters of DBN (QHS-DBN) in quaternion search space. The harmony search algorithm is selected because of its efficiency in optimization. Moreover, the harmony search algorithm updates probable solutions one by one in a single iteration, not at once. Thus, it is suitable for the fine-tuning of the DBN parameters [26].

2.1.5. Self-Organizing Deep Belief Network. The self-organizing DBN (SODBN) based on the growing and pruning algorithm is the integration of the self-organizing ANN and DBN. Different from the original DBN, the SODBN simultaneously considers its structure and learning algorithm. The best number of hidden layers and units can be determined automatically by the SODBN, and weight adjustment is performed during the self-organizing structure dynamic process [27].

2.1.6. Competitive Deep Belief Network. The competitive DBN (CDBN) is constructed by introducing a competitive learning algorithm mechanism into the DBN. The competitive learning algorithm improves the discriminate information of the deep features among the groups [28].

2.1.7. Continuous Deep Belief Network. The continuous DBN (CoDBN) deals with the actual data instead of the discrete data in the standard RBM. The CRBM is designed by introducing zero-mean Gaussian noise to the visible layer of the RBM. Thus, the RBM can improve its capability to deal with actual data. The CoDBN is constructed by sequentially arranging the CRBM and can work with continuous data [21, 29, 30].

2.1.8. Cost-Sensitive Adaptive Differential Evolution Deep Belief Network. The cost-sensitive DBN (CS-DBN) with adaptive differential evolution (ADE) is introduced to eliminate the problem of classical DBN in dealing with imbalanced data. The DBN does not effectively work on imbalanced data given that the DBN assumes equal cost for every class. The misclassification cost is optimized before embedding into the DBN to create CS-DBN. The parameters of the CS-DBN are updated using adaptive differential evolution to construct CS-DBN-ADE [15].

2.2. Generative Adversarial Network. GAN, as shown in Figure 4, is a class of feedforward ANN. It is composed of two feedforward ANNs, namely, the generator (G) and discriminator (D). The two networks, G and D, compete against each other. The adversary D evaluates the quality of the new candidate produced by G. The G ANN model generates forged data from random uniform space, whereas D differentiates between the forged generated data and the original data. The distinguishing of the forged and original data by the D ANN model assists G in generating data with good precision without making reference to the original data. Thus, the G model is refined. This approach is the main idea behind the GAN. G and D are deep ANN models comprising many layers. The connections in the deep ANN model are conducted in such a manner that the output of the neuron in each layer is the input of the neurons in the next layer [31].

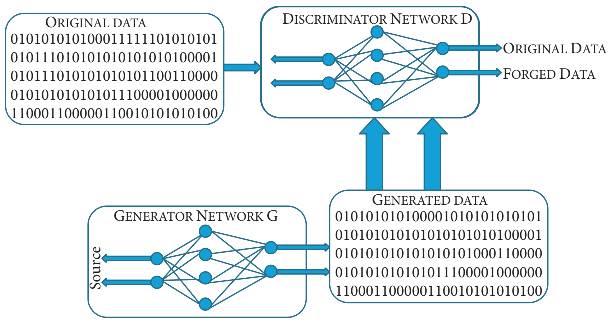


Figure 4: Generative adversarial network.

The objective of G is to learn the probability distribution of the training data to generate forged data as close as possible to the original data. On the contrary, the objective of the adversarial D is to distinguish the forged data from the original data. It is performed by penalizing the work of G in generating forged data. This process continues until G and D improve their ability until an equilibrium is reached, where forged and original data cannot be distinguished. G is trained to deceive D to believe that the generated data are actual data. The training of G is performed by minimizing prediction error, whereas that of D is performed by maximizing the prediction error. This approach has resulted in a competitive battle between G and D. The challenging issue in the training of GAN is the lack of stability between its component networks. In training GAN, when the performance of G is significantly better than that of D in the competition, the complete GAN fails. In the initial stage, D gains superior performance to G. G has to struggle to compete with D [31]. The core GAN capability includes image synthesis [32]. GAN is also effective in fraud detection [33].

2.2.1. Coupled Generative Adversarial Network. The coupled GAN (CoGAN) mitigates the requirement of the tuples of the corresponding images in the dataset with a different domain. The CoGAN has the ability to learn the joint distribution without requiring tuples for the corresponding images. The joint distribution can be learned with samples that emanate from marginal distribution. Weight-sharing constraint is enforced to limit the capacity of the network and provide preference to the joint distribution solution over the marginal distribution product [34].

2.2.2. Coupled Generative Adversarial Stacked Autoencoder. Coupled generative adversarial stacked autoencoder (CoGASA) is introduced to overcome the limitations of CoGAN, such as the inability to handle noisy dataset, high computational cost, and lack of potential for real-world applications. The CoGASA can transfer data from one domain to another without difficulty in handling noisy dataset, and it has less computational cost [35].

2.2.3. Stacked Generative Adversarial Networks. Stacked GAN (SGAN) comprises a stack of GAN in a top-down hierarchical representation. Each GAN in the stack is learned to generate low-level representation for high-level representations. The architecture also has conditional and entropy loss for using conditional information and maximizing lower bound variation on the conditioned entropy belonging to the G outputs [36].

2.2.4. Conditional Generative Adversarial Network. Conditional GAN (CGAN) is a variant of GAN that introduces a condition to the discriminator and generator. The CGAN is achieved by feeding extra information to the discriminator and the generator as an extra layer of input. The condition introduced to the GAN has the advantage of providing representation for multimodal data generation [37].

2.2.5. Deep Convolutional Generative Adversarial Network. Deep convolutional GAN (DCovGAN) is created to extend the supervised ConvNet to unsupervised deep ConvNet + GAN. The spatial down- and upsampling operators in the DCovGAN use the stride and fractional stride convolutions for learning during the training. The DConvNet has strong DL architecture for unsupervised learning [38].

2.3. Convolutional Neural Network. ConvNet was proposed in [39] and subsequently modified as LeNet-5 to improve its effectiveness and efficiency [40] for the classification of handwriting digits. The architecture of the ConvNet comprises input, hidden, and output layers, as shown in Figure 5. The hidden layer of the ConvNet is composed of convolutional, pooling, fully connected, and normalized layers, and individual features are usually extracted by different layers of the ConvNet in a high-dimensional structure [41]. When an input is supplied to the ConvNet, convolutional operations are applied to the input by the convolutional layer before the result of the operations is passed to the next layer in the ConvNet hidden layers. Each neuron in a feature map is connected to the receptive field of the neuron in the previous layer. The response of a neuron is imitated by the convolution to the visualization of a stimulus.

The role of the convolutional layer is to reduce the high number of free parameters required for training the ConvNet, especially the large input associated with images. Thus, the ConvNet allows the entire network to be deep with a few parameters. Therefore, the problem of vanishing gradient associated with training the classical deep ANN is resolved using the backpropagation algorithm. Global or local spooling may be included in the convolutional network. The convolutional network integrates the results yielded by the cluster of neurons into a single neuron at the subsequent layer. Maximum (max) or average pooling can be used from each of the clusters at the previous layer [40].

The fully connected layer in the ConvNet connects each neuron in one layer to the neuron in another layer. The weights of the ConvNet are shared in the convolutional layer to reduce memory footprint and improve performance [40]. The ConvNet requires activation function to introduce nonlinearity in the network for

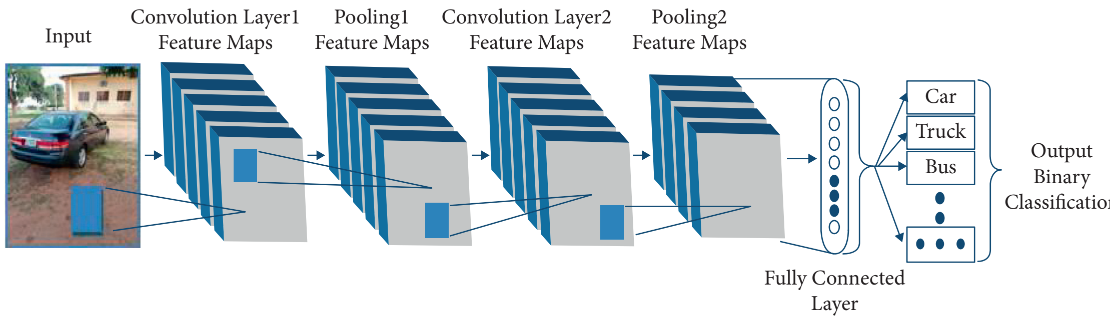


Figure 5: Architecture of convolutional neural network.

detecting nonlinear features. The typical activation function for ConvNet includes the following: ReLU, Tanh, and Sigmoid [42].

2.3.1. Dilated Convolutional Neural Network. The dilated ConvNet (DConvNet) has an additional hyperparameter introduced to the convolutional layer of the ConvNet. In the DConvNet, zero is introduced between the filter elements to increase the size of the network receptive field. This approach can provide room for the DConvNet to cover a large amount of relevant information [43].

2.3.2. Recurrent Convolutional Neural Network. The recurrent ConvNet (RConvNet) has the capacity to use large input; however, the capacity of the RConvNet is limited. Different from the classical techniques, the RConvNet does not rely on segmentation or task-specific features. As long as the size of the context increases with the built-in recurrences, the system adapts to detect and correct its own errors [44].

2.3.3. Tiled Convolutional Neural Network. The tiled ConvNet (TConvNet) tiles and multiplies feature maps to enable the model to learn different types of invariance. The tiling and multiplication of the feature maps allow the model to learn rotational and scale-invariant features contrary to the ConvNet [45].

2.3.4. Network in Network Convolutional Neural Network. The network in network ConvNet (NINConvNet) uses micro networks in place of the convolutional layer linear filter. This approach provides the NINConvNet the capability of approximating abstraction representation more than the classical ConvNet. The main building block of the NINConvNet is the micro network; the stack of the micro networks forms the NINConvNet [46].

2.3.5. Symmetric Convolutional Neural Network. The symmetric ConvNet (SConvNet), contrary to the ConvNet, imposes convolution and deconvolution operations in a symmetric approach to improve segmentation performance. The SConvNet can also perform automatic mandible segmentation from the original data [47].

2.4. Other Deep Learning Architecture

2.4.1. Deep Echo State Network. The deep echo state network (DeepESN) is the extension of the ESN architecture. Contrary to the classical ESN, the recurrent component of the ESN is organized into hierarchical structure as a stack of reservoir layers. Subsequently, the architecture is referred to as the DeepESN [48, 49].

2.4.2. Deep Recurrent Neural Network. The basic recurrent neural network (RNN) is a neural network architecture that accepts the set of input sequence and computes the hidden and output vector sequences by iterations. For a given input vector sequence $x = (x_1, \ldots, x_t)$, hidden vector sequence $h = (h_1, \ldots, h_t)$, and output vector sequence $y = (y_1, \ldots, y_t)$, the iterations start from $T = 1$ to t. However, the deep RNN (DRNN) is built by stacking multiple RNN hidden layers on the top of one another. In this approach, the output sequence of one layer forms the input sequence of the subsequent layer [50, 51].

2.4.3. Deep Feedforward Neural Network. The deep feedforward neural network (DFNN) is the architecture of the ANN that has multiple hidden layers. It is different from the shallow ANN composed of only three layers, namely, input, hidden, and output. The DFNN is carefully constructed to avoid the local minima problem. The number of hidden layers increases the complexity of the DFNN because many parameters are required to be tuned. However, the DFNN can effectively deal with large-scale datasets because recent empirical and theoretical works indicated that local minima are not a serious issue [13].

2.5. Application of Deep Learning Architecture. In this section, the applications of the DL architecture are briefly presented. Recently, the application of DL in image analysis, speech recognition, and text understanding has demonstrated outstanding success. The DL applies the supervised and unsupervised learning techniques for learning multiple-level representation as well as features in hierarchical architectures to solve classification and pattern recognition problems [15]. The DL architecture presented in the previous section has demonstrated excellent performance in different application domains. The DL architecture can be applied in image processing [52, 53], natural language processing [54, 55], video analysis [56], text analysis [57], scene [57], object detection [58, 59], speech processing [60, 61], and dimension reduction [23].

3. Internet of Vehicles

The great revolution that escalated from the Internet has provided opportunity for connecting people at an exceptional magnitude and speed. The success recorded from the Internet revolution brought about significant opportunity that is presently changing the methods by which various objects communicate at present. This rapid development considers the interconnection between objects to realize a smart city, where a device interacts with other connected devices. This communication is achieved through seamless ubiquitous sensing, emerging technologies, and availability of a scalable platform for large data analysis. At present, objects, such as smartphones, vehicles, laptops and tablets, TVs, and other handheld devices, change our surroundings, making them very interactive and informative [62, 63]. Through modern communication, smart devices create a network of interconnected objects with real-time interactions. The growth in the number of devices and the nature of the global network architecture, which includes all existing heterogeneous networks, has shaped our experience. This universal network of things has been identified as a future Internet presently shaped as the IoT [64]. The IoT serves as an enabling environment where sensors and actuator objects interact seamlessly and provide progressively more suitable platforms for data exchange. The recent advancement and adaptation of various wireless communication technologies have positioned IoT to be a promising technology, which benefits from the potential prospects provided through Internet technology. The IoT technology has brought about the development of intelligent systems, which include but are not limited to smart retail, smart water, smart energy, smart grids, smart healthcare, smart homes, and smart transportation [62, 63]. The IoT has created interfaces for smart devices to be connected to a global network with the ability to render services from other connected devices [65]. The IoT enables seamless integration of heterogeneous network of devices through the use of intelligent interfaces. Therefore, one of the key objectives of the IoT is interoperability among heterogeneous devices [62, 64]. The emergence of IoT technology has revolutionized many new research and development areas.

The IoV is an innovation activated by IoT, and this domain evolves from vehicular ad hoc networks (VANETs) to build smart vehicles within smart cities [66]. At present, the number of connected vehicles has witnessed exponential growth, and according to [67], a significant number of vehicles are expected to have an Internet connection.

The global vehicular traffic was projected to escalate to 300,000 exabytes toward the end of 2020. This significant increase in vehicular data results from the advancement in vehicular telematics applications, including in-vehicle infotainment and ITS [68]. Conventional VANETs use vehicle as a node for transmitting or relaying traffic information between vehicles and infrastructures using vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. Many vehicular applications, including ITS services and safety application, have leveraged the potentials offered by the increasing connectivity of modern vehicles. For instance, V2V communication enables sharing of information among vehicles for safety communication propagation. Conversely, V2I communication enables the collection of information from different infrastructure facilities [68]. The IoV can be visualized using the three layers shown in Figure 6. This architecture considers the IoV from the network connection perspective [5].

The taxonomy of the IoV communication system with various information flows is presented in Figure 7.

The taxonomy of IoV communication is shown in Figure 7. This taxonomy presents the different types of interactions that exist between vehicles and other devices. In addition, it identifies the information flow in each IoV communication category as well as the emerging technologies utilized by each communication type. The type of the communication involved vehicle-to-vehicle communications, vehicle-to-infrastructure communications, vehicle-to-roadside unit communications, vehicle-to-sensor (V2S) communications, vehicle-to-personal device (V2P) communications, vehicle-to-pedestrian (V2D) communications, and vehicle-to-home (V2H) communications.

4. Case Studies

This section briefly points out case studies involving IoV. Five case studies are presented for readers to appreciate the level of progress in the concept of IoV. The summary of the case studies is presented in Table 1 and discussed in the subsequent section.

4.1. 5G Internet of Vehicles. A 5G IoV has been built by Nokia in Wuzhen Town, China. The 5G IoV has a 5 km test route that can be used by three vehicles. Two different scenarios are tested on the route. The first scenario shows the vehicle signaling warning while slowing down at a time when a different car at 1000 m away makes an emergency stop. The second scenario shows the capability of the vehicle to issue accurate instructions on changing or packing a lane in complex circumstances. The Nokia 5G IoV solution Car2X has improved the current 1 s delay to less than 20 ms between the vehicle and the mobile communication networks [69].

4.2. Internet-of-Vehicle Platform of Huawei Technologies. In promoting innovation in the IoV, Huawei technologies have developed a connected car solution on its platform—OceanConnect IoV. The connected car solution provides transport-oriented services, such as data, interconnection, fleet, and security. It has a secure network access. The connected car solution generates new value stream and flexible adaptation for multiple terminals, as well as the collection and analysis of large-scale data. The

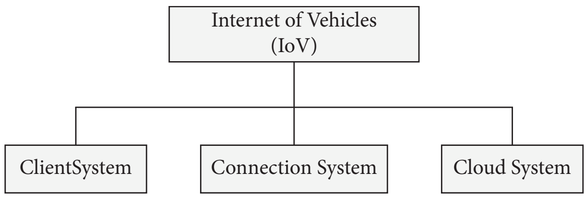


Figure 6: IoV three-level architecture.

connected car solution has been commercialized with FAW group, including Kingdom of Saudi Arabia Zain and Malaysia Axiata. The connected car solution has won the best "IoV Innovation Award at World Intelligent Vehicle Conference 2017" [70]. A DS 7 CROSSBACK vehicle is developed on the OceanConnect IoV platform launched in China and Europe. It is the first vehicle developed on the OceanConnect IoV platform. The OceanConnect IoV platform can support hundreds of millions of connections [74].

4.3. Cadillac Vehicle-to-Vehicle Communications. Cadillac has announced the introduction of V2V communication in CTS-performance sedan since March 2017. The V2V technology equips vehicles to share information about the possibility of a hazard. The Cadillac V2V uses a dedicated short-range communication and GPS. The Cadillac V2V technology operates on the 5.9 GHz spectrum. It can handle 1000 messages in each second from vehicles within almost 1000 feet. The Cadillac V2V technology scans the vicinity to track the position, direction, and speed of other vehicles. Subsequently, the driver is warned on potential risks ahead. The communication within the vehicles can only occur among vehicles with compatible V2V communication technology. The V2V technology is currently included in Cadillac 2017 as a standard feature in the USA and Canada [72].

4.4. Fatal Accident of Autonomous Vehicle. In March 2018, an experimental autonomous Uber vehicle driving on a public road of Arizona struck a pedestrian to death. The Uber vehicle was driving in autonomous mode. The accident is believed to be the first recorded fatal accident involving a full autonomous vehicle. The unfortunate incident killed Elaine Herzberg, 49 years old, while riding on a bicycle across the street. The speed of the Uber autonomous vehicle was estimated at 40 mph within a 35 mph zone, as revealed during the police preliminary investigation. Police claimed that no evidence showed that the autonomous vehicle slowed down before striking Elaine Herzberg [73].

4.5. Test Run of Autonomous Vehicles on Public Roads. In April 2017, over 50 Chevrolet Bolt autonomous vehicles were given a test run on the public roads of San Francisco, Scottsdale, Arizona, and Metro Detroit. The test run of the autonomous vehicles was conducted by the Cruise automation and General Motors engineers [71].

5. Big Data Analytic Platforms That Support Deep Learning in the Internet of Vehicles

The processing of the large-scale data generated from the IoV environment from various sources, such as cameras and sensors, is required. DL can be used for the processing of the IoV big data. BDA platforms that support DL are required for the analysis of IoV BDA. In this section, we present the Apache Spark that supports DL and other BDA platforms that support machine learning, such as Hadoop, AzureML, and BigML (Figure 8). DL is a branch of the machine learning that can solve classification, prediction, and clustering problems in IoV environments.

5.1. Apache Spark. Spark is a big data processing framework based on streaming, machine learning, and graph processing [75]. It is an open-source framework and was developed to overcome some of the limitations of Hadoop MapReduce. Spark uses memory based on processing large amounts of data, and it is faster in terms of data processing than MapReduce framework. As a result, the data are stored in memory using resilient distributed datasets. Moreover, Spark supports real-time analysis. Reference [76] presented Spark's open-source distributed machine learning library, MLlib. Several learning settings exist in MLlib to improve the functionality efficiently, such as optimization, linear algebra primitives, and underlying statistical methods. Moreover, MLlib provides a high-level API and several languages that leverage Spark's rich ecosystem to simplify the development of end-to-end machine learning pipelines. Reference [77] discussed the DL over Apache Spark for mobile BDA. The authors showed how Spark can perform distributed DL on MapReduce. Each partition of the deep model is learned by the Spark worker for the entire mobile big data. Then, the parameters use the master deep model of all partial models through averaging.

5.2. Hadoop. Hadoop has emerged as an important framework for "distributed processing of large datasets across clusters of machines" [78]. Many Hadoop-related projects have been developed over the years to support the framework, such as, Hive, Pig, Tez, Zookeeper, and Mahout. Mahout is one of the distributed linear algebra frameworks for scalable machine learning [79]. Moreover, "scalable advanced massive online analysis" is an open-source platform for data mining and machine learning similar to Mahout, which supports Hadoop for streaming big data processing [80]. Discussion on Twitter's integration of machine learning into the Hadoop platform was done by [81]. The main idea is to utilize Pig extensions to offer predictive analytic capabilities. The authors identified various techniques related to stochastic gradient descent for supervised classification through online learning and ensemble methods, which can scale out to large amounts of data. Recently, DL networks based on backpropagation are implemented with one hidden layer in Mahout to learn arbitrary decision boundaries. Moreover, different machine

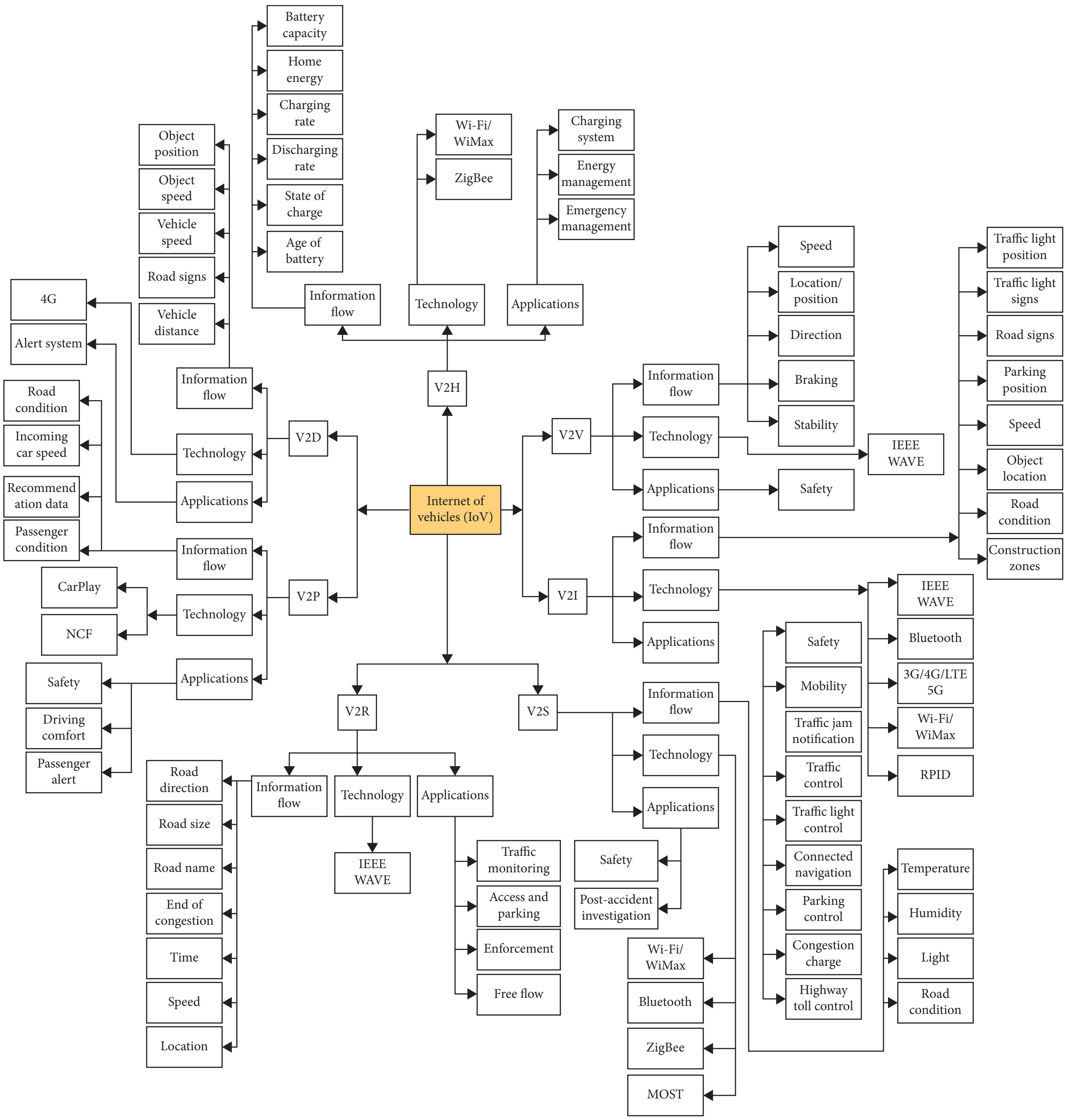


FIGURE 7: Taxonomy of IoV communications.

TABLE 1: Summary of the case studies.

Work	Use case	Description	Application
[69]	IoV route used by three vehicles	Nokia built 5G IoV in Wuzhen	5G IoV
[70]	IoV	Huawei technologies developed connected car solution for advancing IoV	Connected car solution
[71]	Chevrolet Bolt autonomous vehicles	50 Chevrolet Bolts autonomous vehicles were given a test run on the public roads of San Francisco, Scottsdale, Arizona, and Metro Detroit	Autonomous mode
[72]	V2V	Cadillac introduced V2V technology in Cadillac 2017 model	Cadillac V2V
[73]	Uber autonomous vehicle driving	An autonomous vehicle on test drive struck a pedestrian to death	Autonomous mode

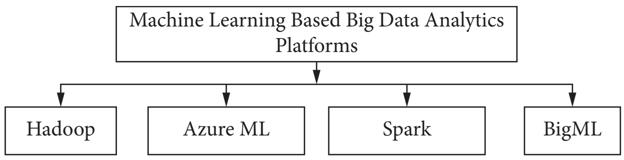


Figure 8: Big data analytic platforms for machine learning.

learning algorithms, including neural networks, and parallel programming methods, such as MapReduce, are mapped to improve processing speed.

5.3. AzureML. AzureML is a collaborative machine learning platform based on predictive analytics in big data, which allows easy development of predictive models and APIs. Numerous unique features, such as easy operationalization, versioning collaboration, and integration of user code, are provided by AzureML [82]. Reference [83] offered a technique for cloud-based AzureML named Generalized Flow, which allows binary classification and multiclass datasets and processes them to maximize the overall classification accuracy. The performance of the technique is tested on datasets based on the optimized classification model. The authors used three public datasets and a local dataset to evaluate the proposed flow using the classification. The result of the public datasets has shown an accuracy of 97.5%. Furthermore, the concept has become indispensable on big data technologies. For example, AzureML supports neural network for regression, two-class classification, and multiclass classification.

5.4. BigML. BigML provides highly scalable ML and predictive analysis services on cloud (Martin & Ortega). The goal of BigML is to assist in developing a set of services given that it is easy to use and seamless to integrate. BigML has been used in many studies for predictive analytics and DL because of its robustness and simplicity in providing a user-friendly interface. For example, a study on the distinguishing features of human footprint images is conducted by [84] to offer deep analysis using BigML. The idea is to exploit the concept of the human footprint for personal identification using many fuzzy rules for predictive analysis. The verification of 440 footprint images is conducted for data quality. GPUs have been applied to speed up the performance. Moreover, [85] presented a predictive analysis on the most popular place for dengue in Malaysia to obtain an early warning and awareness to people using BigML platform. The study is based on the decision tree algorithm model, which builds on BigML to support classification. Moreover, [86] analyzed the game features and acquisition, retention, and monetization strategies as primary drivers of mobile game application success.

6. Harnessing Deep Learning in the Internet of Vehicles in the Context of Big Data Analytics

In the IoV, fully autonomous, semiautonomous, and conventional vehicles equipped with IoV technologies operate in the environment.

IoV has the ability to support big data acquisition, storage, transmission, and computing. The big data can improve the effectiveness and efficiency of the IoV based on the characterization of network, analysis of performance, and protocol design [68]. Big data distinctly have different formats (unstructured). Unstructured data can be in the format of text, images, videos, and graphics. The unstructured component of the big data constitutes 75% [87]. DL is a popular tool for big data processing [77, 88] because of its outstanding result in different applications [26].

The DL architecture is complex with the capability to work on big data generated from the IoV. These complex networks work better than the simple structure of the ANN [89]. DL has shown promising performance in unstructured data analytics. The promising performance of DL in processing unstructured data, for example, in visual object classification, speech recognition, natural language processing, and information retrieval, has been reported in the literature [90].

In the case of autonomous vehicles, DL is highly required because it learns from experience. Despite the fact that almost all available possibilities are fully automated, DL is required to capture new scenarios and perform analytics of accumulated data from the cameras and sensors. This approach enables the vehicles in the IoV environment to take critical decision that can avoid collision and possible loss of life. Progress in sensor networks and communication technology prompted the gathering of big data. Sufficient training objects are provided when big data are exploited. As a result, the performance of DL is improved. Training of large-scale DL models for big data feature requires high-performance systems and architecture, such as graphical processing units (GPUs) and CPU cluster [15]. A recent study has shown that evolutionary ANN has potential application in the IoV. Chen et al. [91] demonstrated that the evolutionary ANN can predict rear-end collision within the IoV environment. Hence, it can help in the development of an effective rear-end collision detection system for vehicles in IoV environments. Kong et al. [92] proposed the application of DBN for the prediction of short traffic flow within the IoV environment. The study is motivated by the accumulation of big data in the IoV, and the shallow artificial neural network algorithm cannot handle such a large amount of data. The DBN is applied for the short traffic flow, and it performs better than the baseline algorithms. Wang et al. [93] proposed a DL model for optimal workload allocation to improve vehicle energy consumption in the IoV. DL provides enhanced energy efficiency and improves the latency of the network. Ning et al. [94] proposed ConvNet to improve the speed of data transmission and enhance the content among vehicles in the IoV environment. The ConvNet is applied for data transmission by exploiting the tri-relationship between vehicles. The result indicates the efficiency of the proposed ConvNet based on latency, message delivery, and percentage of connected devices.

Ning et al. [95] hybridized motif based method (MBM) and ConvNet (MBM-ConvNet) for D2D communication in the IoV. The MBM clusters the intelligent mobile devices in buses and with passengers in a triangular manner whereas the ConvNet predicts the D2D connection. The MBM-ConvNet model performed better than the pair discovery scheme, social aware approach, and MBM. The issue here is that edge network may not be good for emergencies. Gulati et al. [96] hybridized energy estimation scheme (EES), Wiener process model (WPM), and ConvNet (EES-WPM-ConvNet) to ensure enhanced throughput and reduced latency for data transmission in the IoV. The EES checks vehicle's energy level for connectivity by comparing it with a threshold value, WPM estimates vehicles connectivity while the ConvNet predicts the ideal vehicle pairs for data transmission. The proposed EES-WPM-ConvNet performed better than the EES-WPM. The challenge is that connectivity is allowed only for vehicles with sufficient amount of energy.

Wang et al. [93] hybridized greedy algorithm (GA) and ConvNet with simulated annealing (SA) algorithm (GA-ConvNet with SA) to ensure reduced energy level consumption for both vehicles and road sign unit in the IoV. The GA selects the server with minimum power consumption for processing the queuing requests, SA searches for the global optimal solution for the initialization phase of the ConvNet, and the ConvNet predicts the optimal workload allocation for the computational facilities. The result showed that the GA consumes less power compared to the ConvNet and SA whereas the ConvNet has the least network delay compared with the GA and SA. However, the paper assumed that all vehicles move on a straight line. Ning et al. [94] hybridized Edmonds–Karp Algorithm (EKA) and DRL with deep Q-network (DQN) (EKA-DDQN) to minimize the amount of energy consumed during computational offloading in the IoV. The EKA ensures flow redirection among RSUs while the DDQN minimizes the overall energy consumption. The result obtained showed that the EKA performed better than the greedy method and exhaustive method while the DDQN outperformed Q-learning and cloudlet computing models. The issue is that if the rate of data offloads is above the computational capability of the vehicles, say 80 MB, the rate of energy consumption increases rapidly.

Liu et al. [97] hybridized practical Byzantine fault tolerant algorithm (PBFTA) and DRL based scheme in blockchain enabled (PBFTA-DRL-BCE) IoV for performance optimization. The PBFTA appends a particular block to blockchain through agreement on the block that is recently realized. The DRL makes block producers (BPs), block size (BS), and block interval (BI) in the PBFTA-DRL-BCE conversant with various instances of the IoV so as to maximize throughput. The PBFTA-DRL-BCE model performs better than the PBFTA-DRL-BCE without BPs selection, PBFTA-DRL-BCE with fixed BS, PBFTA-DRL-BCE with fixed BI, and existing static scheme. The transactional throughput was unstable at some point during learning process.

Dai et al. [98] hybridized DRL based on deep deterministic policy gradient (DDPG) and Manhattan grid model (MGM) for edge caching and content delivery latency reduction in the IoV. The MGM defines direction of vehicle's movement while DDPG optimizes vehicle edge caching and minimizes content delivery latency. The result obtained shows that the DDPG scheme performed better than random edge caching without bandwidth allocation, optimization of edge caching, and content delivery without bandwidth allocation schemes. Kong et al. [92] proposed a deep belief network (DBN) model for short-term traffic flow prediction in smart multimedia system (SMS) in the IoV. The DBN model predicts short-term traffic flow in SMS for SMS to driver communication. The result obtained shows that the DBN model performed better than the ANN, backpropagation, support vector regression machine (SVRM), and autoregressive moving average. The issues here are that the DBN model cannot handle a large-scale dataset of up to 10 million for feature mining and prediction, and if data complexity and randomness are increased in the traffic, the output cannot be ascertained.

Goudarzi et al. [99] hybridized DBN, backpropagation algorithm (BPA), and firefly algorithm (FFA) (DBN-BPA-FFA) for traffic flow prediction in the IoV. FFA optimizes the DBN topology and learning rate parameters, the BP fine-tunes the weight parameters of RBMs, and the optimized DBN predicts the traffic flow. The result shows that DRBM-FFA performed better than the autoregressive integrated moving average (ARIMA), multilayer perception (MLP) optimized FFA (MLP-FFA), and ARIMA optimized particle swarm optimization (PSO) (ARIMA-PSO). It is assumed that traffic behaviors are concurrent at peak periods. Sharma et al. [100] proposed a deep neural network (DNN) for security system in the IoV. The DNN detects and thwarts various cyberattacks. The DNN scheme performed better than the traditional security system (TSS).

Deep reinforcement learning [101] can also play a vital role within the IoV environments because of the complexity of real-world driving. In autonomous vehicles, DL, high-performance computing system, and advanced algorithms are required for the vehicles to adapt to changing situations. This approach can be performed through 3D high-definition maps. The cameras and sensors in the autonomous vehicles generate large-scale data for compilation. The data are required to be analyzed to keep the vehicle moving on the lane. Without DL that uses the information from high-definition maps that contain geocoded data, fully autonomous driving becomes a mirage. Without high-definition maps containing geocoded data and DL that uses this information, fully autonomous driving stagnates in Europe [8]. Artificial intelligence software and DL models are used in Baidu's AutoBrain to train computers to drive the same way as humans [102].

6.1. Deep Learning for IoV in the Context of Big Data Analytics Compared to Other AI Techniques. Unlike DL architectures, other artificial intelligence (AI) techniques like the shallow neural network, support vector machine, fuzzy systems, random forest, and k-nearest neighbor typically witness deteriorating performance as the amount of data increases, which makes them unfit for BDA. As discussed in Ali et al. [3], support vector machine has the challenge of dealing with fast authentication mechanism for large-scale IoV architecture. Fuzzy system has the limitation of dealing with IoV multimedia communications. Shallow algorithms like the random forest, multilayer perceptron, and AdaBoost are facing the challenge of securing decision for safety in the V2X traffic.

In addition, other AI techniques require separate techniques for feature extraction before feeding the data to the algorithm for processing, which increases computational cost and requires human intervention, whereas DL has embedded automatic feature extraction mechanism that makes the DL algorithm eliminate the requirement for extra feature extraction techniques, thereby reducing the effort of data engineering. Therefore, it gives DL advantage in BDA over other AI techniques. It is well known in the literature that DL architecture, specifically ConvNet, has proven to be outstanding in image processing compared to other AI techniques. DL has the advantage of dealing with natural unlabeled data better than other AI techniques.

Furthermore, the application of DL in BDA has the following strengths: ability to generate intrinsic features, effective processing of unlabeled data, high accuracy in providing results, and efficiency with multimodal data [77]. We discuss it in the context of the IoV as follows.

Accuracy in the IoV is a crucial issue because the vehicles in the IoV environment depend on the decision of the DL system. Accurate analysis can prevent chaos on the public roads that can lead to accidents, injury, and possibly death. For example, inaccurate capturing of new scenario by the DL system might cause a fatal accident in the IoV environment.

The 3D road map data are recorded by the automated driving maps. Within the distance of a few centimeters away, the 3D road map data are accurate for the vehicle position. The vehicle detects and follows other vehicles with a high level of accuracy, recognizes lanes, and measures distance and speed. This condition typically occurs when the object and environmental technology of the car is enabled [8]. The DL system plays a significant role in this circumstance.

The sensors embedded in the vehicles within the IoV environment generate data with intrinsic feature because the data are obtained from the sensors. BDA requires intrinsic features, and DL has the ability to generate the intrinsic features required by BDA. The feature is a characteristic of sensor data. High-level features can be learned automatically by DL without manual intervention.

A large portion of the data generated from the sensors embedded in vehicles in the IoV environment refers to natural data. Different from conventional machine learning techniques that require significant engineering works, DL can effectively deal with natural unlabeled data with minimal human intervention. Thus, human effort in labelling data is minimized. The sensors generate a variety of data (images, audio, and speech), and DL can work with multimodal input data.

7. Proposed Model of IoV Integrated into the Cloud Equipped with High-Performance Computing Server, Deep Learning Models, and Apache Spark

The paper proposes a model that integrates the IoV into cloud equipped with high-performance computing server, large-scale DL models, and Apache Spark. Low-end devices have limitation in terms of handling the application of large-scale DL models for data processing [15]. Therefore, computers in the vehicles within the IoV environment have limitation in terms of handling large-scale DL models for processing massive large-scale data expected to be generated from the IoV environment with millions of vehicles. Reference [8] suggested that the computers in the vehicles within the IoV environment should be connected to a cloud processing platform for instantaneous data integration and move to the selected terminal.

Figure 9 shows the networks of wireless access technology involving vehicles and the Internet, as well as the heterogeneous network commonly referred to as the IoV. The figure shows the representation of the IoV in large-scale distributed environment in terms of wireless communication of various devices. In the proposed model, the IoV environment comprises autonomous, semiautonomous, and conventional vehicles equipped with IoV technologies.

Autonomous vehicles are equipped with sensors for self-controlling self-driving vehicles and monitoring road conditions, energy consumption, tire pressure, traffic information, water temperature, speed control, and parking services. As the sophistication of autonomous vehicles increases, the number of sensors in the vehicle increases at the same rate. A single vehicle is expected to be equipped with 200 sensors by 2020 given the increase in communication between the vehicle and its surrounding environments. Semiautonomous and conventional vehicles equipped with IoV technologies within the IoV environment are also equipped with sensors. However, the number of sensors in semiautonomous and conventional vehicles can differ from that in autonomous vehicles because the latter are more sophisticated. These embedded sensors in the vehicles generate diverse and complex data at a faster rate in real time and on a massive large scale given that the number of the vehicles with large number of sensors gains acceptability and continues to increase exponentially.

These data are generated from the IoV through sensors, cameras, road infrastructure, vehicles, home, Internet, pedestrians, and personal devices that can provide information about the representation of the IoV environment. Such dataset from the IoV environment has extremely high dimension and is unstructured. The data are transferred in real time to the cloud equipped with large-scale DL models, Apache Spark platform, and high-performance computing server equipped with multiple GPUs for processing IoV big data and storage in the cloud, as shown in Figure 9.

The DL model requires a large-scale dataset as the main component in solving classification, clustering, and prediction problems related to the big data from the IoV environment. The data generated from the IoV could include speech, visual objects, signals, audio, video, and text. The DL concepts perform excellently in processing such data (Section 2).

We propose GPU for the high-performance computing server because studies [15, 103] have shown that processing large-scale data based on DL is more effective and efficient when run on GPU than on CPU. Currently, a special processor for DL is under development and is expected to run DL experiments faster than the GPU to reduce

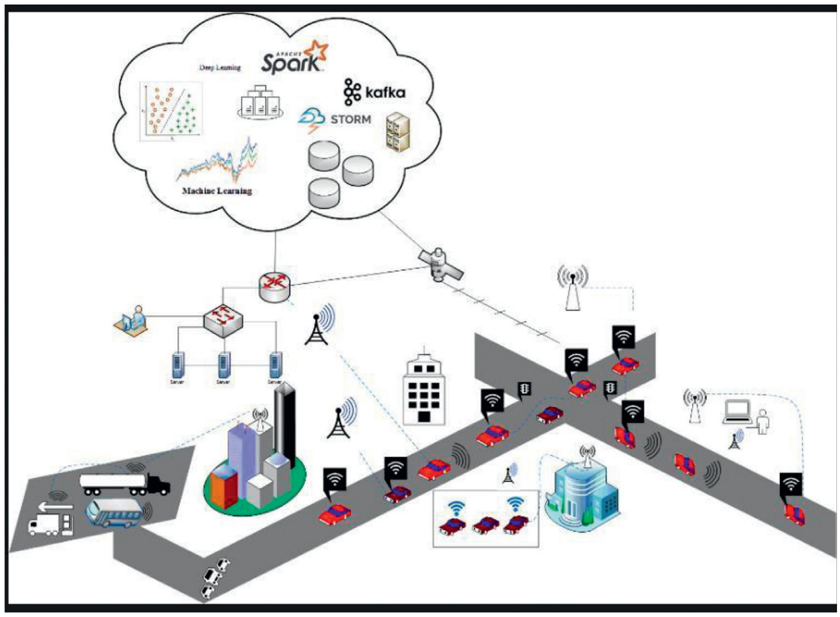


Figure 9: Proposed model of the IoV integrated into the cloud equipped with a high-performance computing server with multiple GPUs, large-scale DL models, and Apache Spark.

computational time [15]. Apache Spark is the proposed big data platform for the large-scale DL to process the big data generated from the IoV environment because the BDA platform supports DL.

The results of the analytics can be forwarded to the relevant companies, such as automobile makers and insurance companies, for use in making crucial decisions, such as designing new business models, detecting component malfunction, reducing the number of recall vehicles, and predicting component failure. The autonomous vehicles can use the result in making decisions, such as predicting rear collision and warning regarding change of lane. This application can prevent unexpected failure prior to occurrence. These decisions are uniform throughout the entire IoV environment, thereby improving the reliability, effectiveness, and efficiency of the IoV environment.

The IoV involves drastic communications (Section 3). These communications continue to increase as long as the vehicles continue to grow in number within the IoV environment. Extensive research and test run of the IoV in complex and challenging environments can also create new opportunities for new communications within the IoV environment.

8. Challenges and Future Research Directions

8.1. Internet-of-Vehicle Dataset Problem. Performing data analysis in the IoV requires datasets generated from the IoV environment. However, the IoV is an emerging concept mostly pilot-tested by different companies. The data required by researchers to apply DL for carrying out meaningful analysis in the IoV within the context of big data are scarce, so working in the area of DL is challenging. Most IoV technologies are in the trial phase; thus, releasing data to third-party researchers for analysis is difficult. Data are the key component of DL; without data, the algorithm is ineffective even with excellent DL architecture. Therefore, we suggest the building of public IoV data repository for use by the research community to run the proposed DL algorithms in the context of the IoV.

The availability of public IoV repository will encourage studies on DL within IoV environments. With such a public repository, additional effective, robust, and efficient models of the IoV can be built for further improvement. In-depth research is required to fully understand the emerging concept and improve the state-of-the-art progress. Data analysis is a key ingredient in timely resolving potential challenges in the IoV. As an alternative, PTV VISSIM, a leading simulator for simulating microscopic traffic [104], can be used to create an IoV environment similar to [105] and generate relevant IoV data for the DL application. The OceanConnect IoV platform developed by Huawei is a good platform for researchers to explore.

8.2. Limited Deep Learning Approaches in the Internet of Vehicles. Despite the excellent performance of DL in different application domains as revealed in the literature, very few studies applied the DL architecture in the IoV for data analysis. Despite the fact that the IoV is projected to generate large-scale data (Section 1), the application of the DL architecture in IoV data analysis is highly limited in the literature. The application of DL in the IoV to solve problems is in its infancy stage. The following DL concepts remain unexplored in the context of IoV: GAN, efficient inference technique, attention models, memory augmented neural network, transfer learning, biologically plausible deep network, and few-shot learning.

The DL, IoV, and big data research communities should deploy massive efforts in the application of DL in the IoV within the context of BDA. The DL architecture deserves exploration on the dataset acquired from the IoV environments—real-life or simulated environments. This approach can provide insights into the development of effective and efficient IoV models, the concept of which is yet to be fully understood. The metaheuristic optimization of the DL architecture should be tuned by considering its parameters in the context of the IoV because it is effective in solving problems, as proven by [106].

8.3. Restriction of Uniform Decision in the Internet-of-Vehicle Environment. Compatibility issue is another challenge facing the smooth operation of the IoV. The communications between vehicles, especially V2V, are challenging. The V2V technology in a vehicle should be compatible prior to exchange of data between the vehicles. If the V2V technology in a vehicle is not compatible with another V2V technology in another vehicle, no communication between the vehicles exists. Thus, these vehicles cannot communicate within the IoV environment. The data generated from the vehicles and transferred to central processing system for data analysis cannot easily provide uniform decision to the vehicles within the IoV environment. The data generated from a particular vehicle obtain a decision different from the data generated from vehicles with different V2V technologies. Therefore, having uniform decision is restricted only to vehicles with compatible V2V technologies.

The V2V technology in the IoV environment should be compatible among all the vehicles in the same environment to provide smooth communications. The data generated from the vehicle sensors and cameras can be transferred to a central location for analysis by DL on the BDA platform in a high-performance computing platform. Therefore, the decision taken as a result of the analysis will be uniform, and all the vehicles will benefit from the decision.

8.4. Unknown Effect of Autonomous Vehicles on the Internet of Vehicles. The effect of autonomous vehicles on the traffic operations and infrastructure of the transportation system is unknown [104]. Lack of IoV data limits the understanding of the effect and its consequences. In addition, the IoV is an emerging technology, and its idea is not fully understood [64]. However, an ongoing initiative aims to fully operate it in the near future. The IoV currently attracts unprecedented attention from the industries and the academia.

This concept requires in-depth research and development to fully understand the effect of autonomous vehicles on traffic operations and transportation infrastructure. The DL research community can consider a research in this direction given that determining the effect of autonomous vehicles on traffic operations and transportation infrastructure of the IoV can assist in developing a robust IoV infrastructure that can accommodate autonomous vehicles comfortably.

8.5. Loss of Internet Connectivity Can Cause Missing Data Points. The IoV heavily depends on Internet connectivity for its smooth and efficient operation. A loss of Internet connectivity between fast moving vehicles in the IoV can cause the loss of data points in the data generated from the IoV environment. The loss of Internet connectivity can be caused by extreme weather, natural disaster, and interruption as a result of limited Internet coverage. Reference [68] argued that the high mobility in the IoV environment can cause frequent interruptions of Internet connectivity. Thus, the quality of the data generated from the IoV environment is affected, thereby resulting in noisy large-scale data. Processing of noisy data requires extra effort to improve the quality of data. However, obtaining real-life dataset without missing points is difficult. The DL models are capable of handling datasets with missing data points. We recommend the application of DL models to handle the IoV dataset with missing data points for BDA. The performance of the DL models does not require complete information to perform contrary to expert systems.

8.6. New Perspective Based on Deep Learning for Solving Challenges Raised in [68]. The IoV big data sources data in different forms, and preprocessing is required. The issue of sourcing different data from different sources is expected from the IoV, and bigger data from larger scope of IoV can also be collected [68]. In view of the fact that the DL does not require extra preprocessing techniques to process data, we recommend that the DL algorithm can be applied to process the IoV big data in conjunction with the framework proposed in Section 7 as shown in Figure 9. Big data can be collected from the IoV network protocol. The big data collected from the IoV network protocol [68] can be analyzed using deep learning to gain insight. The new insight from the data analytics can be used to improve the efficiency, quality, security, and effectiveness of the IoV network protocol. It is reported that the data collected from the roads by the vehicles can be aggregated to form HD maps [68]. Because the HD maps are in form of images, the images can be processed via deep learning especially the ConvNet architecture to get value from the HD images for improving the overall vehicular mobility in the IoV, thereby improving the services rendered by the big data IoV powered services.

8.7. Security Challenges in the Internet-of-Vehicle Environment. The security of an IoV network is vital, and some of the possible attacks on the IoV are discussed as follows.

8.7.1. Ransomware Attacks. Ransomware attacks are classified into three types, namely, crypto, locker, and crypto-locker. The crypto ransomware works by applying encryption schemes on device data. The locker ransomware works by restricting user access to system functionalities, whereas the crypto-locker ransomware supports encrypting and locking devices. This attack is dangerous because the device data and functionality could be compromised. The device is only released back to the user after a ransom has been paid via any of the blockchain technology online payment systems, such as Bitcoin [107].

The threat of ransomware attacks in the IoV environment can be devastating when fully deployed because of the possibility of vehicle hijack using remote connectivity via IoV protocols until a ransom is paid. Vehicles can also be hijacked to commit crimes by impersonation given that the cryptolocker ransomware can encrypt and lock devices and compromise computerized vehicular systems. In addition, the IoV is a source of big data generation given that vehicle signals, vehicle routing information, packing information, and GPS information should be securely stored in massive storage facilities, such as the cloud infrastructure, big data processing, distribution, e-commerce, and IoV transactions [108]. These storage facilities are also a potential target for ransomware attacks, leading to the compromise of data integrity.

8.7.2. DDoS/DoS Attacks. The DDoS/DoS attacks in the IoV environment are used to flood a target vehicle with unsolicited traffic to deny legitimate communication. This attack can lead to system jamming, malfunction, or failure, which will eventually cause vehicular accident in an IoV environment. A number of DDoS/DoS detection and prevention algorithms have been presented in the VANET environment [109–111]. However, these algorithms are ineffective in an IoV situation. One of the best efforts in detecting DDoS/DoS attacks in the IoV was presented by [112]. The study introduced a broadcast authentication protocol called Paralleling Broadcast Authentication Protocol, which aims at improving energy efficiency and providing network security in the uninterrupted communication between vehicles in the IoV environment.

DoS and DDoS attacks can drain the resources of a target autonomous vehicle. Bandwidth resources can be very limited for IoV entities depending on the nature of vehicular communication. Exhaustion of the bandwidth for a certain time interval can lead to inaccessibility of the server or an autonomous vehicle within that time. The resources of an autonomous vehicle range from processing capacity, number of ports, memory, to storage space. Therefore, exhaustion of available resources of the autonomous vehicle can lead to adverse state of the vehicle during which the cybercriminals can compromise the confidentiality, availability, and integrity of the data in the autonomous vehicle [113]. In the IoV environment, DoS/DDoS attacks are frequently achieved in two ways, namely, reflection and amplification methods. In the reflection method, the attacker sends different packets with a bogus IP address of the target vehicle as the source address of the packets to many endpoints. This method is deployed by cybercriminals to hide trails of the attacker. In the amplification method, an insignificant number of packets are sent from cybercriminals to stimulate an enormous number of packets directed to the targeted vehicle. The amplification method is often used together with the reflection method to launch a huge attack against an unsuspecting autonomous vehicle.

8.7.3. Malware and Spyware Attacks. Malware is generally referred to as viruses or worms. These viruses are generally propagated via outside unit software and firmware updates. Malware can affect autonomous vehicles in IoV environment, thereby permitting remote enemies to gain access and control the target vehicles. Remote access spyware combines with the innovative communication services that VANETs convey to the IoV, which is likely to gain access of the autonomous vehicle to interrupt vital facilities and services. Isolated malware threats are commonly established and have been revealed in test beds to put drivers and passengers at risk. Recent studies on spyware targeting vehicles have revealed that the spread of spyware is likely to be realized via weaknesses in the in-built systems deployed to analyze vehicles throughout the service period. The broad consequence is that many vehicles within the IoV network may be infected given that the malware or spyware is transmitted via trusted service platform, possibly infecting a complete product line [114].

Reference [115] introduced a verification method to ensure that only the verified IoV user can use the autonomous car. The authors also used a cloud-based vehicle malware defense mechanism to address the malware and spyware challenges. However, the main issue is the maintenance of updated patches and signature files in the IoV vehicles.

The DDoS/DoS, ransomware, malware, spyware, and MITM attacks are dynamic in nature. Therefore, the attacks can change to disguise and bypass the security system in the Internet of Vehicles. The DL models are adaptive in nature with capability of adapting to new circumstances. Therefore, we suggest the application of DL models for the development of a powerful adaptive intrusion detection system that can detect dynamic security threats in the IoV environment. Thus, the impact of the DDoS/DoS, ransomware, malware, spyware, and MITM attacks in the IoV is minimized.

9. Conclusions

We present a survey on leveraging DL in the IoV within the context of BDA. The relationship that exists between DL, IoV, and BDA has been unveiled to provide researchers with a clear perspective on the empirical application of DL in the IoV within the context of BDA. The results show that empirical works on DL in the IoV are highly limited and public repository data for IoV are unavailable to researchers. The paper presents current development issues, potential challenges, and new direction for emerging research on DL in the IoV within the context of BDA. We believe that this study can help expert researchers to easily identify areas that require solutions and novice researchers can use it as a benchmark.

Abbreviations

ACO:	Ant colony optimization
ADE:	Adaptive differential evolution
AFDBN:	Adaptive functional deep belief network
AI:	Artificial intelligence
ANN:	Artificial neural network
API:	Application programming interface
ARIMA:	Autoregressive integrated moving average

AzureML: Azure machine learning
BCE: Blockchain enabled
BDA: Big data analytics
BI: Block interval
BigML: Big machine learning
BMW: Bayerische Motoren Werke
BPA: Backpropagation algorithm
BPs: Block producers
BS: Block size
Car2X: Car-to-every thing
CDBN: Competitive deep belief network
CGAN: Conditional generative adversarial network
CoDBN: Continuous deep belief network
CoGAN: Coupled generative adversarial network
CoGASA: Coupled generative adversarial stacked autoencoder
ConvNet: Convolutional neural network
CPU: Central processing unit
CRBM: Continuous restricted Boltzmann machine
CS-DBN: Cost-sensitive deep belief network
CTS: Catera touring sedan
DBN: Deep belief network
DConvNet: Dilated convolutional neural network
DCovGAN: Deep convolutional generative adversarial network
DDBN: Discriminative deep belief network
DDoS: Distributed denial of service
DDPG: Deep deterministic policy gradient
DDQN: Double deep Q-network
DeepESN: Deep echo state network
DFNN: Deep feedforward neural network
DL: Deep learning
DNN: Deep neural network
DoS: Denial of service
DRBN: Deep recurrent belief network
DRL: Deep reinforcement learning
DRNN: Deep recurrent neural network
DQN: Deep Q-network
D2D: Device-to-device
EES: Energy estimation scheme
EKA: Edmonds–Karp algorithm
FFA: Firefly algorithm
GA: Greedy algorithm
GAN: Generative adversarial network
GHz: Gigahertz
GPS: Global positioning system
GPU: Graphics processing unit
HD: High definition
IEEE: Institute of Electrical and Electronics Engineering
IoT: Internet of things
IoV: Internet of vehicles
ITS: Intelligent transportation system
MBM: Motif based method
MGM: Manhattan grid model
MITM: Man-in-the-middle
MLlib: Machine learning library
MLP: Multilayer perception
MOST: Media oriented system transport
mph: Meter per hour
NCF: Near field communication
NINConvNet: Network in network convolutional neural network
PBFTA: Practical Byzantine fault tolerant algorithm
PSO: Particle swarm optimization
PTV VISSIM: Planung Transport Verkehr visual simulation
QHS-DBN: Quaternion-improved harmony search deep belief network
RBM: Restricted Boltzmann machine
RConvNet: Recurrent convolutional neural network
RFID: Radio frequency identification
ReLU: Rectified linear unit
RNN: Recurrent neural network
SA: Simulated annealing
SConvNet: Symmetric convolutional neural network
SGAN: Stacked generative adversarial network
SMS: Smart multimedia system
SODBN: Self-organizing DBN
SVRM: Support vector regression machine
TConvNet: Tiled convolutional neural network
TSS: Traditional security system
TVs: Televisions
USA: United States of America
VANETs: Vehicular ad hoc networks
V2D: Vehicle-to-device
V2H: Vehicle-to-home
V2I: Vehicle-to-infrastructure
V2P: Vehicle-to-pedestrian
V2R: Vehicle-to-roadside units
V2S: Vehicle-to-sensor
V2V: Vehicle-to-vehicle
V2X: Vehicle-to-everything
WAVE: Wireless access for vehicular environment
Wi-Fi: Wireless fidelity
WiMAX: Worldwide interoperability for microwave access
WPM: Wiener process model
3G LTE: Third generation long term evolution
3D: Three-dimensional
4G LTE: Fourth generation long term evolution
5G LTE: Fifth generation long term generation.

Data Availability

No data were used to support the findings of this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

This work was funded by the Federal Ministry of Education, Federal Government of Nigeria, Tertiary Education Trust Fund (TETFund), Institutional Based Research (IBR) Fund, through Federal College of Education (Technical), Gombe, with grant no. TETFund/R&D/FCETGombe/IBR/0001, 2018.

References

[1] Huawei Technologies Co, *Huawei*, Huawei, Shenzhen, China, 2015, https://www.huawei.com/en/.

[2] IEEE, *IEEE Transmitter*, IEEE, Piscataway, NJ, USA, 2018.

[3] E. S. Ali, M. K. Hasan, R. Hassan et al., "Machine learning technologies for secure vehicular communication in internet of vehicles: recent advances and applications," *Security and Communication Networks*, vol. 2021, Article ID 8868355, 23 pages, 2021.

[4] N. Lu, N. Cheng, N. Zhang, X. Shen, and J. W. Mark, "Connected vehicles: solutions and challenges," *IEEE Internet of Things Journal*, vol. 1, no. 4, pp. 289–299, 2014.

[5] N. Liu, "Internet of vehicles: your next connection," *Huawei WinWin*, vol. 11, pp. 23–28, 2011.

[6] H. Lu, Q. Liu, D. Tian, Y. Li, H. Kim, and S. Serikawa, "The cognitive internet of vehicles for autonomous driving," *IEEE Network*, vol. 33, no. 3, pp. 65–73, 2019.

[7] Transparency, "Transparency market research," 2013, https://www.transparencymarketresearch.com/.

[8] D. M. West, *Moving Forward: Self-Driving Vehicles in China, Europe, Japan, Korea, and the United States*, Center for Technology Innovation at Brookings, Washington, DC, USA, 2016.

[9] M. Pinelis, "Automotive sensors and electronics: trends and developments in 2013," in *Proceedings of the 2013 Automotive Sensors & Electronics Expo*, Detroit, MI, USA, 2013.

[10] Miller, "Analytics powers the internet of things (IoT) for connected vehicles," 2018, https://www.youtube.com/watch?v=4jQyQdW-yN0.

[11] X.-W. Chen and X. Lin, "Big data deep learning: challenges and perspectives," *IEEE Access*, vol. 2, pp. 514–525, 2014.

[12] T. Gong, "Deep belief network-based multifeature fusion music classification algorithm and simulation," *Complexity*, vol. 2021, Article ID 8861896, 10 pages, 2021.

[13] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, p. 436, 2015.

[14] J. Schmidhuber, "Deep learning in neural networks: an overview," *Neural Networks*, vol. 61, pp. 85–117, 2015.

[15] C. Zhang, K. C. Tan, H. Li, and G. S. Hong, "A cost-sensitive deep belief network for imbalanced classification," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 1, pp. 109–122, 2018.

[16] S. Yu, C. Wang, K. Liu, and A. Y. Zomaya, "Editorial for IEEE access special section on theoretical foundations for big data applications: challenges and opportunities," *IEEE Access*, vol. 4, pp. 5730–5732, 2016.

[17] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, Cambridge, MA, USA, 2016.

[18] G. E. Hinton, "Deep belief networks," *Scholarpedia*, vol. 4, no. 5, p. 5947, 2009.

[19] I. Chaturvedi, Y.-S. Ong, I. W. Tsang, R. E. Welsch, and E. Cambria, "Learning word dependencies in text by means of a deep recurrent belief network," *Knowledge-Based Systems*, vol. 108, pp. 144–154, 2016.

[20] G. E. Hinton, "Training products of experts by minimizing contrastive divergence," *Neural Computation*, vol. 14, no. 8, pp. 1771–1800, 2002.

[21] H. Chen and A. F. Murray, "Continuous restricted Boltzmann machine with an implementable training algorithm," *IEE Proceedings—Vision, Image and Signal Processing*, vol. 150, no. 3, pp. 153–158, 2003.

[22] N. Le Roux and Y. Bengio, "Representational power of restricted Boltzmann machines and deep belief networks," *Neural Computation*, vol. 20, no. 6, pp. 1631–1649, 2008.

[23] G. E. Hinton and R. R. Salakhutdinov, "Reducing the dimensionality of data with neural networks," *Science*, vol. 313, no. 5786, pp. 504–507, 2006.

[24] M. Ma, C. Sun, and X. Chen, "Discriminative deep belief networks with ant colony optimization for health status assessment of machine," *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 12, pp. 3115–3125, 2017.

[25] K. Mannepalli, P. N. Sastry, and M. Suman, "A novel adaptive fractional deep belief networks for speaker emotion recognition," *Alexandria Engineering Journal*, vol. 56, no. 4, pp. 485–497, 2017.

[26] J. P. Papa, G. H. Rosa, D. R. Pereira, and X.-S. Yang, "Quaternion-based deep belief networks fine-tuning," *Applied Soft Computing*, vol. 60, pp. 328–335, 2017.

[27] J. Qiao, G. Wang, X. Li, and W. Li, "A self-organizing deep belief network for nonlinear system modeling," *Applied Soft Computing*, vol. 65, pp. 170–183, 2018.

[28] H. Yang, S. Shen, X. Yao, M. Sheng, and C. Wang, "Competitive deep-belief networks for underwater acoustic target recognition," *Sensors*, vol. 18, no. 4, p. 952, 2018.

[29] H. Shao, H. Jiang, X. Li, and T. Liang, "Rolling bearing fault detection using continuous deep belief network with locally linear embedding," *Computers in Industry*, vol. 96, pp. 27–39, 2018.

[30] T. B. Tang and A. F. Murray, "Adaptive sensor modelling and classification using a continuous restricted Boltzmann machine (CRBM)," *Neurocomputing*, vol. 70, no. 7–9, pp. 1198–1206, 2007.

[31] I. Goodfellow, J. Pouget-Abadie, M. Mirza et al., "Generative adversarial nets," in *Proceedings of the 2014 Advances in Neural Information Processing Systems*, Montreal, Canada, 2014.

[32] A. Creswell, T. White, V. Dumoulin, K. Arulkumaran, B. Sengupta, and A. A. Bharath, "Generative adversarial networks: an overview," *IEEE Signal Processing Magazine*, vol. 35, no. 1, pp. 53–65, 2018.

[33] U. Fiore, A. De Santis, F. Perla, P. Zanetti, and F. Palmieri, "Using generative adversarial networks for improving classification effectiveness in credit card fraud detection," *Information Sciences*, vol. 479, pp. 448–455, 2017.

[34] M.-Y. Liu and O. Tuzel, "Coupled generative adversarial networks," in *Proceedings of the 2016 Advances in Neural Information Processing Systems*, Barcelona, Spain, 2016.

[35] M. A. Kiasari, D. S. Moirangthem, and M. Lee, "Coupled generative adversarial stacked auto-encoder: CoGASA," *Neural Networks*, vol. 100, pp. 1–9, 2018.

[36] X. Huang, Y. Li, O. Poursaeed, J. Hopcroft, and S. Belongie, "Stacked generative adversarial networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Honolulu, HI, USA, 2017.

[37] M. Mirza and S. Osindero, "Conditional generative adversarial nets," 2014, https://arxiv.org/abs/1411.1784.

[38] A. Radford, L. Metz, and S. Chintala, "Unsupervised representation learning with deep convolutional generative adversarial networks," 2015, https://arxiv.org/abs/1511.06434.

[39] Y. LeCun, B. E. Boser, J. S. Denker et al., "Handwritten digit recognition with a back-propagation network," in *Proceedings of the 1990 Advances in Neural Information Processing Systems*, Denver, CO, USA, 1990.

[40] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.

[41] S. Zou, W. Chen, and H. Chen, "Image classification model based on deep learning in internet of things," *Wireless Communications and Mobile Computing*, vol. 2020, Article ID 6677907, 16 pages, 2020.

[42] J. Gu, Z. Wang, J. Kuen et al., "Recent advances in convolutional neural networks," *Pattern Recognition*, vol. 77, pp. 354–377, 2018.

[43] F. Yu and V. Koltun, "Multi-scale context aggregation by dilated convolutions," 2015, https://arxiv.org/abs/1511.07122.

[44] P. H. Pinheiro and R. Collobert, "Recurrent convolutional neural networks for scene labeling," in *Proceedings of the 31st International Conference on Machine Learning (ICML)*, Beijing, China, 2014.

[45] J. Ngiam, Z. Chen, D. Chia, P. W. Koh, Q. V. Le, and A. Y. Ng, "Tiled convolutional neural networks," in *Proceedings of the 2010 Advances in Neural Information Processing Systems*, Vancouver, Canada, 2010.

[46] M. Lin, Q. Chen, and S. Yan, "Network in network," 2013, https://arxiv.org/abs/1312.4400.

[47] M. Yan, J. Guo, W. Tian, and Z. Yi, "Symmetric convolutional neural network for mandible segmentation," *Knowledge-Based Systems*, vol. 159, pp. 63–71, 2018.

[48] C. Gallicchio, A. Micheli, and L. Pedrelli, "Deep reservoir computing: a critical experimental analysis," *Neurocomputing*, vol. 268, pp. 87–99, 2017.

[49] C. Gallicchio, A. Micheli, and L. Silvestri, "Local Lyapunov exponents of deep echo state networks," *Neurocomputing*, vol. 298, pp. 34–45, 2018.

[50] J. L. Elman, "Finding structure in time," *Cognitive Science*, vol. 14, no. 2, pp. 179–211, 1990.

[51] A. Graves, A.-r. Mohamed, and G. Hinton, "Speech recognition with deep recurrent neural networks," in *Proceedings of the 2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, Vancouver, Canada, 2013.

[52] G. Litjens, T. Kooi, B. E. Bejnordi et al., "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, 2017.

[53] Y. Liu, X. Chen, Z. Wang, Z. J. Wang, R. K. Ward, and X. Wang, "Deep learning for pixel-level image fusion: recent advances and future prospects," *Information Fusion*, vol. 42, pp. 158–173, 2018.

[54] J. R. Neterer and O. Guzide, "Deep learning in natural language processing," *Proceedings of the West Virginia Academy of Science*, vol. 90, no. 1, 2018.

[55] R. Sarikaya, G. E. Hinton, and A. Deoras, "Application of deep belief networks for natural language understanding," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 22, no. 4, pp. 778–784, 2014.

[56] M. U. Yaseen, A. Anjum, O. Rana, and N. Antonopoulos, "Deep learning hyper-parameter optimization for video analytics in clouds," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 49, no. 1, pp. 253–264, 2018.

[57] Y. Tang and X. Wu, "Scene text detection using superpixel-based stroke feature transform and deep learning based region classification," *IEEE Transactions on Multimedia*, vol. 20, no. 9, pp. 2276–2288, 2018.

[58] A. Pathak, M. Pandey, and S. Rautaray, "Application of deep learning for object detection," *Procedia Computer Science*, vol. 132, pp. 1706–1717, 2018.

[59] Y. Zhang, X. Li, Z. Zhang, F. Wu, and L. Zhao, "Deep learning driven blockwise moving object detection with binary scene modeling," *Neurocomputing*, vol. 168, pp. 454–463, 2015.

[60] H. M. Fayek, M. Lech, and L. Cavedon, "Evaluating deep learning architectures for speech emotion recognition," *Neural Networks*, vol. 92, pp. 60–68, 2017.

[61] Y. Ji, L. Liu, H. Wang, Z. Liu, Z. Niu, and B. Denby, "Updating the silent speech challenge benchmark with deep learning," *Speech Communication*, vol. 98, pp. 42–50, 2018.

[62] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of things (IoT): a vision, architectural elements, and future directions," *Future Generation Computer Systems*, vol. 29, no. 7, pp. 1645–1660, 2013.

[63] I. A. T. Hashem, V. Chang, N. B. Anuar et al., "The role of big data in smart city," *International Journal of Information Management*, vol. 36, no. 5, pp. 748–758, 2016.

[64] O. Kaiwartya, A. H. Abdullah, Y. Cao et al., "Internet of vehicles: motivation, layered architecture, network model, challenges, and future aspects," *IEEE Access*, vol. 4, pp. 5356–5373, 2016.

[65] Elsaddik, "Multimedia communications research laboratory," 2016, http://www.mcrlab.net/research/social-networks-for-the-internet-of-vehicles/.

[66] F. Yang, S. Wang, J. Li, Z. Liu, and Q. Sun, "An overview of internet of vehicles," *China Communications*, vol. 11, no. 10, pp. 1–15, 2014.

[67] BI, "Business insider intelligence," 2016, https://www.businessinsider.com.

[68] W. Xu, H. Zhou, N. Cheng et al., "Internet of vehicles in big data era," *IEEE/CAA Journal of Automatica Sinica*, vol. 5, no. 1, pp. 19–35, 2017.

[69] X. Shi and J. Shi, "Nokia drives ahead with internet of vehicles," 2016, https://www.chinadaily.com.cn/business/3rdWuzhenWorldInternetConference/2016-11/19/content_27427550.htm.

[70] Huawei Technologies Co Ltd, *Huawei Connected Car Solution Wins Best IoV Innovation*, Huawei, Shenzhen, China, 2018, https://www.huawei.com/en/.

[71] Isidore, "GM doubles down on self-driving cars, hiring 1,100. CNNMoney," 2017, https://www.google.com/search?sxsrf=ALeKk02tcb48jnKCCph4U2S7LIxjZ-9QoQ:1583042482904&q=CNN+money+by+Isidore+c.+2017+GM+doubles+down+on+self-driving+cars,+hiring+1,100&tbm=isch&source=univ&sa=X&ved=2ahUKEwi_i-7mzPjnAhUnSxUIHTUwBcoQsAR6BAgIEAE.

[72] Motors, "V2V safety technology now standard on cadillac CTS sedans," 2017, https://media.gm.com/media/us/en/cadillac/news.detail.html/content/Pages/news/us/en/2017/mar/0309-v2v.html.

[73] M. McFarland, *Uber Self-Driving Car Kills Pedestrian in First Fatal Autonomous Crash*, CNN, Atlanta, GA, USA, 2018.

[74] C. Blackman and S. Forge, *European Leadership in 5G. CEPS Special Report*, European Parliament, Brussels, Belgium, 2016.

[75] M. Zaharia, R. S. Xin, P. Wendell et al., "Apache spark: a unified engine for big data processing," *Communications of the ACM*, vol. 59, no. 11, pp. 56–65, 2016.

[76] X. Meng, J. Bradley, B. Yavuz et al., "MLlib: machine learning in apache spark," *Journal of Machine Learning Research*, vol. 17, no. 1, pp. 1235–1241, 2016.

[77] M. A. Alsheikh, D. Niyato, S. Lin, H.-P. Tan, and Z. Han, "Mobile big data analytics using deep learning and apache spark," *IEEE Network*, vol. 30, no. 3, pp. 22–29, 2016.

[78] T. White, *Hadoop: The Definitive Guide*, O'Reilly Media, Inc., Newton, MA, USA, 2012.

[79] D. R. Owen, *A First Course in the Mathematical Foundations of Thermodynamics*, Springer Science & Business Media, Berlin, Germany, 2012.

[80] N. Kourtellis, G. D. F. Morales, and A. Bifet, "Large-scale learning from data streams with apache SAMOA," *Learning from Data Streams in Evolving Environments*, Springer, Berlin, Germany, pp. 177–207, 2019.

[81] J. Lin and A. Kolcz, "Large-scale machine learning at twitter," in *Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data*, Scottsdale, AZ, USA, 2012.

[82] AzureML Team, "AzureML: anatomy of a machine learning service," in *Proceedings of the 2016 Conference on Predictive APIs and Apps*, Sydney, Australia, 2016.

[83] M. Bihis and S. Roychowdhury, "A generalized flow for multi-class and binary classification tasks: an Azure ML approach," in *Proceedings of the 2015 IEEE International Conference on Big Data (Big Data)*, Santa Clara, CA, USA, 2015.

[84] K. K. Nagwanshi and S. Dubey, "Statistical feature analysis of human footprint for personal identification using bigML and IBM watson analytics," *Arabian Journal for Science and Engineering*, vol. 43, no. 6, pp. 2703–2712, 2018.

[85] Z. Zainudin and S. M. Shamsuddin, "Predictive analytics in Malaysian dengue data from 2010 until 2015 using BigML," *International Journal of Advances in Soft Computing and its Applications*, vol. 8, no. 3, 2016.

[86] K. M. Alomari, C. Ncube, and K. Shaalan, "Predicting success of a mobile game: a proposed data analytics-based prediction model," in *Proceedings of the 2018 International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*, Montreal, Canada, 2018.

[87] A. Samuel, M. I. Sarfraz, H. Haseeb, S. Basalamah, and A. Ghafoor, "A framework for composition and enforcement of privacy-aware and context-driven authorization mechanism for multimedia big data," *IEEE Transactions on Multimedia*, vol. 17, no. 9, pp. 1484–1494, 2015.

[88] K. Yu, "Large-scale deep learning at Baidu," in *Proceedings of the 22nd ACM International Conference on Information & Knowledge Management*, San Francisco, CA, USA, 2013.

[89] N. Straton, R. R. Mukkamala, and R. Vatrapu, "Big social data analytics for public health: predicting facebook post performance using artificial neural networks and deep learning," in *Proceedings of the 2017 IEEE International Congress on Big Data (BigData Congress)*, Honolulu, HI, USA, 2017.

[90] J. Dean, G. Corrado, R. Monga et al., "Large scale distributed deep networks," in *Proceedings of the 2012 Advances in Neural Information Processing Systems*, Lake Tahoe, NV, USA, 2012.

[91] C. Chen, H. Xiang, T. Qiu, C. Wang, Y. Zhou, and V. Chang, "A rear-end collision prediction scheme based on deep learning in the Internet of Vehicles," *Journal of Parallel and Distributed Computing*, vol. 117, pp. 192–204, 2018.

[92] F. Kong, J. Li, B. Jiang, and H. Song, "Short-term traffic flow prediction in smart multimedia system for internet of vehicles based on deep belief network," *Future Generation Computer Systems*, vol. 93, pp. 460–472, 2019.

[93] X. Wang, X. Wei, and L. Wang, "A deep learning based energy-efficient computational offloading method in Internet of vehicles," *China Communications*, vol. 16, no. 3, pp. 81–91, 2019.

[94] Z. Ning, P. Dong, X. Wang et al., "Deep reinforcement learning for intelligent internet of vehicles: an energy-efficient computational offloading scheme," *IEEE Transactions on Cognitive Communications and Networking*, vol. 5, 2019.

[95] Z. Ning, Y. Feng, M. Collotta et al., "Deep learning in edge of vehicles: exploring trirelationship for data transmission," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 10, pp. 5737–5746, 2019.

[96] A. Gulati, G. S. Aujla, R. Chaudhary, N. Kumar, and M. S. Obaidat, "Deep learning-based content centric data dissemination scheme for internet of vehicles," in *Proceedings of the 2018 IEEE International Conference on Communications (ICC)*, Kansas City, MO, USA, 2018.

[97] M. Liu, Y. Teng, F. R. Yu, V. C. Leung, and M. Song, "Deep reinforcement learning based performance optimization in blockchain-enabled internet of vehicle," in *Proceedings of the 2019 IEEE International Conference on Communications (ICC)*, Shanghai, China, 2019.

[98] Y. Dai, D. Xu, Y. Lu, S. Maharjan, and Y. Zhang, "Deep reinforcement learning for edge caching and content delivery in internet of vehicles," in *Proceedings of the 2019 IEEE/CIC International Conference on Communications in China (ICCC)*, Changchun, China, 2019.

[99] S. Goudarzi, M. Kama, M. Anisi, S. Soleymani, and F. Doctor, "Self-organizing traffic flow prediction with an optimized deep belief network for internet of vehicles," *Sensors*, vol. 18, no. 10, p. 3459, 2018.

[100] S. Sharma, K. K. Ghanshala, and S. Mohan, "A security system using deep learning approach for internet of vehicles (IoV)," in *Proceedings of the 2018 9th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, New York, NY, USA, 2018.

[101] V. Mnih, A. P. Badia, M. Mirza et al., "Asynchronous methods for deep reinforcement learning," in *Proceedings of the 2016 International Conference on Machine Learning*, New York, NY, USA, 2016.

[102] Bloombag, "Baidu enters the global race for driverless car domination," 2016, https://www.bloomberg.com/news/articles/2016-01-24/baidu-enters-the-global-race-to-dominate-era-of-driverless-cars.

[103] Y. Wang, B. Li, R. Luo, Y. Chen, N. Xu, and H. Yang, "Energy efficient neural networks for big data analytics," in *Proceedings of the 2014 Design, Automation & Test in Europe Conference & Exhibition (DATE)*, Dresden, Germany, 2014.

[104] A. Evanson, "Connected autonomous vehicle (CAV) simulation using PTV vissim," in *Proceedings of the 2017 Winter Simulation Conference (WSC)*, Las Vegas, NV, USA, 2017.

[105] Y. Wang and L. Wang, "Autonomous vehicles' performance on single lane road: a simulation under VISSIM environment," in *Proceedings of the 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, Shanghai, China, 2017.

[106] H. Chiroma, A. Y. u. Gital, N. Rana et al., "Nature inspired meta-heuristic algorithms for deep learning: recent progress and novel perspective," in *Proceedings of the 2019 Science and Information Conference*, Las Vegas, NV, USA, 2019.

[107] I. Yaqoob, E. Ahmed, M. H. ur Rehman et al., "The rise of ransomware and emerging security challenges in the internet of things," *Computer Networks*, vol. 129, pp. 444–458, 2017.

[108] M. S. A. Latiff, "A checkpointed league championship algorithm-based cloud scheduling scheme with secure fault tolerance responsiveness," *Applied Soft Computing*, vol. 61, pp. 670–680, 2017.

[109] N. Lyamin, A. Vinel, M. Jonsson, and J. Loo, "Real-time detection of denial-of-service attacks in IEEE 802.11 p vehicular networks," *IEEE Communications Letters*, vol. 18, no. 1, pp. 110–113, 2013.

[110] S. Patil and S. Chaudhari, "DoS attack prevention technique in wireless sensor networks," *Procedia Computer Science*, vol. 79, pp. 715–721, 2016.

[111] S. RoselinMary, M. Maheshwari, and M. Thamaraiselvan, "Early detection of DOS attacks in VANET using attacked packet detection algorithm (APDA)," in *Proceedings of the 2013 International Conference on Information Communication and Embedded Systems (ICICES)*, Chennai, India, 2013.

[112] N. Ruan, M. Li, and J. Li, "A novel broadcast authentication protocol for internet of vehicles," *Peer-to-Peer Networking and Applications*, vol. 10, no. 6, pp. 1331–1343, 2017.

[113] K. Angrishi, "Turning internet of things (IoT) into internet of vulnerabilities (IoV): IoT botnets," 2017, https://arxiv.org/pdf/1702.03681.pdf.

[114] L. A. Maglaras, A. H. Al-Bayatti, Y. He, I. Wagner, and H. Janicke, "Social internet of vehicles for smart cities," *Journal of Sensor and Actuator Networks*, vol. 5, no. 1, p. 3, 2016.

[115] T. Zhang, H. Antunes, and S. Aggarwal, "Defending connected vehicles against malware: challenges and a solution framework," *IEEE Internet of Things Journal*, vol. 1, no. 1, pp. 10–21, 2014.

Hindawi
Mathematical Problems in Engineering
Volume 2021, Article ID 3697733, 15 pages
https://doi.org/10.1155/2021/3697733

Research Article

B5G Ultrareliable Low Latency Networks for Efficient Secure Autonomous and Smart Internet of Vehicles

Sultan S. Alshamrani,[1] **Nishant Jha**,[2] **and Deepak Prashar**[2]

[1]*Department of Information Technology, College of Computer and Information Technology, Taif University, P.O. Box 11099, Taif 21944, Saudi Arabia*
[2]*School of Computer Science and Engineering, Lovely Professional University, Phagwara, India*

Correspondence should be addressed to Deepak Prashar; deepak.prashar@lpu.co.in

Received 8 June 2021; Revised 23 July 2021; Accepted 21 August 2021; Published 15 September 2021

Academic Editor: Haruna Chiroma

Copyright © 2021 Sultan S. Alshamrani et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Recently, 5G and beyond 5G (B5G) systems, Ultrareliable Low Latency Network (URLLC) represents the key enabler for a range of modern technologies to support Industry 4.0 applications, such as transportation and healthcare. Real-world implementation of URLLC can help in major transformations in industries like autonomous driving, road safety, and efficient traffic management. Furthermore, URLLC contributes to the objective of fully autonomous cars on the road that can respond to dynamic traffic patterns by collaborating with other vehicles and surrounding environments rather than relying solely on local data. For this, the main necessity is that how information is to be transferred among the vehicles in a very small time frame. This requires information to be transferred among the vehicles reliably in extremely short time duration. In this paper, we have implemented and analyzed the Multiaccess Edge Computing- (MEC-) based architecture for 5G autonomous vehicles based on baseband units (BBU). We have performed Monte Carlo simulations and plotted curves of propagation latency, handling latency, and total latency in terms of vehicle density. We have also plotted the reliability curve to double-check our findings. When the RSU density is constant, the propagation latency is directly proportional to the vehicle density, but when the vehicle density is fixed, the propagation latency is inversely proportional. When RSU density is constant, vehicle density and handling latency are strictly proportional, but when vehicle density is fixed, handling latency becomes inversely proportional. Total latency behaves similarly to propagation latency; that is, it is also directly proportional.

1. Introduction

Connecting vehicles with each other and the infrastructure around them could play a significant role in autonomous vehicles' future and improving safety. Vehicles can communicate with one another, respond to traffic signals, and even see around corners. 5G is on the way to making this a reality, delivering the higher speeds and more space needed for smart traffic control systems and fully autonomous vehicles. However, autonomous vehicles are not the only way to connect cars; they compete with Wi-Fi technologies called Dedicated Short-Range Communication (DSRC) or Cellular Vehicle to Everything (C2VX) that will eventually use the 5G networks. Vehicles connected to cellular networks are becoming accessible and more common due to recent telecommunications industry developments. Indeed, because of critical applications such as autonomous vehicles, automotive monitoring, traffic control, and traffic management, the network's link will be inseparable from future vehicles communication systems. Vehicles would be able to communicate among themselves or with the network infrastructure via this link to exchange vital data, and accidents will be avoided, and lives can be saved by using them. A crucial piece of information for safety applications is the location or, in general, the vehicles kinematic condition [1]. Together with the evolution of radio and transport technologies, a profound approach has been established. The management and maintenance of these networks have been active in the revolution, to achieve high versatility, from manually built and programmed infrastructures to systems that can self-manage themselves, equipped with advanced intelligence. Many of these skills have been accepted by all of the new criteria. The so-called 5G architecture is currently the latest revision of the mobile network specifications, based on the 15th release published in 2019 by the 3GPP Consortium [2]. According to this scenario, research activities in the field of mobile networks are an important activity for opening the way to new requirements and satisfying customer and operator requests [3]. Operating a network infrastructure is a vital activity that requires a high degree of accountability when information goes through the device. Over the last 20 years, general network monitoring solutions have been established to obtain this type of information, focusing in particular on big data center network infrastructures. On the other hand, no standard for the retrieval of real-time monitoring data from the mobile network has been defined by 3GPP [3]. In addition, only aggregated counters are available, which provides information at an inadequate frequency for real-time operations.

Automation is one of 5Gs main drivers [4] and through the definition of 5G self-organizing networks are supposed to reduce the life-cycle expense of the infrastructure, as observed by operators who have implemented it in Long-Term Evolution (LTE) networks [5]. Automation in the next-generation mobile networks would also presume that a strategic position requires advanced agents to organize the infrastructure and maintain it. The authors of [6, 7] discussed the importance of Artificial Intelligence (AI) and Machine Learning (ML) for improving vehicles and agents connectivity and quality of service. Ideally, these will be motivated by algorithms from AI [8]. However, AI algorithms need a wide base of data to be trained upon to enable systems to take accurate actions. Thus, the 5G core network's flow tracking and other metrics are one of the enablers of this technology. The 5G system is an extension of previous systems, but it can be seen as a big technological change that will alter certain paradigms based on conventional mobile networks.

Since 5G wireless networks must be capable of addressing the problems encountered by 4G networks, such as higher bandwidth, lower end-to-end latency, high data rate, large device connectivity, and consistent quality of experience provisioning [9, 10], hence, they must have the potential to address these issues. The proposed general 5G infrastructure is built on the interconnection of numerous new technologies, such as Massive MIMO networks, Cognitive Radio Networks, and Mobile and Static Cell Networks [9]. Traditional performance metrics, such as spectral quality and network bandwidth, must be increased due to the continued advancement of 5G technologies, and a wide range of connectivity modes must be offered to increase customer experience [9]. Ultrareliable Low Latency Communication (URLLC) [11] is one of the most important 5G use cases. URLLC is expected to play a key role in providing networking for emerging technologies like autonomous vehicles, smart factories, and so on [11]. URLLC is a 5G New Radio technology with stringent latency and reliability [12]. Due to hard latency conditions, URLLC traffic is usually scheduled on top of ongoing enhanced Mobile Broadband (eMBB) transmissions and cannot be queued [12]. Because of the advent of multiservice networking [13], beyond 5G networks (B5G) or 6G systems have significant interest, and the reliability and latency considerations in 6G may be use case specific [13]. B5G is also required to accommodate ultralong battery life, eliminating the need for charging devices [14]. The advent of multiservice technologies will be useful for improving network intelligence due to an improvement in network complexity [13].

To make autonomous vehicles (AVs) work efficiently, the V2I system must be fast, capable of exchanging messages without any delay, and capable of working under low latency. Current techniques are not capable of offering a reliable environment for faster exchange of information between the AVs. The architecture suggested in this paper is based on Multiaccess Edge Computing (MEC) architecture on baseband units (BBUs), which will allow the processing of tasks to be performed by AVs locally without depending upon the remote cloud servers. Current studies based on remote cloud servers are having various research gaps, such as small cell base stations having restricted resources for computation, and they can be overloaded easily. Furthermore, the quality-of -service (QoS), end-to-end latency management is very challenging without effective computing resource management.

The major contributions of this paper are as follows:

(i) Analysis of the literature, identification of challenges of the existing works, and techniques to resolve them

(ii) Examination of the architecture based on mobile edge computing (MEC) running together with Virtualized Radio Access Network (vRAN) services on Edge Servers improving the efficiency and security of autonomous vehicles and enabling a 5G-based URLLC networks for smart Internet of Vehicles (IoVs)

(iii) Testing of the suggested architecture to show how MEC enabled autonomous vehicles is more efficient and secure

The rest of the paper is organized as follows. The related work is covered in Section 2. In Section 3, the challenges of 5G-based autonomous vehicles are discussed, as well as the importance of the work. Section 4 covers the research significance. The combination of MCC and MEC is defined in Section 5. The MEC-based BBU architecture for autonomous vehicles is explained in Section 6. The conclusions are explained in Section 7, limitations are mentioned in Section 8, and the article is concluded in Section 9.

2. Related Work

5G comes with a few new interesting technologies that may be of great use in the remote control and Industrial Internet of Things. Ultrareliable Low Latency Communication

(URLLC), enhanced Mobile Broadband (eMBB), and massive Machine Type Communication (mMTC) are three of these technologies [15]. URLLC stands for Ultrareliable Low Latency Communication and is one of the many advantages that 5G can have. URLLC is projected to provide one-digit millisecond cycle times [16] and 99.9999% efficiency of transmission over one square kilometer, while multiple gNB (next-generation node B) provides the signal [17]. Combining with the ability to mount smaller gNBs on rooftops made it possible for urban environments to have these low latencies over wide areas. According to researchers Kim et al., more base stations would also make it possible to reduce access times and enable support for more devices [18]. Earlier on ether-net-based networks, stable low latencies were most prevalent, and even there, they required TSN (Time-Sensitive Networking) for the versatile and linked delay requirements [19]. As it has the capacity to carry large payloads at high transmission rates [19], eMBB is similar to 4G LTE. The eMBB speeds are in Gigabit per second (Gbps) range and are ideal for heavy network use.

Traffic, such as video content handling, is a type of job that suits eMBB well as every day more video data is generated and consumed, which places a large load on today's networks. eMBB can use high-bandwidth channels, resulting in higher usable bitrates and is thus more suitable for handling video traffic [20]. Another 5G functionality that targets massive IoT (Internet of Things) is Massive Machine Style Communication or mMTC for short. The use case for mMTC is the provision of network connectivity for many devices that communicate over long distances through short messages [19, 21]. In general, IoT devices are not reliant on reliability and data rate but rely on the ability to communicate over long ranges instead. According to [22], a single technology for remote operation is not appropriate. For accurate monitoring, low latency from URLLC is needed, eMMB is required to transmit the vehicle's view, and mMTC is suitable for sensor readings and similarly small intermittent data transmissions. Other researchers are investigating if 5G is to be used along with the upcoming V2X [23] (vehicle-to-everything) standard. In terms of latency, reliability, and range, the researchers proposed specifications similar to what URLLC can provide, but with the bit rates that the only eMBB can deliver [24]. Remote operating vehicles have been used in recent years to perform different kinds of work. Three types of vehicle design trends have contributed to these jobs: exploration rovers, Unmanned Ground Vehicles (UGV), or hazardous duty machines [25]. Therefore, it is necessary to research the field of remote vehicles to collect information on suitable vehicle designs and input devices for vehicle control.

In [26], the authors have developed an industry-service classification of autonomous vehicles based on 5G. In order to extract the advantages of the next generation of cellular networks for positioning, several works have been done. The authors of [27] propose a 5G-based radio network architecture that combines various radio access technologies and cloud-based radio access network functionalities to provide a stable and privacy-preserving CAV network. The autonomous driving requirements of high precision and low latency can be met by 5G-based positioning techniques. However, cellular systems are not intended to maintain LOS for the UE all the time [1]. A simplified model for the probability, frequency, and length of blockage in mm-wave cellular systems was proposed by Jain, Kumar, and Panwar [28], and in their paper, they explained that the design of mm-wave networks can often be motivated by blockage rather than capacity requirements. As described above, the use of INS could support full-form GNSS in the failure times and during the outages, it could be able to compensate for high errors of 5G-based positioning systems.

In [29], the authors surveyed the field of video streaming over wireless technology and explained how to calculate users' quality of experience (QoE) in both subjective and objective ways. They explained how encoding works and how the outcome of the encoded video can be calculated. When it was streamed over an unreliable mobile network, they also presented the encoded video's product. They believe that there is a trade-off between precision and computer power by using QoE metrics and that simplified QoE metrics on cellular networks are less taxing. This paper contributes to the research by sharing the peak signal-to-noise ratio (PSNR) equation as a metric for measuring streamed video signal loss in order to determine which wireless technology is best for remote service. The 5G environment is designed to accommodate multiple use cases [30], and very versatile and intelligent network architecture is needed to serve all of them. The 5G framework is designed to take full advantage of Software Defined Networks (SDN) and network functions virtualization (NFV) to achieve this purpose, incorporating it into a special IP-oriented physical infrastructure system [31]. All modern networks (e.g., longer routes or packet losses) are expected to incorporate certain self-healing systems in order to maximize the resources and to avoid bottlenecks and other network problems, which can track the resource status and act accordingly, directing the implementation of new infrastructures towards the principle of SDN [32, 33].

3. Challenges for 5G-Based Autonomous Vehicles

The future of mobility will benefit greatly from autonomous driving technologies. This allows us to focus on our jobs rather than the stressful job of driving, and it aids in the elimination of human mistakes, enhancing response times, increasing traffic flow quality, and lowering the incidence of road injuries [34]. URLCC is the most recent 5G service tier, targeted at mission-critical communications with a target latency of 1 milliseconds, end-to-end security, and 99 percent reliability [34]. This type of wireless communication technique will be ultrafast and ultrareliable in autonomous driving, which helps enable real-time communication between the vehicles (V2V communication) and its roadside environments (V2I Communication). A brief comparison between 4G LTE and 5G is shown in Table 1.

Although various researches have been done for securing the vehicular networks, some of the major challenges, such as security, privacy, and efficient resource management,

Table 1: Comparison between 4G LTE and 5G.

Parameters	4G LTE	5G
Frequency (mm-waves)	Low (600 MHz–2.5 GHz)	High (24 GHz–52 GHz) and (62 GHz–82 GHz)
Cells	High	Small
MIMO	Larger	Smaller
Duplex nature	Half duplex	Full duplex

need to be investigated more in the field of 5G-enabled autonomous systems. These challenges are discussed in detail in the upcoming subsections.

3.1. Security Challenges. V2I and V2V services enable 5G vehicles to communicate with the core network and with other vehicles [35]. Because of the large-scale M2M communications, efficient and reliable mobility management is a major challenge. Several studies have identified general security services for cooperative vehicular systems, but IPv6 integration has not been well performed. In [36], the authors have used Internet Protocol Security (IPSec) and Internet Key Exchange version 2 (IKEv2) for securing Internet Protocol Version 6 Network Mobility (NEMO) in vehicular communication and tried to resolve the challenge for securing the vertical handover condition between 3G and 802.11p. Safe mobility control schemes are currently unable to effectively accommodate group-oriented collaboration scenarios. Cooperative driving is a new technology of 5G vehicular networks that enable autonomous vehicles to travel in platoons to save fuel and reduce the risks associated with driver errors.

Falsification, covert falsification, Sybil assault, emergency braking obstruction, and vehicle location hijacking [37] are just some of the attacks that can damage the V2V service and cause serious road accidents. Message verification methods can be used to counteract these attacks. The batch verification technique is still in use for authentication, but the main problem is determining which signatures are invalid. A highly efficient group testing technique was suggested for the identification of invalid signatures with fewer batch verifications [35]. Forged identity, forged venue, and any forged occurrence that can raise the likelihood of road collisions are all possible attacks [38] that the sender of an update may initiate. To protect the credibility of the communications, necessary countermeasures should be taken to combat these assaults. Potential attacks [38] which the sender of an update launches may include a forged identification, forged location, and any forged event, which may increase the risks of road accidents. Necessary countermeasures should be taken to overcome these attacks to ensure the integrity of the messages.

3.2. Privacy Challenges. Most of the applications for VANETs are dependent on the periodic broadcasting of the beacon messages by vehicles [39]. This message contains the real identity, status of the vehicles, and timestamp. Exchanging information cooperatively between the vehicles and other roadside entities can help in avoiding a collision. However, there's a major privacy threat for vehicles as their states' information and location in a broadcasted message could be collected and tampered. If a malicious party has access to the passengers' records, it is extremely risky. Furthermore, combining IoV and social networks will aid in improving vehicle safety by giving vehicles social attributes [40]. This makes the passengers in the autonomous vehicles anonymous to each other before cooperation connected through wireless connectivity, unlike the traditional online social networks. In this case, the major challenge is the exploration of the efficiency of common attributes for cooperation among autonomous vehicles in proximity. In certain cases, there's also a risk of disclosing passenger personal details to the general public. As a result, it is important to safeguard passengers' personal details. Some critical systems, such as autonomous vehicles, must report high precision real-time map updates and face problems, such as the need for information to be validated with the help of a server, which will guarantee the message's accuracy ahead of time due to computing and storage space limitations. Thus, some of the vehicles' key information like location is required by the servers for comparing this information for confirming the authenticity of the messages and determining whether the traffic information uploaded by the vehicles in the same area is consistent. The server is unable to acquire detailed vehicle details. As a result, a more reliable and effective multiparty set intersection protocol enabling big data processing is needed for privacy-preserving data sharing.

3.3. VNG Management and Resource Allocation. Due to a large number of autonomous vehicles, new challenges in 5G-SDVN are posed by VNG management [41]. The huge scale of VNG is advantageous for improving services in VNG because it allows for the sharing of newer content while still allowing for a large management overhead. As the size is reduced, all shared content and available capacity are limited, threatening normal services and negatively impacting customer satisfaction. Normally, the network contains a few isolated VNGs [41]. A vehicle can join several VNGs and serve as a coordinator, allowing VNGs to communicate with one another. Two proximal vehicles can communicate directly with each other using D2D communication to allow high-rate content distribution. D2D connectivity, on the other hand, results in inference for wireless communication due to the reuse of a cellular user's bandwidth. To address this problem, numerous spectrum-optimization resource allocation strategies have been developed [42]. These methods can be paired with resource selection for D2D communication so that the control plane can select the best decision-making approach.

4. Research Significance

For handling a range of resources in VNGs, 5G URLLC has more scalability. Controllers can be used by managers to allocate new management policies to any switch due to the highly efficient reconfigurability and programmability of network equipment, which helps to improve network management. An efficient cooperation among the vehicles is encouraged by adopting and is encouraged by adopting global-aware controllers, enabling unprecedented flexibility of the resource scheduling. Resources available are allocated on demand. According to their requirements and resource capabilities, these resources are shared among the vehicles, thereby improving resource optimization. The proposed architecture takes into account vehicle mobility assistance and topology differences, as well as quality of service (QoS) for different services. This type of architecture restricts the development and deployment of new network features by separating the social plane, control plane, and the data plane and making the network strong and centralized contributing to sustainable development.

Vehicles can benefit from feedback obtained from roadside facilities or other vehicles in order to conduct automatic overtaking, cooperative collision avoidance, and high-density platooning. At smart intersections, cars can connect with traffic signals and other networks, allowing emergency responders and buses to be prioritized [34]. Both of these implementations necessitate a high level of redundancy and strict end-to-end latencies, which can only be provided by a URLLC communication network [34]. Furthermore, using either onboard processing capability or cloud storage would not be adequate for storing and processing the massive amounts of data provided by vehicles from their high-resolution cameras and sensors, as well as achieving a higher level of safety than the best human driver by processing real-time traffic conditions within latency of 100 ms [34]. There were limitations on energy and power constraints onboard computing and storage capacities. GPUs used for low latency processing and inference, for example, have high power consumption needs, which are increased by the cooling load to satisfy thermal constraints, reducing the vehicle's operating range and fuel performance substantially. Local storage units, such as SSDs, can be filled with sensor data in a matter of hours [34]. Although on-board processing capabilities can be adequate for passenger-vehicle interactions, they may not be adequate for managing workload between vehicles or between vehicles and infrastructure. In the meantime, long latencies and large bottlenecks in data processing as cloud storage are not an adequate solution for the IoV to connect with intelligent vehicles together [34].

5. Combination of MEC and MCC

In order to get better insights of the work done, this section explains why there is a need for MEC. This section will compare MEC and MCC. MEC, together with the increase in popularity of mobile phones, is the natural progression of cloud technologies. In a network infrastructure, mobile edge computing uses mobile base stations to get cloud computing as close to the mobile device as physically possible [43]. Cloud computing is described by the National Institute of Standards and Technology (NIST) as a model for gaining access to a common pool of configurable computing services that can be configured and delivered with minimal management effort and service provider involvement [44]. Cloud storage allows more resources to be shared, resulting in improved performance and lower costs. This model has become well-known, and its exceptional simplicity has enabled a wide variety of applications. Cloud computing is a rapidly adapting model that has the potential to become a viable mobile computing approach. One of the most popular applications of cloud computing is to increase the capacity of mobile devices. MCC is the name given to this one-of-a-kind technology. MCC can supplement mobile devices in terms of data capacity, processing power, and mobility [43]. Mobile devices can attach to the Internet in a variety of ways. Mobile networks, Wi-Fi, and satellite connections, for example, can provide access to the Internet through Internet Service Providers (ISPs). ISPs provide the network infrastructure that routes the connections across the appropriate paths on the Internet in order to connect the mobile user to the cloud controller. Cloud controllers manage the incoming requests from mobile clients and distribute them to the relevant cloud providers. Utility computing, virtualization, and service-oriented architecture were used to create these networks [45]. Furthermore, the word "mobile cloud computing" has another meaning. It envisions a set of nearby mobile devices pooling their resources in order to share them. This model is referred to as an "ad hoc mobile cloud." A mobile application task is spread and processed on the computers that belong to the ad hoc mobile cloud in a shared manner in this model. This model was demonstrated in Virtual Cloud Provider [46] by distributing a Map-Reduce architecture across a variety of mobile devices.

The architecture of the MCC still has challenges. Increased latency, device availability sensitivity, operation reliability, and bandwidth constraints are all costs of connecting to cloud servers. These considerations also limited MCC's ability to support a wide range of applications. For example, augmented reality or assisted cognition rely on sending streams of sensor data and video to a server with enough resources to process them and produce a near-real-time outcome [47]. As a result, a cloudlet, a third mobile cloud computing vision, was proposed. A cloudlet is a compact, resource-rich, self-managed system that can be deployed on a company's premises. It is decentralized and locally operated, and it uses LAN latency and bandwidth to serve only a few users at a time. In this model, a mobile device also taps into cloud computing space. In contrast to the MCC architectures described earlier, the cloudlet paradigm proposes bringing the cloud closer to the user by placing a device on the first hop of the network [47]. This is beneficial to certain actors. Second, the apps would be more responsive to the end-user, allowing for the deferral of critical applications. Additionally, network carriers may use the cloudlets' location to store media and files, reducing latency, and energy consumption on the core network. Finally, since their software can be hosted on cloudlets, application service providers benefit from increased scalability. Cloudlets are still being researched in academia, but commercial implementations based on the same model have only recently become available. The industry has called this paradigm as mobile edge computing (MEC).

MEC and cloudlets are similar in that they are both located at the network's first hop, provide storage and computing to neighboring computers, and are accessible by mobile users using wireless connections. A MEC server can be mounted at an LTE macrobase station's UMTS Radio Network Controller (RNC) or at a multitechnology cell aggregation site (eNodeB). A multitechnology aggregation site [48] manages a range of local multitechnology access points to have on-site radio coverage. MEC, on the other hand, differs from cloudlets in that it is operated by a mobile network carrier, it contains knowledge specific to network providers, and MEC servers are broadly spread and accessible to all mobile devices. MEC servers also provide access to knowledge about location and mobility [49]. MEC began as an Industry Specification Group (ISG) under the auspices of the European Institute for Telecommunications Standards (ETSI).

According to the ISG's Introductory Technical White Paper [50], MEC is described by being on site, proximity, reduced latency, location awareness, and network context information. MEC's first benefit is that it is located on site. This ensures that the MEC server is disconnected from the rest of the network and can run independently. In the case of a link loss to the core network, an application operating on a MEC server will be unaffected and continue to operate normally. Mobile devices, which are the basis of information, are often close to MEC servers. Because of their close proximity, MEC servers can function as data aggregators and gather big data and analytics. Since all data collected from crowd sensing apps and Internet of Things (IoT) sensors can be aggregated and preprocessed on a MEC server before being uploaded to a central repository, this feature gains the most from them. As a result, data flow and mobile networks are limited. Both the provider and the creator of the application benefit from reducing bandwidth usage [50]. The MEC architecture [53] is shown in Figure 1.

In Figure 1, Multiaccess Edge Orchestrator or ME Orchestrator (MEO) manages the mobile edge application packages along with resource orchestration across edge DC and selecting the right mobile edge hosts for instantiation of application with triggering, termination, and relocation with the help of reference points such as MM1, MM9, MM3, and MV1. The MM1 reference point acts as an instantiation triggering agent between the MEO and operation support system (OSS) along with termination of applications in mobile edge system. The MM9 reference point is used for managing the mobile edge applications requested by the UE application. The MM3 reference point between the MEO and ME platform manager is used for managing the application lifecycle, rules, and requirements for keeping track of available mobile edge services. The MV1 reference point is under research and evaluation. However, a few studies have shown that it acts as a connection agent between MEAO and NFVO, associated with the Os-Ma-nfvo reference point and is also called ETSI-NFV.

Another advantage of the MEC server is the reduction in the latency. Reduced latency enables technologies like augmented reality and cloud gaming to react quickly. MEC servers also exchange information about their location as well as low-level signaling data with applications. This allows for location-based applications, analytics, and distinction in terms of network conditions and location of the content served [50]. A Novel MEC-based framework was developed by Nokia. This framework is called the Redundant Array of Cloud Services (RACS) [51]. It is a MEC Solution that covers all the elements needed to develop and build apps packaged as virtual machines, which are managed. This is the only practical implementation of MEC to date. Therefore, an efficient and more secure system is needed to be worked upon. Table 2 summarizes the whole paragraph.

6. MEC-Based BBU Architecture for Autonomous Vehicles

Autonomous vehicles will become one of the main members of 5G in the coming years [54]. Vehicular networks (VANETs) are developing as a significant application for 5G services. In 5G VANETs, autonomous vehicles are more reliant on URLLC than traditional vehicles [53, 54]. Vehicles may use information obtained from roadside units (RSUs) or other vehicles to perform automatic overtaking and crash avoidance in autonomous driving [34]. These applications require a high level of stability and latency, which URLLC can only provide. However, since storage capacities are limited by resource and power constraints, using only cloud computing would not be adequate for processing and storing the vast amount of data provided by autonomous vehicles from numerous sensors and cameras within a latency of 100 ms. The developers of studies have explored some 5G vehicular network infrastructure, and our architecture is based on that. The architecture is given in Figure 2.

In Figure 2, it has been shown that MEC is able to improve the idea of a RSU to higher level and work with no strict deployment of 5G components, such as massive MIMO and beamforming [55]. A fairly recent networking approach is SDN, where the network setup and control take place in an environment that is more cloud-like than standard networking [3]. In this approach, network devices are managed by a central authority responsible for managing the various network devices, rather than relying on a distributed configuration per system. This transformation turns the network into a more modular technology, opening the way for programmable and self-organizing networks. An auxiliary network layer to transport called the control plane to transport signaling and management messages to incorporate this technology. In comparison, most of the data traffic flows through the so-called data plane, which is applied on top of the data plane-configured computers [3].

Although traditional networks rely on a strict relationship between hardware and applications, the various features are not linked to the physical devices in an NFV-based network but rather are implemented in general-purpose commodity servers. Consider a typical router system to understand the idea further. The router features are performed on a dedicated,

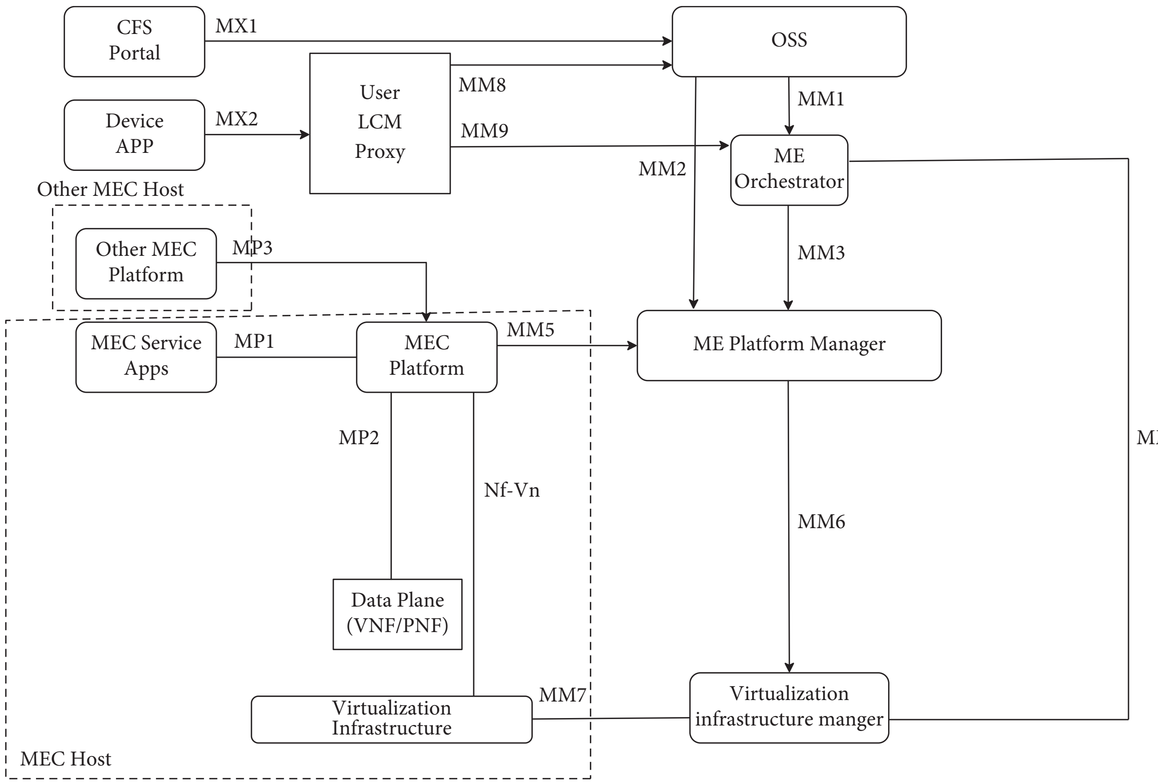


FIGURE 1: MEC architecture.

TABLE 2: Comparison between MCC and MEC [52].

Criteria	MEC	MCC
Latency	Shorter (around 1 ms)	Longer (around 30–100 ms)
Energy savings	Satisfies the latency condition and increases the battery life by 30%–50%	Cannot reduce the consumption of energy of IoT devices simultaneously and thus satisfy the latency requirements
Awareness of context	High	No awareness of context
Privacy and security	High	Low

specialized computer in a conventional network: the router. Instead, these can be performed with the NFV method in a commodity server or, more commonly, in a virtual environment. With respect to conventional networking, this decoupling provides tremendous flexibility, enabling the tenant to scale the various resources of a network accordingly, to the actual load or to the relevant use-case specifications. Thus, by allocating more resources to the physical framework and creating more instances of the desired functions, it is easy to scale and adapt a network's implementation. Usually, this strategy is applied in strict conjunction with SDN technology: the network becomes a massive, programmable device that can be easily controlled and tailored to the use-case scenario accordingly. It is worth noting that the definitions of the SDN and the NFV do not depend on each other. Indeed, regular network devices equipped with an SDN approach can be deployed and an NFV system without an SDN can be equipped. However, the two technologies will take advantage of each other and, when implemented together, communicate the best functionalities [3].

6.1. Network Slicing. There is no universal definition for network slicing, even though the principle of considering it as the separation of network traffic is accepted by most authors, through various logical networks, all operating on the same physical infrastructure. Network slicing is the enabler of certain main features of the system in the 5G architecture, enhancing scalability and versatility. A portion of the network can require a different collection of physical nodes, with different functionalities installed in a different network infrastructure location. In this case, the number of nodes used to process user packets can be increased. In the case of an eMBB slice, the URLLC slice would be designed to achieve a lower latency (e.g., by assigning nodes to the edge of the network). This method is also of the utmost importance when using Mobile Edge Computing. The Network Slicing Architecture [56] is given in Figure 3.

As previously mentioned, onboard computing capacities may be adequate for handling passenger-vehicle interactions, but they may not be sufficient for managing workload between V2V and V2I. Cloud storage is therefore insufficient

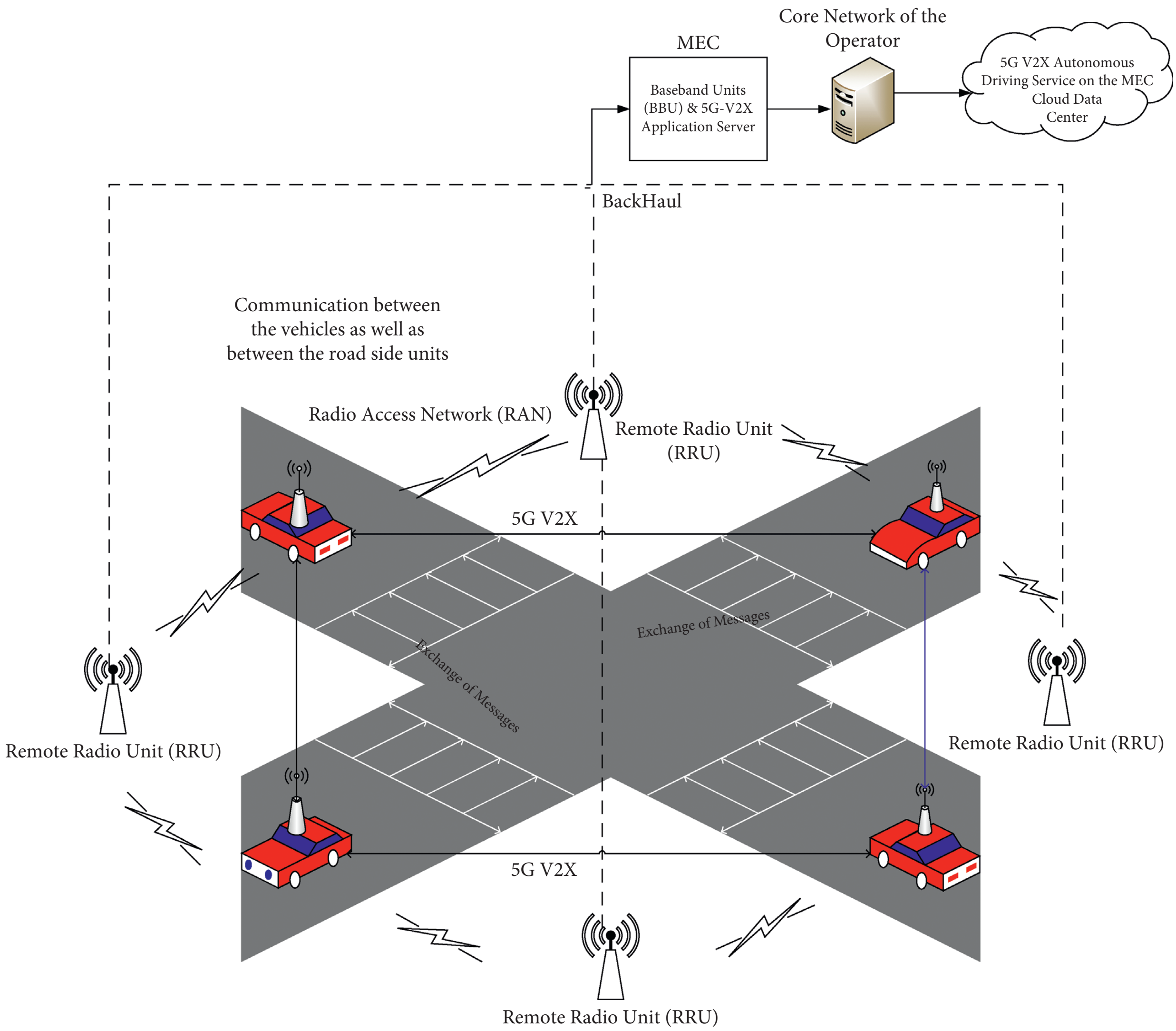


Figure 2: MEC-based BBU architecture for autonomous vehicles.

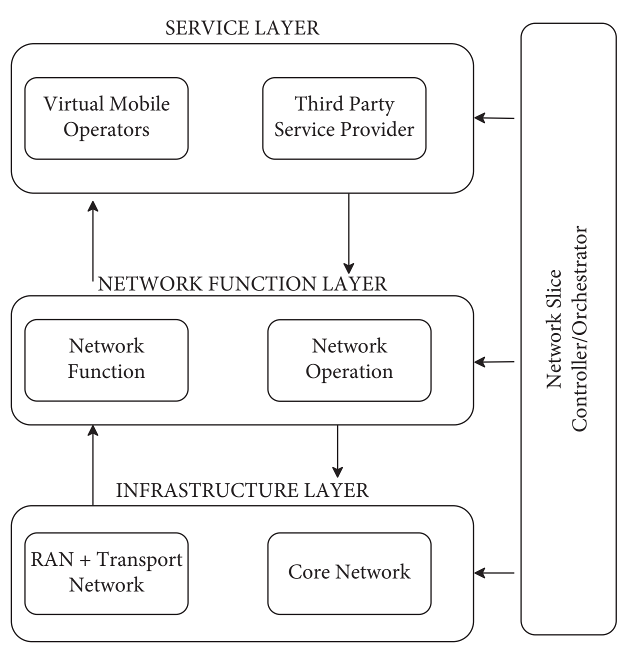


Figure 3: Network slicing framework.

for creating a link between intelligent vehicles due to massive data delivery and long latencies [34]. To address this problem, we must install all computation and storage capabilities at the wireless network edge, like edge caching and edge computing, using a MEC network infrastructure that runs on BBU servers at radio access points along the roadsides. Since it is entirely software-defined and reconfigurable on request, a cloud-native BBU server can be adapted for DRAN and CRAN installation. It can also run virtualized RAN services with network feature virtualization, as well as MEC-based software like self-driving. This architecture is useful for network slicing, which enables the URLLC network to operate on the same physical networks as other 5G networks, saving money on bandwidth, and network running costs.

6.2. Optimal CPU Scheduling. All data processing takes place at the edge server, and only the energy used for transmitting at mobile devices is considered. This energy is usually greater than the total energy expended by the coordination chain's subunits. Let us consider an OFDMA system [57]. Let *P(t) and H(t)* denote transmission power of the *mth* UE over the subcarrier *n*. As the time interval of transmission is fixed, the total energy consumption [57] is given as follows:

$$A_m(t) = \sum_{n\in X_m} A_{mn}(t) \tag{1}$$

where X_m is defined as the set of subcarriers assigned to UE and $A_{mn} = \phi P(t)$ is defined as the consumption of energy over the subcarrier n. In URLLC, high reliability is a must. As a result, using the most recent advancements in information theory, the maximum achievable rate for a finite block length can be calculated as [57]

$$R_{mn}(t) \approx B_{mn}(t) - \frac{K}{\ln(2)}\sqrt{\frac{y_{mn(t)}}{L}}\cdot Q^{-1}(\beta_m), \tag{2}$$

where $B_{mn}(t)$ is the formula for Shannon capacity [13] given as

$$B_{mn}(t) = K\log_2\left(1 + \frac{H(t)A_{mn}(t)}{\phi\gamma K}\right), \tag{3}$$

where γ is defined as the spectral density of the noise power. K is the channel dispersion, Q^{-1} is defined as the inverse of the Gaussian Q-function, β_m is defined as the maximum block error rate, and L is the length of the block, which can also be given as $L = \phi K$. Let all of the computational tasks be offloaded to the MEH. Consider a local communication queue at each UE, which contains the bits to be transmitted to AP, which further enables the amount of the computations to be performed [57]. The arrival of the data can be given as

$$Q_m^1(t+1) = \max\left(0, Q_m^1(t) - \phi R_m(t)\right) + \alpha_m(t), \tag{4}$$

where $Q_m^1(t)$ is defined as the local queue at time t and $\alpha_m(t)$ is defined as the arrival of the new data, which is available for the transmission from the next time, which is an unknown distribution with random variables. During the process, another queue is called a remote queue, which is given as [58]

$$\begin{aligned} Q_m^p(t+1) = \max\left(0, Q_m^p(t) - \phi f_m(t)x_m\right) \\ + \min\left(Q_m^p(t), \phi R_m(t)\right), \end{aligned} \tag{5}$$

where $R_m(t)$ is defined as the CPU cycles per second, which is assigned by MEH to UE m during t time, and x_m shows the number of bits in a CPU cycle. To address the Resource Allocation Challenge, which includes UE's long-term energy consumption, we must incorporate the idea of virtual queues. This can be given as [58]

$$X_m(t+1) = \max\left\{0, X_m(t) + Q_m^{\text{total}}(t+1) - Q_m^{\text{average}}\right\}, \tag{6}$$

where $m = 1, 2, 3, \ldots, m$.

6.2.1. Rate Allocation Challenge. Since the users in the OFDMA scheme are orthogonal, various issues affect different users. As a result, the problem can be expressed as follows [57] for each user m:

$$\min\left[\overline{Q_m}\phi\sum_{n\in X_m} B_{mn} + Y\sum_{n\in m}\frac{\phi K\gamma}{H(t)}\exp\left(\frac{B_{mn}\ln(2)}{K}\right)\right]. \tag{7}$$

The above equation is subject to

(1) $B_{mn} \geq 0, \forall n \in X_m$

(2) $\sum_{n\in X_m} B_{mn} \leq \widehat{B_{m,max}}$

$\overline{Q_m} = -2Q_m^p + 2Q_m^q - X_m - \mu_m Y_m$. As $\sum_{n\in X_m} B_{mn}$ and multiplier Y are the nondecreasing of B_{mn}. Then, the optimal solution is $B_{mn} = 0 \forall n \in X_m$ when $\overline{Q_m} \geq 0$. If $\overline{Q_m} < 0$, then the solution can be given as Lagrangian solution [13]:

$$\begin{aligned} \psi = \overline{Q_{m\phi}}\sum_{n\in X_m} B_{mn} + Y\sum_{n\in X_m}\frac{\phi K\gamma}{H(t)}\exp \\ \left(\frac{B_{mn}\ln(2)}{K} - \sum_{n\in X_m}\eta_{mn}B_{mn} + \lambda_m\left(B_{mn} - \widehat{B_{\max,m}}\right)\right), \end{aligned} \tag{8}$$

where η_{mn} and λ_m are Lagrangian multipliers.

6.2.2. CPU Scheduling at MEH. The second problem deals with the optimization of the scheduling at MEH and can be given as [57]

$$\min_{(f_m)_m} = \sum_{m=1}^{M=1}\phi\left(X_m + \mu_m Y_m + 2Q_m^p\right)f_m A_m. \tag{9}$$

The above equation is subject to the following conditions:

(1) $0 \leq f_m \leq (Q_m^p/\phi A_m)\forall m$

(2) $\sum_{m=1}^{M=1} f_m \leq f_{\max}$

There is a linear and optimal solution obtained by the use of simple iterative steps as defined in Algorithm 1. The

Input: $\{X_m(t)\}_m$, $\{Y_m(t)\}_m$, $\{Q_m^p(t)\}_m$, $\{A_m\}_m$ F_{max}, M
$f_{average} = f_{max}$, $\psi = \{m = 1, \ldots, M\}$
While $f_{average} > 0$ **do**
(1) $m = \arg\max_{m \epsilon_\psi} \{A_m(X_m + \mu_m Y_m + 2Q_m^p)\}$;
(2) $f_m = \min(Qmp/\Phi A_m, f_{average})$;
(3) $\psi = \psi - \{m\}$;
(4) If ψ = null→break;
(5) $f_{average} = f_{average} - f_m$;
(6) **End**

Algorithm 1: Optimal CPU scheduling.

algorithm ensures that all virtual queues are mean-rate stable in this situation. The algorithm's path appears to be as close to the optimal available solution as possible. This is measured in terms of the time it takes to arrive at a stable solution.

In this algorithm, to solve the problem linearly with optimal CPU scheduling, we have adopted the technique of virtual queues [57]. $X_m(t)_m$, $Y_m(t)_m$ is defined as the virtual queue of UE. $Q_m^p(t)_m$ is defined as the nondifferentiability of the maximum function. A_{mm} is defined as the conversion factor, which is used for converting the number of CPU cycles to be processed at MEH into its equivalent bits for adding the length of the two queues of UE [57]. The smaller the values of A_m are, the more computationally intensive the applications would be there, and F_{max} is defined as the computational power of MEHs.

7. Results and Discussion

For evaluation purposes, we have taken 20 UEs, which are embedded in a wireless framework based on mm-waves with path loss values as given in [66]. We have distributed the users uniformly to an area of 500 m^2. We have composed an orthogonal frequency-division multiplexing (OFDM) system of 200 subcarriers/user, with a spacing of 30 kHz. The noise power spectral density is taken as -180dBm/Hz with a transmission time of 20 ms and a block length of 100. The computational power of Mobile Edge Hosts (MEH) is taken as 5.0×109 CPU cycles/second. The results obtained are shown in Table 3. A trade-off is plotted, which is found to be increasing along the abscissa from right to left.

Furthermore, the reliability and convergence have also been plotted. The graph shows the boundation imposed on the remote queues on their average long-term lengths. The probability at which the sum of the queue lengths increases is a predefined threshold. The challenges are resolved using a dynamic algorithmic framework that is solved using optimization without having a prerequisite knowledge of the radio channel data arrivals. Through these graphs, we can interpret a fast-converging behaviour and the capacity of the system to adapt in the nonstationary environment. By looking at the transient intervals, in the graphs when the convergence is not achieved, the probability converges quickly to the expected levels. Larger values of μ_m give a lower convergence time, with a larger variance and vice versa. This can be explained by Figures 4 and 5, respectively.

Now, for analyzing the reliability and latency of the 5G autonomous vehicles, Monte Carlo Simulations [54] were performed with configurations as follows: weight factor is taken as 20 and the length of the road covered by the RSU is taken as 800 meters. The vehicle density [54] is taken as 0.5 vehicles per minute. The message generation exchange rate [54] is taken as 80 messages per second, average service time [54] is taken as 10 milliseconds, and transmission power of the vehicle [54] is taken as 50 dBm. The slot duration [54] is 65 microseconds, noise power density [54] is taken as -180dBm/Hz, and the number of the resource blocks are taken as 20 and we are considering a multiple hop situation [54]. The simulation results are shown in Figure 6–8, respectively.

When the RSU density is constant, propagation latency increases, and when the vehicle density is constant, propagation latency decreases.

From Figure 8, it can be concluded that vehicle density and handling latency are directly proportional to each other, keeping the RSU density fixed, and when the handling latency slightly decreases when the vehicle density becomes fixed for a short time.

Although this graph is somewhat skewed, we may deduce that overall latency rises when vehicle density rises. The overall latency reduces when the vehicle density is fixed.

8. Limitations and Future Scope

In autonomous vehicle technology, vehicles can benefit from the information extracted from their surroundings or roadside units to avoid any accident. To enable a fast message exchange mechanism between the autonomous vehicles and roadside units, we require reliable and low latency techniques which only MEC-based BBU URLLC communication can guarantee. However, there are certain limitations of our study, which would become the base for our future study or for other researchers in this fields. AVs work on various sensors, cameras, and techniques, such as LIDAR, and each of the sensors cannot perform fast processing and can cause some delay in exchange of information between the vehicles. Due to the COVID-19 restrictions, our approach cannot be implemented on larger scale and evaluation of image quality using peak signal-to-noise ratio cannot be done to find the best performance of our approach. Our approach can be implemented on small scale and to implement on large scale, it requires high capital investment and time, and the complexity of the system may also increase. Furthermore, some attacks or malicious users can tamper the system, which could lead to accidents. To prevent this, one of the solutions we suggest is integrating 5G URLLC communication with

Table 3: Output of URLLC.

UE	Q_m^{average}	ρ_m	$\Gamma Q_m^{\text{total}}(t) > \{Q_m^{\max}\}$
1	1.08×10^5	0.006	0.0058656
2	1.56×10^6	0.005	0.0038845
3	4.01×10^6	0.004	0.0096214
4	7.02×10^6	0.003	0.0045215
5	3.19×10^6	0.002	0.0054687
6	2.22×10^7	0.001	0.0044568
7	2.39×10^7	0.006	0.0039987
8	1.10×10^7	0.005	0.0028757
9	1.00×10^7	0.004	0.0025647
10	1.24×107	0.003	0.0012354
11	1.28×108	0.003	0.0042318
12	1.12×108	0.007	0.0033320
13	2.54×108	0.006	0.0054222
14	1.38×108	0.002	0.0036987
15	1.55×109	0.007	0.0047785
16	1.64×107	0.005	0.0055447
17	1.89×108	0.001	0.0042300
18	2.01×109	0.002	0.0044798
19	1.96×109	0.008	0.0025447
20	1.71×109	0.003	0.0039886

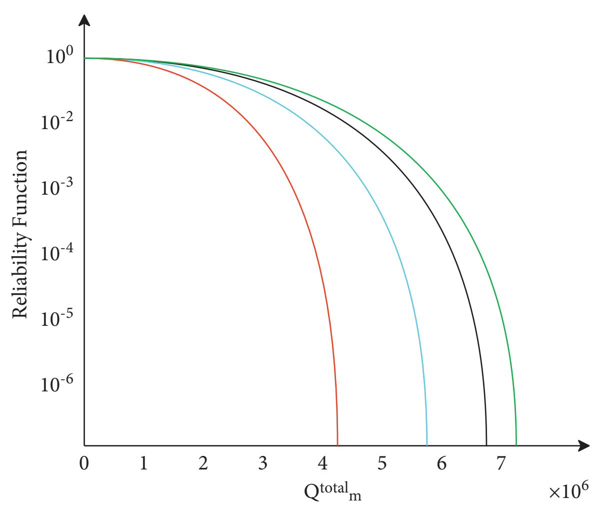


Figure 4: Reliability function curve.

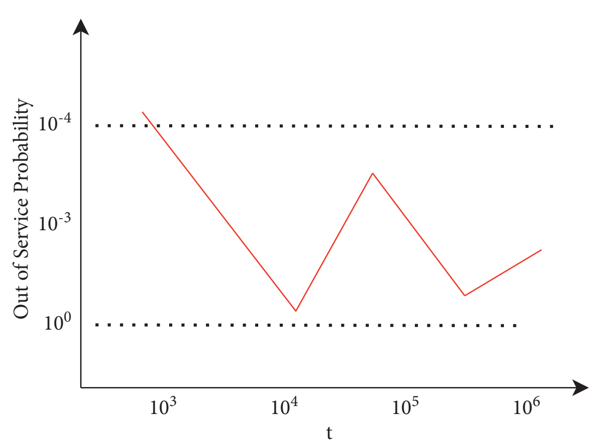


Figure 5: Out of service versus time plot.

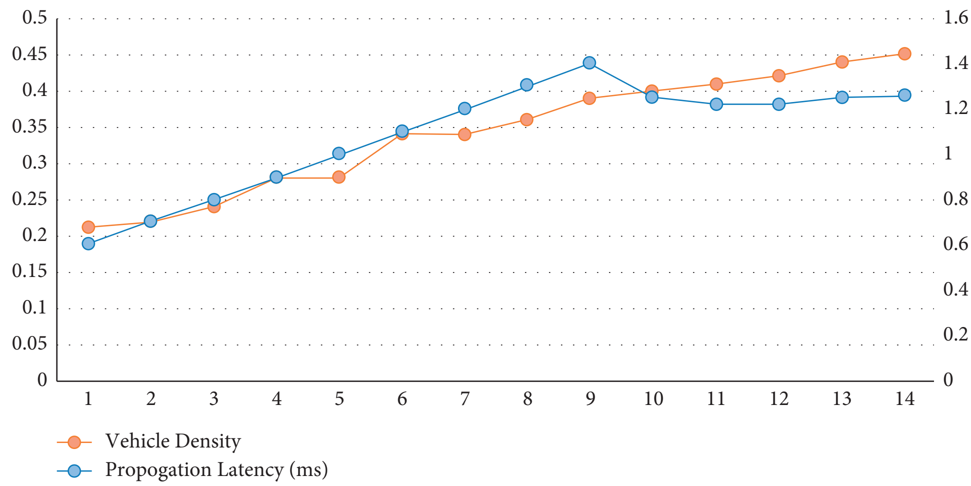


FIGURE 6: Propagation latency with respect to vehicle density.

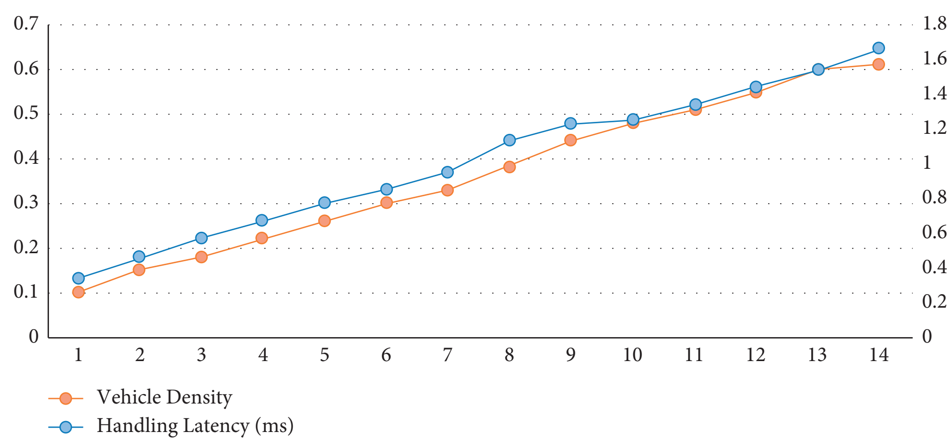


FIGURE 7: Handling latency with respect to vehicle density.

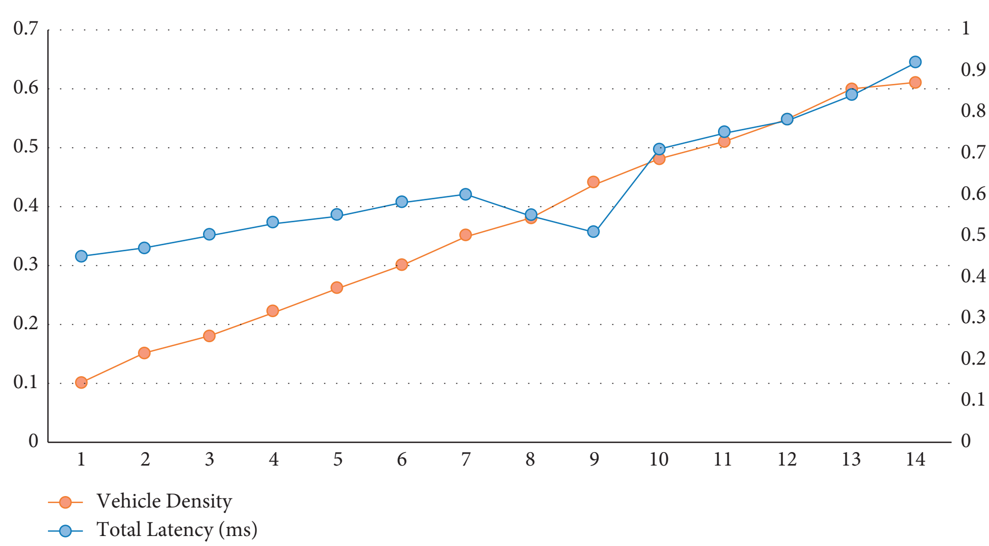


FIGURE 8: Total latency with respect to vehicle density.

blockchain technology, which would secure the cloud infrastructure and prevent system tampering. Further researches are required on improving the system with the help of blockchain technology.

9. Conclusion

Speaking of the device's latency, all the values calculated in this work were below 1 ms. It could be argued that 1 ms is a short period and, with the general Internet Round Trip Time average, the improvement in this value due to the new features is marginal. Although this is valid in most cases, it is crucial to keep this value as low as possible in certain cases of use envisaged by the 5G. Indeed, in URLLC, the overall Round Trip Time (RTT) of the device must be less than 1 ms, and, thus, even a small increment like the one implemented here can be within the service limits. It is also mandatory to study telemetry's effect in such situations, studying both optimizations and trade-offs to reduce latency. The tests carried out on the test bed indicate that with appropriate values for the parameters, the core network prototype's efficiency is not compromised and is therefore a legitimate solution for the implementation of network telemetry in the core network. The rational choices are made regarding the parameters of the system; the assessment should not directly affect the efficiency of the core network services.

Data Availability

Data will be available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

This research was supported by Taif University Researchers Supporting Project no. TURSP-2020/215, Taif University, Taif, Saudi Arabia.

References

[1] S. S. Mostafavi, "Vehicular positioning using 5G and sensor fusion," KTH, Stockholm, Sweden, Master in Communication Systems, 2019.

[2] S. Redana, Ö. Bulakci, A. Zafeiropoulos et al., *5G PPP Architecture Working Group: View on 5G Architecture*, European Commision, Brussels, Belgium, 2019, https://5g-ppp.eu/wp-content/uploads/2019/07/5G-PPP-5G-Architecture-White-Paper_v3.0_PublicConsultation.pdf.

[3] M. Girondi, "Efficient traffic monitoring in 5G core network," Maters thesis, KTH, Stockholm, Sweden, 2020.

[4] S. Rommer, P. Hedman, M. Olsson, L. Frid, S. Sultana, and C. Mulligan, *5G Core Networks: Powering Digitalization*, Academic Press, UK, 2019.

[5] F. Marzouk, J. P. Barraca, and A. Radwan, "On energy efficient resource allocation in shared RANs: survey and qualitative Analysis," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 3, pp. 1515–1538, 2020.

[6] N. Saqib, M. M. Yousuf, and M. Rashid, "January). Design and implementation issues in autonomous vehicles-A comparative review," in *Proceedings of the 2021 2nd International Conference on Computation, Automation and Knowledge Management (ICCAKM)*, pp. 157–162, IEEE, Dubai, UAE, January 2021.

[7] A. Gupta, S. Sundhan, S. K. Gupta, S. H. Alsamhi, and M. Rashid, "Collaboration of UAV and HetNet for better QoS: a comparative study," *International Journal of Vehicle Information and Communication Systems*, vol. 5, no. 3, pp. 309–333, 2020.

[8] X. You, C. Zhang, X. Tan, S. Jin, and H. Wu, "AI for 5G: research directions and paradigms," *Science China Information Sciences*, vol. 62, no. 2, pp. 1–13, 2019.

[9] D. Kombate, "The internet of vehicles based on 5G communications," in *Proceedings of the 2016 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*, pp. 445–448, IEEE, Rhodes Island, Greece, December 2016.

[10] G. Dimitrakopoulos, "Intelligent transportation systems based on internet-connected vehicles: fundamental research areas and challenges," in *Proceedings of the 2011 11th International Conference on ITS Telecommunications*, pp. 145–151, IEEE, St. Petersburg, Russia, August 2011.

[11] Z. Li, M. A. Uusitalo, H. Shariatmadari, and B. Singh, "5G URLLC: design challenges and system concepts," in *Proceedings of the 2018 15th International Symposium on Wireless Communication Systems (ISWCS)*, pp. 1–6, IEEE, August 2018, Lisbon, Portugal.

[12] M. Alsenwi, N. H. Tran, M. Bennis, A. Kumar Bairagi, and C. S. Hong, "eMBB-URLLC resource slicing: a risk-sensitive approach," *IEEE Communications Letters*, vol. 23, no. 4, pp. 740–743, 2019.

[13] M. E. Morocho-Cayamcela, H. Lee, and W. Lim, "Machine learning for 5G/B5G mobile and wireless communications: potential, limitations, and future directions," *IEEE Access*, vol. 7, pp. 137184–137206, 2019.

[14] K. David and H. Berndt, "6G vision and requirements: is there any need for beyond 5G?" *IEEE Vehicular Technology Magazine*, vol. 13, no. 3, pp. 72–80, 2018.

[15] R. Holm, *Wireless Vehicle Control: A Study of the Application of 5G, Master of Science in Engineering*, Mid Sweden University, Sundsvall, Sweden, 2020.

[16] J. Sachs, L. A. Andersson, J. Araújo et al., "Adaptive 5g low latency communication for tactile internet services," *Proceedings of the IEEE*, vol. 107, no. 2, pp. 325–349, 2018.

[17] G. Brown, "Ultra-reliable low-latency 5G for industrial automation," Technol. Rep., Qualcomm, San Diego, CA, USA, 2018.

[18] J. S. Kim, S. Lee, and M. Y. Chung, "Time-division random-access scheme based on coverage level for cellular internet-of-things in 3gpp networks," *Pervasive and Mobile Computing*, vol. 44, pp. 45–57, 2018.

[19] R. M. Rao, M. Fontaine, and R. Veisllari, "A reconfigurable architecture for packet based 5G transport networks," in *Proceedings of the 2018 IEEE 5G World Forum (5GWF)*, pp. 474–477, IEEE, Silicon Valley, CA, USA, July 2018.

[20] P. Popovski, K. F. Trillingsgaard, O. Simeone, and G. Durisi, "5g wireless network slicing for EMBB, URLLC, and MMTC: a communication-theoretic view," *IEEE Access*, vol. 6, pp. 55765–55779, 2018.

[21] S. Li, L. D. Xu, and S. Zhao, "5g internet of things: a survey," *Journal of Industrial Information Integration*, vol. 10, pp. 1–9, 2018.

[22] F. Voigtländer, A. Ramadan, J. Eichinger, C. Lenz, D. Pensky, and A. Knoll, "5g for robotics: ultra-low latency control of distributed robotic systems," in *Proceedings of the 2017 International Symposium on Computer Science and Intelligent Controls (ISCSIC)*, pp. 69–72, IEEE, Budapest, Hungary, October 2017.

[23] A. Hegde and A. Festag, "Mode switching strategies in cellular-V2X," *IFAC-PapersOnLine*, vol. 52, no. 8, pp. 81–86, 2019.

[24] S. Husain, A. Kunz, A. Prasad, E. Pateromichelakis, K. Samdanis, and J. Song, "The Road to 5g V2x: Ultra-high Reliable Communications," in *Proceedings of the 2018 IEEE Conference on Standards for Communications and Networking (CSCN)*, pp. 1–6, Paris, France, October 2018.

[25] T. Fong and C. Thorpe, "Vehicle teleoperation interfaces," *Autonomous Robots*, vol. 11, no. 1, pp. 9–18, 2001.

[26] D. H. Kim, S. J. Park, and C. S. Leem, "An industry-service classification development of 5G-based autonomous vehicle applications," *Journal of Society for e-Business Studies*, vol. 24, no. 2, 2020.

[27] S. Ansari, J. Ahmad, S. Aziz Shah, A. Kashif Bashir, T. Boutaleb, and S. Sinanovic, "Chaos-based privacy preserving vehicle safety protocol for 5G Connected Autonomous Vehicle networks," *Trans Emerging Tel Tech*, vol. 31, p. e3966, 2020.

[28] I. K. Jain, R. Kumar, and S. Panwar, "Driven by capacity or blockage? A millimeter wave blockage Analysis," in *Proceedings of the 2018 30th International Teletraffic Congress (ITC 30)*, pp. 153–159, IEEE, Vienna, Austria, September 2018.

[29] G.-M. Su, X. Su, Y. Bai, M. Wang, A. V. Vasilakos, and H. Wang, "QOE in video streaming over wireless networks: perspectives and research challenges," *Wireless Networks*, vol. 22, no. 5, pp. 1571–1593, 2016.

[30] A. Osseiran, F. Boccardi, V. Braun et al., "Scenarios for 5G mobile and wireless communications: the vision of the METIS project," *IEEE Communications Magazine*, vol. 52, no. 5, pp. 26–35, 2014.

[31] F. Z. Yousaf, M. Bredel, S. Schaller, and F. Schneider, "NFV and SDN-key technology enablers for 5G networks," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 11, pp. 2468–2478, 2017.

[32] J. Hyun, N. Van Tu, and J. W.-K. Hong, "Towards knowledge-defined networking using in-band network telemetry," in *Proceedings of the NOMS 2018—2018 IEEE/IFIP Network Operations and Management Symposium*, pp. 1–7, Taipei, Taiwan, April 2018.

[33] A. Mestres, A. Rodriguez-Natal, J. Carner et al., "Knowledge-defined networking," *ACM SIGCOMM Computer Communication Review*, vol. 47, no. 3, pp. 2–10, 2017.

[34] "An autonomous vehicles network with 5G URLLC technology," 2021, https://www.gigabyte.com/Solutions/Networking/urllc.

[35] C. Lai, R. Lu, D. Zheng, and X. Shen, "Security and privacy challenges in 5G-enabled vehicular networks," *IEEE Network*, vol. 34, no. 2, pp. 37–45, 2020.

[36] P. J. Fernandez, J. Santa, F. Bernal, and A. F. Skarmeta, "Securing vehicular IPv6 communications," *IEEE Transactions on Dependable and Secure Computing*, vol. 13, no. 1, pp. 46–58, 2016.

[37] F. Boeira, M. Barcellos, E. P. Freitas, A. Vinel, and M. Asplund, "Effects of colluding Sybil nodes in message falsification attacks for vehicular platooning," in *Proceedings of the 2017 IEEE Vehicular Networking Conference*, pp. 53–60, Torino, Italy, November 2017.

[38] S. Karnouskos and F. Kerschbaum, "Privacy and integrity considerations in hyperconnected autonomous vehicles," *Proceedings of the IEEE*, vol. 106, no. 1, pp. 160–170, 2018.

[39] Z. Lu, G. Qu, and Z. Liu, "A survey on recent advances in vehicular network security, trust, and privacy," *IEEE Transactions on Intelligent Transportation Systems*, 2018.

[40] T. Luan, R. Lu, X. Shen, and F. Bai, "Social on the road: enabling secure and efficient social networking on highways," *IEEE Wireless Communications*, vol. 22, no. 1, pp. 44–51, 2015.

[41] X. Huang, R. Yu, J. Kang, Y. He, and Y. Zhang, "Exploring mobile edge computing for 5G-enabled software defined vehicular networks," *IEEE Wireless Communications*, vol. 24, no. 6, pp. 55–63, 2017.

[42] A. Asadi, Q. Wang, and V. Mancuso, "A survey on device-to-device communication in cellular networks," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 4, p. 1801, 2014.

[43] E. Castellanos Nájera, "Evaluating mobile edge-computing on base stations: case study of a sign recognition application," Student thesis, Master of Science, 2014.

[44] P. M. Mell and T. Grance, *Sp 800-145. The Nist Definition of Cloud Computing*, US Department of Commerce, Washington, DC, USA, 2011.

[45] X. Fan, J. Cao, and H. Mao, "A survey of mobile cloud computing," *ZTE Communications*, vol. 9, no. 1, pp. 4–8, 2011.

[46] G. Huerta-Canepa and D. Lee, "A virtual cloud computing provider for mobile devices," in *Proceedings of the 1st ACM Workshop on Mobile Cloud Computing & Services: Social Networks and Beyond*, vol. 6, ACM, San Francisco, CA, USA, June 2010.

[47] M. Satyanarayanan, P. Bahl, R. Caceres, and N. Davies, "The case for VM-based cloudlets in mobile computing," *IEEE Pervasive Computing*, vol. 8, no. 4, pp. 14–23, 2009.

[48] E. B. M. E. Computing, "Initiative," https://portal.etsi.org/Portals/0/TBpages/MEC/Docs/MECExecutiveBriefv128-09-14.pdf Tech. Rep., ETSI-European Telecommunications Standards Institute, Sophia Antipolis, France, 2015, https://portal.etsi.org/Portals/0/TBpages/MEC/Docs/MECExecutiveBriefv128-09-14.pdf Tech. Rep..

[49] M. T. Beck, M. Werner, S. Feld, and S. Schimper, "Mobile edge computing: a taxonomy," in *Proceedings of the Sixth International Conference on Advances in Future Internet*, pp. 48–55, Lisbon, Portugal, November 2014.

[50] Y. C. Hu, M. Patel, D. Sabella, N. Sprecher, and V. Young, "Mobile edge computing—a key technology towards 5G," *ETSI white paper*, vol. 11, no. 11, pp. 1–16, 2015.

[51] C. R. Murthy and C. Kavitha, "A survey of green base stations in cellular networks," *International Journal of Computer Networks and Wireless Communications (IJCNWC)*, vol. 2, no. 2, pp. 232–236, 2012.

[52] Y. Liu, M. Peng, G. Shou, Y. Chen, and S. Chen, "Toward edge intelligence: multiaccess edge computing for 5G and internet of things," *IEEE Internet of Things Journal*, vol. 7, no. 8, pp. 6722–6747, 2020.

[53] "MEC-are we getting closer?," August 2018, https://www.netmanias.com/en/post/blog/13893/5g-mec/mec-are-we-getting-closer.

[54] X. Ge, "Ultra-reliable low-latency communications in autonomous vehicular networks," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 5, pp. 5005–5016, 2019.

[55] F. Giust, V. Sciancalepore, D. Sabella et al., "Multi-access edge computing: the driver behind the wheel of 5G-connected cars," *IEEE Communications Standards Magazine*, vol. 2, no. 3, pp. 66–73, 2018.

[56] P. Rost, C. Mannweiler, D. S. Michalopoulos et al. "Network slicing to enable scalability and flexibility in 5G mobile networks," *IEEE Communications Magazine*, vol. 55, no. 5, pp. 72–79, 2017.

[57] M. Merluzzi, P. D. Lorenzo, S. Barbarossa, and V. Frascolla, "Dynamic computation offloading in multi-access edge computing via ultra-reliable and low-latency communications," *IEEE Transactions on Signal and Information Processing over Networks*, vol. 6, pp. 342–356, 2020.

[58] N. Wang, *Resource Management for Edge Computing Systems*, Queen's University Belfast, Belfast, UK, 2020.