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Retraction

Retracted: Metaheuristic Deep Learning-Driven Wireless Communication Security Adaptation Using Multivariate Analysis of Variance (MANOVA)

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] P. Deshpande, N. Suganthi, G. Nirmala et al., "Metaheuristic Deep Learning-Driven Wireless Communication Security Adaptation Using Multivariate Analysis of Variance (MANOVA)," *Security and Communication Networks*, vol. 2022, Article ID 8426997, 7 pages, 2022.

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Research Article

Metaheuristic Deep Learning-Driven Wireless Communication Security Adaptation Using Multivariate Analysis of Variance (MANOVA)

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The implementation of accurate models to improve access technologies, communication transmission, and network slicing is anticipated to play a big part in the edge computing approach, as the demands and needs of individuals are quickly evolving. Deep learning models have tended to deliver more benefits in a wide range of applications; it also assists data providers in demonstrating considerable improvements in tackling complex real-world challenges. While the integration of connected wireless networks and deep learning is still in its infancy, wireless communication networks are increasingly focused on sophisticated technologies to meet the current and future needs of end users. Based on the theoretical and practical aspect that ranges from the basic aspect to future applications of wireless communication, this study is intended in addressing the opportunities of adopting metaheuristic deep learning-driven wireless communication. The researchers intend to apply descriptive design to the study as this enables in understanding the critical aspects of the study in an elaborate manner. The authors use both a primary data sources and a secondary data sources for performing the analysis. The secondary data source is sourced to understand the application of deep learning in the wireless communication area, and primary research is used to gather the data from the respondents to test the hypothesis and provide conclusions based on the analyses. The scope of this work is to utilize a quantitative model to undertake an analysis on evaluating the key parameters in the application of deep learning in wireless communication, which will allow for critical analysis and interpretation based on the findings.

1. Introduction

The current business environment is witnessing immense growth on the mobile data, which are generated due to the adoption of advanced technologies such as the Internet of Things (IoT), metaheuristics-based deep learning models, and the exploration of wireless communication network influencing the augmented virtual reality (AR) and advanced telecommunication technology, and tend to validate high-quality, capacity, and dimensional characteristics [1]. Hence, researchers have stated that the future of wireless communication will become even more demanding as their

benefits and usage are fast changing the business and consumer environment. The Internet of Things (IoT) is a set of technologies that allows individuals, objects, software applications, and platforms to interconnect over the Internet. Smart cities, smart farming, digital commerce, transportation infrastructure, and IoT hubs are just a few of the applications that have emerged as a result of the development of IoT technology. Despite the fact that the Internet of Things is regarded as a breakthrough in the growth of the Internet, it still confronts a number of obstacles, including energy conservation, privacy, efficiency, and QoS support [2]. The application of critical tools such as deep learning, edge computing, and other technologies tend to enhance the service delivery and support in realizing the goals of the end users. Figure 1 shows the deep learning model for the wireless communication network.

With the increased requirements in bandwidth and compulsion, reducing the latency issues has created more opportunities in the wireless communication arena. Companies and customers are looking forward to use the next-generation network system like deep learning to enhance the quality of transmission using wireless communication, support in using the existing resources effectively, offer better and quality signal transfer, and support in multipath remission, which will lead to enhance the double capacity without the need to increase the spectrum or antennas. However, the traditional systems possess serious limitations in the overall deployment of the existing systems, infrastructure, and process [4]. Therefore, the industry is looking to implement new and enhanced technologies, which will address various complicated issues, support the wireless communication industry in offering better services at lower cost, analyse the customer rowing demand, and be more prepared in addressing the requirements of the customers. It has been rowing regarded that deep learning tends to play a significant role in the area of wireless communication and researchers, and business has stated the field of wireless communication as there is a focus on enhancing the efficiency in dealing with complex aspects. Moreover, deep learning tools such as convolutional neural networks and other related networks are being implemented to enhance the overall performance, productivity, and service delivery in the wireless communication network [5]. Although CNN has some great advantages like parameter sharing and affine invariance, it also has some significant drawbacks, including a high processing cost, the difficulty of finding ideal hyperparameters, and the demand of deep structures for complex jobs [1].

The deep learning models are also implemented in signal detection and are gaining importance in the industry, and it has been noted that the tradition model of algorithm detection is mainly based on the estimation of channel information for detection; on the contrary, the deep learning model can enable in using advanced algorithms like sliding bidirectional recurrent neural network to enhance the signal detection, and this model uses the detection, which is highly robust to enable in measuring the changing condition of the channel and support in eliminating the overall requirements for enhanced channel detection estimation [6].

It has been regarded that the critical models such as deep learning and machine learning support service providers and users in offering better communication network, enhance efficiencies, and address the latencies in a greater manner. The deep learning methods are highly competent, and when channelized, we support the providers in using the existing assets for better management. Deep learning is used in these areas as they can overcome critical channels and help meet the needs of the users by improving the specified radio frequency. When compared to traditional models, learning-based methods leverage a large amount of data to improve overall productivity and performance. In-depth learning approaches also help address computer difficulties, lowering the high operational expenses of earlier traditional system applications.

The application of deep learning-based models intends to receive the first estimate of the signal processing and detect issues in the transmission and the method support in forecasting the signal explicitly, and then makes the recovery quickly. The deep learning method also supports in addressing the data-related issues, which enable in reducing the operational cost that was high when the traditional model was previous implemented. Deep learning (DL) is becoming increasingly essential in the field of wireless communications and is regarded as one of the most effective approaches for addressing communication issues due to its tremendous efficiency in processing incredibly complicated computations. Despite the fact that deep learning has performed well in a number of IoT applications, the "no free lunch" theorem shows that a system is not capable of handling all problems simultaneously and that constructing a generic model for a variety of communication scenarios is impossible [3]. The manuscript aims to aid in the consideration and evaluation of the critical indicators in applying deep learning in deep learning-driven wireless communication to improve efficiency. The researcher plans to conduct the analysis using a quantitative model, which will allow for rigorous analysis and interpretation depending on the findings.

The channel estimation and sensing are the main technologies, which are implemented to analyse the overall performance of wireless communication on a real-time basis. The channel estimation is focused on measuring the overall parameters of the channel model based on the data received, whereas the compression sensing is involved in gathering and reconstructing the signals [7]. Deep learning is implemented in these areas as they can overcome the critical channels and support in addressing the needs of the users through enhancing the specified radio frequency. Furthermore, learning-based approximation model uses a large amount of data, which can enhance the overall productivity and performance when compared with the traditional models.

The aim of the paper was to enable in considering and evaluating the major determinants in applying deep learning in deep learning-driven wireless communication for creating better efficiency. The researcher intends to use a quantitative model for performing the analysis; this will enable in making critical analysis and provide interpretation based on the analysis.

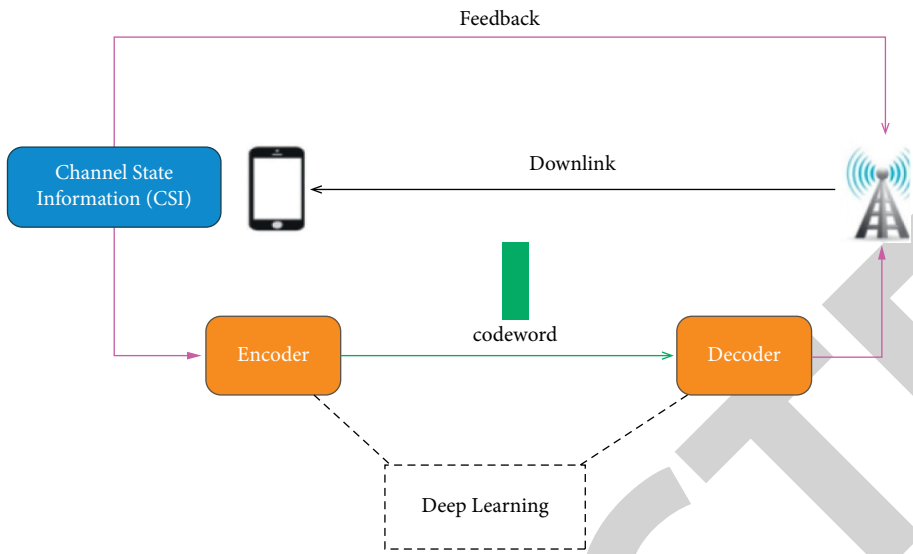

Figure 1: Deep learning model [3].

2. Review of Literature

Wireless communication systems are very vulnerable to attacks, phishing, and spying because of the general and broadcast nature of wireless media; therefore, the confidentiality and reliability of wireless communication has garnered a lot of attention. Furthermore, wireless communication systems have become more complicated, and the system's many elements are becoming increasingly interconnected [8]. The functioning of the wireless communication system will be harmed if an equipment is attacked. Artificial intelligence and integrity concerns are very sensitive when carrying out activities on servers. Because the user refuses to supply sensitive data such as site data solely, relieving artificial intelligence learning models and gathering data on distant servers to train and later process can lead to loss of data [9]. Channel estimation and compression detection are critical concepts for real-time wireless communication system implementation. Compression detection is an uncommon approach for identifying and reconstructing compressed signals, whereas channel estimation is the process of parameterizing a particular channel model from gathered information. Several new publications [10] have presented deep learning-based channel estimation and compression algorithms.

Deep learning-based signal detection is becoming increasingly popular. Unlike traditional detection algorithms, which are based on models on the estimation of instantaneous channel state information (CSI), the deep learning detection method does not require knowledge of the channel state model, knowledge of the underlying channel, or CSI if the model channel is known. A sliding bidirectional repetitive neural network (SBRNN) has been proposed to detect the signals, where the trained detector is resistant to changes in channel conditions; therefore, no immediate CSI evaluation is needed. Unlike standard OFDM receivers, which specifically analyse CSI before using the projected CSI to identify or recover the sent symbols, the deep learning system implicitly analyses CSI before retrieving the signals transmitted directly [11]. Due to the enormous growth in the number of factors created by deep neural networks, the prestigious CSI seeks to overcome the difficulties of massive volumes of training data and high cost of training (DNN).

The main technologies that are used to evaluate the overall performance of wireless communication instantaneously are channel estimation and sensing. The compression sensing is concerned with collecting and rebuilding the signals, whereas the channel estimation is concerned with evaluating the overall characteristics of the channel model based on the information obtained [7]. Deep learning is used in these domains because it can bypass important channels and assist in meeting consumer needs by increasing the designated radio frequency. Furthermore, opposed to traditional models, learning-based approximation models use a massive volume of data, which can improve overall productivity and performance.

A unique channel model is frequently required for training in end-to-end wireless communication systems (containing encoders, channels, and decoders). Mismatch difficulties will emerge if the trained model is not implemented to the appropriate channel model, resulting in a substantial degradation in performance of the system [12]. In real-world scenarios, however, the channel environment can change at any moment and in any location due to a variety of environmental factors such as changes in end-user movement speed and direction, changes in distribution patterns, and changes in the refractive diffusion environment. A substantial quantity of training data is necessary for recuperation after a variation in the channel environment, implying that different channel environments require recurrent training tasks to be done at a specific time, which consumes resources and degrades the system's performance [13].

Deep learning-based signal detection is becoming more popular. Unlike typical detection approaches that are based on programs based on the estimation of simultaneous

channel state information, the deep learning detection methodology does not require information from the channel state model, understanding of the underlying channel, or CSI if the model channel is known (CSI). A sliding bidirectional repetitive neural network (SBRNN) has been developed to identify signals where the trained detector resists changes in channel conditions, eliminating the need for instantaneous CSI evaluation. Unlike classic frequency division multiplexing (OFDM) receivers, which evaluate CSI explicitly before using the predicted CSI to recognize or recover sent symbols, the deep learning method inherently analyses CSI before explicitly evaluating the broadcast signals.

Because the system model does not have sufficient generalization capabilities, retraining would be required whenever the system configuration changes. The installation is carried out on a job-by-job basis and is tailored to the channel model. Changes in the channel environment can result in a significant decrease in performance of the system. As a result, more generalist systems are needed to adjust to the evolving channel environment.

3. Methodology

The authors of the researcher have focused on applying the descriptive research design for performing the analysis, and it can be stated that descriptive research design enables in gathering data from the information to analyse the phenomenon or situation. The researchers use secondary data such as EBSOC, Google Scholar, and other Scopus indexed published journals to understand the application of deep learning *n* wireless communication network. The researchers also use primary data to collect information from the respondents to understand the impact of deep learning in enhancing the opportunities of wireless communication and enable in meeting the growing requirements of the users [14]. The respondents are chosen based on convenience sampling, nearly 153 respondents were chosen, and the data are collected using the questionnaire method. The analysis is made using SPSS data package, and critical analysis is made based on the data collected from the respondents.

4. Hypothesis of the Study

There is no significant link between deep learning-based end-to-end communication and the expansion of wireless communication potential. There is no clear link between improved signal detection and increased wireless communication possibilities. There is no significant link between greater security and privacy based on deep learning and increased wireless communication opportunities.

5. Data Analysis

This section of the study entails doing a complete data analysis based on the information gathered by the researchers; the analysis includes descriptive analysis, correlation analysis, and multivariate analysis of variance (MANOVA).

5.1. Descriptive Analysis. Table 1 shows that 28.1 percent of respondents strongly agree with the assertion that the deep learning model helps to improve mobile data connectivity, and 44.4 percent agree with the statement. Nearly 13.7 percent of the respondents were undecided, while a similar amount disagreed with the assertion. Figure 2 depicts this graphically.

According to Table 2, 28 percent of respondents strongly agreed with the assertion that deep learning focuses on lowering operating costs, 38.6 percent agreed with the statement, and 13.1 percent of respondents were neutral. Figure 3 depicts this graphically.

5.2. Correlation Analysis. The next step in the study is to determine the degree of correlation between the variables, with a coefficient of correlation ranging from -1 to +1.

Based on Table 3, it is noted that the coefficient of correlation between the independent variables: end-to-end communication, signal detection, and security and privacy on the dependent variables: enhancing opportunities. The level of association between them is more than +0.800, which is highly positive in nature. The highest correlation is identified between signal detection and enhancing opportunities with nearly +0.875, and the next highest is between end-to-end communication and enhancing opportunities with nearly +0.874.

5.3. Hypothesis Testing. The next part of the analysis is involved to testing the hypothesis using multivariate analysis of variance (MANOVA). This tool enables in examining the effect of two or more independent variables towards the dependent variable. It is one of the useful methods in analysing the effect existing between the variables.

Based on Table 4, it is noted that the value of Pillai test is 0.988, the Pillai trace lies between 0 and 1, the higher value shows the level of effects contributing higher to the model, and the value is nearly 0.988, which shows that the effects are influencing the model in a positive manner.

The next analysis is involved in measuring the Levene test, which is one of the critical analyses specifying whether the two means are being considered in the sample population that possess equal variance. If the p value of the Levene test is less than 0.05, we tend to state that there is an appropriate variance in the sample variables.

Table 5 shows that the Levene test of statistics is 22.15, with a p value of 0.001, indicating that the variances between the variables are suitable.

H1: There is no significant link between deep learning-based end-to-end communication and the expansion of wireless communication potential.

H2: There is no clear link between improved signal detection and increased wireless communication possibilities.

H3: There is no significant link between greater security and privacy based on deep learning and increased wireless communication opportunities.

Table 1: Mobile data augmentation.

Mobile data augmentation	Frequency	Percent
Strongly disagree	18	11.8
Disagree	3	2
Neutral	21	13.7
Agree	68	44.4
Strongly agree	43	28.1
Total	153	100

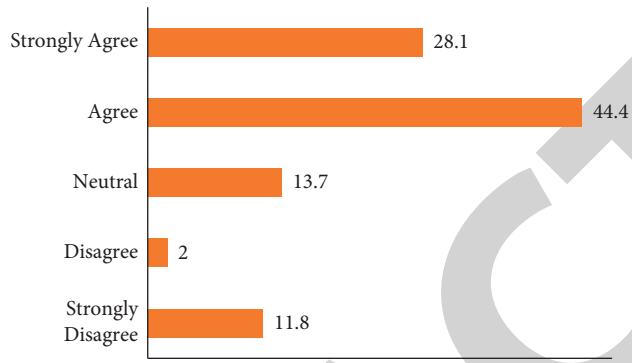

Figure 2: Mobile data augmentation.

Table 2: Deep learning supports in reducing cost.

Deep learning supports in reducing cost	Frequency	Percent
Strongly disagree	13	8.5
Disagree	17	11.1
Neutral	20	13.1
Agree	59	38.6
Strongly agree	44	28.8
Total	153	100

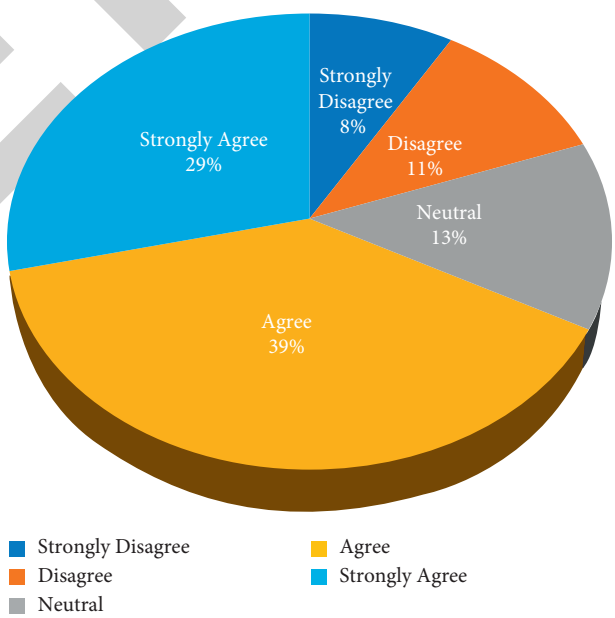

Figure 3: Deep learning supports in reducing cost.

Table 3: Correlation analysis.

Coefficient of correlation	End-to-end communication	Signal detection	Security and privacy	Enhancing opportunities
End-to-end communication	1	0.891	0.827	0.874
Signal detection	0.891	1	0.858	0.875
Security and privacy	0.827	0.858	1	0.836
Enhancing opportunities	0.874	0.875	0.836	1

Table 4: MANOVA test.

Multivariate tests	Value	F	p value
Pillai's trace	0.988	4122.723b	0.001
Wilks' lambda	0.012	4122.723b	0.001
Hotelling's trace	84.713	4122.723b	0.001
Roy's largest root	84.713	4122.723b	0.001

Table 5: Levene test.

Levene's test of equality	F	p value
End-to-end communication	22.159	0.001
Signal detection	7.072	0.001
Security and privacy	17.943	0.001

Table 6: Test between variables.

Dependent variable	Type III	F	Sig.
Corrected model			
End-to-end communication	181.360a	277.637	0.001
Signal detection	219.468b	435.426	0.001
Security and privacy	167.259c	141.291	0.001
Intercept			
End-to-end communication	751.506	4601.81	0.001
Signal detection	769.299	6105.16	0.001
Security and privacy	637.955	2155.64	0.001

The type III sum of squares of the independent variable end-to-end communication is 181.38, signal detection is 219.468, and security and privacy is 167.25, according to the analysis in Table 6. Furthermore, the null hypothesis is rejected, and the alternate hypothesis is accepted, because the p value for all independent variables is 0.001, which is less than 0.05.

6. Findings and Discussion

Opportunities in the field of wireless communication have risen as a result of rising bandwidth demand and the need to eliminate latency issues. Companies and customers hope to use next-generation networking systems, such as deep learning, to improve wireless transmission quality, support efficient use of existing resources, provide better signal transmission quality, and support multipath exclusion and double capacity without increasing spectrum or antennas [15]. Traditional systems, on the other hand, have major constraints in terms of overall system, infrastructure, and process development [16]. As a result, the industry is aiming to offer new and enhanced technology that enables the wireless business to give better services at reduced costs, analyse customer demands, and be better prepared to satisfy customer needs [17]. The field of wireless communication is focused on expediting the management of complex aspects, according to academics and companies [18]. Deep learning plays a pivotal role in the development of wireless communication. In-depth learning methods such as neural cohesion networks and other related networks are also utilized to improve a wireless communication network's overall performance, productivity, and service delivery [19, 20]. When compared to traditional models, learning-based methods leverage a large amount of data to improve overall productivity and performance. In-depth learning approaches also help address computer difficulties, lowering the high operational expenses of earlier traditional system applications. Deep learning models are also used in signal perception and are becoming more popular in the industry; the conventional algorithm detection model is primarily based on evaluating the channel information required for detection, whereas the deep learning model allows for advanced algorithms such as sliding bidirectional repetition [21]. This model combines sensing that is particularly successful at tracking changes in channel states to assist the eradication of global needs for improved detection estimation, and it uses a neural network to improve signal recognition.

7. Conclusion

Channel estimation and detection are the most important technologies used to analyse the overall performance of real-time wireless communication. Channel estimation focuses on measuring the overall parameters of the channel model based on the data obtained, while compression detection is involved in signal acquisition and reconstruction. Deep learning is used in these areas as they can overcome critical channels and help meet the needs of the users by improving the specified radio frequency. In addition, the learning-based method uses a large amount of data that can improve the overall productivity and performance compared to traditional models. Deep learning models have seemed to provide many more benefits across a wider range of applications; they also assist data providers in demonstrating substantial improvements in addressing complex real-world problems. While the integration of relevant wireless networks and deep learning is still in its early stages, wireless communication networks are increasingly focusing on satisfying the present and projected requirements of the customers by utilizing advanced technology. This work is aimed at addressing the prospects of adopting a metaheuristic deep learning-driven

wireless communication based on theoretical and practical aspects that extend from the fundamentals to future applications of wireless communication. Implementing in-depth learning models has several benefits for a variety of applications, as well as helping data providers make significant progress in solving complex real-world problems. With the convergence of connected wireless networks and deep learning still in its infancy, wireless communication networks are now focusing on using advanced technology to meet the current and future needs of end users. This study aims to address the potential for the adoption of wireless communication according to the invention based on deep learning.

8. Future Scope

The research's future scope can include applying multiple models in machine learning, cloud computing, and blockchain technology to assist users in generating quality services while also maximizing investment. As people's needs and demands fluctuate wildly, the future of wireless connectivity is expected to become more complex, with the successful implementation of models for the development of access, communication, and transmission technologies for network components playing a critical role in peak calculation.

Data Availability

The data are made available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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