

## Research Article

# Arrhythmia Classification Techniques Using Deep Neural Network

**Ali Haider Khan** <sup>1</sup>, **Muzammil Hussain** <sup>1</sup> and **Muhammad Kamran Malik**<sup>2</sup>

<sup>1</sup>Department of Computer Science, School of Systems & Technology, University of Management and Technology, Lahore 54000, Pakistan

<sup>2</sup>Punjab University College of Information Technology, University of the Punjab, Lahore 54000, Pakistan

Correspondence should be addressed to Ali Haider Khan; [s2018288001@umt.edu.pk](mailto:s2018288001@umt.edu.pk)

Received 14 March 2021; Revised 2 April 2021; Accepted 8 April 2021; Published 20 April 2021

Academic Editor: Atif Khan

Copyright © 2021 Ali Haider Khan 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.

Electrocardiogram (ECG) is the most common and low-cost diagnostic tool used in healthcare institutes for screening heart electrical signals. The abnormal heart signals are commonly known as arrhythmia. Cardiac arrhythmia can be dangerous, or in most cases, it can cause death. The arrhythmia can be of different types, and it can be detected by an ECG test. The automated screening of arrhythmia classification using ECG beats is developed for ages. The automated systems that can be adapted as a tool for screening arrhythmia classification play a vital role not only for the patients but can also assist the doctors. The deep learning-based automated arrhythmia classification techniques are developed with high accuracy results but still not adopted by healthcare professionals as the generalized approach. The primary concerns that affect the success of the developed arrhythmia detection systems are (i) manual features selection, (ii) techniques used for features extraction, and (iii) algorithm used for classification and the most important is the use of imbalanced data for classification. This study focuses on the recent trends in arrhythmia classification techniques, and through extensive simulations, the performance of the various arrhythmia classification and detection models has been evaluated. Finally, the study presents insights into arrhythmia classification techniques to overcome the limitation in the existing methodologies.

## 1. Introduction

Cardiac disorder may cause a severe warning to public health, and in most cases, some arrhythmias can cause severe damage or death. According to the data provided by World Health Organization (WHO) [1], approximately 25.6 million people died due to cardiovascular disease in 2020. Electrocardiogram (ECG) test is used as a diagnostic tool in healthcare institutes. The electrodes attached to the patients' body surface can record the heart's electrical signal over time. Figure 1 shows the ECG leads attached to the human's body surface to get the heart's electrical signals.

The healthcare professionals manually diagnose the patient heart condition by interpreting the ECG image. In the advent of technology, several automatic diagnostic tools are developed for arrhythmias classification and detection to

assist doctors. PPGs and ECGs are used to diagnose arrhythmia classification. PPG (also known as heart sound auscultation) is commonly listened to or recorded by practitioners through a stethoscope to identify heart irregularities. For this reason, heartbeats have been critically studied to make a diagnosis [2–5]. Khan et al. [6] provided a very thorough introduction of related studies in the problem domain and proposed a technique based on DNN, for the classification of three kinds of arrhythmia beats. CNN is considered a state-of-the-art tool for the classification of arrhythmia, and it has been studied with several variations such as 1-dimensional, 2-dimensional, or the combination of both [7, 8]. According to Xiao et al. [7], a novel arrhythmia classification technique comprises three phases: preprocessing, 1-dimensional CNN architecture based on clique blocks with bidirectional connections between layers

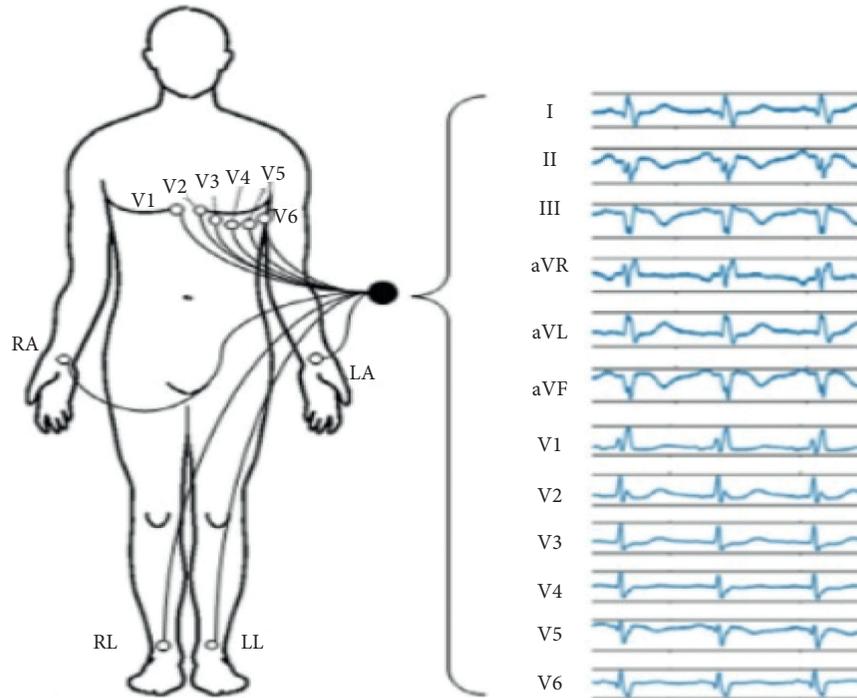


FIGURE 1: Heart electrical signal.

and transition blocks with attention mechanism, and majority voting to predict the final result. Experiments were performed on PhysioNet/CinC 2016 database. However, low-frequency noise considerations recorded in arrhythmia beats are ignored, and 2-dimensional acoustical representation requires additional computation, which cannot be accomplished without hyperparameters. Similarly, Noman et al. [8] proposed a framework based on 1-dimensional CNN for direct feature learning from raw arrhythmia beats and 2-dimensional CNN, which takes 2-dimensional time-frequency feature maps.

In the state-of-the-art studies [4–8], automated system which predicts high accuracy results is developed for arrhythmia detection but still not adoptable by healthcare professionals. The primary concerns which affect the success of the developed arrhythmia detection systems are (i) manual features selection, (ii) techniques used for features extraction, and (iii) algorithm used for classification and the most important is the use of imbalanced data for classification. The automated arrhythmia detection required the feature extraction of ECG images that required domain knowledge. In the last few years, deep learning-based systems are being recognized as a tool in healthcare institutes that have capabilities to automatically extract high-level abstract features, avoiding laborious manual feature design. A deep neural network is configured in the same fashion as the human brain works. A single neuron understands and recognizes the pattern based on the logical principles among different components. The proposed work's major concern is to review the recent trends of arrhythmia classification techniques and enlist the limitation and future requirements. This study can help the researcher get a deeper understanding of arrhythmia

classification and the deep learning methods used to develop automated systems.

The remainder of the paper is organized into six sections. The methods used in the proposed study are discussed in Section 2, and the research community's related work in the current field is presented in Section 3 with a close comparison. Recent trends of arrhythmia classification and limitation of the current study are discussed in Sections 4 and 5, respectively. The paper is concluded in Section 6.

## 2. Methodology

In this research study, the authors follow the mapping techniques for arrhythmia classification techniques using a deep neural network. Figure 2 demonstrates the systematic methodology in a four-step process. The primary objective of this study is to critically review the existing methods based on arrhythmia classification on the publishing forums [9].

*2.1. Research Objectives.* The primary goal of this research is to review the development of arrhythmias classification techniques over time, i.e., January 2010 to January 2020, using the machine and deep learning approach. The primary objectives of this research study are

- (1) To examine the arrhythmia classification techniques as practically implementable.
- (2) To overview the existing research studies based on arrhythmia classification benefits and future research direction.
- (3) Identify the latest research trends and publication interests based on arrhythmia classification.

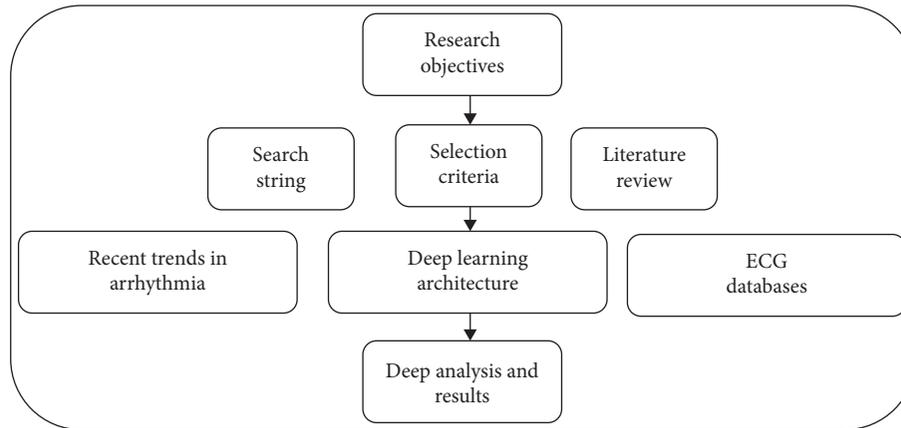


FIGURE 2: Systematic methodology.

**2.2. Search String.** The most reliable and trusted data sources available in the digital world to get the required articles for selected research studies are ACM, Elsevier, Google Scholar, IEEE Digital Library, Nature Scientific Reports, Springer, Science Direct, and Web of Science. The two main search strings are used in all data repositories to download the related articles.

- (1) (“arrhythmia” OR “arrhythmia classification” OR “cardiac arrhythmia” OR “arrhythmia detection” OR “cardiac disorder” OR “electrocardiogram” OR “cardiac care”) AND (“deep neural network” OR “dnn” OR “deep learning” OR “dl” OR “neural network” OR “nn” OR “convolutional neural network” OR “cnn” OR “recurrent neural network” OR “rnn” OR “Long Short Term Memory” OR “lstm”)
- (2) (“heartbeat” OR “heart disorder” OR “cardiac” OR “cardiac abnormality” OR “arrhythmia” OR “heart sound” OR “heart signals” OR “ECG” OR “ECG signals” OR “ECG Images”) AND (“deep neural network” OR “dnn” OR “deep learning” OR “dl” OR “neural network” OR “nn” OR “convolutional neural network” OR “cnn” OR “recurrent neural network” OR “rnn” OR “Long Short Term Memory” OR “lstm”)

The peer-reviewed best quality articles published online from January 2010 to January 2020 only were selected for this research study.

**2.3. Selection Criteria.** Identifying and selecting the best-suited articles that match the primary objectives of this research study are to identify the latest trends of deep neural networks for arrhythmia classification techniques. Table 1 shows the inclusion and exclusion criteria used in this study.

### 3. Literature Review

Based on the selection criteria, the fifty technical articles on arrhythmia classification are examined which are published between January 2010 to January 2020. The selected articles are critically examined, and if any selected articles are available on more than one scientific repository or database, it is considered only once. The different kinds of

methodologies, classification algorithms with their accuracy results, and optimization methods used for arrhythmia classification are reviewed from the selected articles. Table 2 shows the literature survey on arrhythmia classification techniques that are used in this study.

The authors present the recent trends for arrhythmia classification, the techniques used for features extraction, and the variation of deep neural networks. The study is beneficial for the scientific community to select the arrhythmia classification techniques as per their desires. Table 3 identified the latest trends from recently proposed studies for arrhythmia classification.

### 4. Recent Trends in Arrhythmia Classification

The primary objective of this study is to present the techniques used in arrhythmia classification with a publicly available ECG database used in deep/machine learning algorithms. The selected state-of-the-art research studies show the most common methods used for arrhythmia classification and their accuracy results. The accuracy results represent the learning algorithm’s success rate that how well the machine was trained to identify the ground truth automatically. The primary objective of this study is to help the scientific community to list the methodologies used in arrhythmia classification with prediction results that researchers can easily select the techniques as per their requirements. Figure 3 shows the statistics of most adopted arrhythmia classification techniques used in selected studies.

**4.1. Deep Learning Architectures.** Deep learning techniques are commonly used in medical image analysis. A deep neural network (DNN) is configured in the same fashion as the human brain works. A single neuron understands and recognizes the pattern based on the logical principles among different components. The deep neural network’s fundamental unit is a neuron trained by repetitive tasks and gets experienced just like a human brain through acquired knowledge attained in training. The focus of training and acquiring knowledge is to establish a connection between input and output. After training, the system is capable of

TABLE 1: Selection criteria.

Inclusion criteria	Exclusion criteria
InC-1: articles presenting good foundation knowledge for arrhythmia classification	ExC-1: articles that are not limited to arrhythmia classification
InC-2: articles that are presenting technical solutions using deep neural networks for arrhythmia detection	ExC-2: articles that only discussed arrhythmia but not focused on deep learning/machine learning-based solutions
InC-2: articles that used publicly available ECG dataset	ExC-3: articles whose datasets are not publicly available as open source
InC-2: articles that are written in the English language	ExC-4: articles that are not available in the English language
	ExC-5: articles that are published before January 2010

TABLE 2: Arrhythmia classification techniques from 2010 to 2020.

Ref.	Publication year	No. of leads	Classification techniques	Optimization techniques	Accuracy (%)
[9]	2020	02	CNN	BAROA	93.19
[10]	2020	12	Extreme gradient boosting tree	Low pass filter	97
[11]	2020	02	1D-CNN	—	95
[12]	2019	04	DNN	PCA	97.8
[13]	2019	03	DNN	—	92.07
[14]	2019	05	1 D CNN-2D CNN	—	90.93
[15]	2019	05	Residual networks	Data augmentation	99.81
[16]	2018	06	EMD	LDA	87
[17]	2018	05	CNN LSTM	DL	98.10
[18]	2018	02	Deep belief networks	—	95.57
[19]	2017	02	DNN	—	92
[20]	2017	04	SVM	—	98.9
[21]	2017	05	GRNN	—	88
[22]	2016	05	NN	—	97
[23]	2016	02	Dynamic Bayesian	PCA	99
[24]	2015	03	ANFIS	—	96
[25]	2014	03	Feed forward PNN	—	96.5
[26]	2014	16	SVM	PCA	86
[27]	2014	5	ML classifier	—	99.48
[28]	2013	05	SVM	PCA-LDA	99.28
[29]	2013	05	NN	PCA	94.52
[30]	2013	02	MLPNN	—	95.1
[31]	2013	02	MLPNN	—	85
[32]	2013	03	BMLPNN	—	76
[33]	2012	02	MNN-generalized FFNN	—	86.67
[34]	2012	08	PNN	PCA-LDA	99.71
[35]	2011	05	NN	—	95
[36]	2011	02	FCM	—	99.05
[37]	2011	03	MLPNN	—	96.7
[38]	2010	05	MDPSO	—	95.58

detecting the objects about what it has been trained. By reviewing the arrhythmia classification research studies, the most common DNN methods used for arrhythmia classification are given as follows:

- (1) Recurrent neural network (RNN)
- (2) Long short-term memory (LSTM)
- (3) Autoencoder
- (4) Convolutional neural network (CNN)
- (5) Deep neural network (DNN)
- (6) Deep belief network (DBN)

**4.1.1. Recurrent Neural Network (RNN).** RNN architecture belongs to the family of neural networks. RNN allows

information to be stored in loops within the adjacent layers. RNN is a popular network that uses reasoning from past experiences to train upcoming events. RNN-based deep architecture is widely used in arrhythmia classification systems that can train the sequence vectors. Figure 4 shows the internal working of RNN architecture.

**4.1.2. Long Short-Term Memory (LSTM).** LSTM is the reproduction of RNN architecture [59] commonly used in the field of deep learning. In general feedforward, neurons have forward connections, but LSTM has reversible feedback connections. LSTM processes data points like images or it has the capabilities to process the sequences of data, such as continuous images, video, or speech signals. LSTM architecture has the capabilities to recognize unsegmented speech

TABLE 3: Top arrhythmia classification techniques.

Ref.	Publication year	Database	Classification techniques	Optimization	Accuracy (%)
[39]	2018	PTB	FCN	MFB-CNN	99.95
[40]	2018	PTB	CNN	CNN	100
[41]	2018	MITDB	CNN	—	84
[42]	2018	PhysioBank	CNN	—	84
[43]	2018	PhysioNet challenge	FCN	FFT	81
[44]	2018	MITDB AFIB	DNN	Fourier transform	98.34
[45]	2018	PhysioBank	CNN	—	96.36
[46]	2018	PhysioNet challenge	MLP-CNN	—	76.79
[47]	2018	MITDB	CNN	—	98.6
[48]	2018	MITDB	AlexNet VGGNet	Transformation	99.05
[49]	2017	PhysioNet challenge	ResNet	—	72.1
[50]	2018	MITDB	FCN-CNN	—	91.33
[51]	2019	Multiple DB	CNN	—	95.98
[52]	2017	MITDB	FCN	1D-CNN	97.5
[53]	2017	MITDB PhysioNet 2000	RNN	CNN	94.03
[54]	2017	PAF	CNN	—	93.6
[55]	2019	Multiple	RNN	—	99.26
[56]	2018	MITDB	SVM	GD-DBM	99.5
[57]	2017	MITDB	RNN	LSTM	99.4
[58]	2017	MITDB	RNN	—	95

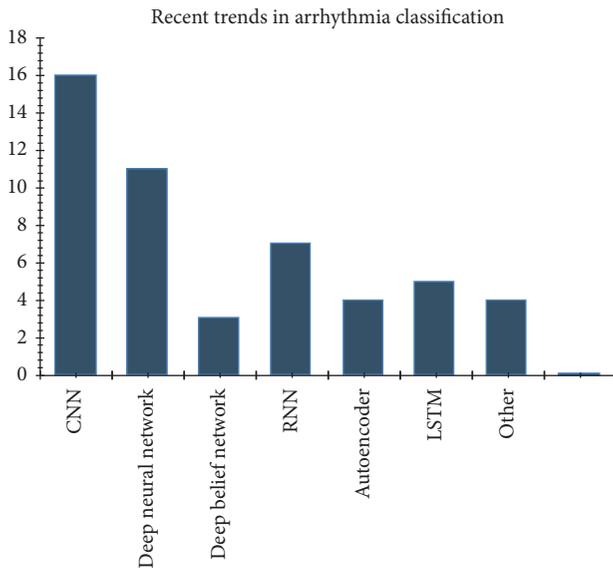


FIGURE 3: Arrhythmia classification techniques.

and detect similar patterns. LSTM also has the ability to recognize the heart sounds signals or ECG beats. The basic architecture of LSTM contains four major elements, i.e., cell, input gate, output gate, and forget gate. The cell has a responsibility to remember the values over specific time intervals and the gates regulate the flow of information between the cells. Figure 5 shows the internal working of LSTM architecture.

**4.1.3. Autoencoder.** Autoencoder belongs to the family of artificial neural network- (ANN-) based architecture, which is used for training efficient data coding in an unsupervised

manner. They are recognized as a tool to learn basic patterns for a similar set of data. Autoencoder also performs dimensionality reduction, and it tries to generate a class similar to its original input. In the cited research studies, the author proposed different variations in autoencoder-based architecture. Figure 6 shows the basic architecture of the autoencoder.

**4.1.4. Convolutional Neural Network (CNN).** CNN is a deep learning-based algorithm. CNN is widely recognized as a tool in the field of computer vision and image processing. It consists of an input layer, hidden layers, and the last output layer. In forward pass convolutional neural network, the middle layers are called hidden layers that are masked with activation function (ReLU), pooling layer, and convolution. Figure 7 shows the structure of the forward pass convolutional neural network. In the state-of-the-art research studies, CNN is widely recognized as a tool for the detection of ECG beats signals.

**4.1.5. Deep Neural Network (DNN).** A simple DNN contains multiple hidden layers that can process the input to output layers [60]. The DNN can recognize different kinds of unstructured data. In arrhythmia classification, authors proposed different kinds of neural networks but the proposed network is composed of the same components: neuron, weight, bias, and function. All these components are capable and act just like the human brain. The deep neural network is widely recognized approach for ECG image classification. Figure 8 shows the basic structure of DNN-based architecture.

**4.1.6. Deep Belief Network (DBN).** DBN is a class of deep neural networks; it consists of multiple layers that have a

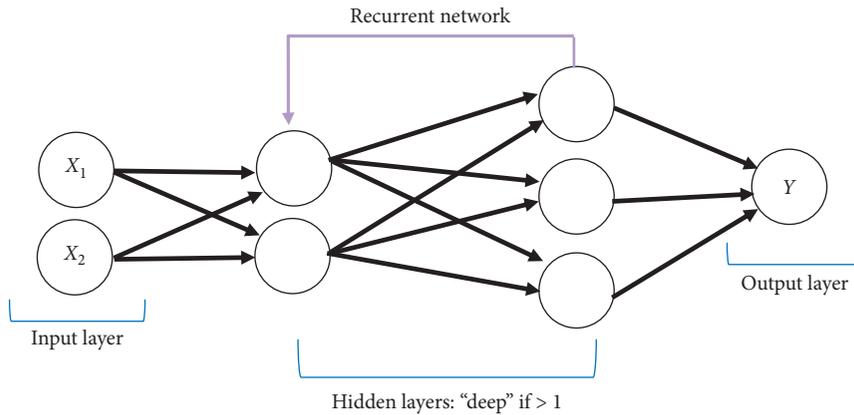


FIGURE 4: RNN architecture.

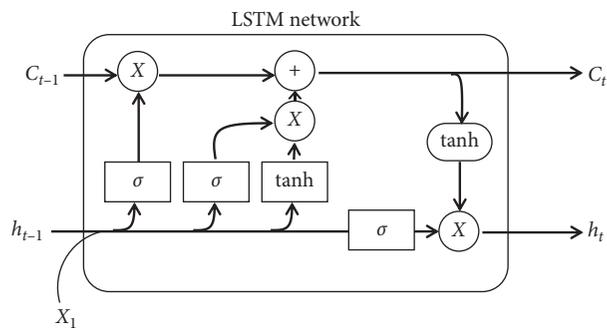


FIGURE 5: LSTM-based architecture.

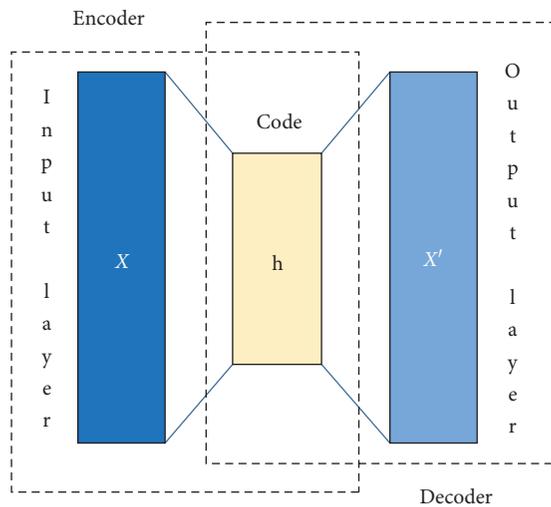


FIGURE 6: AE-based architecture.

connection between all the layers in the network but not with units of each other layers. DBN can be trained by supervision to achieve better prediction. Figure 9 shows the basic structure of DBN-based architecture.

**4.2. ECG Databases.** The expert systems for automatic detection of arrhythmia disease required training data to

understand different patterns of each class. Authors of the selected research study critically analyze arrhythmia classification systems and enlist the most cited/publicly open access ECG databases. The ECG databases available for the scientific community used as a data source are listed in Table 4.

The database as mentioned above contains variations of ECG beats with different types of arrhythmia classification. The data sources have unique importance with domain-specific characteristics. The description of the patient population in which these ECG beats were obtained is important in interpreting the methodology and clinical utility in context.

## 5. Limitations

Arrhythmia classification techniques are critically analyzed; the researcher puts lots of effort into developing the automated system with good accuracy results. The developed system may act as clinical support for the healthcare professionals but with having few limitations. The majority of the selected systems are limited to the following:

- (1) The most ECG databases are not specific to their clinical context.
- (2) The description of the patient population in which these ECGs were obtained is lacking. This is important in interpreting the methodology and clinical utility in context.

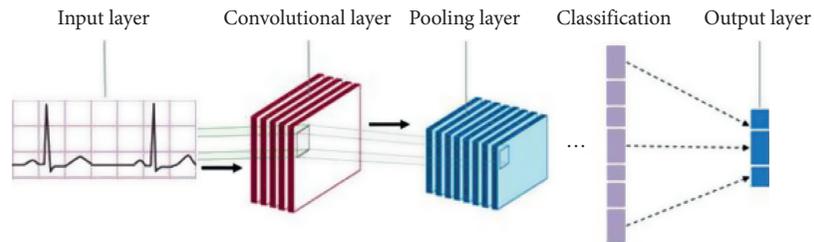


FIGURE 7: Structure of a forward-pass CNN.

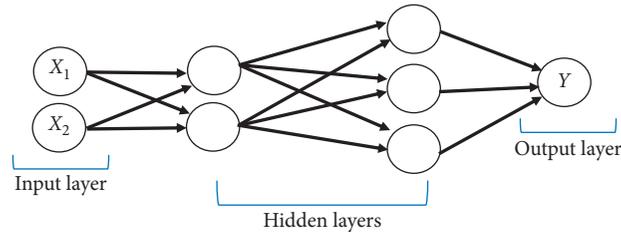


FIGURE 8: Structure of basic DNN architecture.

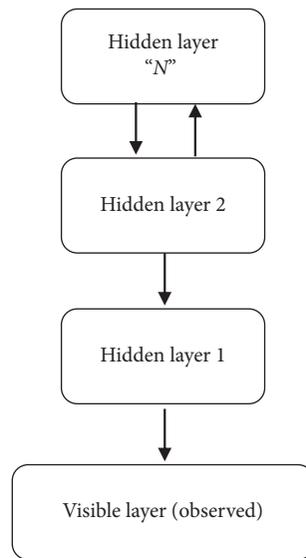


FIGURE 9: Structure of basic DBN architecture.

TABLE 4: ECG databases for arrhythmia classification.

Database	No. of records	ECG leads	Annotation
MITDB	47	02	Normal, abnormal
PTB	549	15	MI
PhysioNet challenge	Train 8528 Test 3658	01	Normal, noise, other, and AF
QT	105	02	P Q R ST waves
CART 12-lead	75	12	AF, AV
PAF	50	16 beats/sample	Normal, abnormal
AFIB	25	02	MI types
PhysioBank	Train: 6877 Test: 2954	12	Normal Abnormal
Mendeley ECG data	1687	12	Normal/abnormal/MI/PMI

- (3) The algorithms are trained based on specific environments, and the generalized methodologies are ignored.

## 6. Conclusion

Cardiac disorder or arrhythmia is the most dangerous disease that leads to human death. The researcher proposed lots of arrhythmia classification systems to assist the doctors every year. The automated systems predict the high accuracy results used for arrhythmia detection but still not adoptable by healthcare professionals because in the recent studies, authors used time-series data, which is not adaptable in different application environments. Moreover, ECG's time-series data with signal leads are not appropriate for stable baseline wanders, muscle contraction, and power line interface. In general, the practical methods generally adopted by a cardiologist for screening cardiac patients are 12 leads-based ECG images. The major concerns that affect the success of the developed arrhythmia detection systems are (i) manual features selection, (ii) techniques used for features extraction, and (iii) algorithm used for classification and the most important is the use of imbalanced data for classification. The automated arrhythmia detection required the feature extraction of ECG images that required domain knowledge. Further, the balanced dataset used for classification methods is required to avoid overfitting. In the last few years, deep learning-based systems are being recognized as a tool in healthcare institutes that have capabilities to automatically extract high-level abstract features, avoiding laborious manual feature design. Finally, this study can help the researcher get a deeper understanding of arrhythmia classification and the deep learning methods used to develop automated systems.

## Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## References

- [1] World Health Organization, *Cardiovascular Diseases (cvds)*, World Health Organization, Geneva, Switzerland, January 2021, <http://www.who.int/mediacentre/factsheets/fs317/en/>.
- [2] O. Deperlioglu, "Segmentation of heart sounds by Re-sampled signal energy method, BRAIN," *Broad Research in Artificial Intelligence and Neuroscience*, vol. 9, no. 2, 2018.
- [3] S. Ali, S. M. Adnan, T. Nawaz, M. Obaid Ullah, and S. Aziz, "Human heart sounds classification using ensemble methods," *Technical Journal, University of Engineering and Technology (UET)*, vol. 22, no. 1, pp. 113–120, 2017.
- [4] L. Bahekar, A. Mishal, M. Bisen, D. Koche, and S. Alone, "Heart valve diseases detection using anfis and wavelet transform," *International Journal of Research in Science & Engineering*, vol. 3, no. 2, pp. 279–291, 2017.
- [5] M. V. Shervegar and G. V. Bhat, "Automatic segmentation of Phonocardiogram using the occurrence of the cardiac events," *Informatics in Medicine Unlocked*, vol. 9, no. 1, pp. 6–10, 2017.
- [6] A. H. Khan, M. Hussain, and M. K. Malik, "Cardiac disorder classification by electrocardiogram sensing using deep neural network," *Complexity*, vol. 2021, Article ID 5512243, 8 pages, 2021.
- [7] B. Xiao, Y. Xu, X. Bi, J. Zhang, and X. Ma, "Heart sounds classification using a novel 1-D convolutional neural network with extremely low parameter consumption," *Neurocomputing*, vol. 392, pp. 153–159, 2019.
- [8] F. Noman, C. M. Ting, S. H. Salleh, and H. Ombao, "Short-segment heart sound classification using an ensemble of deep convolutional neural networks," in *Proceedings of the ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1318–1322, IEEE, Brighton, UK, May 2019.
- [9] D. Kumar Atal and M. Singh, "Arrhythmia classification with ECG signals based on the optimization-enabled deep convolutional neural network," *Computer Methods and Programs in Biomedicine*, vol. 196, Article ID 105607, 2020.
- [10] J. Zheng, H. Chu, D. Struppa et al., "Optimal multi-stage arrhythmia classification approach," *Scientific Reports*, vol. 10, no. 1, p. 2898, 2020.
- [11] J. Ferretti, V. Randazzo, G. Cirrincione, and E. Pasero, "1-D convolutional neural network for ECG arrhythmia classification," in *Progresses in Artificial Intelligence and Neural Systems. Smart Innovation, Systems and Technologies*, A. Esposito, M. Faundez-Zanuy, F. Morabito, and E. Pasero, Eds., vol. 184, Singapore, Springer, 2021.
- [12] W. Zhu, X. Chen, Y. Wang, and L. Wang, "Arrhythmia recognition and classification using ECG morphology and segment feature analysis," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 16, no. 1, pp. 131–138, 2019.
- [13] R. He, Y. Liu, K. Wang et al., "Automatic cardiac arrhythmia classification using combination of deep residual network and bidirectional LSTM," *IEEE Access*, vol. 7, pp. 102119–102135, 2019.
- [14] J. Huang, B. Chen, B. Yao, and W. He, "ECG arrhythmia classification using STFT-based spectrogram and convolutional neural network," *IEEE Access*, vol. 7, pp. 92871–92880, 2019.
- [15] P. Wang, B. Hou, S. Shao, and R. Yan, "ECG arrhythmias detection using auxiliary classifier generative adversarial network and residual network," *IEEE Access*, vol. 7, pp. 100910–100922, 2019.
- [16] E. Izci, M. A. Ozdemir, R. Sadighzadeh, and A. Akan, "Arrhythmia detection on ECG signals by using empirical mode decomposition," in *Proceedings of the 2018 Medical Technologies National Congress (TIPTKNO)*, pp. 1–4, Magusa, Cyprus, November 2018.
- [17] S. L. Oh, E. Y. K. Ng, R. S. Tan, and U. R. Acharya, "Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats," *Computers in Biology and Medicine*, vol. 102, pp. 278–287, 2018.
- [18] M. S. Mathew, C. Kambhamettu, and K. E. Barner, "A novel application of deep learning for single-lead ECG classification," *Computers in Biology and Medicine*, vol. 99, pp. 53–62, 2018.
- [19] I. Ali and S. Ozdalili, "Cardiac arrhythmia detection using deep learning," *Procedia Computer Science*, vol. 120, pp. 268–275, 2017.

- [20] S. Sahoo, B. Kanungo, S. Behera, and S. Sabut, "Multi-resolution wavelet transform based feature extraction and ECG classification to detect cardiac abnormalities," *Measurement*, vol. 108, pp. 55–66, 2017.
- [21] P. Li, Y. Wang, and J. He, "High-performance personalized heartbeat classification model for long-term ECG signal," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 1, pp. 78–86, 2017.
- [22] S. Shadmand and B. Mashoufi, "A new personalized ECG signal classification algorithm using block-based neural network and particle swarm optimization," *Biomedical Signal Processing and Control*, vol. 25, pp. 12–23, 2016.
- [23] L. S. C. de Oliveira, R. V. Andrao, and M. Sarcinelli Filho, "Bayesian network with decision threshold for heart beat classification," *IEEE Latin America Transactions*, vol. 14, no. 3, pp. 1103–1108, 2016.
- [24] P. B. Sakhare and R. Ghongade, "An approach for ECG beats classification using adaptive neuro fuzzy inference system," in *Proceedings of the 2015 Annual IEEE India Conference (INDICON)*, pp. 1–6, New Delhi, India, December 2015.
- [25] M. Vijayavanan, V. Rathikarani, and P. Dhanalakshmi, "Automatic classification of ECG signal for heart disease diagnosis using morphological features," *International Journal of Computer Science Engineering and Technology (IJCSET)*, vol. 5, no. 4, pp. 449–455, 2014.
- [26] N. P. Joshi and P. S. Topannavar, "Support vector machine based heartbeat classification," in *Proceedings of the of 4th IRF International Conference*, pp. 140–144, New Delhi, India, April 2014.
- [27] M. K. Das and S. Ari, "ECG beats classification using mixture of features," *International Scholarly Research Notices*, vol. 2014, Article ID 178436, 12 pages, 2014.
- [28] R. J. Martis, U. R. Acharya, and L. C. Min, "ECG beat classification using PCA, LDA, ICA and discrete wavelet transform," *Biomedical Signal Processing and Control*, vol. 8, no. 5, pp. 437–448, 2013.
- [29] R. J. Martis, U. R. Acharya, C. M. Lim, K. M. Mandana, A. K. Ray, and C. Chakraborty, "Application of higher order cumulant features for cardiac health diagnosis using ECG signals," *International Journal of Neural Systems*, vol. 23, no. 04, p. 1350014, 2013.
- [30] V. S. R. Kumari and P. R. Kumar, "Cardiac arrhythmia prediction using improved multilayer perceptron neural network," *Research and Development (IJEICERD)*, vol. 3, no. 4, pp. 73–80, 2013.
- [31] V. K. Srivastava and D. Prasad, "Dwt-based feature extraction from ECG signal," *American journal of Engineering Research (AJER)*, vol. 2, no. 3, pp. 44–50, 2013.
- [32] A. Khazae, "Heart beat classification using particle swarm optimization," *International Journal of Intelligent Systems and Applications*, vol. 5, no. 6, pp. 25–33, 2013.
- [33] S. M. Jadhav, S. L. Nalbalwar, and A. A. Ghatol, "Artificial neural network models based cardiac arrhythmia disease diagnosis from ECG signal data," *International Journal of Computer Applications*, vol. 44, no. 15, p. 813, 2012.
- [34] J.-S. Wang, W.-C. Chiang, Y.-T. C. Yang, and Y.-L. Hsu, "An effective ECG arrhythmia classification algorithm," *Bio-Inspired Computing and Applications*, Springer, vol. 6840, pp. 545–550, Berlin, Germany, 2012.
- [35] C. Kamath, "ECG beat classification using features extracted from teager energy functions in time and frequency domains," *IET Signal Processing*, vol. 5, no. 6, pp. 575–581, 2011.
- [36] A. Dallali, A. Kachouri, and M. Samet, "Classification of cardiac arrhythmia using WT, HRV, and fuzzy C-means clustering," *Signal Processing: An International Journal*, vol. 5, no. 3, pp. 101–109, 2011.
- [37] E. Zeraatkar, S. Kermani, A. Mehridehnavi, A. Aminzadeh, E. Zeraatkar, and H. Sanei, "Arrhythmia detection based on Morphological and time-frequency Features of t-wave in Electrocardiogram," *Journal of Medical Signals and Sensors*, vol. 1, no. 2, pp. 99–106, 2011.
- [38] Z. Slimane and A. Nait-Ali, "QRS complex detection using empirical mode decomposition," *Digit Signal Process*, vol. 20, no. 4, pp. 1221–1228, 2010.
- [39] M. Liu and Y. Kim, "Classification of heart diseases based on ECG signals using long short-term memory," in *Proceedings of the 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 2707–2710, IEEE, Honolulu, HI, USA, July 2018.
- [40] R. D. Labati, E. Muñoz, V. Piuri, R. Sassi, and F. Scotti, "Deep ECG: convolutional neural networks for ECG biometric recognition," *Pattern Recognition Letters*, 2018.
- [41] J. Takalo-Mattila, J. Kiljander, and J.-P. Soinen, "Inter-patient ECG classification using deep convolutional neural networks," in *Proceedings of the 2018 21st Euromicro Conference on Digital System Design (DSD)*, pp. 421–425, IEEE, Prague, Czech Republic, August 2018.
- [42] M. Chen, G. Wang, P. Xie et al., "Region aggregation network: improving convolutional neural network for ECG characteristic detection," in *Proceedings of the 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 2559–2562, IEEE, Honolulu, HI, USA, July 2018.
- [43] J. Rubin, S. Parvaneh, A. Rahman, B. Conroy, and S. Babaeizadeh, "Densely connected convolutional networks for detection of atrial fibrillation from short single-lead ECG recordings," *Journal of Electrocardiology*, vol. 51, no. 6, pp. S18–S21, 2018.
- [44] Y. Xia, N. Wulan, K. Wang, and H. Zhang, "Detecting atrial fibrillation by deep convolutional neural networks," *Computers in Biology and Medicine*, vol. 93, pp. 84–92, 2018.
- [45] Z. Zhao, Y. Zhang, Y. Deng, and X. Zhang, "ECG authentication system design incorporating a convolutional neural network and generalized s-transformation," *Computers in Biology and Medicine*, vol. 102, pp. 168–179, 2018.
- [46] R. Kamaleswaran, R. Mahajan, and O. Akbilgic, "A robust deep convolutional neural network for the classification of abnormal cardiac rhythm using single lead electrocardiograms of variable length," *Physiological Measurement*, vol. 39, no. 3, Article ID 035006, 2018.
- [47] X. Zhai and C. Tin, "Automated ECG classification using dual heartbeat coupling based on convolutional neural network," *IEEE Access*, vol. 6, pp. 27465–27472, 2018.
- [48] T. J. Jun, H. M. Nguyen, D. Kang, D. Kim, D. Kim, and Y.-H. Kim, "ECG arrhythmia classification using a 2-d convolutional neural network," 2018, <https://arxiv.org/abs/1804.06812v1>.
- [49] F. Andreotti, O. Carr, M. A. Pimentel, A. Mahdi, and M. De Vos, "Comparing feature-based classifiers and convolutional neural networks to detect arrhythmia from short segments of ECG," in *Proceedings of the 2017 Computing in Cardiology (CINCOM)*, pp. 1–4, IEEE, Rennes, France, September 2017.
- [50] Ö. Yildirim, P. Özal, R.-S. Tan, and U. R. Acharya, "Arrhythmia detection using deep convolutional neural network with long duration ECG signals," *Computers in Biology and Medicine*, vol. 102, pp. 411–420, 2018.

- [51] U. R. Acharya, H. Fujita, S. L. Oh et al., "Deep convolutional neural network for the automated diagnosis of congestive heart failure using ECG signals," *Applied Intelligence*, vol. 49, no. 1, pp. 16–27, 2019.
- [52] D. Li, J. Zhang, Q. Zhang, and X. Wei, "Classification of ECG signals based on 1d convolution neural network," in *Proceedings of the 2017 IEEE 19th International Conference on e-health Networking, Applications and Services (healthcom)*, pp. 1–6, IEEE, Dalian, China, October 2017.
- [53] B. Chandra, C. S. Sastry, S. Jana, and S. Patidar, "Atrial fibrillation detection using convolutional neural networks," in *Proceedings of the 2017 Computing in Cardiology (CINeC)*, pp. 1–4, IEEE, Rennes, France, September 2017.
- [54] B. Pourbabae, M. J. Roshtkhari, and K. Khorasani, "Deep convolutional neural networks and learning ECG features for screening paroxysmal atrial fibrillation patients," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 48, no. 12, pp. 2095–2104, 2017.
- [55] L. Wang and X. Zhou, "Detection of congestive heart failure based on LSTM-based deep network via short-term RR intervals," *Sensors*, vol. 19, no. 7, p. 1502, 2019.
- [56] G. Sayantan, P. Kien, and K. Kadambari, "Classification of ECG beats using deep belief network and active learning," *Medical & Biological Engineering & Computing*, vol. 56, no. 10, pp. 1887–1898, 2018.
- [57] C. Zhang, G. Wang, J. Zhao, P. Gao, J. Lin, and H. Yang, "Patient-specific ECG classification based on recurrent neural networks and clustering technique," in *Proceedings of the 2017 13th International conference on biomedical engineering (biomed)*, pp. 63–67, IEEE, Innsbruck, Austria, February 2017.
- [58] V. Sujadevi, K. Soman, and R. Vinayakumar, "Real-time detection of atrial fibrillation from short time single lead ECG traces using recurrent neural networks," in *Proceedings of the International Symposium on Intelligent Systems Technologies and Applications*, pp. 212–221, Springer, Manipal, India, September 2017.
- [59] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [60] J. Schmidhuber, "Deep learning in neural networks: an overview," *Neural Networks*, vol. 61, pp. 85–117, 2015.