DOI: http://dx.doi.org/10.26483/ijarcs.v15i2.7065

ISSN No. 0976-5697

Volume 15, No. 2, March-April 2024

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

Analysing and Evaluating the Performance of Deep-Learning-Based Arrhythmia Detection Using Electrocardiogram Signals

Shaista khanam
Research Scholar
Shri Jagdish Prasad Jhabarmal Tibrewala University,
Rajasthan

Dr.Rana Quadri
Assistant Professor, ECE,
Nawab Shah Alam Khan College of Engineering and
Technology, Telangana

Abstract: Cardiac arrhythmia is a cardiac irregularity that impacts a significant number of individuals globally. Certain arrhythmias may be benign or occur only once, while recurring arrhythmias have the potential to cause organ failure, increase the risk of stroke by a factor of five, and even lead to sudden cardiac death. Thus, in order to identify and treat arrhythmia and prevent potentially fatal cardiac problems, the rapid detection and categorization of Electrocardiogram (ECG) signals is of paramount importance. The non-invasive technique employs electrodes to examine the electrical potentials of the heart, facilitating the detection of structural and functional irregularities that contribute to the diagnosis of cardiovascular illnesses. Nevertheless, the high likelihood of manual interpretation, which is both time-consuming and susceptible to error caused by weariness, poses a significant challenge for cardiologists in identifying and diagnosing cardiac issues. In recent times, there has been a growing utilization of Deep Learning (DL) models in the field of arrhythmia prediction, with the aim of enhancing clinical decision-making and potentially mitigating the likelihood of valetudinarian fatality. These models enhance the diagnostic capabilities of electrocardiography by detecting pathological situations, extracting anatomically meaningful data, evaluating cardio-motion, and assessing the quality of echo images. As a result, they serve as an alternative tool for precise diagnosis and treatment of arrhythmias. In order to forecast and categorize arrhythmias based on ECG signal data, this study provides a comprehensive review of various deep learning approaches. The initial section of the study provides a concise overview of various deep learning-based prediction models that have been developed by multiple researchers for echocardiography systems. Subsequently, a comparative analysis is undertaken to comprehend the limitations of those algorithms and propose a novel approach to improve the accuracy of cardiac view classification in echocardiography systems.

Keywords: electrocardiogram, deep learning and clinical decision making, cardiac arrhythmia

I. INTRODAUCTION

The term "cardiac arrhythmia" encompasses an atypical heart rate or rhythm. An arrhythmia refers to a condition when the heart beats at an abnormally fast, slow, or irregular rate [1]. The occurrence of these atypical rhythms can be attributed to disruptions in the electrical impulses governing cardiac function. Arrhythmias often manifest in healthy hearts and are typically transient and benign. Nevertheless, severe arrhythmias that persist for an extended period and greatly impair cardiac function pose a major risk [2]. Indeed, specific forms of arrhythmia have the potential to result in Sudden Cardiac Arrest (SCA) and mortality within a short span of time following its initiation. During these critical instances, the heart experiences a loss of ability to efficiently circulate blood throughout the body and to the essential organs. When the heart fails to provide adequate oxygen to the brain, a rapid occurrence of syncope (fainting) and death can ensue [3].

Classification of Arrhythmias

Arrhythmias can be categorized based on two main factors: their impact on heart rate and their location inside the heart. The heart's rate of contraction and relaxation varies in response to the body's oxygen requirements. An optimal heart rate for a physically fit person at rest falls within the range of 60 to 100 beats per minute (bpm)

- **Tachycardia:** Refers to a heart rate that surpasses 100 bpm.
- **Bradycardia:** refers to a heart rate that falls below 60 bpm.
- **Supraventricular arrhythmia:** These arrhythmias are aroused due to abnormalities occurring in the atria, the superior chambers of the cardiac organ. The classification of supraventricular arrhythmias includes atrial flutter, atrial fibrillation and paroxysmal supraventricular tachycardia.
- **Ventricular arrhythmia:** refers to irregular heart rhythms that arise in the ventricles, which are the lowest chambers of the heart. A less severe form of ventricular arrhythmia known as pre-ventricular contractions refers to additional irregular heartbeats that originate from the ventricles rather than the sinus node. These cardiac contractions can induce a sensation of fluttering, resembling a missed heartbeat, and are relatively prevalent. Ventricular fibrillation and ventricular tachycardia are two potentially fatal arrhythmias that can lead to sudden cardiac arrest.

Cardiologists are medical professionals that specialize in the study and treatment of cardiovascular diseases. The primary factors contributing to the escalating risks include obesity, tobacco use, psychological stress, hypertension, high cholesterol levels, diabetes, and other related conditions [4]. The Holter monitor, ECG, angiography screening and blood test are the most commonly used tools for detecting arrhythmias. Out all these options, ECG is the most favoured method for detecting cardiac issues because it is painless and non-invasive. This test is a straightforward and rapid method used to assess the heart [5]. ECG electrodes, which are little plastic patches stuck to the skin, are placed in certain spots on the body, such as the arms, legs, and chest. An ECG equipment is connected to the electrodes using lead wires [6]. The next step is to measure, analyses, and record the cardiac electrical activity. There is no electrical current going to the body. In order to keep blood circulating properly, the heart's intrinsic electrical impulses synchronize the contractions of its different components [6]. By recording the electrical impulses as they travel through the heart, an electrocardiogram (ECG) can reveal the heart's rhythm, the strength and timing of the signals, and whether the heart beats regularly or not. Variations in an ECG can reveal a number of heart conditions [7].

ECG signals can detect cardiac arrhythmias. By analyzing the different characteristics found in the signal, different types of arrhythmias can be identified, such as tachycardia and bradycardia. The presence of the R-peak in the ECG signal is utilized for illness detection. The timely detection of diseases is of utmost importance, since failure to do so might result in severe complications and perhaps fatal outcomes. The P wave, QRS complex, and T wave are the three primary parts of an electrocardiogram basic waveform. The diagrammatic representation of ECG wave form is shown in Fig. 1. In the typical cardiac cycle, the contraction of the atrium is accompanied by a P-wave, which is characterized by atrial depolarization. This P-wave exhibits a low amplitude due to the comparatively thin nature of the atria muscle. The QRS complex, on the other hand, represents the depolarization of the ventricles brought about by the electrical impulse's transmission through them. The initial deviation of the QRS complex is referred to as the Q-wave, a negative wave that initiates the process of septal depolarization. The R-wave is indicative of the depolarization of the left ventricular myocardium, whereas the subsequent negative deflection referred to as the S-wave signifies the final depolarization. The T-wave is observed subsequent to the aforementioned event and signifies the repolarization of the ventricles [8, 9].

In recent times, scholars have made advancements in the field of technology, namely the utilization of AI for the automated and timely anticipation of arrhythmia through the analysis of ECG signal data [10]. ML and DL models are AI methods that can automatically identify different cardiac disorders. This makes them a desirable choice for early diagnosis and therapy, as they help to simplify clinical processes and improve the effectiveness of clinical judgments [11]. In the realm of soft-tissue examination activities, ML methodologies are commonly employed to forecast the progression and management of malignant diseases, hence enhancing the diagnostic accuracy. Efficient image interpretation and precise decision-making are offered by these systems, leading to enhancements in cardiovascular care and the mitigation of inequities [12, 13]. Nevertheless, machine learning models are susceptible to errors and experience significant variability in both intra- and inter-reader environments. The challenge of manually estimating cardiac indices in fetuses/infants arises from their relatively small heart size and the lack of distinct limits.

DL models outperform ML frameworks in terms of arrhythmia prediction and classification [14]. DL systems offer a prompt, less subjective, and cost-effective alternative to the manual method. These systems have the capability to manage variability within and across readers, significantly decrease the computational load, and tackle the scarcity of cardiological competence in settings with limited resources [15]. Several deep learning models are available, such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short Time Memory (LSTM), and Deep Belief Network (DBN). These models aid doctors in delivering an unbiased and dependable identification of arrhythmia and its many kinds, relying on distinguishing and distinctive characteristics derived from ECG signal data [16]. Fig. 2 represented the DL structure.

Fig. 3 illustrates a prototype model for detecting arrhythmias using a deep learning model and ECG signal data. There are three primary stages involved in the prediction of arrhythmia using ECG signals: pre-processing, feature extraction, and classification. During the initial stage, the signal will undergo pre-processing or filtering to eliminate extraneous data. Following the pre-processing stage, the subsequent step involves conducting feature extraction. This procedure entails selecting the most effective characteristics through the utilization of a feature extraction algorithm. The next step is to classify the best attributes using the DL algorithm to predict whether arrhythmia will occur and what kinds of arrhythmia it will be.

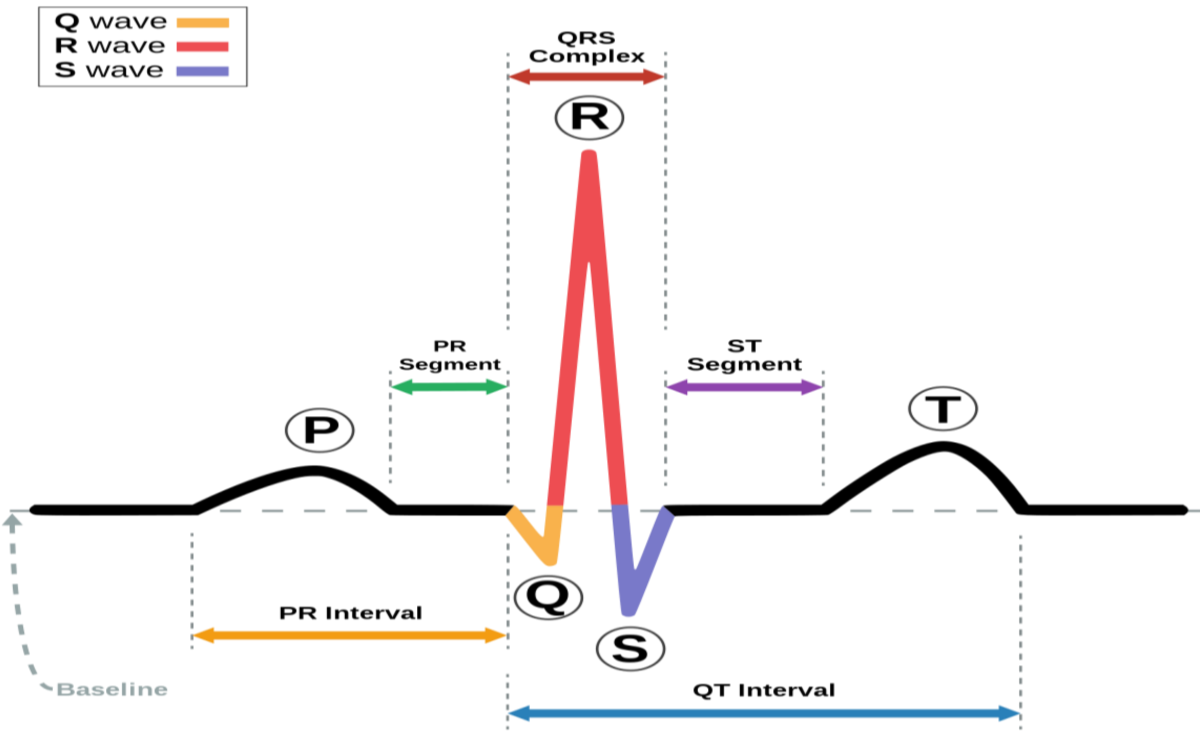

Figure 1. Normal ECG waveforms

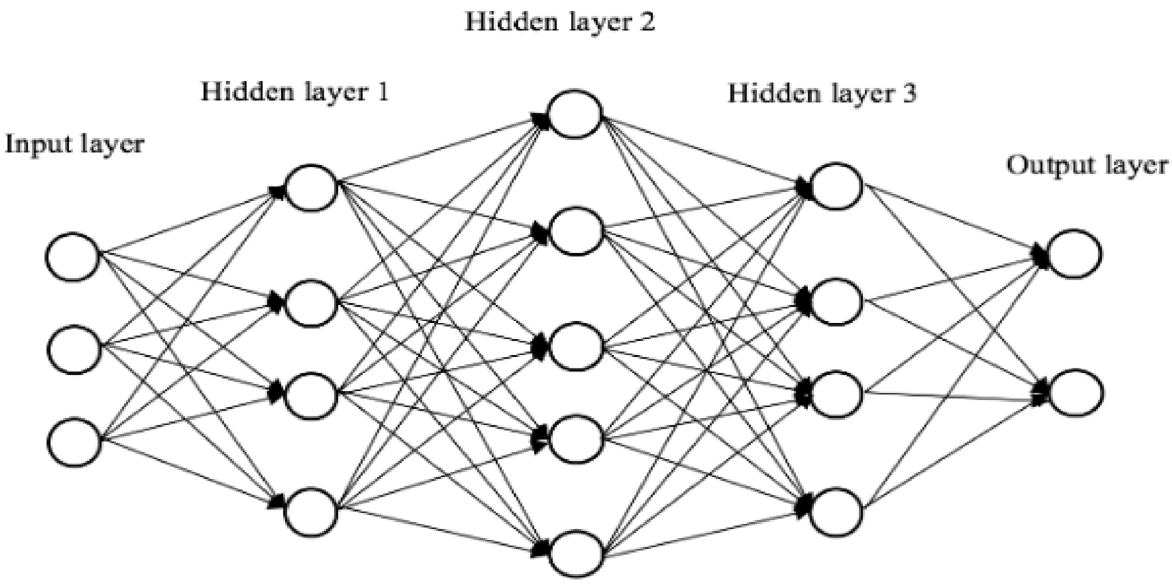

Figure 2. Deep Learning Structure

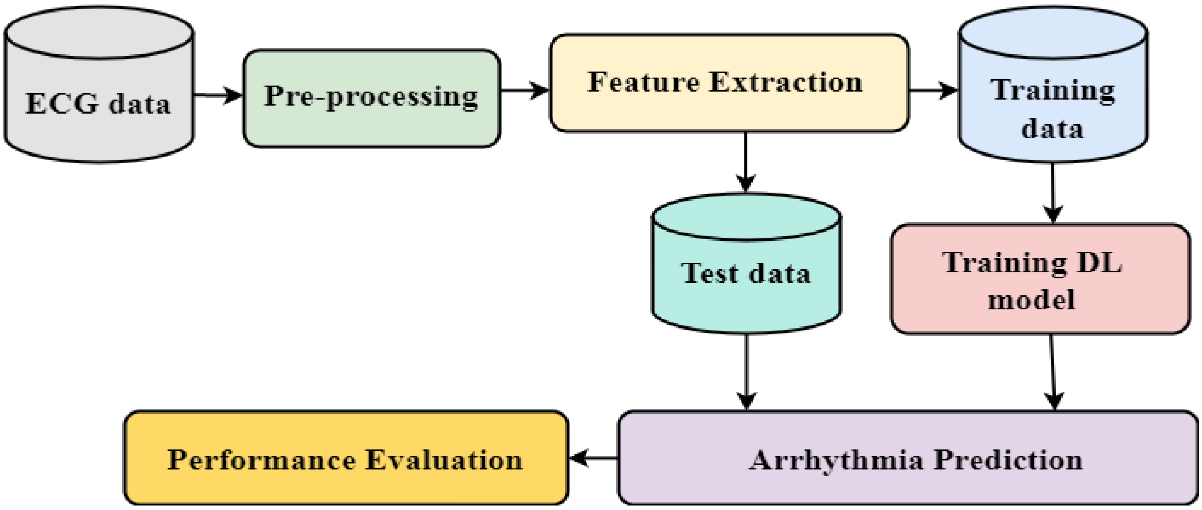

Figure 3. Arrhythmia detection by DL model using ECG signal data

The primary objective of this work is to conduct a comprehensive examination of diverse deep learning models and their utilization in the prediction and categorization of arrhythmia through the analysis of ECG signals. This study also examines the advantages, disadvantages, and performance of various frameworks, with the aim of offering recommendations for their potential future use. The subsequent sections are structured as follows: Section II examines different deep learning models that have been developed for the purpose of predicting and classifying arrhythmia based on ECG signal data. In Section III, a comparative study of the aforementioned models is presented. Section IV provides a comprehensive overview of the entire study and proposes future directions.

II. SURVEY ON ARRHYTHMIA DETECTION AND CLASSIFICATION USING DEEP LEARNING MODEL

Authors of [17] created a novel and effective one-dimensional CNN architecture for the autonomous detection of cardiac arrhythmias using 10-second ECG signal segments. Initially, the unprocessed ECG impulses underwent pre-processing and adjustment procedures, which involved systematic element suppression and amplitude elimination. Subsequently, a 16-layer DCNN was employed to classify the pre-processed ECG data according to the dysrhythmia.

The authors introduced a 1D DCNN model [18] for the purpose of classifying different cardiac conditions based on modified ECG signals. The initial step involved decomposing raw ECG signals using Empirical Mode Decomposition (EMD). Subsequently, the modified ECG signals were generated by combining the higher-order Intrinsic Mode Functions (IMFs). Subsequently, the aforementioned signals were inputted into the DCNN, wherein a softmax regressor was employed at the network's final layer to classify the heart illnesses.

A 6-layer DCNN was introduced [19] to accurately identify ECG rhythms for future arrhythmia prediction. Initially, the initial ECG impulses were split into numerous wavelets by the use of the Continuous Wavelet Transform (CWT). The deconstructed inputs were subsequently fed into the DCNN framework, which successfully classified the different types of arrhythmias.

A 2D CNN framework was introduced [20] for the purpose of categorizing ECG data into distinct arrhythmia categories. The 1D ECG time signals were initially subjected to the short-time Fourier transform to produce the 2D spectrograms. Subsequently, the ECG data are transmitted via a 2-

dimensional CNN structure comprising of 4 convolutional layers and 4 pooling layers in order to extract resilient characteristics. And categorize them into several kinds of atypical cardiac rhythms.

An approach for identifying arrhythmias was developed [21] based on the Multi-Resolution Representation (MRR) of ECG information. The proposed MRR procedure was utilized to combine each potential feature extracted from ECG signals through the application of a feature fusion method. The feature vector was further trained using various deep learning architectures known as channel models, including GoogLeNet, ResNet, SeInceptionNet, and SeResNet, in order to categorize multiple kinds of arrhythmia disorder.

The authors introduced a sophisticated healthcare framework [22] that utilizes ensemble deep learning and feature fusion techniques to predict heart diseases. The initial step involved the application of the feature fusion approach to combine the extracted features from the sensor and e-health data. Subsequently, the information gain method was employed to eliminate duplicate and unnecessary features, thereby selecting the most critical aspects. The conditional probability technique was used to determine the specific feature weight for all classes. Furthermore, the ensemble deep learning framework, which utilizes a feed-forward neural network and boosting technique, was trained with the objective of predicting cardiac diseases.

The researchers developed a system called Attention based Time-Incremental CNN (ATI-CNN) [23]. This system utilizes CNNs, recurrent cells, and attention units to integrate spatial and temporal information. Its purpose is to classify ECG data into several categories of arrhythmia. This system employed two independent methodologies: the combination of spatial features using CNNs and the integration of behavioural features using RNNs and attention mechanisms. The models utilizing distinct methodologies were subsequently integrated into a unified neural network framework in order to develop a continuously trained algorithm capable of detecting various forms of aberrant cardiac diseases.

A new Multi-data Fusion Convolutional Bidirectional RNN (MFCBRNN) was created for the purpose of automatically detecting arrhythmia [24]. The system was developed with two concurrent composite divisions that enable simultaneous focus on beat-based properties in electrocardiogram (ECG) data and sequence characteristics in adjacent regions of the impulses. The morphological data was acquired from a solitary ECG pattern. The temporal data was enhanced by the adjacent segment of the ECG beat. Furthermore, across all branches, a hybrid approach involving CNN and Bidirectional Long Short-Term Memory (BLSTM) was employed to extract features from the input signal. The many criteria that were gathered were subsequently merged in order to determine the resulting type of arrhythmia.

A Bat-Rider Optimization Algorithm (BaROA) was employed to categorize arrhythmia in an optimized DCNN [25]. The initial step in constructing the attribute matrix involved establishing the Gabor, wave, and duration time of the ECG signal. The attribute matrix was subsequently inputted into the BaROA-based DCNN algorithm, which accurately identified the individual's dysrhythmia status based on the ECG values.

The authors proposed the utilization of a Multi-Scale Fusion-CNN (MSF-CNN) for the purpose of classifying arrhythmias based on ECG signals [26]. This framework employs multi-scale features in order to improve generalization and performing data pre-processing to eliminate power-line interferences. Data augmentation is a technique used to improve the distribution of data by generating new samples that closely resemble the original data, in order to train the CNN. The study employed a feature mining technique based on MSF-CNN to detect and diagnose arrhythmias by analysing anticipated signals derived from ECG signals.

A hybrid model was developed [27] utilizing the AlexNet-SVM architecture for the purpose of classifying the arrhythmia. The SVM and KNN algorithms were employed to categorize the raw ECG data. Subsequently, the unprocessed ECG signals were classified using the LSTM model, which acquires knowledge of long-term relationships. In addition, the unprocessed frequencies were transformed into spectrogram data, and the AlexNet patterns were obtained. The property that was obtained was subsequently classified using the SVM.

The authors introduced an innovative and resilient network architecture known as the Hybrid Convolutional Recurrent Neural Network (HCRNN) [28]. This network architecture is designed to autonomously analyse the time-sequence pulses of electrocardiograms (ECGs) and identify various forms of cardiac arrhythmias. Initially, a suitable methodology was employed to tackle the problem of inconsistency in ECG data during the pre-processing stage. Subsequently, a hybrid connection framework was utilized to establish connections between different CNN and RNN layers in order to detect different types of arrhythmias from time series ECG readings.

A CNN model was proposed [29] to integrate time- and frequency-domain data from ECG signals in order to detect arrhythmias. An adaption of multi-scale wavelet decomposition is employed to filter the ECG signal. Individual cardiac cycles are segmented using R-wave localization, and frequency domain information is extracted from each cardiac cycle using fast Fourier transform. The neural network is used to classify data by combining temporal and frequency domain information. Given that cardiac cycle segmentation is influenced by ECG signal noise, the effectiveness of this method relies on the quality of the ECG data's denoising.

A combination of a Residual Network and LSTM was proposed [30] for the purpose of classifying arrhythmias. This method use ResNet in combination with SE block and BiLSTM to extract features from raw ECG data, aiming to achieve distinct intersubject characteristics. The new technique, when combined with SMOTE, demonstrated superior performance compared to previous augmentation procedures in addressing imbalance difficulties in arrhythmia categorization. Although the suggested model shows potential, it requires a longer training period and more computational resources than what is typically accessible in a clinical setting.

A novel ResNeXt model, namely G2-ResNeXt, was introduced [31] to enhance the accuracy of automatic feature extraction and classification in ECG signal classification. In order to enhance the detection of signal fluctuations, this model incorporates a double-edged Grouping Convolution (G2) and an updated Convolutional Block Attention Module (CBAM). While the overall accuracy of the model is very high, there is room for improvement in terms of its ability to accurately identify class-F heartbeats and operate with reduced computational complexity and time.

HeartNet, a revolutionary deep learning technique, was developed [32] utilizing Generative Adversarial Networks (GAN) for the purpose of predicting arrhythmias. The recommended deep learning approach is condensed by a multi-head attention mechanism on a CNN architecture. Adversarial data synthesis addresses this issue by employing a GAN to generate novel training instances in situations where the available labels are insufficient. The total performance of the suggested strategy is improved by a range of 5-10% for each category that lacks adequate data labels.

A highly effective approach was presented [33] for categorizing ECG arrhythmias using the 2DCNN model. The ECG signals that were collected were transformed into two-dimensional images in order to bypass the filtering and feature extraction processes, utilizing the Pillow and OpenCV libraries. Subsequently, the 2DCNN model was utilized to identify and categorize arrhythmias. Furthermore, the use of the TensorRT model was utilized for real-time implementation in emergency departments through the utilization of edge computation on portable devices.

An innovative hybrid architecture consisting of LSTM and MLP was proposed [34] for the purpose of predicting cardiac disease. The input layer of the MLP takes data from the current heart rate, while the LSTM block receives a sequence of coefficients that represent the morphology of ECG beats. When the blocks undergo simultaneous training, the network as a collective entity is confronted with the task of acquiring characteristics that will ultimately facilitate the process of forming decisions. The present methodology exhibits a superior amalgamation of computing efficiency and precision in the identification of anomalous signals.

The authors of [35] presented a deep learning model that utilizes electrocardiogram (ECG) signal data to automatically detect cardiac arrhythmia. The ECG signal was de-noised in this model using decomposition approaches such as DWT, EMD, and Variational Mode Decomposition (VMD). De-noised signals were used to extract time-frequency based multi-domain characteristics utilizing sub-band coefficients. In order to enhance classification accuracy, the Chi-squared test and Particle Swarm Optimization (PSO) methods are employed to rank the gathered features based on their informativeness. A Deep Neural Network (DNN) was employed to classify the hybrid properties using a ten-fold cross validation technique for predicting arrhythmias.

A novel method for detecting arrhythmias using an integrated voting mechanism and a dual channel 1DCNN model was proposed [36]. The findings from inter-patient experiments indicate that, on average, the integrated model exhibits superior classification accuracy for disorders falling under the F-category.

A revised DL approach was created [37] to analyse ECG data for arrhythmia disease detection. The input ECG signal was captured and subjected to pre-processing using CWT to eliminate noise and artifacts. Subsequently, the signal was graphically represented as an image for subsequent analysis. Subsequently, the CNN-LSTM model was employed to perform the task of identifying and categorizing arrhythmias.

A deep learning model was developed [38] to screen for Obstructive Coronary Artery Disease (ObCAD) using ECG data. In this study, the ResNet architecture was utilized to extract relevant information from ECG\ data in individuals diagnosed with ObCAD compared to those without ObCAD. The model's performance was compared to that of Acute Myocardial Infarction (AMI) in order to assess the normal and abnormal ECG border line for the identification of ObCAD.

A 1D-CNN was introduced [39] for the purpose of detecting and classifying CHD using ECG signal data. The initial ECG dataset was gathered, subjected to pre-processing, and standardized. The feature selection operation was performed using the elastic-net model. The chosen characteristics were inputted into a 1D-CNN model to forecast cardiac heart problems.

A method for detecting cardiac arrhythmia was proposed [40] employing a deep learning model and representing ECG signals in terms of time and frequency. The model employs an analytic Morse wavelet to convert time series signals into two-dimensional images that represent time and frequency. This process uncovers both concealed and observable features of nonstationary signals. Ultimately, the arrhythmia classification performance was achieved by employing fine-tuned pre-trained AlexNet and ResNet 50 models.

III. COMPARATIVE ANALYSIS

This section presents a comparative analysis of the advantages, disadvantages, dataset, and performance evaluation of arrhythmia prediction and classification using various deep learning methods. The aforementioned section provides a brief overview of the methods, while the comparison is presented in Table 1.

Table.1 Evaluation of DL based Arrhythmia Prediction from ECG Databases

Ref. No.	Algorithms	Merits	Demerits	Data Source	Performance
[17]	16-layer DCNN	Extremely effective, user-friendly, and swift real-time categorization.	It is impossible to classify ECG signals that have many labels.	MIT-BIH Arrhythmia database	Accuracy= 91.33% Precision= 89.52%; F-measure= 85.38%
[18]	1D DCNN	Proficient in identifying a broader range of arrhythmia (beats) from ECG, demonstrating strong resilience	The integration of lower-order IMFs with higher-order IMFs resulted in a decline in categorization efficiency.	St.-Petersberg, PTB databases	Accuracy (St.-Petersberg) = 99.71%; Accuracy (PTB)= 98.24%
[19]	CWT and 6-layer DCNN	Pre-processing, denoising, R-peak detection and GPU for learning were not needed.	There was no requirement for pre-processing, denoising, R-peak identification and GPU for learning.	PhysioBank database	Accuracy= 97.78%; Specificity= 98.82%; Sensitivity= 99.76%
[20]	Short-time Fourier transform and 2D CNN	The extraction of sturdy features enables the attainment of optimal efficiency	The evaluation exclusively focuses on single-lead ECG readings and does not consider the impact of multiple ECG	MIT-BIH database	Average accuracy= 99%, Sensitivity= 97.26%; Precision= 98.69%; F1-score= 98%;

			inputs		Specificity= 99.67%
[21]	GoogLeNet, ResNet, Se InceptionNet and SeResNet	The system exhibits excellent scalability and has the capability to integrate valuable characteristics for classification.	The increased number of parameters in these network models may result in a longer training period.	The dataset obtained from the Tianchi platform in the Hefei High-Tech Cup ECG Human-Machine Intelligence Competition	GoogleNet: Precision= 93.98%; ResNet: Precision= 93.99%; SeInceptionNet: Precision= 94.8% SeResNet: Precision= 94.27%
[22]	Ensemble feed-forward neural network and boosting algorithm	It attains the utmost precision by isolating the most advantageous characteristics and their significance.	In order to enhance the quantity of ECG data, it is imperative to employ sophisticated methodologies for feature selection.	Cleveland and Hungarian datasets	Accuracy= 98.5%; Precision= 98.2%; Recall= 96.4%; F-measure= 97.2%; Root Mean Squared Error (RMSE)= 0.21; Mean Absolute Error (MAE)=0.12
[23]	ATI-CNN	Less computation burden.	Its classification efficiency was less.	Data collected from the China Physiological Signal Challenge	Average precision=82.6%; Average recall= 80.1%; Average F1-score= 81.2%
[24]	MFCBRNN	It does not need any handcrafted features to identify arrhythmias.	Its efficiency was less for small datasets because of imbalanced data.	MIT-BIH databases	Accuracy= 96.77%; F1-score= 77.83%; Sensitivity= 74.89%; Precision= 81.24%; Specificity= 95.16%
[25]	BaROA-based DCNN	The main benefit of this algorithm was the ability of handling the multiple objectives.	It was not able to handle the dynamic features.	MIT-BIH database	Accuracy= 93.19%; Specificity= 95%; Sensitivity= 93.98%; Computation time=6.12sec
[26]	MSF-CNN	Effectively removes the noisy data reduce overfitting and improve generalization ability.	CNN requires a significant amount of data and time for the learning stage due to the use of cross-validation.	MIT-BIT arrhythmia database	Accuracy = 98%; Sensitivity = 96.17%; and Specificity = 96.38%,
[27]	AlexNet-SVM	Better classification efficiency and less complexity.	The number of ECG data and diseases were limited.	MIT-BIH arrhythmia database	Accuracy= 96.77%
[28]	HCRNet	It can effectively differentiate 9 different ECG signals. High accuracy and processing speed.	It was time-consuming since the time cost of the training process was high. Also, it needs large quantity of data.	MIT-BIH atrial fibrillation database	Average accuracy= 99.01%; Average sensitivity=99.58%; Average positive predictive= 99.44%; Average F1 score=99.51%
[29]	Time and Frequency domain fusion ,	Successfully identifies and labels ECG signals for each heartbeat.	The quality of the denoised ECG signal determines the outcome.	MIT-BIH dataset	Accuracy = 96.16%

	CNN				
[30]	SMOTE, ResNet with squeeze-and-excitation block and biLSTM,	best generalization ability and interpretability	High classification performance for the F1-score in minority classes	MIT-BIH arrhythmia dataset	Accuracy = 99.74%
[31]	G2-ResNeXt	Excellent consistency; there is just a one percent variation in accuracy between sessions of training.	Recognition rate of class-F heartbeats is low	MIT-BIH database	Overall Accuracy = 96.16%
[32]	HeartNet CNN-GAN	Anticipate the imbalanced class distribution and label shortage caused by a lack of training data.	Loss plateaus, which can force the model to take more time to train	MIT-BIH dataset	Accuracy = 99.67 %; Matthews Correlation Coefficient (MCC)= 89:24%
[33]	2DCNN, TensorRT	High data interpretability and performance speed	This model was trained with limited amount of data	MIT-BIH arrhythmia database	Accuracy = 95.3%; Sensitivity = 95.27%; Specificity = 98.82%,
[34]	LSTM MLP	Lowest computationally complexity with higher anomalous signal detection accuracy	Recognition rate of class-F heartbeats is low	MIT-BIH arrhythmia	Accuracy = 97%
[35]	PSO, DNN	Less computational time and utilized in hospitals to automatically detect and screen abnormal ECG beats.	This model was poor adaptable to larger arrhythmia datasets	MIT-BIH arrhythmia database	Accuracy = 99.7%; Sensitivity = 99.2%; Specificity = 99.7 Computational time = 0.043s;
[36]	1D-CNN	Alleviate the shortage problem in ECG samples and provide superior results	Temporal dependent relation of signal feature not considered	MIT-BIH arrhythmia	Accuracy = 94.4%; 80% results for class-F heartbeats
[37]	CWT, CNN-LSTM	This model will significantly reduce the amount of involvement necessary by physicians	High computational complexity and excess redundancy.	MIT-BIH cardiac arrhythmias dataset	Accuracy = 99.1%; Sensitivity = 98.35 %; Specificity = 98.38 %
[38]	ResNet	Works efficiently on larger CAG dataset	High computational complexities and over-fitting issues	Coronary Angiography (CAG) reports	Accurcay = 0.885; Precision= 0.769; Recall = 0.921, and F1-Score = 0.758
[39]	Elastic-net, 1D-CNN	This model learns non-linear mapping of complex feature combinations for easy prediction	The data interpretability was poor and	National Health and Nutrition Examination Survey (NHANES)	Accuracy=80.1%; Sensitivity = 76.92%; Specificity = 79.93%;
[40]	Pre-trained AlexNet and ResNet 50	This model works well on both large and small scale databases and lesser diagnosis time	High time complexity and overfitting issues	MIT-BIH databases	AlexNet Accuracy = 99.1% ResNet50 Accuracy = 99.8%

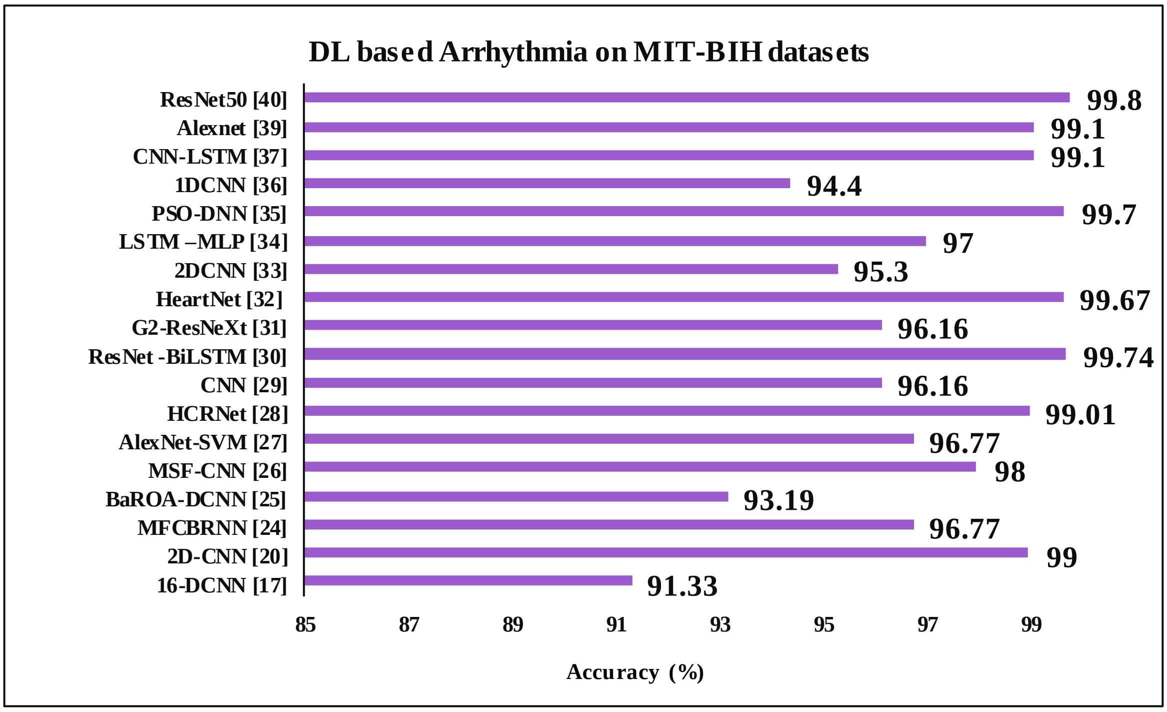

Figure 4. DL based arrhythmia prediction using MIT-BIH datasets

IV. Performance Evaluation

The purpose of this study is to evaluate the performance of the existing deep learning approaches, as presented in Fig. 4, with the aim of demonstrating their accuracy in predicting and classifying arrhythmia.

The majority of the publications employed the MIT-BIH arrhythmia datasets, which consist of 48 half-hour segments of two-channel ambulatory ECG recordings acquired from 47 participants. These extracts were used to evaluate prediction models for arrhythmia and other cardiac illnesses. This section assesses the accuracy of different deep learning-based algorithms for detecting arrhythmias using the MIT-BIH datasets.

The DL-based arrhythmia prediction using MIT-BIH datasets is depicted in Fig. 4. Based on the aforementioned data, it is evident that the pre-trained CNN model, namely the ResNet model, demonstrates effective performance in the classification and prediction of arrhythmias. The ResNet enhances the efficiency of the initial training process by reducing the number of layers in the network. Upon retraining, the layers undergo expansion, so enabling the residual components to delve deeper into the feature spaces present in the input images, thereby enhancing interpretability. The ResNet architecture mitigates the problem of vanishing gradients, hence offering significant advantages in terms of improved classification and prediction capabilities. In the aforementioned comparison, it can be shown that the article [40] exhibits superior accuracy results compared to other detection models. This study used the AlexNet and ResNet50 models for the categorization of arrhythmias, with ResNet50 demonstrating superior performance in comparison to AlexNet. ResNet50 shown a high level of suitability for both large and small scale ECG databases, exhibiting reduced diagnostic time for the classification and prediction of arrhythmias.

V. Conclusion

This article presents a thorough examination of arrhythmia prediction and categorization systems that utilize different deep learning approaches and rely on ECG data. This comparative investigation revealed that numerous researchers has expertise in developing deep learning algorithms for the efficient prediction and classification of arrhythmia or cardiac disorders. The advantages, limitations, and predictive accuracy of the comparative models are also examined to enhance comprehension of the sickness prediction issue. The identified challenges and achievements serve as crucial starting points for researchers to develop comprehensive models that could assist in predicting and diagnosing arrhythmia, ultimately leading to personalized treatments for individuals with cardiac disease. Consequently, future research will focus on developing advanced computational models for efficient real-time diagnosis prediction of cardiac conditions and heart issues using ECG data.

VI. References

[1] S. Sossalla and D. Vollmann, “Arrhythmia-induced cardiomyopathy: causes, clinical significance, and treatment”, Deutsches Ärzteblatt International, vol. 115, no. 19, pp. 335, 2018, doi:10.3238%2Farztebl.2018.0335.

[2] R. Gopinathannair, S. P. Etheridge, F. E. Marchlinski, F. G. Spinale, D. Lakkireddy and B. Olshansky, “Arrhythmia-induced cardiomyopathies: mechanisms, recognition, and management”, Journal of the American College of Cardiology, vol. 66, no. 15, pp. 1714-1728, 2015, doi:10.1016/j.jacc.2015.08.038.

[3] U. R. Acharya, H. Fujita, M. Adam, O. S. Lih, T. J. Hong, V. K. Sudarshan and J. E. Koh, “Automated characterization of arrhythmias using nonlinear features from tachycardia ECG beats”, In 2016 IEEE international conference on systems, man, and cybernetics (SMC), IEEE, pp. 000533-000538, 2016, doi:10.1109/SMC.2016.7844294.

[4] D. G. Fu, “Cardiac arrhythmias: diagnosis, symptoms, and treatments”, Cell biochemistry and biophysics, vol. 73, no. 2, pp. 291-296, 2015, doi:10.1007/s12013-015-0626-4.

[5] E. J. D. S. Luz, W. R. Schwartz, G. Cámara-Chávez and D. Menotti, “ECG-based heartbeat classification for arrhythmia detection: A survey”, Computer methods and programs in biomedicine, vol. 127, pp. 144-164, 2016, doi:10.1016/j.cmpb.2015.12.008.

[6] H. P. da Silva, C. Carreiras, A. Lourenço, A. Fred, R. C. das Neves and R. Ferreira, “Off-the-person electrocardiography: performance assessment and clinical correlation”, Health and Technology, vol. 4, no. 4, pp. 309-318, 2015, doi:10.1007/s12553-015-0098-y.

[7] Y. P. Sai, “A review on arrhythmia classification using ECG signals”, In 2020 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), IEEE, pp. 1-6, 2020, doi:10.1109/SCEECS48394.2020.9.

[8] T. Anbalagan, M. K. Nath, D. Vijayalakshmi and A. Anbalagan, “Analysis of various techniques for ECG Signal in Healthcare, Past, Present, and Future”, Biomedical Engineering Advances, pp. 100089, 2023, doi:10.1016/j.bea.2023.100089.

[9] N. Rafie, A. H. Kashou and P. A. Noseworthy, “ECG interpretation: clinical relevance, challenges, and advances”, Hearts, vol. 2, no. 4, pp. 505-513, 2021, doi:10.3390/hearts2040039.

[10] V. D. Nagarajan, S. L. Lee, J. L. Robertus, C. A. Nienaber, N. A. Trayanova and S. Ernst, “Artificial intelligence in the diagnosis and management of arrhythmias”, European heart journal, vol. 42, no. 38, 3904-3916, 2021, doi:10.1093/eurheartj/ehab544.

[11] S. Naik, S. Debnath and V. Justin, “A review of arrhythmia classification with artificial intelligence techniques: Deep vs machine learning”, In 2021 2nd International Conference for Emerging Technology (INCET) IEEE, pp. 1-14, 2021, doi:10.1109/INCET51464.2021.9456394.

[12] S. Dhyani, A. Kumar and S. Choudhury, “Analysis of ECG-based arrhythmia detection system using machine learning”, MethodsX, vol. 10, pp. 102195, 2023, doi:10.1016/j.mex.2023.102195.

[13] S. Sahoo, M. Dash, S. Behera and S. Sabut, “Machine learning approach to detect cardiac arrhythmias in ECG signals: A survey”, Irbm, vol. 41, no. 4, pp. 185-194, 2020, doi:10.1016/j.irbm.2019.12.001.

[14] N. Katal, S. Gupta, P. Verma and B. Sharma, “Deep-Learning-Based Arrhythmia Detection Using ECG Signals: A Comparative Study and Performance Evaluation”, Diagnostics, vol. 13, no. 24, pp. 3605, 2023, doi:10.3390/diagnostics13243605.

[15] Z. Ebrahimi, M. Loni, M. Daneshtalab and A. Gharehbaghi, “A review on deep learning methods for ECG arrhythmia classification”, Expert Systems with Applications: X, vol. 7, pp. 100033, 2020, doi:10.1016/j.eswax.2020.100033.

[16] T. A. Abdullah, M. S. B. M. Zahid, T. B. Tang, W. Ali and M. Nasser, “Explainable Deep Learning Model for Cardiac Arrhythmia Classification”, In 2022 International Conference on Future Trends in Smart Communities (ICFTSC), IEEE, pp. 87-92, 2022, doi:10.1109/ICFTSC57269.2022.10039860.

[17] Ö. Yıldırım, P. Pławiak, 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, doi:10.1016/j.compbiomed.2018.09.009.

[18] N. I. Hasan and A. Bhattacharjee, “Deep learning approach to cardiovascular disease classification employing modified ECG signal from empirical mode decomposition”, Biomedical Signal Processing and Control, vol. 52, pp. 128-140, 2019, doi:10.1016/j.bspc.2019.04.005.

[19] H. Fujita and D. Cimr, “Decision support system for arrhythmia prediction using convolutional neural network structure without preprocessing. Applied Intelligence, vol. 49, no. 9, pp. 3383-3391, 2019, doi:10.1007/s10489-019-01461-0.

[20] 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, doi:10.1109/ACCESS.2019.2928017.

[21] D. Wang, Q. Meng, D. Chen, H. Zhang and L. Xu, “Automatic detection of arrhythmia based on multi-resolution representation of ECG signal”, Sensors, vol. 20, no. 6, pp. 1-12, 2020, doi:10.3390/s20061579.

[22] F. Ali, S. El-Sappagh, S. R. Islam, D. Kwak, A. Ali, M. Imran and K. S. Kwak, “A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion”, Information Fusion, vol. 63, pp. 208-222, 2020, doi:10.1016/j.inffus.2020.06.008.

[23] Q. Yao, R. Wang, X. Fan, J. Liu and Y. Li, “Multi-class arrhythmia detection from 12-lead varied-length ECG using attention-based time-incremental convolutional neural network”, Information Fusion, vol. 53, pp. 174-182, 2020, doi:10.1016/j.inffus.2019.06.024.

[24] A. Chen, F. Wang, W. Liu, S. Chang, H. Wang, J. He and Q. Huang, “Multi-information fusion neural networks for arrhythmia automatic detection”, Computer Methods and Programs in Biomedicine, vol. 193, pp. 1-11, 2020, doi:10.1016/j.cmpb.2020.105479.

[25] D. K. 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, pp. 1-28, 2020, doi:10.1016/j.cmpb.2020.105607.

[26] H. Dang, Y. Yue, D. Xiong, X. Zhou, X. Xu and X. Tao, “deep biometric recognition and diagnosis network with residual learning for arrhythmia screening using electrocardiogram recordings”, IEEE Access, vol. 8, pp. 153436-153454, 2020, doi:10.1109/ACCESS.2020.3016938.

[27] A. Çınar and S. A. Tuncer, “Classification of normal sinus rhythm, abnormal arrhythmia and congestive heart failure ECG signals using LSTM and hybrid CNN-SVM deep neural networks”, Computer Methods in Biomechanics and Biomedical Engineering, vol. 24, no. 2, pp. 203-214, 2021, doi:10.1080/10255842.2020.1821192.

[28] X. Luo, L. Yang, H. Cai, R. Tang, Y. Chen and W. Li, “Multi-classification of arrhythmias using a HCRNet on imbalanced ECG datasets”, Computer Methods and Programs in Biomedicine, vol. 208, pp. 1-14, 2021, doi:10.1016/j.cmpb.2021.106258.

[29] B. Wang, G. Chen, L. Rong, Y. Liu, A. Yu, X. He and B. Hu, “Arrhythmia disease diagnosis based on ECG time–frequency domain fusion and convolutional neural network”, IEEE Journal of Translational Engineering in Health and Medicine, vol. 11, pp. 116-125, 2022, doi:10.1109/JTEHM.2022.3232791.

[30] Y. K. Kim, M. Lee, H. S. Song and S. W. Lee, S.W, “Automatic cardiac arrhythmia classification using residual network combined with long short-term memory”, IEEE Transactions on Instrumentation and Measurement, vol. 71, pp.1-17, 2022, doi:10.1109/TIM.2022.3181276.

[31] S. Hao, H. Xu, H. Ji, Z. Wang, L. Zhao, Z. Ji and I. Ganchev, "G2-ResNeXt: a novel model for ECG signal classification", IEEE Access, 2023, doi:10.1109/ACCESS.2023.3265305.

[32] T. H. Rafi and Y. W. Ko, "HeartNet: Self Multihead Attention Mechanism via Convolutional Network With Adversarial Data Synthesis for ECG-Based Arrhythmia Classification", IEEE Access, vol. 10, pp.100501-100512, 2022, doi:10.1109/ACCESS.2022.3206431.

[33] P. Seitanidis, J. Gialelis, G. Papaconstantinou and A. Moschovas, "Identification of Heart Arrhythmias by Utilizing a Deep Learning Approach of the ECG Signals on Edge Devices", Computers, vol. 11, no. 12, pp. 176, 2022, doi:10.3390/computers11120176.

[34] G. Sivapalan, K. K. Nundy, S. Dev, B. Cardiff and D. John, "ANNet: A lightweight neural network for ECG anomaly detection in IoT edge sensors", IEEE Transactions on Biomedical Circuits and Systems, vol. 16, no. 1, pp.24-35, 2022, doi:10.1109/TBCAS.2021.3137646.

[35] S. Sahoo, P. Dash, B. S. P. Mishra and S. K. Sabut, "Deep learning-based system to predict cardiac arrhythmia using hybrid features of transform techniques", Intelligent Systems with Applications, vol. 16, pp. 200127, 2022, doi:10.1016/j.iswa.2022.200127.

[36] L. H. Wang, Y. T. Yu, W. Liu, L. Xu, C. X. Xie, T. Yang, I. C. Kuo, X. K. Wang, J. Gao, P. C. Huang and S. L. Chen, "Three-heartbeat multilead ECG recognition method for arrhythmia classification", IEEE Access, vol. 10, pp. 44046-44061, 2022, doi:10.1109/ACCESS.2022.3169893.

[37] A. Anbarasi, T. Ravi, V. S. Manjula, J. Brindha, S. Saranya, G. Ramkumar and R. Rathi, "A modified deep learning framework for arrhythmia disease analysis in medical imaging using electrocardiogram signal", BioMed Research International, 2022, doi:10.1155/2022/5203401.

[38] S. H. Choi, H. G. Lee, S. D. Park, J. W. Bae, W. Lee, M. S. Kim and W. K. Lee, "Electrocardiogram-based deep learning algorithm for the screening of obstructive coronary artery disease", BMC Cardiovascular Disorders, vol. 23, no. 1, pp. 1-11, 2023, doi:10.1186/s12872-023-03326-4.

[39] M. M. R. Khan Mamun and T. Elfouly, "Detection of Cardiovascular Disease from Clinical Parameters Using a One-Dimensional Convolutional Neural Network", Bioengineering, vol. 10, no. 7, pp. 796, 2023, doi:10.3390/bioengineering10070796.

[40] Y. D. Daydulo, B. L. Thamineni and A. A. Dawud, "Cardiac arrhythmia detection using deep learning approach and time frequency representation of ECG signals", BMC Medical Informatics and Decision Making, vol. 23, no. 1, pp. 232, 2023, doi:10.1186/s12911-023-02326-w.

