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A Review of Machine Learning, Deep Learning, Time-Frequency Domain Fusion, and Ensemble Techniques for ECG Signal Analysis

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Abstract

Arrhythmia, a condition of abnormal heart rhythms, affects millions globally, making accurate diagnosis essential for effective treatment. Electrocardiogram (ECG) signals are commonly used for arrhythmia detection, but traditional methods often struggle with accuracy and efficiency. Recent advancements in deep learning, particularly CNNs and LSTMs, have significantly improved ECG-based classification of arrhythmias. CNNs does good at identifying spatial features, while LSTMs can see temporal patterns, allowing for more accurate and efficient diagnosis. Additionally, time-frequency domain fusion techniques combine both temporal and spectral features from ECG signals, further enhancing detection capabilities. This paper presents an overview of current approaches in ECG-based arrhythmia diagnosis, highlighting key signal processing methods, deep learning models, and evaluation metrics. It discusses challenges such as limited labeled data and computational complexity, as well as gaps in existing research. The paper also emphasizes the need for future research to improve model interpretability, scalability, and integration into clinical practice. The goal is to enhance real-world clinical applications and more effective management of arrhythmias.

Keywords: ECG Arrhythmia, CNN-LSTM, Ensemble Learning, Deep Learning, Arrhythmia Detection ECG Signal Analysis, Time-Frequency Fusion, Ensemble Learning, Voting and Stacking Classifiers,Spatial Feature Extraction

1 Introduction

Detecting arrhythmia through Electrocardiogram signals plays a vital role in diagnosing heart conditions. In recent years, advancements in ML and DL have significantly enhanced the accuracy and efficiency of automated arrhythmia classification. Numerous studies have introduced various approaches to improve arrhythmia detection. For instance, deep learning techniques, particularly CNNs, have been highly effective in processing raw ECG signals for arrhythmia classification. [1] demonstrated the utility of combining deep learning with time-frequency representations to detect arrhythmia, highlighting the role of frequency-domain information in boosting model performance. Similarly, [2] explored time-frequency domain fusion with CNNs for arrhythmia diagnosis, underscoring the value of combining temporal and frequency features. Additionally, some models integrate CNNs with other deep learning architectures for advanced temporal sequence analysis. Recently LSTM networks have been introduced for better analysis with deep learning models. [6] applied CNN-LSTM models for arrhythmia classification, utilizing CNNs for spatial feature taken and LSTMs to grab dependencies. Transformers, typically used in natural language processing, have also been adapted for ECG analysis. [12] proposed ECGformer, a Transformer-based approach, for arrhythmia classification, utilizing self-attention mechanisms to capture long-range dependencies across ECG sequences. Hybrid models have emerged more recently, combining architectures like Bi-directional Gated Recurrent Units (GRUs), Bi-directional LSTMs, and CNNs for improved sequential data processing. [14] highlighted the effectiveness of hybrid models for arrhythmia detection, which combine different architectures to enhance feature extraction and model performance. Machine learning-based models have also come into use for heartbeat classification. For instance, [19] presented a new deep learning architecture combining feature extraction methods such as PR and RT intervals with demographic features such as age and sex for enhancing classification accuracy. Their work also explored cross-database generalization, which showed difficulties in porting models across different ECG datasets. This review highlights the latest trends in arrhythmia classification, with a focus on combining time-frequency representations, CNNs, LSTMs, Transformers, hybrid models, and feature engineering methods. These advancements give insight into how deep learning will be able to push the boundaries of accurate and reliable arrhythmia classification, leading to more efficient diagnostic tools in medicine.

2 Literature Survey

Table 1: Existing works

Author(s)	**Title of the paper**	**Techniques used**	**Field of study**
Yared Daniel Daydulo et al. [1]	*Cardiac arrhythmia detection using deep learning approach and time frequency representation of ECG signals*	ResNet50, AlexNet, Time-Frequency Domain Representation	Deep Learning
Bocheng Wang et al. [2]	*Arrhythmia Disease Diagnosis Based on ECG Time–Frequency Domain Fusion and Convolutional Neural Network*	Time-Frequency Domain Fusion, Multi-scale Wavelet Decomposition, Fast Fourier Transform (FFT), 1D-CNN	Deep Learning
D. Jyothirmai et al. [3]	*Detection of Cardiac Arrhythmia using Machine Learning*	Machine Learning (SVM, Logistic Regression, Decision Trees, Deep Learning), Feature Extraction, Model Evaluation	Machine Learning
Ruan, Hongpeng et al. [4]	*Arrhythmia Classification and Diagnosis Based on ECG Signal: A Multi-Domain Collaborative Analysis and Decision Approach*	Graph Neural Networks (GNN), ECG signal classification	Deep Learning
Din, Sadia et al. [5]	*ECG-based cardiac arrhythmias detection through ensemble learning and fusion of deep spatial–temporal and long-range dependency features*	CNN, CNN-LSTM, Transformer, Majority Voting Classifier	Deep Learning
Abdullah, Lana et al. [6]	*CNN-LSTM Based Model for ECG Arrhythmias and Myocardial Infarction Classification*	CNN and LSTM	Deep Learning
Toulni, Youssef et al. [7]	*Electrocardiogram signals classification using discrete wavelet transform and support vector machine classifier.*	DWT and SVM	Machine Learning

Author(s)	**Title of the paper**	**Techniques used**	**Field of study**

Guan, Yuxia et al. [8]	*HA-ResNet: Residual Neural Network With Hidden Attention for ECG Arrhythmia Detection Using Two-Dimensional Signal*	Recurrence Plot, Squeeze-and-Excitation Block, Bi directional ConvLSTM (BConvLSTM), Deep Learning	Deep Learning
M S, Supriya et al. [9]	*Cardiac Arrhythmia Detection using Ensemble Machine Learning Techniques*	Random Forest, Gradient Boosting, K-Nearest Neighbors, Logistic Regression, Decision Trees, Ensemble Methods	Machine Learning
Liu, Qingshan et al. [10]	*ECG Abnormality Detection Based on Multi-domain Combination Features and LSTM.*	Features in the time domain, subband spectrum, harmonic ratio, and LSTM	Deep Learning
Degirmenci, M. et al. [11]	*Arrhythmic Heartbeat Classification Using 2D Convolutional Neural Networks*	2D CNN, ECG to 2D images, Cross validation, Hyperparameter tuning	Deep Learning
Akan, T. et al. [12]	*ECGformer: Leveraging Transformer for ECG Heartbeat Arrhythmia Classification.*	Transformer, Multi head Attention, Feed-Forward Networks, Dropout, Sparse Categorical Cross-Entropy	Deep Learning
Izci, E. et al. [13]	*Arrhythmia Detection on ECG Signals by Using Empirical Mode Decomposition.*	Linear Discriminant Analysis, SVMs, Empirical Mode Decomposition, and Naive Bayes Classifier	Machine Learning
Islam, M.S. et al. [14]	*New Hybrid Deep Learning Approach Using BiGRU-BiLSTM and Multilayered Dilated CNN to Detect Arrhythmia*	BiGRU, BiLSTM, Multilayered Dilated CNN, GANs, Adam Optimizer, Categorical Cross-Entropy.	Deep Learning
Neha, S. et al. [15]	*Photoplethysmography based on arrhythmia detection and classification*	Noise removal (Median Filter), Bandpass Butterworth Filter, Low-pass Filter, Normalization, SVM, ANN, LR, DT and RF.	Machine Learning
Tandale, S. et al. [16]	*Arrhythmia classification using neuro fuzzy approach*	Wavelet Transform (Daubechies db3), R-Peak Detection, PCA, Adaptive Neuro-Fuzzy Inference System	Machine Learning
SairaAziz et al. [17]	*ECG-based machine-learning algorithms for heartbeat classification*	Autoregressive (AR) coefficients, Support Vector Machines, MLPs, 2-Event Related Moving Averages, and Discrete Wavelet and Fractional Fourier Changes	Machine Learning

Author(s)	Title of the paper	Techniques used	Field of study
Kavyshree B et al. [18]	*Prediction of Cardiac Arrhythmia using Machine Learning*	LR and DT and SVMs, Feature Selection, Data Normalization, Flask-based Web Application	Machine Learning
Sonain Jamil et al.[19]	*A Novel Deep-Learning-Based Framework for the Classification of Cardiac Arrhythmia*	Continuous Wavelet Transform and Deep CNN with Attention Block, Clump of Features, k-means Clustering, Support Vector Machine (SVM)	Deep Learning
Roshan Joy Martis et al.[20]	*Automated Screening of Arrhythmia Using Wavelet Based Machine Learning Techniques*	SVMs, Gaussian Mixture Model, DWT, PCA, Error Back Propagation Neural Networks,	Pantompkins Algorithm.
Machine Learning			

3 ECG Signal processing and Feature Extraction

3.1 ECG Data Preprocessing

Noise badly affects the quality of ECG signals and prohibits accurate classification. Therefore, adequate preprocessing is quite essential for bringing out reliable features from the original ECG signals. Among two popular preprocessing methods that are in discussion in recent literature, are DWT or Discrete Wavelet Transform, and EMD or Empirical Mode Decomposition.

3.1.1 Noise Removal Using Discrete Wavelet Transform (DWT)

[7] points out the uses of DWT for the classification and preprocessing of ECG signals. DWT is used to divide ECG signals into different frequency bands, which is important for noise removal. The noise components, such as high-frequency noise (due to powerline interference) and low-frequency drift (baseline wander), can significantly degrade the quality of ECG recordings. They suggested a method that involves the wavelet decomposition wherein the first two detail coefficients of the wavelet decomposition capture the high-frequency noise, and then remove them at the preprocessing stage. The remaining coefficients are used to correct the low-frequency baseline wander by presenting a smoothed version of the ECG signal. Therefore, the use of DWT can be important to preserve the signal information that can be critical to the detection and isolate noise better. This methodology works efficiently by adapting to inherent characteristics of a signal, especially in noisy ECG signals, and is particularly effective for its multiresolution analysis, providing the ability to capture both the high-frequency variability and low-frequency trends in an ECG signal. [20] provides further elaboration on wavelet-based preprocessing application by integrating DWT with Principal Component Analysis for noise removal and feature extraction. The authors in this paper discussed how PCA on DWT sub-bands gave a more compact and informative presentation of the ECG signal than the other mentioned methods that provide dimensionality reduction without loss of critical features, thus enhancing input data quality in classification models toward better overall accuracy in arrhythmia detection.

3.1.2 Empirical Mode Decomposition (EMD) for Noise Removal

ECG signal decomposing based on their IMFs in the research in [13], applied using the empirical mode decomposition, since the former doesn't demand predefined basis function for any particular basis that wavelet transforms, or even the Fourier transform need, however for a specific number of Intrinsic Mode Functions as can capture some kind of the evolutions in different time-dependent frequency components. A removing oscillation procedure of sifting begins with a process and iteratively reduces the oscillations in the signal, so that the remainder satisfies conditions of smoothness and frequency separation. This process produces IMFs that contain both low- and high-frequency components useful to isolate noises from meaningful signal data. Another advantage of EMD for processing ECG signals is that it deals effectively with complex real-world signals associated with both short-term and long-term fluctuations. The most important information in the detection of arrhythmia is both high- and low-frequency patterns, which often represent different types of abnormalities. Decomposing the ECG signal into IMFs, EMD ensures that feature extraction focuses on the most relevant information while minimizing the impact of noise. The first few IMFs are often the most relevant for arrhythmia classification, as they capture the key characteristics of heartbeats and rhythm. This step also preserves transient features, which could be due to arrhythmic events, while removing irrelevant noise such as powerline interference. The adaptive preprocessing technique improves the quality of the signal in feature extraction, which is a crucial step for the accurate classification and diagnosis.

3.2 Time Frequency Domain Analysis

3.2.1 Short Time Fourier Transform (STFT) for ECG Signals

[2] proposes the merging of timefrequency domain features along with 1D Convolutional Neural Networks (1D-CNNs) for classifying ECG signals. This methodology starts off with the signal decomposition of an ECG by the Daubechies wavelet (db5), as this helps remove the high frequency noise components away from the original signal. It then undergoes FFT, which decomposes the signal into its frequency components so that signal can be analyzed at a very granular level with respect to frequency content. The key insight of this approach is that combining wavelet decomposition-based time-frequency features with FFT provides a more comprehensive representation for the ECG signal-capture fast as well as slow variations in the signal which is vital for classification of different types of arrhythmias. That particular fusion technique allows model to exploit complementary information from both domains where representations are optimally suited for extraction in the time as well as frequency domains to enhance classification accuracy. The study presents how this technique can classify with high precision five different types of heartbeats, such as normal and abnormal rhythms. Some of the important challenges addressed in this method involve the accurate segmentation of ECG signals, more specifically the place of the R wave peak which is a crucial point in the accurate segmentation of the cycle of heartbeat. The processing of the signal is done in such a way that only the relevant heartbeat cycle is analyzed so that the classification process is based on the most representative portion of the signal. Also, as the use of time-frequency fusion is made, this approach is maintained at high classification accuracy even with noise and artifacts in real-world data for the ECG.

3.2.2 Wavelet Transform for Multi-Resolution Analysis

[1] presents a novel approach that brings together time-frequency domain analysis with deep learning seeks for arrhythmia detection. In this case, ECG signals, by nature nonstationary, are converted into 2D images using Morse wavelet transforms. This is very effective because Morse wavelet transforms can represent well both the time , frequency content of the signal, which will be important when arrhythmia occurs over arbitrary time intervals. The Morse wavelet transforms are advantageous because they allow for adaptation with the non-stationary ECG signals; hence, capturing transient abnormalities not easily detectable in the time or frequency domain alone. This 2D time-frequency images can then be processed by pre-trained deep learning models, namely AlexNet and ResNet50, on a large dataset in order to learn subtle patterns from the ECG signals. This transformation into 2D representation allows joint analysis of time and frequency information, providing richer features for classification. The major advantage of this approach is the ability to give localized time-frequency representations, which can more precisely capture the changes in heart rate and rhythm that are important in detecting arrhythmic events. In addition, transfer learning significantly reduces the computational price and time taken to train the models, thus making this approach highly efficient in clinical settings.

3.2.3 Combining time and frequency domain features

There is a method that mixes time domain, subband spectrum, and harmonic ratio characteristics for the detection of abnormalities in ECGs in [10]. The RR interval, or the interval between consecutive R waves, and other statistical measures that characterize the signal’s form and symmetry, such as skewness and kurtosis, are examples of temporal domain features. The time domain and it's related features of the ECG signal are taken by STFT, which is used for frequency domain analysis. The ECG data is fed into the LSTM network for classification after these domains are fused to create a better, more comprehensive representation. The model will capture both short and long term dynamics of heart's electrical activity due to the combination of time and frequency domain features, such as subband spectra and harmonic ratios. This is crucial for identifying abnormal patterns linked to different kinds of arrhythmias. In real-time ECG monitoring, where both time and frequency domain features can provide crucial information about health of heart, this multi-domain feature extraction method is especially useful. It increases the ability of deep learning models to differenciate between normal and abnormal ECG patterns, increasing the precision of diagnosis.

3.3 Importance of Feature Extraction for Arrhythmia Diagnosis

3.3.1 Role of Temporal and Spectral Features in ECG Analysis.

Feature extraction will play a big role in arrhythmia classification and diagnosis; it captures much of the vital information from raw ECG signals. Temporal features are characteristics derived from a time-domain signal, such as heart rate variability and time duration of most components of ECG waveform (P waves, QRS complexes, T waves). These will be very significant in detecting mild rhythm abnormalities in arrhythmia. In contrast, spectral features, derived from frequency domain using techniques like fourier transform or Wavelet Transform, help capture the periodicities and oscillations within the signal that can highlight abnormal rhythms more effectively. [4] introduces the use of spectral representations, including techniques like GNN, which leverage spectral domain to better model the intra- and inter-series relationships of multi-lead ECG signals. This approach captures temporal patterns and spectral correlations, allowing the model to better classify arrhythmias. This is through the incorporation of the complementary strengths of both domains. Similarly, [11] highlights how 2D CNNs automatically extract features from ECG signal to image transformation, allowing model to be focused on features both using time and frequency domain in training. When incorporating both the domains, superior performance can be achieved by a classification model while dealing with complicated arrhythmic patterns.

3.3.2 Challenges in Feature Extraction for Noisy ECG Data

Noisy ECG data presents one of the major challenges in feature extraction because signal distortion by motion artifacts, baseline wander, or electrode contact can interfere with accurate classification.
[11] addresses this challenge by removing the use for manual feature extraction, relying instead on CNN model to automatically identify most useful features for classification. This helps reduces effects of noise during traditional preprocessing, where filtering noise may delete relevant information. This model minimizes the possibility of losing features while processing noisy or incomplete ECG signals since it can learn from raw data, like a CNN. On the other hand, [4] addresses the issue by using strong preprocessing techniques to make multi-lead ECG data consistent, where noise is most pronounced due to the differences in electrode placement and patient-specific characteristics. The Graph Neural Network approach makes it possible to include complex relations between the different leads, thereby enhancing classification performance even when the signals are noisy or corrupted. This makes the GNN-based model to even better extract features and classify them even when there are noisy ECG signals.

4 DL and ML models for Arrhythmia diagnosis

4.1 Multi-Layer Perceptron(MLP)

ECG-based heartbeat classification involved a machine learning classifier that is a multi-layer perceptron, as applied in [17]. The MLP is an artificial network, a type of multi layer network, that models complex, non linear relationships within the data. Unlike traditional linear classifiers such as SVMs, MLP is best for tasks wherein the input features have intricate interactions that need to be learned from the data. The authors used the MLP to classify ECG signals into various categories of Cardiovascular Disease (CVD). MLP classifier is trained using the features that have been taken from ECG signals. They include both PR and RT intervals, the AR coefficients, as well as age and sex as patient demographics. These are used because they relate to heart conditions and help describe the temporal characteristic of the ECG waveform. It was inspired by the high capacity of MLP in dealing with vast amounts of data and learning complex, hierarchical feature representations. Given the diversity of the datasets, namely MIT-BIH, SPH, and INCART, MLP was considered a good candidate to further improve classification accuracy. Results obtained for the MLP classifier in [17] demonstrated its strong performance in the tasks of classification of ECG signals. On MITBIH dataset, MLP got and accuracy of 80% using PR and RT intervals, age, sex, and AR coefficients as input features. This result is slightly lower than the 82.2% accuracy achieved by the Support Vector Machine (SVM), but still notable, considering MLP's complexity and capability to adapt to different data patterns. However, when tested on the SPH dataset, the MLP outperformed SVM at 90.7 percent accuracy against SVM's 84.2 percent. This indicates the superior generalization aptitude of the MLP classifier while dealing with the SPH dataset comprising ECG signals from more than 10,000 patients. MLP's ability to learn from a bigger and more diversified dataset might have led to its higher performance here. One interesting finding from this experiment is that MLP outperformed SVM in SPH, but cross-database generalization was difficult. The MIT-BIH trained model's accuracy crashed to 68% when it was tested on the SPH dataset. It shows one of the weaknesses of the MLP method, which, like SVM, failed to hold its performance very well when trained on ECG data from another source.

4.2 Convolutional Neural Network

4.2.1 Architecture and Layers:

A typical CNN architecture for ECG classification is described as follows as 4 layers which are input, convolutional, pooling, and fully connected layers. [2] proposed a 1D-CNN model in which the input layer feeds raw ECG waveforms to the model for direct processing. The convolutional layers use various filters that enable automatic feature extraction by taking nearby dependencies in the time-series data. Pooling layers, such as max pooling, are used to downsample feature maps, reducing computational complexity while preserving significant information. The final fully connected layers use learned features for classification, distinguishing between different arrhythmia types. [8] extended CNN architectures by incorporating attention mechanisms. Their model, HA-ResNet, modifies traditional CNN layers by integrating hidden attention, allowing the network to focus on critical ECG segments. In the study, transformation of ECG signals into 2D recurrence plots was tested, and further processed with 2D convolutional filters that extract spatial relations. This methodology enhances feature learning by using CNN's image-processing strength without destroying the integrity of the ECG signal. In [11], a CNN-based model transforms the ECG signals into grayscale images before the 2D convolutional layers. This input layer accepts transformed ECG images, which then go through numerous convolutional and pooling layers to undergo feature extraction. Of note, the architecture uses CNNs' ability to identify spatial hierarchies for strong classification. In fact, the study showed that 2D CNNs better capture morphological variations of an ECG signal compared to traditional 1D CNNs. DWT [19] applied pre-processing eliminating baseline drift, high frequency noises prior to propagating the signal through the layers of CNN and used the application of the fused technique, two event-related moving averages along with FrFT-based detection for peaking at an R-level was done. Based on this the performance enhancement concerning the well-established architecture, good pre-processing with a well-articulated technique was utilized leading to excellent outcomes.

4.2.2 Applications of CNN in ECG Signal Classification:

CNNs were widely adopted in classification tasks for ECG and showed impressive performance in differentiating normal and abnormal heart rhythms. [2] proved that a pure 1D-CNN model, without any handcrafted feature extraction, might be used to classify arrhythmias properly. It directly learned patterns from the raw ECG waveforms and gained high accuracy across multiple databases. Attention-enhanced ResNet architectures were successfully implemented by [8] in detecting arrhythmia. Their approach improved interpretability by highlighting crucial ECG segments that contributed most to classification decisions. The use of recurrence plots in the study further supported the capability of CNNs to extract both time-domain and spatial features, which leads to better generalization.

[11] showed that applying 2D CNN architectures to ECG images improved the classification accuracy by taking advantage of spatial feature extraction. The model took advantage of the strengths of CNNs in image recognition by processing ECG signals as images with minimal preprocessing requirements. This points out the main of CNNs in different representations of ECG's signals, thus making them a good fit for various frameworks for arrhythmia detection. [19] further validated CNNs' ECG classification with a comparison study of MLP/SVM classifiers vs. CNN-based models. Its results

showed CNNs outperformed traditional ML approaches, specially when large sets of data are used for the training process; however, when cross-database validation was tested, CNN-based models were affected by dataset generalization, accuracy dropping when an external dataset is used. This calls for strong training strategies and adaptive feature normalization techniques in order to improve CNN performance on diverse ECG databases.

4.3 LSTM Networks

4.3.1 Architecture and Layers:

LSTM networks have been used very much for arrhythmia detection based on their power to grab a long term temporal dependencies in sequential ECG data. A typical network would consist of multiple layers of LSTMs, with a goal seekings temporal patterns from input given in the form of raw ECG signals or feature vectors, and then of fully connected layers used to classify the extracted features. Several studies used different architectures of LSTMs to improve performance in arrhythmia diagnosis. [6] proposed a hybrid CNN-LSTM model for divison of arrhythmia, using an 1d CNN that extracts spatial features from ECG signals before inputting them to an LSTM network for classify the temporal dependencies in the signals. The architecture consisted of 4 convolutional layers using different filter sizes which are of 7x7 and 9x9, 5x5, and 3x3 for spatial feature extraction as well as 2 LSTM layers with 120 hidden units to model temporal dependencies in the ECG signals. Finally, for fully connected layers, 2 dense layers followed by a softmax activation function for classification.
[10] gave an LSTM based method for detecting ECG abnormality. The proposed method combines the techniques of feature extraction with sequential learning. The extracted feature vectors from time domain, sub band spectrum, and harmonic ratio features were combined and passed through an LSTM network for classification. [14] proposed a hybrid deep learning model that combined BiGRU and BiLSTM with a CNN for hierarchical feature extraction. The bidirectional nature of BiLSTM and BiGRU enabled the model to learn both past and future dependencies within the ECG signals, improving accuracy.

4.3.2 Applications of LSTM in Capturing Temporal Dependencies in ECG Signals:

LSTM networks have been found to be excellent at modeling long-range dependencies in ECG signals, which makes them highly suitable for arrhythmia classification. A number of studies have shown the effectiveness of LSTM-based models in improving classification accuracy and real-time monitoring capabilities. In [6] the CNN-LSTM model was tested on the MIT-BIH Arrhythmia Database and the PTB Diagnostic ECG Database. Using a 10-fold cross-validation approach, the model was able to classify arrhythmia with an accuracy of 98.66% and detect myocardial infarction with an accuracy of 98.13%. The LSTM component is crucial for modeling the sequential nature of ECG signals and hence improves classification performance over CNN-only approaches. In [10], the 3R-TSH-L method was proposed to handle fixed-length ECG sample issues. It applied variable-length ECG sample extraction along with multi-domain feature fusion. It achieved a classification accuracy of 97.74%. On these concatenated feature vectors comprising time-domain, spectrum of the signals of signals, and the harmonic ratio features, the LSTM network further demonstrated its capabilities in the success of high precision and recall values. In contrast, this work in [14] obtained test accuracy at 99.00% for five ECG categories by the proposed model BiGRU-BiLSTM-CNN. The integration of BiLSTM and BiGRU layers captured both short-term and long-term dependencies, leading to improved generalization and performance on unseen ECG data. The confusion matrix results confirmed the model’s ability to classify different arrhythmia types with high accuracy.

4.4 Hybrid CNN-LSTM Models

4.4.1 Combining Spatial and Temporal Features for Improved Diagnosis:

Hybrid CNN LSTM models have been proposed for arrhythmia classification in order to leverage the spatial and temporal features of ECG signals. CNN captures spatial features, and LSTM captures long-term dependencies that improve diagnostic accuracy. Many more studies have utilized CNN-LSTM architectures for enhanced ECG classification. [5] proposed an ensemble learning technique by integrating CNN, CNN LSTM and Transformer models. The CNN-LSTM model can be broken down as a CNN having two convolutional layers with 16 filters in each followed with an LSTM layer of 120 units, dropout regularization along with a dense layer with ReLU activation. The features extracted from CNN-LSTM were combined with Transformer extracted features, passed through the traditional classifier: SVM, Logistic Regression and Random Forest. The majority voting ensemble was used for final classification, and the accuracy achieved was 99.56% with an F score of 99.34%. [6] proposed a CNN LSTM model that was trained on the MIT BIH Arrhythmia and PTBDB databases. The CNN was made up of four convolutional layers with different kernel sizes which are 7x7, 9x9, 5x5, and 3x3. Following the convolutional layers were the batch normalization and dropout layers. The LSTM had two layers with 120 hidden units for each. The model was evaluated using 10 fold cross-validation, achieving 98.66% accuracy for arrhythmia classification and 98.13% for myocardial infarction detection, outperforming previous methods. [14] proposed a hybrid CNN-BiGRU-BiLSTM model for ECG classification. The model used a BiGRU layer for bidirectional dependencies, a BiLSTM layer for the long term memory, and a CNN for feature extraction. The dataset is preprocessed by Z score normalization and noise filtering using Daubechies wavelet transform. The final classification gets a test accuracy of 99.00%.

4.4.2 Fusion Layer for Integrating CNN and LSTM Outputs:

The combination of CNN and LSTM outputs is critical to achieve maximum complementary strength of spatial and temporal feature extraction. [5] used a feature fusion technique in which CNN-LSTM outputs were concatenated with Transformer-based features before classification. The hybrid feature representation improved performance in arrhythmia pattern detection. [6] used a dense layer for integrating CNN and LSTM outputs before final classification via softmax activation. This led to an accuracy of 98.66% in the classification of arrhythmia, where the feature fusion proves to be useful in the deep learning approach. [14] used a new fusion method using BiGRU, BiLSTM, and CNN extracted features to improve ECG classification. The superior performance of this model was in comparison to CNN-LSTM based architecture, in which the validation gave an F1-score of 96.86%. The effectiveness of the CNN-LSTM hybrid models for arrhythmia diagnosis has been well proven by several studies; it emphasizes that spatial and temporal feature extraction together is essential. Feature fusion techniques further improve model accuracy and robustness, so they are possible solutions for the real-world task of ECG classification.

4.5 Traditional Machine Learning Models

4.5.1 Support Vector Machines (SVM):

SVM has a huge role to play in ECG classification: the frequency and nature of non-linear relationships in physiological signals. Kernel functions may be made use of, ensuring that higher-dimensional spaces may be attained where a linear separation between classes is viable. In [7], SVM was coupled with DWT in the context of denoising ECG signals. The DWT removed noise and baseline wander, ensuring that the SVM model was trained on clean and reliable features. This method helped SVM achieve high accuracy, sensitivity, and specificity in distinguishing normal ECG signals from arrhythmic ones, making it an ideal choice for automated ECG classification. SVM has shown its effectiveness in arrhythmia detection across various signal types. [7] showed that SVM with wavelet-based feature extraction was effective in arrhythmia detection from ECG data. Similarly, [15] used SVM for photoplethysmography (PPG) signals where it outperformed other classifiers such as ANNs and Logistic Regression. The SVM model obtained 97.674% accuracy in detecting arrhythmias with high precision and recall, thus underlining its potential for high-performance arrhythmia detection in real-world settings. [20] reported on the usage of wavelet-based machine learning techniques for fully automated arrhythmia screening. The work adopts a structured methodology, starting from noise filtering and baseline drift removal as preprocessing. Then, detection of R-peaks was applied using the Pan-Tompkins algorithm. For feature extraction purposes, DWT was used while PCA was then applied to achieve dimensionality reduction. Validated features were made through statistical testing like t-test and F-test before classification. Out of these classifiers, among GMM, EBPNN, and many others, the SVM showed good performance with accuracy at 95.60%. The main focus of the paper was to prove that the SVM is much stronger in cases of non-linearly separable problems and was, therefore, a better alternative for ECG-based arrhythmia detection. However, the study was limited in scope as it treated arrhythmia detection as a binary classification problem and relied on fixed feature selection, which may not generalize across different datasets. Despite these limitations, the findings reinforce SVM's capability in robust ECG classification, particularly when combined with wavelet-based feature extraction. [18] further explored SVM's effectiveness in arrhythmia prediction using a dataset from the UCI Machine Learning Repository. The study involved preprocessing, feature selection, and splitting the data into different training and testing ratios. SVM outperformed Decision Trees and Logistic Regression with 91.41% accuracy on the 80/20 train-test split. A Flask-based web application was also introduced in the study to make real-time arrhythmia prediction, reinforcing SVM's practical applicability. The dataset size was too small, there were no comparisons of deep learning models, and there was no clinical validation in the study. [17] further supports the SVM importance in classifying ECG, in which it is presented as being used in combination with MLP in classifying heartbeats. Here, the authors use SVM on MIT-BIH, SPH, and INCART databases for the classification of ECG signals. SVM performs well with an accuracy of 82.2% in the MIT-BIH database, using features such as PR and RT intervals, age, and sex. The accuracy dropped down to 68% during the testing procedure on the SPH database as a result of cross-database performance issues, but SVM, however, excelled over others, proving strong in automated cardiovascular disease (CVD) detection.

4.5.2 Decision Trees and Random Forests:

Decision Trees are very interpretable, allowing features that most influence classifications to be readily identified. This is especially helpful for arrhythmia detection because certain patterns in the ECG or PPG signal indicate abnormal heart rhythms. Random Forest is a form of ensemble learning, which creates numerous decision trees and aggregates their predictions to make better predictions. The ensemble approach also helps in mitigating overfitting and handling imbalanced datasets, which can be a common challenge in arrhythmia detection with unequal representation of normal and abnormal signals. As reported in [3], tuning the hyper-parameters of Random Forests significantly improved the performance by reaching an accuracy of 96.613%. The model could use the ECG signals to discern critical features including the R-R interval and duration of QRS complex, resulting in its performance. Application of Random Forest and Decision Trees also appeared in classifying arrhythmia, integrating these models with ensemble learning techniques in [9]. Combining the predictions of multiple classifiers such as Random Forest, Gradient Boosting Classifier, KNN, and SVM, ensemble method led to achieving a final accuracy of 98.49%. This high performance shows the strengths of ensemble learning, which aggregates individual classifier strengths to get over the limitations of individual classifiers. Hyperparameter tuning of Random Forest gave it an accuracy of 96.613%. In addition to that, the accuracy of Decision Trees also made significant contributions to the overall ensemble accuracy, hence the importance of including them in arrhythmia detection. Such findings demonstrate the improvement of performance that ensemble learning can bring about to traditional models in machine learning applied to medical diagnosis. [18] further validated the role of Decision Trees in arrhythmia prediction using a dataset from the UCI Machine Learning Repository. The study employed preprocessing, feature selection, and data splitting, ultimately finding that Decision Trees achieved 60.43% accuracy. While not as high-performing as SVM, Decision Trees provided interpretability advantages that can be valuable for medical practitioners in understanding classification outcomes.

4.5.3 Logisitic Regression:

Logistic Regression is a very simple yet powerful algorithm, used for binary classification, such as distinguishing between normal and abnormal ECG or PPG signals. Its key strength lies in interpretability, where healthcare professionals understand how certain features contribute to the model's predictions. Although Logistic Regression is much less complex than the deep learning models, it can yield insights valuable enough, particularly in datasets which are not large, and overfitting may be an issue. In [3], the authors tested Logistic Regression in conjunction with other machine learning algorithms for arrhythmia detection. With a meagre accuracy of 54%, it still yielded reasonably good benchmarks against more complex models, like SVM and CNN-based techniques. Although it is simple, Logistic Regression was applied in many studies on arrhythmia detection with mixed results. [15] applied it for arrhythmia detection using photoplethysmography (PPG) signals, achieving an accuracy of 86.046%. Although this performance is not as high as that of more sophisticated models like SVM (97.674%), Logistic Regression's reliability and ease of implementation make it a practical choice for real-time applications, particularly where computational resources are limited or interpretability is essential. [18] also evaluated Logistic Regression for arrhythmia detection using the UCI dataset, where it achieved an accuracy of 53.84%. Even though it was the worst performer among the three models, the work has been reported to be applicable for practical application for quick and interpretable arrhythmia prediction in resource-constrained environments.

4.5.4 K-Nearest Neighbors(KNN):

KNN is a non-parametric classifier. It uses the distance metric in order to classify new instances. The classification can be done depending on the similarity of the data with the training data. Due to its properties, KNN can be a good classifier when dealing with physiological signals, since these are commonly complex and nonlinear. The success of the algorithm depends on distance metrics (such as Euclidean or Manhattan distance) and on the number of nearest neighbors used (k). In [9], KNN was applied to arrhythmia detection with an accuracy of 89.654%. It was not the most accurate, however, in comparison to models like Random Forest and SVM. Yet, it remains a reliable alternative when used as part of other classifiers in ensemble learning frameworks. KNN has been applied to various signal modalities, both ECG and PPG, for arrhythmia detection. Authors of [15] were able to observe that KNN was also beneficial in the arrhythmia detection using PPG, achieving accuracy of 95.348%. Although it had not performed significantly better than state-of-the-art algorithms like SVM, it also showed its efficiency in simple computationally less burdensome models with real-time detections, mainly where ease of portability in such portable healthcare systems is an utmost priority.

4.5.5 Adaptive Neuro-Fuzzy Inference System (ANFIS):

ANFIS is an advanced machine learning approach that integrates fuzzy logic and neural networks. The model, along with the predictive power of neural networks, provides the interpretability of fuzzy logic, which is why this hybrid system is particularly suitable for classification tasks requiring handling uncertainty, such as detection of arrhythmia. In [16], ANFIS was applied for ECG classification using features wavelet transformed and PCA-reduced data. This gave an excellent classification accuracy of 97.75% and hence stands as a promising candidate for arrhythmia detection. Also, ANFIS integrates fuzzy logic with neural networks, thereby enabling human-readable decision-making processes that can be extremely useful in clinical settings where interpretability is a critical issue in diagnosis. Use of ANFIS in the classification of arrhythmias is gaining momentum since it is able to model complex, nonlinear relationships in data without losing interpretability. [16] showed the ANFIS system's potential in classifying ECG signals into four classes of arrhythmia: Left Bundle Branch Block, Normal, Atrial Premature Contraction, and Paced Beats with high sensitivity and specificity. Real-time classification robustness of ANFIS has shown promise in its application in clinical environments, where accurate and interpretable results are of paramount importance.

4.6 Comparative Analysis of Deep Learning Models

4.6.1 Strengths and Limitations of CNN, LSTM, and Hybrid Models

Many studies have investigated the efficiency and limitation of deep learning models for arrhythmia classification, with a focus on CNNs, LSTMs, and hybrid models. CNNs are applied for feature extraction from ECG signals due to their capability in learning spatial dependencies. [5] applied a CNN model with 2 convolutional layers followed by max pooling, which resulted in high efficiency in feature extraction. CNNs have poor performance in learning long term temporal dependencies in ECG signals and therefore are not suitable for sequential heartbeat classification. For this issue, hybrid models that inculcate CNNs and LSTMs were introduced to counter the shortcomings of pure CNN models. [5] presented a CNN LSTM model that combines CNN's spatial feature extraction with an LSTM layer to learn temporal dependencies. The CNN LSTM model outperformed individual CNNs by efficiently modeling sequential heartbeat data. The incorporation of LSTMs increases computational complexity, which makes real time processing more difficult.[5] also presented Transformer architectures with 6 encoder layers and two attention heads, which perform well in identifying long range dependencies. Unlike CNNs and LSTMs, transformers utilize self attention mechanisms, improving feature representation. The computational cost is much higher also. [9] and [17] compared deep learning methods with conventional machine learning models, including Random Forest, Logistic Regression, SVM, and Gradient Boosting Classifier. Although RF and GBC performed very good after hyperparameter optimization, deep learning methods performed well over conventional classifiers in feature extraction and classification accuracy. [17] also pointed out that MLP performed better than SVM when large datasets were used for training, especially in cross validation across multiple databases.

4.6.2 Performance Metrics for Model Evaluation

[5] reported that their hybrid CNN-LSTM model achieved an accuracy of 99.56% and an F-score of 99.34%, outperforming standalone deep learning models. Supriya et al. [9] achieved 98.49% accuracy using an ensemble approach, while Aziz et al. [17] noted a decline in accuracy when transitioning from MIT-BIH to external datasets, highlighting generalization challenges. The recall metric is crucial in medical applications, ensuring the model correctly identifies arrhythmic events. [5] showed that their ensemble classifier has a high recall rate, and [17] report a decrease in recall value when the external test datasets were used for validation, thereby needing further cross-database generalization. [17] report considerable accuracy drops from 99.85% to 68% when they applied their model trained on the MIT-BIH to the SPH dataset. This infers the need for diversity in datasets and better domain adaptation techniques for deep learning-based arrhythmia detection. [5] compared their model with standalone CNN, CNN-LSTM, and Transformer models to show that hybrid models outperform standalone models in arrhythmia detection. In the same direction, [9] compared ensemble machine learning approaches with previous works and found improved accuracy and generalization.

5 Ensemble Learning Techniques for Arrhythmia diagnosis

5.1 Voting Classifier

Ensemble learning techniques, especially voting classifiers, have been used for the improvement of accuracy and robustness in the diagnosis of arrhythmia. [9] applied ensemble machine learning techniques with voting classifiers for the improvement of classification performance for the detection of arrhythmia. The paper used various base classifiers like RF, LR, KNN, DT, SVM, and GBC. The ensemble method combined these classifiers using majority voting, where the final prediction was determined by aggregating the outputs of individual models. This reduced misclassification errors and improved diagnostic reliability. Additionally, it explored weighted averaging, where classifiers were assigned weights based on their individual performance, further refining the ensemble's predictive accuracy.

5.2 Stacking Classifier

[5] They used stacking ensemble techniques, which combined deep learning models with conventional classifiers to improve the classification of arrhythmia. Their strategy was to develop three deep learning models for feature extraction: CNN, CNN-LSTM hybrid, and Transformer. The features were then fused and classified using three conventional classifiers: SVM+LR+RF. These base estimators, in the form of classifiers, produced outputs that were aggregated by a meta-estimator: specifically, a LightGBM (LGBM) classifier. The stacking classifier showed excellent performance as it leveraged the strengths of various models to capture spatial, temporal, and long-range dependencies in ECG signals. This hierarchical approach improved the accuracy of classification and robustness against variations in patient-specific ECG patterns. This paper's authors claim that their stacked ensemble method beats the individual models. The accuracy is 99.56% and the F-score is 99.34%.

5.3 Role of Ensemble Learning in Enhancing Diagnostic Performance

Ensemble learning techniques have a significant contribution in reducing overfitting and improving generalization in arrhythmia diagnosis. We already know that [5] highlighted the fact that feature fusion and ensemble classifiers enhanced the model robustness by integrating multiple perspectives from different classifiers. In their study, they compared the performance of individual classifiers with the ensemble approach and demonstrated that ensemble learning consistently gave better accuracy and recall scores. Moreover, [9] highlighted the role of ensemble techniques in improving diagnostic performance by overcoming the limitations of standalone classifiers. Their work demonstrated that the hyperparameter tuning and ensemble methods improved the classification accuracy significantly and finally achieved 98.49% through stacked classifiers. Comparative analyses with existing methods indicated that ensemble learning produced better classification results, which makes it an important technique for reliable and accurate arrhythmia detection.

6 Datasets and Evaluation Metrics

6.1 ECG datasets

MITBIH Arrhythmia database : It is one of the most widely used datasets for detecting arrhythmias.It includes 48 ECG recordings, each lasting around 30 minutes, and used in studies like [1] and [2]. These recordings are from patients with a range like atrial fibrillation, premature ventricular related contractions, and regular sinus rhythms. Cardiologists created the dataset, which shows the R wave peaks and offers thorough categorization for every kind of pulse. Because it accurately depicts a variety of arrhythmias, it is a valuable tool for training deep learning and machine learning models in ECG analysis.

PTB Diagnostic ECG Database (PTBDB): Like in [1] and [5], the PTBDB dataset includes a sizable collection of signals of ECG from 549 hospital patients, both who are healthy and ill as well. Because this database contains 12-lead ECG recordings, it is crucial for diagnosis of arrhythmias related problems. Because of the variety of people and situations, this dataset is used to assess how robust ECG signal classification methods are. The PTBDB is useful for multiclass model classification because it has labels for a variety of arrhythmias.

6.2 Evaluation Metrics:

Accuracy measures the percentage of the correct instances as against the total instances. This is a measure widely used in performance measurement, such as that presented in [1], [2] and [5]. Precision is the percentage of relevant instances gotten back. Precision measures that, given an ECG segment which is classified by the model to be an arrhythmia, it indeed so is. Recall measures how well the model classifies positive instances, such as trying to identify arrhythmias from normal ECG segments. F1 Score is mean of precision and recall, which gives a correct view of both metrics, especially in datasets where there is an imbalance between classes. AUC-ROC is a measure of the model's ability to distinguish between classes. It evaluates the performance across various thresholds, and a higher AUC means good performance in differenciating positive and negative samples. These metrics were used by [1] to evaluate traditional models, such as CNNs, as well as deep learning architectures of a more recent type, namely AlexNet and ResNet50. Similarly, [2] used these metrics to show how time-frequency features could be used with a 1D-CNN to get an accuracy higher than 99% when classifying ECG signals.Cross validation is one of the crucial techniques for estimating the robustness of a model. [1] and [5] cross validated their models on different subsets so that they cannot overfit with the training set and performed quite consistently. Generalizing, people usually use the k-fold procedure for cross-validation i.e, divide a dataset into k subsets, with the model retrained k times, each trained on all but one subset while using the other subset for the test. This gives a better estimation of model performance on unseen data, thereby making sure that the models generalize properly.

6.3 Comparative performance analysis

This focuses on DL models like, CNN, LSTM network, also other hybrid models which combine CNN and LSTMs through and as done in [5] and [2], which compared all these models individually with hybrid or ensemble models based on their relative performance in this task of distinguishing arrhythmia. It was observed that CNNs were good for automatically learning spatial features from the ECG signal, whereas LSTMs and CNN-LSTM hybrids excelled in capturing temporal dependencies in the signal. Feature extraction with CNN and sequence modeling with LSTM produced strong performance on all datasets. Ensemble techniques were also investigated where [5] combined CNN, LSTM, and Transformer models for better classification performance by grabbig in both the spatial and temporal dependencies of these ECG signals. Both the MITBIH and PTBDB datasets were utilized in these comparative performance studies for benchmarking. [1] obtained 99.43% accuracy by using a 1D-CNN with time frequency domain fusion, which results in significant accuracy improvements over the earlier works by using traditional signal processing methods. [5] shows that the proposed ensemble model - combining CNN and CNN-LSTM features with classiffiers - SVM, Random Forest (RF) and Logistic Regression (LR)-outperforms individual models of CNN, CNN-LSTM with 99.56% accuracy and a 99.34% F-score on the benchmark for this problem type. [9] explored methods of ensemble of machine learning that resulted in obtaining a final accuracy rate of 98.49fl. While stacking further ameliorates their performance in these three Random Forest, Gradient Boosting, or other classifiers. This research results give the growth curve for multiple model combinations, bringing improvement to classify better accuracy regarding arrhythmia detection.

7 Research gaps and challenges

[4] pointed out the challenge of multi-domain collaborative analysis in arrhythmia classification. Graph Neural Networks have been applied for ECG sequence prediction, and there are many challenges that exist, such as the complexity of integrating multiple ECG databases like BIDMC-CHF, MIT-BIH, whose data characteristics vary and need to be harmonized to standardize feature representations. The difficulty of optimizing model hyperparameters, especially with traditional grid search methods, which are computationally expensive. Bayesian optimization and AutoML techniques have been proposed for efficient tuning. The high computational cost of processing multi-lead ECG calls for model pruning, quantization, and lightweight architectures to classify real-time signals. [5] discuss computational challenges in the feature extraction as well as fusion related process, specifically in deep learning architectures, namely CNNs, CNN-LSTMs, and Transformers, whose issues lie in the inability of CNNs to be time-sensitive while it does well at spatial feature extraction. Hybrids such as CNN-LSTMs or attention based improve temporal awareness but increase computation complexity. There is redundancy for feature fusion among multiple domains that are time or frequency, demanding adaptive fusion approaches to dynamically assign weights to both time and frequency domain contribution. Ensemble learning techniques, such as majority voting and stacking classifiers, are required to compensate for the weaknesses of individual models. [1] highlights the shortcomings of ECG datasets, including dataset size and class imbalance. The BIDMC Congestive Heart Failure Database has only 30 recordings. It still suffers from a class imbalance problem, because some kinds of arrhythmia have a significantly smaller number of samples than the normal heartbeat. Techniques for data augmentation like synthetic oversampling (for example, SMOTE) and GAN-based synthesis of ECG signal have been studied. Challenges of feature extraction and preprocessing in ECG have been discussed in [5]. Standard normalization techniques cannot account for the differences between patients. It has been suggested that adaptive normalization methods that consider patient-specific characteristics of ECG signals be developed. Variability in heartbeat segmentation can affect the accuracy of classification, and therefore, more robust segmentation techniques must be used to preserve meaningful temporal features. The effectiveness of wavelet transforms and Fourier analysis-based preprocessing methods relies on the tuning of precise parameters to avoid loss of information. [2] discuss challenges in time-frequency fusion for ECG classification, particularly in 1D-CNN-based models. FFT provides a frequency-domain representation but lacks temporal resolution. Wavelet transforms offer joint time-frequency analysis but introduce additional computational complexity. The amount of misalignment in the localisation of the R-wave causes a lot of inaccuracy for classification, necessitating DTW and adaptive peak detection techniques. The optimal combination of time-domain and frequency-domain features remains an open question, and recent research explores attention-based fusion techniques to dynamically weigh different features. [4] points out that integrating multi-lead ECG signals poses some challenges, which include GNNs proposed for multi-domain feature fusion but where the fusion process is a challenge, particularly to ensure alignment across different representations. Adaptive fusion mechanisms that dynamically weigh time and frequency features can enhance classification accuracy across different datasets like MIT-BIH, BIDMC-CHF. Generalizing cross-domains requires methods like domain adaptation ones to counteract dataset-specific biases.

8 Conclusion

We conclude that for detecting arrhythmia, both ML and DL are the models that have potential. Some ML approaches, such as SVM and Random Forest, coupled with preprocessing techniques like DWT and EMD, show great accuracy and robustness but are limited in generalization or computational intensity. DL models especially CNN, LSTM did good in capturing spatial and temporal features and offered superior performance, though they required large datasets and higher computational resources. Hybrid and ensemble approaches, including CNN+LSTM and Voting Classifiers, achieved higher accuracy and robustness. However, all these developments were not able to overcome the problem of clinical application in real-life scenarios due to issues of small dataset size, noise handling, and computational costs. Future research should focus on hybrid approaches, advanced feature engineering, and better generalization that will help realize practical, real-time arrhythmia detection systems.

9 Future work

Our future work will be in the direction of advancing cardiac arrhythmia diagnosis by integrating deep learning techniques, particularly CNNs, LSTMs, time-frequency domain fusion. This will focus on refining and building upon the current methodologies, ensuring that the system delivers superior performance and practical utility. To further improve feature extraction, the future work will be to explore more advanced fusion methods. This includes incorporating Advanced Transformations i.e utilizing refined wavelet related transforms and STFT for deeper study of ECG signals, capturing both short- and long-term features. Further more, we aim to improve the integration of spatial, temporal, and frequency-domain features, creating a richer set of inputs for the deep learning models. We also propose integrating attention mechanisms within CNN-LSTM networks for complex patterns and dependencies in the ECG signals. We would also like to enhance the Voting Classifier and Stacking Classifier with more base models to improve prediction accuracy. In addition, we are going to expand the capabilities of the system so that it could classify other forms of arrhythmias rather than the usual types so that the system would have a strong and complete diagnosis capability. An important feature of the future system is the design of a user-friendly web interface, which will provide easy interaction of healthcare professionals and patients with the system to upload ECG data and receive a diagnosis of arrhythmia.

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