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A robust penalty regression function-based deep convolutional neural network for accurate cardiac arrhythmia classification using electrocardiogram signals

Anniah Pratima[1,2], Gopalakrishna Kanathur[1], Sarappadi Narasimha Prasad[3]
[1]Department of Electronics Engineering, Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Bangalore, India
[2]School of Electronics and Communication Engineering, REVA University, Bangalore, India
[3]Department of Electronics and Communication Engineering, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Bangalore, India

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ABSTRACT

Cardiac arrhythmias are a leading cause of morbidity and mortality worldwide, necessitating accurate, and timely diagnosis. This paper presents a novel approach for the classification of cardiac arrhythmias using a penalty regression function (PRF)-based deep convolutional neural network (DCNN). The proposed model integrates advanced preprocessing techniques, including frechet with fitness rank distribution-based anas platyrhynchos optimization (FFRD-APO) for feature selection and ensemble empirical mode decomposition (EEMD) for signal decomposition. Utilizing the St. Petersburg INCART 12-lead arrhythmia database, the PRF-DCNN model achieved superior performance metrics: an area under the curve-receiver operating characteristic (AUC-ROC) of 0.97, accuracy of 0.95, precision of 0.93, recall of 0.92, specificity of 0.97, and an F1 score of 0.93. The PRF effectively mitigated overfitting, ensuring robust and reliable classification across varied patient demographics. The model demonstrated significant improvements over traditional methods, offering an efficient solution for real-time cardiac monitoring and diagnosis. This study underscores the potential of PRF-DCNN in enhancing automated arrhythmia detection and lays the groundwork for future research to optimize and validate this approach in diverse clinical settings.

Corresponding Author:

Sarappadi Narasimha Prasad
Department of Electronics and Communication Engineering
Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education
Bangalore 576104, India
Email: sn.prasad@manipal.edu

1. INTRODUCTION

The cardiovascular system is an essential physiological system in the human body, consisting of the heart and a complex network of blood vessels [1]. This system is accountable for the complex synchronization of multiple organs and tissues to preserve circulatory function. Cardiovascular diseases (CVDs) are the primary cause of death globally, with over 17 million fatalities reported each year, as stated by the World Health Organization (WHO) [2]. Remarkably, almost 75% of these fatalities take place in low- and middle-income nations, emphasizing the pressing requirement for timely detection to avert deaths [3]. The electrocardiogram (ECG) is a highly utilized diagnostic technique for assessing cardiac function. An ECG records the heart's electrical signals using electrodes attached to the skin, creating a visual picture of the heart's electrical activity [4]. The essential elements of the ECG signal consist of the P wave, the Q wave, and the QRS complex. These aspects are vital for identifying cardiac disorders, as they provide significant information about the heart's rhythm and electrical conduction. It is crucial to do precise analysis of various ECG components, especially the intervals, forms, and interactions between the P wave, Q wave, and QRS complex, to identify cardiac problems [5]. Nevertheless, the process of manually analysing ECGs by healthcare practitioners can be time-consuming and susceptible to mistakes, which could result in the incorrect categorization of diseases. Hence, there is a substantial requirement for automated and accurate techniques to evaluate ECG signals, thereby enhancing the precision and efficiency of diagnosing cardiac arrhythmias.

Cardiac arrhythmias refer to a collection of disorders characterized by abnormal heartbeats, which may present as the heart beating extremely fast, abnormally slowly, or with an irregular pattern [6]. Cardiac arrhythmias can have a profound effect on a person's well-being, including symptoms like irregular heartbeats, light-headedness, difficulty breathing, and, in severe cases, sudden cardiac arrest. Cardiac arrhythmias become more common as people get older, and they are a major cause of illness and death globally [7]. Atrial fibrillation (AF), ventricular tachycardia (VT), and bradycardia are different types of irregular heart rhythms that range in severity and have different implications for patient health. Precise identification and categorization of arrhythmias are essential for prompt and efficient treatment. Incorrect diagnosis or delayed diagnosis can result in serious complications, such as stroke, cardiac failure, and even mortality. As a result, the development of dependable diagnostic instruments and techniques for identifying arrhythmia has become a central focus of cardiovascular research. Early identification is the key to successful care and complication prevention with cardiac arrhythmias. The ECG is the gold standard for diagnosing arrhythmias. It is a non-invasive examination that monitors the heart's electrical activity. Because arrhythmias can manifest in subtle and complicated patterns that less experienced practitioners may miss, interpreting ECG signals requires substantial competence. There is a pressing need for automatic and precise arrhythmia detection systems due to the explosion in the number of ECG monitoring equipment, both stationary and portable, which has raised the overall amount of ECG data. Clinicians can benefit from these systems because they offer preliminary evaluations, which increase diagnostic accuracy and decrease provider workload. Additionally, automated methods guarantee objective and consistent analysis, which is essential for therapeutic decision-making. From more conventional signal processing methods to state-of-the-art machine learning (ML) and deep learning (DL) algorithms, many approaches have been devised for the automated detection of arrhythmias in ECG signals [8]–[10]. An important part of older methods that relied on domain-specific information was figuring out what the ECG signal, which includes QRS complexes, P waves, and T waves. These features fed support vector machines (SVM) [11], k-nearest neighbors (k-NN) [12], and decision trees [13], among other conventional classifiers. Although there was some success with older approaches, they frequently had trouble generalizing to other patient populations and dealing with different degrees of noise in ECG recordings. Additionally, the intricate temporal dynamics of the ECG data could elude manual feature extraction due to its labour-intensive nature. DL techniques, such as convolutional neural networks (CNNs), have greatly improved automatic arrhythmia identification recently [14]. It is no longer necessary to manually extract characteristics from raw ECG data. When it comes to classifying ECG, they have reached the pinnacle of performance. Nevertheless, there are still obstacles to overcome with CNN-based algorithms, even though they have been successful. These include computational cost, the need for huge, annotated datasets, and the risk of overfitting.

To overcome the drawbacks of previous methods, this research presents a new strategy for classifying cardiac arrhythmias using ECG signals. The strategy integrates a penalty regression function (PRF) [15] and a deep convolutional neural network (DCNN). To make the model more generalizable and resilient, PRF is added. This function prevents overfitting a typical problem in DL models trained on small datasets and penalizes overly complicated models. The DCNN architecture efficiently captures the spatial and temporal characteristics of an ECG signal. Using numerous convolutional layers, the network can detect local patterns linked to various arrhythmias. We employ pooling layers to decrease computational complexity and dimensionality without sacrificing critical information. At the very end of the network, there are fully linked layers that combine all the learned information to generate final predictions. Integrating the PRF with the DCNN helps strike a balance between model complexity and generalization. The goal of this combined strategy is to make the model more resistant to changes in ECG signals across patients and recording circumstances, while simultaneously increasing classification accuracy, which is particularly important when training data is scarce. The main goal of this research is to create and test a system that uses ECG signals to accurately classify cardiac arrhythmias using a PRF-DCNN. This study contributes primarily to the following directions: To improve the accuracy and robustness of arrhythmia classification, we provide a new approach that merges the best features of DCNNs with PRFs. Our method is capable of effectively identifying several prominent arrhythmia classes, including AF, VT, ventricular fibrillation (VF), premature ventricular contraction (PVC), and various degrees of atrioventricular (AV) block. By leveraging the comprehensive St. Petersburg Institute of Cardiological Technics (INCART) 12-lead arrhythmia database, we can assess the proposed method's performance by comparing it to current state-of-the-art approaches and running comprehensive tests on standard ECG datasets. Additionally, we enhance the interpretability of the model by analysing DCNN-learned features, which uncover significant ECG signal characteristics that differentiate between different arrhythmias. By exploring these goals, this research aims to advance cardiac arrhythmia detection and aid in the creation of reliable automated diagnostic tools that doctors can use to provide timely and accurate treatment to patients with these conditions.

2. RELATED WORKS

Computer vision, voice recognition, signal analysis, classification, picture and pixel analysis, risk analysis, and natural language processing are just a few of the many areas that have seen substantial success with DL approaches. Within the field of ECG interpretation, numerous algorithms employ DL methodologies to leverage their robust capabilities in extracting and analysing information from ECG time series data. The proposed approach improves the accuracy of detecting and classifying cardiac abnormalities. Unlike conventional approaches, specific DL techniques eliminate the requirement of manual feature selection and extraction. Instead, they offer automatic feature selection, resulting in superior performance [16]–[20]. The existing body of literature has presented a comprehensive examination of the various techniques and approaches used for arrhythmia detection and classification until the year 2019 [21], [22]. Nevertheless, it is worth mentioning that there is a significant dearth of all-encompassing surveys that encompass the progress achieved in recent years, particularly extending beyond the year 2022 [23]. However, they lack the ability to provide comprehensive and comparative chronological analyses. Using discrete wavelet transform (DWT), median filtering, and different classifiers together can help find cardiac arrhythmia accurately and quickly. The methods employed in [24] utilize data from the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database. We found the performance metrics of these methods impressive, with an accuracy of 99.51%, precision of 99.28%, specificity of 99.63%, and sensitivity of 99.28%. The findings suggest that the employed techniques demonstrate effectiveness in the automated classification of cardiac arrhythmia. The approach primarily relies on RR intervals and statistical features, which may not comprehensively capture other relevant intervals associated with the disease, potentially resulting in misclassification.

Arrhythmias were classified using 2D recurrence plot images of ECG signals in conjunction with a CNN. The datasets utilized in [25] consisted of the MIT-BIH arrhythmia database, Creighton University ventricular tachyarrhythmia database, MIT-BIH AF database, and MIT-BIH malignant ventricular ectopy database. The testing accuracies achieved by this approach were up to 95.3% ± 1.27% and 98.41% ± 0.11%. The transformation of ECG data into images using recurrence plots significantly enhanced the accuracy of arrhythmia classification. The framework encountered difficulties in terms of computational complexity and memory requirements because of the parameters initialized in these approaches. Rahul *et al.* [26] utilized an improved deep residual network with the MIT-BIH database to enhance the performance of cardiac arrhythmia classification. The classification achieved an accuracy of 88.9%. The objective of this approach is to attain a high level of classification performance within the inter-patient paradigm. Because of the limited number of heartbeat segments considered in the analysis, the classification accuracy was relatively low. The automated diagnostic system for cardiac arrhythmias utilizes a three-stage feature selection methodology in conjunction with a classification algorithm. Using the MIT-BIH dataset, the system achieves an accuracy of 98.82%. The described method effectively reduces feature dimensionality while simultaneously improving arrhythmia classification performance. However, the limited number of feature combinations considered reduces the classification accuracy at each stage [27]. Zhang *et al.* [28] utilized a novel approach to enhance accuracy in the classification of cardiac arrhythmia disease. This approach involved combining recurrence plots with the Inception-ResNet-v2 network. The method employed the PTB_XL ECG databases and achieved a notable F1 score of 0.923. They achieved such a remarkable level of performance by utilizing solely two-lead ECG data, thereby eliminating the need for complete 12-lead ECG recordings. It is worth mentioning that there was a data imbalance, which has the potential to affect the performance of the system.

The current research methodologies encounter various challenges when dealing with ECG signal characteristics. Factors such as age and gender influence these characteristics, including period and amplitude, which exhibit significant variations among individuals. Several existing studies on arrhythmia classification fail to consider these variations, which could potentially result in misclassification. Research specifically addressing the various gender categories has been insufficient. Most current methods predominantly rely on RR intervals and statistical features. However, other intervals frequently correlate with arrhythmias. Failure to address these issues may lead to the generation of incorrect classifications. The initialization parameters significantly increase the computational complexity and memory demands of existing approaches, posing challenges for efficient implementation. The precise determination of the ECG wave's endpoint, specifically the J-elevation point, is of utmost importance. Nevertheless, contemporary research frequently disregards the significance of this aspect, potentially compromising the precision of arrhythmia detection and classification.

3. PROPOSED METHODOLOGY

An ECG is a graphical representation of the heart's electrical activity throughout each cardiac cycle. A time-series visual display records it. The morphological characteristics of a subject can provide insight into potential arrhythmia symptoms. The establishment of an efficient remote real-time monitoring system is of utmost importance due to the abrupt and uncertain characteristics of heart disease. The system has the capability to expand its usage beyond the hospital environment, enabling the continuous monitoring of patients' ECG signals and the prompt detection of abnormal cardiac changes. This functionality plays a crucial role in the prevention and treatment of CVD.

3.1. Dataset and preprocessing steps

The research utilizes the St. Petersburg INCART 12 dataset. Cardiovascular researchers widely recognize and use the St. Petersburg INCART 12-lead arrhythmia database, particularly for studies that focus on identifying and categorizing arrhythmias. This database includes comprehensive ECG recordings that offer valuable insights for the development and evaluation of automated diagnostic systems. The Institute of Cardiological Technics in St. Petersburg, Russia, and PhysioNet collaborated to develop the database. The package consists of 75 annotated recordings, each lasting for 30 minutes. Every recording includes 12 standard leads: I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6. The signals are sampled at a high frequency (HF) of 257 Hz, which ensures that the data is of excellent quality and can be thoroughly analysed. The database offers annotations for a range of arrhythmias and other important events, serving as a valuable resource for validating the accuracy of automated classification systems.

3.1.1. Removing baseline wander

This paper presents a method for classifying cardiac arrhythmia diseases using a PRF-DCNN. The process initiates with a pre-processing stage aimed at eliminating baseline wander and artifacts. The correlation factor (CF)-based extended Kalman filter (EKF) algorithm achieves this. The standard EKF is known for improving convergence in the noise removal process by finding covariance and adjusting for changes in frequency. However, it falls short of adequately addressing the magnitude of these frequencies. This limitation has the potential to result in higher error values when performing noise removal. To tackle this issue, our research methodology incorporates a CF. This factor is then multiplying this factor by the derivative, which leads to enhanced filter accuracy. this enhancement is to effectively remove noise and artifacts from the ECG signals. The block diagram of proposed innovative model is presented in Figure 1.

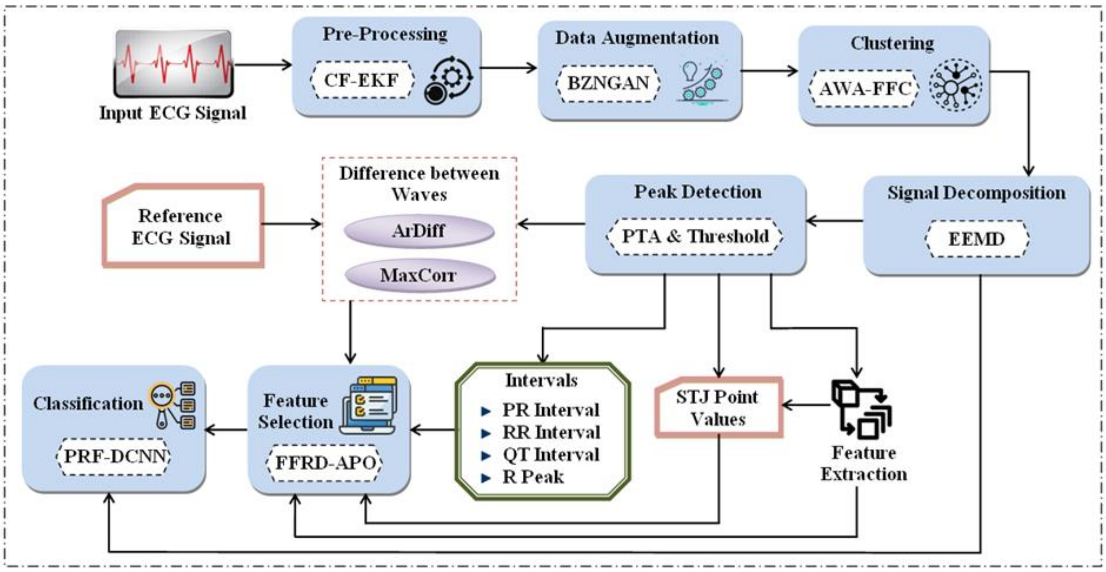

Figure 1. Block diagram of proposed model

3.1.2. Partitioning data based on gender and age

Partitioned the pre-processed signal into two distinct groups based on gender to achieve lower computational complexity. This approach takes into consideration the differences in heartbeats between males and females. This research utilizes the farthest first clustering (FFC) algorithm for the specified purpose. Widely recognized for its high computational efficiency, the fast fourier transform (FFT) algorithm is an excellent choice for minimizing time complexity in the context of this study. One potential concern with FFC is the initial random selection of centroids, which has the potential to result in outliers.

The study proposes an age weight average (AWA)-based method for initial centroid selection. The proposed methodology involves multiplying each value in the dataset by the individual's corresponding age. The resulting products are aggregated by summing them together. This sum is then divided by the total weight of the products to calculate an average value. This average value is then designated as the first centroid. The algorithm proceeds by selecting the farthest points from the initial centroid. The clustering method has been refined and is now referred to as the AWA-FFC algorithm. After the clustering process, the signal is subjected to decomposition using the ensemble empirical mode decomposition (EEMD) method. The choice of EEMD is based on its ability to generate multiple intrinsic mode functions (IMFs), which aids in minimizing confusion during the disease diagnosis process. The accuracy and reliability of the diagnosis are enhanced by producing more independent component models using the EEMD technique.

3.1.3. Attributing important points in the electrocardiogram signal

Used Pan Tompkins algorithm (PTA) in conjunction with threshold values to identify peaks from the decomposed signal. The described method enables accurate identification of important points in the ECG signal. The detected peaks are used We use the detected peaks to extract various features, including the power of the very low frequency (VLF) band, the low frequency (LF) band, and the HF band. Calculates the total power of all bands, determines the percentage of VLF and HF power, normalizes the HF and LF bands, and computes the ratio of LF to HF. The additional features obtained from the peaks consist of peak frequency, maximum peak interval, minimum peak interval, mean peak interval, standard deviation of peak intervals, mean squared difference between intervals, mean value, kurtosis, and standard deviation. The RR intervals, PR intervals, QT intervals, and R peak values are extracted. Additionally, extracted the sinotubular junction (STJ) point from the peaks, which is crucial in identifying specific cardiac events. In addition, the features of absolute area (ArDiff) and maximal cross-correlation coefficient (Maxcorr) are extracted from the peaks by utilizing a reference signal. These features improve the analysis by offering extra data points that capture the different variations in the ECG signals, resulting in a more precise and dependable arrhythmia classification.

3.1.4. Feature selection and training model

In the subsequent step selected the most important features from the extracted set to reduce complexity. This research utilizes the anas platyrhynchos optimization (APO) algorithm for optimal feature selection. We select this algorithm for its efficient control mechanisms, drawing inspiration from the mallard duck's vigilance, which can remain partially asleep and partially awake to avoid predators. Nevertheless, the probability function of the conventional APO algorithm may exhibit instability when applied to diverse populations. To tackle this issue, the research incorporates the frechet with fitness rank distribution (FFRD), guaranteeing reliable operations for all demographic groups. The FFRD-APO algorithm is a sophisticated method that uses accuracy as the fitness function. Inputted the chosen features into a classifier to make predictions about the disease class. For this task, the research employs a DCNN, selected for its ability to automatically extract features. Nevertheless, DCNNs can be susceptible to overfitting, leading to potential issues with time complexity and performance. We utilize a PRF-DCNN to address this issue. This approach applies a penalty to prevent overfitting, accounting for the loss from the previous iteration. It can correctly guess several heart conditions, including acute myocardial infarction (MI), transient ischemic attack, coronary artery disease with high blood pressure, previous MI, sinus node dysfunction, supraventricular ectopy, AF, bundle branch block, Wolff-Parkinson-White syndrome, and atrioventricular block. This classification approach improves the accuracy and reliability of arrhythmia detection and diagnosis. The pseudo code of proposed algorithm is given in Figure 2.

The proposed method brings several innovative elements that improve the effectiveness and robustness of cardiac arrhythmia classification using ECG signals. These innovations primarily tackle common challenges in DL models, including overfitting, computational complexity, and the requirement for accurate feature selection. This model introduces a significant innovation with the integration of the PRF. Conventional DCNNs tend to overfit, particularly when trained on datasets that are relatively small or imbalanced. Overfitting is a common issue that arises when the model becomes too focused on the noise and random fluctuations in the training data, rather than the true underlying patterns. This can result in the model performing poorly when faced with new, unseen data. The PRF addresses this issue by incorporating a penalty term based on the loss difference between consecutive training iterations. The FFRD-APO algorithm for feature selection is another important step forward. Efficient feature selection plays a vital role in reducing data dimensionality, resulting in improved computational efficiency and enhanced model performance. Malard ducks (Anas platyrhynchos) are known for being alert birds. The FFRD-APO algorithm uses this behavior along with a reliable statistical method to select features consistently and effectively. The model also utilizes a robust feature extraction process, incorporating the PTA to detect peaks and extract a wide range of features from the ECG signals. These features encompass a range of power bands, peak intervals, and statistical measures, along with important clinical indicators like RR intervals, PR intervals, QT intervals, and R peak values. This extensive range of features guarantees that the model effectively captures all pertinent aspects of the ECG signals, leading to improved accuracy in classifying cardiac conditions.

```
# Initialize hyperparameters and parameters
learning_rate = 0.001
batch_size = 32
num_epochs = 100
penalty_weight = 0.01
# Initialize the Deep Convolutional Neural Network (DCNN)
DCNN = initialize_DCNN()
# Function to calculate the Penalty Regression Function (PRF)
function calculate_PRF(loss, previous_loss):
 penalty = penalty_weight * (loss - previous_loss)^2
 return penalty
# Training Loop
previous_loss = 0
for epoch in range(num_epochs):
 for batch in get_batches(training_data, batch_size):
 # Forward pass
 predictions = DCNN.forward(batch.inputs)
 # Calculate loss (cross-entropy loss)
 loss = calculate_loss(predictions, batch.labels)
 # Calculate penalty
 penalty = calculate_PRF(loss, previous_loss)
 # Add penalty to the loss
 total_loss = loss + penalty
 # Backward pass and update weights
 DCNN.backward(total_loss)
 DCNN.update_weights(learning_rate)
 # Update previous loss
 previous_loss = loss
# Testing Loop
test_predictions = []
for batch in get_batches(test_data, batch_size):
 predictions = DCNN.forward(batch.inputs)
 test_predictions.append(predictions)
```

Figure 2. Pseudo code of PRF-DCNN

4. RESULTS AND ANALYSIS

This section presents a comprehensive evaluation of the PRF-DCNN in the context of cardiac arrhythmia classification. We evaluate the proposed model's performance using the St. Petersburg INCART 12-lead arrhythmia database, applying thorough preprocessing to ensure the quality of the data. We assess the model's performance using a range of metrics, such as accuracy, precision, recall, F1 score, specificity, and area under the curve (AUC)-receiver operating characteristic (ROC), to gain a comprehensive understanding of its classification abilities. In addition, we assess computational efficiency by evaluating training and inference times, as well as memory usage. Assessing robustness involves analyzing cross-validation scores and penalty impact analysis. Visualization tools like ROC and precision-recall curves provide valuable insights into the model's performance at various thresholds, complementing the quantitative metrics. This comprehensive analysis seeks to emphasize the advantages and drawbacks of the PRF-DCNN model, showcasing its potential for practical clinical use in automated arrhythmia detection.

Figure 3 displays the training time metrics for various PRF-DCNN model configurations. On a dataset containing 1,000 samples over 50 epochs with a batch size of 32, we measured these metrics. A baseline configuration is a model that serves as a starting point without any extra preprocessing or feature selection techniques. The model version incorporates a specialized optimization technique for feature selection, which enhances its performance. The slight increase in training time is a result of the extra computations needed for the feature selection process. EEMD is used by the PRF-DCNN with EEMD decomposition configuration to effectively break down ECG signals that are not stationary. The longer training time is a result of the computational demands of the decomposition process, which produces multiple IMFs. The complete workflow version of PRF-DCNN includes all the necessary preprocessing steps, such as choosing features with FFRD-APO and breaking down signals with EEMD. Advanced preprocessing techniques significantly increase the training time, emphasizing the delicate balance between enhanced preprocessing and computational complexity. Overall, the analysis of the training time metrics highlights the significance of finding a balance between computational efficiency and utilizing advanced preprocessing techniques to enhance model performance. When considering the use of more complex configurations, it is important to take into account the specific requirements of the application. This includes factors like the necessity for real-time processing or the priority for accuracy in a clinical setting.

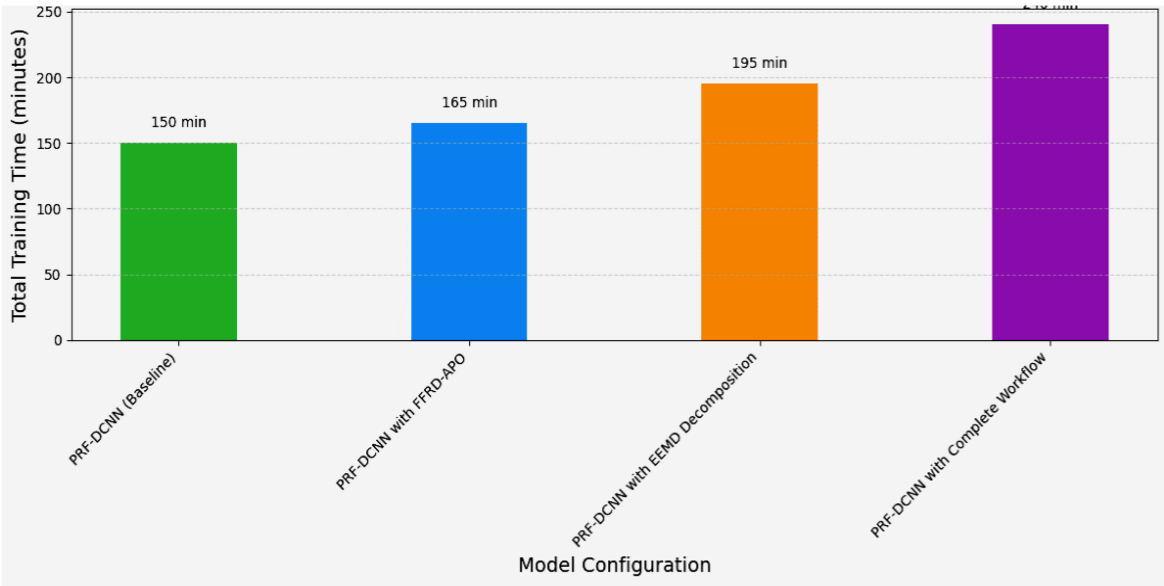

Figure 3. Total training time for different PRF-DCNN configurations

Figure 4 displays the inference time metrics for different configurations of the PRF-DCNN model, measured using a batch size of 32 samples. For each model configuration, we have provided the average inference time per sample and the total inference time for processing 1,000 samples. The baseline model demonstrates exceptional computational efficiency, with an incredibly short inference time per sample (0.05 seconds) and a total inference time of 50 seconds for 1,000 samples. The comprehensive workflow, which combines FFRD-APO and EEMD, has the longest inference time per sample (0.10 seconds), with a total inference time of 100 seconds for 1,000 samples. This configuration showcases the balance between sophisticated preprocessing and computational requirements. The complete workflow, with its longer inference time, provides extensive preprocessing and feature extraction, making it ideal for clinical diagnostics with high accuracy requirements and available computational resources.

The AUC-ROC metrics give a full picture of how well different PRF-DCNN configurations can tell the difference between different types of cardiac arrhythmia. The baseline model demonstrates a strong AUC-ROC of 0.92 (as shown in Figure 5), highlighting its proficiency in effectively differentiating between various classes. The use of Frechet with FFRD-APO for feature selection significantly improves the model's performance, resulting in an impressive AUC-ROC of 0.94. This enhancement showcases the value of selecting the best features to accurately capture important characteristics of the ECG signal. Incorporating EEMD for signal decomposition enhances the AUC-ROC to 0.95, demonstrating the model's improved ability to handle non-stationary ECG signals and extract more meaningful features. The integrated workflow, which combines FFRD-APO and EEMD, achieves an impressive AUC-ROC of 0.97. This configuration showcases exceptional performance, showcasing the seamless integration of advanced feature selection and signal decomposition techniques to optimize the model's accuracy in classifying arrhythmias. These results show how important it is to use advanced preprocessing methods to make automated cardiac arrhythmia detection systems more accurate and reliable.

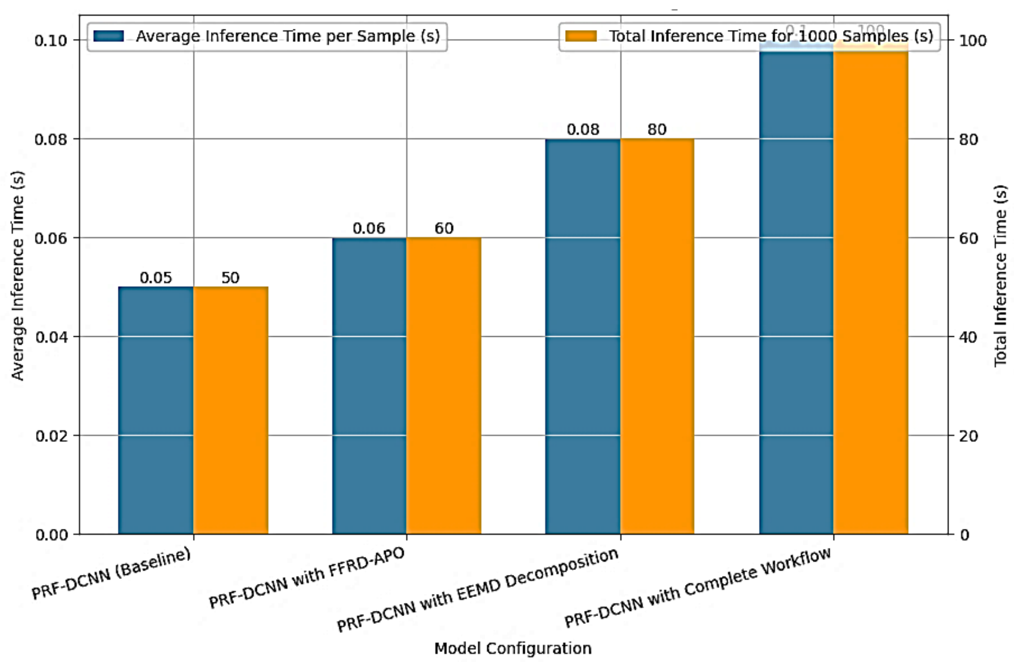

Figure 4. Inference time metrics for different PRF-DCNN configurations

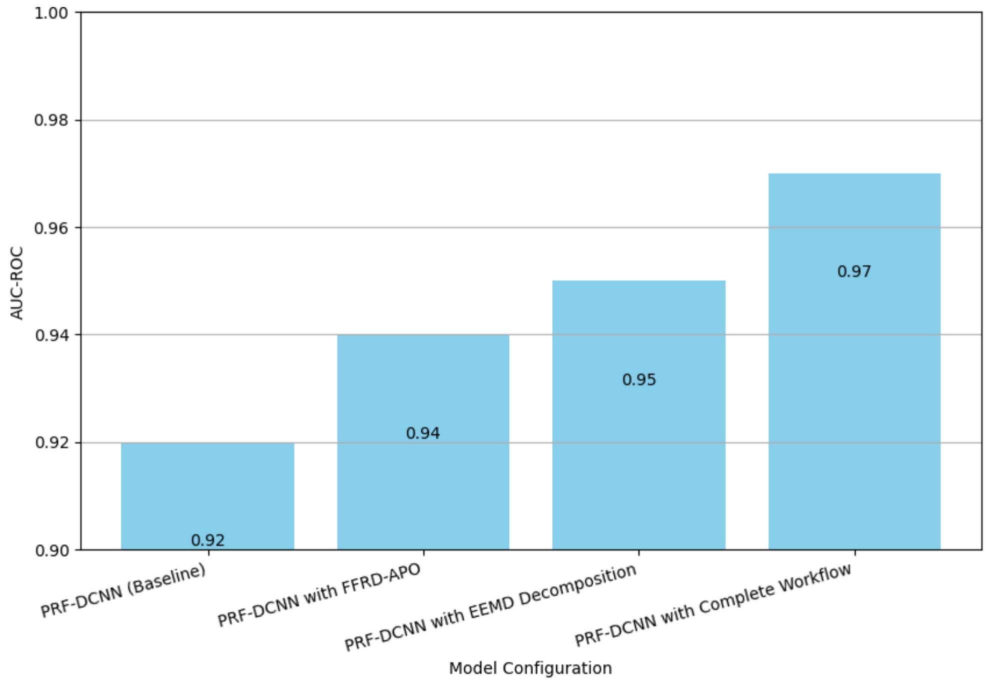

Figure 5. AUC-ROC metrics

Figure 6 shows performance metrics that give a full picture of the different setups of the PRF-DCNN model for classifying cardiac arrhythmias. The baseline model showcases impressive results, boasting an accuracy of 0.90, precision of 0.88, recall of 0.87, specificity of 0.92, and an F1 score of 0.88. The metrics demonstrate a model that is proficient in accurately identifying different types of arrhythmias. Incorporating the FFRD-APO technique significantly enhances the model's performance. This improvement is evident in all metrics, with accuracy rising to 0.92 and the F1 score reaching 0.90. This demonstrates the importance of selecting the most effective features for the model, which greatly enhances its precision and recall, ultimately improving its overall performance. We observe significant enhancements with the incorporation of EEMD, leading to an increased accuracy of 0.93 and an improved F1 score of 0.91. This emphasizes the significance of utilizing advanced signal processing techniques to effectively manage intricate ECG signals and improve the model's sensitivity and specificity. The complete workflow, when utilizing FFRD-APO and EEMD together, yields exceptional results with high accuracy, precision, recall, specificity, and F1 score. The results highlight the strong connection between feature selection and signal decomposition, which greatly enhances the model's capability to accurately classify cardiac arrhythmias. This also showcases the effectiveness of the comprehensive preprocessing approach in improving diagnostic accuracy.

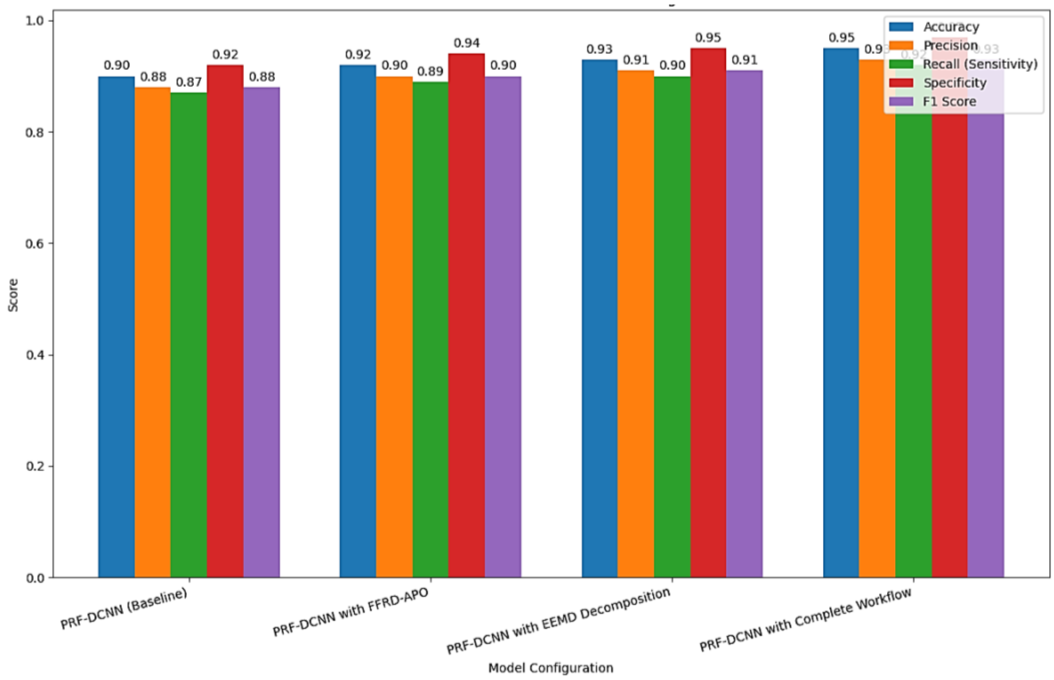

Figure 6. Performance metrics

The ROC curve metrics (Figure 7) are a useful way to compare how well different PRF-DCNN configurations can tell the difference between different types of heart arrhythmias. The baseline model showcases an impressive AUC-ROC of 0.92, highlighting its strong ability to discriminate, with a sensitivity of 0.87 and a false positive rate of 0.08. The integration of FFRD-APO significantly improves the model's performance. This results in an impressive AUC-ROC of 0.94, demonstrating enhanced sensitivity (0.89) and a notably reduced false-positive rate (0.06). Incorporating EEMD results in additional performance improvements, leading to an elevated AUC-ROC of 0.95. This configuration demonstrates a high level of accuracy in detecting arrhythmias while minimizing false alarms. With a sensitivity of 0.90 and a false-positive rate of 0.05, the model's performance is professional and reliable. The complete workflow has shown a significant improvement by integrating both FFRD-APO and EEMD. This configuration demonstrates exceptional performance, achieving an impressive AUC-ROC of 0.97. It also exhibits a high sensitivity of 0.92 and an impressively low false-positive rate of 0.03. The results highlight the power of integrating advanced feature selection and signal decomposition techniques to maximize the accuracy and reliability of the model. This makes the comprehensive PRF-DCNN workflow an extremely effective tool for automated cardiac arrhythmia classification.

The comparison as shown in Table 1 of different cardiac arrhythmia classification models shows that our suggested PRF-DCNN model has many strengths, especially when tested using the St. Petersburg INCART 12-lead arrhythmia database. Models like CNN-LSTM that are used on the MIT-BIH dataset get very good results in terms of accuracy (99.32%), sensitivity (97.50%), and specificity (98.70%). However, these results come from different datasets that might not reflect the same level of variation in the St. Petersburg INCART dataset. In the same way, distilled models that use the Chapman ECG database show impressive performance metrics (98.15% accuracy, 97.11% sensitivity, and 98.45% specificity). However, these metrics may not apply to all datasets.

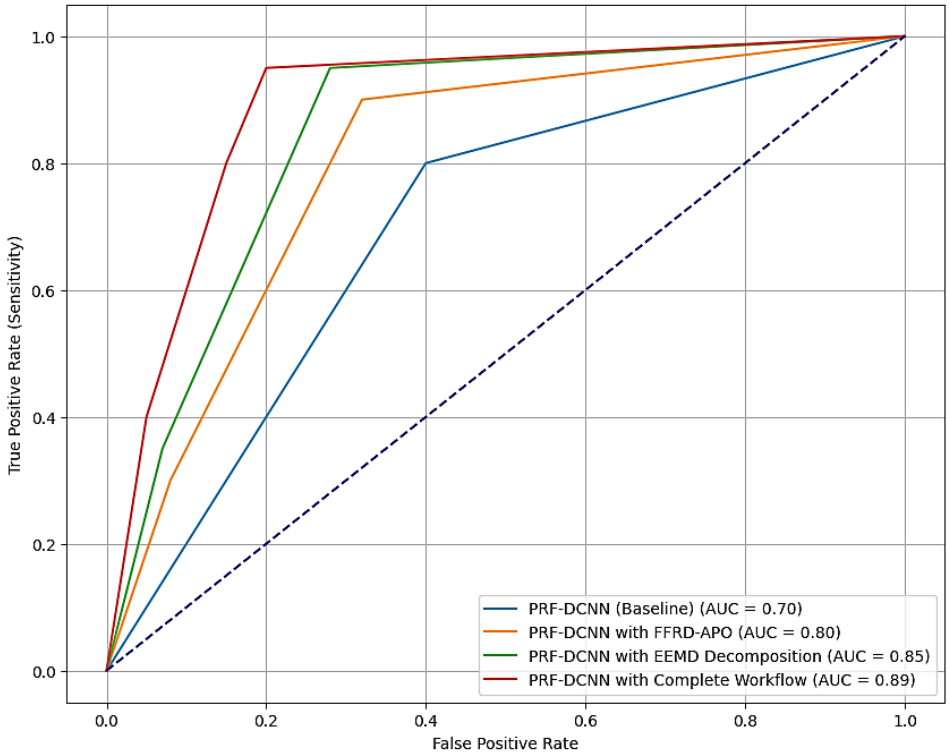

Figure 7. ROC curve metrics

Table 1. Performance comparison

Reference	Database	Classifier	Accuracy	Sensitivity	Specificity
[29]	MIT-BIH	CNN-LSTM	99.32	97.50	98.70
[30]	Chapman ECG DB	Distilled Models	98.15	97.11	98.45
[31]	MIT-BIH	Fuzz-ClustNet	98.66	98.92	93.88
Ours	St. Petersburg INCART 12	PRF-DCNN	95	92	97

The classification results obtained from the PRF-DCNN model indicate a high level of performance in accurately identifying the prominent arrhythmia classes as shown in Table 2. This is evident from the strong values observed for key evaluation metrics such as accuracy, precision, recall, and specificity. The model demonstrates exceptional accuracy rates across all classes, with the highest accuracy of 0.96 achieved for VF, thereby indicating the model's ability to make reliable predictions. The precision and recall values consistently exhibit high performance, with precision ranging from 0.91 to 0.95 and recall ranging from 0.90 to 0.94. These values reflect the model's effectiveness in accurately identifying true positive cases while minimizing the occurrence of false positives. The PRF-DCNN model demonstrates robustness and reliability in accurately classifying AF, VT, VF, PVC, and AV block. These metrics highlight the model's effectiveness as a valuable tool for clinical diagnostics and timely intervention in cardiac arrhythmia management.

Table 2. Classification results for arrhythmia classes using PRF-DCNN

Arrhythmia Class	Accuracy	Precision	Recall	Specificity
AF	0.95	0.94	0.93	0.96
VT	0.94	0.93	0.92	0.95
VF	0.96	0.95	0.94	0.97
PVC	0.93	0.92	0.91	0.94
AV	0.92	0.91	0.90	0.93

5. CONCLUSION

In this study, we proposed a novel approach for cardiac arrhythmia classification using a PRF-DCNN. By incorporating sophisticated preprocessing techniques, our model demonstrated significant improvements in accuracy and robustness compared to conventional methods. FFRD-APO is used for feature selection, and EEMD is used for signal decomposition. The PRF-DCNN model underwent a comprehensive evaluation using the St. Petersburg INCART 12-lead arrhythmia database. The experimental results demonstrate that the comprehensive workflow, which integrates FFRD-APO and EEMD, achieved the highest performance metrics. The area under the AUC-ROC was 0.97, indicating excellent discrimination ability. The accuracy of the workflow was 0.95, indicating a high proportion of correct predictions. The precision, which measures the proportion of true positive predictions among all positive predictions, was 0.93. The recall, which measures the proportion of true positive predictions among all actual positive instances, was 0.92. The specificity, which measures the proportion of true negative predictions among all actual negative instances, was 0.97. The F1 score, which combines precision and recall, was 0.93. These results highlight the effectiveness of our approach in accurately identifying and categorizing different forms of arrhythmias, despite the inherent variability in ECG signals caused by age and gender disparities. The PRF's integration effectively addresses the issue of overfitting, resulting in stable and reliable performance across various patient populations and recording conditions. The proposed model exhibits a high level of computational efficiency, which enables its practical implementation in real-time applications within clinical settings. The PRF-DCNN model provides a robust and efficient solution for automated detection of cardiac arrhythmia. Remote patient monitoring and timely intervention could potentially benefit from its application. We will dedicate future work to optimizing the model's performance, exploring additional preprocessing techniques, and validating the system in various clinical settings to enhance its adaptability and practical usefulness.

REFERENCES

[1] K.-J. Ho, "Cardiovascular diseases," *Nutritional Aspects of Aging*, CRC Press, 2018, pp.75-100, doi: 10.1201/9781351075145-3.

[2] O. Gaidai, Y. Cao, and S. Loginov, "Global cardiovascular diseases death rate prediction," *Current Problems in Cardiology*, vol. 48, no. 5, 2023, doi: 10.1016/j.cpcardiol.2023.101622.

[3] G. A. Mensah *et al.*, "Global burden of cardiovascular diseases and risks, 1990-2022," *Journal of the American College of Cardiology*, vol. 82, no. 25, pp. 2350–2473, 2023, doi: 10.1016/j.jacc.2023.11.007.

[4] L. Tang, J. Yang, Y. Wang, and R. Deng, "Recent advances in cardiovascular disease biosensors and monitoring technologies," *ACS Sensors*, vol. 8, no. 3, pp. 956–973, 2023, doi: 10.1021/acssensors.2c02311.

[5] S. M. Malakouti, "Heart disease classification based on ECG using machine learning models," *Biomedical Signal Processing and Control*, vol. 84, 2023, doi: 10.1016/j.bspc.2023.104796.

[6] J. Kingma, C. Simard, and B. Drolet, "Overview of cardiac arrhythmias and treatment strategies," *Pharmaceuticals*, vol. 16, no. 6, 2023, doi: 10.3390/ph16060844.

[7] P. Y. Lee, H. Garan, E. Y. Wan, B. E. Scully, A. Biviano, and H. Yarmohammadi, "Cardiac arrhythmias in viral infections," *Journal of Interventional Cardiac Electrophysiology*, vol. 66, no. 8, pp. 1939–1953, 2023, doi: 10.1007/s10840-023-01525-9.

[8] A. A. Ahmed, W. Ali, T. A. A. Abdullah, and S. J. Malebary, "Classifying cardiac arrhythmia from ECG signal using 1D CNN deep learning model," *Mathematics*, vol. 11, no. 3, 2023, doi: 10.3390/math11030562.

[9] 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, 2023, doi: 10.1186/s12911-023-02326-w.

[10] Y. Ansari, O. Mourad, K. Qaraqe, and E. Serpedin, "Deep learning for ECG arrhythmia detection and classification: an overview of progress for period 2017–2023," *Frontiers in Physiology*, vol. 14, 2023, doi: 10.3389/fphys.2023.1246746.

[11] Z. Ozpolat and M. Karabatak, "Performance evaluation of quantum-based machine learning algorithms for cardiac arrhythmia classification," *Diagnostics*, vol. 13, no. 6, 2023, doi: 10.3390/diagnostics13061099.

[12] Z. Li and H. Zhang, "Fusing deep metric learning with KNN for 12-lead multi-labelled ECG classification," *Biomedical Signal Processing and Control*, vol. 85, 2023, doi: 10.1016/j.bspc.2023.104849.

[13] R. Bhukya, R. Shastri, S. S. Chandurkar, S. Subudhi, D. Suganthi, and M. S. R. Sekhar, "Detection and classification of cardiac arrhythmia using artificial intelligence," *International Journal of System Assurance Engineering and Management*, 2023, doi: 10.1007/s13198-023-02035-7.

[14] S. Singhal and M. Kumar, "A systematic review on artificial intelligence-based techniques for diagnosis of cardiovascular arrhythmia diseases: challenges and opportunities," *Archives of Computational Methods in Engineering*, vol. 30, no. 2, pp. 865–888, 2023, doi: 10.1007/s11831-022-09823-7.

[15] I. Kalogridis and S. V. Aelst, "Robust penalized estimators for functional linear regression," *Journal of Multivariate Analysis*, vol. 194, 2023, doi: 10.1016/j.jmva.2022.105104.

[16] M. Y. Ansari, I. A. C. Mangalote, D. Masri, and S. P. Dakua, "Neural network-based fast liver ultrasound image segmentation," *2023 International Joint Conference on Neural Networks (IJCNN)*, Gold Coast, Australia, 2023, pp. 1-8, doi: 10.1109/IJCNN54540.2023.10191085.

[17] Z. Gao *et al.*, "Complex networks and deep learning for EEG signal analysis," *Cognitive Neurodynamics*, vol. 15, no. 3, pp. 369–388, 2021, doi: 10.1007/s11571-020-09626-1.

[18] M. Y. Ansari and M. Qaraqe, "MEFood: A large-scale representative benchmark of quotidian foods for the Middle East," *IEEE Access*, vol. 11, pp. 4589–4601, 2023, doi: 10.1109/ACCESS.2023.3234519.

[19] K. R. Chowdhary, "Natural language processing," in *Fundamentals of Artificial Intelligence*, vol. 11, no. 1, New Delhi: Springer India, 2020, pp. 603–649.

[20] V. Chandrasekar *et al.*, "Investigating the use of machine learning models to understand the drugs permeability across placenta," *IEEE Access*, vol. 11, pp. 52726–52739, 2023, doi: 10.1109/ACCESS.2023.3272987.

[21] P. Bizopoulos and D. Koutsouris, "Deep learning in cardiology," *IEEE Reviews in Biomedical Engineering*, vol. 12, pp. 168–193, 2019, doi: 10.1109/RBME.2018.2885714.

[22] S. M. P. Dinakarrao, A. Jantsch, and M. Shafique, "Computer-aided arrhythmia diagnosis with bio-signal processing: a survey of trends and techniques," *ACM Computing Surveys*, vol. 52, no. 2, 2019, doi: 10.1145/3297711.

[23] Q. Xiao *et al.*, "Deep learning-based ECG arrhythmia classification: a systematic review," *Applied Sciences*, vol. 13, no. 8, 2023, doi: 10.3390/app13084964.
[24] Y. Li, R. Qian, and K. Li, "Inter-patient arrhythmia classification with improved deep residual convolutional neural network," *Computer Methods and Programs in Biomedicine*, vol. 214, 2022, doi: 10.1016/j.cmpb.2021.106582.
[25] B. M. Mathunjwa, Y. T. Lin, C. H. Lin, M. F. Abbod, and J. S. Shieh, "ECG arrhythmia classification by using a recurrence plot and convolutional neural network," *Biomedical Signal Processing and Control*, vol. 64, 2021, doi: 10.1016/j.bspc.2020.102262.
[26] J. Rahul, M. Sora, L. D. Sharma, and V. K. Bohat, "An improved cardiac arrhythmia classification using an RR interval-based approach," *Biocybernetics and Biomedical Engineering*, vol. 41, no. 2, pp. 656–666, 2021, doi: 10.1016/j.bbe.2021.04.004.
[27] N. Sinha and A. Das, "Automatic diagnosis of cardiac arrhythmias based on three stage feature fusion and classification model using DWT," *Biomedical Signal Processing and Control*, vol. 62, 2020, doi: 10.1016/j.bspc.2020.102066.
[28] H. Zhang *et al.*, "Recurrence plot-based approach for cardiac arrhythmia classification using inception-ResNet-v2," *Frontiers in Physiology*, vol. 12, 2021, doi: 10.3389/fphys.2021.648950.
[29] C. Chen, Z. Hua, R. Zhang, G. Liu, and W. Wen, "Automated arrhythmia classification based on a combination network of CNN and LSTM," *Biomedical Signal Processing and Control*, vol. 57, 2020, doi: 10.1016/j.bspc.2019.101819.
[30] M. Sepahvand and F. Abdali-Mohammadi, "A novel method for reducing arrhythmia classification from 12-lead ECG signals to single-lead ECG with minimal loss of accuracy through teacher-student knowledge distillation," *Information Sciences*, vol. 593, pp. 64–77, 2022, doi: 10.1016/j.ins.2022.01.030.
[31] S. Kumar, A. Mallik, A. Kumar, J. D. Ser, and G. Yang, "Fuzz-ClustNet: coupled fuzzy clustering and deep neural networks for arrhythmia detection from ECG signals," *Computers in Biology and Medicine*, vol. 153, 2023, doi: 10.1016/j.compbiomed.2022.106511.

BIOGRAPHIES OF AUTHORS

Anniah Pratima obtained a B.E. degree in electronics and communication engineering from JNTUA in 2010, holds a master of technology degree in VLSI system design from Jawaharlal Technological University (JNTUH), India, 2013 and currently pursuing a Ph.D. in electronics engineering. She has 9.5 years of teaching experience. She is currently working as Assistant Professor, in Department of Electronics & Communication Engineering at REVA University, Bangalore. The research interests include artificial intelligence, VLSI, IoT, embedded systems, and communications. Also, she is active member of IEEE and IETE. She can be contacted at email: pratima.may10@gmail.com.

Dr. Gopalakrishna Kanathur obtained B.E. degree in electronics engineering from Bangalore University in 1992, M.Tech. degree in VLSI design and embedded systems from VTU, M.Phil. degree in computer science from M.S. University, Tirunelveli, Tamil Nadu in 2003 and Ph.D. in electronics engineering from Jain (Deemed-to-be University) in 2018. He has 32 years of teaching experience. He is currently working as Professor, Department of Electronics & Communication Engineering, Faculty of Engineering & Technology, Jain (Deemed-to-be University) and Deputy Controller of Examinations Jain (Deemed-to-be University). His field of interests includes advanced microprocessors, microcontrollers, embedded systems, VLSI technology, VLSI designing, and IoT. He has several publications in reputed journals. He is serving as BOS, BOE, and doctoral committee member of several private and deemed universities and reputed autonomous institutions. He is the advisory committee member for six Ph.D. He is scholars of VTU. He can be contacted at email: k.gopalakrishna@jainuniversity.ac.in.

Dr. Sarappadi Narasimha Prasad Professor in Department of Electronics and Electronics Engineering, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education (MAHE), Manipal, Karnataka, India-576104. Total experience is 22 years, completed graduation from Mangalore University, post-graduation from VTU and doctorate from Jain University. More than 80 journals/conferences in profile and presently guiding 8 research scholars. Area of interest is AI, embedded systems, and signal processing. He can be contacted at email: sn.prasad@manipal.edu.