Detection and Classification of Cardiovascular Arrhythmias from ECG Signals Using Deep Learning Algorithms (CNN1D)

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Abstract: **Recent progress in Artificial Intelligence (AI), especially in Machine Learning (ML) and Deep Learning (DL), has revolutionized medical science by introducing more precise and efficient techniques for diagnosing, predicting, and treating serious health conditions. This research emphasizes the importance of the human circulatory system, particularly the heart's role in sustaining proper blood flow. Although Electrocardiograms (ECGs) are widely used to identify heart-related disorders, traditional manual analysis is often slow and prone to inaccuracies. To overcome this limitation, we introduce an automated classification system using a one-dimensional Convolutional Neural Network (1D-CNN). The model was trained and tested on real-world ECG data from the MIT-BIH Arrhythmia Database, delivering exceptional performance with 100% training accuracy and 99% testing accuracy. These findings highlight the system's capability for fast and reliable arrhythmia detection, supported by strong precision and recall scores. Additionally, this deep learning framework holds potential for broader applications, such as integrating with other biosignals like EEG to improve cardiovascular anomaly detection and enable earlier diagnosis through multimodal analysis**

Keywords—Cardiac Arrhythmia, Electrocardiogram(ECG), Cardiac Arrhythmia, XQRS, Convolutional Neural Network (1D-CNN).

I. INTRODUCTION

Globally, cardiovascular disorders claim approximately 17.9 million lives each year, maintaining their position as the primary mortality factor worldwide [1]. A significant proportion of these fatalities are due to undetected or late-detected arrhythmias—abnormalities in the heart's rhythm that signal disruptions in electrical conduction. Early and accurate arrhythmia detection plays a pivotal role in improving clinical outcomes, reducing mortality, and optimizing treatment planning.

Electrocardiography (ECG) serves as a vital non-invasive tool for evaluating cardiac function. The characteristic ECG pattern comprises distinct waveforms—labeled P, Q, R, S, and T—that reflect the heart's electrical activity during atrial activation, ventricular contraction, and ventricular recovery phases (Figure 1). Clinicians particularly focus on the QRS complex, ST segment, and key intervals (PR, RR, QT) when identifying rhythm abnormalities. These diagnostic markers often exhibit altered morphology in arrhythmia cases, where irregular electrical impulses disrupt normal heartbeats. Accurate waveform interpretation is therefore essential for detecting conduction system pathologies and guiding therapeutic decisions.

ECG analysis employs diverse signal processing approaches: temporal characteristics can be evaluated through time-based measurements, spectral properties via frequency analysis, and dynamic features using combined time-frequency representations or fractional calculus techniques. Recent advances in artificial intelligence have demonstrated particular promise for arrhythmia detection. Ebrahimi et al. [2] systematically evaluated machine learning applications in clinical ECG interpretation, identifying convolutional neural networks (CNNs) as the predominant architecture—employed in 52% of surveyed studies from 2017-2018. Their meta-analysis of 75 publications confirmed the superior feature extraction capabilities of CNNs compared to recurrent networks (RNNs) and long short-term memory (LSTM) models in cardiac rhythm classification tasks.

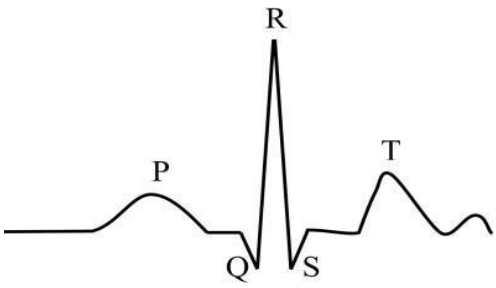

Fig.1. Typical Features of an ECG Signal

The relevance of this study lies in its strong potential to advance both the knowledge and application of deep learning (DL) techniques based on ECG signal processing, ultimately contributing to faster and more accurate cardiac care diagnosis. The deployment of artificial intelligence for early arrhythmia detection carries significant clinical importance, particularly given cardiovascular disorders' persistent status as the foremost global mortality factor. By enabling timely identification of cardiac rhythm abnormalities, AI-driven diagnostic systems can facilitate earlier medical interventions while improving diagnostic precision and creating vital opportunities for preventive cardiac care. Dhyani et al. [3] presented a hybrid approach combining the 3D Discrete Wavelet Transform and Support Vector Machine (SVM) for ECG signal classification. Using the dataset from the China Physiological Signal Challenge, their SVM-based model effectively categorized heartbeat types with high accuracy, outperforming other classifiers such as the Complex Support Vector Machine (CSVM). In another study, Alamatsaz et al. [4] suggested a lightweight deep learning model designed for the classification of eight types of arrhythmias. Their method

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incorporated data preprocessing steps such as resampling and baseline wander removal, followed by a hybrid CNN-LSTM model, achieving high classification accuracy with computational efficiency suitable for deployment in portable diagnostic systems. These and other studies underscore the growing body of literature demonstrating the effectiveness of machine learning algorithms in the automated diagnosis of cardiac arrhythmias. Among them, Convolutional Neural Networks (CNNs) have emerged as particularly effective for both feature extraction and classification tasks due to their hierarchical learning capabilities. Specifically, 1D-CNNs are exceptionally well-suited for ECG signal classification tasks, especially in real-time and resource-constrained environments. Their ability to capture temporal dependencies in sequential data, combined with low computational overhead, makes them ideal for integration in embedded healthcare monitoring systems [5].

This study focuses on the development and evaluation of a 1D-CNN model for ECG signals classification and arrhythmias detection. Initially, morphological features of ECG waveforms from the MIT-BIH Arrhythmia Database were analyzed. The model was developed in Python, beginning with binary classification to distinguish normal from abnormal ECG patterns. The system was subsequently adapted for multiclass classification, enabling differentiation between various cardiac rhythms: standard sinus rhythm, both right and left bundle branch block patterns, along with premature contractions originating from ventricular (PVC) and atrial (PAC) foci. The implementation relied on popular DL libraries such as TensorFlow, Keras, Scikit-learn, Pandas, and NumPy.

A distinctive aspect of this study involves its cyclical optimization approach, incorporating clinician input at each stage to enhance both the model's transparency and practical utility in medical settings. This participatory development process significantly enhanced the model's robustness and highlighted its practical utility in real-world healthcare scenarios. Moreover, similar advancements are being made in the analysis of electroencephalography (EEG) signals, which share many characteristics with ECG as both are time-series biomedical signals [6,7]. Deep learning models such as CNNs and LSTMs have also been successfully applied to EEG data for the diagnosis of neurological and cardiovascular anomalies, including arrhythmia-related conditions influenced by brain-heart interactions [8,9]. The integration of ECG and EEG modalities, often referred to as multimodal learning, offers promising opportunities for improving early diagnosis and providing a more holistic understanding of complex physiological states.

The paper is organized as follows: Section2 present a 1D-CNN model is developed to classify four types of cardiac arrhythmias using preprocessed ECG Lead II signals from the MIT-BIH data base. Section3 details Balanced CNN-Based Multiclass ECG Arrhythmia Classification. Section 4 presents the findings of the proposed approach and provides an in-depth discussion of the results. Finally, Section 5 concludes the paper, outlining key take a ways and suggesting potential avenues for future research.

I. CARDIAC ARRYTHMIA CLASSIFICATION APP|ROACH

Our developed 1D convolutional neural network architecture follows a four-phase workflow: (1) acquisition of ECG signals, (2) preprocessing and feature extraction, (3) network training, and (4) comprehensive assessment. This framework specifically targets the automated classification of various cardiac rhythm abnormalities, with the complete methodological pipeline illustrated in Figure 2.

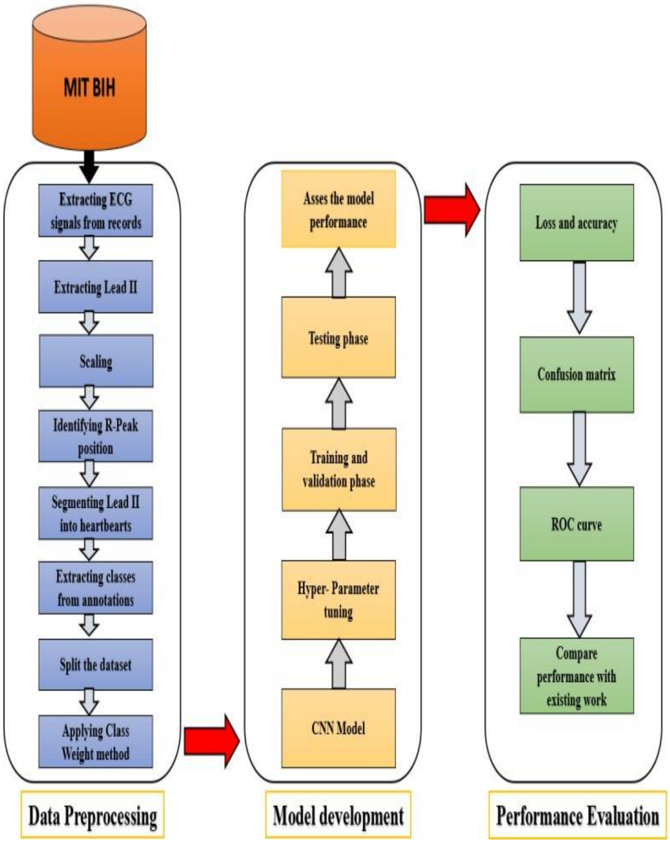

Fig.2. The global architecture of the classification of ECG arrhythmias.

In this work, we use raw ECG signals with noise attenuation from the MIT-BIH database [10] as the basis for classifying four types of arrhythmias, following the EC57 standard set by the AAMI. The dataset includes 48 ECG recordings, each 30 minutes long, containing two signal types: Lead II and V5. For this study, we extracted, scaled, and segmented the Lead II signals into four arrhythmia categories to train and evaluate our 1D-CNN model. We propose a simple yet effective method for heartbeat extraction from the MIT-BIH database.
This method involves several key steps:

- Extracting and Transforming ECG Lead II signals into NumPy arrays from patient records
- Standardizing the extracted signals to maintain consistent mean and standard deviation for precise arrhythmia classification.
- Using the WFDB library's XQRS to identify the R-peak position and segment the heartbeats.
- Using the R-peak point as the center of each window to segment the data into 180-feature heartbeats.
- Identifying each heart beat class based on the annotations provided by cardiologists in the dataset.

Figure 3 illustrates the steps involved in extracting heartbeats from Lead II ECG signals.

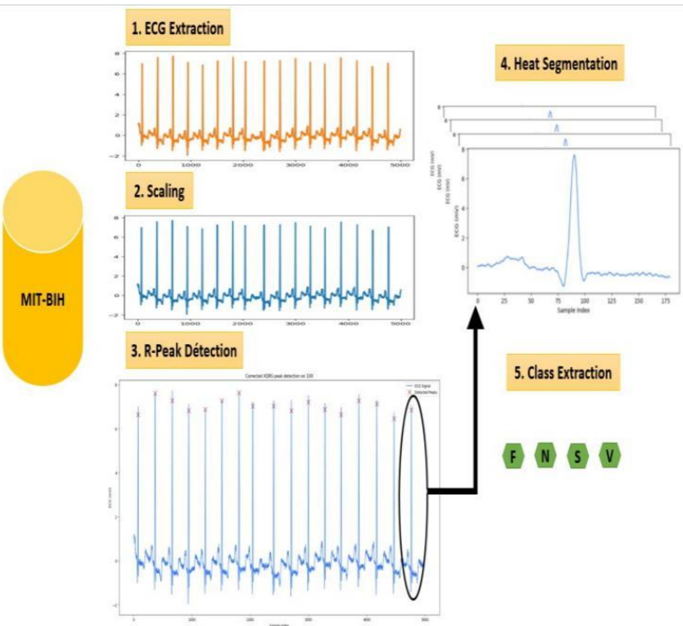

Fig 3. Pipeline for heartbeat extraction from ECG signals.

This study introduces a streamlined 1D convolutional neural network specifically developed for ECG-based arrhythmia detection. The architecture employs an efficient design with carefully tuned hyperparameters to achieve optimal classification accuracy. A principal strength of 1D CNNs lies in their capacity to capture consistent temporal patterns across signals, ensuring reliable performance despite noise or variability. These networks excel at identifying localized waveform characteristics crucial for interpreting complex cardiac rhythms. Their position-independent pattern recognition further enhances diagnostic capability by detecting abnormalities at any point in the ECG sequence. Collectively, these attributes establish 1D CNNs as a powerful solution for precise cardiac rhythm classification.

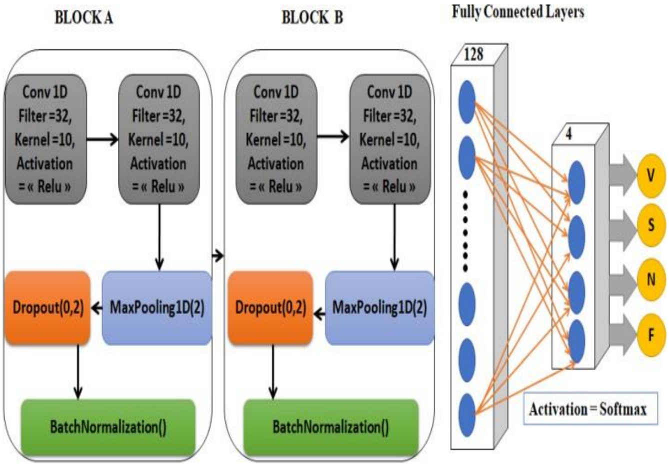

Fig 4. Architecture of our 1D-CNN

The proposed framework implements a 1D convolutional network structured into two sequential modules (A and B). Every module contains:

- Dual 1D-convolutional operations (32 filters, kernel=10, ReLU activation)
- A feature-condensing max-pooling operation (size=2)
- Regularization components (dropout=0.2, batch norm)

This configuration efficiently captures temporal patterns while preventing model over-specialization through its normalization and randomization safeguards.

The network architecture incorporates a dense layer (128 units) followed by a 4-class softmax classification layer. Class probabilities are generated via softmax activation, with model optimization performed using the Adam algorithm and accuracy as the primary metric. Hyperparameters were fine-tuned through experimental validation to achieve peak performance. This configuration boosts the model's representational capacity, speeds up convergence through dimensionality reduction, and enhances training generalization.

II. ECG Classification with CNN

The dataset was employed for both binary and multi-class categorization tasks, implemented in Python with CNN architectures. Each signal contains expert annotations labeling heartbeat types, ranging from normal sinus rhythm to pathological variants like atrial fibrillation. This arrhythmia manifests through missing P waves and irregular R-R intervals in the PQRST complex. Figure 5 illustrates the distinct morphological patterns characterizing each ECG class.

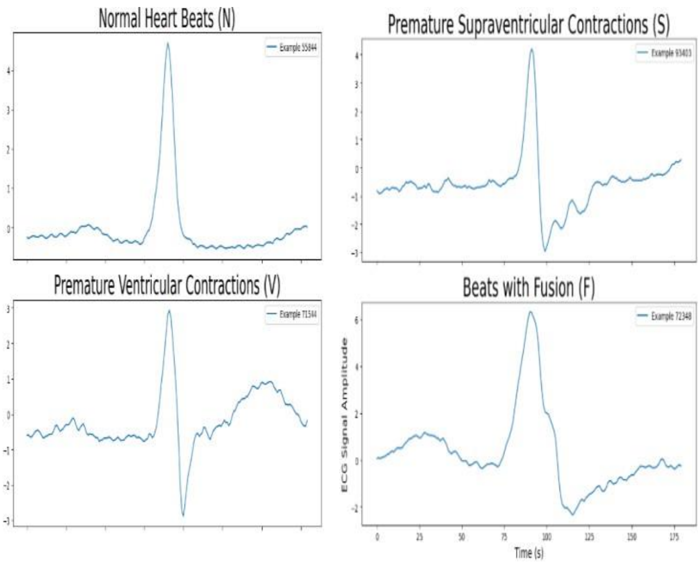

Fig 5. ECG waveforms for various types of arrhythmias.

Following heartbeat segmentation, the processed dataset contained 99,774 cardiac cycles extracted from 48 ECG recordings, distributed across categories as follows: 89,694 normal (N), 6,487 ventricular ectopic, 2,814 supraventricular ectopic, 779 fusion, and 24 unclassified beats. The limited quantity of unclassified beats reflects their natural rarity in clinical recordings.

The dataset was partitioned with 75% (74,830 beats) designated for model development (training/validation) and 25% for final evaluation. To maintain proportional class representation, we applied stratified sampling during this split. The development set was further divided using an 80:20 ratio for training versus validation subsets.

Addressing class imbalance was crucial to prevent predictive bias toward prevalent categories. Our solution incorporated class-weighted learning, which modifies the loss function to increase penalty for errors in minority classes (ventricular ectopic, supraventricular ectopic, fusion). This compensation mechanism enhances detection sensitivity for less frequent arrhythmia patterns while preserving overall classification performance.

A. Performance Matrices

The model's performance was evaluated using the confusion matrix and the AUC-ROC curve, common metrics for evaluating machine learning models [11,12]. These metrics are explained below:

- **Accuracy**: the frequency with which the model is correct.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

- **Precision**: The proportion of correctly predicted positive instances among all instances predicted as positive, relative to all positive instances across all classes.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

- **Recall**: The ratio of correctly predicted positive instances to all actual positive instances in the dataset.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

- **F1-score** represents the harmonic average between precision and recall, serving as a comprehensive performance measure that equally weights both false positives and false negatives in classification tasks.

$$\text{F1\_Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

- **The Area Under the Curve** (AUC) evaluates the balance between true positives and false positives, as illustrated by the ROC curve. The x-axis represents the false positive rate, while the y-axis represents the true positive rate. Higher AUC values indicate better performance in distinguishing between classes.

$$\text{Precision} = \frac{1}{2}\left(\frac{\text{TP}}{\text{TP+FN}} + \frac{\text{TN}}{\text{TN+FP}}\right) \quad (5)$$

B. Performance of the Proposed Method

The first stage of the experiments involved partitioning the dataset, with 75% allocated for training and validation, and the remaining 25% reserved for testing. The model was trained for 60 epochs using a batch size of 512 per epoch. Figure 6 presents the accuracy and loss curves over the training process. In the 1D-CNN [13], the loss function measures the difference between predicted and actual outcomes, quantifying how much the estimated value deviates from the true value [14]. For this multi-class classification task, the sparse categorical cross-entropy loss function was used. This function computes the logarithm of the predicted probability corresponding to the ground truth index, resulting in a single-instance loss calculation without summation, which contributes to improved performance.

The equation is given by:

$$J(w) = -\log(y_y) \quad (6)$$

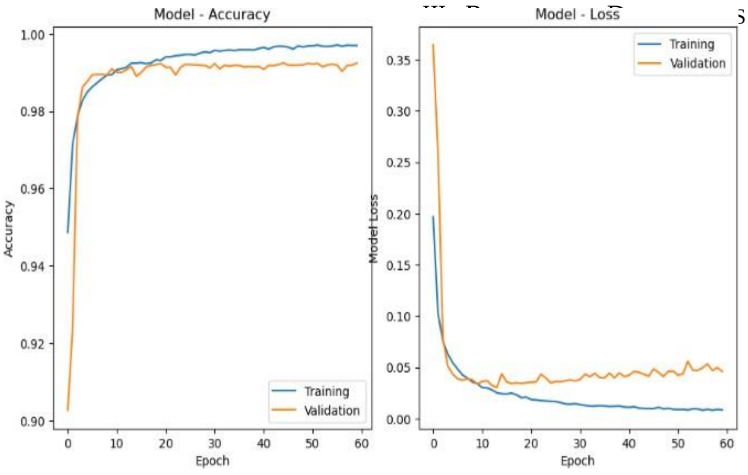

Fig 6.Accuracy and loss

Table 2 presents the model's performance metrics, with all numerical values rounded to two decimal places. The "Average" column in the table shows the mean of all classes for each metric, regardless of their proportions in the dataset. On the training dataset, the model achieves an average recall of 0.98, precision of 1.00, and F1-score of 0.99. Classes N, S, and V attain perfect scores of 1.00 across all metrics, while class F records lower values, with a precision of 0.99, F1-score of 0.95, and recall of 0.91.

TABLE1.CLASSIFICATION MODEL PERFORMANCE PARAMETERS (TRAINING DATA SET)

Class	Precision	Recall	F1-Score	Loss	Accuracy
N	1.00	1.00	1.00	0.003	1.00(0.999)
S	1.00	1.00	1.00		
V	1.00	1.00	1.00		
F	0.99	0.91	0.95		
Average	**1.00**	**0.98**	**0.99**		

TABLE2.CLASSIFICATION MODEL PERFORMANCE PARAMETERS (TESTING DATA SET)

Class	Precision	Recall	F1-Score	Loss	Accuracy
N	1.00	1.00	1.00	0.04	0.99
S	0.94	0.88	0.91		
V	0.98	0.98	0.98		
F	0.91	0.80	0.85		
Average	**0.96**	**0.91**	**0.93**		

From the detailed evaluation in Tables [1] and [2], it is evident that the model achieved high precision, F1-score, and recall across all classes, demonstrating effective identification of various arrhythmias. These results highlight the model‘s efficacy in handling multi-class classification and underscore its potential for real-world applications in computer-aided arrhythmia diagnosis.

Figure 7 shows the counts of accurately and inaccurately classified samples .

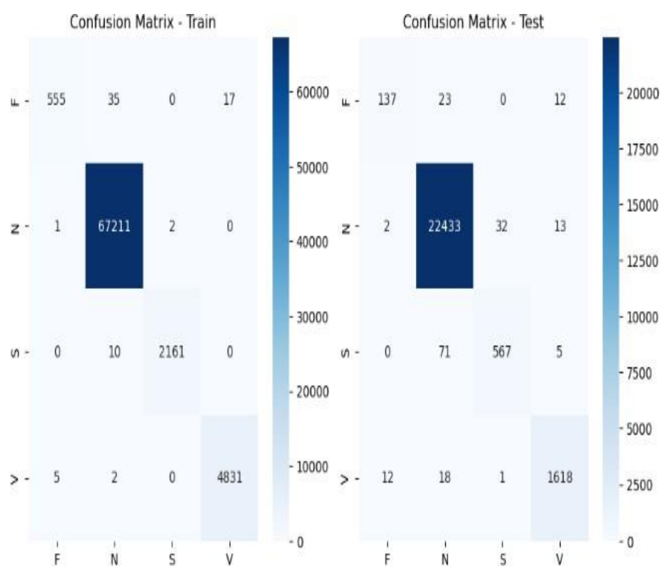

Fig 7.Confusion Matrix.

In the testing dataset, there was a slight decrease of 0.04, 0.07, and 0.06 percentage points in average precision, F1-score, and recall across all classes compared to the training dataset. The overall precision, F1-score, and recall were 0.96, 0.93, and 0.91, respectively. Class N remained the top performer, achieving perfect scores in all evaluation metrics. In contrast, Class V exhibited a minor decline of 0.02 percentage points in precision, F1-score, and recall. Class S showed a more noticeable decrease, with drops of 0.06 in precision, 0.12 in recall, and 0.09 in F1-score.

Despite the use of class weights to adjust the model's cost function, Class F remained the lowest performing class, scoring 0.91 across all metrics—representing a 0.09 percentage point decrease. The reduced performance for Class F is likely due to its limited sample size, with only 555 and 137 instances in the training and testing datasets, respectively, of which 52 and 35 were misclassified.

The AUC metric evaluates the model's ability to distinguish between classes by balancing true positive and false positive rates, as illustrated by the ROC curve. Figure 8 displays the ROC curves, showing near-perfect scores for all classes in the testing set, except for Class S, which achieved a score of 0.99.

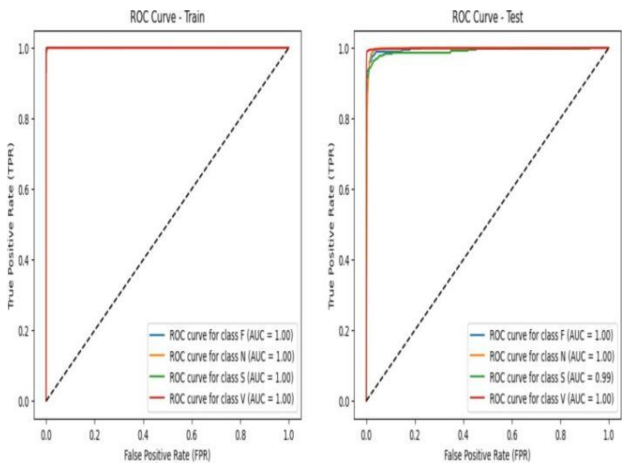

Fig 8.ROC Curve(Train, Test).

C. Comparison of the proposed method with prior studies.

Further comparison with existing literature demonstrates the superiority of our proposed network over traditional and deep learning models in effectively distinguishing between various classes. Additionally, the experiments outlined in this paper achieved remarkable accuracy compared to previous studies, with rates of 1.00 and 0.99 for the training and testing datasets, respectively.

TABLE3.Comparative Analysis of the Proposed Method with Prior Research

Authors	Classifier	Classes	Accuracy	Recall
[15]	(SVM)	4	0.93	0.47
[16]	(CNN-LSTM)	4	0.96	0.69
[17]	(CNN-BiLSTM)	5	0.96	0.96
[18]	(1D-CNN)	12	0.95	0.77
Our work	**1D-CNN**	**4**	**0.99**	**0.91**

The proposed method, based on a 1D-CNN architecture, achieved an impressive accuracy of 0.99, surpassing all other referenced approaches. It also attained a recall of 0.91, which is notably higher than that of most existing methods. In particular, when compared to the best-performing model by Essa et al. [16], which employed a CNN-LSTM architecture, the proposed method demonstrated superior accuracy and recall. Furthermore, it achieved a high specificity of 0.99, reflecting its strong ability to correctly identify negative cases. These results underscore the method's effectiveness and represent a meaningful advancement in the field, outperforming prior studies in both accuracy and recall.

IV.CONCLUSIONS

Classifying cardiac arrhythmias is essential for diagnosing and managing cardiovascular diseases. This study presents a 1D-CNN model comprising two convolutional blocks, specifically designed to detect arrhythmias from Lead II ECG signals. The model achieves high accuracy in identifying four arrhythmia types, demonstrating its potential as a dependable diagnostic tool and support for reducing clinicians' workload. Despite strong results, the model faces limitations. A primary concern is the class imbalance in the MIT-BIH database used for training and testing, which may affect generalization. While a class-weighting strategy was employed to counter this, its effectiveness remains a consideration.

The variability of arrhythmias across different patients underscores the need for more extensive and diverse datasets to improve the model's adaptability and performance on unseen cases. To address this, future work will focus on enhancing the model's generalization to broader populations. Ongoing research will also explore implementing the model on FPGA-based platforms, such as the Pynq-Z2 and Zynq Z-7020 boards, to evaluate its real-time performance. Additionally, efforts will be made to integrate the model into portable or wearable devices for continuous arrhythmia monitoring. To overcome data scarcity, the exploration of data augmentation techniques or GAN-based [19] synthetic ECG generation will be pursued. Moreover, hybrid architectures such as CNN-LSTM or transformers will be investigated to improve the model's temporal feature extraction capabilities, further boosting its overall effectiveness.

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