J. Electrical Systems 20-1 (2024):511-524

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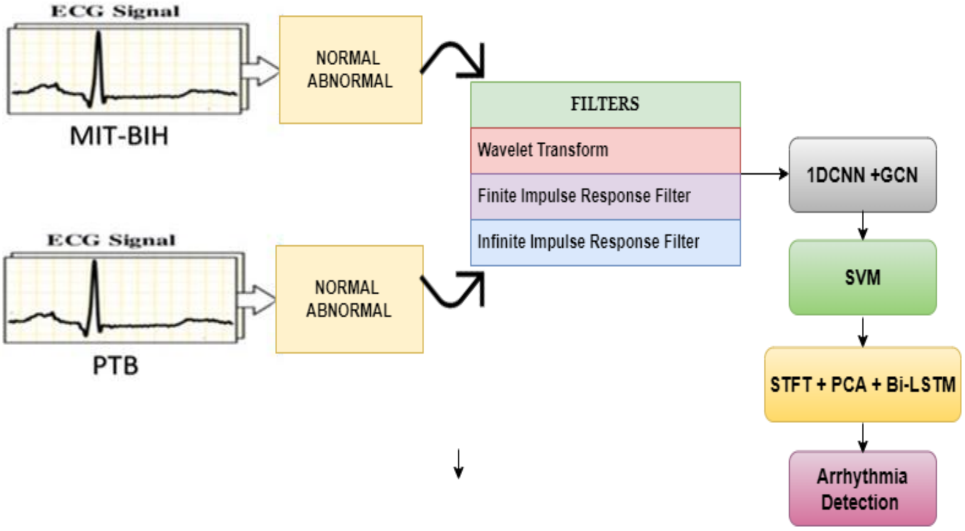
Enhanced Arrhythmia Detection Using Filtered Data, CNN, Graph Convolutional Networks, and SVM on MIT-BIH and PTB Databases

Journal of Electrical Systems

Abstract: - Arrhythmia classification and detection are essential for the early diagnosis of heart diseases, but accurately identifying arrhythmias is challenging due to the inherent noise in electrocardiogram (ECG) data. This study presents a novel method for arrhythmia detection that follows a systematic approach. First, ECG data from the MIT-BIH Arrhythmia Database and the PTB Diagnostic Database are preprocessed using three distinct filters: wavelet transform (WT), finite impulse response (FIR), and an innovative infinite impulse response (IIR) filter to remove noise. The filtered data are then processed through a one-dimensional convolutional neural network (1D-CNN) and graph convolutional networks (GCNs) for feature extraction. These features are initially classified using a support vector machine (SVM) into normal and abnormal categories. For further detection, the classified data undergo additional processing through Short-Time Fourier Transform (STFT) for time-frequency analysis, followed by Principal Component Analysis (PCA) for dimensionality reduction. Finally, a Bidirectional Long Short-Term Memory (BiLSTM) network is employed to detect specific arrhythmias within the classified signals. The proposed method is evaluated using the MIT-BIH and PTB datasets, demonstrating that the combination of STFT, PCA, and BiLSTM significantly enhances the detection of specific arrhythmias. The inclusion of GCNs and the innovative IIR filter further improves classification accuracy. This approach's effectiveness is validated through comparisons with existing arrhythmia identification methods, highlighting its advancements in both classification and detailed arrhythmia detection.

Keywords: ECG, Arrhythmia, 1DCNN, GCN, SVM, WT, FIR Filter, IIR Filter, STFT, Bi-LSTM



GRAPHICAL ABSTRACT FOR ARRHYTHMIA DETECTIO

INTRODUCTION

The word ”arrhythmia,” derived from the Greek ”a-” (without) and ”rhythmos” (rhythm) [1], refers to irregular heartbeats, which can lead to significant health problems. While some arrhythmias are harmless, chronic or serious ones require medical attention to prevent issues like fainting or stroke. The heart’s rhythm is controlled by

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an electrical system, and problems in this system can impair the heart's ability to pump blood efficiently [2]. This can lead to symptoms such as palpitations, lightheadedness, and difficulty breathing. Un-derstanding the types, causes, and treatments of arrhythmias is crucial for effective management [3]. Treatment varies based on age, health, and lifestyle, aiming for personalized care to achieve the best results [4]. The PQRST waves of an ECG help explain arrhythmias [5]. The P wave indicates atrial depolarization, which is irregular in atrial fibrillation; the QRS complex represents ventricular depolarization, which widens in ventricular tachycardia; and the T wave, indicating cardiac repolarization, is distorted in situations such as prolonged QT syndrome. Analyzing these waveforms is essential for identifying arrhythmias, determining their severity, and developing specialized treatment plans. Figure 1 shows the typical waveform of a PQRST complex in ECG signals.

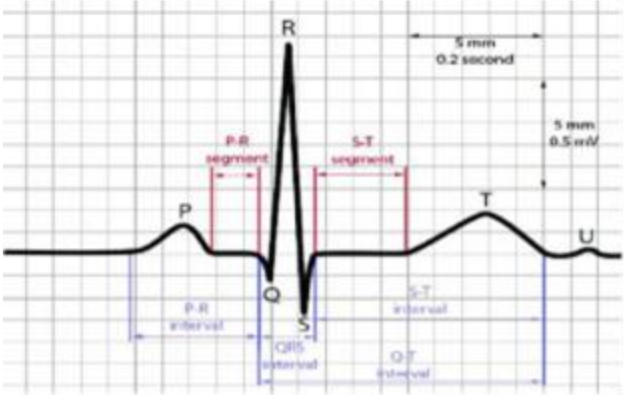


Figure 1. The typical shape of a PQRST complex in ECG data

ECG data processing is challenging due to noises such as muscular activity, motion artifacts, and electrical interference ([6]). These distortions hamper effective arrhythmia detection and need complex signal processing methods to reduce noise and enhance data quality. Integrating machine learning (ML) and deep learning (DL) methods into this process has enormous promise. These technologies have the potential to transform the area of arrhythmia detection by giving clinicians more accurate diagnostic tools, possibilities for early intervention, and individualized treatment regimens that may greatly improve patient outcomes.

Several studies have used machine learning (ML) and deep learning (DL) approaches to develop en-hanced automated algorithms to detect arrhythmias. Ali Isin et al. (citem7) used AlexNet to achieve 98.51% identification rates and 92% testing accuracy. Mohamed Hammad et al. [8] developed a DNN technique with genetic algorithm tweaking, which improved the F1 score by 0.953% and average accuracy by 0.94%. Mo-hamed Sraitih et al. [9] created an automated classification approach utilizing SVM, KNN, and RF models that achieved 83% accuracy. Jia Rong et al. [10] created IoT-based frameworks for finding arrhythmias. They used the MCHCNN and DHCAF systems to improve their work's accuracy. Varun Gupta and Monika Mittal [11] employed chaos theory and STFT to identify R-peaks, which is critical for correct arrhythmia categorization. Ruxin Wang et al. (citem12) created DMSFNet to find multi-class arrhythmias. It got F1 scores of 82.8% on the CPSC-2018 dataset and 84.1% on the CinC-2017 dataset. Amin Ullah et al. [13] achieved excellent classi-fication accuracy by employing CNN models and image conversion. Jing Zhang et al. [14] used STA-CRNN to extract spatial and temporal arrhythmia features, resulting in an average F1 score of 0.835. Paweł Pławiak et al. [15] created DGEC for quick ECG classification, achieving high sensitivity (94.62%), accuracy (90.37%), and specificity (96.66%). Mehmet Baygin et al. (citem16) achieved 92.95% and 97.18% classification accu-racy by combining manually produced features with deep learning. Sadman Sakib et al. (citem17) used FL architectures to classify arrhythmias in a way that protected privacy.

A. *Outline of the Problem*

Arrhythmias, abnormal heart rhythms, are critical indicators of various cardiac diseases, and their timely detection is essential for preventing severe cardiac events. However, accurately classifying and detecting arrhythmias from electrocardiogram (ECG) signals is challenging due to the presence of various types of noise, which can significantly affect the analysis and interpretation of the signals.

B. Major Contributors and Their Findings

- Phuphanin et al. [18] (2024): Implemented wavelet transform for noise reduction in ECG signals, demon-strating its effectiveness in enhancing signal clarity.

- Saha et al. [19] (2024): Utilized finite impulse response (FIR) filters, achieving significant noise reduction but encountering limitations in certain noise environments.

- Ait Bourkha et al. [20] (2024): Proposed a convolutional neural network (CNN) approach for feature extraction, which improved arrhythmia classification accuracy.

- Zhang et al. [21] (2024): Developed a hybrid model combining deep learning with traditional signal processing techniques for ECG feature extraction. Their study focused on the MIT-BIH dataset, highlighting enhanced diagnostic accuracy.

- Rai et al. [22] (2022): Investigated ensemble learning methods for arrhythmia detection, utilizing the PTB dataset to validate their approach’s efficacy in diverse clinical settings.

C. Statement of Unsolved Problems

Despite these advancements, current methods still face limitations:

- The existing filters do not effectively eliminate all types of noise in ECG signals.

- The integration of Graph Convolutional Networks (GCNs) in feature extraction has not been fully explored.

- There is a need for a novel filtering technique that can outperform existing filters in terms of noise reduction and arrhythmia prediction accuracy.

D. New Contributions of This Study

To address these challenges, our study introduces the following contributions:

- A novel infinite impulse response (IIR) filter designed to enhance noise reduction in ECG signals.

- The integration of a one-dimensional convolutional neural network (1DCNN) with Graph Convolutional Networks (GCNs) for improved feature extraction.

- A two-stage classification approach that utilizes Support Vector Machines (SVMs) to first classify ECG signals into normal and abnormal categories, followed by the detection and categorization of specific arrhythmias within these classified signals.

- Incorporation of Short-Time Fourier Transform (STFT) and Principal Component Analysis (PCA) for enhanced time-frequency feature extraction and dimensionality reduction, leading to more accurate and efficient arrhythmia detection.

- Application of a Bidirectional Long Short-Term Memory (BiLSTM) network to capture temporal dependencies in the ECG data, further refining the detection and classification of arrhythmias within both normal and abnormal categories.

This study provides a systematic approach to addressing the issue of cardiac arrhythmia detection. The introduction of this study provides essential background on cardiac arrhythmias, setting the context for subsequent discussions. The proposed method section outlines a novel approach to improving arrhythmia detection through advanced techniques in feature extraction, classification, and noise reduction. Following this, the results and discussion section presents findings from the study, offering comparisons with existing methods to highlight advancements and limitations. Finally, the conclusion section summarizes key findings, highlights the study's contributions to arrhythmia detection methodologies, and suggests potential implications and directions for future research.

II. METHODOLOGY

We utilized the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Dataset, starting with signal preprocessing using Wavelet Transform, Finite Impulse Response, and an innovative Infinite Impulse Response filter. After filtering, features were extracted using a combination of 1D-CNN and GCNs. For classification, a two-stage SVM approach was applied: first to categorize signals as normal or abnormal, and then to detect and classify specific arrhythmias. The classified data were further processed with STFT for time-frequency analysis and PCA for dimensionality reduction. Finally, a BiLSTM network was used for detailed arrhythmia detection. The effectiveness of this method was validated through comparative analysis on both datasets. Figure 2 illustrates the methodology in detail , with each step detailed below.

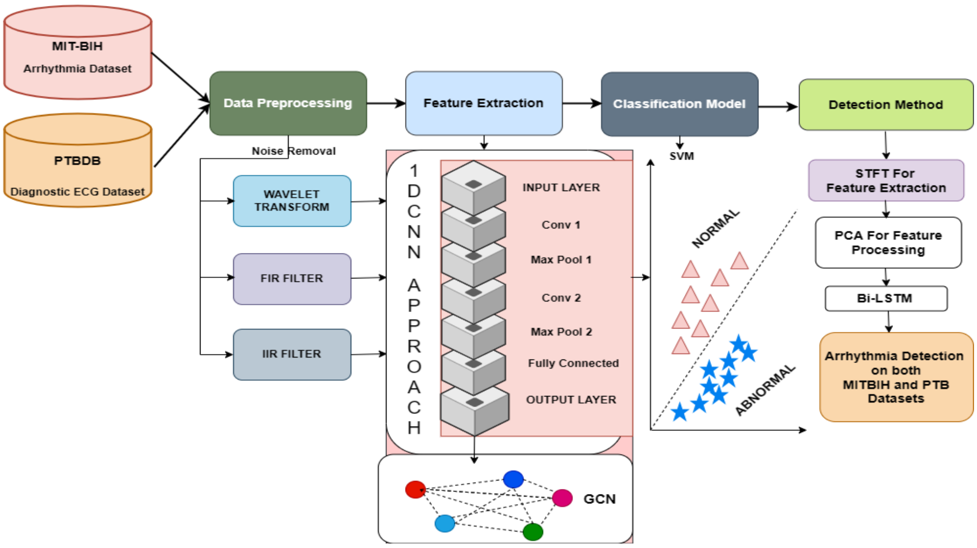


Figure 2. Architecture of the Proposed Method

A. Datasets

For our simulations, we use two well-known datasets: the MIT-BIH Arrhythmia Dataset [23] and the PTB Diagnostic ECG Dataset [24]. The MIT-BIH dataset includes ECG recordings from 47 patients over four years, available at PhysioNet. It contains 48 half-hour excerpts of two-channel ambulatory ECGs from Boston's Beth Israel Hospital, with 5 classes namely Normal Beat, Supraventricular Beat, Ventricular Contraction, Fu-sion, and Unclassifiable Beat.The first class, Normal Beat, is considered normal, while the other four classes are classified as abnormal. The PTB Diagnostic ECG Dataset, available at PhysioNet, categorizes samples into normal and abnormal classes. Information about these two datasets is presented in Table 1 and Table 2.

DB1 Classes	No. of Records	Balanced Records	DB2 Classes	No. of Records	Balanced Records
Normal (0)	10506	4046	Normal (0)	72471	15083
Abnormal (1)	4046	4046	Abnormal (0)	15083	15083

Table 1 : DB1: PTB ECG Dataset details

Table 2 : DB2 : MIT-BIH Arrhythmia Dataset details

B. *Data Preprocessing*

This study applied three noise reduction filters to preprocess ECG signals: wavelet transform [25], Finite Impulse Response (FIR) filter [26], and Infinite Impulse Response (IIR) filter [27].
Wavelet transform is used for analyzing non-stationary signals like ECG recordings x(t). It decom-poses the signal into frequency components through:

W_Tx(a, b) = ∫ _{−∞}^{∞}x(t) ·\psi_({a, b}(t)\,) dt -- (1)

where $\psi_{a,b}(t)$ is the scaled and translated wavelet function, aiding in noise removal while preserving ECG features such as QRS complexes and P waves.

Finite Impulse Response (FIR) filters process discrete-time ECG signals x[n]:

y[n] = \sum_{k = 0}^{N − 1} h[k] \cdot x[n − k] -- (2)

Where y[n]: The output signal at time nnn.

∑k=0N−1\sum_{k=0}^{N-1}∑k=0N−1: The summation from k=0k = 0k=0 to N−1N-1N−1.

The impulse response of the FIR filter. x[n−k]x[n - k]x[n−k]: The input signal at time n−kn - kn−k. These filters attenuate noise like baseline wander and powerline interference while maintaining waveform in-tegrity, crucial for real-time ECG analysis. Our proposed Infinite Impulse Response (IIR) [28] filter combines highpass and bandstop characteristics.

H(z) = \frac{Y(z)}{X(z)} = \frac{b_0 + b_1 z^{−1} + b_2 z^{−2}}{1 + a_1 z^{−1} + a_2 z^{−2}}--------- (3)

where:
\(H(l+1) \): Represents the output at layer

\(l+1 \). - \(\sigma \): Represents the activation function.

- \(D^{-\frac{1}{2}} \): Represents the degree matrix raised to the power of -1/2.

- \(A \): Represents the adjacency matrix.

- \(H(l) \): Represents the input from the previous layer \(l \).

- \(W(l) \): Represents the weight matrix at layer \(l \).

It attenuates low-frequency noise and suppresses specific frequencies around $f_{bandstop}$, enhancing ECG signal clarity for accurate arrhythmia detection.

C. *Feature Extraction*

For feature extraction, a 7-layered Inception-style convolutional neural network (ID-CNN) was uti-lized [29]. The 1DCNN architecture begins with sequential ECG voltage measurements input to the initial 1D convolutional layer (1DConv), which extracts local signal patterns. Subsequent max pooling layers down-sample and retain significant information. Another 1D convolutional layer (1DConv2) refines features for higher-level representations, followed by fully connected layers for complex relationship learning. The output layer employs sigmoid for binary or softmax for multi-class classification.

D. *SVM for Classification:*

After feature extraction with the ID-CNN, SVMs [30] were used for Classification. SVMs are a powerful supervised learning method that finds the optimal hyperplane. This process is explained in the following theorem. SVM classifies ECG signals into normal and abnormal by finding the optimal hyperplane wTx+b=0that maximizes the margin w∥2 between the two classes. The goal is to minimize classification errors while ensuring the largest possible separation between classes, using an optimization problem with regularization.

E. *STFT:*

STFT is a technique used to analyze non-stationary signals by dividing them into short overlapping segments and computing the Fourier Transform for each segment. This approach allows for the examination of how the frequency content of a signal changes over time. It is computed as $X(t,f)=\int x(\tau)w(t-\tau)e-j2\pi f\tau d\tau$, where w(t−τ)w(t - \tau)w(t−τ) is a window function. This technique helps capture how the frequency content of the signal varies over time, useful for identifying transient arrhythmias. It is depicted in Figure 3.

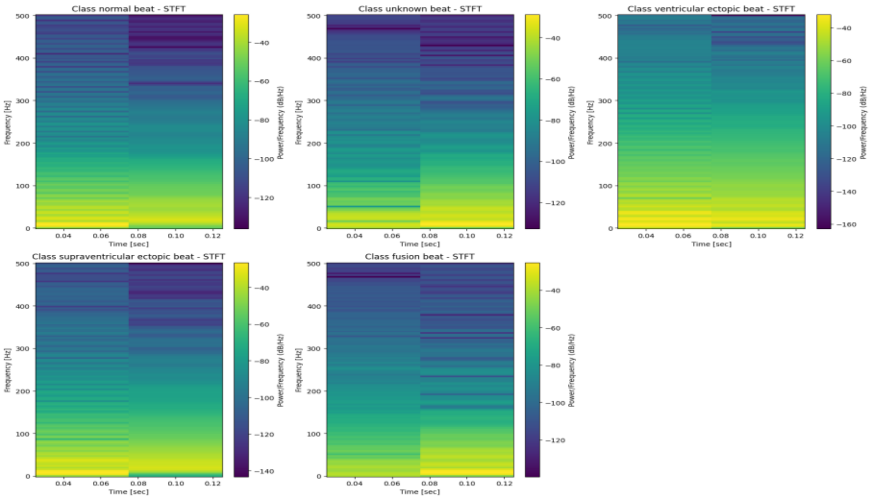


Figure 3.STFT for Feature Extraction

F. *PCA*

PCA reduces the dimensionality of ECG features while retaining the most variance. It involves calculating the covariance matrix C, and then performing eigenvalue decomposition $C=V\Lambda V^T$. The principal components V represent directions of maximum variance, simplifying the feature space and improving computational efficiency.

G. *BiLSTM:*

BiLSTM enhances arrhythmia detection by processing ECG sequences in both forward and backward directions, capturing temporal dependencies from past and future contexts. This involves passing data through LSTM cells in both directions and combining the outputs, allowing for a comprehensive understanding of sequential patterns and improving classification accuracy.

H. *Performance Metrics*

In this section, we evaluate our study's models and methodology [31] using precision, recall, F1 score, sensitivity, and specificity metrics. Accuracy is defined as the fraction of correctly predicted positive cases. Recall, or sensitivity, measures accurately predicted positive cases in the dataset. F1 score balances precision and recall. Specificity quantifies reliably predicted dataset-negative cases. These metrics are represented by the following equatios (5),(6),(7) and (8).

$$Precision = TP / (TP + FP) \text{ ---------------------------------- } (5)$$

$$Recall\ (or\ Sensitivity) = TP / (FN + TP) \text{ ------------------ } (6)$$

$$Specificity = TN / (FP + TN) \text{ --------------------------------- } (7)$$

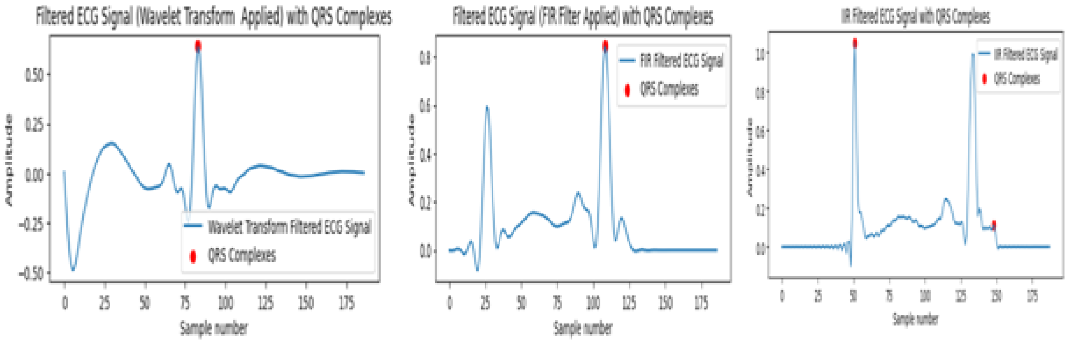
$$F1 - score = 2 * (Precision * Recall) / (Precision + Recall) \text{ ------ } (8)$$

III. RESULTS AND DISCUSSIONS

To address the significant noise in ECG data and ensure accurate arrhythmia detection, we imple-mented a comprehensive preprocessing and filtering pipeline followed by feature extraction using advanced neural network techniques. Figures 3 and 4 illustrate the effectiveness of the filtering techniques on the MIT-BIH and PTB datasets, respectively.

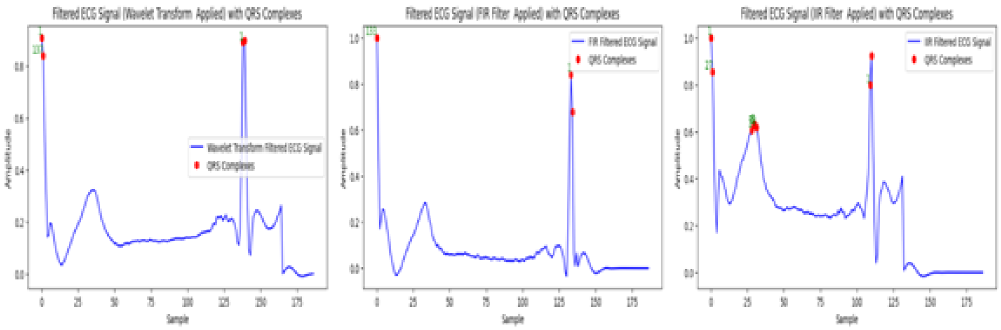
A. Data Preprocessing and Filtering

The wavelet transform (WT), FIR filter, and IIR filter were applied to the ECG signals to remove baseline wander, high-frequency noise, and other signal artifacts such as baseline drifts. As shown in Figures 4(a), 4(b), and 4(c) for the MIT-BIH dataset, the IIR filter effectively preserved the QRS complexes while eliminating noise components. Similarly, Figures 5(a), 5(b), and 5(c) for the PTB dataset demonstrate the application of the same three filters, with the IIR filter highlighting the reduction in noise and enhancement of signal quality, particularly around the QRS complexes. To address specific noise bands that the WT and FIR filter could not adequately suppress, we proposed a novel infinite impulse response (IIR) filter [28]. The effectiveness of the IIR filter is evident in both datasets, where the filtered signals show improved clarity and definition of the QRS complexes.



(a) Wavelet Transform Signal (b) FIR Filtered Signal (c) IIR Filtered Signal

Figure 4. Filtered Signals from MITBIH Dataset



(a) Wavelet Transform Signal (b) FIR Filtered Signal (c) IIR Filtered Signal

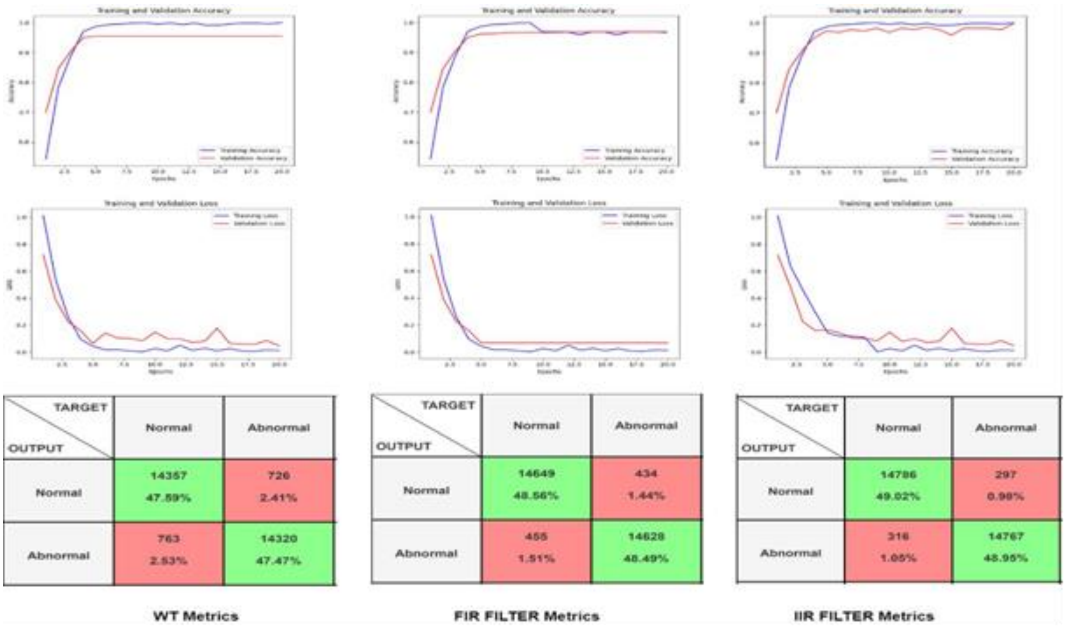
Figure 5. Filtered Signals from PTB Dataset

B. *Feature Extraction*

After filtering, feature extraction was performed using a 1D convolutional neural network (1DCNN) enhanced with graph convolutional networks (GCNs). The 1DCNN and GCNs extracted critical features like QRS complexes, P waves, and T waves, crucial for accurate arrhythmia detection and classification. This inte-gration significantly improved feature extraction, enabling more accurate identification of arrhythmic patterns.

C. *Classification Performance*

We evaluated the proposed method on the MIT-BIH and PTB datasets, studying performance metrics and prediction results with SVMs. The IIR filter dramatically improved arrhythmia prediction accuracy using ECG data. The combination of GCNs and a 1DCNN increased feature extraction, resulting in a more accurate arrhythmia diagnosis. Performance criteria such as accuracy, precision, recall, and F1-score indicated the method's ability to handle noisy ECG data. Figure 6 presents classification performance measures for the MIT-BIH dataset, whereas Figure 7 shows classification results. Figure 8 depicts performance measures, whereas Figure 9 shows classification results for the PTB dataset. In the MIT-BIH dataset, class 0 is classified as normal, whereas classes 1, 2, 3, and 4 are labeled as aberrant. In contrast, the PTB dataset comprises its own normal and pathological signals. The PTB dataset produced better results, likely due to differences in signal types that were not seen in the MIT-BIH dataset.



TARGET / OUTPUT	Normal	Abnormal
Normal	14357 47.59%	726 2.41%
Abnormal	763 2.53%	14320 47.47%

WT Metrics

TARGET / OUTPUT	Normal	Abnormal
Normal	14649 48.56%	434 1.44%
Abnormal	455 1.51%	14628 48.49%

FIR FILTER Metrics

TARGET / OUTPUT	Normal	Abnormal
Normal	14786 49.02%	297 0.98%
Abnormal	316 1.05%	14767 48.95%

IIR FILTER Metrics

Figure 6. Classification Performances of three filters with MIT-BIH dataset

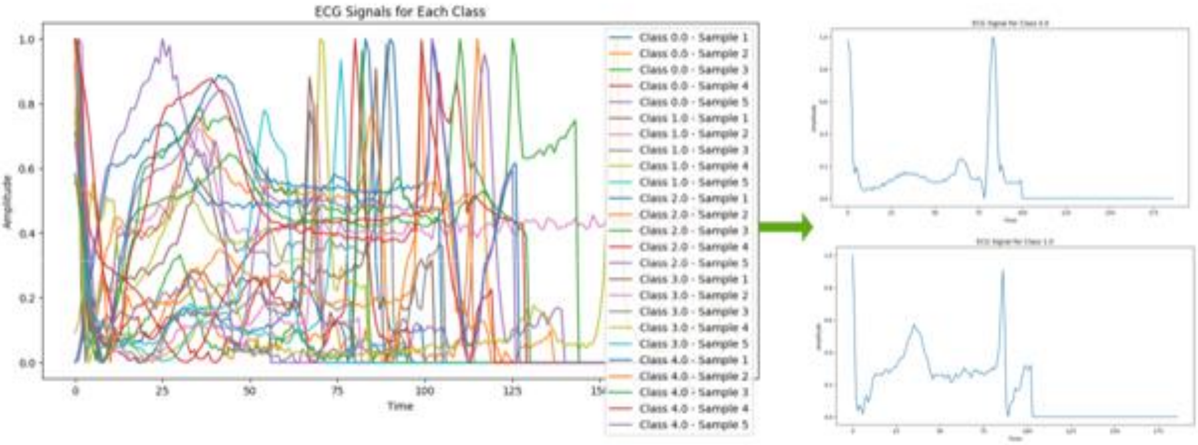
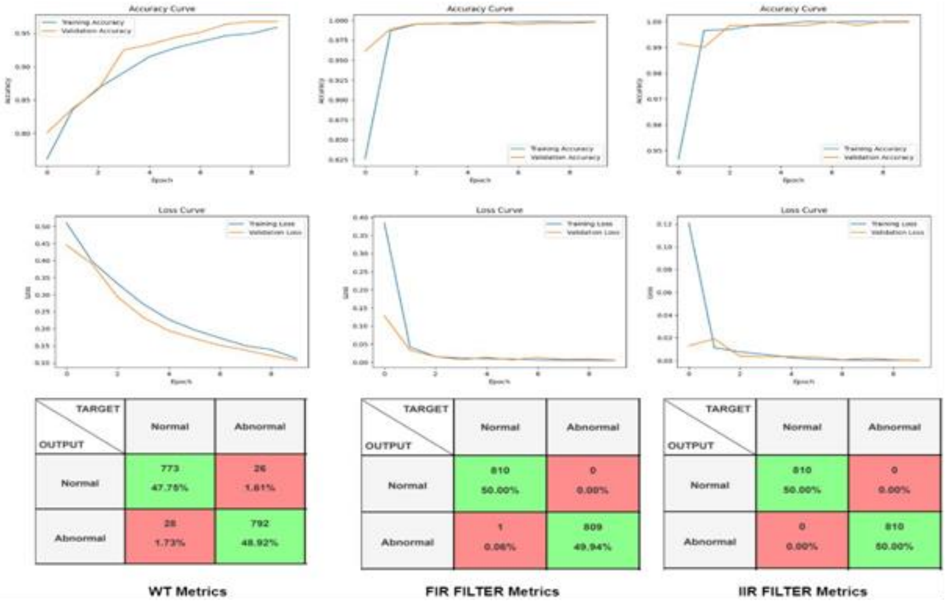


Figure 7. Classification Result from MIT-BIH dataset



TARGET / OUTPUT	Normal	Abnormal
Normal	773 47.75%	26 1.61%
Abnormal	28 1.73%	792 48.92%

WT Metrics

TARGET / OUTPUT	Normal	Abnormal
Normal	810 50.00%	0 0.00%
Abnormal	1 0.06%	809 49.94%

FIR FILTER Metrics

TARGET / OUTPUT	Normal	Abnormal
Normal	810 50.00%	0 0.00%
Abnormal	0 0.00%	810 50.00%

IIR FILTER Metrics

Figure 8. Classification Performances of three filters with PTB dataset

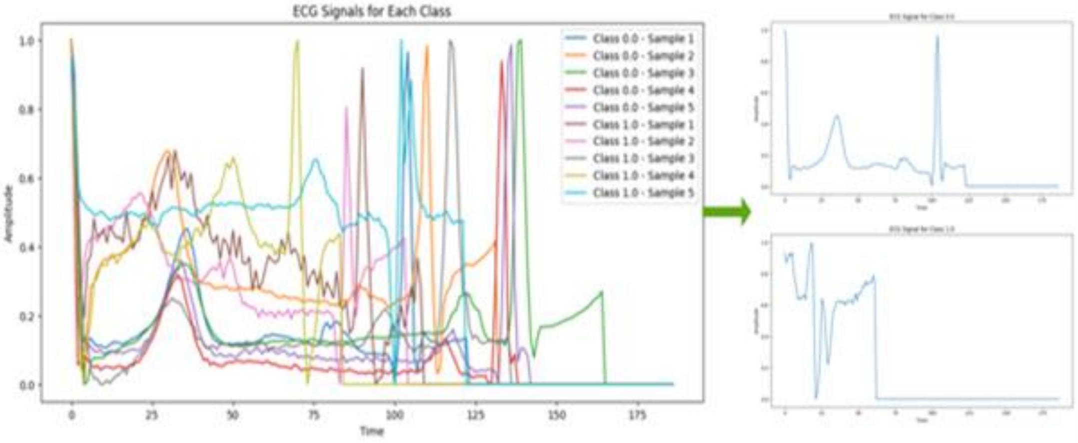
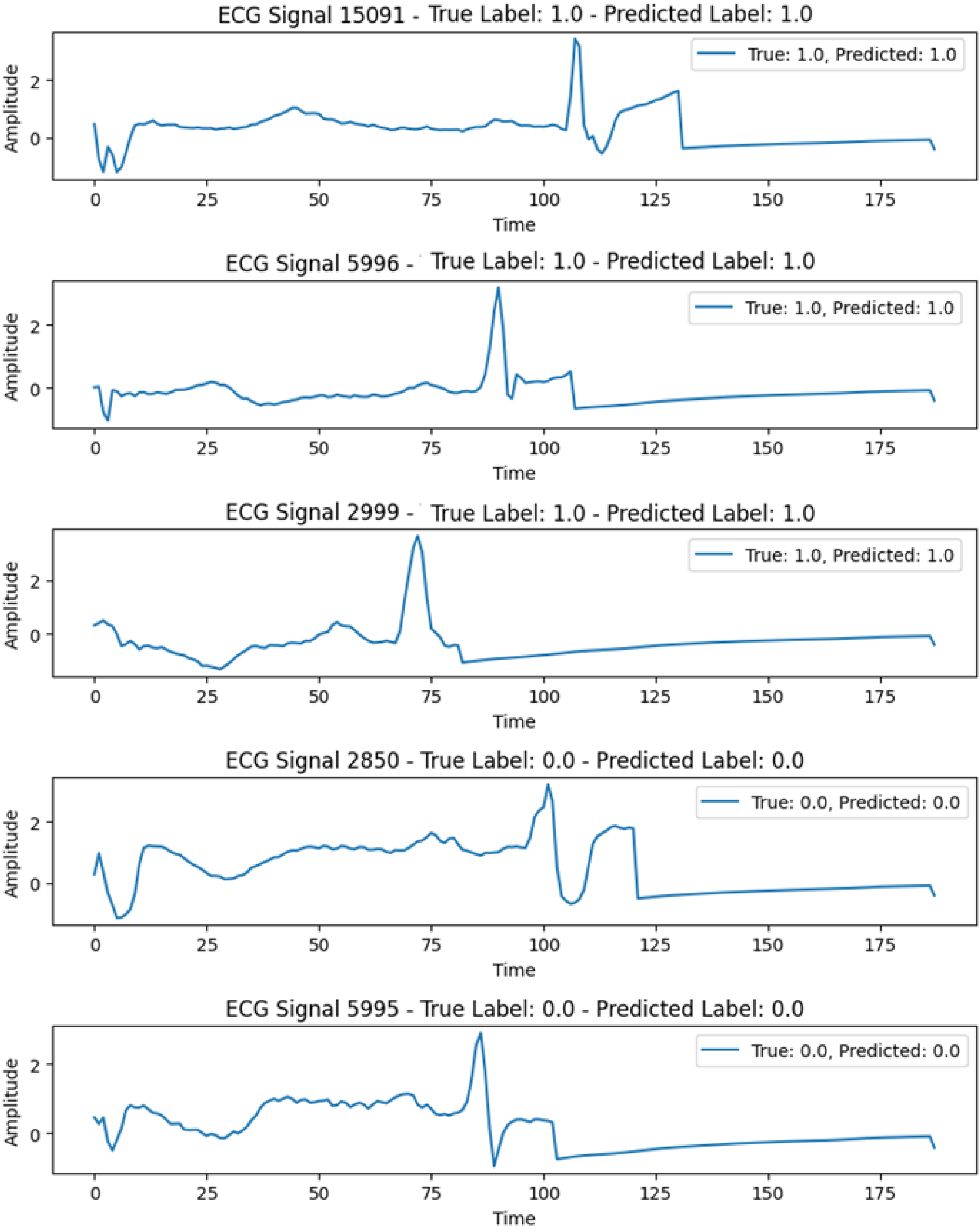


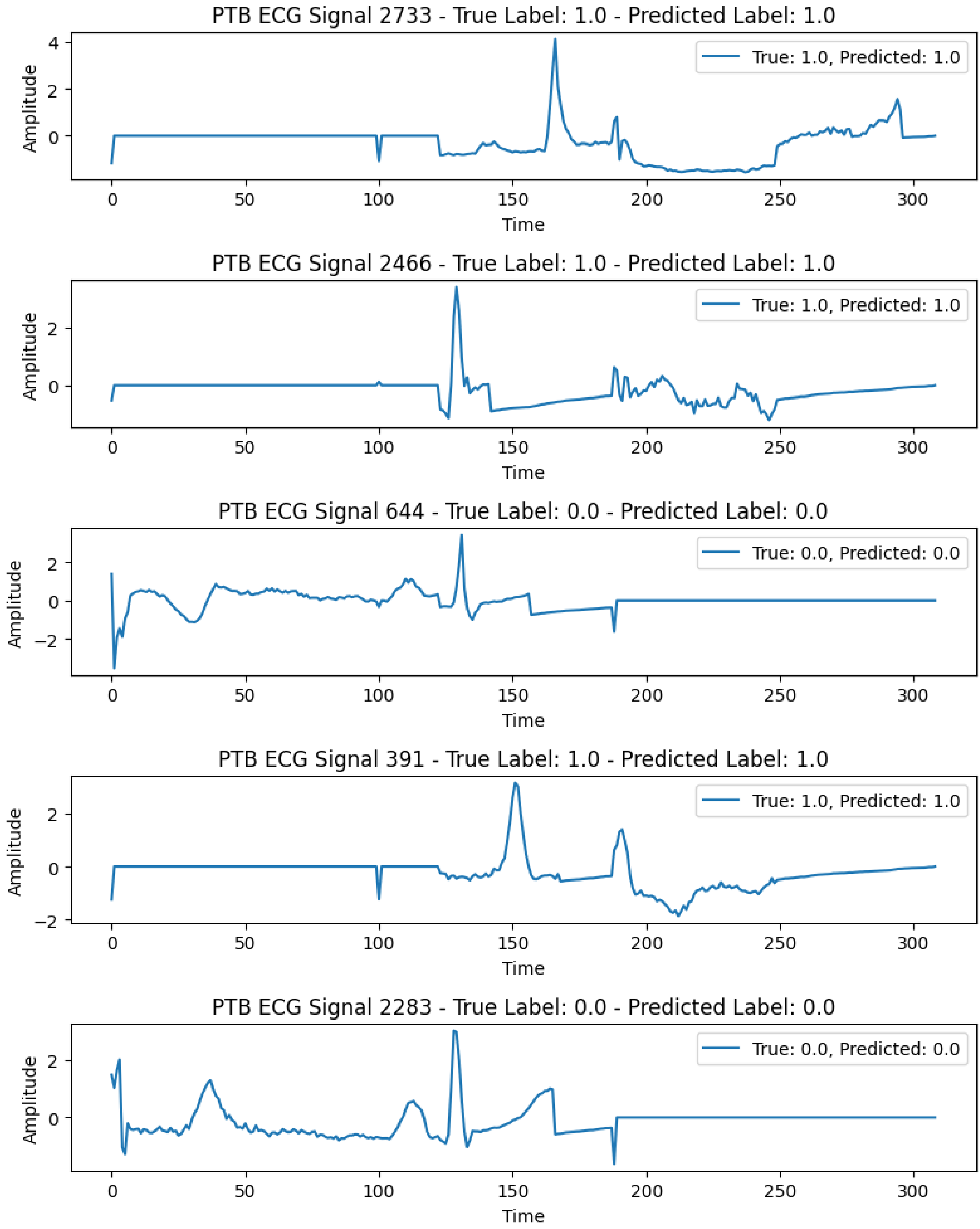
Figure 9. Classification Result from PTB dataset

D. Arrhythmia Detection

After classifying the ECG signals into normal or abnormal, we further analyze the abnormal signals using Short-Time Fourier Transform (STFT) to extract time-frequency features, computed with `frequencies, times, Zxx = stft(signal, fs=fs, nperseg=256)`. Principal Component Analysis (PCA) is then applied to reduce dimensionality, using `X_pca = pca.fit_transform(X)`. Subsequently, a Bidirectional Long Short-Term Memory (BiLSTM) network is employed to capture temporal dependencies in both forward and backward directions, which enhances the detection of complex arrhythmia patterns by processing sequences of features to identify arrhythmia types more accurately. These results are shown in Figures 10 and 11.



. **Figure 10.** Resultant Arrhythmia Detection in MITBIH DB



. **Figure 11.** Resultant Arrhythmia Detection in PTB DB

E. Comparison of Filter Performance Prediction on MIT-BIH and PTB Datasets

The performance of the proposed filtering methods combined with BiLSTM for arrhythmia detection was evaluated on the MIT-BIH and PTB datasets. Table 3 presents the metrics for the MIT-BIH dataset, and Table 4 presents the metrics for the PTB dataset. Both tables include precision, recall, specificity, and F1 score for three filters: Wavelet Transform (WT), FIR Filter, and IIR Filter. The results demonstrate that the IIR Filter consistently outperforms the other filters across all metrics.

Table 3. Performance metrics of three filters on MIT-BIH dataset

Filter	Precision	Recall	Specificity	F1 SCORE
WT	0.970	0.968	0.969	0.969
FIR FILTER	0.980	0.990	0.990	0.980
IIR FILTER	0.999	0.999	0.999	0.999

Table 4 . Performance metrics of three filters on PTB dataset

Filter	Precision	Recall	Specificity	F1 SCORE
WT	0.968	0.965	0.967	0.967
FIR FILTER	0.978	0.988	0.988	0.978
IIR FILTER	0.997	0.998	0.996	0.997

IV. COMPARISON WITH EXISTING METHODS

This section provides a comparison of arrhythmia detection methods with existing research. Wusat Ullah [32] used MIT-BIH and PTB databases to classify arrhythmia with CNN, CNN+LSTM, and CNN+LSTM+Attention models, achieving accuracies of 99.12%, 99.3%, and 99.29%, respectively. Limitations include unspecified individual dataset performance, computational cost, and real-time implementation challenges. Md. Atik Ahamed et al. [33] applied machine learning approaches on imbalanced MIT-BIH and PTB databases, using class weights in ANN, achieving 98.06% and 97.664% accuracy respectively, outperforming other state-of-the-art methods. Limitations include handling imbalanced data and computational efficiency not discussed in detail. R. Saravana Ram et al. [34] utilized MLPs, DBNs, and RBMs on MIT-BIH and PTB-ECG datasets for heart disease detection, achieving accuracies of 98.6%, 97.4%, and 96.2% (MIT-BIH) and 97.1%, 96.4%, and 95.3% (PTB-ECG), respectively. Limitations include the need for further validation on diverse datasets and the de-tailed computational cost analysis. Tanvir Mahmud et al. [35] proposed a lightweight method for arrhythmia detection on MIT-BIH and PTB databases, achieving accuracies of 97.3% and 98.9%, respectively, with high F1 scores and specificity. Limitations include the potential need for further validation on larger datasets and detailed analysis of computational efficiency. Hasnain Ali Sha et al. [36] introduced ECG-TransCovNet, a hybrid CNN-Transformer model for arrhythmia detection, achieving 98.6% accuracy on MIT-BIH and Phys-ioNet databases. Limitations include the need for further evaluation on real-world datasets and analysis of the model’s computational complexity.. Marwa Fradi et al. [37] proposed a multistage technique using R–R peak extraction and a CNN-based architecture, achieving accuracies of 99.37%, 99.15%, and 99.31% (PTB dataset) and 99.5%, 99.16%, and 99.34% (MIT-BIH dataset), with an F1-score of 0.99. Limitations include the need for further validation on diverse datasets and real-world deployment scenarios.

Table 5. Comparison of Arrhythmia Detection Methods

Ref	**Method**	**Accuracy (MIT-BIH) (%)**	**Accuracy (PTB) (%)**
[32]	CNN	99.12	99.12
	CNN + LSTM	99.3	99.3
	CNN + LSTM + Attention	99.29	99.29
[33]	ANN	98.06	97.664
[34]	MLP	98.6	97.1
	DBN	97.4	96.4
	RBM	96.2	95.3
[35]	Lightweight Method	98.9	9, 99.2
[36]	ECG-TransCovNet	98.3	98.3
[37]	Multistage Architecture	99.37	99.5
Proposed Model	IDCNN+GCN+SVM	99.9	99.7

V. CONCLUSION

This study underscores the critical role of precise arrhythmia detection in the early diagnosis and management of cardiac conditions. By employing a combination of 1D Convolutional Neural Networks (1DCNN), Graph Convolutional Networks (GCNs), and Bidirectional Long Short-Term Memory (BiLSTM) networks, our approach achieves remarkable accuracy, with 99.9% on the MIT-BIH dataset and 99.7% on the PTB dataset, surpassing existing methods. The integration of the Infinite Impulse Response (IIR) filter significantly enhances performance across all metrics, including accuracy, recall, specificity, and F1 score. This method demonstrates a notable improvement in ECG-based arrhythmia detection. Future research should focus on evaluating the feasibility and scalability of this approach for real-time clinical applications to further enhance cardiac care.

Funding Statement: “No particular funds were received by the author(s) for this investigation.”

Conflicts of Interest: “All authors stated that they were not involved in any financial conflicts that could have affected the results of this study.”

ACKNOWLEDGMENT

I would like to express my gratitude to Dr. Syed Khasim Sir for his helpful and constructive guidance during the planning and implementation of this research endeavor. We are grateful for his willingness to volunteer so much of his time. I would also like to thank Dr. Y Mohamed Sirajudeen, sir, of the HPC laboratory for assisting me in obtaining the resources required to execute the program.

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