Automated Heartbeat Classification for Arrhythmia Patients Using a Deep Convolutional Neural Network

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***Abstract*—The electrocardiogram (ECG) is widely used for diagnosing heart diseases, including arrhythmia, due to its non-invasive nature and simplicity. Accurate detection and classification of arrhythmic types are crucial in preventing heart disease and reducing mortality. To enhance ECG heartbeat classification, we propose an automated system based on a fine-tuned deep convolutional neural network consisting of 13 residual blocks with 28 layers in total. This model was trained using a dataset of 103247 single-lead ECG recordings. Our deep convolutional neural network achieved remarkable results by validating the independent test dataset from the MIT-BIH Arrhythmia Database. It demonstrated an Accuracy of 99%, a Macro avg Precision of 96%, a Macro avg Recall of 93%, a Weighted avg of 99%, and an impressive Macro avg F1-score of 94%. Notably, our approach has demonstrated superior performance to the original architecture, with a 3% increase in F1-score. These findings showcase the potential of our improved deep learning approach to effectively classify a wide range of arrhythmias from single-lead ECGs, yielding high diagnostic performance comparable to that of cardiologists.**

***Index Terms*—Convolutional Neural Network, Electrocardiogram (ECG), Arrhythmia Patient, HeartBeat Classification.**

I. Introduction

According to the World Health Organization (WHO), cardiovascular disease (CVD) is one of the leading causes of premature deaths worldwide [1]. As a result, the diagnosis and timely detection of arrhythmia [2], a common cardiac disorder, plays a critical role in the effective management and treatment of cardiovascular diseases [3]. Arrhythmia encompasses various types, ranging from benign to life-threatening conditions [4], making accurate classification essential for appropriate intervention and risk assessment [5], [6]. Electrocardiogram (ECG) signals have long been utilized for arrhythmia diagnosis due to their non-invasive nature and widespread availability [5]. However, the manual analysis of ECGs is time-consuming and subject to inter-observer variability.

Various machine learning (ML) algorithms have been employed for heartbeat classification, including decision trees [7], support vector machines (SVM) [8]–[10], random forests (RF) [11], and neural networks (ANN) [12]. Each algorithm has its strengths and limitations, and the choice depends on the specific requirements and characteristics of the dataset.

In recent years, deep learning approaches have gained significant attention across various fields [13]–[15]. Among them, the field of ECG analysis [16]–[18] offers the potential for automated and accurate arrhythmia classification. Deep neural networks have demonstrated remarkable capabilities in extracting complex features from raw ECG signals [19]–[21], enabling precise categorization of different arrhythmia types. Haotian et al [3]. implemented a system that utilizes a combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) network, incorporating multiple input layers. Zhi et al [5]. proposed a novel deep learning method for classifying cardiac arrhythmias based on the Deep Residual Network (ResNet). Awni et al [22]. developed a Deep Neural Network (DNN) using a single-lead ambulatory ECG monitoring device to classify 12 rhythm classes. Mathews et al [23]. utilized Restricted Boltzmann Machines (RBM) and Deep Belief Networks (DBN) for heartbeat classification. Jing et al [24]. proposed a deep compressive sensing scheme for ECG signals based on a modified Inception block and Long Short-Term Memory (LSTM).

Cao et al [25]. introduced a deep transfer learning framework designed to tackle classification tasks with limited training data. Their approach involves fine-tuning the ResNet-18, a general-purpose image classifier, using the MIT-BIH arrhythmia dataset [26] following the AAMI EC57 standard [27]. Additionally, the paper by Cao et al. delves into the examination of various deep learning models to assess their vulnerability to data leakage in violation of AAMI recommendations. Furthermore, the researchers conducted comparative analyses to explore the effects of different data splitting techniques on model performance. Jing et al. [28] in their article introduced an enhanced ResNet-18 model for classifying electrocardiogram (ECG) signals based on heartbeats. They achieved this improvement by conducting appropriate model training and fine-tuning the model parameters.

Xie et al. [29] proposd an efficient and effective inter-patient heartbeat classification approach featuring a dual attention mechanism. Their method involves the creation of a lightweight residual block, primarily utilizing residual and depthwise separable convolution techniques to minimize parameter count. The dual attention mechanism combines the ”Squeeze-and-Excitation” (SE) module with an innovative ”Convolutional Squeeze-and-Excitation” (Conv-SE) module.

Our study focuses on enhancing the performance of heartbeat classification by proposing an automated system for detecting and classifying arrhythmia. Our approach revolves around an improved deep convolutional neural network architecture capable of extracting discriminative features directly from ECG signals, eliminating the need for manual feature engineering. We built upon the architecture initially proposed by Awni et al [22]. as a foundation for our work. However, we have made significant improvements to align it with our specific objectives and dataset.

The proposed system utilizes an improved deep convolutional neural network architecture that comprises 13 residual blocks. Each block incorporates two 1D convolutional layers, two batch normalization (BN) layers, two rectified linear unit (ReLU) layers, and an ”identity shortcut connections” structure. Additionally, we incorporate a final fully connected softmax layer to generate a probability distribution across the five output classes. The primary goal of our system is to enhance the accuracy, efficiency, and reliability of arrhythmia classification, ultimately facilitating timely diagnosis and improving patient outcomes.

The remainder of this paper is organized as follows. Section II describes our proposed methodology, including data preprocessing, model architecture, and the training process. Experimental results and performance evaluation are presented in Section III. After that, the results are discussed in Section IV. Finally, Section V summarizes the essential discoveries and explores future research directions in the realm of deep learning-based ECG analysis.

II. Materials and Method

Fig1 illustrates the streamlined ECG Classification Flowchart of our proposed system. The first step involves noise removal from the electrocardiogram, followed by heartbeat detection. These detected heartbeats are then fed into a deep convolutional neural network for classification. The final output indicates the class to which each heartbeat belongs.

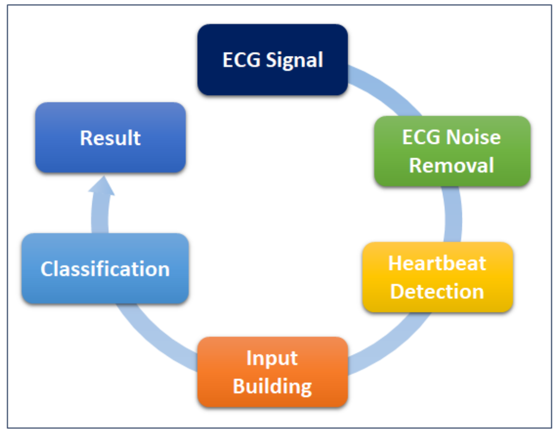

Fig. 1. Streamlined ECG Classification Flowchart

A. Data Description

In this study, we utilized the MIT-BIH Arrhythmia Database [26] from physiotNet [26], a widely recognized and extensively used dataset in arrhythmia analysis and cardiovascular research. The MIT-BIH Arrhythmia Database includes 48 records from various patients with different types of arrhythmias, as presented in Table I. The recordings were sampled at a frequency of 360 Hz and typically have a duration of 30 minutes each. The ECG signals were acquired using standard leads, such as Lead II. The dataset served as the foundation for our research, enabling us to evaluate the performance of our proposed methodology in an established and benchmarked setting.

TABLE I
HEARTBEAT TYPES IN MIT-BIH ARRHYTHMIA DATABASE: AN OVERVIEW OF ARRHYTHMIA ANNOTATION

Dataset	Sampling rate (HZ)	Labels	Description
MIT-BIH Arrhythmia Database [26]	360 Hz	N	Normal
		A	Atrial premature contraction
		R	Right bundle branch block
		L	Left bundle branch block
		!	Ventricular flutter
		P	Paced beat
		V	Premature ventricular contraction
		J	Nodal (junctional) premature beat
		a	Aberrated atrial premature beat
		e	Atrial escape beat
		j	Nodal (Junctional) escape beat
		E	Ventricular escape beat
		f	Fusion of paced and normal beat
		F	Fusion of ventricular and normal beat
		Q	Unclassifiable beat
Total labels		103247	Beat

To classify the different types of heartbeats in our study, we adopted the widely accepted American Association for the Advancement of Medical Instrumentation (AAMI) [27] classification scheme. The AAMI classification defines five categories: Normal/Healthy Beats (N), Supraventricular ectopic Beats (S), Ventricular ectopic Beats (V), Fusion Beats (F), and Unclassifiable Beats (Q) As summarized in the Table II [5]. We aligned these categories with the annotations available in the MIT-BIH Arrhythmia Database, facilitating our analysis of arrhythmias. By leveraging the annotations provided in the database, we could accurately categorize the heartbeats based on the AAMI classification and further investigate the characteristics and patterns associated with each type.

TABLE II
ARRHYTHMIA CLASSIFICATION BY AAMI: A CATEGORIZATION OF FIVE HEARTBEAT CLASSES [5]

AAMI Clesses	Description
N	Normal Beats
S	Supraventricular ectopic Beats
V	Ventricular ectopic Beats
F	Fusion Beats
Q	Unclassified Beats

We utilized a dataset of 103,247 heartbeats for our training, testing, and validation. To ensure unbiased evaluation, we randomly selected 20% of the total dataset as a validation set to monitor the model's performance during training. At the same time, the remaining 80% of the data was allocated for training. We employed a 20% holdout within the training data as a testing set, as shown in the fig 2. This approach allowed us to train our model on substantial data while maintaining a robust evaluation process using independent test and validation sets.

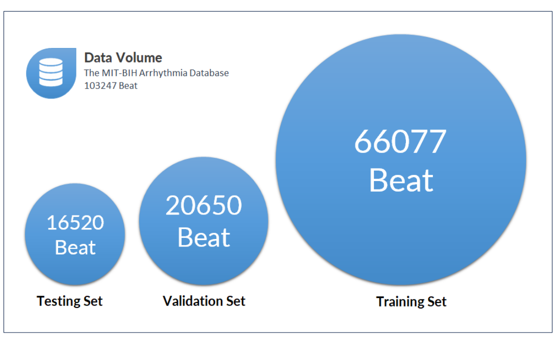

Fig. 2. Data Distribution Overview: Training, Testing, and Validation Sets

B. Dataset preprocessing

The raw ECG signals are susceptible to various types of noise, including power frequency interference, baseline drift, and high-frequency artifacts caused by muscle contraction and electrode movement [10]. In our study, we employed a filter to remove baseline wander [30], [31] from ECG signals, as shown in the Fig 4 . This technique effectively reduced the low-frequency variations caused by noise, movement artifacts, and other factors [32]. By implementing this filter, we enhanced the clarity and accuracy of the ECG signals, enabling more reliable analysis and interpretation of cardiac activity.

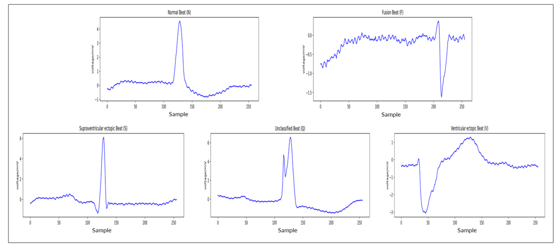

Fig. 3. The five types of heartbeats defined by AAMI

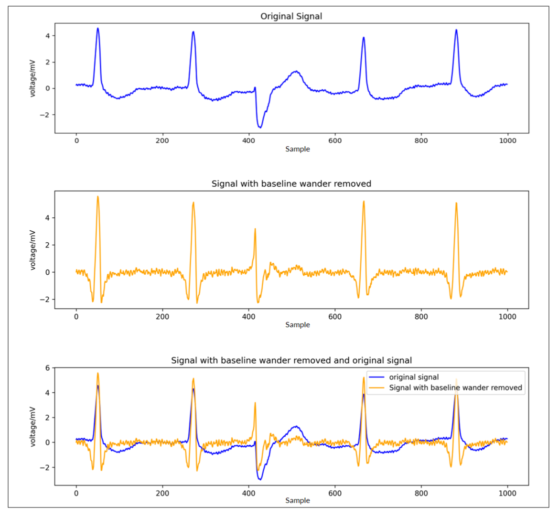

Fig. 4. Improving ECG Clarity: By removing the baseline wander.

C. Automated ECG heartbeat classification system based on an improved deep convolutional neural network

In our research, we adopted an architecture initially proposed by Awni et Al [22] as a foundation for our work. However, we made significant modifications and improvements to the original architecture to better suit our specific objectives and dataset. These modifications were necessary to improve the architecture's performance, address potential limitations, and tailor it to the characteristics of our ECG data. By customizing the architecture, we aimed to achieve better accuracy, robustness, and efficiency in our analysis, ultimately contributing to advancements in arrhythmia detection and classification.

This architecture is designed to process raw ECG data, taking a single beat of 256 samples as input and generating one prediction for five different arrhythmia classes. The revised network architecture consists of 28 layers, compared to the original 34 layers. We introduced shortcut connections inspired by the residual network architecture [33], enhancing the network's gradient flow and enabling efficient training. Instead of 16 blocks, our architecture comprises 13 residual blocks, each containing two convolutional layers. The kernel size of the convolutional layers is set to 10, and the filter width is determined by 32×2^K filters, where k is a hyper-parameter. Importantly, we adjust k for every eighth residual block instead of every fourth.

In line with best practices, we applied batch normalization [34] and rectified linear activation before each convolutional layer, adhering to the preactivation block design [35]. Dropout [36] regularization was also employed between the convolutional layers and after the nonlinearity, with a dropout probability of 0.2. These measures help prevent overfitting and improve the network's generalization ability.

The first and last layers of the network underwent special handling due to the pre-activation block structure. Furthermore, we incorporated a final fully connected softmax layer, producing a probability distribution across the five output classes.

We aimed to optimize the network architecture for arrhythmia classification through these modifications, enhancing its efficiency, adaptability, and performance on our specific dataset. Fig5 showcases the structure of our proposed network, offering a concise visual representation of its architecture.

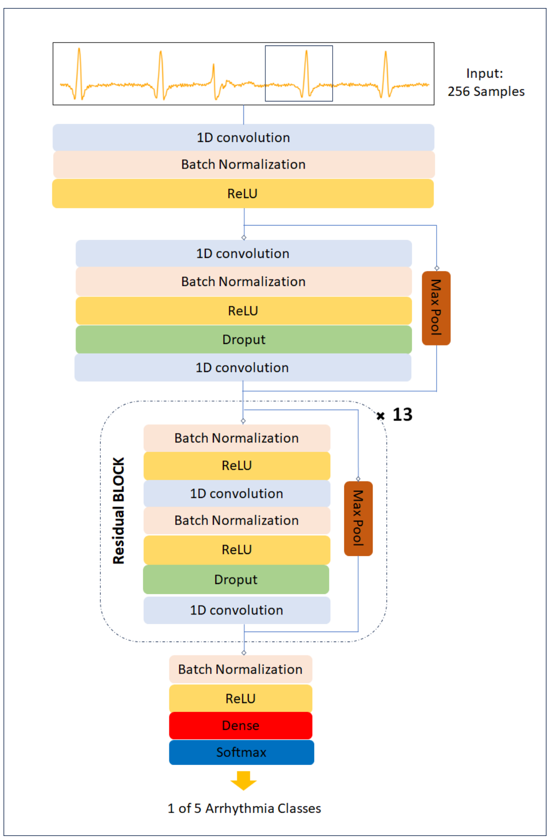

Fig. 5. The proposed improved deep convolutional neural network

III. Experimental Results

A. Experimental Setup

The network was trained from scratch with random weight initialization, following the methodology described by He et al [37]. We employed the Adam optimizer [38] with default parameters ($\beta 1 = 0.9$ and $\beta 2 = 0.999$) and used a mini-batch size of 256. The learning rate was initially set to 1×10^{-4} and was reduced by a factor of 50 when the loss on the development dataset did not improve for fifty consecutive epochs. Furthermore, the training process was conducted over 85 epochs. The model selected for further evaluation was based on achieving the lowest error on the development dataset.

This work was implemented using the Keras [39] deep learning framework with TensorFlow as the backend.

B. Evaluation measures used

The evaluation metrics for each category are defined as follows: True Positives (TP): The number of beats correctly detected and classified as belonging to the specific category. True Negatives (TN): The number of beats correctly identified as not belonging to the specific category. False Positives (FP): The beats of other categories that were misclassified as belonging to the specific category. False Negatives (FN): The beats of the specific category that were misclassified as belonging to other categories.

In this study, we employed various metrics to evaluate the classification system's performance. These included overall accuracy (Acc), Macro average (Macro avg), and Weighted average (Weighted avg) for assessing overall classification accuracy. Precision (P) was calculated for each class to evaluate the successful classification of beats. At the same time, Recall (R), Area Under the Curve (AUC), and F1-Score were computed for all classes to analyze the system's performance comprehensively.

$$\text{Precision} = \frac{\text{TP}}{\text{TP + FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP + FN}}$$

$$\text{Acc} = \frac{\text{TP + TN}}{\text{TP + TN + FP + FN}}$$

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Macro avg Precision} = \frac{1}{N}\sum_{i=1}^{N} \text{Precision}_i$$

$$\text{Macro avg Recall} = \frac{1}{N}\sum_{i=1}^{N} \text{Recall}_i$$

$$\text{Macro avg F1-score} = \frac{1}{N}\sum_{i=1}^{N} \text{F1-score}_i$$

$$\text{Weighted avg} = \frac{\sum_{i=1}^{N}(\text{Metric}_i \times \text{Weight}_i)}{\sum_{i=1}^{N}\text{Weight}_i}$$

where $Weight_i$ is the number of samples in class (i).

$$\text{AUC} = \int_{-\infty}^{+\infty} \text{TP Rate}(\text{FPR})\, d(\text{FPR})$$

These metrics provide a comprehensive understanding of the classification performance for each category, allowing for a detailed assessment of the system's accuracy in differentiating between different types of beats.

C. Results

Fig 6 and 7 illustrate the training and validation losses, as well as the accuracy, throughout the training phase. These graphical representations indicate the absence of overfitting, as the validation curve closely tracks the trajectory of the training curve, and both curves show consistent improvement over time. This alignment indicates that the model generalized well to new data, resulting in consistent performance on both the training and validation sets.

In Fig8, we showcase the confusion matrix representing the test results of our model. This matrix provides a detailed overview of the model's performance for each type of heartbeat. Notably, our model demonstrates high accuracy across all heartbeat categories, indicating its effectiveness in accurately classifying different arrhythmia types.

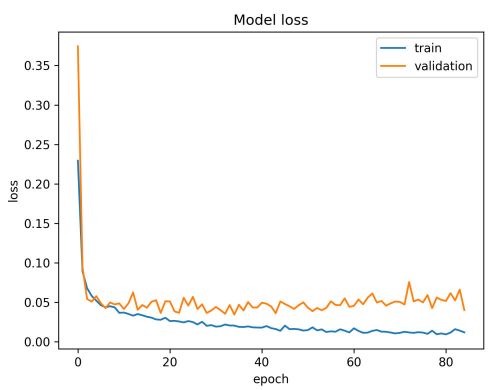

Fig. 6. Monitoring the training and validation loss in our approach throughout the training process.

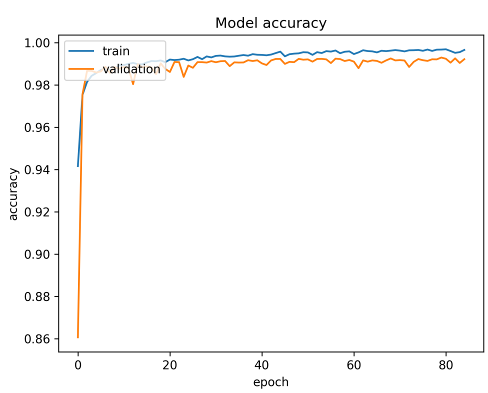

Fig. 7. Tracking Training and Validation Accuracy in our proposition during training process

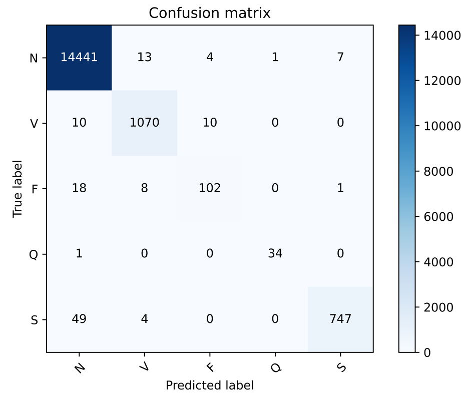

Fig. 8. A Confusion Matrix of Testing Data: Our Model

The evaluation metrics of our model are summarized in Table III, providing a comprehensive overview of its performance. Notably, among the five classes, the F1-score exceeded 96% for four of them, demonstrating high precision and recall. Classes N, V, Q, and S exhibited Precision and Recall values exceeding 94% and a perfect AUC of 100%. Although the F class's performance showed a lower F1-score of 81%, this can be attributed to the limited number of instances in this class.

Overall, our model achieved exceptional results, with an overall Accuracy of 99%, a Macro avg Precision of 96%, a Macro avg Recall of 93%, a weighted avg of 99%, and an impressive Macro avg F1-score of 94%. These metrics collectively illustrate the model's effectiveness in accurately classifying most heartbeat types, yielding high precision and recall rates.

TABLE III
PROVIDING A COMPREHENSIVE OVERVIEW OF OUR MODEL PERFORMANCE IN TESTING DATA

	AUC	Precision	Recall	F1-score	Support
N	1.00	1.00	1.00	1.00	14477
V	1.00	0.98	0.97	0.98	1123
F	0.99	0.85	0.78	0.81	126
Q	1.00	0.97	0.94	0.96	35
S	1.00	0.98	0.95	0.97	759
Accuracy				0.99	16520
Macro avg		0.96	0.93	0.94	16520
Weighted avg		0.99	0.99	0.99	16520

IV. Discussion

In order to comprehensively evaluate the system's performance and effectiveness, it is essential to analyze it based on experimental results. The system has demonstrated exceptional performance, achieving an impressive Accuracy of 99.25%. This signifies that among the 16,520 test heartbeats, 126 were misclassified, highlighting the system's high precision and reliability.

Table IV presents a comprehensive analysis of the original model [22] performance on the testing data. Although the performance of the F class exhibited a lower F1 score of 85% in our model, it was notably higher compared to [22], which did not exceed 79%. This suggests that our model was more effective in accurately classifying the F class of heartbeats, resulting in improved performance and a higher F1 score for this class.

Overall, [22] achieved acceptable results, with an overall Accuracy of less than 98%, a Macro avg Precision of 95%, a Macro avg Recall of 88%, a Weighted avg of 98%, and a Macro avg F1 score of 91%. While these results are commendable, our modifications to our model demonstrated greater effectiveness in accurately classifying the majority of heartbeat types. Our higher overall Accuracy, improved Macro and Weighted avg, and elevated F1 score evidenced this.

TABLE IV
PROVIDE A COMPREHENSIVE OVERVIEW OF THE PERFORMANCE OF THE ORIGINAL MODEL [22] IN TESTING DATA

	AUC	Precision	Recall	F1-score	Support
N	099	0.99	1.00	0.99	14470
V	1.00	0.96	0.97	0.97	1101
F	1.00	0.85	0.74	0.79	120
Q	1.00	0.98	0.84	0.91	58
S	1.00	0.97	0.88	0.92	771
Accuracy				0.98	16520
Macro avg		0.95	0.88	0.91	16520
Weighted avg		0.98	0.98	0.98	16520

Furthermore, improved classification accuracy can be attributed to the modifications made to the Awni et al [22]. architecture tailored to our specific requirements. These architectural adjustments significantly enhanced the model's performance and accuracy in heartbeat classification. The results presented in TableV validate the positive impact of these modifications, as evidenced by the improved Macro avg F1-score, which increased by 3%. Moreover, the overall Accuracy improved to 99% from the original 98%, indicating a substantial enhancement in the model's predictive capabilities. Additionally, there was a notable improvement in Macro avg Recall, increasing from 88% to 93%.

We present a comparative analysis of established models in the literature, showcasing their performance distinctions in Table VI. Notably, our model exhibited outstanding superiority in terms of overall accuracy.

Our work offers the following advantages:

- Direct Training and Classification: Our method eliminates the need for feature extraction, enabling direct training and classification using pre-processed ECG signals.

TABLE V
COMPARISON OF THE RESULTS OF OUR PROPOSED SYSTEM WITH THE ORIGINAL MODEL

	Accuracy	Precision	Recall	f1-score
Awni et al [22]	0.98	0.95	0.88	0.91
proposed	0.99	0.96	0.93	0.94

TABLE VI
COMPARING THE PERFORMANCE OF OUR PROPOSED SYSTEM WITH VARIOUS CLASSIFICATION MODELS IN TERMS OF OVERALL ACCURACY

Method	Dataset	Sampling rate (Hz)	Heartbeat types	Overall accuracy (%)
Jing et al (2021) [28]	The MIT-BIH Arrhythmia Database	360 Hz	Classes of the AAMI standard (N, S, V, F, Q)	96.50%
Cao et al (2023) [25]				90.8%
Xie et al (2023) [29]				98.68%
Awni et al [22]				98%
Proposed Method				99.26%

- Proven Effectiveness: The proposed method has undergone evaluation on test data, demonstrating its effectiveness in accurately classifying heartbeats.
- Improved Computational Complexity: Our approach has improved computational complexity compared to the original model.

On the other hand, there is room for improvement in the performance of the smaller classes.

V. CONCLUSIONS

Ensuring the prompt diagnosis of arrhythmia is crucial for the effective treatment of cardiovascular diseases. This paper introduces an automated system for classifying heartbeats, aiming for precise arrhythmia detection. The proposed system utilizes an enhanced deep convolutional neural network comprising 13 residual blocks. Each block consists of two 1D convolutional layers, two batch normalization (BN) layers, two rectified linear unit (ReLU) layers, and an "identity shortcut connections" structure. Consequently, the improved network architecture comprises a total of 28 layers. A final fully connected softmax layer is incorporated to produce a probability distribution across the five output classes.

To evaluate the system's performance, we used the MIT-BIH arrhythmia database. Our improved deep convolutional neural network achieved remarkable results, demonstrating an Accuracy of 99.26%, a Macro avg Precision of 96%, a Macro avg Recall of 93%, a Weighted avg of 99%, and an impressive Macro avg F1-score of 94%. Notably, our approach surpassed the performance of the original architecture, yielding a 3% improvement in the F1-score.

The proposed automated heartbeat classification system demonstrates its potential for enhancing arrhythmia's timely detection and treatment. By leveraging the power of an improved deep convolutional neural network architecture, our approach exhibits high diagnostic performance comparable to that of cardiologists. These findings underscore the effectiveness of our system in accurately classifying arrhythmias, contributing to improved patient care and clinical decision-making in cardiovascular diseases.

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