

RNN Based Deep Learning Approach for ECG Beat Classification

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Abstract: - The electrical patterns of the heart, captured through an electrocardiogram (ECG/EKG), serve as a diagnostic tool to identify potential issues such as heart attacks, irregular heart rhythms, heart failure, and arrhythmia, which manifests as irregularities in the heartbeat's rhythm. Deep Learning (DL) architectures have been successfully employed for arrhythmia detection and classification and offered superior performance to traditional shallow Machine Learning (ML) approaches. This paper introduces a novel approach utilizing deep learning techniques, specifically a Bidirectional Gated Recurrent Unit (Bi-GRU) model a variant of RNN, to classify ECG arrhythmia beats into distinct categories. The Bi-GRU model is employed in this work due to its capability to capture temporal dependencies in ECG signals, enabling a nuanced understanding of beat sequences for precise classification. Leveraging the MIT-BIH arrhythmia database, a comprehensive dataset containing annotated ECG signals, this study explores the efficacy of deep learning in accurately categorizing beats in to five super classes as per the standard of Association for the Advancement of Medical Instrumentation (AAMI). Evaluation metrics encompassing accuracy (Acc), specificity (Spe), sensitivity (Sen), positive predictive value (Ppv), and F1-score are utilized to assess the model performance in distinguishing between diverse arrhythmia classes.

Keywords: *Electrocardiogram, Classification, Deep learning, Recurrent Neural Network (RNN), Bidirectional Gated Recurrent Unit (BiGRU)*

1. Introduction

Electrocardiograms (ECGs) have the capability to identify and document the subtle electrical changes occurring during the activation of the heart repolarization and depolarization patterns. Cardiologists and medical professionals widely rely on ECG for cardiac health monitoring. However, manually analysing ECG signals, like many other time-series data, poses challenges in identifying and classifying various waveforms and patterns. This task is not only time-consuming but also prone to errors. Proper diagnosis of cardiovascular diseases is critical, as they account for approximately one-third of global fatalities[1]. Irregular heartbeats, experienced by millions, can be life-threatening in certain instances. Hence, achieving accurate and cost-effective diagnosis of arrhythmic heartbeats is greatly sought after[2]. Figure 1 illustrates the formation of an ECG signal, a critical aspect in understanding the test outcomes.

In the representation of an ECG signal, the various waves, segments, and intervals are denoted by the letters P, Q, R, S, and T. The first wave, the slightly rounded and positively upright P wave, signifies atrial depolarization. The PR interval measures the duration taken for the depolarization wave to travel from the atria to the ventricles. The three successive deflections after the P wave collectively indicate ventricular depolarization, known as the QRS complex. The ST segment, which spans from the end of the S wave to the start of the T wave, signifies the time between ventricular depolarization and the onset of repolarization. The round, positively upright wave following the QRS complex within the ST segment represents ventricular repolarization and is termed as the T wave.

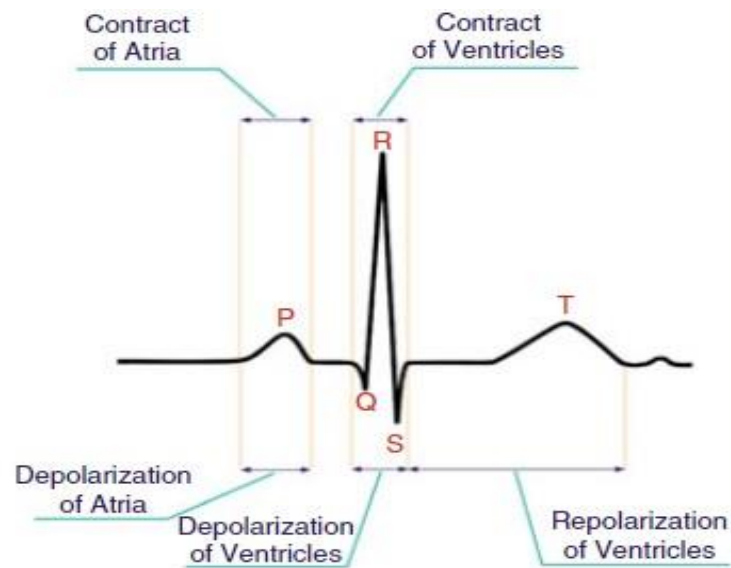


Fig. 1 ECG Signal.

Assessing an electrocardiogram is a crucial method used to identify the existence of cardiovascular disease. Deviations in the heart rhythm's ECG pattern can serve as a signal of potential underlying cardiovascular issues. Various methodologies for classifying ECG arrhythmias and several machine learning (ML)[3]–[10] and deep learning (DL) frameworks for the effective categorization of arrhythmic heartbeats have been extensively documented over time in literature. Machine learning methods [11] typically depend on handcrafted features extracted using traditional signal processing methods while deep learning algorithms can autonomously extract features without manual intervention for ECG beat classification. Deep learning algorithms [12] have become increasingly popular due to their efficacy and the ability to automatically derive features from input data [13], [14][15], [16]. Kiranyaz et al. [17] introduced a 1-D CNN designed for categorizing real-time ECG signals. Xuexiang et al. [18] proposed a CNN based ECG heartbeat classification method to classify Supra ventricular ectopic beats, ventricular ectopic beats. Zahid et al. proposed [19] Self-operational neural networks with feature injection in order to classify the ECG beats in to three categories. Prakash et al. [20] presented Patient-Specific ECG Beat Classification approach using modified 1-D U-Net architecture and achieves good accuracy.

Wang et al. [21] used Binarized Convolutional Neural Network (BCNN), Shu Lih oh et al. [22] used modified U-net, Ganguly B et al. [23] used LSTM for ECG beat five class classification. Mohamed Hammad et al. [24] presented a work based on integration of LSTM-features with KNN, further utilizing a DNN method that combines cross-validation with genetic algorithms for optimizing both features and parameters in classification. Although researchers shared a common goal, each one adopted a distinct approach for the extraction and categorization of features. Hence, this research focuses on categorizing ECG arrhythmias into one of five classes as per the MIT-BIH arrhythmia database. In this work a RNN using Bi-GRU architecture is employed due to its capability to capture temporal dependencies in ECG signals, enabling a nuanced understanding of beat sequences for precise classification. The model is trained on a sizable dataset, utilizing a combination of data augmentation techniques to enhance generalization and robustness. Evaluation metrics encompassing accuracy, precision, recall, and F1-score are utilized to assess the model's performance in distinguishing between diverse arrhythmia classes. Preliminary results demonstrate promising classification accuracy and efficacy in identifying various arrhythmia types, showcasing the potential of deep learning in ECG analysis. This study contributes to the advancement of automated arrhythmia detection systems, offering a reliable and efficient means of diagnosing cardiac irregularities, with implications for real-time clinical applications and telemedicine.

2. Objectives

The objectives of the study using the Bidirectional Gated Recurrent Unit (Bi-GRU) model which is a variant of RNN for classifying ECG arrhythmia beats into distinct categories using deep learning techniques are as follows.

1.Temporal Dependency Understanding: Focus on capturing the temporal dependencies present in ECG signals. The Bi-GRU model's ability to comprehend sequences of beats over time is essential to achieve a more nuanced understanding of these signals, enabling precise classification.

2.Dataset Utilization and Exploration: Utilize the MIT-BIH arrhythmia database, a comprehensive dataset containing annotated ECG signals, to train and validate the deep learning model. Explore the dataset to understand its characteristics, complexities, and the variations in ECG patterns among different arrhythmia types.

3.Classification into Five Super Classes: Classify the ECG arrhythmia beats into five super classes, N, S, V, F, Q aligning with the standards of the AAMI.

4.Performance Evaluation: Evaluate the model's performance using various metrics such as accuracy (Acc), specificity (Spe), sensitivity (Sen), positive predictive value (Ppv), and F1-score. These metrics will gauge the model's ability to accurately differentiate and classify the diverse arrhythmia classes, providing a comprehensive assessment of its performance.

5.Comparison with Traditional Approaches: Compare the performance of the deep learning-based Bi-GRU model with traditional shallow machine learning and other deep learning methods.

3. Methods

In this work a novel approach to classify N, S, V, F, and Q classes of ECG heartbeats was proposed. Using Deep learning approach, a Bi GRU model is trained and its performance is assessed on MITBIH arrhythmia dataset. Outline of proposed Deep learning approach for ECG beat classification is shown in figure 2

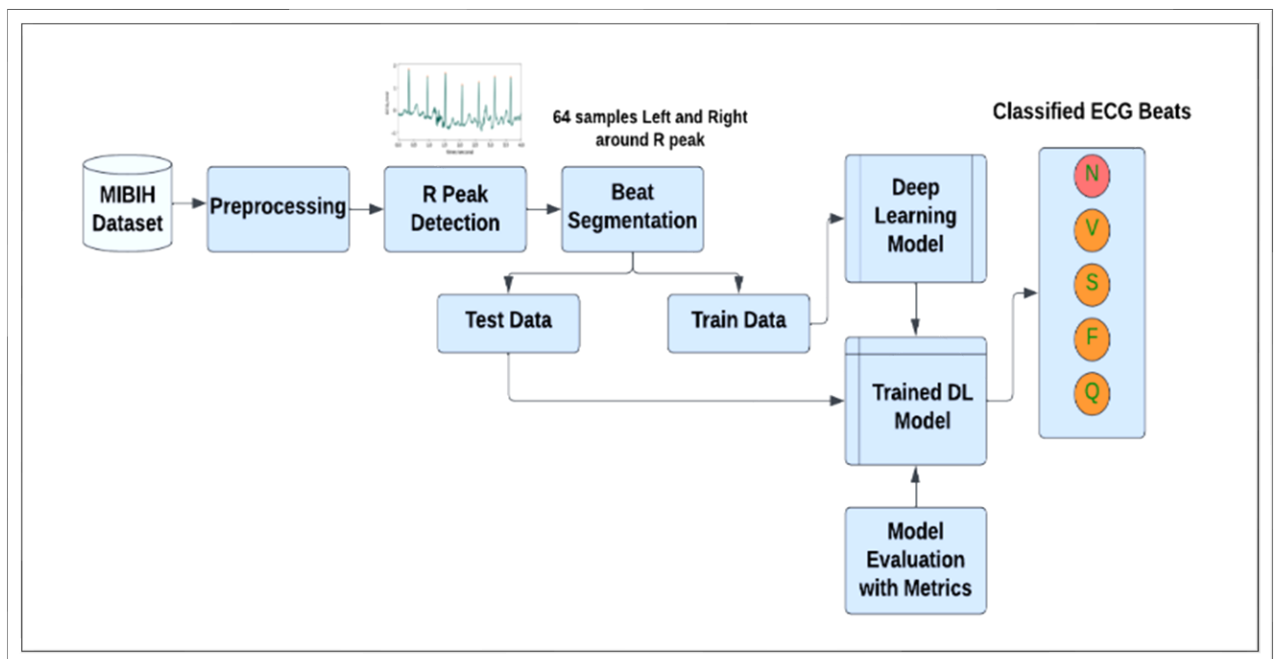


Fig. 2 Outline of proposed Deep learning approach for ECG beat classification

A. ECG Data Processing

This work utilized the ECG dataset sourced from the MITBIH arrhythmia database [25] to assess the effectiveness of the suggested RNN based DL model. The reference database comprises 48 sets, each consisting of two-channel ECG signals spanning a 30-minute duration extracted from 24-hour recordings of 47 individuals.

The ECG signal experiences rapid changes in amplitude information and instantaneous frequency owing to its non-constant nature. To mitigate these effects, it undergoes normalization to achieve a mean of zero and a standard deviation of one. Following this step, a band-pass filter ranging from 0.1 to 100 Hz is employed in the preprocessing stage to eliminate noise. The Pan-Tompkins algorithm [26] is utilized to detect R-peak locations. These identified R-peak locations are then used to segment individual beats from the ECG signal, considering a window of 64 samples to the left and 64 samples to the right around each R-peak location. This window spans a duration of each beat within a range of +178ms to -178ms around the R-peak, allowing for precise isolation of individual beats for further analysis and processing. As most of the information of the ECG signal is allocated at the QRS complex that provides beat information. Total 128 samples are collected in beat segmentation process to gain in-depth information on each ECG beat precisely.

AAMI guidelines advise the classification of each ECG beat into one of five super classes: N represents beats originating in the sinus mode, S indicates supraventricular ectopic beats, V denotes ventricular ectopic beats, F indicates fusion beats, and Q represents unclassifiable beats. This work focuses solely on the classification of ECG beats within these five classes. The table 1 provided the count of beats within each class. The total number of beats in the data set are 55,127. The data is divided, allocating 80% for training and 20% for testing purposes. This train, test split ensures that 80% of the data is utilized for training the model, while the remaining 20% is reserved for evaluating the model's performance. The allocation of data samples across the five individual classes is shown in figure 3.

TABLE 1
NO. OF INSTANCES IN EACH CLASS OF DATASET

S. No	Class	No. of Beats
1	N	44601
2	V	5405
3	S	2486
4	Q	1845
5	F	790

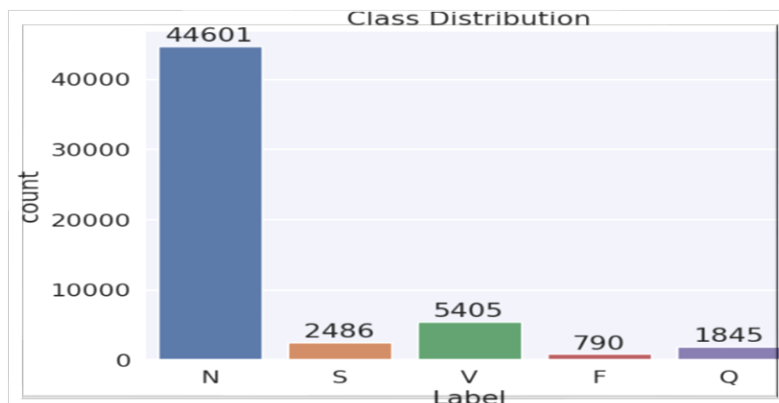


Fig. 3 Allocation of data samples across the five individual classes

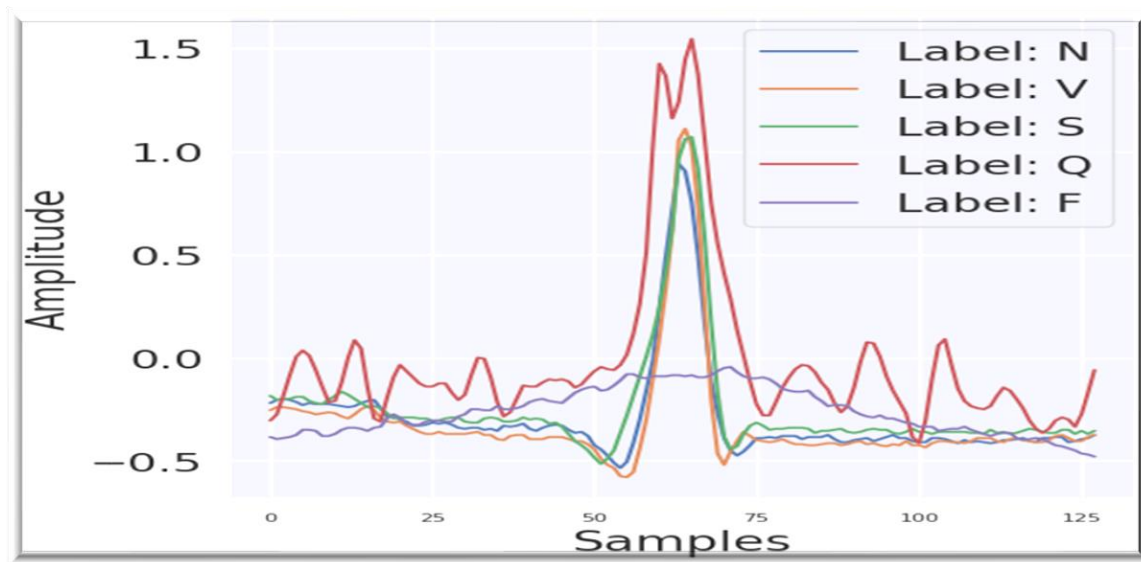


Fig. 4 ECG beats corresponding to five classes The figure 4 depicts ECG beats associated with each of the five distinct categories.

B. Convolutional Neural Network

Convolutional Neural Networks, a specialized form of deep learning algorithms, are tailor-made for handling structured grid-like data, such as images or time-series data. They take inspiration from the human visual system and use a sequence of layers to autonomously and flexibly acquire spatial hierarchies of features from the input data. The CNN comprises three interconnected layers that undergo specific operations. Convolutional layers employ convolutional kernels to learn distinct spatial features from input data. Pooling layers then condense the dimensionality of these features, ensuring shift-invariance. Following this, fully connected layers execute final classification or predictions [27]. The incorporation of batch normalization can enhance training rates by preventing internal covariate shifting. Dropout mechanisms are employed to mitigate overfitting by preventing complex co-adaptations to the training data. Activation functions, like sigmoid, tanh, and rectified linear unit (ReLU), introduce essential nonlinearities to neural networks [28]. The loss function determines the disparity between the actual and predicted values, while the optimizer works during training to minimize this loss function and derive the most fitting parameters.

C. Bidirectional Gated Recurrent Unit (Bi GRU)

The Recurrent Neural Network (RNN) is extensively utilized in processing time series data due to its capability to retain sequential information. RNN executes a recursive function where the output relies on all historical data. But conventional RNNs have limitations on their overall memory capacity. The Long Short-Term Memory (LSTM) is structured to circumvent excessive loss of information when learning long-term dependencies by addressing the vanishing gradient issue. Within LSTM, a memory block continually manages and refreshes memory through three gates: input, output, and forget gates. The input gate recognizes crucial new information that should be preserved in the previous state, while the output gate determines the information passed on to the subsequent state. The forget gate identifies relevant information to maintain in the previous state. The Gated Recurrent Unit (GRU) [29] is developed as an enhanced version of LSTM that selectively extracts features using a reset gate and an update gate. Unlike LSTM, GRU operates without a cell state and directly employs the hidden state for information transmission.

A Bidirectional Gated Recurrent Unit (Bi-GRU) is a type of recurrent neural network which is structured by integrating two Gated Recurrent Units (GRUs) that operate in tandem one processing the input in a forward

direction while the other processes it in a backward direction. The Bi-GRU consists of dual GRU layers within its architecture: one processes the input sequence in a forward direction, while the other handles the sequence in reverse. The LSTM [30] method demonstrated effective results in classifying arrhythmia beats. Nonetheless, due to LSTM's intricate structure and numerous parameters, GRU is adopted to mitigate computational complexity and expedite the process. GRU, a variant of LSTM, focuses on capturing temporal dependencies in ECG signals without incorporating memory cells, employing update and reset gates.

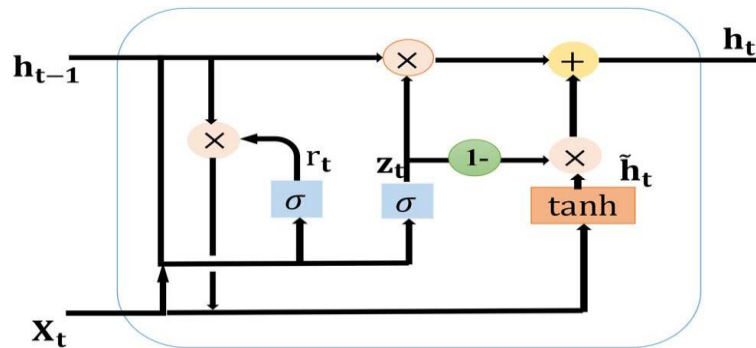


Fig. 5 GRU network structure

The inner structure of GRU neurons is shown in Figure 5. Equations (1) to (4) describe how the GRU updates itself according to its inputs (X_t, h_{t-1}) at any time step t . Firstly, reset gate (r_t) and update gate (Z_t) are computed by the following equations.

$$r_t = \sigma(W_{xr}X_t + H_{hr}h_{t-1} + b_r) \quad (1)$$

$$Z_t = \sigma(W_{xz}X_t + H_{hz}h_{t-1} + b_z) \quad (2)$$

The candidate activation h_t is calculated using the following equations, where the reset gate r_t controls the flow of the hidden state from the previous time step into the current time step(t) of candidate hidden state.

$$h_t = \tanh(W_{xh}X_t + H_{hh}(r_t X h_{t-1} + b_h)) \quad (3)$$

Ultimately, the GRU's final activation h_t at time t is determined through a linear interpolation between the previous activation h_{t-1} and the candidate activation h_t by incorporating the current update gate Z_t

$$h_t = Z_t X h_{t-1} + (1 - Z_t) X h_t \quad (4)$$

Where h_{t-1} represents the previous neuron's output, h_t signifies the informational content learned at the current state following the reset gate r_t . h_t denotes the neuron's hidden state. W_{xz} , W_{xr} , W_{xh} , are the weight matrices. Additionally, b_z , b_h and b_r denote the bias terms. The functions $\sigma(\cdot)$ and $\tanh(\cdot)$ denote the sigmoid function and hyperbolic tangent function, respectively.

D. The Architecture of Proposed RNN model

This proposed model architecture for ECG beat classification involves a hybrid neural network that amalgamates Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) components. The network is structured to effectively capture both spatial and temporal characteristics of the ECG data. The CNN branch initially processes the input sequences through multiple Conv1D layers, using residual blocks to learn hierarchical

representations. Additionally, a separate CNN branch and an RNN component are introduced. The CNN branch incorporates Conv1D and MaxPooling1D layers to capture spatial features and the RNN section utilizes a Bidirectional GRU layer to detect temporal patterns. Following this, the outputs from both the CNN and RNN branches are combined via concatenation and undergo subsequent dense layers for further feature extraction and combination. The model eventually performs classification through a Dense layer with 5 units, using ReLU activation for each stage. This architecture leverages the strengths of both CNN and RNN, allowing the model to effectively classify ECG beats into their respective categories.

In Model Architecture first the input layer is created to accept sequences of length 128 and 1 feature. A CNN branch is initiated with a Conv1D layer using 32 filters, stride of 2, and employing same padding. This is followed by a series of residual blocks containing Conv1D layers, Batch Normalization, ReLU activation, and shortcut connections for effective feature learning. The spatial features are condensed using Global Average Pooling. In addition to the primary CNN branch, there exists a separate CNN branch involving Conv1D and MaxPooling1D layers. The output from this branch is flattened to create a 1D representation of spatial features. Simultaneously, an RNN branch, utilizing a Bidirectional GRU layer with 128 units and ReLU activation, captures temporal patterns in the sequence data. The outputs obtained from both the CNN and RNN branches are concatenated. Further processing involves a Dense layer with 256 units and ReLU activation. A custom Multiply Layer is employed to combine outputs, followed by a Dense layer with 32 units and ReLU activation. The final classification (output) layer is a Dense layer with 5 units for corresponding 5 classes, utilizing ReLU activation for accurate beat classification.

The model is compiled using 'categorical cross entropy' loss and the 'adam' optimizer. It further incorporates early stopping by monitoring validation loss with a specified level of patience. The model is trained and validated with the provided training and test datasets, ensuring its efficiency in classifying ECG beats accurately.

4. Results

Following the model training with the training data, the DL model undergoes testing using the test dataset. The model's performance is assessed using performance metrics to determine its effectiveness compared to other approaches, aiming to ascertain whether it delivers superior results or not. The frequently employed performance measures for assessing arrhythmia classification methods: accuracy (Acc), specificity (Spe), sensitivity (Sen), positive predictive value (Ppv), and F1-score.

$$Acc = \frac{TP + TN}{TP + FP + TN + FN} \times 100$$

$$Ppv(Precision) = \frac{TP}{TP + FP} \times 100$$

$$Sen(Recall) = \frac{TP}{TP + FN} \times 100$$

$$Spe = \frac{TN}{TN + FP} \times 100$$

$$F1\ Score = \frac{2 * Ppv * Sen}{Ppv + Sen} \times 100$$

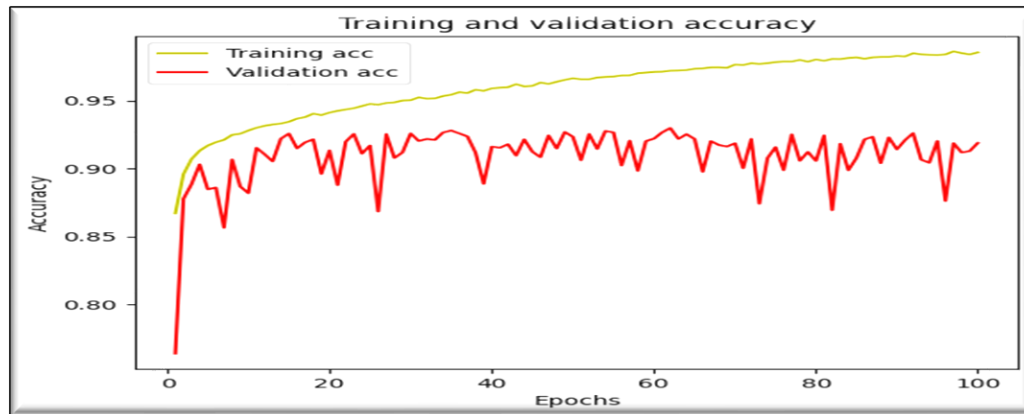


Fig. 6 Training progress and validation accuracy of proposed model

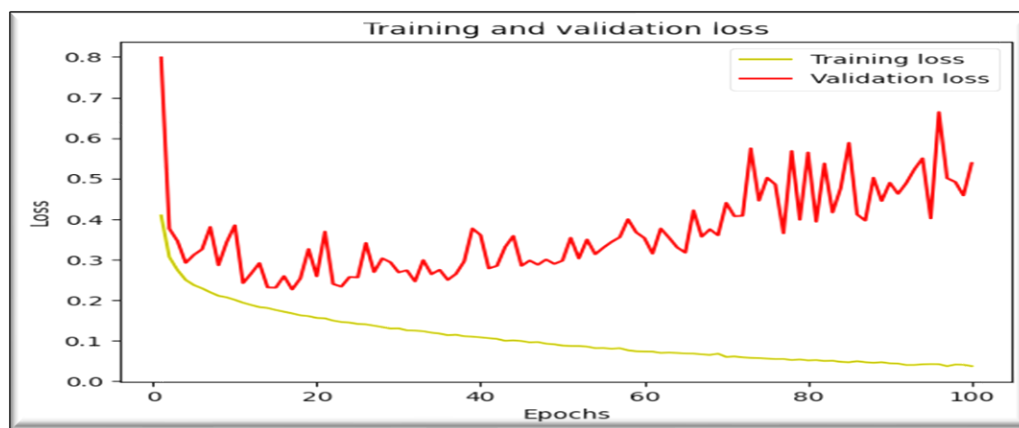


Fig. 7 Training and validation loss of proposed model

		Confusion Matrix				
Actual	N	8587	95	200	18	8
	S	87	397	6	0	2
	V	340	2	704	23	20
	Q	16	0	14	338	0
	F	46	0	18	0	105
		N	S	V	Q	F
		Predicted				

Fig. 8 Confusion Matrix

The Training progress and validation accuracy of proposed model is shown in Figure 6. Training and validation loss of proposed model is shown in Figure 7. The performance comparison of the proposed model with findings from various studies that utilize the MIT-BIH database and different methodologies is presented in table 3.

TABLE 2

Classification Performance of the model

Beat	TP	TN	FP	FN	Acc	Ppv	Sen	Spe	F1 score
N	8587	1629	489	321	93 %	95 %	96 %	77%	95 %
S	397	10437	97	95	98 %	80 %	81 %	99 %	81 %
V	704	9699	238	385	98 %	75 %	65 %	98 %	69 %
Q	338	10617	41	30	99 %	89 %	92 %	100 %	90 %
F	105	10827	30	64	99 %	78 %	62 %	100 %	69 %

*TP: True Positive, FP: False Positive, TN: True Negative, FN: False Negative.

TABLE 3

Comparison table of the proposed model with some other existing architectures

S. No	Reference	Database	Approach	No of Classes	Acc	Ppv	Sen	Spe
1	[11]	MITBIH	SVM	4	86.66	-	-	-
2	[2]	MITBIH	Deep Residual CNN	5	95.9 %	95.2 %	95.1 %	-
3	[21]	MITBIH	BCNN	5	95.67	96.2	94.8	-
4	[22]	MITBIH	Modified U-net	5	97.32	94.7	94.44	98.26
5	[23]	MITBIH	LSTM	5	97.3	-	96.5	99.2
6	Proposed method	MITBIH	RNN with BiGRU	5	91.8 %	91.5 %	91.8 %	95.3 %

5. Discussion

This work focuses on the significant importance of arrhythmia classification in healthcare, particularly in identifying and distinguishing the five classes (N, S, V, F, and Q) of ECG heartbeats. The research introduces a deep learning approach using a BiGRU, RNN model to automatically detect and categorize these heartbeats. The results of this work demonstrate that the suggested framework exhibits good performance when compared to previous state of the art methods concerning the MIT-BIH arrhythmia database. This model's ability to accurately classify the five types of ECG heartbeats makes it a valuable potential addition to computer-aided diagnosis (CAD) systems, offering quick and dependable cardiac arrhythmia diagnoses. Ultimately, the proposed model could serve as a supplementary tool in clinical settings, aiding cardiologists in interpreting ECG heartbeat signals more efficiently.

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