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RESEARCH ARTICLE

AD-BRU: ARRHYTHMIA DISEASE IDENTIFICATION USING ATTENTION GUIDED Bi-GRU

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Abstract – An arrhythmia is a disorder where the heartbeat is very fast or irregular. In the medical field, detecting arrhythmias is among the most challenging tasks. Arrhythmia detection is extremely challenging due to the volume and complexity of ECG data involved. Identifying arrhythmias by traditional methods requires a lot of effort and money. For the purpose of addressing these challenges, the researchers propose an advanced deep learning-based approach, known as AD-BRU, with features specifically designed for identifying arrhythmias through ECG data. Utilizing a variety of datasets derived from the MIT-BIH database, the approach can be applied to a wide range of problems. Data quality is enhanced by preprocessing the ECG input images with a discrete wavelet integrated filter. A primary objective of this study is to create and test an AD-BRU model that can detect arrhythmias effectively. Several metrics, such as precision, F1 score, specificity, recall, and accuracy, are used to evaluate the model's performance. Compared to Wavelet transformation, LSTM deep learning, and EnsCVDD, respectively, the suggested AD-BRU increases overall accuracy by 0.36%, 5.42%, and 10.98%. The results demonstrate that the AD–BRU approach significantly outperforms previous methods, achieving an average accuracy of 98.86%. According to the study's findings, the AD-BRU model provides a more precise and effective method for detecting arrhythmias, which could increase the accuracy and dependability of the diagnosis of cardiovascular disease.

Keywords *– Arrythmia disease, deep learning, discrete wavelet integrated filter, attention guided Bi-GRU.*

1. INTRODUCTION

Arrhythmia is abnormal electrical activity in the heart bringing about less effective pumping. Cardiovascular arrest can occur from certain arrhythmias, can create a hazard to life [1]. The World Health Organization (WHO) has reported that Cardio Vascular Diseases (CVDs) cause 17.9 million deaths in the world each year. 80% of coronary vascular disease events are caused by heart attacks and strokes. The purpose of this study is to precisely forecast frequent cardiac conditions like arrhythmia (ARR) [2]. The heart may beat excessively rapidly, too slowly, or irregularly as a result of an electrical impulse that deviates from its regular sequence [3]. Gated recurrent units (GRU) are a bidirectional convolutional recurrent neural architecture to produce both past and future contexts via bidirectional GRU layers. This is one of several variations of the conventional RNN architecture that address these problems [4]. A more thorough and precise examination of the ECG signal is made possible by the distinctive features that are produced when CNN, residual blocks, and Bi-GRU are combined. This is particularly important for the detection and tracking of heart problems. Ultimately, the random forest algorithm is trained and tested using the retrieved deep feature set [5].

The MIT-BIH database was used to compare common standard tests for diagnosing arrhythmias. The BIH Arrhythmia Laboratory acquired 48 half-hour segments of 24-hour ECG recordings from 47 subjects using two channels. A Physion Net connection is used to retrieve ECG data from the MIT-BIH arrhythmia database [6]. One usual class and four problematic classes were eliminated the MIT-BIH arrhythmia dataset. Sixty-one features (TSFEL) were extracted from the data using a time series feature extraction package [7]. Arrhythmia in recorded ECG data is identified using DNNs. Modern computer-aided diagnosis uses DNNs to diagnose arrhythmia in the records ECG signal and reduce the cost of continuous cardiac observation [8]. Recently, the medical field has seen tremendous advancements because of convolutional neural networks and other deep learning approaches, especially when it comes to medical imaging [9]. Morphology of clinical data is analysed using CNN. CNN has the potential to extract useful information even in cases when the input signal is noisy. The layer-by-layer construction of the network structure reflects these performance traits. With a greater number of layers, features are learned and conveyed more succinctly and abstractly [10]. Therefore, this study introduces discrete wavelet integrated filter, median filter and attention guided Bi-GRU for detecting Arrhythmia disease. The following are the major contributions of the proposed work.

- Primary purpose of the study is to design an Attention guided Bi-GRU for identifying Arrhythmia disease.
- Discrete wavelet integrated filtering is used to preprocess the input images in order to eliminate the noise artifacts.
- The pre-processed images are taken as input to the signal reconstruction to reconstruct the process of identifying an initial continuous signal from a series of samples that are equally spaced.
- An amplifier performance is assessed by applying signals to the noise figure signal.
- The forward and backward feature of the byte sequences in a session are extracted using attention graded Bi-GRU.

The purpose of this study is to identify arrhythmia diseases and the methods are as follows: . Section 2 explains the Literature survey in detail. Section 3 explains the proposed attention graded Bi-GRU method. Section 5 explains the conclusion.

2. LITERATURE SURVEY

In recent days several frameworks are introduced by the researchers primarily to increase the detection accuracy for identifying arrhythmia disease. Some of those frameworks are studied briefly in this section.

In 2021 Taloba, A.I., et al., [1] introduced an ECG-based machine algorithm for monitoring heartbeat and identifying arrhythmias. A new method for improving the assessment of ECG signals is proposed, which is based on fractional Fourier transform (FFT) algorithms and TERMAs (two event-related moving averages). Therefore, the major goal of research on electrocardiograms (ECGs) is to precisely identify arrhythmias as potentially lethal so that a suitable course of therapy can be provided and lives can be preserved. Cross-database analysis is a drawback and results in a decrease in average classification accuracy.

In 2022 Ketu, S., and Mishra, P.K., [2] introduced An empirical analysis of methods for machine learning using an imbalanced ECG-based arrhythmia dataset for the purpose of detecting heart disease. This research proposed a data balancing method for synthetic minority over-sampling. Furthermore, each class's accuracy has increased individually as well, in addition to the overall algorithm's accuracy. The minority class accuracy will not be weakened as an outcome.

In 2022 Fradi, M., et al., [3] introduced Real-time cardiac arrhythmia detection system utilizing several optimizers-networks based on CNN architecture. An electrocardiogram (ECG) that is automatically classified for the patient data is proposed using a deep Learning architecture that complies with ANSI-AAMI standards. Noise is removed from the ECG raw data by using a low pass filter after performing a R-R peak extraction and a fully connected layer architecture is also used to optimized.

In 2021 Khan, M.A. and Kim, Y., [4] introduced an LSTM-based deep learning approach to classification of cardiac arrhythmia diseases. The proposed approach is based on a high-dimensional cardiac arrhythmia dataset with 279 attributes. The approach used in this research involved employing the LSTM DL algorithm to create an effective intelligent system for the purpose of classifying individuals with cardiac arrhythmias. 93.5% is the highest classification accuracy for the disease based on DL.

In 2020 Wang, R., et al., [5] introduced Deep Multi-Scale Fusion Neural Network for Multi-Class Arrhythmia Recognition. Deep Multi-Scale Fusion (DMSFNet) is a revolutionary end-to-end convolutional neural network architecture that is proposed in this paper to identify multi-class arrhythmias. Using cross-scale information complementarity and multiscale feature extraction of ECG signals, The proposed method can detect anomalous disease patterns and get rid of noise interference.

In 2020 Gupta, V., and Mittal, M., [6] introduced Analyzing the ECG signal for cardiac arrhythmias in a unique manner. The proposal method is to separate noise from the actual ECG signal. Selecting right ECG sample is crucial to the accuracy of the study. Make the signal stronger and pay closer attention in future efforts.

In 2023 Pandey, S.K., et al., [7] introduced Arrhythmia Heartbeat Detection from ECG Signal Using CNN Model Based on Wavelet Transform. Currently, disorders are detected by examining ECG data, which is a type of medical monitoring that monitors cardiac activity. It is evident that the proposed method performs better than the existing model because it attained an average f1 score of 98.74, recall of 98.78%, precision of 98.78%, accuracy of 99.40%. In future, decreases the cost in subsequent tasks.

In 2023 Daydulo, Y.D., et al., [8] introduced ECG signals are represented in time-frequency and deep learning algorithms are used to detect cardiac arrhythmia. Developing an automated deep learning model that could precisely classify ECG signals was the primary objective of this work. Averaging 99.2% for overall classification accuracy, 99.2% for average sensitivity, 99.6% for average specificity, and 99.2% for average F-measure, recall, and precision were demonstrated by the proposed deep learning model. It is advised that ECG signals be used in future research to expand the class of data collection, reduce processing time, and simplify the procedure.

In 2024 Khan, H., et al., [9] introduced heart disease prediction using novel Ensemble and Blending based Cardiovascular Disease Detection Networks. The objective of this research is to accurately forecast CVDs while minimizing the difficulties caused by unbalanced data, taking into account the health and socioeconomic circumstances of the patient. The findings show that, with 88% accuracy, 88% F1score, 91% precision, 85% recall, and 777s execution time, the EnsCVDD-Net performs better than the baseline models.

In 2023 Oleiwi, Z.C., et al., [10] introduced Effective ECG Beats Classification Methods Using Wavelet Transformation for the identification of Cardiac Arrhythmia. This study proposes an ECG classification model to categorize four different heartbeat types in order to identify arrhythmias early on. Based on all DWT decomposition levels, the outcomes of the studies show using RF archives, the proposed paradigm has a classification accuracy of 98.5%.

In 2022 Aamir K.M., et al., [11] introduced Machine Learning-Based Classification of Ventricular Arrhythmias on ECG for Automated Heart Disease Identification. The signal detection process is only utilized to ascertain whether a signal was obtained from a healthy or ill subject. The signal detection process is only utilized to ascertain whether a signal was obtained from a healthy or ill subject. Additionally, the instantaneous frequency (IF) range of 0.08-1.1 Hz is associated with premature ventricular contraction and ventricular tachycardia.

From the literature survey, various approaches were focused on single input images for accurately detecting the arrhythmia disease. This research mainly focused on identifying the normal and abnormal ECG signal via deep learning. The primary goal of the proposed Bi-GRU network is to employ deep learning (DL) to increase the accuracy of identifying normal and abnormal ECG signal to detect arrythmia disease. Preprocessed images are sent into a Bi-GRU Network to distinguish between normal and abnormal images.

3. PROPOSED METHODOLOGY

In this section, the discrete wavelet integrated filtering has been proposed with attention guided Bi-GRU (Bidirectional Gated Recurrent Unit) for detecting Arrhythmia disease. The below block diagram represents the flow of disease detection in arrhythmia

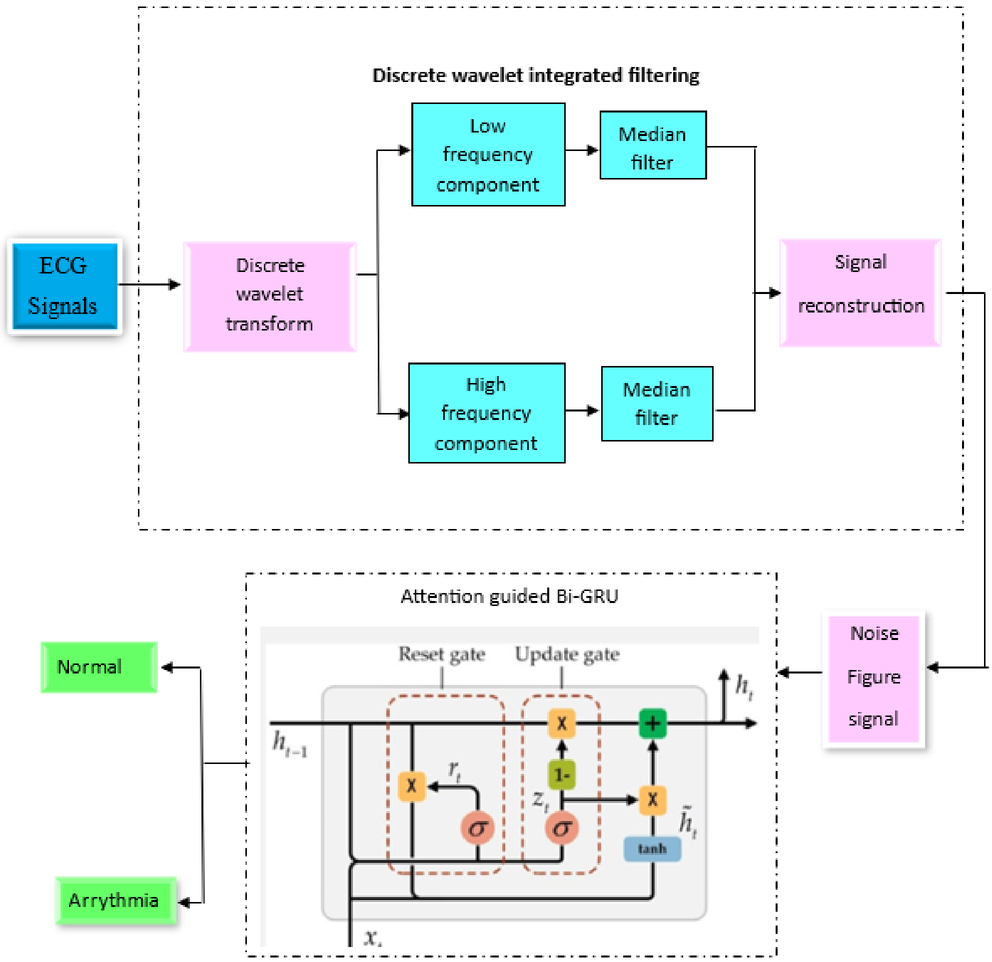


Figure 1. The workflow of proposed AD – BRU network

3.1 Dataset description

Arrhythmia is an irreversible condition that causes damage in heart, and leads to cardiac arrest. MIT-BIH arrhythmia database is a freely accessible dataset that offers common research materials for cardiac arrhythmia identification. The MIT-BIH dataset exhibits significant imbalances, with distinct differences in the quantity of the heartbeat samples within each arrhythmia class when compared to the other arrhythmia classes**.** PhysioBank is a repository for PhysioBank, which includes the MIT-BIH arrhythmia database, which accessible via PhysioNet. Database access is available for ECG records used for research and commercial use.

MIT-BIH database contains thirty-minute records, each with extensive annotations.

3.2 Data preprocessing

A method for signal processing called the discrete wavelet transform that turns a time sequence into an orthogonal set of data points to each other. Frequency filter bank makes the discrete wavelet transform (DWT) more effective by eliminating undesirable frequencies and breaking the signal down into five different levels of decomposition, each of which comprises a sample that has been broken down into two components. In order to assure efficacy, DWT is utilized for feature extraction as, when compared to alternative methods, it consistently yields accurate feature extracting results. Wavelet is a fast-fading function that oscillates in both frequency bands and duration. DWT varies in degrees depending on the number of mother wavelets. Moreover, the discretization of the continuous wavelet transforms yields DWT. Discretization of both the scale a and shift b is achieved by using Eq. (3) to demonstrate the discrete values' substitution into Eq. (1). DWT is then obtained by the application of Eq. (4).

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\Psi\left(\frac{t-b}{a}\right) \tag{1}$$

$$C\big(a, b, s(t), \Psi(t)\big) = \int_{-\infty}^{+\infty} s(t)\Psi_{a,b}^{*}(t)dt = \langle s(t), \Psi_{a,b}(t)\rangle \tag{2}$$

$$\Psi_{j,k}(t) = \frac{1}{\sqrt{2j}}\Psi\left(\frac{t}{2j} - k\right) \tag{3}$$

$$d_{j,k} = \int_{-\infty}^{+\infty} s(t)\Psi_{a,b}^{*}(t)dt = \langle s(t), \Psi_{j,k}(t)\rangle \tag{4}$$

where the scale parameter is a and the shift parameter is b. In complex conjugate notation, $\Psi_{a,b}^{*}(t)$ represents $\Psi_{a,b}(t)$. With respect to a given signal s (t), a group of wavelet coefficients C (a, b, s(t), ψ(t)) is obtained by adjusting the scale parameter a and shift parameter b. The wavelet detail coefficient at level j and location k is represented by the internal coefficient $d_{j,k}$

3.2.1. Median filter

Median filter is a non-linear digital filtering method that keeps features and edges intact while eliminating noise from data. Median filter enhances the electrocardiogram (ECG) signals to detect the abnormal heart rhythms. By removing noise and artifacts, the filter improves the signal quality,

3.2.2 Signal reconstruction

Signal reconstruction aims to recreate the original signal from its processed or transformed version, often after some form of modification, filtering, or decomposition. Signal reconstruction, decompose the signal by applying a pair of filters to the signal. This is done iteratively at multiple levels. In Level 1, the signal's coefficients are divided into low-frequency approximation components and high-frequency detail components. The approximation coefficients from the previous level are further broken down into more precise approximations and details in the subsequent levels. Take the detail and approximation coefficients out of the DWT. Combine approximation and detail coefficients from the current level of decomposition for each level by utilizing the proper upsampling and filtering techniques. Increase the size of the coefficients by inserting zeros. Apply the reconstruction filters to merge the coefficients for each level of decomposition. During the reconstruction process, the quality of the reconstructed signal is influenced by the amount of noise introduced at various stages of processing. Higher noise figures typically mean that the noise level is higher, which affects the fidelity of the reconstructed signal.

3.3 Noise figure signal

Noise Figure quantifies how much noise a system adds to the signal compared to an ideal system. The signal-to-noise ratio (SNR) declines as the signal moves through a part or system, and this is measured. Impact on Signal: A higher noise figure means more noise is added to the signal, which degrades the quality and clarity of the signal. Signal-to-Noise Ratio (SNR) SNR of a signal is crucial for determining how well the signal can be reconstructed after processing. Higher noise figures lead to lower SNR, making it more challenging to accurately reconstruct the original signal.

3.4 Attention guided Bi-GRU

ECG signals can be used to extract long-term dependencies with a bi-directional gated recurrent unit (Bi-GRU). The bidirectionality of Bi-GRU allows it to process input sequences in both directions at the same time. The Attention Mechanism examined the output of the Feature Extraction component, which only received waveforms as input, in order to identify significant portions and model dependencies across timesteps. Different waveform and temporal parameters were encoded to a hidden state by the feature extraction component. Long-term dependency, hierarchical & condensed, and distributed representative features are extracted. Concatenation and fusion techniques are employed to create deep features from these retrieved features. The final characteristics are able to represent the ECG signal's temporal dynamics as well as its morphology. These characteristics work better in distinguishing between various arrhythmia types, forecasting upcoming cardiac events, and eliminating noise and artifacts. A more thorough and precise examination of the ECG signal is made possible by the distinctive features that are produced when CNN, residual blocks, and Bi-GRU are combined. This is particularly important for the detection and treatment of heart problems. This is especially helpful for jobs that call for a grasp of the dependencies within the input ECG beat segment. The Attention Mechanism examined the output from the framework's Feature Extraction component, which only took waveforms as input, to find important portions and model dependencies throughout the input's timesteps. The Attention Mechanism examined the output from the framework's Feature Extraction component, which only took waveforms as input, to find important portions and model dependencies throughout the input's timesteps. The A feature in the extraction component, different waveform and time attributes were encoded to a hidden state.

The input sequence is processed by the Bi-GRU both forward and backward. Forward GRU is calculated in below equation:

$$h_t^{\rightarrow} = GRU\ (x_t, h_{t-1}^{\rightarrow}) \tag{5}$$

Backward GRU is calculated in below equation:

$$h_t^{\leftarrow} = GRU\ (x_t, h_{t+1}^{\leftarrow}) \tag{6}$$

Concatenate forward and backward hidden states equation is given below:

$$h_t = [h_t^{\rightarrow}; h_t^{\leftarrow}] \quad (7)$$

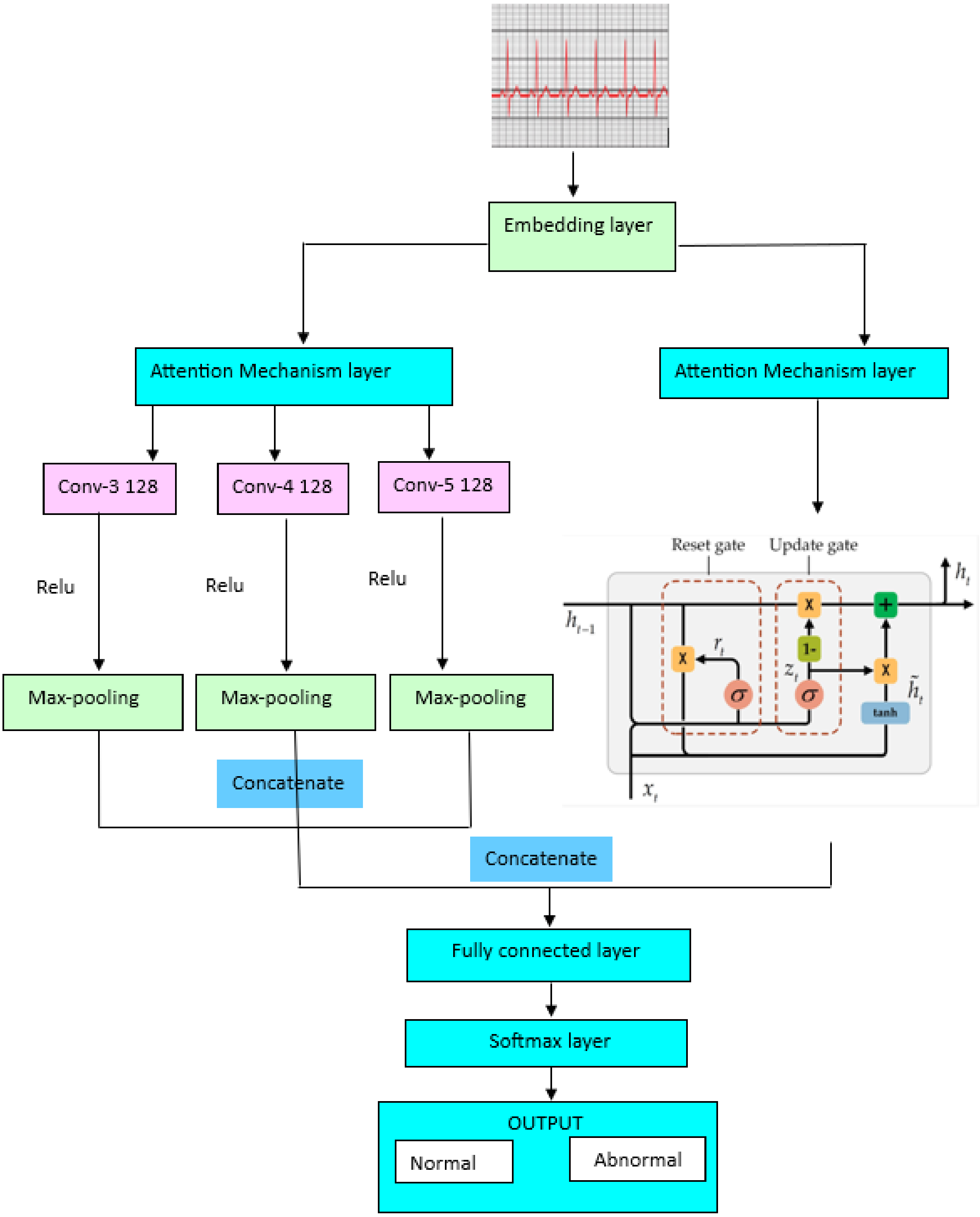


Figure 2. Architecture of attention guided BiGRU

4. RESULTS AND DISCUSSION

This section presents an assessment of the proposed AD-BRU Network using the gathered datasets and a variety of metrics, such as accuracy, specificity, precision, recall, and F1 score. Performance of AD – BRU and its overall accuracy rate is specifically defined and assessed are included in the benchmark.

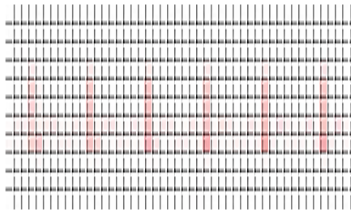
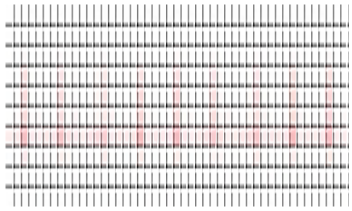
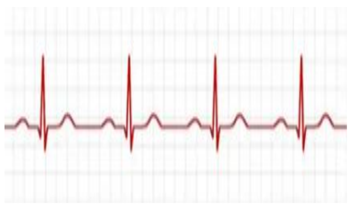
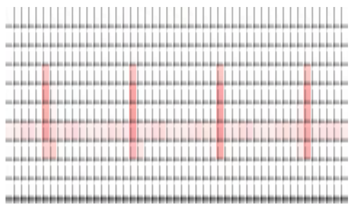
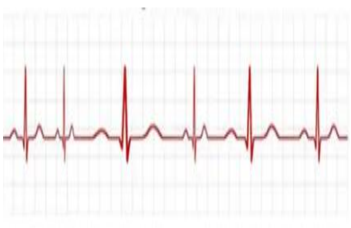
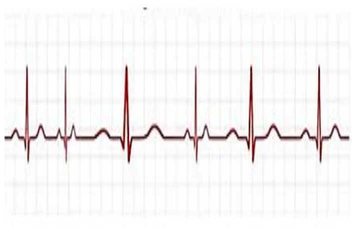
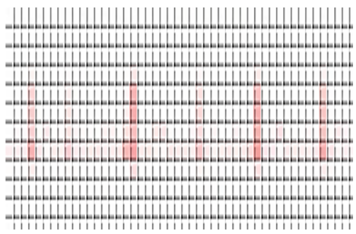
Input image	Preprocessing	Feature extraction	Classification
			Normal heartbeat
			Fast heartbeat
			Slow heartbeat
			Irregular heartbeat

Figure 3. Classification results of proposed AD - BRU

Figure.3 depicts the results of proposed AD - BRU with the sample of imaging modality such as ECG for identifying the arrhythmia disease detection. The medical images from the gathered MIT-BIH dataset is processed using pre-processing techniques like discrete wavelet integrating filter to eliminate the unwanted disortions. After that, a noise figure signal is applied to the previously processed pictures. The results from the noise figure signal are further refined. The output images are taken as input to AD - BRU to extract the relevant Arrhythmia disease.

4.1 Performance analysis

The evaluation metrices of accuracy, specificity, recall, f1 score and precision, can be used to gauge the effectiveness of the proposed AD – BRU network.

$$\text{Specificity} = \frac{T_{neg}}{T_{neg} + F_{pos}} \tag{8}$$

$$\text{Precision} = \frac{T_{pos}}{T_{pos}+F_{pos}} \tag{9}$$

$$\text{Recall} = \frac{T_{pos}}{T_{pos}+ F_{neg}} \tag{10}$$

$$\text{Accuracy} = \frac{T_{pos}+T_{neg}}{Total\ no.\ of\ samples} \tag{11}$$

$$\text{F1 score} = 2\left(\frac{Precision+Recall}{Precision+Recall}\right) \tag{12}$$

where T_{pos} *and* T_{neg} represents the actual positives as well as negatives of one of the images. False positives and negatives for the sample images are indicated by F_{Pos} and F_{neg}.

Table 1. Performance assessment of the proposed AD – BRU network

Classes	**Specificity**	**Precision**	**Recall**	**F1 score**	**Accuracy**
Normal	95.12	96.24	96.25	96.19	99.32
Abnormal	96.12	95.31	97.05	96.02	98.41

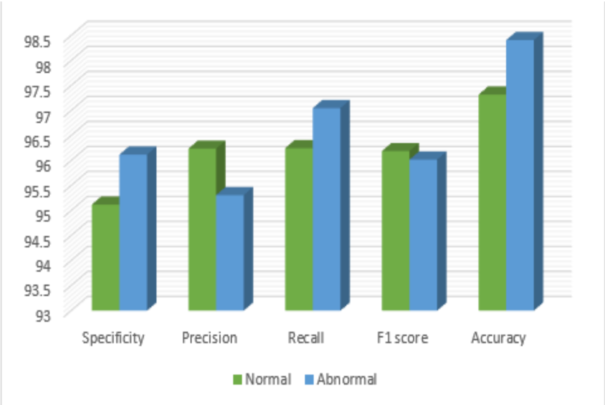


Figure 3. A graphic representation of performance analysis for arrhythmia disease detection

The performance outcome obtained by the proposed AD – BRU Network for categorizing the normal and abnormal signal in ECG. i.e., normal or abnormal is exposed in table 1. A performance evaluation's metrics include specificity, precision, recall, f1 score, and accuracy. With the suggested AD-BRU, an overall accuracy of 96.76% is attained. Overall, the suggested AD-BRU achieved 95.62%, 95.77%, 96.65%, and 96.10% in terms of specificity, precision, recall, and f1 score. The performance assessment of the proposed AD-BRU Network is graphically depicted in Figure 3.

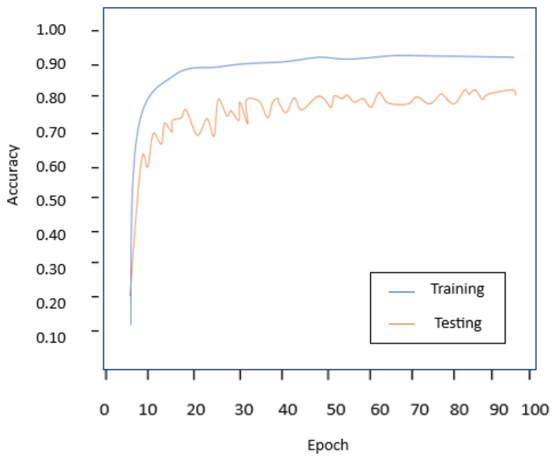


Figure 4. Training and testing accuracy of proposed attention guided Bi-GRU

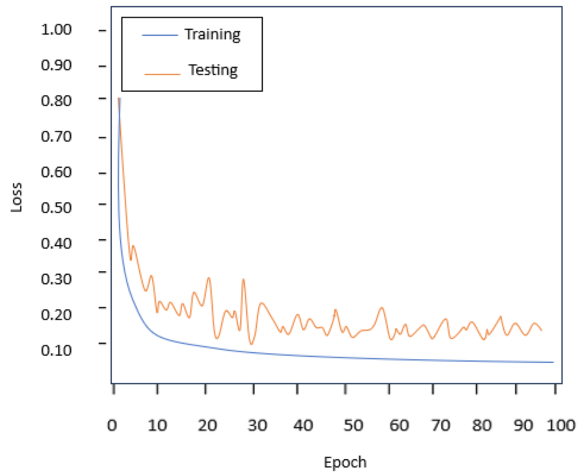


Figure 5. Training and testing loss of proposed attention guided Bi-GRU

The training and testing accuracy is seen in Fig. 4, which also displays epochs on the x- and y-axes. Based on its training and testing accuracy curves, the proposed exhibits an accuracy level of 98.86% when accounting for the epochs. A loss curve plotted against epochs is shown in Figure 5 showing that the loss reduces with increasing epochs. The proposed procedure yields an accurate result with a reasonably low loss of 1.14%. Tested and trained, the proposed AD – BRU network exhibits good performance.

4.2 Comparative analysis

The efficacy of deep learning network was evaluated in order to verify that the proposed AD – BRU network produces high-frequency outputs. The proposed AD – BRU with DNN and CNN were compared and evaluated. The specificity, precision, recall, f1 score and accuracy of each DL methodology was employed to assess the performance. The proposed AD-BRU's network accuracy was 98.86%, which was greater than that of the conventional neural networks.

Table 2. Comparison between traditional deep learning networks and proposed Bi-GRU

Networks	Specificity	Precision	Recall	F1 score	Accuracy
DNN	88.7	86.2	85.3	85.7	89.5
CNN	89.2	87.5	84.6	86.0	91.2
Attention guided Bi-GRU network	95.62	95.775	96.65	96.105	98.86

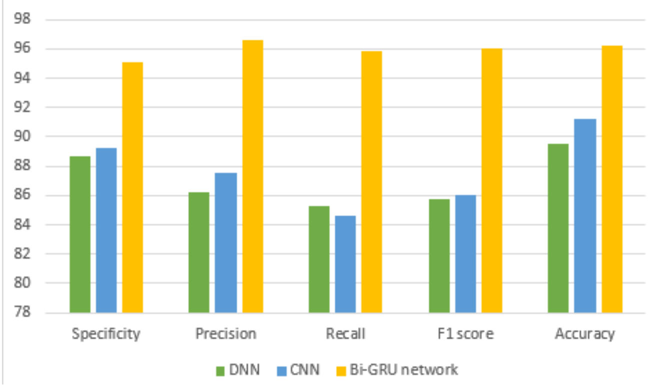


Figure 6. A graphic representation of performance analysis for arrhythmia disease detection

The proper proportion of classification accuracy was obtained from Table 2, and several DL networks were compared based on performance criteria. But when measured against the proposed AD – BRU, the conventional networks were unsuccessful as well. By 89.5% and 91.2% respectively, more accuracy is achieved in the proposed AD – BRU Network compared to CNN and DNN.

Table 3. Comparing the accuracy of current models with the proposed AD – BRU network

Authors	**Methods**	**Accuracy**
Oleiwi Z.C., et al., (2023) [10]	Wavelet Transformation	98.5%.
Khan M.A. and Khan Y, (2021) [4]	LSTM Deep Learning	93.5%
Khan H., et al., (2024) [9]	EnsCVDD-	88%
Proposed	AD - BRU	98.86 %

Table 3 indicates the experimental duration of the sample images from the collected dataset during the testing phase, which has been calculated to assess the precision of various methods. The most recent models were compared using performance criteria by determining the proper percentage of classification accuracy. The proposed TC-MRF achieves higher overall accuracy than Wavelet transformation, LSTM deep learning, and EnsCVDD by 0.36%, 5.42%, and 10.98%, respectively. The proposed network outperforms the current networks in terms of performance. The following table demonstrates how superior our technique is over other approaches. Thus, the proposed AD – BRU are extremely reliable.

5. CONCLUSION

In this research, an AD – BRU has been proposed for identifying the arrhythmia disease from the ECG signal image. The proposed technique identifies, normal and abnormal ECG signal for detecting arrhythmia disease. Initially the input images are gathered from the MIT-BIH datasets. The input images are pre-processed using discrete wavelet integrated filter for eliminating noise artifacts and signal reconstruction. The signal's image is applied to the noisy figure signal's subsequent stage. The performance of the AD-BRU is evaluated using a number of metrics, including accuracy, precision, recall, specificity, and F1 score measurements. The experiment findings demonstrate that by differentiating between normal and abnormal ECG signals, the proposed method achieves a greater accuracy range of 98.86% for diagnosing the arrhythmia condition. In future, the proposed AD-BRU's precision will be increased to detect the signal image in a matter of seconds.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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