ECG SIGNAL CLASSIFICATION USING TUNING TECHNIQUES BASED STACK OF NEURAL NETWORKS

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ABSTRACT

Daily cardiac health monitoring can benefit from the automatic identification of irregular heart rhythms from electrocardiogram (ECG) signal. A vibrant ECG signal is used to detect cardiac problems resembling heart attacks, and coronary ailments. From the ECG analysis doctors can adequately treat patients for a given condition. We used tuned techniques like regularization and global max-pooling and open-source databases like MIT-BIH and PTBDB. Data is pre-processed using resampling and normalization processes. The suggested method enables unique features like high accuracy with less bottleneck problems. The proposed Bi-LSTM, CNN and Attention has an F1-score of 94.7 % and an accuracy of 98.9 %. The approach improves accuracy over existing systems. On the databases PTBDB and MIT-BIH, the suggested approach was evaluated. According to experimental findings, the trained CNN-LSTM-attention was able to forecast the missing segments with greater accuracy. The quality of the projected signal ensures that the suggested method will find widespread use in medical applications and is applicable to any single channel ECG signal. A comparison of the performance with previously published research for the prediction of ECG missing data revealed improved results.
Keywords: *Tuning Techniques, Electrocardiogram Signal, Deep Learning, And Classification.*

1. INTRODUCTION

The electrocardiogram (ECG) is a specific device frequently used to track cardiac problems noninvasively by detecting the heart's electrical activity. The lack of the P wave, a minor swaying in the TQ interval, and an irregular inter-beat timing brought on by rapid and irregular atrial contraction is further ECG features of AF [1]. As a result, the regularity of the heartbeats' rhythm and morphology in the ECG signal is largely examined for arrhythmia detection. An ECG demonstrates the electrical conductivity of the heart. A doctor can identify cardiovascular diseases by examining irregularities in the ECG wave [2]. Therefore, developing autonomous methods for analyzing heart signals is very advantageous. DNN is used in the majority of biological signal-processing applications. Because before separating the features from the raw data, CNN won't undertake any pre-filtering. Time series signals include ECG signals. Therefore, avoiding a long-term dependence scan using a Bi-LSTM recurrent neural network is possible [3]. DL approaches are extensively used in systems designed to aid specialists. ECG categorization is currently crucial because of many contemporary medical applications. Tools for machine learning (ML) can analyze and classify ECG data. To address the demand for computerized feature collection and classification of ECG data, end-to-end DL approaches, such as CNN and RNN, are currently being widely deployed. These methods stand out for their ability to automatically acquire intrinsic, easily recognizable properties from unprocessed inputs without needing specialized expertise or professional assistance [4]. Therefore, the LSTM is often utilized in current ECG classification tasks. With self-recurrent connections, these models make it easier to extract globally time-dependent features, but they have the drawback of requiring a lengthy training period and adding conversion overhead. On the other hand, CNN can quickly and successfully understand local features. Despite

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their outstanding performance and entirely autonomous learning capabilities, CNNs frequently increase the number of training parameters since they perform well as the network gets deeper. As a result, it has become challenging to intuitively interpret taught characteristics via deep learning models' inherent complicated architectures [5]. We use DL architecture rather than ML because there aren't enough labelled datasets.

2. RELATED WORK

ECG signals have been utilized to track and identify cardiac disease symptoms and aberrant body signals. ECG machines are frequently used for various purposes, particularly for the elderly. However, environmental noise frequently interferes with ECG signals [6].

These sounds must be eliminated for the ECG signal to be of higher quality. Cardiovascular issues are simple to diagnose with a clear ECG signal. The signal's noises will be more noticeable, though, and it will be challenging to use filters to eliminate them. Many papers have been published about the ordering of ECG signals, mainly when employing ML approaches [7]. The Neuro-Fuzzy Algorithm, SVM, ANN models CNN and RNN for time-frequency analysis have all been used in previous studies as machine classification algorithms. To further explain the significance of the ECG signal and the resulting outcomes of the applied analysis, we discuss relevant studies by other authors in this section. Figure 1 shows an ECG signal with the P wave, QRS complex, and T wave that is quite common. The muscle contractions in both atria produce the P waves. T waves are lastly generated by ventricular muscular activity. Therefore, because they include a wealth of helpful information, the P, QRS, and T waves are crucial ECG components that should be examined and assessed [8].

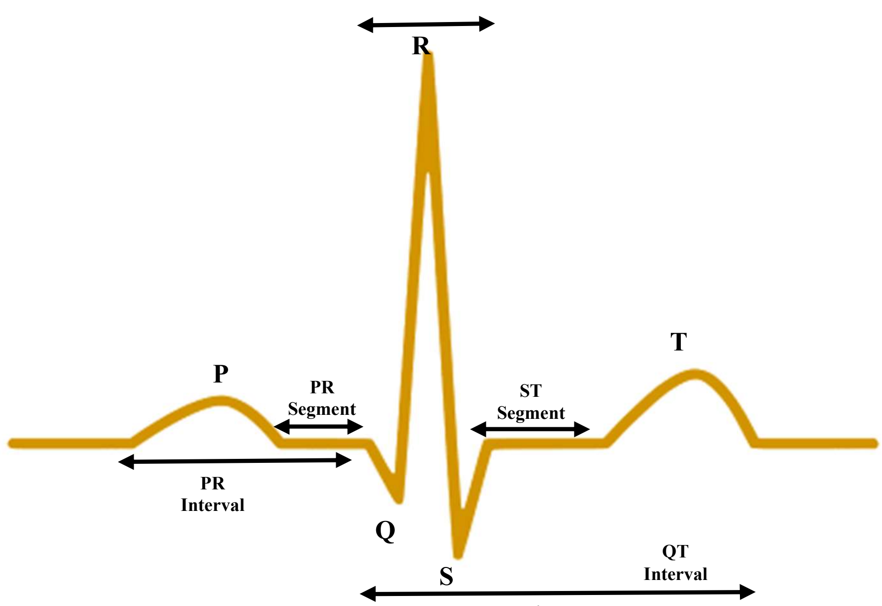

Figure 1. ECG signal.

The most common causes of death were cardiovascular disease, which accounted for 70% of all fatalities, according to the WHO 2017 World Health Statistics report [9]. When compared to cancer and other diseases, the cardiovascular disease claimed the lives of more than 40% of people, placing it first. AF is the most prevalent clinically persistent cardiac arrhythmia disease, with a prevalence of just under 1% in the general population [10]. Shuihua Wang served as the assistant editor who oversaw the evaluation of this paper and gave it the green light for publishing. With age, the likelihood of it rises [11]. AF classified as paroxysmal, persistent, and permanent atrial fibrillation, is characterized by fast and erratic ventricular contractions. The increased risk of stroke, heart disease, and cardiovascular disease is associated with irregular cardiac rhythm. Obesity, hypertension, mitral or tricuspid valve diseases, and drinking are also closely associated with AF and can shorten life expectancy and raise mortality risk. As a result, AF is the most prevalent arrhythmia disorder, making automatic AF detection essential for early diagnosis, therapy, and the avoidance of associated problems. Table 1 provides a summary of the history of research on ECG classification.

Table 1. DL techniques for ECG signal analysis.

Ref.	Description	Dataset	Tuning Techniques	Limitations
[12]	Run a lot of trials on a dataset that is frequently utilized. In our studies, the overall accuracy was 93.23%, and the accuracy of detecting high-risk arrhythmias from just supraventricular and ventricular beats was 97.4% and 96.3%, respectively.	MIT-BIH	---	Model was not validated by extracting most of the performance indices.
[13]	The LSTM network was trained using the data set that had been processed in this manner. The networks were trained on unprocessed and spectrally modified data during the studies. Then, the thusly trained networks were contrasted with one another.	Customized (3121 signals)	Hyper parameters tuned	Unique dataset was considered
[14]	The presented Classifier DRNN model demonstrates that in the NSRDB, the overall precision, recall, accuracy, and F1-score were all 100%.	NSRDB and MITDB	Normalization was performed	More tuning techniques are not considered
[15]	The person identification task is carried out using a multiresolution 1D-CNN that automatically learns.	CEBSDB	Dropout analysis was performed	Unique dataset was considered
[16]	The validity of performance stability concerning CC rate. To justify the generalizable use of the optimised computationally efficient CNN model.	OHCA	Regularization techniques was used	Model was not validated by extracting most of the performance indices.
[17]	A number of tests were done to compare our model's FPGA implementation to the most recent state-of-the-art techniques using their assessment methodologies.	MIT-BIH	---	More tuning techniques are not considered

1.1. Motivation

According to WHO statistics, more people are developing cardiovascular issues, particularly among the elderly. Therefore, it is becoming increasingly urgent and crucial to monitor cardiovascular disorders. The ECG is a frequently used non-invasive measuring technique when screening and diagnosing various diseases. Health monitoring and diagnostics is one of the crucial uses. It offers one of the critical pieces of evidence supporting the stroke diagnosis. Monitoring of electrocardiograms aids in the early detection and identification of stroke causes. The ECG signal's quality directly influences the success of the diagnostic process. The R peaks are crucial in determining the patient's heart rate, and they are one of the four waves that make up the ECG signal, along with the Q, S, and T waves. It will be more beneficial to distinguish the elements of an ECG signal [18]. It was discussed how stacks of DL models play a special role in processing ECG signals. Before building the network, we exhibited the attributes of the input data to aid in understanding. We'll use the DNN stack ensemble approach in this model. A new model can learn how to successfully combine the predictions of various current models with the ensemble integration tuning technique. Using the model averaging method, the constraints of each neural network algorithm are merged to produce predictions. The proposed model combines convolution, recurrent neural, and attention mechanism networks. We utilized RNN to process sequential data.

1.2. Problem Statement

First off, a lack of pertinent data, clearly specified test protocols, and unclear labels prevent the development of an automatic interpretation system for ECG categorization. The PTBD and MIT-BIH Arrhythmia databases, two well-known datasets provided by Physionet, were insufficient. The research questions that the project addresses. To train ANN for categorization of arrhythmias, a detailed understanding of the many types of available NNs and their layers is required. We usually employ numerous assemblies. Neural networks use a variety of techniques. Since it gives performance metrics, including accuracy, precision, F1 score, and recall, the algorithm's performance analysis is essential.

2. METHODOLOGY

The unique role of stack of DL models in ECG signal analysis was presented. To help with understanding, we displayed the properties of the input data before the network construction. In this model, we'll employ the DNN stack ensemble technique. With the help of the ensemble integration technique known as "stacked generalisation," a new model can learn how to combine the predictions of several different existing models effectively. The restrictions of each neural network algorithm are combined to make predictions using this model averaging technique. Convolution, recurrent neural networks, and attention mechanism networks are all combined in the suggested model. To process sequential data, we used RNN. The technique for this investigation is explained in full in Figure 2. The use of tuning strategies that regulate the behavior of the algorithms, such as normalization, and dropout.

Our research has made the following contributions overall:

• We dissected the critical elements of the ECG signal. How to design filters to remove noise and how noise influences the signal are both affected.

• We looked at ECG signals from the BIT/MIH database at various sampling rates. To associate the differences between the conventional signals, we use filters.

• To gather real-time signs, we suggested an ECG signal gaining paradigm based on substantial production components. We also use filters to reduce noise from the device's various sampling frequencies. We evaluate the parameters and make judgments.

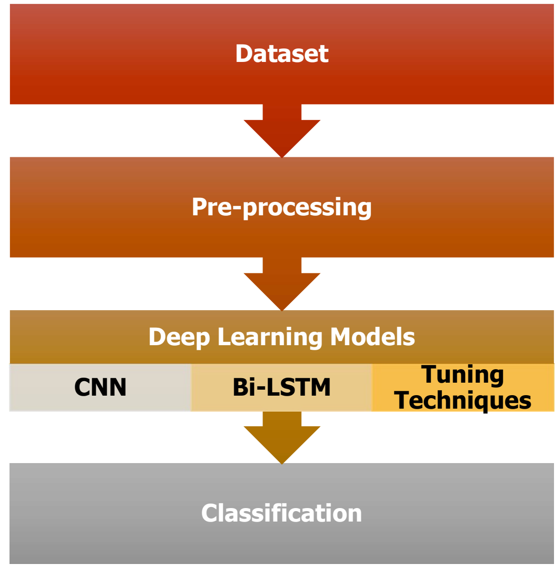

Figure 2. Detailed research.

3. IMPLEMENTATION

More people are acquiring cardiovascular problems, especially among the elderly, according to WHO figures. Therefore, it is crucial to keep an eye on cardiovascular issues. When diagnosing and screening for different disorders, the ECG is a regularly utilized non-invasive measurement technique. One of the most important uses is for health monitoring and diagnosis. It provides one of the crucial pieces of proof that the stroke diagnosis is accurate. Monitoring electrocardiograms helps identify and locate stroke causes early on. The quality of the ECG signal directly influences the effectiveness of the diagnostic procedure. Along with the Q, S, and T waves, the R peaks are one of the four waves that make up the ECG signal and are essential in calculating the patient's heart rate. It will be more advantageous to recognize the components of an ECG signal.

3.1 Datasets

The MIT-BIH and PTBD Databases, provided two collections of heartbeat signals used to create the dataset. Both sets' combined sample counts are sufficient to train a DNN. Using DNN architectures, this dataset is used for heartbeat classification. The MIT-BIH dataset is split into training and testing halves. The information categorised arrhythmias into five primary categories. These classes cover arrhythmias of various sorts. The PTB Database on the Physionet website serves as the dataset's additional source. The two categories that make up this dataset are Normal and Abnormal. Each of the 48 records in the MIT-BIH database has the information. A total of 290 subjects contributed 549 recordings to the PTBDB ECG database.

3.2. Stack of Neural Networks

A popular DNN type for categorization is called CNN. CNN doesn't need feature extraction techniques, reducing network processing time. The following layers make up CNN. Convolutional, pooling, and a layer with no gaps. The basic building block of a CNN is the convolutional layer, where most computation takes place. The size of the feature maps is decreased by using the Max Pooling and Average Pooling layers. The fully linked layer's job is to categorise the characteristics taken out of the preceding layers and their various filters. A variety of RNNs is frequently applied to time series and sequence data. The data travels in both directions through LSTM layers. It provides the output with features and saves historical data in mixed hidden states inside the layers. It is one of the most significant advancements in DL in recent years. This is an imperfection in the model where accuracy is good, but in situations where there is a lot of information, the summarization is poor, and the model performs poorly; this is known as the long-range dependency problem of RNN. We shall employ a method known as the Attention Mechanism to address these limitations. This improves input data characteristics that produce better outcomes when dealing with long-range dependency issues. CNNs, which form the foundation of deep learning, have made significant strides in object detection, semantic segmentation, and picture categorization in recent years. Due to improvements in the CNN model, GPU technology, and large-scale data collection, deep learning has dramatically changed how research problems in computer vision are solved.

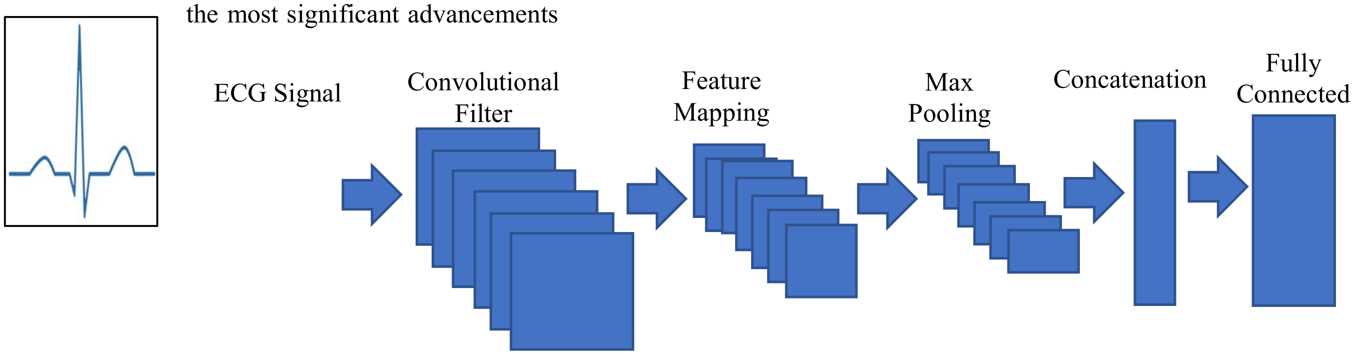

Figure 3. CNN for ECG signal Classification.

This model had a 96-batch training set with a 40-epoch epoch. Figure 4 displays the model accuracy and loss according to the number of epochs. Looking at the curves allows us to assess how well our model has been trained. The total accuracy of this model was 95.6% after 31.2 minutes of simulation.

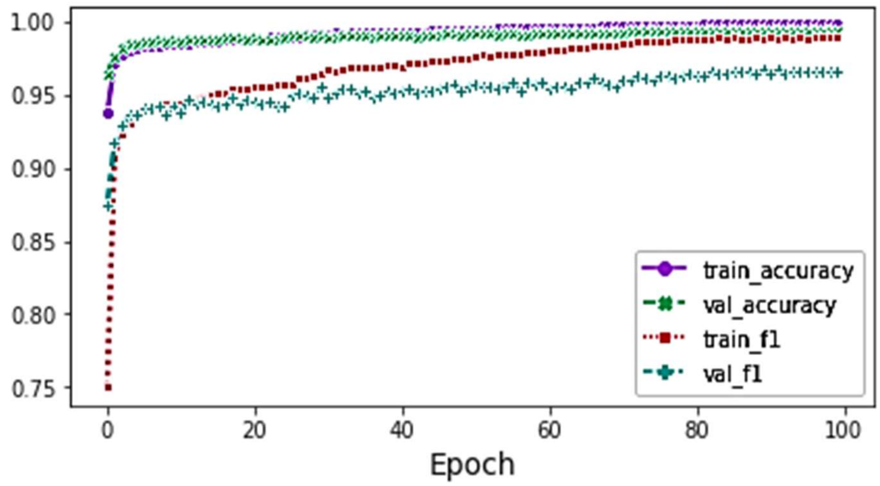

Figure 4. CNN Model Classification Report.

This model uses an epoch of 10 and has a batch size of 96. The model loss and accuracy for the number of epochs are shown in Figure 6. With a dropout of 0.2, added the Bi-LSTM to CNN. Within 42.5 minutes of simulation, this model accuracy of 97%.

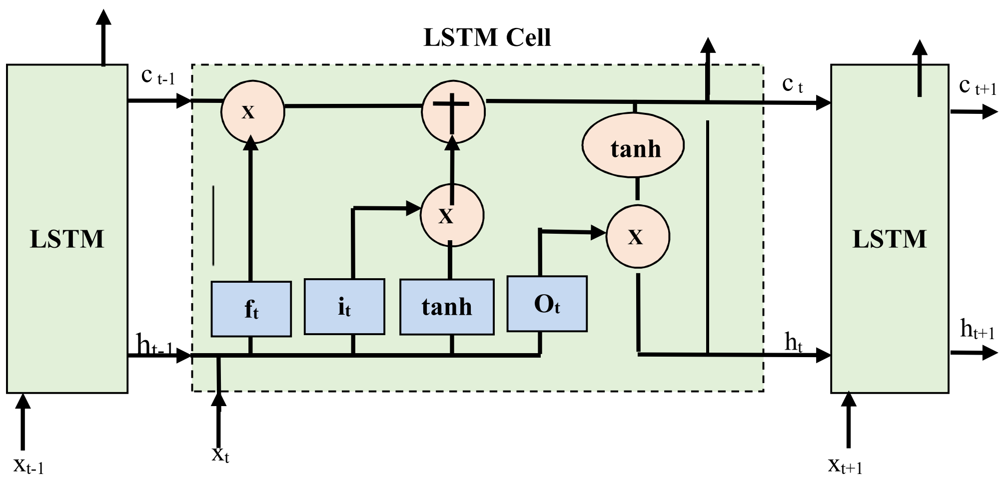

Figure 5. LSTM network.

Additionally, it is challenging to increase detection accuracy and speed. Deep CNN and Bi-LSTM network, a revolutionary deep arrhythmia detection technique, are introduced to detect AF from ECG signals automatically. The model is trained using an epoch of 100 and has a batch size of 96.

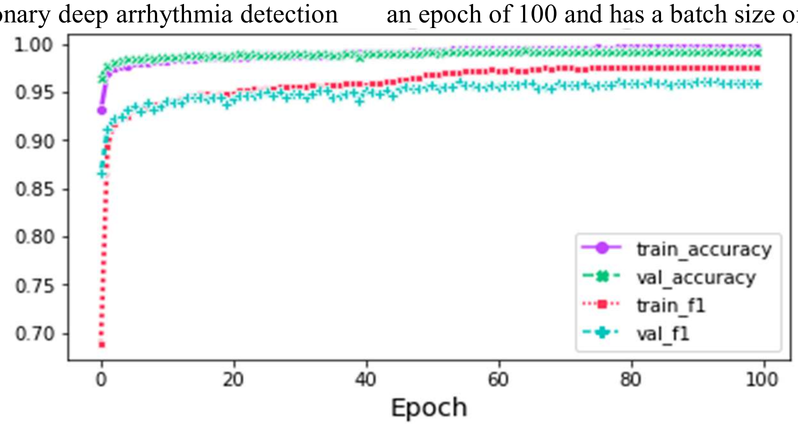

Figure 6. Bi-LSTM and CNN model classification report

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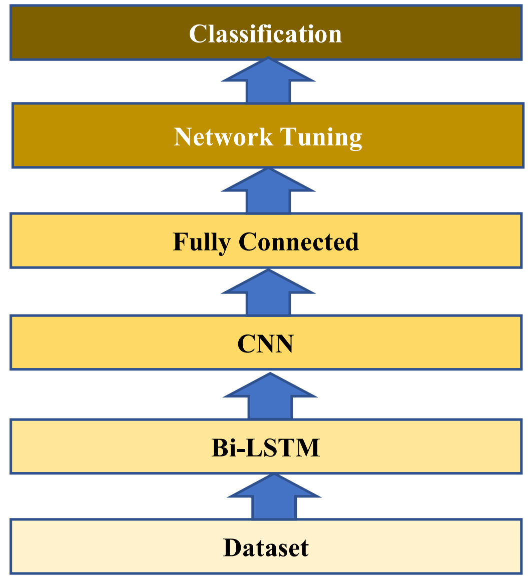
3.3. Presented DL approach

As seen in Figure 7, we created a DL algorithm here. Three components make up our model: Bi-LSTM, CNN, and an attention mechanism. Our dataset is balanced first, and then CNN is used to extract the features. Bi-LSTM is then given the dataset to carry out the classification, and an attention is employed to enhance performance. The balanced ECG signal is now sent to the module with the 1D convolution layer. Convolutional, maximum pooling, and dense layers make up CNN. Batch-normalization is employed. Batch normalisation is used between each convolutional layer and the maximum pooling layer. Each module in CNN contains three convolutional layers. The size of the filter in this model's convolution layer is 5. The first layer's hidden layer size is 256 bytes, the second layer is 128 bytes, and the third layer is 64 bytes. Here, we'll take a single stride. According to the data set, the input and batch sizes are 96. The outputs from the first and third layers will be combined at the third layer before being passed to the global maxpooling layer. Data that has been previously processed is supplied to CNN, which then uses the ECG training data to extract the features. The features are then delivered to RNN, which uses time series data such as ECG signals. The hidden layer dimensions of the RNN model, which is a single-layered Bi-LSTM, are 64. The input size for this model is similarly to 1 in this case. A dropout of 0.2 reduces overfitting to improve model performance because RNN tends to overfit the data easily. The output size 1 Adaptive Average pooling layer receives it next. Whether they are features from an RNN model or a CNN model, we will utilize an attention method to provide more weight to the significant features. This layer has the exact 64 dimensions as the RNN Layer. This layer receives its inputs from the RNN model's hidden layers. This generates a scalar value score and computes attention scores for each of its encoder states. The most straightforward approach for calculating weights and inputs of the dot product will be used.



This will be followed by the inclusion of biased terms, which will ultimately give us the attention scores. Following the application of tanh, average pooling with a stride of 1 will be used. It is finally passed on to the softmax layer.

The network becomes non-linear due to activation functions. The softmax function is employed in the output layer to forecast the probability distribution. A swish activation function is chosen because it performs better on DNN than ReLU. The values of the cell state are determined by the Bi-LSTM's application of the Tanh activation function. Tanh's value is limited to -1 and 1, and it functions better with Bi-LSTM. Less computation is required to produce its gradient. Typically, the FC layer is connected at the output's end. The FC layer receives the output of the final pooling layer. FC layer classifies data using extracted features. Due to its features of low dimensionality and little memory, the end-to-end deep Bi-LSTM + CNN + Attention network was presented to replace the handmade features with Bi-LSTM and CNN for detecting AF signals. As inputs to the network, we designed multi-scale signals with RR intervals and Heartbeat sequences. The network model's generalization can be enhanced by using this design to extract multi-scale features. A thorough experimental investigation that considerably enhanced the performance of classifying ECG signals. The network under discussion produces cutting-edge findings on datasets and complete comparisons with other approaches. CNNs, which excel in classifying images, and time-series data are both enhanced by Bi-LSTM. Deep learning uses learning to extract features.

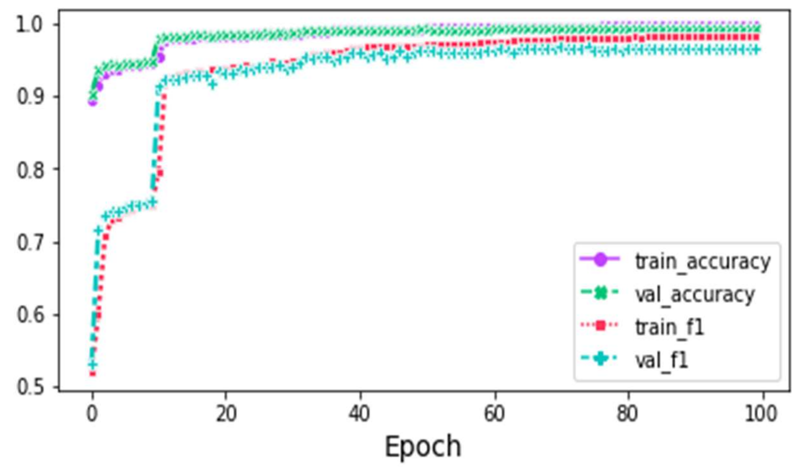


Figure 7. Loss and accuracy metrics.

Table 2. DL analysis on ECG signal.

<table>
<tr><th>DL approach</th><th>Layers</th><th>Time in minutes</th><th>Epochs</th><th>Accuracy</th></tr>
<tr><td rowspan="4">CNN</td><td>Convolution</td><td rowspan="4">31.2</td><td rowspan="4">40</td><td rowspan="4">95.6</td></tr>
<tr><td>Max-pooling</td></tr>
<tr><td>Dropout</td></tr>
<tr><td>Global Avg pooling</td></tr>
<tr><td rowspan="7">CNN + Bi-LSTM</td><td>Convolution</td><td rowspan="7">42.5</td><td rowspan="7">10</td><td rowspan="7">97.1</td></tr>
<tr><td>Max-pooling</td></tr>
<tr><td>Dropout</td></tr>
<tr><td>1-Bi-LSTM</td></tr>
<tr><td>Global Avg Pooling</td></tr>
<tr><td>FC</td></tr>
<tr><td>Softmax</td></tr>
<tr><td rowspan="10">Bi-LSTM + CNN Attention Mechanism</td><td>Bi-LSTM</td><td rowspan="10">47.9</td><td rowspan="10">10</td><td rowspan="10">98.9</td></tr>
<tr><td>Convolution</td></tr>
<tr><td>Feature mapping</td></tr>
<tr><td>Max-pooling</td></tr>
<tr><td>Dropout</td></tr>
<tr><td>Attention</td></tr>
<tr><td>Dot product</td></tr>
<tr><td>Global Avg Pooling</td></tr>
<tr><td>FC</td></tr>
<tr><td>Softmax</td></tr>
</table>

Our classification of five different ECG heartbeat types, essential for the early detection of cardiac diseases, will be presented in this paper. The system we utilized can more correctly and quickly classify five different heartbeat classifications. Using Bi-LSTM and Attention methods to avoid long-term reliance and unbalanced datasets is the work's main contribution. In comparison to other functions, accuracy was improved overall. This model only looks at arrhythmia, a disorder of the heart. New ECG data must be incorporated to increase our method's applicability and identify more heart diseases.

4. CONCLUSION

This study will present our classification of five different ECG heartbeat types, which is crucial for the early diagnosis of cardiac disorders. The methodology we used can quickly and generally categories five different heartbeat classifications more accurately. The work's key contribution is using Bi-LSTM and Attention mechanisms to prevent long-term dependence and unbalanced datasets. Compared to other functions, accuracy overall was enhanced. This model exclusively examines the heart condition known as arrhythmia. To broaden the applicability of our algorithm, more ECG data must be included in order to detect more cardiac disorders. As a result, our suggested stack of deep neural network algorithms demonstrates the promise of a deep learning-based strategy for feature extraction of the MIT-BIH arrhythmia database. These results demonstrate that the suggested methodology is a practical automatic cardiac arrhythmia classification method. It does not require training from scratch but provides a trustworthy detection system based on pre-existing structures. It could deliver precise ECG signal categorization in clinical settings.

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