AUTOMATED DETECTION OF ATRIAL FIBRILLATION USING DEEP LEARNING

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ABSTRACT

The condition of atrial fibrillation (Afib) involves irregular beating of the heart's upper chambers (atria), which can increase the risk of stroke caused by a blood clot. The identification of paroxysmal AF can be improved through prolonged cardiac monitoring. To identify AF beats in Heart Beat (HR) signals, a machine learning model was employed, where the dataset is divided into sliding windows of 100-beat sequences. These sequences are then fed into a model that comprises a Bi-Directional LSTM layer, a Global max pooling layer, a Dense layer, a Dropout layer, and an output layer. The model was trained and tested using the MIT-BIH Atrial Fibrillation Database. The approach achieved high accuracy rates during training and validation, with a 98.15% accuracy rate. Additionally, the 7-fold cross-validation on 20 subjects yielded an accuracy rate of 93.43%, while testing with unknown data from 3 subjects resulted in an accuracy rate of 99.2%. The model performed well on untrained data, as demonstrated by the complete setup. The neural network architecture used in the proposed model was straightforward and consisted of simple deep-learning layers. Moreover, the proposed model demonstrated better efficiency.

Keyword: - *Atrial Fibrillation, MIT- BIH Database, Bi-Directional LSTM, Global Max pooling, Blind fold Validation, Cross- Validation.*

1. INTRODUCTION

Atrial Fibrillation (AF) is a common cardiac rhythm disorder in adults and is the most frequent sustained one [1]. Its prevalence rate ranges from 0.4% to 1% [2-3]. Although AF itself is not fatal, it is associated with several complications that increase mortality risk [4]. These complications include heart failure, stroke, and other cardiac-related ailments. Aging is expected to contribute to the increasing prevalence of AF. AF is characterized by abnormalities in blood flow dynamics, which raises the risk of systemic thromboembolism and stroke, leading to a high mortality rate [5]. Although ECG is among the best techniques for AF detection, identifying AF in short-term monitoring is challenging due to its paroxysmal nature. ECG of a patient affected by AF is irregularly irregular with no pattern for recognition. Cardiologists can visually identify AF in a patient's ECG, but this is only feasible for short-duration ECGs. In the last two decades, several algorithms, Volume 12 Issue 04, April 2023 ISSN 2456 – 5083 Page: 2 have been developed that can automatically detect AF in ECG recordings. Recently, a multitude of methods have been proposed for AF detection, with most detectors using the RR interval series as a starting point [6]. Paroxysmal AF is characterized by intermittent episodes of AF with normal sinus rhythm in between, and the episodes can occur unpredictably at any time. ECG recordings can be conducted during a single session or an extended period of 24 hours, as in Holter monitoring. However, recent studies have shown that the rate of AF recurrence in heartbeats following catheter ablation procedures is underestimated, and the success rate of the procedure is overestimated when determined from 24-hour Holter ECG recordings [7].

2. LITERATURE SURVEY

Detection of AF through Automation plays a major role in the present era, as it requires long- intervals of Electrocardiogram (ECG) data. Moreover, it is very difficult to manually detect all the Abnormal ECG sequences over long intervals of data. There are various approaches to the detection of AF. But the famous and most used approach is using RR interval sequences where R represents the peak of every heart Rate sequence. The interval is made as a set of features and is fed into a deep learning network for detecting whether the sequence has signs of AF or not. It can be easy to detect the AF using RR interval sequences as the electric impulses are irregular for patients affected with AF. Moreover, this strategy is more simple and more efficient to implement. Another approach for detection of AF is a combination of deep learning and a context-aware heuristics-based model which reduces the false positives in the first approach. Although the next approach is quite different, as it is low complexity based AF detection for battery-powered devices for continuous long-term monitoring. It uses 8 beat window instead of 128 beat window to fed to the model which drastically reduces the complexity of the model. Other approach includes novel data augmentation method. It is supposedly better than sliding window and permutation technique when compared with a 10-fold cross validation. Some approaches show us that combination of irregular RR intervals and electrical Atrial Activity has much better results compared to individual results. However, the complexity of the approach increases as it uses two parameters to detect AF. So after reviewing advantages and disadvantages of various approaches and came up with the following approach which uses RR interval irregularity in a 100-beat sequence window sliding technique and the output is fed to a deep learning layer consisting of Bidirectional LSTM as a primary building block, global max pooling layer, dense layer and a dropout as a neural network.

3. MATERIALS AND METHODS

This section of the research discusses the dataset utilized in the proposed model, the significant elements of the model, the model's architecture, and the training process.

3.1 Data Used

The experiments utilized the MIT-BIH Atrial Fibrillation Database as the data source. This database includes 23 long- term ECG (Holter) recordings from different subjects, sampled at 250Hz and annotated with R peaks. The RR interval sequences were derived from these annotations and divided into overlapping sequences of 100 beats, forming the Beat sequence of the 23-subject dataset. Of these, 20 subjects' data were utilized for training, validation, and cross-validation, while the remaining three subjects' data were reserved for blindfold validation.

3.2 Deep Learning

The aim of deep learning algorithms is to build models that leverage all the available input data to extract implicit knowledge that facilitates robust decision-making. As a result, compared to traditional machine learning methods such as Support Vector Machine (SVM) [8], the deep learning approach is generally more practical.

3.3 Bi- Directional LSTM

In most contemporary applications, where the output is reliant on the input, Recurrent Neural Networks (RNNs) are employed. They are primarily used for sequential inputs, such as Natural Language Processing. RNNs leverage the data from previous states, which gives them a distinct advantage in capturing the features of sequences in the data. However, Bengio et al. showed that RNNs are inefficient for long intervals of training. [9]. LSTM units, with their gating mechanism, are a better alternative to RNNs, particularly when handling long- term input sequences with step sequences. The Bi-Directional LSTM is an advanced version of the LSTM that allows data to be passed in both directions, making it possible to capture features in both directions. Bidirectional LSTM models have been found to be very effective in various domains, including speech recognition. The work of Graves and Schmidhuber highlighted the potential of bidirectional networks, as they can outperform unidirectional LSTM architectures [10].

3.4 Proposed System Architecture

The proposed model includes forward and backward LSTM layers, with the number of LSTM cells being twice the length of the input sequence. For the final classification of the sample, two fully connected layers are utilized. In between the bidirectional LSTM layers and the top model, a global max pooling layer is incorporated to condense the generated features. The global max pooling layer is a one- dimensional layer.

3.5 Model Training

The Xavier initialization was employed to initialize the model's weights to prevent them from being empty. The Adam optimizer was used with gradient descent backpropagation to update the weights. A batch size of 3000 input sequences was used during training to balance GPU memory and training speed. To improve efficiency and avoid overfitting, recurrent Volume 12 Issue 04, April 2023 ISSN 2456 – 5083 Page: 4 dropout [11] was applied to the inputs and hidden states of the LSTM cells during training, with a probability of 0.3, while standard dropout [12] was implemented between the fully connected layers, with a probability of 0.1. The binary cross-entropy function was employed to compare the predicted probability distribution with the true probability distribution and to obtain a better understanding of the search landscape. To evaluate the model's effectiveness and optimize its architecture and hyperparameters, a stratified 7-fold cross- validation approach was adopted. This approach ensured that each fold worked effectively with the model and provided a more comprehensive understanding of different training and validation splits.

4. RESULTS AND DISCUSSION

This section of the study covers several aspects of the proposed model, including the data utilized, the key components of the model, as well as the training process.

4.1 7- Fold Cross- Validation Results

The figures demonstrate that the proposed model's performance is slightly superior on the training set than on the validation set. However, there are no indications of overfitting, such as the training performance continually improving while the validation performance stagnates or worsens. Figure 1 shows the confusion plot obtained from the stratified 7-fold cross- validation process, while Figure 2 displays the Receiver Operating Characteristic (ROC) curve. The results were obtained by applying the model to the validation set in each of the seven folds, and then combining the outcomes to generate the confusion plot and the ROC curve.

Figures 1 and 2 illustrate the results of the stratified 7-fold cross- validation, demonstrating that the bi-directional LSTM classifier proposed in this study achieves an outstanding classification accuracy of 93.28% overall.

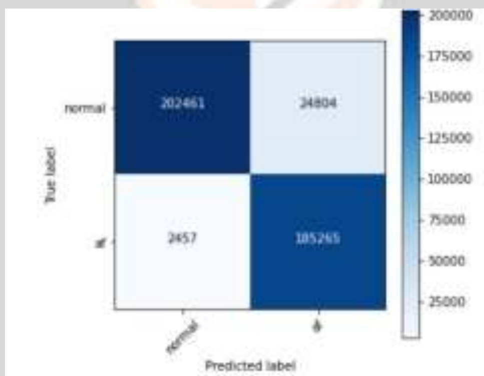

Fig -1: Confusion Matrix of 7- Fold Cross- Validation

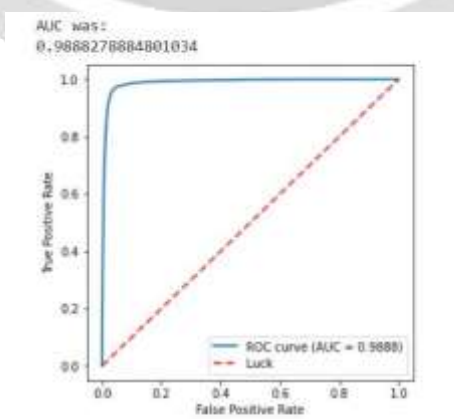

Fig -2: Area under the ROC Curve of 7- Fold Cross- Validation

4.2 Blind Fold Validation Results

Once the stratified 7-fold cross-validation was completed, the subsequent step involved assessing the blind-fold validation outcomes for AF and normal heart rate (HR) sequences obtained from three unseen patients.

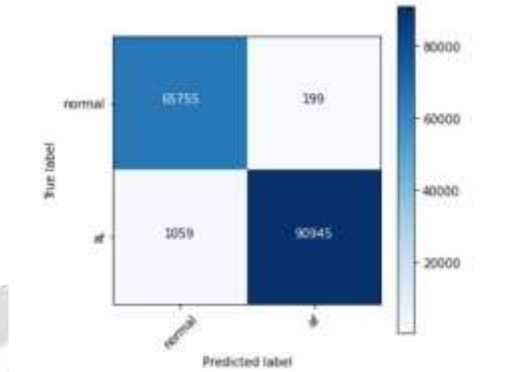

Fig -3: Confusion Matrix of Blind Fold Validation

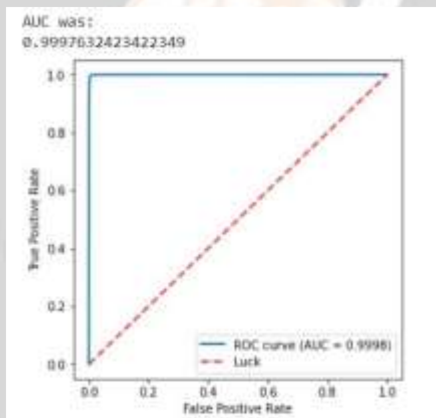

Fig -4: Area under the ROC Curve of Blind Fold Validation

5. CONCLUSIONS

Our method for detecting atrial fibrillation (AF) has demonstrated a notable level of accuracy. The approach involves breaking down the data into a sequence of 100 heart rate (HR) beats, which is then inputted into a deep learning model featuring a bidirectional LSTM layer consisting of both a forward and backward LSTM layer. The output from the bi-directional LSTM is then fed into a Global max pooling 1D layer. Since no feature extraction is required, there is no need to reduce information. The resultant data is then fed to the top model, with the algorithm using available information to create knowledge for the decision-making process.

This approach enables the decision-making system to achieve accuracy and robustness, as evidenced by the model's high level of accuracy: 93.28% with 7-fold cross-validation and 99.25% with blindfold-validation. These results are highly efficient and can be applied to a wide range of data, with the accuracies comparable to CAD systems that are considered reliable. The use of RR intervals in our model enables long-term monitoring of ECG signals, emphasizing the need for accuracy and robustness. Long-term monitoring involves a greater amount of patient health-related information, which can be better understood by deep learning, reducing the workload on clinicians. As the model receives more data, its accuracy in AF diagnosis is expected to increase. Additionally, the algorithm can be updated to enhance accuracy, leading to an improved decision support system overVolume 12 Issue 04, April 2023 ISSN 2456 – 5083 Page: 6 time. Our study is aimed at improving AF detection through the use of deep learning systems.

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