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A Hybrid Attention-based LSTM-XGBoost Model for Detection of ECG-based Atrial Fibrillation

Furkan BALCI[1*]

[1]*Gazi University, Faculty of Technology, Department of Electrical Electronics Engineering, Ankara, Turkey*

Keywords
LSTM
Atrial Fibrillation
Classification
Deep Learning

Abstract
Atrial fibrillation (AF) is a frequently encountered heart arrhythmia problem today. In the method followed in the detection of AF, the recording of the Electrocardiogram (ECG) signal for a long time (1-2 days) taken from people who are thought to be sick is analyzed by the clinician. However, this process is not an effective method for clinicians to make decisions. In this article, various artificial intelligence methods are tested for AF detection on long recorded ECG data. Since the ECG data is a time series, a hybrid model has been tried to be created with the Long Short Term Memory (LSTM) algorithm, which gives high results in time series classification and regression, and a hybrid method has been developed with the Extreme Gradient Boosting algorithm, which is derived from the Gradient Boosting algorithm. To improve the accuracy of the LSTM architecture, the architecture has been strengthened with an Attention-based block. To control the performance of the developed hybrid Attention-based LSTM-XGBoost algorithm, a public data set was used. Some preprocessing (filter, feature extraction) has been applied to this data set used. With the removal of these features, the accuracy rate has increased considerably. It has been proven to be a consistent study that can be used as a support system in decision-making by clinicians with an accuracy rate of 98.94%. It also provides a solution to the problem of long ECG record review by facilitating data tracking.

Cite
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Author ID (ORCID Number)
F. Balcı, 0000-0002-3160-1517

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1. INTRODUCTION

The incidence of atrial fibrillation (AF) in individuals after childhood is 2.3%. This type of arrhythmia can cause consequences such as stroke and thrombosis. However, the duration of the attack is very short, so it is difficult to diagnose (Hagiwara et al., 2018). According to a report published by the World Health Organization, a total of 8.7 million people in the USA and Europe have a diagnosis of atrial fibrillation. This number is predicted to increase in the calculated future data (Guo et al., 2019; Wang et al., 2020; Shoeibi et al., 2021;). Measures should be taken against this expected increase. Atrial fibrillation, which has a reduction in a human's quality of health, is also an economic burden. Electrocardiogram, which is a noninvasive approach, provides clinicians with various information about atrial activities. It is considered by some experts to be the most understandable biomedical sign. A healthy electrocardiogram sign has three basic parts: P wave, QRS wave, and T wave (Acharya et al., 2017; Shoeibi et al., 2021). There are two main anomalies that clinicians make use of when detecting atrial fibrillation. These anomalies are the alteration of the P wave and the RR interval occurring at different times from the normal range. Classification is made according to the frequency of attacks in atrial fibrillation. These classifications are called paroxysmal atrial fibrillation, which occurs in less than 7 days and can end without any intervention, persistent atrial fibrillation that takes longer than 7 days, and permanent atrial fibrillation, which requires electrical cardioversion to be terminated (Acharya et al., 2017). An accurate and effective diagnosis is a critical issue to prevent people from being in danger.

*Corresponding Author, e-mail: furkanbalci@gazi.edu.tr

However, one of the most important obstacles here is the length of data that clinicians need to examine for diagnosis. Processing and analyzing large ECG data takes quite a long time. For patients with the paroxysmal variant, more than 24 hours of recording is required compared to Holter monitoring. In particular, these problems have led to the development of an artificial intelligence-based approach for the detection of atrial fibrillation. In recent years, very high results have been obtained in studies.

In the field of health, the performance of artificial intelligence-based algorithms that support clinicians in decision-making is increasing. Especially machine learning and deep learning techniques have shown high performance in classification studies in recent years. The parallel processing capability of deep learning methods by taking advantage of the high number of cores in the graphics processing units (GPU) allows them to perform high-performance processing, provided that there is sufficient data. Deep learning methods show high performance in time series data-based classification studies. Therefore, deep learning algorithms are used in the classification of biomedical signals. High accuracy can be achieved by using different methods in the classification of ECG beats and the detection of anomalies. Kiranyaz et al. (2015) performed the classification of ventricular and supraventricular ectopic beats using a CNN-based algorithm. Many artificial intelligence techniques are used to detect different beats like this. Apart from artificial intelligence methods, anomaly detections are also carried out by methods such as entropy (Li et al., 2014), wavelet transform (Sadeghi et al., 2022), and spectrum-based analyzes (Zarei et al., 2016). However, these methods have lower accuracy values. In artificial intelligence-based studies, the accuracy value can reach very high levels with different approaches. Time series such as ECG recording can be used in artificial intelligence-based studies, but due to the abundance of this data, it significantly increases the processing time. Therefore, feature extraction is used. In the attribute step, the data is divided into meaningful small pieces. In this way, systems that support clinicians' decisions and give faster results can be developed. Classification and regression processes can be performed with deep learning and machine learning algorithms. In particular, algorithms based on windowing techniques are used for the detection of arrhythmias. In this type of study, various features are generally extracted. Some of the deep learning and machine learning algorithms are known to show high performance in classifying time series due to their architecture. Examples of these algorithms are CNN, RNN, and LSTM. Pourbabaee et al. (2018) detect atrial fibrillation by visualizing time series data using CNN architecture. Pourbabaee et al. (2018) used a 4-layer structure in their CNN model. Xiong et al. (2017) detected atrial fibrillation using a 16-layer CNN architecture. Similar studies have been carried out according to the number of layers in the CNN architecture. The advantages of RNN and LSTM architectures in studies using time series data are known. Therefore, various hybrid approaches are implemented with the CNN architecture. Andersen et al. (2019) used a hybrid CNN-LSTM for a classification, taking into account the RR interval. There are many CNN and LSTM-based studies similar to this study (Chen et al., 2020; 2021; Petmezas et al., 2021). Besides hybrid approaches, there are also studies using LSTM and RNN architectures (Pascanu et al., 2012; Zhang et al., 2016; Kim & Cho, 2019; Yao et al., 2020). In addition, some studies have been revealed by combining RNN and LSTM architecture. Faust et al. (2018) used a hybrid RNN-LSTM architecture to perform a classification study between atrial fibrillation and normal sinus rhythm.

In this study, the hybrid LSTM-XGBoost algorithm that detects atrial fibrillation using electrocardiogram data is proposed. A publicly available data set was used to analyze the performance of the algorithm. Various features are extracted before the model directly uses the data. Thanks to these extracted features, the time spent by processing directly on the time series is saved. It is known that the performance of the LSTM architecture in time series is high. However, it is desired that the accuracy of the decision aid systems used by clinicians for detection and diagnosis is quite high. Therefore, in this study, a hybrid method was developed by combining the LSTM architecture with the XGBoost algorithm developed from Gradient boost. This hybrid approach has greatly improved the performance of the LSTM algorithm. First of all, the data is classified by LSTM. Then, the weights of the LSTM architecture are optimized with XGBoost and reclassified. In this way, a model with high accuracy that can be compared with the studies in the literature was obtained.

The remainder of this article consists of 3 parts. In Chapter 2, general information about the data set to be used in this hybrid model and the LSTM and XGBoost architectures to be used in the hybrid model are given. Section 3 shows the results of the proposed hybrid method. It is also discussed by showing the position of the experimental results in the literature. In Chapter 4, the article ends.

2. MATERIAL AND METHOD

A hybrid Attention-based LSTM-XGBoost model that detects atrial fibrillation anomalies is recommended in this study. The flowchart of this model is presented in Figure 1.

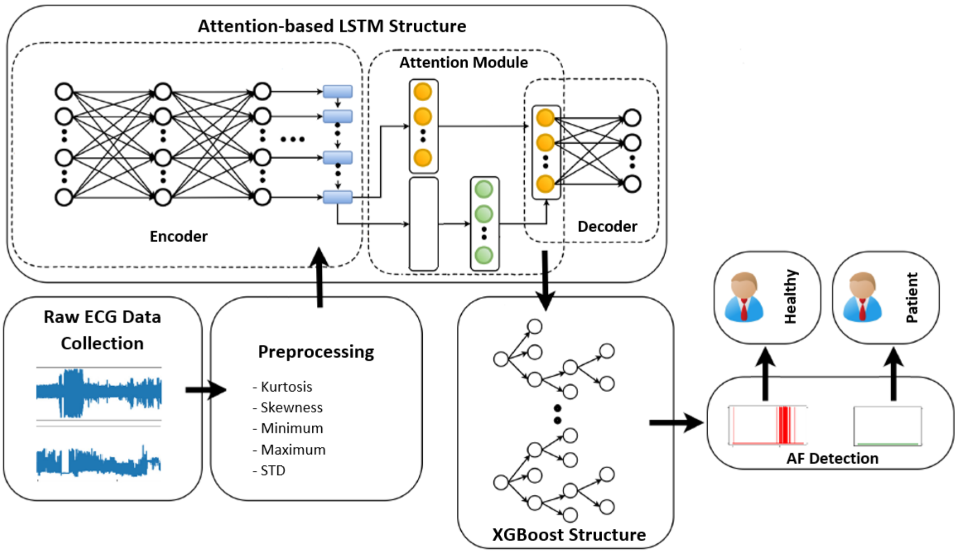


Figure 1. *Flowchart of Hybrid Attention-based LSTM-XGBoost Architecture*

2.1. Datasets

The data sets used in the study are shared publicly. Dataset from sick individuals MIT-BIH Atrial Fibrillation (AFDB) is a dataset that mostly includes records from patients with paroxysmal atrial fibrillation. In this data set, which consists of long-term recordings, there are ECG signals from 25 subjects. The duration of data from each patient is approximately 10 hours. General features of the recorder; Two-channel ECG electrode sampling at 250 samples per second with the accuracy of the voltage output is ±10 mV with a 12-bit resolution (Moody & Mark, 1983). There is also a data file about the data from each subject, which was obtained using the R-peak detection algorithm. The average total recording time is approximately 10.2 hours. The number of atrial fibrillations is 291, the duration is 1155.4 seconds. A total of 828000 R-peaks were observed in the data set. MIT-BIH Long-Term ECG dataset was used to classify healthy individuals. There is a recording with the same recording parameters as the AFDB dataset but with a longer duration (14 hours) from 7 subjects. The data set consisting of healthy individuals was used only for educational purposes in the detection of atrial fibrillation. Because deep learning architectures such as LSTM require a lot of data.

2.2. Pre-processing

The AFDB and MIT-BIH Long-term ECG dataset includes data from each patient. For atrial fibrillation detection, the data was first segmented so that it could be processed into windows. Although the data was divided into claws, there was no change in the processing time as there was no reduction in the number of data. Therefore, after windowing the data, meaningful features should be extracted. Five different attributes were extracted for each window. These are Skewness, kurtosis, minimum, maximum, and standard deviation. The general formulas for these attributes are listed in Eq. 1-5. Thanks to the feature extraction together with the windowing process, the processing times can be shortened considerably.

$$Skewness = \frac{1}{N}\frac{\sum_{i=1}^{N}(x_i - mean)^3}{STD^3} \tag{1}$$

$$Min = min(x_i) \tag{2}$$

$$Max = max(x_i) \tag{3}$$

$$Kurtosis = \frac{1}{N}\frac{\sum_{i=1}^{N}(x_i - mean)^4}{STD^4} \quad (4)$$

$$STD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - mean)^2} \quad (5)$$

2.3. Long Short Term Memory Algorithm Architecture

In this study, a hybrid approach based on deep learning and machine learning is proposed. This deep learning structure is based on the Recurrent Neural Network (RNN) structure. The value to be estimated in RNN structures does not only analyze based on the current value but also based on historical data. Therefore RNN structures are frequently used in time series data (Ciregan et al., 2012; Deng & Yu, 2014). RNN structures do not delete old data, such as the work of the human brain. Classical neural network structures delete after using old data in the weighting setting (Ciregan et al., 2012). RNN structures have been developed to cover this gap. The data used in RNN-based structures are stored in memory units until the cycle is completed. RNN structure has the same structure as classical neural networks (Fukushima & Miyake, 1982). This structure is formed by listing the same networks. The input of each network be attached to the output of the previous RNN cells. There are varieties of RNN structures. Long Short Term Memory (LSTM) structure is used in this study to create hybrid Algorithm for detection of atrial fibrillation. LSTM structure has begun to be used widely in estimation processes based on historical data. RNN structure has a single-layer network structure. The LSTM structure has a four-layer network structure. There are structures called gates in the LSTM structure. These gate structures carry out tasks such as adding and removing information to the neural cell. The sigmoid function used in the neural network layer gives values between 0 and 1. The sigmoid function determines how much of the signal is allowed to pass. This value varying between 0 and 1 is used as a ratio. The first of these gates is called the forget gate. This gate makes an investigation between the prior output and the current input and produces a value between 0 and 1. On the off chance that the produced value is 0, it signifies "forget this state", assuming the produced value is 1, it signifies "keep this state" (Deng & Yu, 2014). The forget gate is indicated by f_t. Eq. 6 shows the equation of the forget gate result.

$$f_t = sigmoid(W_f[h_{t-1}, x_t] + b_f) \quad (6)$$

Another gate layer is the input gate. This gate structure decides which new values to keep. In this step, both sigmoid and tanh functions are used. The sigmoid structure produces the value to be updated and the tanh structure produces the intermediate value C_{tx}. Eq. 7 shows the equation of the sigmoid function. Eq. 8 shows the equation of the tanh function. Then these values are combined.

$$i_t = sigmoid(W_i[h_{t-1}, x_t] + b_i) \quad (7)$$

$$C_{tx} = sigmoid(W_c[h_{t-1}, x_t] + b_c) \quad (8)$$

Using it and C_{tx} values, C_t is generated that allows the old data to be transferred to the next cell. Eq. 9 shows the current data equation C_t obtained with old data and new entries.

$$C_t = f_t * C_{t-1} + i_t * C_{tx} \quad (9)$$

In the next step, the output of that cell must be calculated. This calculated output is branched to be used in the next cell. It is necessary to decide which data will be used as output from the cell. Sigmoid function is used to make this decision. Eq. 10 shows the equation of the sigmoid function. The tanh function is used to convert the result of the sigmoid function to between -1 and 1. The final cell output is obtained after this transformation. Eq. 11 shows the equation of the final cell output.

$$o_t = sigmoid(W_o[h_{t-1}, x_t] + b_o) \tag{10}$$

$$h_t = o_t * \tanh(C_t) \tag{11}$$

The Multivariate LSTM structure used in this study is similar to the classical LSTM structure described above. It has 2 differences from the classical LSTM structure. The dependent variable estimation result is estimated with more than one independent variable. LSTM architecture is used in the study carried out in various academic fields such as biomedical data in time series, economic data, and time series data related to the process (Stollenga et al., 2015; Song et al., 2019; Balci & Oralhan, 2020; Yin et al., 2021).

2.4. Extreme Gradient Boosting Architecture

The Extreme Gradient Boosting (XGBoost) algorithm is an application that has become a frequently preferred tool in decision trees and machine learning. It is an algorithm developed by determining the deficiencies of the Gradient Boost algorithm. This developed approach is accepted as an important tool in the field of supervised learning, which provides high performance in classification, regression, and ranking tasks (Jin et al., 2020). Supervised learning refers to a predictive model inference task from a set of labeled training examples. With this predictive model, it is possible to find solutions to problems such as determining whether a manufacturing defect has occurred or predicting temperature or humidity on a particular day. In this context, the XGBoost algorithm can be expressed as a supervised learning algorithm that applies a process called augmentation to produce accurate models (Mitchell & Frank, 2017). Augmented trees in the XGBoost algorithm are divided into regression and classification trees. The essence of this algorithm is based on optimizing the objective function value (Król-Józaga, 2022). The most important point of the XGBoost structure is its scalability in all situations. XGBoost algorithm runs more than 10 times faster than current popular tree-based solutions on a single machine and scales to billions of instances in distributed or memory-limited settings (Mitchell & Frank, 2017). If the dataset is represented by D; m features, n samples. y_i indicates the value predicted by the model. If the predicted value is shown as in Eq. 12, f_k represents the independent regression tree. The f_k function set in the regression tree model can learn by minimizing the target function (Chen & Guestrin, 2016).

$$y_i = \sum_{k=1}^{K} f_k(x_i)\,, f_k \epsilon F \tag{12}$$

When defining the XGBoost machine learning algorithm, certain parameters and values need to be entered. Parameter selection can be shaped according to the application to be used. Information about the default parameters and the value ranges of the parameters is shown in Table 1.

Table 1. *Parameters of XGBoost Architecture*

Parameter	Definition	Range	Default
Nround	Number of trees	[1, ∞]	10
Eta	Learning rate	[0,1]	0.3
Gamma	Lowest partition loss reduction	[0, ∞]	0
max_depth	Highest tree depth	[0, ∞]	6
minimum_child_weight	Minimum observation for new tree	[0, ∞]	1
Subsample	Random sample ratio to be used for training	[0, 1]	1
Lambda	Regulation term in weights	[0, ∞]	1
Alpha	Regulation term in weights	[0, ∞]	0
column_sample_tree	The columns ratio for the training of each tree	[0, 1]	1
column_sample_level	The column ratio for the training of the separation of each tree	[0, 1]	1

2.5. Hybrid Architecture Details

In this study, a hybrid model is proposed for the detection of atrial fibrillation. In this proposed method, the LSTM model, which shows superior performance in time series, and the XGBoost algorithm, which is a developed based on decision tree machine learning method, are combined. If the model is to be summarized in general, first of all, feature extraction was performed on the dataset. Studies in the literature were used to determine these extracted features. Later, these attributes were included in the hybrid LSTM-XGBoost structure. Atrial fibrillation detection has been performed and these points are given as the output of the algorithm.

Since this proposed hybrid method is a classification method, comparison will be made using the most important performance metrics currently used. These metrics are Accuracy (ACC), sensitivity (SEN), and specificity (SPF). General formulas of these metrics are given in Eq. 13-15.

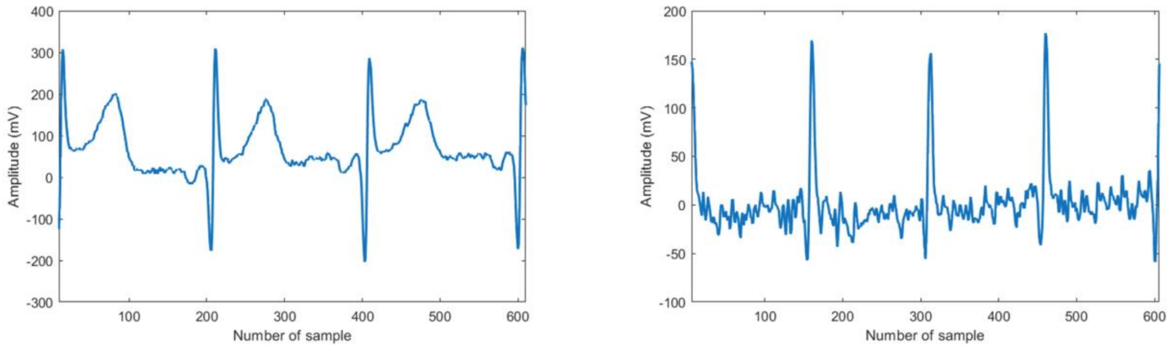
$$ACC = \frac{TP+TN}{TP+TN+FP+FN}, \quad (13)$$

$$SEN = \frac{TP}{TP+FN}, \quad (14)$$

$$SPF = \frac{TN}{TN+FP}, \quad (15)$$

3. RESULTS AND DISCUSSION

A hybrid Attention-based LSTM-XGBoost method is proposed to detect these diseases in individuals with atrial fibrillation in this study. In this context, first of all, two different datasets were combined to perform the detection and classification process. An example graph of these datasets is shown in Figure 2a,b.



(a) (b)

Figure 2. a) *A Sample of Normal Sinus Rhythm Segments,* ***b)*** *A Sample of Atrial Fibrillation Segment*

Each dataset has a column containing ECG data. The average recording time is approximately 10 hours in this dataset, which was obtained using a recorder that takes 250 samples per minute. This situation duplicates the data. Although deep learning architectures such as LSTM are suitable for big data, the large amount of data increases the processing time considerably. Therefore, feature extraction was done under the specified window size. In this way, both the data have been made more meaningful and the processing time has been shortened considerably. The features used were determined by the characteristics of the dataset. These attributes allow reducing the data of each window size to a single data. These attributes are Kurtosis, Skewness, minimum, maximum, and standard deviation. 65% of this dataset was used for training. The remaining 45% is used for testing purposes. For the LSTM structure, the n_{hidden} parameter is set to 30 and the number of layers to 5. Learning rate and lameda parameters were determined as 0.001. An attention-based block is embedded in the LSTM structure. Softmax is used in this block. The weights obtained here are used for detection and classification in the XGBoost machine learning algorithm.

Detection of optimum parameter values is important for maximizing performance in any machine learning algorithm. It involves defining all parameter probabilities and then testing all combinations to select the sets with the best values of the classification results. Grid search means creating grid intervals using parameter values suitable for the algorithm. Random search means randomly selecting different parameter values and testing the results. In this study, the intervals determined by grid search were tested. The most suitable 5 parameters and their values were selected and the other parameters were used with their default values. The values determined for the most suitable parameters selected are given in Table 2. Therefore, the classification model of the XGBoost algorithm was created with these parameter values.

Table 2. *Optimized Parameters of XGBoost Algorithm*

Parameter	Grid Values	Best
Eta	0.05, 0.2, 0.3, 0.4	0.2
Nrounds	1, 10, 100, 150, 200	170
max_depth	1, 4, 6, 10, 12, 20	12
Subsample	0.5, 0.6, 0.7, 0.9, 1	1
column_sample_level	0, 1	1

Some test results of the proposed method are shown in Figure 3a,b. Figure 3a shows some predicted erroneous points and correctly predicted points during the detected normal sinus rhythm (NSR) of the hybrid Attention-based LSTM-XGBoost algorithm. Noisy data taken during the measurement makes it difficult to detect the R-peaks. Therefore, incorrect classifications may occur on segments. Faulty points are shown in Fig. 3(b) on normal sinus rhythm.

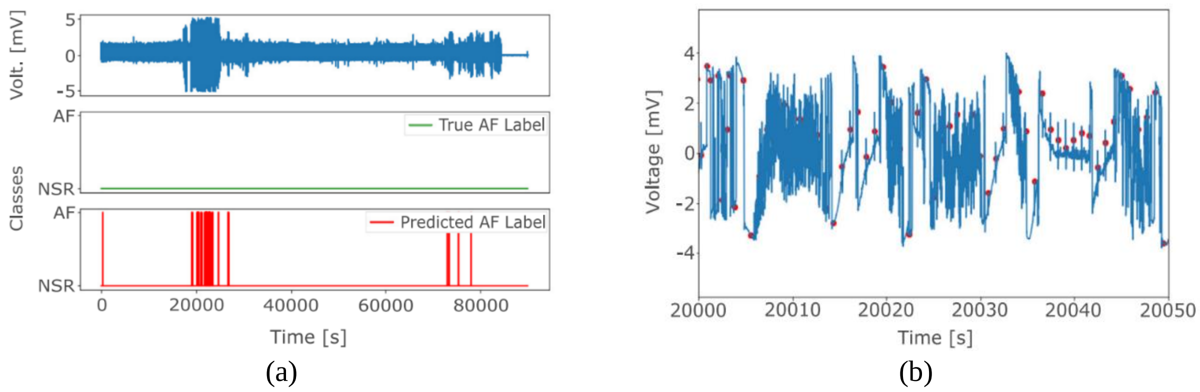


Figure 3. *False Prediction Points During Normal Sinus Rhythm*

The classification obtained at the output of the XGBoost algorithm has higher accuracy than the classification obtained at the output of LSTM. The result shown in Figure 4 is the blue graph showing the ECG recording. The green graph represents the actual atrial fibrillation points, the red graph represents the atrial fibrillation points obtained from the LSTM result, and the black graph represents the atrial fibrillation points obtained from the XGBoost result. When the graphics are examined, the proposed hybrid Attention-based LSTM-XGBoost method reveals a noticeable improvement compared to the approach determined only according to the LSTM result.

A comparative summary using machine and deep learning methods on the same dataset to compare the superiority of the hybrid Attention-based LSTM-XGBoost algorithm over other algorithms is shown in Table 3. Accuracy, sensitivity and specificity metrics of the algorithms used for comparison are shown in this table.

Table 3. *Summary of the Results of Different Deep and Machine Learning Algorithms*

Methods	Accuracy	Sensitivity	Specificity
kNN	92.41%	92.19%	92.65%
Decision Tree	89.80%	89.67%	89.56%
LSTM	92.98%	92.23%	92.35%
Random Forest	86.15%	86.11%	86.06%
MLP	95.00%	94.14%	94.76%
SVM	94.14%	94.79%	93.94%
Feature+LSTM+XGBoost	**98.90%**	98.47%	98.67%

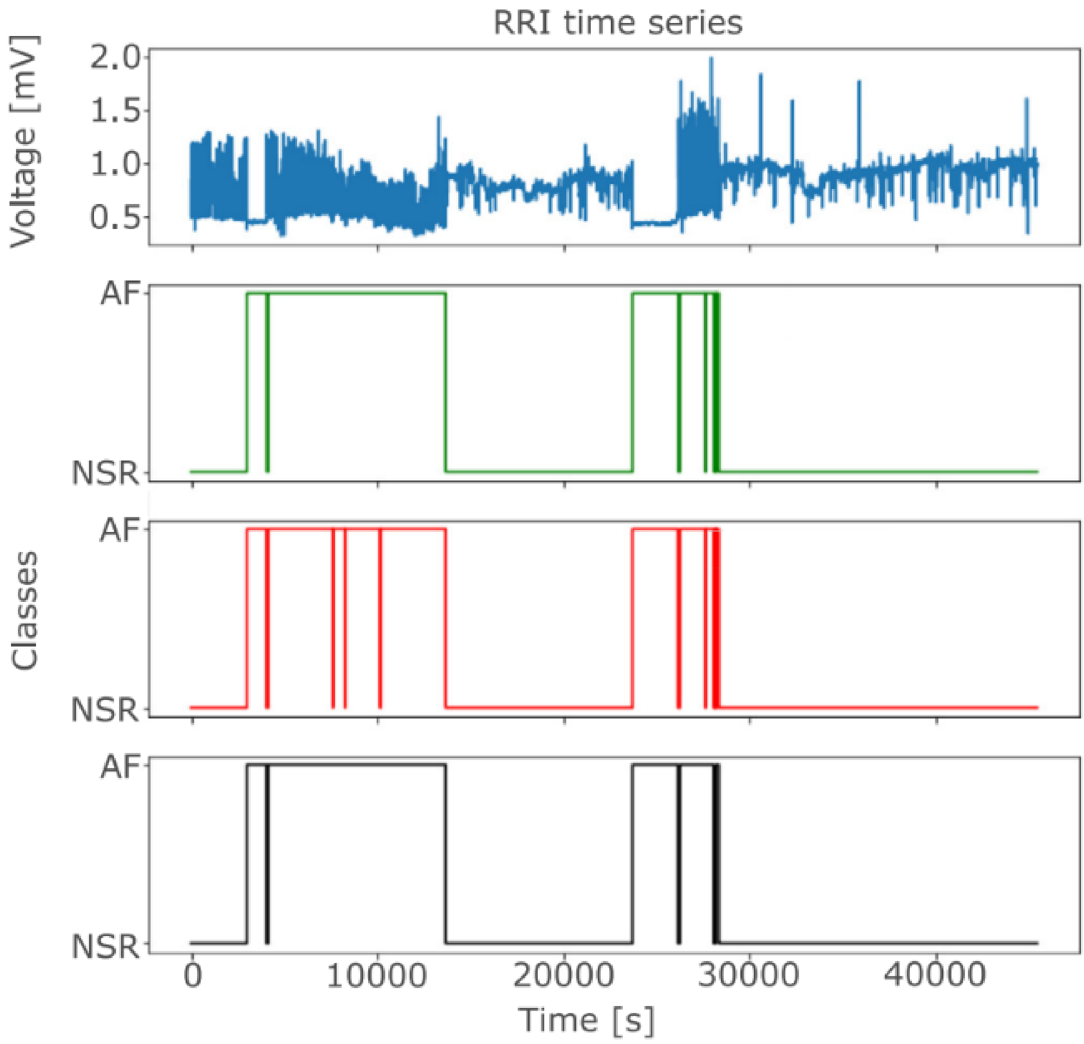


Figure 4. *Example Prediction Results of the Hybrid Approach*

To compare the accuracy and the other performance metrics of the proposed approach, a comparison is made with the results of the studies in the literature. This comparison is shown in Table 4. When this table is examined, it can be seen that the results obtained have higher accuracy values than the "hybrid CNN-LSTM with Feature extraction" method made in 2019 (Kim & Cho, 2019). With these results, it is thought that the proposed method can be used as a mechanism to help clinicians make decisions.

Table 4. *Comparison of the Studies in the Literature and Hybrid LSTM-XGBoost Algorithm*

Authors	Methods	ACC	SEN	SPF
Xiong et al., 2017	CNN architecture	86.0%	-	-
Zhang et al., 2016	CNN architecture	95.50%	98.09%	-
Pourbabaee et al., 2018	CNN architecture with feature extraction	-	76.50%	93.60%
Kim & Cho, 2019	Hybrid CNN-LSTM architecture with feature extraction	98.51%	98.39%	98.67%
Faust et al., 2018	Random forest with entropy-based feature extraction	96.80%	95.80%	-
Andersen et al., 2019	Hybrid CNN-LSTM architecture	97.80%	98.98%	96.95%
Król-Józaga, 2022	Feature extraction and CNN architecture	94.59%	94.28%	-
Kumar et al., 2018	RR features and Discrete state Markov model	-	97.40%	98.60%
Chen et al., 2020	RR features and Hybrid CNN-LSTM architecture	97.15%	97.11%	97.06%
Wei et al., 2019	Feature extraction and SCP architecture	95.00%	-	-
Kalidas & Tamil, 2019	Attention-based LSTM	-	98.14%	98.76%
Petmezas et al., 2021	Hybrid CNN-LSTM architecture	-	97.80%	-
Chen et al., 2021	CNN architecture with multi-feature extraction	98.92%	97.19%	97.04%
Buscema et al., 2020	CNN architecture with spectrogram features extraction	95.00%	-	-
Proposed Method	Hybrid Attention-based LSTM-XGBoost architecture with feature extraction	**98.94%**	98.47%	98.67%

Some limitations were encountered while carrying out this study. The first of these limitations is that this hybrid algorithm designed is focused only on detecting atrial fibrillation. Therefore, the hybrid LSTM-XGBoost architecture seems to be insufficient when tests are performed with different diseased data. Therefore, by expanding the dataset, classification can be made for the diagnosis of different diseases.

4. CONCLUSION

In this study, hybrid LSTM-XGBoost architecture is proposed for the detection of atrial fibrillation signals with using long or short term ECG data. The data of the patients and healthy individuals on the used dataset were first divided into certain windows. Various feature extraction techniques were applied before these windows were used for testing and training. To improve the accuracy of the detection, LSTM architecture is combined with attention-based structure. In the next step, a hybrid model was obtained by combining it with the XGBoost architecture. Thanks to the windowing technique used, the atrial fibrillation classification, which was the aim of this study, could also be determined locally. Since the designed algorithm has sufficient speed in terms of processing time, it might be used in real-time atrial fibrillation detection applications. Thanks to the features used, the processing time is considerably shortened. It is important for clinicians that it has a high accuracy rate compared to studies in the literature. As a result of the tests performed using the MIT-BIH AF dataset, an accuracy rate of 98.94% was obtained.

A system that supports decision-making for clinicians by directly integrating this system into portable ECG measuring devices may be the subject of future studies. The proposed approach may be insufficient because different diseases are not classified. Therefore, the proposed hybrid method in future studies can be trained with different data and become a more comprehensive study.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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