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Detection of Atrial Fibrillation Based on Long Short-Term Memory

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ABSTRACT

Atrial fibrillation is a quivering or irregular heartbeat (arrhythmia) that can lead to blood clots, stroke, heart failure, and even sudden cardiac death. This study used several public datasets of electrocardiogram (ECG) signals, including MIT-BIH Atrial Fibrillation, China Physiological Signal Challenge 2018, MIT-BIH Normal Sinus Rhythm based on QT-Database, and Fantasia Database. All datasets were divided into 3 cases with the experiment windows size 10, 5, and 2 seconds for two classes, namely Normal and Atrial Fibrillation. The recurrent neural networks method is appropriate for processing sequential data such as ECG signals, and k-fold Cross-Validation can help evaluate models effectively to achieve high performance. Overall, LSTM performance achieved accuracy, sensitivity, specificity, precision, F1-score, is 94.56% 94.67%, 94.67%, 94.43%, and 94.51%.

Keywords: Atrial Fibrillation, Electrocardiogram, Recurrent Network

1. INTRODUCTION

Atrial fibrillation (AF) is a disturbance in the function of the heart's electrical system, which is characterized by an irregular heartbeat. Globally, more than 35 million people have AF, with diagnoses ranging from mild dizziness to death [1]. Conventional AF detection is often diagnosed through data visualization using electrocardiographs by cardiologists [2][3]. Electrocardiography has an important role in the medical field, and this is because its function is to evaluate electrical activity and conditions in the human heart [4]. The evaluation result is a recording in the form of a graphic or signal wave representing the human heartbeat per unit time or commonly known as an electrocardiogram (ECG) [5].

An ECG is a digital signal recording that comes from attaching electrodes to the human body's surface to produce electrical energy from the heart. The diagnosis method is usually using ECG interpretation, which requires the help of an accurate device and high expertise from a doctor's point of view. Conventionally, cardiologists claim that a 12-lead ECG waveform is in a digital image format. However, ECG signals that can last for hours or even days also need to be analyzed. As an important note, this is one procedure that is significantly time-consuming and limits the impartiality of the diagnosis. It should be noted that this limitation can be removed by using computational techniques in detecting arrhythmias and ECG classification [6]. Objectively, an electrocardiogram is significant to use to show the presence or absence of AF. The ECG signal is collected to diagnose AF in a long time, which is less than 48 hours, using a heart monitor device [7].

In general, a standard ECG signal has a P wave, QRS complex and a T wave in one heartbeat [4]. The AF signal is very different from the normal heart rhythm in the ECG signal. Throughout the AF signal, the RR interval is completely irregular and a continuous irregular F wave replaces the P-wave, this is an important feature of the AF signal [8]. In AF, because the heart rhythm is irregular, the heart can pump more than 150 times per minute. It will generally pump 60 to 100 times per minute [3]. In several studies, deep learning is used to detect beats in AF in Heart Rate (HR) signals. The data are partitioned using a sliding window of 100 beats. The resulting signal is then directly entered into the Long Short-Term Memory (LSTM) model with the Recurrent Neural Networks (RNN) method. The system was validated and tested using data from MIT-BIH Atrial Fibrillation, resulting in an accuracy of 98.51% with ten fold cross-validation (20 subjects) and 99.77% with blindfold validation (3 subjects) [9]. Several approaches to deep learning can increase the value of performance, such as Deep Neural Networks (DNN), Convolution Neural Networks (CNN), and especially Recurrent Neural Networks (RNN) where this one method is very appropriate to be used to process sequential data such as ECG signals [10]. Thus, classifying ECG signals from AF heart disease based on rhythm can be done using the RNN method to obtain good performance values and data sharing with k-fold Cross-Validation to evaluate the model effectively on sequential data.

2. MATERIAL AND METHODS

2.1 ATRIAL FIBRILLATION

AF is a type of arrhythmia or abnormality in the human heart, in which the heart beats too fast and can even be too slow. This is caused by the electrical impulse activity in the atria that are out of sync and irregular. The presence of AF will trigger the lower heart chambers and ventricles to pump blood faster, so that the ventricles cannot drain blood throughout the body optimally. If the heart has AF, the heart's ability to pump blood will decrease by about 20% - 25%. Other common factors that also cause AF include diabetes mellitus, hypertension, obesity, and smoking, usually in men. AF generally occurs in patients with coronary heart disease at a younger age[11]. A normal heart will generally be able to pump 60-100 times per minute, whereas a heart that has AF tends to pump blood very quickly, about 150 times per minute or even more. AF can be divided into 3 types, namely [12]; (1) paroxymal atrial fibrillation, which this type of AF often appears and goes away suddenly and can last for hours or even days, (2) persistent atrial fibrillation, which this type of AF lasts for more than a week and doesn't go away on its own, and (3) permanent atrial fibrillation, which this type of AF tends to be permanent, in which the heart rhythm does not beat normally and cannot return to a normal heart rhythm, even with medical treatment.

2.2 DISCRETE WAVELET TRANSFORM

Discrete Wavelet Transform (DWT) has a scale and translation that does not change continuously but can change discretely, so it can be expressed by the following equation.

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$$\psi_{s,\tau} = \frac{1}{\sqrt{s_0^s}}\,\psi\left(\frac{t-\tau\,\tau_0 s_0^s}{s_0^s}\right) \qquad (1)$$

where s and τ are integers and $\mathbf{s_0^s}$ is a dilation step that has met the dyadic rules, where the value must be greater than one. τ_0 is also a translation parameter which must have a value greater than zero, depending on the change in the dilation. As for the effect of discretizing the Wavelet, of course it has an impact on the time and scale which becomes discrete intervals. By using this discrete wavelet function, the corresponding transformation of discrete wavelets is obtained, as follows [13].

$$T_{s,\tau} = \int_{-\infty}^{\infty} x(t)\,\psi_{s,\tau}\,(t)dt \qquad (2)$$

DWT has two types of filters, including Low Pass Filter (LPF) and High Pass Filter (HPF). Before reconstructing, the reduction of signal noise from the decomposition results was carried out using the thresholding method. There are two types of thresholding methods, including soft thresholding and hard thresholding. The soft thresholding method is often used because the results are more stable and have a higher bias value than hard thresholding. This method can also provide better performance than other methods, especially in the process of denoising ECG signals [14]. There are two types of thresholding methods, namely [14]:

1. Soft Thresholding

$$c\widehat{D}_j = \begin{cases} cD_j, & |cD_j| \geq t \\ 0, & |cD_j| \leq t \end{cases} \qquad (3)$$

2. Hard Thresholding

$$c\widehat{D}_j = \begin{cases} sign(cD_j)(|cD_j| - t), & |cD_j| \geq t \\ 0, & |cD_j| \leq t \end{cases} \qquad (4)$$

It is known that $c\widehat{D}_j$is the wavelet coefficient after thresholding, while cD_j is the coefficient before thresholding [14].

2.3 RECURRENT NEURAL NETWORKS

Recurrent Neural Networks (RNN) is a technique of deep learning in the form of a network that contains one feedback connection. The activation can flow in a loop so that the network can process temporally and repeatedly to process input which is usually sequential data [15]. The RNN method is commonly used to predict data related to time or time series data very well [16].

2.3.1 LONG SHORT-TERM MEMORY

Long Short Term Memory (LSTM) is commonly used to solve exploding and vanishing gradients problems in ordinary RNN architectures [17],[18]. The use of Long Short Term Memory (LSTM) architecture is to model sequential or sequential data, as well as as a memory reserve from Recurrent Neural Networks (RNN), which plays an important role in increasing accuracy and effectiveness [16,19]. It is known that in the LSTM model training process, two directions can be used, including unidirectional and bidirectional. The LSTM unidirectional training only covers the learning process of previous input data or past data. Where this unidirectional process occurs in the forward pass condition. Meanwhile, bidirectional includes the use of input data information from the past and the future. In this study only unidirectional LSTM was used. The image of the LSTM unidirectional structure at the time of the forward pass is shown in Figure 1.

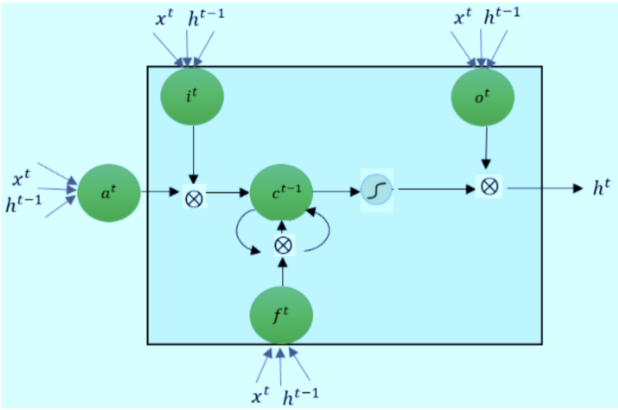

FIGURE 1. LSTM unidirectional structure for the forward pass [20]

where f is the position of the forward pass, so that the LSTM equation is obtained when the forward pass is shown by equation[21].

$$o_t{}^f, h_t{}^f, c_t{}^f = LSTM^f(c_{t-1}^f, h_{t-1}^f, x_t;\ W^f) \qquad (5)$$

3. RESULTS AND DISCUSSION

In this research, the object to be carried out is the ECG signal classification using the Recurrent Neural Networks Long Short Term Memory (LSTM) architecture method. This study aims to design an LSTM model that can classify Atrial Fibrillation and Normal signals using the python programming language. The design of the LSTM model will be used as a classifier in classifying ECG signals. After that, the LSTM model's performance that has been designed will be evaluated using a configuration matrix based on assessment parameters such as accuracy, sensitivity, specificity, precision, and F1 value. Several types of libraries in the python programming language used in this study are NumPy, pandas, matplotlib, scikit-learn, tensorflow, and wfdb.

This study using a research framework in the form of a flow chart. The research flow diagram can be shown in Figure 2.

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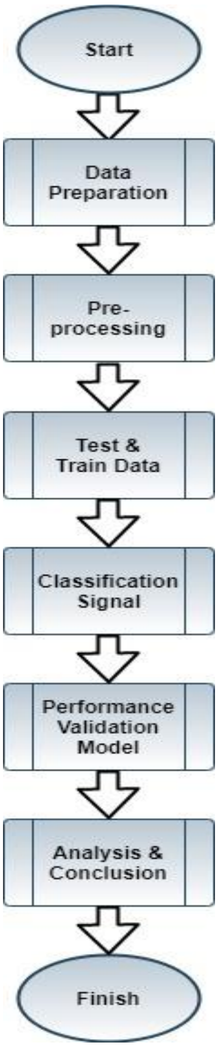


FIGURE 2. Research Flowchart

This study uses four datasets, including MIT-BIH Atrial Fibrillation [22], MIT-BIH Normal Sinus Rhythm based on QT Database [23], Fantasia Database [24], and China Physiological Signal Challenge 2018 [25]. The data initially consisted of many classes (multi-class) will be sorted by Python programming using a .csv file, which consists of the name and label of the ECG signal into two classes. The AF class is taken from AFDB data and the China Physiological Signal Challenge 2018. Meanwhile, the Normal class is taken from the MIT-BIH Normal Sinus Rhythm data based on the QT Database and the Fantasia Database. It can be seen in Table 1 a class list of some of the data above used in this study. From the four data, it will be sorted into 2 classes, namely AF and Normal. In this study, it is divided into 3 case data with windows size experiments 10 seconds, 5 seconds, and 2 seconds. For the time steps it uses 1 second. In the 2-second window size ECG signal data, the normal amount of data is 119,828, while the AF signal data is 96,214. In the ECG window size of 5-second signal data the normal amount of data is 47,941 data, while the AF signal data is 38,788 data. In the ECG window size 10 seconds signal data, the normal amount of data is 23,982, while the AF signal data is 19,606.

TABLE 1
List of data classes used

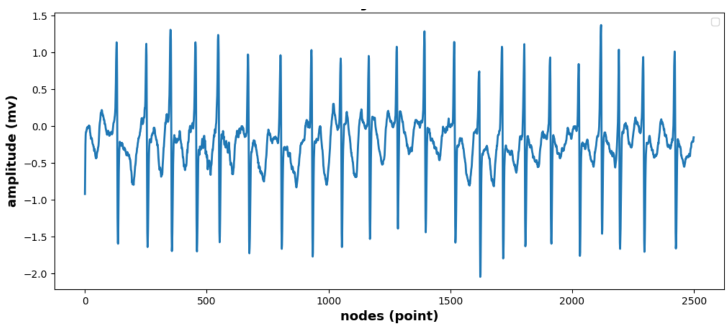
Database	Class	Label
MIT-BIH Atrial Fibrillation	AFIB (Atrial Fibrillation)	AFIB
MIT-BIH Normal Sinus Rhythm basis QT Database	Normal	N
Fantasia Database	Normal	N
China Physiological Signal Challenge 2018	Atrial Fibrillation (AF)	(2)

In the .csv file, the ECG signal data has an N label for normal ECG signals which is then quantified with the number 0, label A for the AF ECG signal which is then quantified with the number 1 (refer to Table 2).

TABLE 2
Label Class

Class	Label	Label “Number”
Normal	N	0
Atrial Fibrillation	A	1

Data before processing is available in .dat format containing ECG signals and .hea files containing waveform information. Data for the China Physiological Signal Challenge 2018 is provided in the .mat format, which contains ECG signals and information on the patient's gender and age. The shape of the signal from each class can be seen in Figure 3.



(a)

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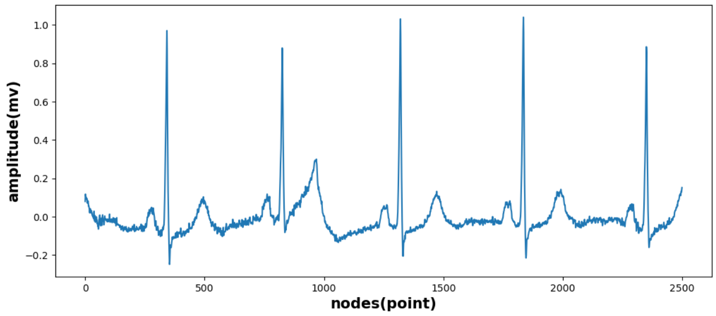
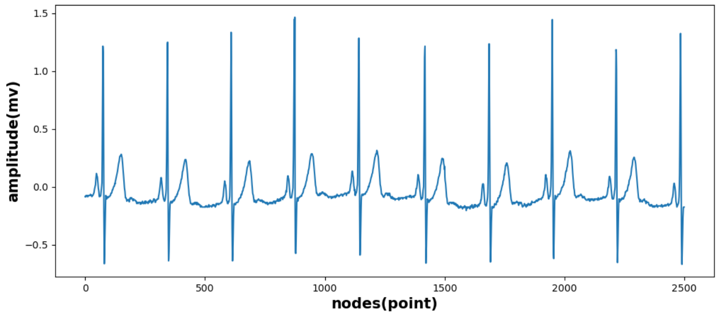
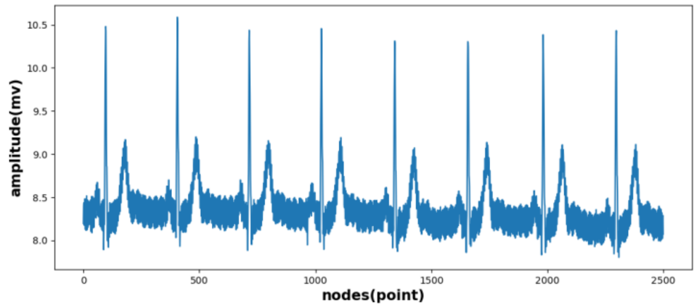


(b)



(c)



(d)

FIGURE 3. Form of raw signal for each class (a) MIT-BIH Atrial Fibrillation (b) China Challenge 2018 (c) MIT-BIH Normal Sinus Rhythm base QT Database (d) Fantasia Database

Pre-processing is the initial step that needs to be done to process raw data in designing an ECG signal classification model from Atrial Fibrillation (AF) disease using the LSTM Recurrent Neural Network (RNN) method. This aims to be able to get more structured data. There are three stages of data pre-processing in this study, namely denoising, normalizing, and segmenting. The stage begins by reducing the noise in the signal using discrete wavelet transform (DWT). Then, the signal is normalized and segmented based on the class that will be used based on the rhythm of the signal. Figure 4 shows a flow chart carried out in the pre-processing stage.

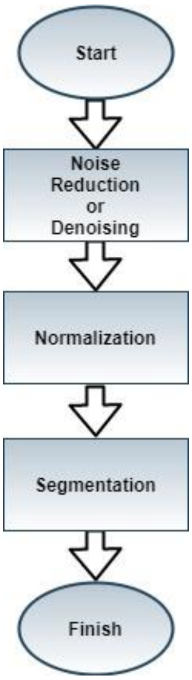


FIGURE 4. Pre-processing flow chart

Table 3 shows the overall results of all models against 2 classes of normal ECG and AF signals using the LSTM model with K-fold Cross Validation. Based on table 3, model 1 and model 4, both of which are 10 second case data, achieve poor evaluation results when compared to model 2, model 3, model 5, and model 6 with a learning rate parameter of 0.0001 and batch size 8. As for the comparison reference All models use learning rates and batch sizes taken from the best 2 second data model. Model 1, model 2, and model 3 use epoch 100, while model 4, model 5, and model 6 use epoch 200. The use of large learning rate values such as 0.1 and 0.01 in all models is not able to produce good performance. However, the use of a very small learning rate is also not good. Therefore, the best learning rate is 0.0001 from the whole model. Model 3 and model 6 with a window size of 2 seconds have a higher performance result difference than model 1 and model 4 with a window size of 10 seconds, and model 2 and model 5 with a window size of 5 seconds.

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TABLE 3
All Model Evaluation Results

Average Model Evaluation Value with K-fold	Model	Rating Parameters (%)				
		Sensitivity	Precision	Specificity	Accuracy	F1
Model 1	LSTM	88,91	88,83	88,91	88,125	88,117
Model 2	LSTM	91,23	91,62	91,23	91,36	91,221
Model 3	LSTM	93,57	93,48	93,57	93,49	93,42
Model 4	LSTM	89,87	90,12	89,87	89,91	89,78
Model 5	LSTM	92,69	92,8	92,69	92,64	92,55
Model 6	LSTM	94,67	94,43	94,67	94,56	94,51

Based on the performance of the results of training and testing of 6 LSTM models using K-fold Cross-Validation, the model parameters that show the best results for training and testing are obtained from the 6 LSTM 2 seconds model with LR 0.0001, and 1 HL with average accuracy and F1-scores was 94.56% and 94.51%. After testing, it can be said that the LSTM model with k-fold Cross-Validation is good in helping to increase the accuracy and F1-score values of the data. However, the accuracy and loss charts for testing data are still overfitting. The following is a graph of the accuracy and loss of model 6 (refer to Figure 5).

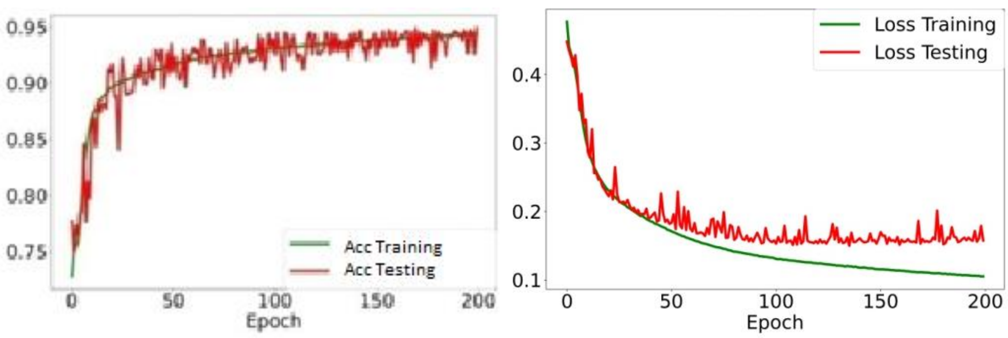

FIGURE 5. Graph of accuracy and loss for the training and testing process of the 2-second LSTM 6 model

4. CONCLUSION

Based on the results and analysis of the ECG signal classification process, including normal and AF using RNN with LSTM architecture, it can be concluded that the RNN method with LSTM architecture can be used to classify ECG signals properly. The process of sharing testing data and training data using K-fold Cross

Validation is also able to evaluate model performance and find the best data combination, both in terms of accuracy, specificity, precision, error, and others.

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