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Classification of arrhythmic and normal signals using continuous wavelet transform (CWT) and long short-term memory (LSTM)

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Abstract

An electrocardiogram (ECG) can detect heart abnormalities through signals from the rhythm of the human heartbeat. One of them is arrhythmia disease, which is caused by an improper heartbeat and causes failure of blood pumping. In reading ECG signals, a common problem encountered is the uncertainty of the prediction results. An accurate and efficient heart defect classification system is needed to help patients and healthcare providers carry out appropriate therapy or treatment. Several studies have developed algorithms that are more effective in Machine Learning (ML) in automatically providing initial screening of patients' heart conditions. This study proposed the Long Short-Term Memory (LSTM) method as a classifier of heart conditions experienced by humans and Continuous Wavelet Transform (CWT) as a feature extractor to eliminate noise during data collection. CWT and LSTM methods are believed to perform well in feature extraction and classification of ECG signals. The dataset used in this study was taken from the MIT-BIH Arrhythmia Database. The results of this study successfully extracted ECG signals using CWT, thus improving the understanding of ECG characteristics. This research also succeeded in classifying ECG signals using the LSTM method, which obtained an accuracy training value of 98.4% and an accuracy testing value of 94.42 *%.*

1. Introduction

An electrocardiogram (ECG) is a device that presents electrical signals from the heart recorded non-invasively from the body surface. In 1902, a Dutch doctor named Einthovan invented the ECG, and his outstanding contributions to clinical studies over ten years resulted in full recognition of the technique's clinical potential. ECG can diagnose most cardiovascular diseases, so this tool is very much needed in the medical field [1], [2]. Along with the development of technological sophistication in the medical world, several studies conducted early screening to determine possible abnormalities based on the results of ECG signals automatically [3]. In the classification of ECG signals, a general problem encountered is the uncertainty of the prediction results. In this case, it is important to develop a classification method for patients with heart disease that is accurate and efficient, to help patients and health care providers determine the appropriate therapy or treatment.

This development continues to be carried out using more effective algorithms in Machine Learning (ML), which allows epidemiologists to provide more effective and efficient methods [4], [5]. There are some algorithms that ML has, one of which is Long Short-Term Memory (LSTM). LSTM is very suitable for time series prediction, and the interval delay is relatively long. LSTM consists of an input gate, forget gate, output gate, and unit cell to update and maintain historical information [6]. The algorithm of the LSTM method has been used in many previous studies in fields related to ECG signal classification [7]-[10]. Based on previous research [7], ECG signals contain a lot of subtle information and a large amount of data. LSTM networks are very effective in deciphering the timing features in complex ECG signals [8]. Therefore, LSTM is very suitable for classifying arrhythmia based on ECG signals based on time series [11]. To improve the classification of arrhythmia, an extraction filter can be used to remove noise or signals that are not needed in classifying ECG signals.

Based on the analysis in a study conducted by Mounaim Aqil et al., the best and most suitable Mother Wavelet used for ECG signals is Morlet (Morl) [12]. The results obtained are Continuous Wavelet Transform (CWT) or "CWT Coefficient." In this research, ECG signals are extracted first using CWT, which provides a complete representation of signal information by continuously performing wavelet convolution on the signal [13]. Applying the LSTM and CWT

methods to classify ECG signals in this study can produce maximum accuracy and better separation of arrhythmia and normal classes. The contributions of this research are as follows:
1. Extract ECG signals based on parameters and time-frequency decomposition using the CWT method.
2. Testing the performance of ECG signal classification using the LSTM method.
3. CWT and LSTM for classifying arrhythmia and normal classes based on ECG signals.
4. The effectiveness of the method proposed in this study to classify normal and arrhythmic ECG signals is proven by calculating the confusion matrix value of CWT and LSTM.

2. Method
2.1 Dataset Aritmia
Arrhythmia is an abnormal change in heart rate, which is an irregularity in the rate or rhythm of the heartbeat caused by an improper heartbeat and causes failure of blood pumping. Several arrhythmia conditions are called tachycardia, bradycardia, or regular or irregular heartbeat. Tachycardia is a rapid resting heart rate, usually more than 100 beats per minute, while bradycardia is a slow resting heart rate, less than 60 beats per minute. Abnormal electrical activity of the heart can be life-threatening. Arrhythmias are more common in people suffering from high blood pressure, diabetes, and coronary artery disease [14].

This study utilized the Arrhythmia database obtained from MIT-BIH containing 48 excerpts over a half-hour duration of two-channel ambulatory ECG recordings obtained from 48 subjects studied by the BIH Arrhythmia Laboratory. Twenty-three datasets were randomly drawn from a collection of over 4000 Holter recordings, and the remaining 25 datasets were selected to include arrhythmia examples, as shown in Figure 1 [15]. Recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10-mV range. Two or more cardiologists independently annotated each record, i.e., disagreements were resolved to obtain computer-readable reference annotations for each beat (approximately 110,000 annotations in total) included with the database. The total ECG data in the arrhythmia database is 110,000 and is classified into 5 classes: 82,170 normal data, 8,910 Left Bundle Branch Block (LBBB) data, 8,030 Right Bundle Branch Block (RBBB) data, 7,810 Ventricular Premature Beat (VPB) data, and 3,080 Atrial Premature Beat (APB) data.

2.2 Continuous Wavelet Transform (CWT)
An essential first step before classifying ECG signals is to minimize various noises, such as baseline drift, cable interference, and high-frequency noise that may be caused by muscle contraction or electrode movement [16]. Several steps are taken to extract features using CWT, as shown in Figure 2. Noise reduction performed in this study uses a band-pass filter consisting of low-pass and high-pass filters [17]. Continuous Wavelet Transform (CWT) describes the correlation between the analyzed continuous-time signal x(t) and a function called a wavelet and is defined by Equation 1 and Equation 2.

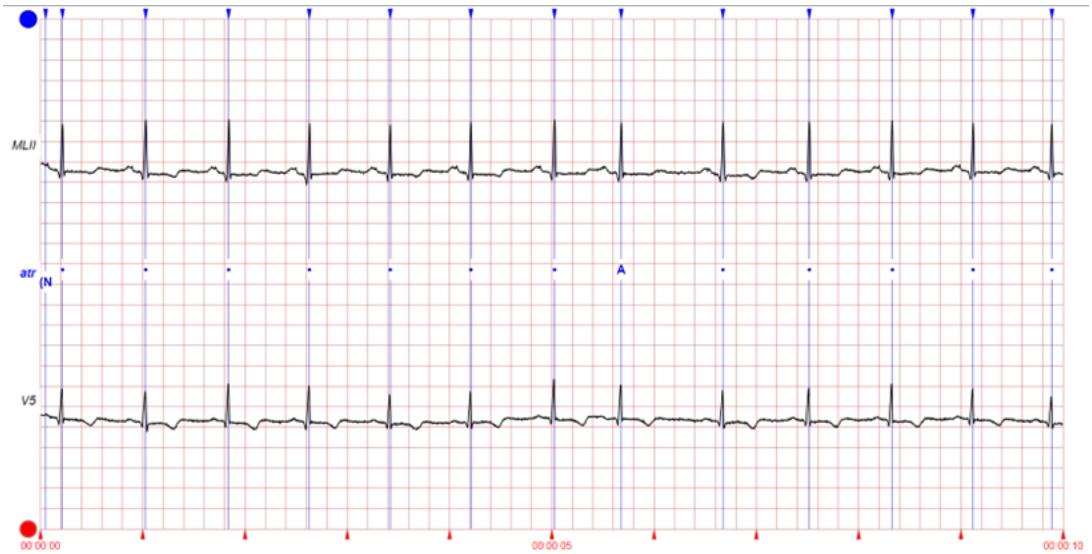

Figure 1. ECG Signal on Physionet

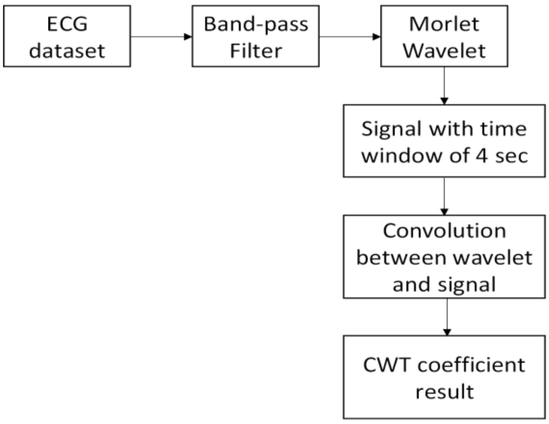

Figure 2. Feature Extraction using CWT

$$c(\tau,\sigma)=\int_{-\infty}^{+\infty} x(t)\Psi^{*}_{\tau,\sigma}(t)\,dt \qquad (1)$$

Where,

$$\Psi_{\tau,\sigma}(t)=\frac{1}{\sqrt{\sigma}}\Psi\left(\frac{t-\tau}{\sigma}\right) \qquad (2)$$

Energi wavelet $\frac{1}{\sqrt{\sigma}}$ has to be equal to value of σ diffirent scale. Scale σ can be changed to be frequency $(\frac{1}{\sigma})$ that represent a frequency. Parameter τ represent the wavelet location all the time lokasi. As become to be a wavelet funtion Untuk, $\psi(t)$ has to be limited in time, in order to ful fill the condition with the result with Equation 3.

$$\psi(\omega)|_{\omega=0}=\int_{-\infty}^{+\infty}\psi(t)e^{-j\omega t}dt\Big|_{\omega=0}=\int_{-\infty}^{+\infty}\psi(t)dt=0 \qquad (3)$$

There are various types of Mother Wavelet, such as Morl, Meyr, Mexh, Gaus, Coif, Sym, Db, and Haar. The selection of the kind of Mother Wavelet is based on the criteria for its use. It can be seen in Table 1 that Morlet Mother Wavelet provides the best L collinearity ratio to save the maximum local splint energy during the acquisition period. Therefore, this research uses Morlet in ECG signal feature extraction because it is the best and most suitable wavelet for ECG [12]. In the CWT convolution stage, Morlet is multiplied by the ECG signal at each position and the overall signal scale, and the results are summarized. The ECG signal feature extraction results using CWT are then used as attributes to classify arrhythmia and normal using LSTM.

Table 1. Mother Wavelet Comparison based on Collinearity Ratio L [12]

Mother Wavelet	Collinearity Ratio L
Morl	0.9621
Meyr	0.9508
Mexh	0.8721
Gaus 4	0.5897
Coif 4	0.0606
Sym 4	0.0598
Db 4	0.0598
Haar	0.0549

2.3 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a developed type of Recurrent Neural Network (RNN) introduced by Hochreiter and Schmidhuber in 1997 [18]. The main advantage of LSTM networks is the ease of training because it does not face problems such as vanishing gradients. LSTMs can process entire input sequences (source code, video, speech, images) [19]-[22]. LSTM consists of four attributes: cell state, forget gate, input gate, and output gate. The cell state remembers the information of the entire sequence, and the three gates control the input and output of the cell.

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At the beginning of the process, the forget gate checks which information to discard and which data to keep in the cell state. Equation 4 for the forget gate is calculated on the cell state using the hidden form and input. The output of the forget gate is between 0 and 1, generated by a sigmoid function [21]. Forget gate controls the extent to which the value remains in the memory cell. The output Gate decides how much content or value is in the memory cell and is used to calculate the output [23]. The calculations for LSTM cells in their layers are shown in Equation 4 to Equation 8.

- Forget gate

$$f_t = \sigma\left(W_f \, o\left[h_{t-1,} x_t\right]\right) + b_f \tag{4}$$

- Input gate

$$i_t = \sigma\left(W_i \, o\left[h_{t-1,} x_t\right]\right) + b_i \tag{5}$$

- The cell states

$$c_t = \tanh\left(W_c \, o\left[h_{t-1,} x_t\right]\right) + b_c \tag{6}$$

$$C_{t\,=}\, f_i \,.\, C_{t-i} + i_t \,.\, c_t \tag{7}$$

- Output gate

$$o_t = \sigma\left(W_0 \, o\left[h_{t-1,} x_t\right]\right) + b_0 \tag{8}$$

Where, X_t is an initial input, h_{t-1} is a value of *Previous output,* c_t is cell renewal dari Wf, Wi, Wc, Wo, and weight matrix of bf, bi, bc, bo is bias vector. The bias vector is specified as a numerical array and becomes the learned parameter. When training the network, the bias vector in the first iteration is replenished with zero. The weight matrix is specified as a numeric array. It is a learnable parameter. This study divides the dataset into two classes: 25 from people with arrhythmia and 23 from ordinary. The data generated by CWT feature extraction will be divided into training and testing data, namely 70% training data and 30% testing data. The training data is trained to form an optimal classifier model by first going through the learning process. After obtaining the optimal LSTM model, the model is tested using testing data as much as 30% of the total data. The test results can recognize and classify two classes based on the trained ECG signals: Arrhythmia and Normal.

2.4 Confusion Matrix

Confusion Matrix is a visual evaluation tool used in ML consisting of columns and rows. The Confusion Matrix columns present the results of the predicted class, and the rows show the results of the actual class [24]. Accuracy performance against classification is evaluated by receiver operating characteristic (ROC) parameters such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). TP is data with the number in the True actual class, which is positive data and correctly classified as a positive prediction class. TN is data with the number in the True actual class, which is negative data and correctly classified as a negative prediction class. FP is data with the sum of the False class, which is negative data but classified as a positive prediction class. FN is data with several false classes, namely positive data, but it is classified as a negative prediction class. These parameters are used to calculate accuracy, Recall (Sensitivity), specificity, and F1-score using Equation 9 to Equation 12 [25].

$$\text{Accuracy} = \text{TP} + \frac{\text{TN}}{\text{TP+FP+TN+FN}} \times 100 \tag{9}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \times 100 \tag{10}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \times 100 \tag{11}$$

$$\text{F1-Score} = 2\,\frac{\text{TP}}{\text{2TP+FP+FN}} \tag{12}$$

3. Results and Discussion

3.1 CWT Feature Extraction Result

The output produced by CWT in extracting ECG signal features creates a signal with reduced noise and delivers richer features because it adds frequency features to the signal (Table 2). In detail, the x-axis represents time in seconds, the y-axis represents frequency, and the image's color represents amplitude. The yellow color of the image, the higher the amplitude. These results are used as input for the LSTM model, which is trained sequentially. Based on Table 2 of the original CWT Normal signal feature extraction results, it can be seen that this graph shows that the heart is functioning normally and the heartbeat is regular. The analysis of the normal ECG signal after the application of CWT reveals more detailed frequency characteristics of the heart activity. The CWT graph shows a more detailed time-frequency representation, with the brightness level reflecting the intensity of the frequency features in the signal. These CWT results make it possible to identify more subtle changes or patterns that may not be visible in the original signal while maintaining the stability and constancy of normal ECG characteristics.

Then, the ECG signal with a medical condition called LBBB. You can see the difference in the QRS waveform, which is the part of the ECG that reflects the depolarization or contraction of the ventricles of the LBBB heart. It usually makes the QRS wave broader and more unusual than a normal ECG. This happens because there is an obstacle in the path of electrical impulse delivery in the heart. ECG signals that show LBBB undergo more detailed analysis after passing through the CWT process. The CWT results break down the LBBB ECG signal into finer frequency components, providing a more in-depth understanding of the cardiac conduction disturbances. With the analysis after CWT, one can see the changes in the frequency spectrum in the ECG signal at various time scales.

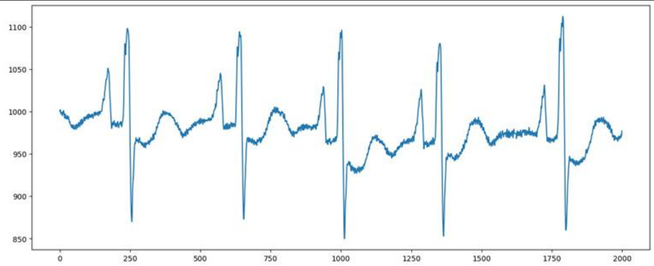
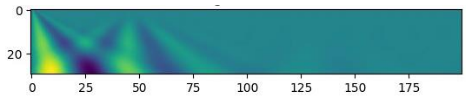
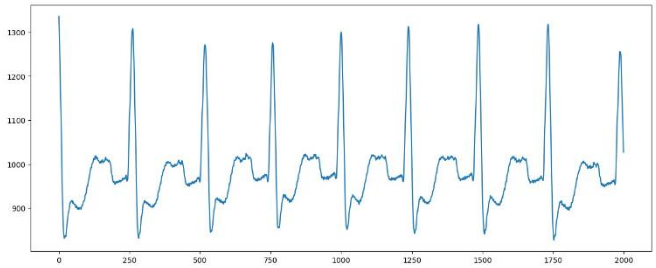
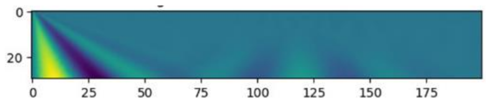
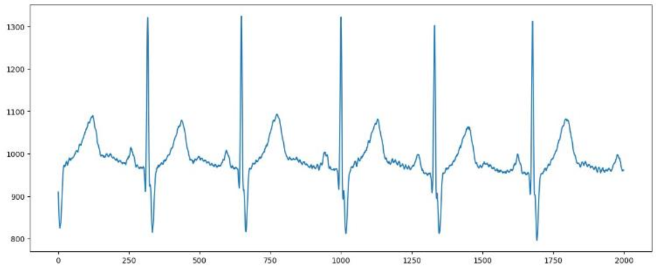
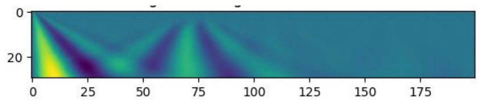
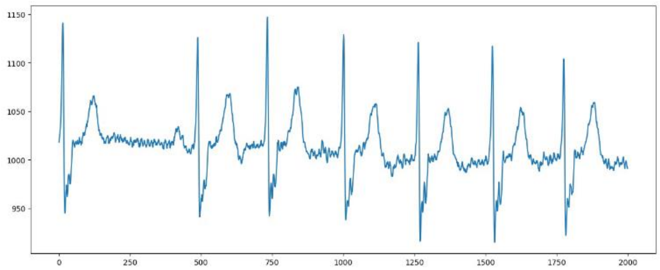
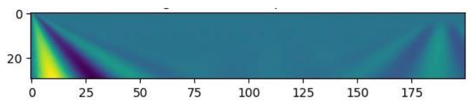
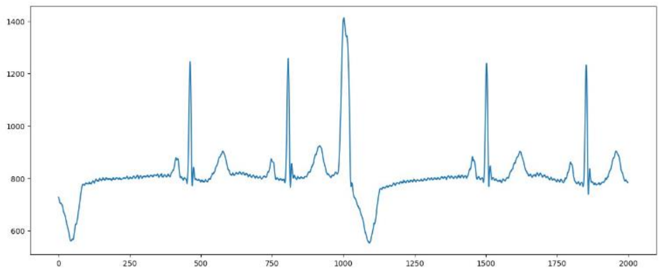
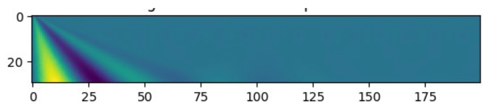
Furthermore, the ECG signal resulting from the medical condition is the RBBB. RBBB is detected by the distinctive characteristic in the graph, which is the widening of the QRS complex. This broadening reflects the presence of an obstacle in the conduction of an electrical impulse through one of the two main branches of the cardiac bundle RBBB is characterized by a difference in the QRS wave in the ECG, and this is reflected in the graph by an increase in the duration of the QRS complex. A widened QRS complex indicates a delay in ventricular depolarization, an RBBB feature. Analysis of the CWT results on the color graph of the ECG showing RBBB provides more in-depth knowledge of the characteristics of the cardiac signal. The color graph visualizes the frequency intensity in the signal at any given time, with bright colors reflecting the predominant vibration strength. Areas with lighter colors indicate places where significant vibrations or cardiac activity occur. This analysis allows us to more easily understand how RBBB affects cardiac signal dynamics. The visual analogy with color images makes it easier to understand this process. By utilizing CWT results and color graphs, we can visually see the changes in ECG signals, providing a deeper understanding of the impact of RBBB on the heart.

Then, there are ECG signals indicating the presence of an APB, an event where an irregular heartbeat prematurely originates from the atria (upper chambers of the heart). In an ECG chart, APB can be recognized by the appearance of extra P (atrial) waves that appear earlier than expected, disrupting the regular rhythm of the heartbeat. When analyzing an ECG chart with APB, attention is paid to the timing of the appearance of the extra P wave and its impact on the following QRS complex. This can result in characteristic changes in the RR interval (between heartbeats) and the QRS waveform. After passing through the CWT process, the color of the ECG signal reflecting APB presents the frequency changes visually. The colors on this graph indicate the intensity of the frequencies in the signal. When APB occurs, areas of the chart with lighter or more conspicuous colors indicate an increase in signal strength at that time. This color graph helps us to see more clearly when an APB occurs in the ECG signal and how this affects the heartbeat pattern. With this color graph analysis, we can understand the frequency changes in the ECG signal more visually. The analysis results in the CWT color graph provide a more robust and visual understanding of the changes that occur during APB episodes in the cardiac signal.

Finally, the ECG signal depicts the occurrence of VPB, a condition when an irregular heartbeat prematurely originates from the ventricles (lower chambers of the heart). In an ECG chart, VPB can be recognized by extra QRS waves appearing earlier than the heartbeat should, disrupting the normal heart rhythm. VPB can affect the regular heartbeat pattern and is often characterized by characteristic changes in the RR interval (the interval between heartbeats) and the QRS waveform. This presents as a 'skip' in the heart rhythm that disrupts the regular pattern. It is crucial to understand VPB in the context of an ECG, as it can be a clue to an underlying heart rhythm disorder. Further analysis may be required to identify the cause and appropriate follow-up measures to manage this heart rhythm problem. After passing through the CWT process, the resulting colors of the ECG signal reflecting VPB offer a more in-depth visual understanding. The colors in this graph reflect the intensity of the frequencies in the signal. When VPB occurs, areas of the chart with lighter or more conspicuous colors indicate an increase in signal strength at that time. This color graph helps researchers see when VPB occurs in the ECG signal and how this affects the heart rhythm. With this color graph analysis, changes in ECG signal frequency can be understood more visually. The results of the study in the CWT color graph provide a more substantial and more visual insight into the changes that occur during VPB episodes in the cardiac signal.

Based on the results, it is important to understand the class types in the context of the ECG, as it may provide clues to the underlying heart rhythm disturbance. Further analysis may be required to identify the cause and appropriate follow-up measures to manage these heart rhythm problems. The feature extraction results of the ECG signal are obtained in the form of CWT coefficient values that decompose the time-frequency signal. Furthermore, determining the value of these results by wavelet transformation and analyzing the CWT function by calculating the convolution of the LBBB ECG signal with the wavelet function. Feature extraction is used to characterize the LBBB, RBBB, APB and VPB ECG signals.

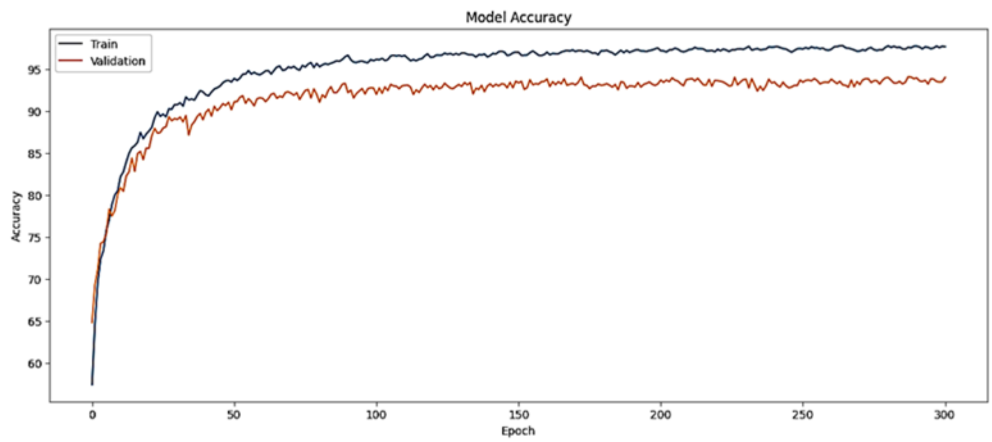
Table 2. The Result of Feature Extraction

Category	Raw data	Extract feature CWT
Normal		
Left Bundle Branch Block		
Right Bundle Branch Block		
Atrial Premature Beat		
Ventricular Premature Beat		

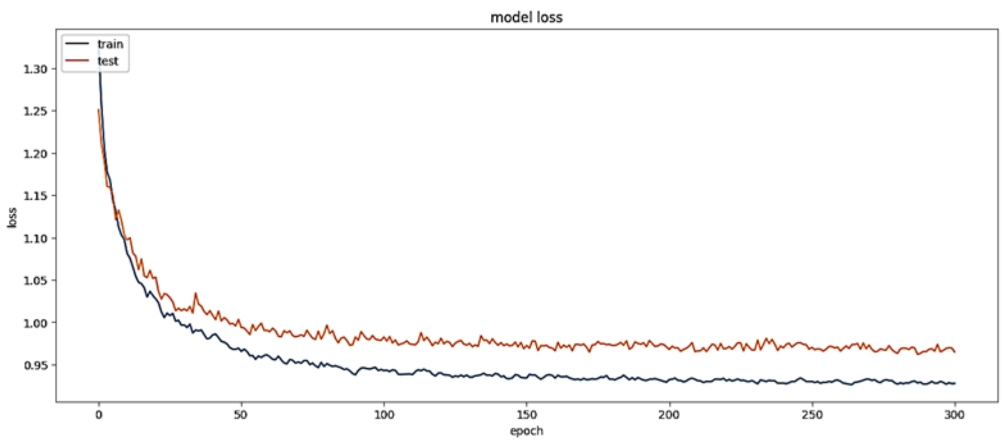
3.2 LSTM Result

The dataset has been divided into two classes, namely arrhythmia and normal, with LTSM as the classifier of the dataset. Resulting in accuracy, recall, f1-score, and precision. The features produced by Continuous Wavelet Transform (CWT) consist of three components, namely time, frequency, and amplitude. The results are then fed into the LSTM model as input and trained using 300 epochs, batch size 64, and Adam optimizer with a learning rate 0.0001. The result is a learning curve consisting of the accuracy and loss of the model used, as shown in Figure 3. The accuracy results of training and validation are obtained from the training accuracy and validation accuracy curve value graphs experiencing an upward state. This can be said to experience a good state during training and validation. In the Loss graph, the training loss and validation loss curve values continue to decrease until the data validation process is complete. The model generated from the training and validation process is then tested with data that has never been seen before, namely through testing using testing data. The test results provide accuracy of 94.42%, recall of 93.13%, f1-score of 93.13%, and precision of 93.32%. This data is reinforced by calculating the confusion matrix on the test data, which results in an accuracy for normal data of 87%, LBBB data of 97%, RBBB of 89%, AVP of 97%, and VPB of 95%. This information can be observed in the confusion matrix and can be seen in Figure 4.

Based on these values, the accuracy of model performance using confusion matrix with the use of LSTM and CWT produces an accuracy value of 94%, recall of 93.13%, f1 score of 93.13%, and precision of 93.32%. It can be concluded that the resulting model is accurate and produces a good system model with an accuracy rate of 98.4%. These results provide an overall overview of how the system model built achieves a good level of accuracy, so that it is able to classify various types of ECG data accurately. Based on the results of this study, the classification of normal and arrhythmic ECG signals has been successfully carried out. This method has a high accuracy value and is effective compared to previous research. It is shown that classifying arrhythmia ECG signal data using the CWT method as extraction and LSTM has a higher accuracy than previous research using the Fourier-Bessel method and LSTM, which is only 90.07% [8]. Similarly, the results of a prior study using the principal component analysis (PCA) method only had an accuracy of 93.5% [9].



(a)



(b)

Figure 3. The Learning Curve of LTSM (a) Model Accuracy (b) Model Loss

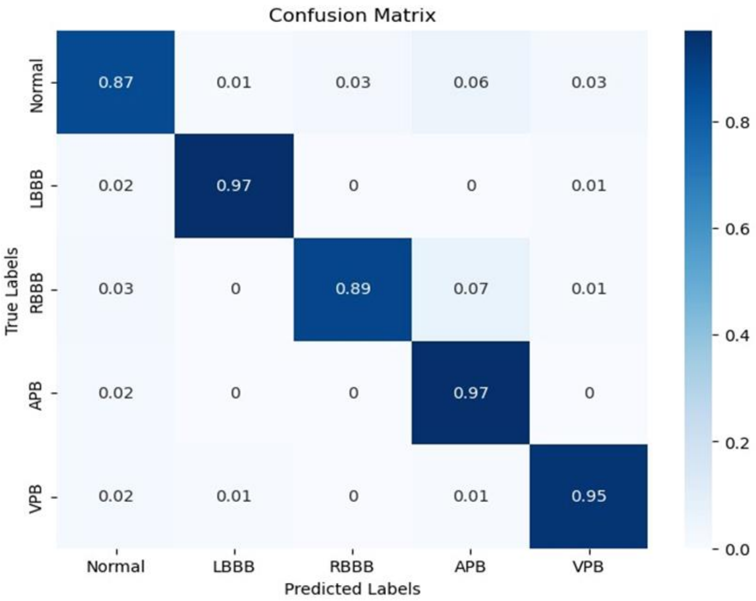


Figure 4. Result of the Confusion Matrix

4. Conclusion

This study has successfully extracted ECG signals using the CWT, thus improving the understanding of ECG characteristics by the model used in classifying the classes of ECG signals based on the input data. In addition, the LSTM model trained with CWT features could classify the conditions of the ECG signal with a high accuracy of 98.4%. This helps researchers understand how LBBB, RBBB, APB, and VPB affect the ECG signal in more detail. Furthermore, it can help clinicians and researchers dig deeper into these heart rhythm disorders and provide more detailed information to more accurately diagnose and plan appropriate treatments for patients with heart rhythm disorders. Future work can be done by expanding the number of datasets or the variety of medical conditions to help the model improve the overall performance of the model.

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