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Deep Learning for ECG-Based Arrhythmia Classification Based on Time-Domain Features

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ABSTRACT

Arrhythmia is a disturbance in the electrical activity of the heart that can affect the rhythm and duration of the heartbeat. Early detection of arrhythmia is crucial to prevent more serious complications. Electrocardiogram (ECG) is an effective non-invasive diagnostic tool in detecting arrhythmia, but manual detection by experts takes time. To overcome this limitation, this research develops an arrhythmia classification system by utilizing deep learning. This study involves a series of stages, starting from pre-processing, feature extraction, and arrhythmia classification models using convolutional neural networks (CNN) and long short-term memory (LSTM). The results showed that feature extraction successfully improved model efficiency and accuracy. Evaluation of model performance using accuracy, recall, precision, specificity, and F1-score metrics showed that the LSTM model achieved 95% accuracy, 96% recall, 96% precision, 99% specificity, and 96% F1-score, outperforming the CNN model which achieved 91% accuracy, 90% recall, 89% precision, 98% specificity, and 89% F1-score. Thus, these results indicate that the LSTM model is superior in arrhythmia classification.

Keywords: ECG arrhythmia, Feature extraction, Time-domain analysis,

1. INTRODUCTION

According to the World Health Organization (WHO), arrhythmia is a serious global problem, affecting more than 350 million people worldwide [1]. Arrhythmia is a disturbance in the electrical activity of the heart that can affect the rhythm and duration of the heartbeat and can lead to serious conditions such as stroke or even sudden death [2]. Cardiovascular disease, including arrhythmia, is one of the leading causes of death in the world. In 2019 alone, cardiovascular disease caused 17.9 million deaths globally, accounting for 32% of all registered deaths, and 85% of those deaths were caused by heart attack and/or stroke [2].

Early detection of arrhythmia is crucial to prevent sudden death, given that 80% of sudden cardiac deaths are caused by arrhythmia [3][4]. Early detection of arrhythmia is essential to prevent more serious complications. An electrocardiogram (ECG) is a non-invasive diagnostic tool that is effective in detecting various types of arrhythmias, but manual detection by experts takes time and risks misclassification [2][5]. To overcome these limitations, an automated system for arrhythmia classification was developed that aims to speed up the diagnosis process and improve its accuracy [6][7].

With the advancement of technology, the use of Artificial Intelligence (AI) and Deep Learning (DL) in ECG analysis and classification has shown significant

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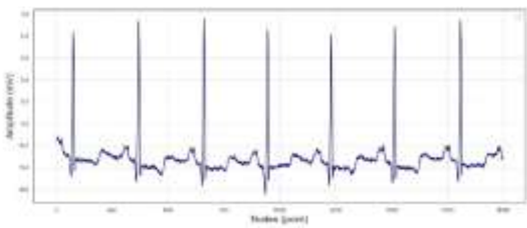
potential to improve diagnosis accuracy [8][9]. These methods can extract abstract features from ECG data automatically, reducing the need for time-consuming manual feature design [6][10][11]. With the development of DL algorithms and increased availability of medical data, various DL models have been proposed for arrhythmia classification from ECG signals. Detecting arrhythmias quickly and accurately through ECG signal analysis is becoming increasingly important as the prevalence of cardiovascular diseases increases worldwide [12].

Various recent studies have been conducted to develop more effective arrhythmia classification techniques. Various methods, such as k-nearest neighbor (KNN) algorithm, long short-term memory (LSTM), convolutional neural networks (CNN), recurrent neural networks (RNN), etc., have been widely used in arrhythmia classification using ECG signals [3][13]. Although various classification methods have been developed, many of them still have limitations in terms of accuracy and efficiency [12]. Therefore, this study aims to develop a more effective arrhythmia classification model by integrating deep features.

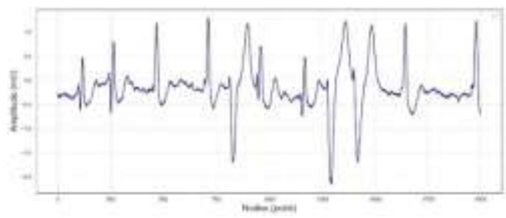
2. MATERIAL AND METHOD

2.1. DATA PREPARATION

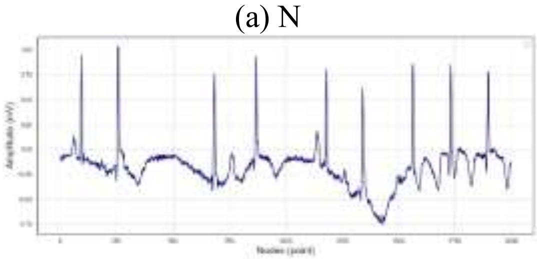
The data used was the MIT-BIH Arrhythmia Database [14], derived from more than 4000 long-term Holter recordings obtained from the Arrhythmia Laboratory at Beth Israel Hospital between 1975 and 1979. There are 48 recordings (23 recordings from 100 to 124 and 25 recordings from 200 to 234) that are randomly selected and include rare clinically important phenomena. Each recording was approximately 30 minutes in duration. From this database, we labeled the rhythm of each recording, except paced rhythm, into six classes, including Normal Sinus (N), Atrial Fibrillation (AFIB), Atrial Flutter (AFL), Ventricular Bigeminy (B), Premature Ventricular Contraction (PVC), and Sinus Bradycardia (SBR) (refer to Figure 1).



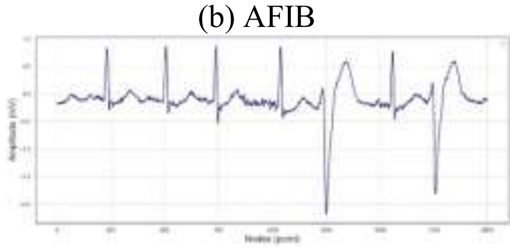
(a) N



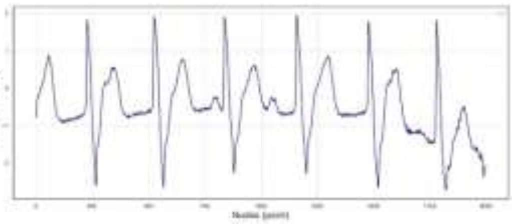
(b) AFIB



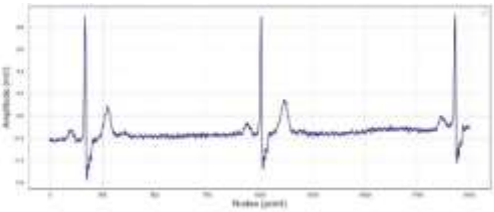
(c) AFL



(d) B



(e) PVC



(f) SBR

FIGURE 1. The six classes of ECG normal sinus and arrhythmia records

2.2. ECG PRE-PROCESSING

In this section, the result of a series of data pre-processing processes aimed at improving the quality of ECG signals before proceeding to the feature extraction and classification. There are two ECG pre-processing stages:

2.2.1 ECG Denoising

ECG Denoising is the process of reducing interference or noise present in ECG signals [15]. Noise in ECG signals can come from various sources, such as electrical interference, patient body movements, or other disturbances that can affect signal quality. One of the commonly used methods for denoising is the discrete wavelet transform (DWT) [16], which is effective in handling noise present in one-dimensional (1D) signals such as ECG signals. DWT helps to separate high-frequency components that may be noise from low-frequency components that contain important information from the signal. In this denoising process, researchers used DWT with various wavelets and decomposition levels to obtain the best SNR results. The types of wavelets tested are *db4, db7, db8, db9, sym4, sym5, sym6, bior2.4, bior4.4, bior5.5*, and *coif5*. Each type of wavelet has certain characteristics in decomposing signals, and the selection of the right wavelet can affect the quality of the signal. Therefore, researchers used various wavelets to determine which one gave the best results. In addition to choosing a wavelet, setting the decomposition level also plays an important role in determining the signal quality after denoising.

In this study, the decomposition levels were tested at levels 7, 8, and 9. Testing these wavelets and decomposition levels provided the best signal-to-noise ratio (SNR) results. SNR is a measure that describes the comparison between the strength of the desired signal and the strength of the noise present. The higher the SNR value, the better the quality of the processed signal, which will affect the accuracy of the classification results. The sample visualization of ECG records for before and after denoising can be presented in Figure 2.

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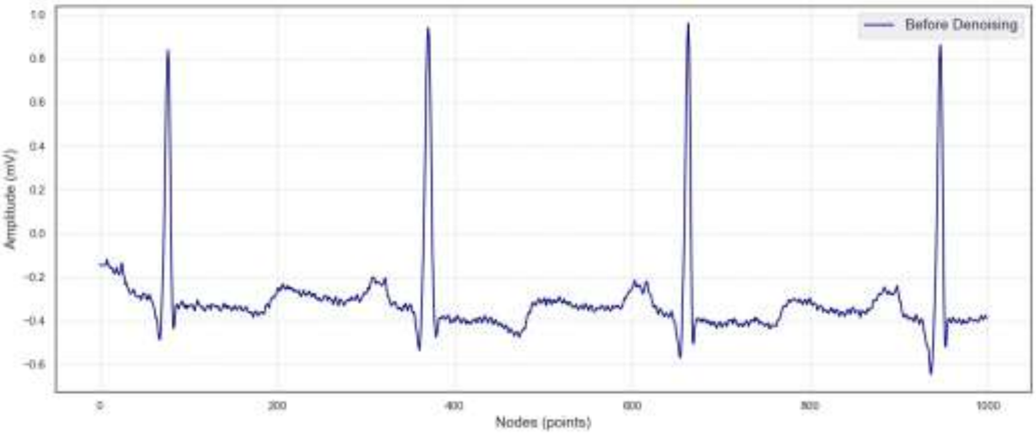
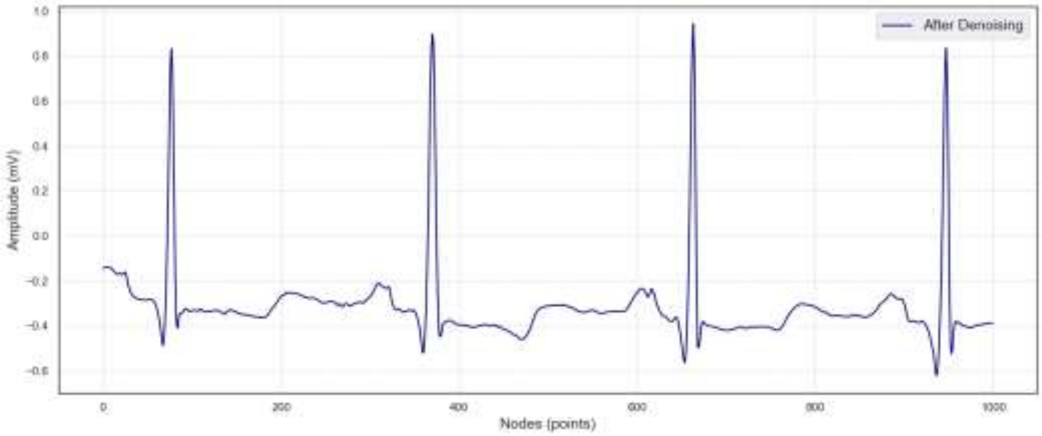


(a) Before denoising



(b) After denoising

FIGURE 2. The plot of ECG Denoising, (a) before and (b) after

2.2.2 ECG NORMALIZATION

After the ECG denoising, the next step is ECG signal normalization. ECG normalization is used to scale the ECG signal into a consistent range of values, so that all features have an equal contribution in the model. It is also important to ensure that the classification model used is not affected by the scaling differences between different features. The method used is Min-Max Scaling. In this method, the ECG signal is mapped into the range [0,1] by calculating the difference between the minimum and maximum values of the signal and adjusting it to fall within the desired range.

2.2.3. TIME-DOMAIN FEATURE EXTRACTION

Feature extraction is an important process in signal processing, especially in the analysis of biomedical signals such as ECG, which aims to transform raw data into information that can be used in machine learning and artificial intelligence models. One method of feature extraction is time domain analysis, which evaluates how the signal changes over time without transformation to the frequency domain. Time domain feature extraction is the process of retrieving characteristic information from signals in the time domain, which aims to analyze and interpret signal data in more depth. [17].

The method is very useful in various applications, including analysis of ECG signals, electromyography, and vibration signals in machine fault diagnosis [18]. In biomedical signal analysis, time domain features calculated from signal amplitude values play an important role in identifying key patterns and specific characteristics in the signal that can aid in the detection of physiological or pathological conditions such as cardiac arrhythmias [17]. Some of the features that can be extracted from the time domain and their mathematical formulas that include statistical parameters such as *mean, peak value*, and *kurtosis*, to factors such as *crest factor* and *shape factor* are described as below, where $\boldsymbol{x(n)}$ is the amplitude value of the signal at the nth data point, $\boldsymbol{n}$ is the index of each data point in the signal that ranges from 1 to $\boldsymbol{N}$, and $\boldsymbol{N}$ is the total number of data points or length of the signal that includes all samples in the analyzed signal series [17][18][19]. Table 1 listed the values of time-domain feature extraction from ten ECG records.

TABLE 1.
The sample values of time-domain feature extraction from ECG records

Mean	STD	Variance	RMS	Peak	Skewness	Kurtosis	Crest Factor	Margin Factor	Shape Factor	Impulse Factor
0.58	0.04	0.0021	0.58	1	4.41	25.26	1.71	1.71	1.0031	1.71
0.52	0.04	0.0022	0.52	1	2.85	21.61	1.91	1.92	1.0040	1.92
0.47	0.06	0.0040	0.47	1	2.13	7.07	2.09	2.12	1.0089	2.11
0.41	0.05	0.0031	0.42	1	3.45	18.62	2.37	2.41	1.0089	2.40
0.44	0.06	0.0041	0.44	1	1.24	7.94	2.23	2.26	1.0104	2.25
0.51	0.06	0.0036	0.52	1	0.89	9.70	1.91	1.93	1.0067	1.92
0.40	0.07	0.0063	0.40	1	2.41	10.86	2.44	2.51	1.0193	2.49
0.45	0.12	0.0164	0.47	1	0.03	0.78	2.11	2.24	1.0386	2.19
0.52	0.05	0.0031	0.52	1	0.04	11.95	1.91	1.92	1.0057	1.92
0.46	0.07	0.0062	0.47	1	1.97	6.55	2.10	2.15	1.0140	2.13

2.2.4. LONG SHORT-TERM MEMORY

Long Short-Term Memory (LSTM) is an artificial neural network architecture developed as an enhancement of Recurrent Neural Network (RNN) designed to overcome the problem of vanishing gradient and long-term dependencies in sequential data. In feedforward neural networks such as multilayer perceptron (MLP), information only flows in one direction (feedforward). Meanwhile, RNNs introduce feedback loops, thus allowing sequential data. However, RNNs have a disadvantage in remembering long-term information due to the vanishing gradient problem, which makes it difficult for the model to learn patterns with long-distance dependencies [3]. LSTM overcomes this problem by using a structure of gates that regulate the flow of information, allowing the model to retain or forget information based on its relevance to the task at hand [20].

The performance evaluation of LSTM was conducted using important classification metrics such as accuracy, precision, specificity, recall, and F1-score.

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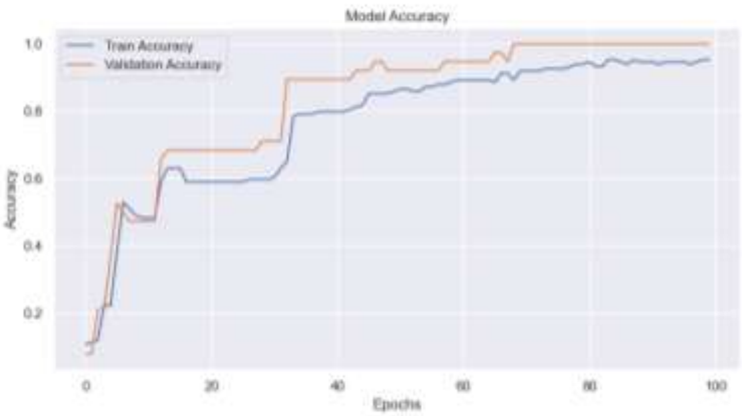
These metrics provide an overview of each model's ability to correctly recognize arrhythmia classes.

3. RESULTS AND DISCUSSION

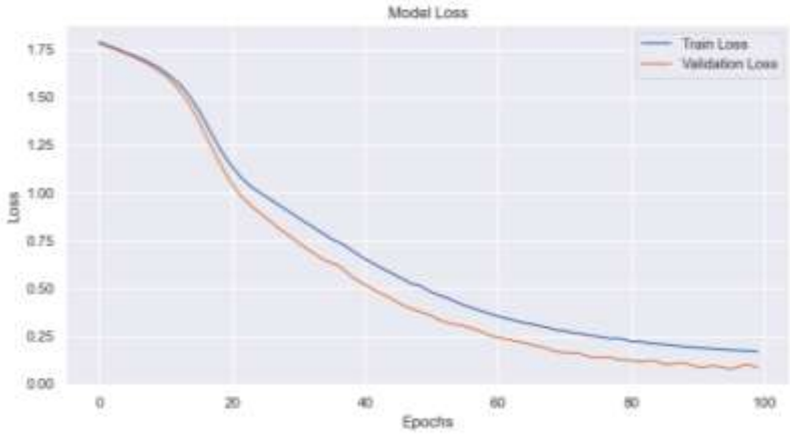
The experimental dataset contains 48 recordings (23 records from 100 to 124, and 25 records from 200 to 234) that are randomly selected and include rare, clinically important phenomena. Each recording is approximately 30 minutes long, and labeled based on the type of heart rhythm detected. The denoising process was performed using various wavelet options and levels. The wavelets tested were *db4, db7, db8, db9, sym4, sym5, sym6, bior2.4, bior4.4, bior5.5,* and *coif5,* and the levels tested were 7, 8, and 9. The best results were obtained by using the *bior3.3* wavelet at level 7 with an SNR value of 31.16 dB, providing optimal results in removing noise without reducing important information in the ECG signal. These results were then applied to the entire dataset.

In this study, the LSTM model is used to analyze ECG signals by considering the temporal characteristics of the data. LSTM is generally effective in understanding long-term relationships between data points in time signals. Figure 3 showed the learning curves, (a) accuracy curve, and (b) loss curve, that present how the LSTM model learns during the training and validation process. Figure 3 (a) illustrates how the LSTM model learns from the training data and how its performance is tested on the validation data. At the beginning of training, the accuracy is still low, but the model improves in the first few epochs. After a few epochs, the training accuracy and validation accuracy continue to improve, with the validation accuracy slightly higher than the training accuracy. To ensure the model is not overfitting or underfitting, further analysis using loss graphs is required.

In addition, Figure 3 (b) presents the loss curve during the training and validation process. The loss curve is necessary because it shows whether the model has consistently decreased in error during training or has stagnated, which can be used to determine whether the model is overfitting or underfitting. The loss curve shows a decrease with the train loss and validation loss continuously decreasing. The validation loss being lower than the train loss indicates that the model is not significantly overfitting. At the end of training, the train loss reaches around 0.1, while the validation loss is close to 0.08, indicating that the model performs quite well.



(a) Accuracy curve



(b) Loss curve

FIGURE 3. The learning curves of LSTM, (a) accuracy curve, and (b) loss curve

For the classification's performance metrics, this study presented the confusion matrix (CM) results in Figure 4. Figure 4 presented the LSTM model shows quite good classification performance in distinguishing six classes. The model is able to correctly classify all samples from the AFIB, AFL, B, PVC, and SBR classes. However, in class N, there were two samples that were incorrectly classified as AFL and SBR classes. Overall, the LSTM model showed fairly high accuracy, but still needs improvement in distinguishing signal characteristics that have similar patterns.

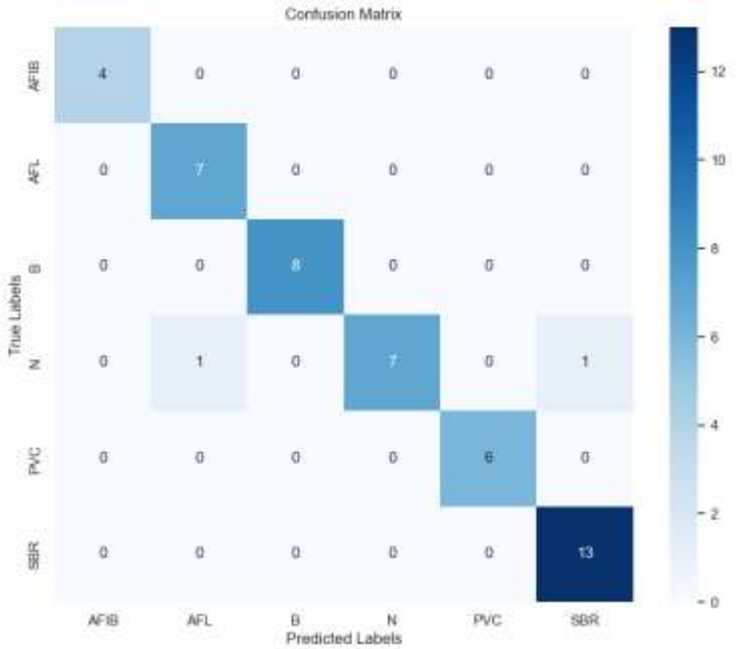


FIGURE 4. The heatmap of Confusion Matrix

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To make the results more comprehensive, this study has compared the LSTM to convolutional neural networks (CNN). The comparison of classification results between CNN and LSTM models aims to evaluate the performance of both models in classifying arrhythmia based on ECG signals. CNN is often used in image and signal processing due to its ability to extract complex spatial features. However, CNNs have limitations in capturing temporal relationships in sequential data such as ECG signals. Meanwhile, LSTM is specifically designed to handle sequence-based data, making it more effective in recognizing long-term patterns in ECG signals. Therefore, this comparison aims to see how well the two models classify arrhythmia types based on several evaluation metrics, such as accuracy, recall, precision, specificity, and F1-score (refer to Figure 5).

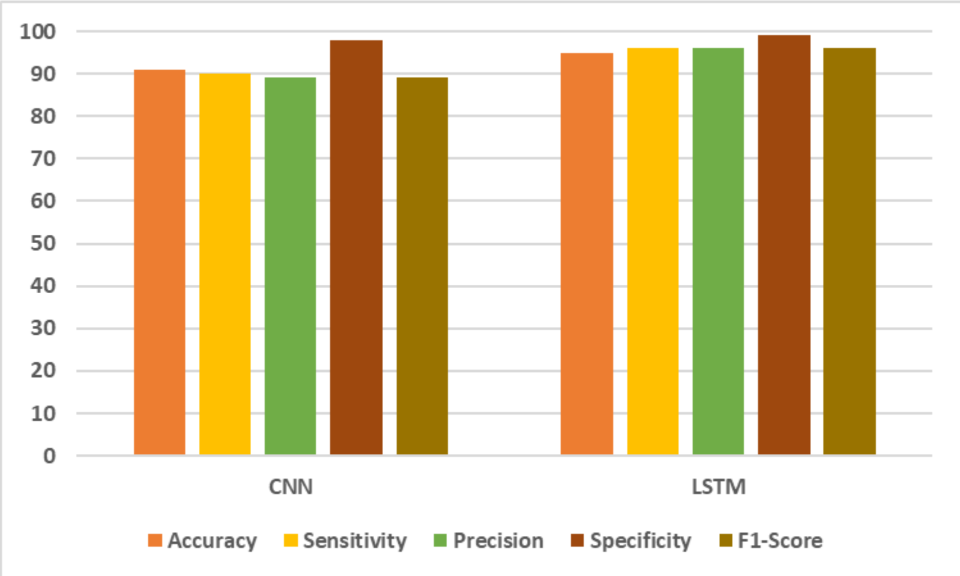

FIGURE 5. The comparison results of CNN and LSTM

Based on Figure 5, it can be seen that the LSTM model has better performance than the CNN model. LSTM achieved 95% accuracy, while CNN achieved 91% accuracy. In addition, the LSTM recall of 96% shows that this model is better at recognizing positive classes than CNN which has a recall of 90%. In terms of precision, LSTM also excels with 96% compared to CNN which reaches 89%, indicating that the LSTM model produces fewer false positives in prediction. Specificity of LSTM reached 99% compared to CNN with 98% indicating that LSTM is more effective in correctly identifying negative classes. In addition, LSTM's f1-score also reached 96%, superior to CNN's 89%, indicating a better balance between precision and recall. Overall, the LSTM model showed superiority in each evaluation metric, indicating that the approach using LSTM is more effective in capturing temporal patterns in arrhythmia data than CNN, which focuses more on spatial features.

4. CONCLUSION

Based on the research that has been conducted, researchers have successfully designed a deep learning model for arrhythmia classification that is more accurate and efficient by integrating feature extraction techniques. The process of signal denoising with discrete wavelet transform and time domain feature extraction helps improve data quality before classification using CNN and LSTM models. Evaluation of the model performance was carried out using various metrics that show that the developed model has good performance in detecting various types of arrhythmias. The results show that CNN accuracy reaches 91% and LSTM accuracy reaches 95%. Then the LSTM model managed to achieve recall, precision, specificity, and F1-score values of 96%, 96%, 99%, and 96%, respectively. In the future work, the research can be further developed by testing various optimization methods to see their effectiveness in selecting the best features and the use of larger and more diverse datasets.

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