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Study of Arrhythmia Classification Algorithms on Electrocardiogram Using Deep Learning

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Abstract: Arrhythmia is a heart disease that occurs due to a disturbance in the heartbeat that causes the heart rhythm to become irregular. In some cases, arrhythmias can be life-threatening if not detected immediately. The method used to detect is electrocardiogram (ECG) signal analysis. To avoid misdiagnosis by cardiologists and to ease the workload, methods are proposed to detect and classify arrhythmias by utilizing Artificial Intelligence (AI). In recent years, there has been a lot of research on the detection of this disease. However, many of such studies are more likely to use machine learning algorithms in the classification process, and most of the accuracy results still do not reach optimal levels in general. Therefore, this study aims to classify arrhythmias using deep learning algorithms. There are several stages of performing arrhythmia detection, namely, preprocessing, feature extraction, and classification. The focus of this research is only on the classification stage, where the Long Short-Term Memory (LSTM) algorithm is proposed. After going through a series of experiments, the performance of the proposed algorithm is further analyzed to compare accuracy, specificity, and sensitivity with other machine learning algorithms based on previous research, with the aim of obtaining an optimal algorithm for arrhythmia detection. Based on the results of the study, the Long Short-Term Memory (LSTM) algorithm managed to outperform the performance of other machine learning algorithms with accuracy, specificity, and sensitivity results of 98.47%, 99.24%, and 97.67%, respectively.

Keywords: Arrhythmia; Classification; Deep Learning; Electrocardiogram (ECG); Machine Learning

INTRODUCTION

Heart disease is a highly fatal illness globally, particularly in Indonesia. According to a report by the Global Burden of Disease and the Institute for Health Metrics and Evaluation (IHME) spanning from 2014 to 2019, heart disease ranks as the leading cause of death. Findings from the *Riset Kehesatan Dasar* (Riskesdas) in 2013 and 2018 indicate a rising trend in heart disease, with prevalence increasing from 0.5% in 2013 to 1.5% in 2018 (Tarmizi, 2022). There are various kinds of heart disease, one of which is arrhythmia. Arrhythmia is a cardiac condition characterized by irregular electrical signals within the heart, leading to abnormal heart rhythms that can manifest as excessive acceleration, deceleration, or irregular patterns. (Montenegro et al., 2022). There are several types of arrhythmias, such as Atrial Fibrillation (AF), Premature Ventricular Contraction (PVC), Premature Atrial Contraction (PAC), Ventricular Fibrillation (VF), and Ventricular Tachycardia (VT) (Madan et al., 2022). Arrhythmia disease can be detected using electrocardiogram signals, commonly abbreviated as ECG. ECG records the electrical signals of the human heart and is mostly used for the clinical diagnosis of cardiac arrhythmias (Li et al., 2022). By placing a series of electrodes on body surfaces, such as the chest, arms, and neck, ECGs can be used to track the electrical activity of heart rate rhythms over time. Changes in the rhythm of beats in the heart can be detected with these electrodes (Abdelhafid et al., 2022). ECG signals can be used to consistently diagnose and monitor individuals suffering from a variety of cardiac illnesses and severe cardiovascular syndromes, including arrhythmias. Thus, cardiologists use ECG signals to diagnose heart disease. But for now, this can only be done in hospitals (Rawi et al., 2022). By utilizing Artificial Intelligence (AI), detecting and classifying arrhythmias can be done efficiently; it can even ease the human workload and eliminate misanalysis of ECG signals from cardiologists caused by fatigue, differences between operators, and other factors (Rawi et al., 2022).

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According to Almazrouei & Al-Rajab (2022), the current trend of utilizing machine learning approaches for diagnosing arrhythmias still lacks precision. Therefore, deep learning algorithms were chosen for classification. His research shows that the Convolutional Neural Network (CNN) algorithm is proven to outperform machine learning algorithms, with the recommended model achieving an accuracy, specificity, and sensitivity of 98.50%, 93%, and 78% for the Convolutional Neural Network (CNN), 92.3%, 85%, and 71% for the K-Nearest Neighbour (KNN), 91.20%, 83%, and 61% for the Support Vector Machine (SVM), and 88.22%, 82%, and 74% for the Random Forest (RF) method.

However, Almazrouei & Al-Rajab (2022) research exclusively employed the Convolutional Neural Network (CNN) deep learning algorithm. Hence, the objective of this study is to utilize the Long Short-Term Memory (LSTM) deep learning algorithm instead. The focus of this study is the classification of three specific arrhythmia types: atrial fibrillation (AF), Premature Ventricular Contraction (PVC), and Premature Atrial Contraction (PAC). Additionally, the performance of the classification algorithm will be analyzed to determine the optimal outcomes in terms of accuracy, specificity, and sensitivity for classifying AF, PVC, and PAC arrhythmias.

LITERATURE REVIEW

Currently, there have been many studies on methods of detecting arrhythmia (Abdelhafid et al., 2022; Li et al., 2022; Madan et al., 2022; Montenegro et al., 2022) but there are many studies using machine learning algorithms for classification (Chickaramanna et al., 2022; Jahan et al., 2022; Mohanty et al., 2021; Ozpolat & Karabatak, 2023; Xie et al., 2019). Research from (Ozpolat & Karabatak, 2023) conducted classification experiments using the Support Vector Machine algorithm is abbreviated as SVM and the Quantum Support Vector Machine algorithm is abbreviated as QSVM. with accuracy, specificity, and sensitivity results of 86.96%, 95.61%, and 81.70% for SVM and 84.64%, 95.00%, and 81.13% for QSVM, respectively.

METHOD

The following is a research method that will be carried out according to the flowchart in *Figure 1*:

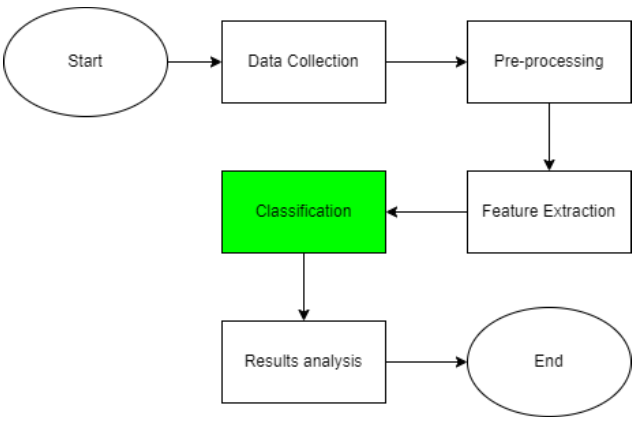

Fig. 1 Research Method

Focus on this research only at the classification stage according to the green color marked in Figure 1. The explanation of each research stage is:

Data Collection

In this research, ECG data were taken from the MIT-BIH Arrhythmia Database (MITDB) v1.0.0 and the MIT-BIH Atrial Fibrillation Database (AFDB) (Philip & Hemalatha, 2022; Ruan et al., 2022; Sahoo et al., 2022) v1.0.0 physionet dataset from records 100 to 234 and 04015 to 08455. From each dataset, only data samples containing AF, PVC, PAC, and normal signals were taken.

Pre-Processing

At this stage, it uses various electrocardiogram (ECG) signal processing processes commonly used in medical analysis. Signal resampling to change the sample rate, using a linear resampling method and converting the signal to a new sample rate, in this case to 250 Hz. Signal distortion to simulate the effect of interference on ECG measurements. To eliminate irrelevant trends and low-frequency components, signal detrending is performed by employing Butterworth filters with a frequency range of 0.5 Hz to 10 Hz. The Butterworth method is utilized to design filters that offer a uniform frequency response within the specified frequency range.Denoising is also

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performed using wavelet threshold the Discrete Wavelet Transform (DWT) to reduce noise levels in the signal (Merino-Monge et al., 2023; Philip & Hemalatha, 2022; Toulni et al., 2023).

Feature Extraction

After pre-processing, the next stage is to extract features. The first step is electrocardiogram (ECG) signal peak detection. Peak detection is a critical stage in electrocardiogram (ECG) signal analysis. (Dhyani et al., 2023). Peak detection is done by setting two important parameters, namely the height and distance between two peaks. Height refers to the threshold that an ECG signal must reach to be considered a peak. Meanwhile, the distance between the two peaks is used to ensure that the detected peaks are not too close to each other. In this research, R peak detection is used as an example. This R peak detection process has the main purpose of identifying the location of R peaks, which is a key feature in ECG analysis. The R peak is the highest point indicator on the QRS wave in the ECG signal (Vijayarangan et al., 2020), which describes the depolarization of the heart ventricles. The height set is 0.5, and the distance set is 50 for the detection of the R peak. The R peak detected in this study can be seen in Fig. 2. By detecting the peak R, we can measure the RR interval, which is useful in analyzing heart speed and rhythm as well as identifying arrhythmias or other heart rhythm disorders. The RR interval is the extraction feature used in this study. The RR interval extraction feature (RR intervals) is a process to identify and calculate several numerical features that describe the characteristics of the RR interval in cardiac data. The recorded heart signal RR interval represents the interval between the next two heartbeats. (Dhyani et al., 2023).

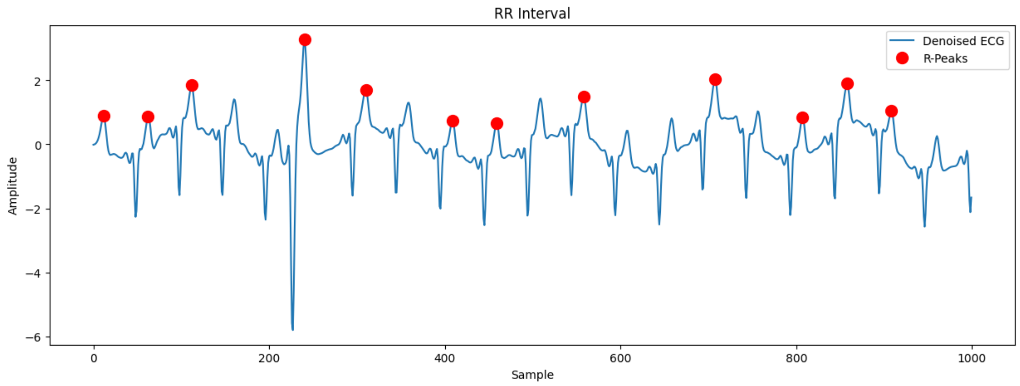

Fig. 2 R-Peaks Detection

Classification

Next is the classification, at this stage, the initiation of AF, PAC, and PVC disease symbols is carried out first on the ECG data. The next step is the implementation of classification modeling and evaluation using the LSTM algorithm. In this modeling implementation, there are several stages to be carried out, including dividing the dataset into training sets and test sets, starting with test_size = 0.2, which means 20% of the dataset will be used as a test set, and random_state = 42, which is used to ensure equal sharing each time the code is executed so that the results can be reproduced. Data Standardization, this process is carried out to ensure that each feature has the same scale and facilitates the classification process by the algorithm used. Learning Rate definition, as part of hyperparameters, learning rate will be utilized in Optimizer parameters that will be used to optimize the model (Fki et al., 2023). Early stopping, a technique used to stop model training if there is no significant improvement in model performance over several Epochs, is done to avoid overfitting or underfitting. Model Definition, creates a classification model using the LSTM algorithm. K-Fold Cross Validation: Evaluate models using k-fold cross-validation. The predetermined number of folds is 5. In each iteration, training and validation data are separated based on indexes generated by K-Fold objects.

The initiated model consists of three consecutive LSTM layers with dropouts between them, followed by a Dense layer as the output layer. The first and second LSTM layers use 64-unit neurons and dropouts with a probability of 0.5 being reused, which means each neuron in the previous layer has a 50% chance of being deactivated during training. The third LSTM layer uses 32-unit neurons. And the last is the Dense layer, which is added as the output layer. The Dense layer is a layer that has full connections, with the number of neurons according to the number of classes you want to predict. In this case, the activation used is softmax to obtain an output probability that can be interpreted as a class probability.

After initializing the model, the evaluation will be carried out by tuning hyperparameters. The parameters to be tuned include Epoch, Learning rate, Batch size, and Optimizer. Aim to find the set of hyperparameters that produces the best performance.

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Result Analysis

After going through several stages, the last step carried out is the analysis of the results. During this stage, the analysis involves evaluating the outcomes of each model. Initially, the focus is on examining the results of hyperparameter tuning for the model to identify the most suitable and optimal hyperparameters for the LSTM algorithm. Subsequently, The effectiveness of the LSTM method is evaluated in comparison to the findings from earlier research that used machine learning techniques.

The performance metrics used in this research are metrics that were also used in previous studies (Kulkarni et al., 2020; Obeidat & Alqudah, 2021; Wu et al., 2021) namely the multi-class confusion matrix. We use a multi-class confusion matrix because the number of classified disease classes is more than two (non-binary), and for each cardiac beat, this performance statistic displays the percentage of actual results that were anticipated. (Montenegro et al., 2022).

$$Accuracy = \frac{\sum_{i=1}^{l} \frac{TP_i + TN_i}{TN_i + FP_i + TP_i + FN_i}}{l} \quad (1)$$

$$Specificity = \frac{\sum_{i=1}^{l} TN_i}{\sum_{i=1}^{l} (FP_i + FN_i)} \quad (2)$$

$$Sensitivity = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} (TP_i + FN_i)} \quad (3)$$

Where "l represents the total number of classes. The abbreviation "TN" refers to True Negatives, representing the count of correctly classified negative instances. "TP" represents for True Positives, indicating the number of accurately classified positive examples. "FP" represents False Positives, which refers to the count of negative instances that were incorrectly classified as positive. Similarly, "FN" represents False Negatives, which indicates the number of positive instances that were mistakenly classified as negative. (Kulkarni et al., 2020).

RESULT

Tuning Hyperparameter

In this research, the model hyperparameter tuning process was carried out manually. there are several parameters that will be tuned such as Epoch, Learning Rate, Batch Size, and Optimizer.

The first parameter to be tested is Epoch. In this research, the Epoch values to be tuned are 50, 80, and 100. The parameter that gets the highest accuracy result and the lowest loss will be selected for the fixed parameter. Epoch will be tested using other parameters: 0.0001, Batch Size 32, and Optimizer Adam. The table below displays the test outcomes:

Table 1. Epoch test results

Epoch	Accuracy	Loss
50	96.17%	0.0872
80	96.06%	0.0802
100	**96.29%**	**0.0754**

In **Table 1**, it can be seen that an Epoch of 100 gets the highest result in terms of accuracy 96.29% and the lowest Loss 0.0754. Therefore, in the next test, we will use Epoch 100.

The second parameter to be tested is the Learning Rate. In this research, the values of the Learning Rate to be tuned are 0.01, 0.001, and 0.0001. The parameter that gets the highest accuracy result and the lowest loss will be selected for the fixed parameter. The Learning Rate will be tested using other parameters: Epoch 100, Batch Size 32, and Adam Optimizer. The table below displays the test outcomes:

Table 2. Learning rate test results

Learning rate	Accuracy	Loss
0.01	97.47%	0.0529
0.001	**97.88%**	**0.0415**
0.0001	96.17%	0.0774

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In **Table 2**, it can be seen that the Learning Rate of 0.001 gets the highest result in terms of accuracy at 97.88% and the lowest at 0.0415. Therefore, in the next test, we will use a Learning Rate of 0.001.

The next parameter to be tested is the Batch Size. In this research, the values of the Batch Size to be tuned are 32, 64, and 128. The parameter that gets the highest accuracy result and the lowest loss will be selected for the fixed parameter. The Batch Size will be tested using other parameters: Epoch 100, Learning Rate 0.001, and Adam Optimizer. The table below displays the test outcomes:

Table 3. Batch size test results

Batch size	Accuracy	Loss
32	97.88%	0.0370
64	**98.82%**	**0.0271**
128	98.64%	0.0399

In **Table 3**, it can be seen that the Batch Size of 64 gets the highest result in terms of accuracy 98.82% and the lowest loss 0.0271. Therefore, our next test will use Batch Size 64.

The last parameter to be tested is the Optimizer. In this research, the values of the Optimizer to be tuned are Adam, SGD, and RMSprop. The parameter that gets the highest accuracy result and the lowest loss will be selected for the fixed parameter. The Optimizer will be tested using other parameters: Epoch 100, Learning Rate 0.001, and Batch Size 64. The table below displays the test outcomes:

Table 4. Optimizer test results

Optimizer	Accuracy	Loss
Adam	97.76%	0.0425
SGD	93.76%	0.1292
RMSprop	**98.47%**	**0.0347**

In **Table 4,** it can be seen that the Optimizer of RMSprop gets the highest result in terms of accuracy at 98.47% and the lowest loss at 0.0347. Therefore, we will use the Optimizer RMSprop.

Classification

After going through several processes, this stage will explain the results of arrhythmia classification with hyperparameters that have been obtained previously and using the LSTM algorithm. Best results obtained in fold 3, The confusion matrix yields the following results:

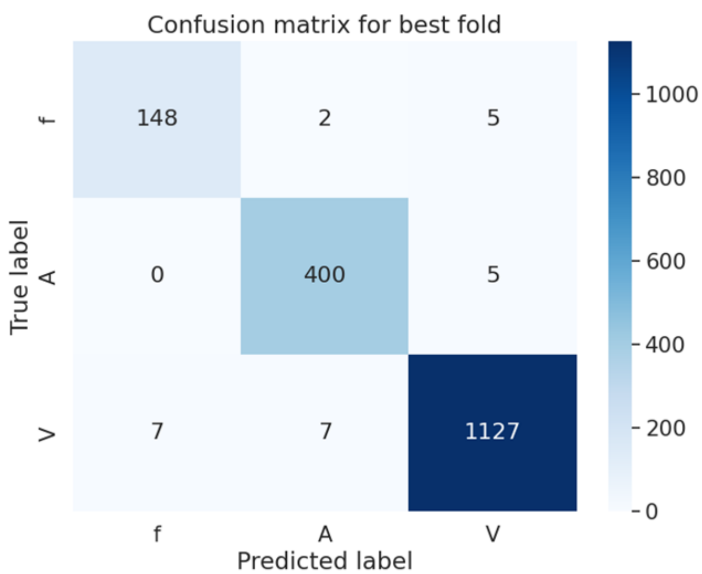

Fig. 3 Confusion Matrix in Fold 3

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Based on the results in **Fig. 3**, the LSTM classification algorithm achieved the highest performance based on the confusion matrix in fold 3, with accuracy, specificity, and sensitivity results of 98.47%, 99.24%, and 97.67%, respectively. Clearer results can be seen in **Fig. 4**.

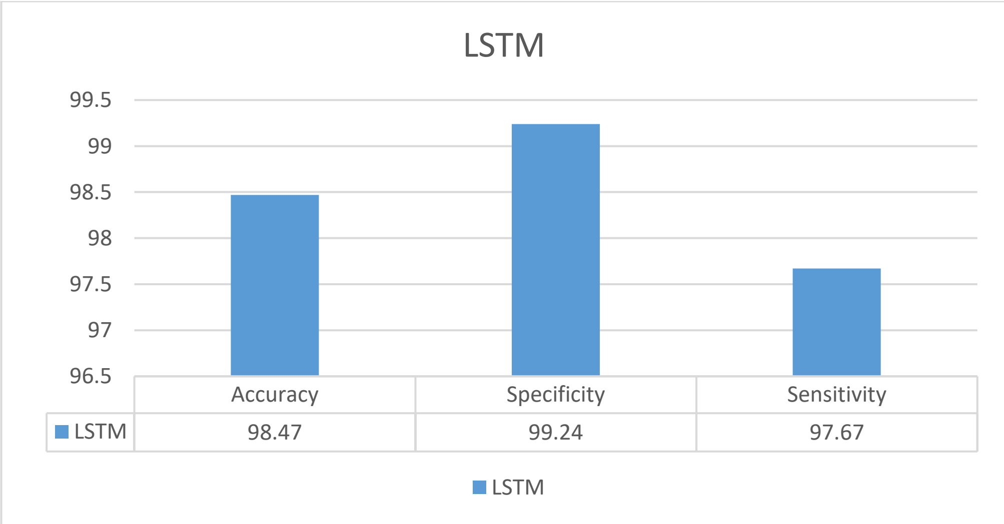

Fig. 4 Performance Results of the LSTM Classification Algorithm

DISCUSSIONS

Finding the optimal or best hyperparameters for an algorithm is a challenging task. It involves experimenting with different ranges of values for hyperparameters and evaluating model performance until the most suitable combination of hyperparameters is identified (Fki et al., 2023). The goal of this manual tuning process is to find the set of hyperparameters that produce the best performance, such as maximizing accuracy, minimizing loss, and achieving high specificity and sensitivity for abnormal beat detection. While this manual technique can be time-consuming, it allows for finer control over model behavior and can result in improved performance compared to using default hyperparameter values.

In this research, after manually tuning hyperparameters, we are getting the most suitable and best hyperparameters for the LSTM algorithm. The results can be seen in Table 5.

Table 5. Hyperparameter Tuning Results

Hyperparameter	**Value**
Epoch	100
Learning Rate	0.001
Batch Size	64
Optimizer	RMSprop

With the results of these parameters, we then conducted arrhythmia classification experiments using the LSTM algorithm, and the best performance results for the LSTM classification algorithm based on the confusion matrix in fold 3 were obtained with accuracy, specificity, and sensitivity results of 98.47%, 99.24%, and 97.67%, respectively.

We then compare these results with other Most Advanced Studies in the classification, which can be seen in **Table 6**.

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Table 6. Performance Comparison with Other State-of-the-Art Studies

Authors	classifier	Result
Almazrouei & Al-Rajab (2022)	CNN	**Acc 98.50%**,, Spec 93%, and Sens 78%
	KNN	Acc 92.3%, Spec 85%, and Sens 71%
	SVM	Acc 91.20%, Spec 83%, and Sens 61%
	RF	Acc 88.22%, Spec 82%, and Sens 74%
Ozpolat & Karabatak (2023)	SVM	Acc 86.96%, Spec 95.61%, and Sens 81.70%
	QSVM	Acc 84.64%, Spec 95.00%, and Sens 81.13%
Our Research	LSTM	Acc 98.47%, **Spec 99.24%**, and **Sens 97.67%**

Based on the comparison results from **Table 6**, the results of the LSTM deep learning algorithm in our study also managed to outperform the results of other machine learning algorithms. And for comparison with CNN algorithms from (Almazrouei & Al-Rajab, 2022), their research managed to outperform 0.03% of our research accuracy, while in specificity and sensitivity, our research managed to outperform with results of 6.24% and 19.67%, respectively. This proves that deep learning algorithms are better used than machine learning in terms of arrhythmia classification to get more optimal results.

CONCLUSION

Based on the results of our research, at the stage of manual tuning of hyperparameters, we are getting the most suitable and best hyperparameters for the LSTM algorithm with Epoch 100, learning rate 0.001, batch size 64, and RMSprop Optimizer. At the classification stage, using the LSTM deep learning algorithm, we obtained accuracy, specificity, and sensitivity results of 98.47%, 99.24%, and 97.67%, respectively. These results managed to outperform machine learning algorithms from the results of previous studies that we compared. With these results, it proves that deep learning algorithms are better used to get more optimal results. For future research, we suggest doing research with other deep learning classification algorithms, doing research at the feature extraction stage to get more optimal results, and doing research at the pre-processing stage to get more optimal results.

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