IJCCS (Indonesian Journal of Computing and Cybernetics Systems)
Vol.x, No.x, July xxxx, pp. 1~5
ISSN (print): 1978-1520, ISSN (online): 2460-7258
DOI: 10.22146/ijccs.xxxx

Electrocardiogram Signal Preprocessing Strategy in the LSTM Algorithm for Biometric Recognition

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Abstrak

Sinyal elektrokardiogram (ECG) merupakan alat yang sangat penting untuk diagnosis klinis dan bisa digunakan sebagai modalitas biometrik baru. Tujuan dari penelitian ini untuk mengetahui hasil pemrosesan sinyal ECG dengan metode RNN seperti algoritma Long Short Term Memory (LSTM) dengan memanfaatkan beberapa teknik preprocessing. Pada penelitian ini sinyal ECG sendiri sebelumnya diuji terlebih dahulu dengan melakukan proses klasifikasi LSTM tanpa melakukan preprocessing dan hasil yang didapatkan adalah 0% akurasi sehingga perlu adanya preprocessing. Metode preprocessing yang diuji dengan metode klasifikasi LSTM adalah Adjacent Segmentation dan R Peak Segmentation untuk mengetahui teknis preprocessing mana yang banyak memberikan pengaruh pada akurasi klasifikasi LSTM. Hasil percobaan yang didapatkan adalah klasifikasi LSTM dengan preprocessing R Peak Segmentation mendapatkan akurasi tertinggi pada dua data yang digunakan yaitu data filtered dan raw dengan akurasi masing-masing 80,7% dan 78,95%. Sedangkan akurasi yang didapatkan dari klasifikasi LSTM saat menggunakan preprocessing Adjacent Segmentation kurang baik. Penelitian ini mengindentifikasi perbandingan akurasi LSTM dari masing-masing tahapan preprocessing yang dilakukan untuk mencari tahu mana kombinasi dengan hasil terbaik pada proses pengklasifikasian data ECG. Penelitian ini juga menawarkan wawasan baru tentang tahapan-tahapan preprocessing yang bisa dilakukan pada data ECG.

Kata kunci *- Biometrik, Elektrokardiogram, Adjacent Segmentation, R Peak Segmentation, LSTM*

Abstract

Electrocardiogram (ECG) signals are a very important tool for clinical diagnosis and can be used as a new biometric modality. The aim of this research is to determine the results of ECG signal processing using RNN methods such as the Long Short Term Memory (LSTM) algorithm by utilizing several preprocessing techniques. In this study, the ECG signal itself was previously tested by carrying out the LSTM classification process without preprocessing, and the results obtained were 0% accurate, so preprocessing was needed. The preprocessing methods tested with the LSTM classification method are Adjacent Segmentation and R Peak Segmentation to find out which preprocessing techniques greatly influence LSTM classification accuracy. The experimental results were that LSTM classification with R Peak Segmentation preprocessing obtained the highest accuracy on the two data used, namely filtered and raw data, with 80.7% and 78.95%, respectively. Meanwhile, the accuracy obtained from LSTM classification when using Adjacent Segmentation preprocessing is not good. This research compares LSTM accuracy

Received June 1st,2012; Revised June 25th, 2012; Accepted July 10th, 2012

from each preprocessing stage to determine which combination has the best results in the ECG data classification process. This research also offers new insights into the preprocessing stages that can be carried out on ECG data.

Keywords *- Biometric, Electrocardiogram, Adjacent Segmentation, R Peak Segmentation, LSTM*

1. INTRODUCTION

Biometric technology can be used for automatic identity verification and to differentiate individuals based on their biological characteristics and personal behavior [1]. Biometrics based on what individuals do or have are often considered a better solution to reduce problems in knowledge and possession-based authentication methods [2]. Description of the biometric modalities used includes various aspects such as facial biometrics, voice biometrics, eye gaze tracking biometrics, three-dimensional face mapping, and vein modalities [3]. Physiological signals are included in the category of hidden biometrics that cannot be seen with the naked eye. Most of the literature studies on signal-based biometrics are related to brain biometrics and heart biometrics [4].

Research using Electrocardiogram data has been previously conducted by [5] yang menggunakan data sinyal Elektrokardiogram (ECG) untuk melakukan identifikasi dan klasifikasi biometrik berbasis ECG dengan menggabungkan metode DCNN dan Bi-LSTM. Untuk melakukan proses klasifikasi seperti penelitian lainnya dataset hasil dari Elektrokardiogram tentunya diperlukan juga proses preprocessing. Ada berbagai teknik preprocessing yang digunakan untuk meningkatkan akurasi. Teknik-teknik pemrosesan ini secara umum terbagi menjadi tiga kelas, yaitu dekomposisi data, reduksi data dan koreksi data [6].

In the study conducted by [7] it is stated that for Electrocardiogram (ECG) identification, specific studies show that RNN models produce the best performance in ECG identification compared to other models [8],[9]. One classification method that adopts RNN is LSTM [10]. Based on this research [11] it is explained that Deep Learning has been used in various biomedical signal processing applications. The LSTM architecture is used to segment ECG waves in several applications. Research utilizing LSTM classification methods on ECG data has also been conducted by [12] which took ECG data from CU-ECG to develop biometric identification and classification systems using LSTM and CNN methods. This research obtained the highest LSTM capability with an accuracy of 95.12%. Then research [13] which also uses ECG signal data from MITDB (ECG-ID) to estimate the performance and effectiveness of deep learning methods by combining VGG16 and LSTM models, thus obtaining an accuracy of 98%.

Based on several descriptions of LSTM methods [10]-[14] and previous foundational research [12],[13] the difference between this and previous research lies in the preprocessing stages to be implemented. If in research [12] Time-Frequency Transform (STFT, Scalogram, FSST, WSST) methods are used, and research [13] utilizes VGG16 pre-trained transfer learning (TL) as preprocessing stages. Then in this study, preprocessing of Adjacent Segmentation and R Peak Segmentation will be utilized as preprocessing stages. The novelty of this research lies in the preprocessing stages to be conducted before being classified using Long Short Term Memory (LSTM). Thus, the purpose of this research is to contribute to the knowledge regarding the LSTM's capabilities in classifying ECG data from various preprocessing results.

2. METHODS

In general, the research flow will compare the classification results from two different preprocessing techniques, namely the Adjacent Segmentation and R Peak Segmentation preprocessing techniques. These two preprocessing techniques are conducted separately despite both being part of the preprocessing stage because in their implementation, each of these two preprocessing techniques will be applied to the same ECG data, resulting in two different preprocessing outcomes to be fed into the data splitting and LSTM model. Additionally, the reason why these two techniques are conducted separately is because they are related to the technique of dividing the Electrocardiogram signals, where each of these two preprocessing techniques has a different approach, hence the outcomes of these two techniques will be compared in the final evaluation of the LSTM. The stages are as follows: collecting Electrocardiogram (ECG) signal data, preprocessing the data using Adjacent Segmentation and R Peak Segmentation respectively, dividing the data into training and testing sets for LSTM method, testing the model, and evaluation. The proposed model can be seen in Figure 1.

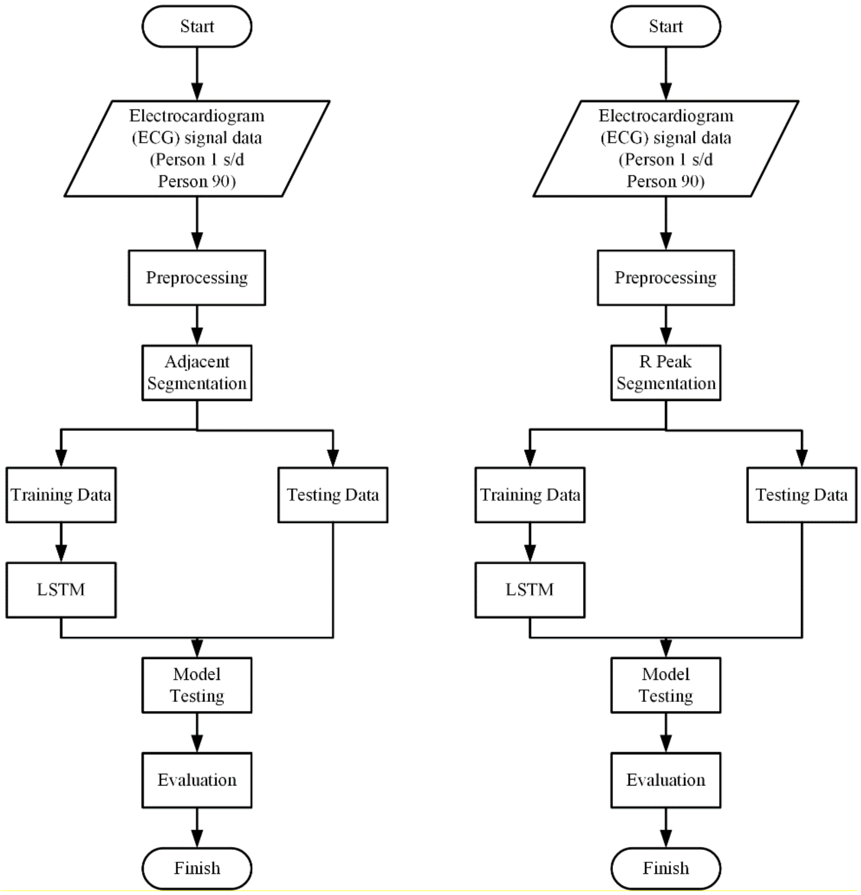

Figure 1 Research Procedure Flow

2.1 Data

The dataset used in this study is available at *https://www.physionet.org/content/ecgiddb/1.0.0/*, which is the MITDB (ECG-ID) electrocardiogram signal data. This dataset consists of ECG signal recordings from 90 individuals obtained using the "on-the-person" recording method. The biometric characteristics successfully recorded in this dataset are observed from each individual's data. It appears to have different numbers of data records, indicating an imbalance in labels per subject, as shown in Table 1. Therefore, to ensure that all data from each individual can be utilized, the biometric characteristics taken from this study will only utilize one data record per person. The datasets used in this study are divided into 2 data sets based on Person ID, namely Ecg-Id-Filtered and Ecg-Id-Raw. Samples from each dataset can be seen in Table 2 and Table 3.

Table 1. Dataset ECG ID

No.	Person ID	Frequency	Number of Record
1.	Person_74	1	1
2.	Person_04, Person_05, Person_06, Person_07, Person_08, Person_12, Person_13, Person_15, Person_17, Person_18, Person_19, Person_20, Person_22, Person_23, Person_24, Person_25, Person_29, Person_31, Person_33, Person_37, Person_38, Person_39, Person_41, Person_43, Person_44, Person_45, Person_47, Person_48, Person_49, Person_50, Person_54, Person_55, Person_56, Person_58, Person_65, Person_66, Person_68, Person_69, Person_73, Person_78, Person_79, Person_80, Person_81, Person_82, Person_83, Person_84, Person_86, Person_87, Person_89, Person_90	50	2
3.	Person_11, Person_14, Person_16, Person_21, Person_27, Person_57, Person_60, Person_62, Person_64, Person_67, Person_70, Person_75, Person_76, Person_77, Person_85, Person_88	16	3
4.	Person_26, Person_40, Person_42, Person_51, Person_61	5	4
5.	Person_03, Person_10, Person_24, Person_28, Person_30, Person_34, Person_35, Person_36, Person_46, Person_53, Person_59, Person_71	12	5
6.	Person_32, Person_63	2	6
7.	Person_09	1	7
8.	Person_72	1	8
9.	Person_52	1	11
10.	Person_01	1	20
11.	Person_02	1	22

Table 2. Dataset Ecg-Id-Filtered

X0	X1	….	X9999	X10000	X10001
-0.115	-0.115	….	-0.035	male	Person_01
0.105	0.06	….	-0.03	male	Person_01
….	….	….	….	….	….
-0.12	-0.09	….	0.195	female	Person_90
0.005	0.015	….	0.09	female	Person_90

Table 3. Dataset Ecg-Id-Raw

X0	X1	….	X9999	gender	person_id
-0.085	-0.08	….	-0.08	male	Person_01
0.105	0.135	….	-0.05	male	Person_01
….	….	….	….	….	….
-0.04	-0.145	….	0.27	female	Person_90
-0.08	-0.16	….	0.165	female	Person_90

2.2 Biometric

Biometrics is a technique that allows individual identity to be authenticated through physical characteristics, which are generally inherent and stable, or behavioral characteristics, which are typically measurable traits. This technology is now globally available for protecting and verifying users' personal identities [15].

Among various biometric characteristics, gait behavior is one example. For instance, in surveillance scenarios where popular biometric characteristics like faces and fingerprints are difficult or even impossible to distinguish, gait recognition utilizes the subject's movement patterns, focusing on specific characteristics such as arm swing amplitude, step frequency, and step length. Depending on specific application scenarios, gait patterns can be captured using visual sensors such as surveillance cameras or inertial sensors like accelerometers and gyroscopes found in wearable devices [16].

2.3 Electrocardiogram

The ECG is a powerful tool in cardiovascular disease research. Abnormal waveforms or intervals can reflect the heart health of patients [17]. An electrocardiogram (ECG) is a graphical representation of the electrical potential changes generated by the excitation of myocardial cells in the heart, detected using electrodes placed at specific locations on the body surface. The ECG itself is a common tool for monitoring heart health and detecting heart diseases in medical practice. Acquiring, analyzing, and labeling electrocardiograms takes a considerable amount of time, requires specialized expertise, and specific equipment. Additionally, using real ECG data from medical patients requires strict compliance with applicable laws and regulations regarding data privacy [18].

2.4 Preprocessing

If the number of ECG signal recordings is limited, the dataset available for efficiently training algorithms is relatively small. Therefore, to generate more data, an augmentation process is needed using various segmentation techniques on each raw ECG signal record. Adjacent Segment and R Peak Segment are preprocessing techniques that can be used to generate more data [19],[20].

Preprocessing Adjacent Segment works by dividing the ECG signal into consecutive segments based on a specified number of features. This segmentation process is divided into segments of equal length, where each segment represents a part of the signal with a fixed number of features, as illustrated in Figure 2. The first segment starts from point 0 and is then cut to a length of 1000 features, while the subsequent segments start from 1001 to point 2000. This process continues in a similar manner until the end point [21]. Consequently, the final outcome of this process is the features divided into segments of the same length. Each data representing these segments will then be input into the data splitting stage before entering the classification model.

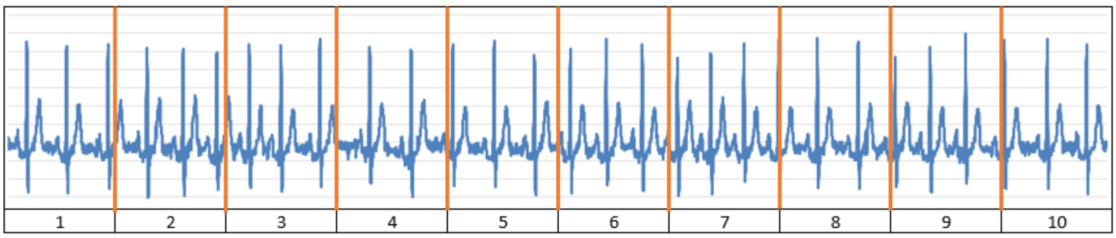

Figure 2 Preprocessing Adjacent Segment

Subsequently, the R Peak Segment is a type of preprocessing that detects R peaks in the electrocardiogram signal, as indicated by the red stars. After the peaks are detected, the ECG signal is divided into segments based on the location of the R peaks. To determine the first segment, it starts from the location of the first R peak plus 1000, and the next segment moves to the location of the next R peak plus 1000. The creation of segments stops after generating 10 segments. Similar to the Adjacent Segment preprocessing, the final outcome of this preprocessing process is the formation of segments representing each data point. However, the process of segmenting for these two preprocessing techniques is done differently. The resulting segmented data will then be divided into the data splitting stage before entering the classification model. The preprocessing process of the R Peak Segment can be seen in Figure 3 [20], [21].

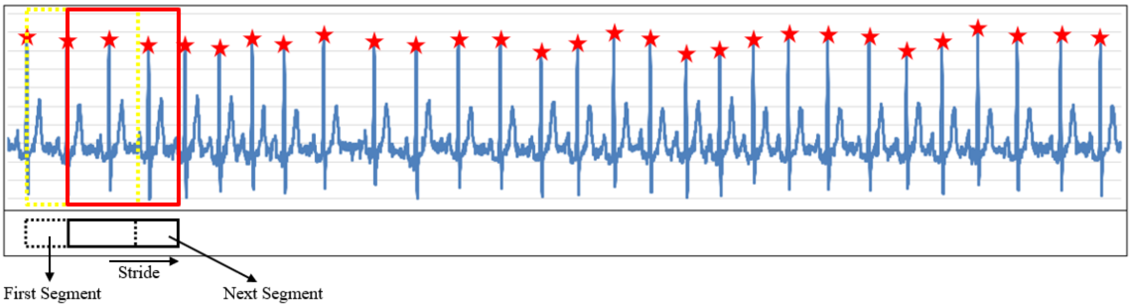

Figure 3 Preprocessing R Peak Segment

2.5 Long Short Term Memory (LSTM)

LSTM is an evolution of the standard RNN, which only has a single memory form. The "A" unit structure in LSTM has gate components that regulate the flow of information within the memory or cell state. LSTM introduces the concept of gates such as the input gate, forget gate, and output gate. The input gate determines the new data to be added to the cell state. The input gate calculates additional values to update the cell status, the forget gate is responsible for determining which information will be removed from the cell state, while the output gate controls the output value based on the cell state [22],[23]. The structure of LSTM includes LSTM gates, there are sigmoid activation functions (σ) that act as producers of values 0 or 1. The output 0 or 1 aims to provide clarity and positive value to the gate. An output of 0 is intended to ignore or eliminate certain features, while a value of 1 is intended to retain those features in the network. The equation for the input gate is expressed by equation (1), the forget gate by equation (2), and the output gate by equation (3).

$$i_t = w_i\,[h_{t-1}, x_t] + b_i \tag{1}$$

$$f_t = w_f[h_{t-1}, x_t] + b_f \tag{2}$$

$$o_t = w_o[h_{t-1}, x_t] + b_o \tag{3}$$

n equation (1), it represents the input gate, w_x is the weight for the 'x' gate h_{t-i} is the output from the previous LSTM unit or output gate (at time t - 1), x_t is the input to the current LSTM unit (at time t), b_x is the bias for the 'x' gate, ft is the forget gate, and ot is the output gate [24].

2.5 Evaluation Metrics

Evaluation metrics are parameters used to measure the quality of a model or machine learning algorithm. The evaluation metrics used in this study are Accuracy, Precision, Recall, and F1-Score. Each of these evaluation metrics is formulated as follows : Accuracy is the value representing the comparison of True Positive (TP) and True Negative (TN) predictions with the total number of data. The formula used can be seen in the equation (4). Precision is the value representing the comparison of True Positive (TP) predictions with the total number of data predicted positive. The formula used is shown in equation (5). Recall is the value representing the comparison of True Positive (TP) predictions with the total number of truly positive data. There is a difference between precision and recall, where precision involves the False Positive (FP) variable, while recall involves the False Negative (FN) variable. The formula used is shown in equation (6). F1-Score is the value representing the weighted average comparison of precision and recall. The formula used can be seen in equation (7) [25].

$$Accuracy = \frac{TP+Tn}{(TP+FN)+(FP+TN)} \quad (4)$$

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$F1\text{-}Score = \frac{2TP}{2TP+FN+FP} \quad (7)$$

3. RESULTS AND DISCUSSION

This section compares the accuracy produced by LSTM from two different preprocessing stages, namely the accuracy of LSTM with Adjacent Segmentation preprocessing and the accuracy of LSTM with R Peak preprocessing, using two datasets: ECG-Id-Raw and ECG-Id-Filtered based on data from person Id. This dataset contains 310 records obtained from 90 individuals, resulting in 90 person Ids, and each person has a different frequency of data. Therefore, only one record is taken for each person. The ECG-Id-Raw dataset represents raw data containing noise and components of high and low frequency noise. Thus, a new dataset called ECG-Id-Filtered is created, which is filtered ECG data free from noise influences like the raw data before filtering. Adjacent Segmentation preprocessing is a technique that divides an ECG signal record by cutting the record according to the desired number of features. In this study, it will be divided into two segments. The first segment starts from point 0 and then is cut for 500 features, then from point 501 to point 1000. The second segment is done in the same way until the end point.

The next step is the LSTM classification stage. Before proceeding to the classification stage, the preprocessed data will be divided. Data division in this study uses a split proportion of 80% training data and 20% testing data. After this data division, the LSTM classification process will be continued based on the preprocessing model plots previously obtained. In the LSTM process itself, there are several divisions of input shapes. The purpose of dividing the input shape is to find the most optimal accuracy result in an LSTM model. The allocation of input shape depends on how much data is used, so the form of the input shape can be freely given while still considering the number of data. Each modeling of input shape will then be input into the LSTM model, so the LSTM model does not need to adjust the shape of the input shape, but the input shape needs to adjust to the LSTM model built. The results of LSTM classification with Adjacent Segment preprocessing can be seen in Table 4.

Table 4. Classification Result LSTM preprocessing Adjacent Segment

Adjacent Segment	Input Shape	(1, 500)	(100, 5)	(125, 4)	(2, 250)	(250, 2)	(4, 125)	(5, 100)	(500, 1)	-	-	-	-
Filtered 500	Accuracy	0.0618	0.2697	0.2247	0.0506	0.0562	0.0843	0.0843	0.0337	-	-	-	-

	Recall	0.0618	0.2697	0.2247	0.0506	0.0562	0.0843	0.0843	0.0337	-	-	-	-
	Prescision	0.0735	0.3479	0.2785	0.064	0.0281	0.117	0.1208	0.0143	-	-	-	-
	F1-Score	0.061	0.2662	0.2168	0.0513	0.0324	0.0901	0.0946	0.0162	-	-	-	-
Adjacent Segment Filtered 1000	Input Shape	(1, 1000)	(10, 100)	(100, 10)	(1000, 1)	(125, 8)	(2, 500)	(200, 5)	(250, 4)	(4, 250)	(5, 200)	(500, 2)	(8, 125)
	Accuracy	0.0506	0.0955	0.3202	0.0337	0.3371	0.073	0.3202	0.264	0.0506	0.0899	0.0449	0.0899
	Recall	0.0506	0.0955	0.3202	0.0337	0.3371	0.073	0.3202	0.264	0.0506	0.0899	0.0449	0.0899
	Prescision	0.0415	0.0806	0.3948	0.0134	0.3995	0.0713	0.3466	0.2998	0.069	0.0787	0.0417	0.127
	F1-Score	0.0378	0.0818	0.3157	0.0181	0.3263	0.0642	0.2984	0.252	0.0427	0.0746	0.0387	0.0836
Adjacent Segment Raw 500	Input Shape	(1, 500)	(100, 5)	(125, 4)	(2, 250)	(250, 2)	(4, 125)	(5, 100)	(500, 1)	-	-	-	-
	Accuracy	0.1292	0.1629	0.0843	0.1685	0.1011	0.1404	0.1461	0.0674	-	-	-	-
	Recall	0.1292	0.1629	0.0843	0.1685	0.1011	0.1404	0.1461	0.0674	-	-	-	-
	Prescision	0.1247	0.2328	0.0829	0.1594	0.0693	0.1389	0.099	0.0231	-	-	-	-
	F1-Score	0.113	0.1681	0.0606	0.144	0.0665	0.1184	0.1019	0.0286	-	-	-	-
Adjacent Segment Raw 1000	Input Shape	(1, 1000)	(10, 100)	(100, 10)	(1000, 1)	(125, 8)	(2, 500)	(200, 5)	(250, 4)	(4, 250)	(5, 200)	(500, 2)	(8, 125)
	Accuracy	0.0787	0.1573	0.0955	0.0506	0.1573	0.118	0.0899	0.0843	0.1292	0.1461	0.0618	0.118
	Recall	0.0787	0.1573	0.0955	0.0506	0.1573	0.118	0.0899	0.0843	0.1292	0.1461	0.0618	0.118
	Prescision	0.0435	0.1258	0.0422	0.011	0.1685	0.1164	0.0777	0.0494	0.1743	0.1137	0.0104	0.1505
	F1-Score	0.0485	0.1269	0.0494	0.0148	0.1417	0.0937	0.0626	0.0484	0.1084	0.111	0.0172	0.1164

Based on Table 4, there are 8 input shapes in the LSTM classification results for electrocardiogram (ECG) data with Adjacent Segment preprocessing Data Filtered 500. From the table, it can be found that the highest accuracy is at input shape (100,5) which is 0.2697. Then, there are 12 input shapes in the preprocessing Adjacent Segment Filtered 1000. The best LSTM classification accuracy is at input shape (125,8) which is 0.337.

Next, Adjacent Segment Raw 500 achieves the best accuracy at input shape (2,250) with an accuracy of 0.1685. Furthermore, preprocessing Adjacent Segment Raw 1000 obtains the best accuracy at input shapes (10,100) and (125,8) because they have the same accuracy, which is 0.1573. Meanwhile, for the LSTM classification results with R Peak Segment preprocessing, they can be seen in Table 5.

Table 5. Classification Result LSTM preprocessing R Peak Segment

R Peak Segment Filtered 500	Input Shape	(1, 500)	(100, 5)	(125, 4)	(2, 250)	(250, 2)	(4, 125)	(5, 100)	(500, 1)	-	-	-	-
	Accuracy	0.655	0.6199	0.5789	0.7661	0.5556	0.807	0.7836	0.4678	-	-	-	-
	Recall	0.655	0.6199	0.5789	0.7661	0.5556	0.807	0.7836	0.4678	-	-	-	-
	Prescision	0.6884	0.6411	0.6165	0.8346	0.5698	0.8707	0.8396	0.4394	-	-	-	-
	F1-Score	0.6427	0.5966	0.5657	0.7635	0.541	0.8096	0.7873	0.432	-	-	-	-
R Peak Segment Filtered 1000	Input Shape	(1, 1000)	(10, 100)	(100, 10)	(1000, 1)	(125, 8)	(2, 500)	(200, 5)	(250, 4)	(4, 250)	(5, 200)	(500, 2)	(8, 125)
	Accuracy	0.5088	0.7544	0.538	0.1988	0.5556	0.7076	0.5439	0.5146	0.7251	0.731	0.345	0.6842
	Recall	0.5088	0.7544	0.538	0.1988	0.5556	0.7076	0.5439	0.5146	0.7251	0.731	0.345	0.6842
	Prescision	0.5268	0.8014	0.564	0.1928	0.6319	0.7555	0.5891	0.5526	0.7732	0.7976	0.378	0.6812
	F1-Score	0.4852	0.7598	0.5224	0.1744	0.5476	0.6912	0.5341	0.4998	0.7042	0.7234	0.3329	0.6592

R Peak Segment Raw 500	Input Shape	(1, 500)	(100, 5)	(125, 4)	(2, 250)	(250, 2)	(4, 125)	(5, 100)	(500, 1)	-	-	-	-
	Accuracy	0.7427	0.5146	0.5614	0.7895	0.5439	0.7544	0.7427	0.3626	-	-	-	-
	Recall	0.7427	0.5146	0.5614	0.7895	0.5439	0.7544	0.7427	0.3626	-	-	-	-
	Prescision	0.8379	0.5928	0.5841	0.8423	0.5756	0.8011	0.7848	0.3196	-	-	-	-
	F1-Score	0.7503	0.5024	0.5356	0.7895	0.5251	0.7426	0.7267	0.3167	-	-	-	-
R Peak Segment Raw 1000	Input Shape	(1, 1000)	(10, 100)	(100, 10)	(1000, 1)	(125, 8)	(2, 500)	(200, 5)	(250, 4)	(4, 250)	(5, 200)	(500, 2)	(8, 125)
	Accuracy	0.5965	0.614	0.4327	0.1404	0.4444	0.7135	0.462	0.4444	0.7193	0.7544	0.2398	0.6667
	Recall	0.5965	0.614	0.4327	0.1404	0.4444	0.7135	0.462	0.4444	0.7193	0.7544	0.2398	0.6667
	Prescision	0.6094	0.685	0.4301	0.1161	0.4258	0.7827	0.4441	0.4467	0.7992	0.8296	0.2661	0.7174
	F1-Score	0.562	0.6072	0.3979	0.1083	0.4008	0.7103	0.4294	0.417	0.7152	0.7568	0.2197	0.6551

From Table 5, the LSTM classification results using R Peak Segment preprocessing on filtered 500 data are shown. In this stage, there are also 8 input shapes. From these 8 inputs, accuracy values are obtained according to their respective inputs, and the highest accuracy is found at input shape (4,125) which is 0.8070. Next, the LSTM classification results using R Peak Segment preprocessing on filtered 1000 data are shown. In this stage, there are 12 input shapes, and the highest accuracy is found at input shape (10,100) which is 0.7544. Furthermore, for the LSTM classification results using R Peak Segment preprocessing on raw 500 data, this stage involves 8 input shapes, and the highest accuracy is found at input shape (2,250) which is 0.7895. Then, for the LSTM classification results using R Peak Segment preprocessing on raw 1000 data is 0.7544.

The evaluation results of the LSTM model in this study are consistent with previous research conducted by [12], [13]. Similarly, the LSTM classification process is in line with the explanation from [10]-[14] that LSTM can be used for processing biomedical signals such as electrocardiograms (ECG). However, the most fundamental difference between this study and previous research lies in the accuracy levels obtained, and this study introduces different types of preprocessing stages compared to the previous ones. While the study by [12] utilized preprocessing methods such as Time-Frequency Transform (STFT, Scalogram, FSST, WSST), and the study by [13] utilized VGG16 pre-trained transfer learning (TL) as part of its preprocessing, this study employs Adjacent Segment and R Peak Segment for the preprocessing stages. The differences in preprocessing stages undoubtedly have a significant impact on the resulting accuracy. In addition to the differences in preprocessing stages, variations are also observed in the data used. Although both studies use electrocardiogram data, they differ in the specific datasets utilized. The study by [12] employed CU-ECG electrocardiogram signal data, while the study by [13] utilized MITDB (ECG-ID) electrocardiogram signal data, which is also used in this study.

The final comparison results of the overall research can be seen in Table 6 and Figure 4. For filtered data, the highest accuracy is achieved in LSTM classification with R Peak Segment preprocessing with a segment count of 500, reaching 0.8070 or 80.7%, whereas for raw data, the highest accuracy is obtained in LSTM classification with R Peak Segment preprocessing with a segment count of 500, reaching 0.7895 or 78.95%. Based on this, it can be concluded that using R Peak Segment preprocessing in LSTM classification results in superior accuracy compared to using Adjacent Segment preprocessing.

Table 6. Comparison of the Accuracy of LSTM Classification Results

Model	Segment Count	Method	Data Type	Input Shape	Accuracy	Recall	Precision	F1 Score
1	500	R Peak	Filtered	(4, 125)	0.8070	0.8070	0.8707	0.8096
2	500	R Peak	Raw	(2, 250)	0.7895	0.7895	0.8423	0.7895
3	1000	R Peak	Raw	(5, 200)	0.7544	0.7544	0.8296	0.7568
4	1000	R Peak	Filtered	(10, 100)	0.7544	0.7544	0.8014	0.7598
5	1000	Adjacent	Filtered	(125, 8)	0.3371	0.3371	0.3995	0.3263
6	500	Adjacent	Filtered	(100, 5)	0.2697	0.2697	0.3479	0.2662
7	500	Adjacent	Raw	(2, 250)	0.1685	0.1685	0.1594	0.1440
8	1000	Adjacent	Raw	(125, 8)	0.1573	0.1573	0.1685	0.1417

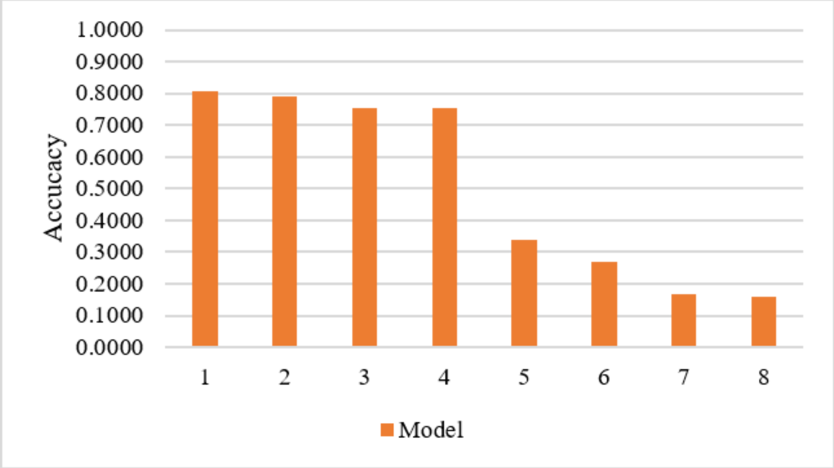

Figure 4 Comparison of the Accuracy of LSTM Classification Results

However, when compared to the studies conducted by [12], [13] the resulting accuracy is still higher. In study [12] the LSTM accuracy obtained was 95.12%, while in study [13], it was 98%. Meanwhile, the highest accuracy achieved in this study is 80.7%. Although the data used in this study is the same as in study [13], there are differences in the preprocessing steps between each study. However, the information obtained from this difference in accuracy indicates that each preprocessing step significantly influences the final outcome of the research process. Thus, the limitation of this study lies in the choice of preprocessing methods for classification by the LSTM model, as evidenced by the comparison of the two preprocessing methods in this study where Adjacent Segment did not achieve results comparable to R Peak Segment accuracy. It is important to note that for future research, experimentation with preprocessing techniques on the CU-ECG electrocardiogram signal data used in study [12] is needed to reassess the preprocessing capabilities on different datasets.

4. CONCLUSIONS

This study presents a discussion on the LSTM classification method implemented on electrocardiogram (ECG) data assisted by preprocessing steps of Adjacent Segment and R Peak Segment. From the classification results using these two preprocessing methods, it was found that classification with R Peak Segment preprocessing achieved the highest accuracy for both Filtered and Raw ECG data, with accuracies of 80.7% and 78.95%, respectively. On the other hand, the highest accuracy obtained by LSTM classification with Adjacent Segment preprocessing was only 0.3371 or 33.71% for filtered data, and 0.1685 or 16.85% for raw data, showing a significant difference in accuracy between the two preprocessing processes. The limitation of this study lies in the Adjacent Segmentation preprocessing stage, which obtained relatively low accuracy, indicating the need for retesting preprocessing with different data or using other classification methods. This will be the task of future researchers to further explore the impact of preprocessing when combined with other methods, aiming to achieve even better outcomes.

ACKNOWLEDGEMENTS

We wish to extend our utmost appreciation to the Ministry of Education, Culture, Research and Technology, as well as Lambung Mangkurat University for invaluable support in facilitating this research endeavour by awarding us the Penelitian Kerjasama - Dalam Negeri research grant for the year 2023.

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