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Arrhythmia Analysis in the Long-term Electrocardiogram Monitoring System

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Abstract: Cardiovascular disease (CVD) is dangerous and has a high mortality rate. One of the signs of CVD is arrhythmia. The method to find out the symptoms of arrhythmia is an electrocardiogram (ECG) long-term monitoring. The duration of ECG analysis on long-term monitoring is 6 hours, 12 hours, or 24 hours. The device used for long-term ECG is a Holter device. Arrhythmia analysis has followed: detect QRS complex and continue arrhythmia classification. Holter data is stored in local memory or on the server. Storage on local storage makes it difficult for cardiologists to perform analysis. However, using server storage causes access times to slow if patient data increases. Because of this, the cardiologist needs a powerful processing unit to analyze arrhythmia. This study proposes Arrhythmia analysis in the long-term ECG monitoring system. ECG acquisition is sent and stored in the processing unit. We use a single-board computer (SBC) Raspberry Pi as a processing unit. Besides storing data, SBC is also analyzing arrhythmias. The analysis steps are detecting R-peak using the Pan-Tompkins (PTK) algorithm, removing P and T waves using the Gaussian filter, and arrhythmia classification using the multi-layer perceptron (MLP). MLP is a low computational deep learning, which is suitable for SBC. The total storage delay consists of sending and storing data in the database. In the experiment, the propagation data to the broker is 0.023 s., and the storage time to the SQLite database is 15.16 s. The limited recording time for acquisition data is 21 hours and 36 minutes. The success rate of the device in detecting the QRS complex has a precision (+*P*) of 98.61% and a sensitivity (*Se*) of 99.8%. Our classification has good in *Acc*, *Se*, *Spe*, +*P*, and F1-scores are 99.77, 99.55, 99.55,99.85, and 99.55, respectively. The method is superior to several other arrhythmia classification studies.

Keywords: ECG, Arrhythmia classification, Holter, Telemedicine, IOT.

1. Introduction

Cardiovascular disease (CVD) is one of the leading causes of death in the world [1]. The method for detecting the disease is by analyzing the Electrocardiogram (ECG) signal. The SA Nodes are pacemakers that generate impulses that cause ventricle contractions [2] with 60 until 100 beats/minute. Impulses generated from the SA Nodes can be sensed with the ECG sensor to produce a signal, as shown in Fig. 1. One period of The ECG signal consists of 3 component waves: P, QRS complex, and T. The P wave is a slight upward curve, indicating the depolarization phase and atrial contraction [3]. The QRS complex indicates depolarization of the ventricle. The amplitude of the QRS complex wave is much larger than the P wave because the muscle mass of the ventricles is more significant than the atrium. The atrial repolarization wave is not visible when it coincides with the QRS complex. Ventricular repolarization triggers the T wave, which is used to recover its electronegativity.

One of the symptoms of CVD is arrhythmia, which occurs due to disturbances in the initiation of electrical potentials or the propagation of electrical impulses due to cardiac activity, which causes irregular heart rhythms [4]. This problem causes worse health and even mortality when not detected and treated early. Factors that increase exposure to

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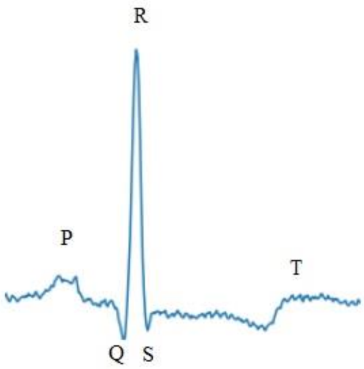

Figure. 1 A period of ECG signal contains 3 waves: P, QRS Complex and T

arrhythmia are age, environment, genetics, lifestyle, ethnicity, race, gender, and history of certain diseases. Detecting an arrhythmia is calculating the distance from the peak of the QRS complex, namely the R-peak, to the next R-peak. It is called the RR interval. The length of the RR interval determines the arrhythmia Tachycardia, Normal, or Bradycardia Arrhythmia. Patients with bradycardia have a heart rate of less than 60 bpm or an average RR interval of more than 1.0 seconds. Meanwhile, the heartbeat tachycardia exceeds 100 bpm or an RR interval of fewer than 0.6 seconds.

Irregular Heartbeat sometimes occurs once a day and beats normally when the patient comes to the cardiologist. When carrying out a short-term ECG test, they often do not find arrhythmia symptoms. A long-term ECG test called the Holter test uses a Holter device or Ambulatory ECG to record ECG signals of a patient continuously for 12, 24, or 48 hours [5]. The Holter device consists of an ECG sensor and a portable electronic device. The user of Holter was recording the time of occurrence of the arrhythmia and his activity when the symptom occurred. Cardiologist uses time of arrhythmia, activity records, and ECG signals to analyze heart conditions. This procedure requires the patient to come directly to the hospital. First, the patient comes to the hospital to install the Holter device. Then, He returned to the hospital 1 or 2 days later to see the results of the Holter test or consult with the doctor. It is a contradiction because patients with CVD have a high risk of contracting infectious diseases when he frequently visits the hospital during a pandemic. The patient is recommended to reduce the frequency of his coming to the hospital.

Someone who has a mobile ECG can check their heart condition independently as an early warning. Several mobile ECG products on the market that can log and display this data in graphic mode include Kardia[6], CardioSecur[7], and Qardiocore[8]. The long storage time for Kardia, CardioSecur, and Qardiocore are 30 seconds, 30 minutes, and 36 hours, respectively. A prototype for storing ECG data for the long-term was proposed in research [9, 10, 11], dan [12]. Authors in [9] proposed recording the data and the device used for early warning system for heart conditions. The sensor node consists of ECG and Seismocardiography (SCG) installed on the patient. The sensor node sends sensing data to the server for analysis. The server warns the patient via the sensor node if the analysis results find an abnormal SCG or ECG. A wearable device with sensors a stethoscope sensor for acoustic heart activity, ECG, and pneumography, is proposed [10]. The data is saved to the local device. Then, the computer analyzes health of the cardiac and pulmonary. Study [11] proposed a differential ECG lead that measures the potential difference between electrodes near the heart. The use of a differential ECG, or what they call a body sensor, is suitable for long-term recording on humans and animals. Research [12] designed a portable ECG using low cost. They claim that the recorded ECG data is of high quality, which means it is free of noise or artifice. The proposed device has the ability to record data in 36 hours.

Arrhythmia classification is preceded by detecting complex QRS waves and R-peaks. We used the RR interval to detect arrhythmias. QRS complex detection has been proposed in studies [13-16]. Study [13, 14] uses a heuristic algorithm, while research [15, 16] implements deep learning to detect the QRS complex. The Pan-Tompkins (PTK) algorithm [13] is the favored method for detecting the QRS complex. The algorithm has steps: bandpass filter, derivative, signal squaring, moving window integration, and thresholding. The bandpass filter is used for noise cancellation and baseline wander. The derivative obtains the slope of the QRS complex. Furthermore, the algorithm amplifies the QRS complex using squaring function. Moving window integration is implemented to get the QRS duration and threshold to get the region of interest (ROI) of the QRS Complex. The study [14] implements an adaptive threshold for detecting QRS waves. They use the statistical parameter kurtosis to double-check the QRS Complex to decrease errors in detection. Researchers in [15] looked for the QRS complex using a deep learning convolutional neural network (CNN) with raw ECG and differentiated ECG as input. Yuen et al. [16] proposed a hybrid Wavelet and CNN. The wavelet is used for noise cancellation and artifacts. The author claims that Wavelet CNN is suitable for detecting QRS complexes with much noise.

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Cardiologists need to classify arrhythmias for diagnosis and plan for the patient's treatment. Previous studies [17-20] have succeeded in classifying arrhythmias into several classes. The research [17] classifies arrhythmias using the sine–cosine algorithm (SCA) method. The SCA method is a classification based on a heuristic approach. The output of the method is normal and abnormal classes. Meanwhile, researchers in [18-20] used machine learning to classify arrhythmias. The author in [18] uses LSTM and SVM to classify arrhythmias into five classes with 1 QRS complex segment as input. Authors [19] use hybrid ensemble learning, deep learning and evolutionary computation. The method's input is a 10-second ECG with 10 to 20 QRS complexes. The author claims that the method has a fast classification since the input segments are more compared to other studies. The study in [20] used CNN as a classifier, and the author added the residual network to the convolution network to avoid saturation during the training process.

Several studies analyze data ECG on the Holter test [21, 22]. Authors at [21] proposed an algorithm to detect and classify arrhythmias from public ECG and their primary data. The method used is one inference step which detects and classifies arrhythmias. They classify each QRS complex sample into four classes: no-QRS, normal QRS, premature ventricular contractions, and premature atrial contractions. In [22], the author proposes using 1D Self Operational Neural Networks called SONN that detect R-Peak from Holter data. Holter data has the characteristic that ECG data has much noise due to the patient's movement. The author claims that using his proposed method can improve the quality of ECG holter detection, which has been used by previous researchers using CNN.

Communication data in IOT applications usually use hypertext transfer protocol (HTTP) or message queuing telemetry transport (MQTT) protocol. In health applications [23,24], doctors must monitor patient conditions in real-time using the MQTT protocol. The otherwise author [25, 26] proposed the application using the HTTP protocol. The large population causes difficulties in providing health services because the ratio of the number of doctors compared to the number of patients is much smaller. Alshammari solved it by proposing that the patient's vital signs be sent to the doctor's smartphone using the MQTT protocol [23]. Vital signs in his paper are blood pressure, heart rate, and body temperature. Doctors or families can view patient vital sign information in real-time by subscribing to a smartphone broker as a subscriber. The drawback is that congestion will occur when increasing the number of publishers. Author in [24] proposed transmission data based on a priority of patient conditions. The patient's heart rate is less than 60 or more than 100, and we call it arrhythmia has a high priority on delivery. The patient's heart rate is evaluated on the smartphone application before being sent to the broker. The author [25, 26] proposed a heart attack alarm system comprising wearable sensors, smartphones, and cloud computing. They use wearable sensors using ECG biosensors that send the ECG data to the smartphone using Bluetooth and then forward it to the server [25] . While the author in [26] uses a wearable device placed on a chair to be sent to the server. The server analyzes the ECG signal. If it finds abnormal conditions, the server sends a message via a smartphone application to the patient's family and doctor using the HTTP protocol.

Cardiologists use a computer or hospital server to detect and classify arrhythmias on long-term ECG. The previous research proposed automatic detection and classification using a computer or a cloud because the process needs a powerful processing unit for extensive data. ECG data storage of the Holter test is in the device's local memory or on the server. Cardiologists cannot access data directly in the data storage device. Meanwhile, accessing data on the centralized server is slow if the patient increases.

Thus, this study proposes an Arrhythmia analysis in the long-term ECG monitoring system. Arrhythmia analysis in this study consists of detection QRS complex and Arrhythmia classification, that is implemented on Edge devices using single-board computer (SBC) Raspberry Pi. The classification steps are: R-peak detection which implements the PTK algorithm, Gaussian filters to preprocess MLP for removing P and T waves, then proceed with classification using the deep learning multi-layer perceptron (MLP). MLP as a classifier has lower computational cost than other deep learning classifiers, for example, recurrent neural network (RNN) and convolutional neural network (CNN). The storage of holter is decentralized because centralized storage requires high-quality processing and storage units. This approach has the goal of an inexpensive arrhythmia analysis device for holter ECG monitoring.

The main contribution of the study can be summarized as follows:

1. Arrhythmia classification is based on the pattern of the QRS complex, which is preceded by R-peak detection using the PTK algorithm.
2. Implementing the Gaussian filter as pre-processing input of the MLP improves the classification quality.

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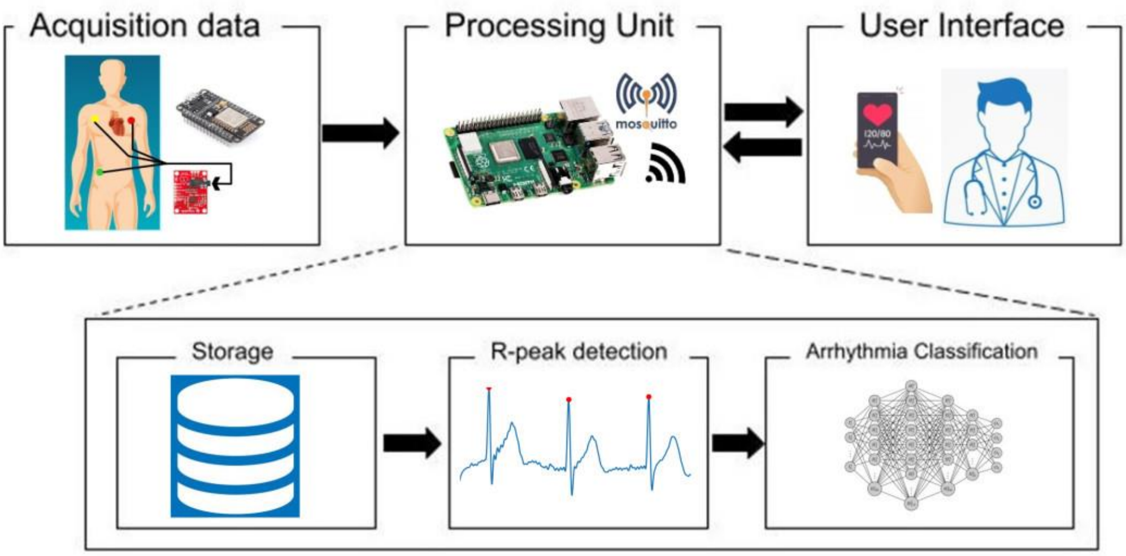

Figure. 2 System architecture of the proposed long-term ECG monitoring system

3. The proposed Holter device saves the data on local database edge devices however cardiologists can monitor in real or non-real-time using MQTT and HTTP protocol.

The paper is organized as follows: section 2 describes our proposed device and the methods used, and several experiments are shown to prove the device's reliability in section 3, and finally, we conclude our works in section 4.

2. Design and system architecture

Our proposed arrhythmia classification is deep learning multilayer perceptron (MLP), which classifies arrhythmias into four classes: normal (NOR), right bundle branch block (RBBB), left bundle branch block (LBBB), and premature ventricular contraction (PVC). We added a Gaussian filter as a classification preprocessing to remove P and T waves. This filter will increase accuracy, sensitivity, specificity, and positive predictive.

The architecture of the study consists of acquisition data, a processing unit, and a user interface shown in Fig. 2. The data acquisition is a holter device consisting of an ECG sensor, AD8232 signal amplifier, and a microcontroller. The processing unit is implemented using Raspberry Pi, and the user interface is a mobile application based on Android. All components communicate using MQTT with data acquisition as a publisher, processing unit as a broker, and mobile application as a subscriber. Other functions of the Raspberry Pi are storage data, QRS complex detection, and arrhythmia classification.

We test the proposed detection and classification algorithm using public data from the MIT-BIH arrhythmia [27] and some volunteer data. The duration is 30 minutes with 360 Hz sampling data. In the classification test, we divide the dataset into training, validation, and testing. The proportion of training, validation, and testing is 80%, 10%, and 10%, respectively.

2.1 Acquisition data

The acquisition data is a proposed portable Holter that is 1 ECG channel installed as lead I, which requires three electrodes: right-arm (RA), left-arm (LA), and right-left (RL). The ECG sensor signal is potential difference from the LA and RA, which are placed on the left and right chest, as well as the RA reference point, which is placed on the right of the stomach [3]. The microcontroller input is the ECG signal from the electrode, which is amplified using the AD8232 module. Another function of the AD8232 module is noise cancellation using a bandpass filter. We use NodeMCU 32 development board based on an ESP32 microcontroller. The microcontroller is a series of low-cost and low-power. The power supply of the proposed Holter is the battery LiFePO4 3.2V. The sensing results from the Holter device are sent to the broker, which is implemented using Raspberry Pi. Data transmission uses the MQTT protocol via Wi-Fi. MQTT is designed as a publish/subscribe messaging ideal for devices with a limited processing unit and minimal network bandwidth. Data sensing proposed holter ECG has a sampling frequency of 165 Hz.

2.2 Processing unit

We implemented a processing unit using Raspberry Pi. This device also works as a broker on the MQTT network. Mosquito is chosen as a software MQTT broker on this SBC. The proposed acquisition device sends ECG signals to the broker on the MQTT data topic. Raspberry Pi receives the message and saves it to the database. The database management system used in this study is SQLite which runs on the local Raspberry Pi. There is one database file for patient ECG record data and user data. Our proposed Holter user is a patient, doctor, and administrator. Users use a mobile application as a user interface using the HTTP and MQTT protocols. There are two processing for arrhythmia analysis: complex QRS detection using the PTK algorithm and Arrhythmia classification using MLP. MLP is a deep learning-based classifier with low computational cost compared to other deep learning.

2.3 Pan-Tompkins

The Pan-Tompkins (PTK) is an algorithm for finding the QRS complex in ECG signals which has the following steps: low pass filtering, high pass filtering, differentiation, signal squaring, moving window integration, and thresholding. The function of a low pass filter is to pass the signals below the cut-off frequency and block the signal above the cut-off frequency. Implementation on our system uses a cut-off frequency of 11 Hz. If y_0 is raw data ECG and y_1 is output filtered signal of Low Pass Filter, Eq. (1) shows the Low Pass Filter equation.

$$y_1(nT) = 2y_1(nT - T) - y_1(nT - 2T) + y_0(nT) - 2y_0(nT - 6T) + y_0(nT - 12T) \quad (1)$$

The high pass filter is a continuation of the Low Pass Filter. The signal above the cut-off frequency is passed, and below the cut-off frequency is blocked. The cut-off frequency on the high pass filter is 5 Hz. The high pass filter function is shown in Eq. (2).

$$y_2(nT) = 32y_1(nT - 16T) - [y_2(nT - T) + y_1(nT) - y_1(nT - 32T)] \quad (2)$$

Derivative operations are used to find slope information on the QRS complex. PTK divides the signal into 8 fractions to produce an amplitude response of 0 to 30 Hz. The goal is to attenuate the P and T waves while the signals associated with the peak-to-peak QRS complex are increasingly elevated. The derivative equation is shown in Eq. (3).

$$y_3(nT) = \left(\frac{1}{8}T\right)[-y_2(nT - 2T) - 2y_2(nT - T) + 2y_2(nT + T) + y_2(nT + 2T)] \quad (3)$$

Squaring is a function that makes all data positive. The procedure is to improve the signal derived from the derivative. The process is done by suppressing the high-frequency signal caused by the QRS complex. The equation used in the procedure is Eq. (4).

$$y_4(nT) = [y_3(nT)]^2 \quad (4)$$

The ECG recording shows many abnormal QRS complexes with large amplitudes and long durations but no steep slopes. Moving average is a process to help find the QRS complex because it has a non-steep slope. The moving average equation corresponds to Eq. (5). N is the number of samples in determining the moving average. The sample selection determines the same window width as the QRS complex because if the window size is too large, it can cause the QRS complex to merge with the T wave. It causes inaccuracy in the detection of the QRS complex.

$$y_5(nT) = \frac{1}{N}[y_4(nT - (N - 1)T) + y_4(nT - (N - 2)T) + \cdots + y_4(nT)] \quad (5)$$

Thresholding is a process to clarify the QRS complex and non-QRS complex. The Thresholding equation can be written Eq. (6). If the output signal from the moving average received is greater than $threshold$, the segment can be detected and is a candidate for the QRS complex. The R peak is located on the ECG with y_6 equal to 1.

$$y_6 = \begin{cases} 1, y_5[n] \geq \text{threshold} \\ 0, \quad y_5[n] < \text{threshold} \end{cases} \quad (6)$$

We use a local maxima algorithm to detect the peak of R from a QRS Complex. In the initial stage, we find the QRS Complex segmentation before running the local maxima. The segmentation is a location between the start and the end of the QRS Complex in ECG. We call it the QRS Complex segmentation Algorithm 1. The algorithm requires a time function input from the high pass filter y_2 and Thresholding y_6 . If x_2 and x_6 are number of samples of digitization ECG, the input algorithm is (x_2, y_2) and (x_6, y_6) . The QRS complex ROI algorithm generates n QRS complexes with coordinates $\left(x_{roi_{i,j}}\right)$, $i \in \{0,1,2 \ldots (n-1)\}$, $j \in \{0,1,2 \ldots (k-1)\}$, k is the number of samples with $y_6 = 1$ in each QRS complex segment. The algorithm's output becomes the local maxima's input, and the peak value of R is detected from the start and the end of the QRS Complex in each segment. The

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Algorithm 1: QRS Complex segmentation algorithm.

```
Data: (x2,y2),(x6,y6)
Result: (x_roi_i,j, y_roi_i,j)
i=0;
while x6 do
    if y6 == 0 then
        ramp = 0;
    end
    if y6 == 1 then
        if ramp == 0 then
            ramp = 1;
            i++ ;
            j=0;
        end
        if ramp == 1 then
            x_roi_i,j = x2 ;
            y_roi_i,j = y2 ;
            j++ ;
        end
    end
end
```

most significant value is the R-peak, the coordinate output from local maxima are

(x_{r_i}, y_{r_i}) with $i \in \{0,1,2 \dots (n-1)\}$

The RR interval is the distance between the R-peak in the current QRS complex and the R-peak in the next QRS complex. In [28], the value of heart rate (HR) in beats per minute is 60 divided by the interval RR as in Eq. (7). We use te equation as a reference for heart rate conditions in arrhythmic or normal, if the heart rate is between 60-100 bpm, then status is normal, and otherwise the heart rate is below 60 bpm or above 100 bpm, the status is Arrhythmia [29, 30].

$$HR\ (bpm) = \frac{60}{RR\ interval\ (sec)} \tag{7}$$

2.4 Multilayer perceptron

Multilayer perceptron (MLP) is a feedforward neural network model that predicts output sets based on corresponding input data sets. The MLP architecture consists of layers, and every layer is connected to the next layer. The layers are an input layer, one or more hidden layers, and an output layer. Each layer has one or more neurons. Each neuron, excluding the neuron in the input layer, is the sum of the multiplication of connected neurons from the previous layer with the weight of the network that connects them. Then the sum output is passed to an activation function. The activation function determines whether the neuron is used for the layer. Several activation functions include rectified linear unit (ReLU), sigmoid, tanh, and softmax. The activation function in the output layer uses the softmax because the softmax produces a probability distribution among possible classes, the largest result indicates the class predicted.

We classify arrhythmias based on QRS complex pattern into four classes: normal, ventricular, LBBB, and RBBB. We proposed deep learning MLP with an input layer, 4 hidden layers, and an output layer, as depicted in Fig. 3. The activation function used in the input and hidden layers is RELU, while the output layer uses softmax. The output layer consists of 4 neurons that classify 4 arrhythmia classes Normal, Ventricular, LBBB, and RBBB, with output targets of 0001, 0010, 0100, and 1000, respectively.

The input layer consists of 180 neurons, symmetrical segments of the QRS complex. If the input layer is I with neurons $I_1 \dots I_{180}$, then the median I (I_{90}) is the peak R_i. The lower limit of the segment is the R peak before R_i, namely R_{i-1}, while the end of the segment is the next R peak or R_{i+1}. Because the number of ECG segments is not equal to 180, it is necessary to convert the ECG signal to 180. We use the function according to Eq. (8) to convert the ECG signal with the number of n samples to 90 samples, with the median being R_i. X_i is the original signal, while K_i is the conversion signal.

Then proceed with eliminating waves other than complex QRS using a Gausian Filter with a multiplication operator, with the Gausian filter equation according to Eq. (9).

$$K_i = \begin{cases} X_{\left\lfloor \frac{n}{90} i \right\rfloor}, & n < 90 \\ X_i, & n = 90 \\ X_{\left\lfloor \frac{n(i-1)}{90} + 1 \right\rfloor}, & n > 90 \end{cases} \tag{8}$$

$$I_i = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x_i - \mu)^2/2\sigma^2}\ K_i \tag{9}$$

The first, second, third, and fourth hidden layer architectures are 256, 512, 256, and 32 neurons, respectively. The MLP hidden layer has a function as feature extraction. The neuron value of the hidden layer follows Eq. (10).

$$M_k^j = \emptyset\left(\sum_{i=1}^{n^{j-1}} W_{ik} \times M_i^{j-1} + b^{j-1}\right) \tag{10}$$

where M_i^j represents neurons in the j layer and i neurons, n^{j-1} corresponds to the number of neurons in the $(j-1)$ layer. W_{ik} denote the connection weights between the *i*th neuron in (*j-1*)th layer and *k*th neuron in jth. b^{j-1} is bias of (*j-1*)th , ϕ(.) is the activation function in a layer.

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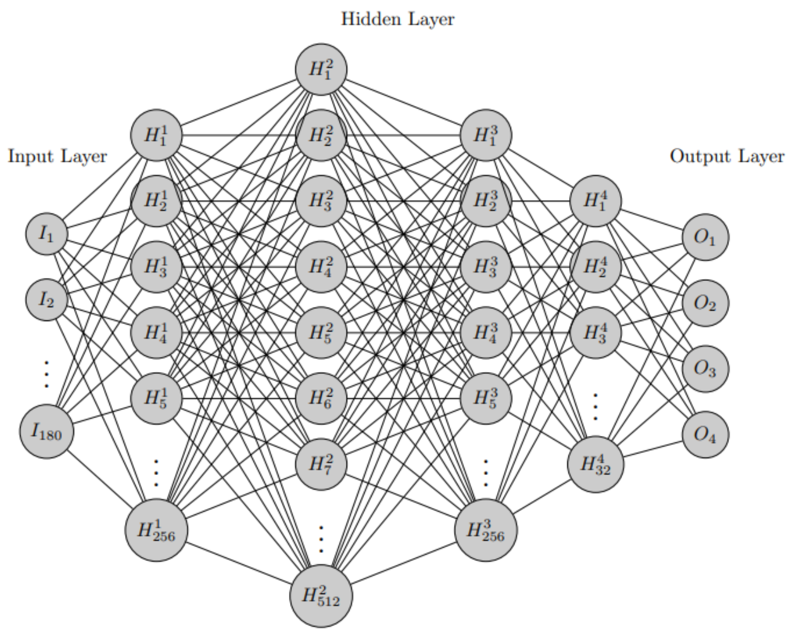

Figure. 3 Architecture of proposed multilayer perceptron (MLP)

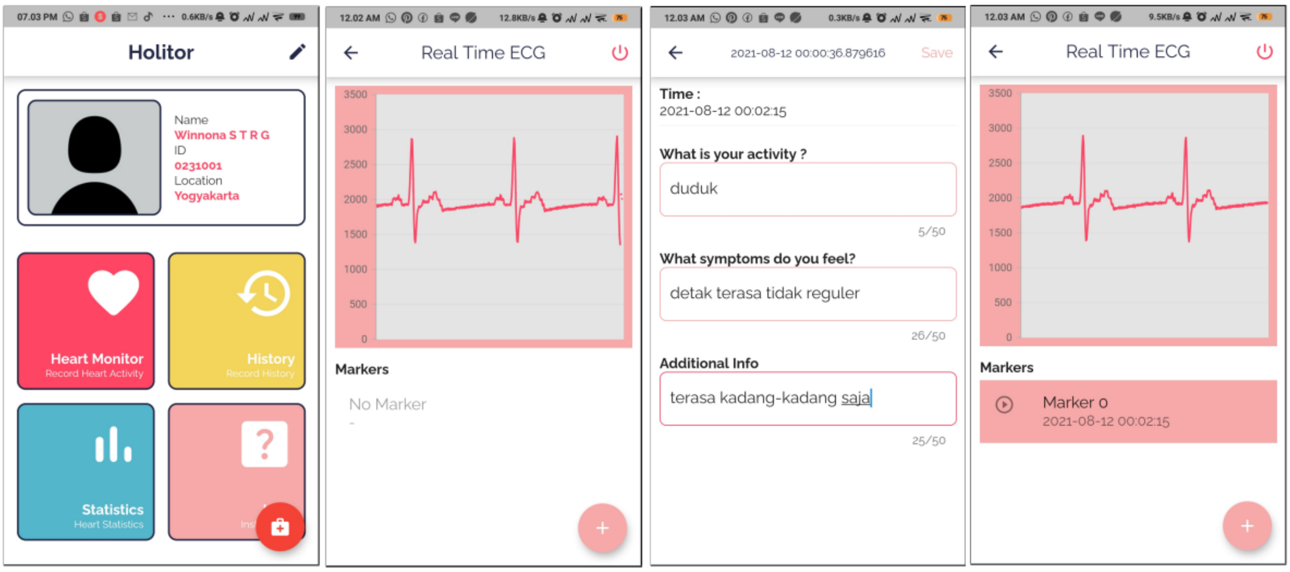

Figure. 4 The mobile application based on Android contains: (a) Patient data, (b) Real-Time ECG, (c) Recording an event, and (d) Displaying an event

2.5 Mobile application

The primary function of the mobile application in the proposed system is as a user interface for patients and cardiologists, as shown in Fig. 4. Smartphones as MQTT subscribers receive real-time ECG data from Holter through the broker. Users use the mobile application to view an ECG signal in graphical mode. The patient recorded when the arrhythmia occurred, the symptoms felt, and the activities using one of the mobile application menus. The cardiologist reads the ECG data and records information directly or when the recording is complete.

2.6 Performance metrics

We measure the robustness of the R-peak detection using metrics: sensitivity (*Se*) and positive predictive (*+P*) following Eqs. (11) and (12). TP stands for true positive, which is the number of detecting R-Peak. False positive (*FP*) is the number of artifacts, noise, P-Peak, or T-Peak identified as R-Peak. Meanwhile, false negative (*FN*) is the number of R-Peak predicted non-R-Peak.

$$Se = \frac{TP}{TP+FN} \times 100\ \% \tag{11}$$

$$+P = \frac{TP}{TP+FP} \times 100\ \% \quad (12)$$

At the same time, we are measuring the arrhythmia classification using the matrix: sensitivity (*Se*), predictive positive (*+P*), accuracy (*Acc*), specificity (*Spe*), and F1-score. Sensitivity is used to measure the classifier correctly classifying data in a class. Sensitivity is defined as the comparison of data that is correctly classified in a positive class with all data in that class, the value of Se corresponds to Eq. (11). Predictive positive is the reliability level of the classifier when providing the predicted value of a particular class. The *+P* percentage is calculated using Eq. (12), which is the ratio of classifying correctly to all the predictions given. Accuracy is a metric used to measure the success rate of classification in predicting the correctness of the classification. This metric is calculated by comparing the number of correct qualifying predictions against all predictions calculated using Eq. (13). *Spe* is the reliability to correctly predict data in the negative class, according to Eq. (14). While the F1-score is a metric used to measure the success of classification at the level of false positives and false negatives simultaneously, the F1-score value corresponds to Eq. (15). True positive (*TP*) is the total number of correctly classified arrhythmias. True negative (*TN*) is a negative class prediction, and the actual arrhythmia class is not that class. False positive (*FP*) is the number of errors that classify a particular class. False negative (*FN*) is a classifier error that does not classify a particular class.

$$Acc = \frac{TP+TN}{TP+FP+FN+TN} \quad (13)$$

$$Spe = \frac{TN}{TN+FP} \quad (14)$$

$$F1 - score = \frac{2\times(+P)\times Se}{(+P)+Se} \quad (15)$$

3. Experiment results

We proved the robustness of the proposed system using several experiments: QRS detection, Arrhythmia classification, data transmission, and data recording.

3.1 R-peak detection

The first experiment is the QRS complex detection test on ten volunteers, lasting 5 minutes with frequency samples 166 Hz. We detect QRS complexes on Raspberry Pi using the Pan-Tompkins algorithm [13] and the local maxima algorithm to find the R-peak on the QRS complex segment. The detected R-peaks are evaluated using manual observation of the ECG signal graph as ground truth. The results are presented in Table 1.

Table 1. QRS detection test using volunteers dataset

No.	**QRS**	***TP***	***FP***	***FN***
1	421	419	2	2
2	346	342	2	6
3	323	387	55	1
4	527	527	0	0
5	429	431	2	0
6	494	494	0	0
7	495	497	2	0
8	480	481	1	0
9	581	581	0	0
10	435	436	1	0
Total	4531	4595	65	9

Table 2. QRS detection test using MIT-BIH dataset

No	**Rec.**	***TP***	***FP***	***FN***
1	100	2264	0	1
2	101	1859	1	1
3	102	2118	45	62
4	103	2075	0	3
5	104	2180	41	43
6	105	2553	33	12
7	107	2122	1	8
8	111	2112	3	6
9	112	2531	0	0
10	113	1789	0	0
11	114	1841	2	31
12	115	1946	0	0
13	116	2380	2	24
14	117	1530	0	0
15	118	2271	0	0
16	119	1981	0	0
17	121	1855	0	1
18	122	2468	0	0
19	123	1509	0	4
20	124	1592	0	21
Total		40976	128	217

The experimental results show that the system detecting the QRS Complex has *+P* of 98.61% and *Se* of 99.8%.

PTK Algorithm implemented on Raspberry Pi was tested using the MIT-BIH Arrhythmia dataset in records 100, 101, 102, 103, 104, 105, 107, 111, 112, 113, 114, 115, 116, 117, 118, 119, 121, 122, 123, and 124. We chose this because all of them because it has

Table 3. The comparison of QRS detection in this study compares to the other methods

No	Author	Method	*Se* (%)	*+P* (%)
1.	This study using volunteer dataset	Heuristic (PTK[13])	99.80	98.61
	This study using MIT-BIH dataset	Heuristic (PTK[13])	99.47	99.69
2.	Rahul et al. [14]	Heuristic	99.90	99.94
3.	Habib et al. [15]	CNN	99.22	-
4.	Yuen et al. [16]	CNN, LSTM	97.07	95.43

the same channel, namely MLII. The QRS complex detection results can be seen in Table 2. For ECG data that is normal and has a little noise, PTK can detect it well. However, for certain records where the non-QRS signal has a magnitude almost the same as the QRS complex, the PTK algorithm detects many mistakes, for example, in records 102 and 104. Using Eqs. (11) and (12), the experimental results in Table 2 have Se and Pe 99.47% and 99.69%, respectively.

The performance of detecting the QRS complex between PTK in this study compared to the other methods that used MIT-BIH [27] as data testing is shown in Table 3. The selected methods have good quality in QRS complex detection since the sensitivity and positive predictive are relatively high, above 97.07% and 95.43%. The heuristic methods in this comparison are better than machine learning. The best value of Se in machine learning is represented CNN which was proposed by Habib et al.[15], still lower than PTK[13] in this study, namely 99.47%. Likewise, *+P* in this study has a better value than the CNN machine learning method proposed by Yuen et al[16]. The best detection result is the heuristic method proposed by Rahul et al. [14], *Se* and *+P* of 99.80% and 98.61%, relatively. This is because their method has a double-check process for QRS detection. They used the statistical parameter kurtosis coefficient to reduce the error as a double-check process. The drawback of the double-checking process is the computational cost, resulting in a longer time. It is not suitable for implementing on edge devices.

3.2 Arrhythmia classification

We classify arrhythmias using a deep learning multilayer perceptron (MLP). The classification dataset is the MIT-BIH arrhythmia database with an MLII data channel. The dataset was grouped into four classes: normal, ventricular, LBBB, and RBBB, having sample data of 3000, 740, 2111, and 3000, respectively. The datasets are divided into training, validation, and testing. The proportion of training and validation compared to test data is 90: 10 while the ratio of training and validation is 90:70. With this

Table 4. Arrhythmia classification test using MIT-BIH dataset

Class	N. Beat	*TP*	*FN*	*TN*	*FP*	*Acc* (%)	*Se* (%)	*Spe* (%)	*+P* (%)	F1-Score
Normal	300	300	0	585	0	100	100	100	100	100
Ventricular	74	72	2	811	0	97.77	97.30	100	100	98.63
LBBB	211	211	0	670	4	99.55	100	98.14	99.41	99.06
RBBB	300	298	2	585	0	99.77	99.33	100	100	99.67
Overall		881	4	2651	4	99.77	99.55	99.55	99.85	99.55

Table 5. The comparison of proposed arrhythmia classification compares to the other methods

No.	Author	Method	Input	Class	*Acc*	*Se*	*Spe*	*+P*
1	This Study	MLP	Filtered ECG using Gaussian	4	99.77	99.55	99.55	99.85
2	Sharma and Dinkar[17]	SVM+DNN with SCA	Filtered ECG using DWT	16	99.11	97.97	-	98.55
		SVM+DNN with LA-SCA	Filtered ECG using DWT	16	99.39	98.01	-	98.64
3	Hou et. al.[18]	LSTM	1D QRS Complex	5	99.74	99.35	99.84	-
4	Plawiak and Acharya [19]	DL + GA	10 s ECG	17	99.37	94.62	99.66	-
5	Li et. al. [20]	CNN	5s ECG	5	94.54	93.33	80.80	-

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scenario, the amount of training and validation data is normal (2700), ventricular (666), LBBB (1900), and RBBB (2700). We balance the data for prediction accuracy by simply augmentation the Ventricular and LBBB, which shifts the R-peak value. The total sample of all classes after augmentation becomes 2700. We use 100 epochs in the training process. The accuracy of training and validation at the end of the epoch is 100% and 99.58%, while the data loss is 4.835e-12 or close to 0% and 0.0482%.

Furthermore, the sample data used in the testing process are 300, 72, 211, and 300 for the normal, ventricular, LBBB, and RBBB classes. The results of the evaluation of the testing process are written in Table 4. Our MLP classifier has no classification errors in the Normal class. However, there is small misclassification in the ventricular (PVC), LBBB, and RBBB classes. Overall the percentage evaluation of *Acc*, *Se*, *Spe*, *+P*, and F1-Score is 99.77, 99.55, 99.55,99.85, and 99.55, respectively.

The robustness of our classification method compared to other arrhythmia classifiers [17-20] is shown in Table 5. All methods, including our proposed MLP, were tested using the MIT-BIH arrhythmia database with different input lengths and numbers of classes. Our proposed MLP that runs on the Raspberry Pi has a better classification than others. In an implementation, we use a symmetrical ECG input with a median R-peak that can increase the classifier. A Gaussian filter also enhances the classification quality as a preprocessing classifier that removes non-QRS complex, e.g. P and T waves.

3.3 Data transmission and recording

In this section, we conduct experiments including data transmission, transaction time (TT), and limited recording time. Using the Python mqtt-ping.py program, we are testing data transmission from publisher and subscriber to the broker. We send 1-byte data using the message queuing telemetry transport (MQTT) protocol. A host or node running the mqtt-ping.py program has publisher and subscriber functions.

The experiment was carried out ten times with 100% data acceptance. The experimental results of data transmission can be seen in Table 6. The average MQTT communication propagation is 0.023 seconds, and the standard deviation is 0.0025 seconds.

TT Database is used to determine the robustness of the database for recording ECG data to the database SQLite. The ECG data was received from the holter device on Raspberry Pi. Data is temporarily stored in a buffer memory. Each data in the buffer memory is equipped with a timestamp flag. Furthermore, the data in the buffer is saved to the database SQLite. The difference between the buffer time and the data successfully stored in the database is the transaction time. We conducted ten experiment tests, and the result is shown in Table 7. The average delay of recording storage was 15.164 seconds, and the standard deviation was 0.528.

Table 6. Propagation test from publisher to broker

No.	Packet (Byte)		Propagation (second)
	Tx	Rx	
1	1	1	0.026
2	1	1	0.019
3	1	1	0.022
4	1	1	0.025
5	1	1	0.018
6	1	1	0.024
7	1	1	0.025
8	1	1	0.024
9	1	1	0.024
10	1	1	0.023
Average			0.023
Standard Deviation			0.0025

Table 7. Transaction time 1 s. ECG in SQL lite

No.	Recording Time (s)
1	15.17
2	15.63
3	16.01
4	14.98
5	14.71
6	14.10
7	14.91
8	15.53
9	14.95
10	15.65
Average = 15.164	
Standard Deviation = 0.528	

In the limited recording time test, the recording has been carried out for as long as possible to determine the maximum usage time of our proposed long-term ECG test. The power supply is Lithium Battery which is 3,200 mAh, 3.2 Volt supply. In our experiment, the ECG device stopped after recording 12,876,046 digital ECG since the battery ran out after recording for 21 hours, 36 minutes, and 58 seconds. The data is successfully stored in the 463,537,481 bytes (442.1 MB) in the SQLite database.

4. Conclusion

In this study, we proposed Arrhythmia analysis in long-term electrocardiogram monitoring systems. Arrhythmia analysis is complex QRS detection and continuing arrhythmia classification. Data communication between all components use the

MQTT protocol with the acquisition device as a publisher, SBC as a broker, and the smartphone as a subscriber. Data transmission from an acquisition device transmits to SBC with a throughput of 166 samples per second. The propagation data of the subscriber to the broker is 0.023 seconds. Meanwhile, the transaction time from the SBC Raspberry Pi buffer to the SQLite database requires a delay of 15,164 seconds. The limited recording time of the proposed device is 21 hours and 36 minutes.

The detection of the QRS complex in this study using the Pan-Tompkins (PTK) algorithm has a predictive positive (*+P*) of 98.61% and sensitivity (*Se*) of 99.8%. The classification of arrhythmias uses a multi-layer perceptron (MLP) that MLP input is an ECG segment with an R-peak before the QRS complex to an R-peak afterwards and the median is R-peak. The proposed classification performs well with *Acc*, *Se*, *Spe*, *+P*, and F1-Score of 99.77, 99.55, 99.55,99.85, and 99.55, respectively. Our method is outperformed in comparison to the other arrthmia classifications, including Sharma et al. [17], Hou et al.[18], Plawiak et. al. and Li et al.[20].

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Arief Kurniawan: conceptualization, methodology, hardware, software, formal analysis, and writing—original draft preparation. Winnona S. T. R. Gultom: software programming. Dion Hayu Fandiantoro: hardware design and programming. Eko Mulyanto Yuniarno: validation and formal analysis. Eko Setijadi: supervision and writing—review. Mochamad Yusuf: medical conceptualization and medical supervision. I Ketut Eddy Purnama: supervision, conceptualization, formal analysis, and writing—review. All authors read and approved the final manuscript.

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