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Detection of multi-class arrhythmia using heuristic and deep neural network on edge device

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ABSTRACT

Heart disease is a heart condition that sometimes causes a person to die suddenly. One indication is a rhythm disorder known as arrhythmia. Multi-class Arrhythmia Detection has followed: QRS complex detection procedure and arrhythmia classification based on the QRS complex morphology. We proposed an edge device that detects QRS complexes based on variance analysis (QVAT) and the arrhythmia classification based on the QRS complex spectrogram. The classifier uses two-dimensional convolutional neural network (2D CNN) deep learning. We use a single board computer and neural network compute stick to implement the edge device. The outcomes are a prototype device cardiologists use as a supporting tool for analysing ECG signals, and patients can also use it for self-tests to figure out their heart health. To evaluate the performance of our edge device, we tested using the MIT-BIH database because other methods also use the data. The QVAT sensitivity and predictive positive are 99.81% and 99.90%, respectively. Our classifier's accuracy, sensitivity, predictive positive, specificity, and F1-score are 99.82%, 99.55%, 99.55%, 99.89%, and 99.55%, respectively. The experiment result of arrhythmia classification shows that our method outperforms the others. Still, for r-peak detection, the QVAT implemented in an edge device is comparable to the other methods. In future work, we can improve the performance of r-peak detection using the double-check algorithm in QVAT and cross-check the QRS complex detection by adding 1 class to the classifier, namely the non-QRS class.

1. Introduction

The heart is one of the organs of the circulatory system that carries essential elements to the body, such as oxygen and nutrients. Seniors people and people have the potential to have heart disease, and regular heart health monitoring is needed. One of the methods to analyze the condition of the heart is to analyze the electrocardiogram (ECG) signal, where the ECG signal is a biopotential electrical signal caused by the electrical activity of the heart. Pomprapa [1] explains that the impulse for cardiac contraction comes from the atrial sinus node (SA) as the pacemaker in normal conditions. The impulse spreads through the two atria causing the pressure in the atrial chambers to increase and forcing more blood to flow across the open atrioventricular (AV) valves into the ventricles. This depolarization causes the P wave. Meanwhile, ventricle depolarization causes a complex QRS that consists of Q, R and S waves.

Repolarization of the ventricle causes a T wave. This event repeats itself continuously. One ECG period consists of a P wave, QRS complex wave, and T wave, as shown in Fig. 1. In normal heart conditions, the formation of P, QRS, and T waves reach 60 to 100 times in 1 minute, PR interval 120 to 200 ms, QRS interval 40 to 100 ms, and ST 80 ms [2].

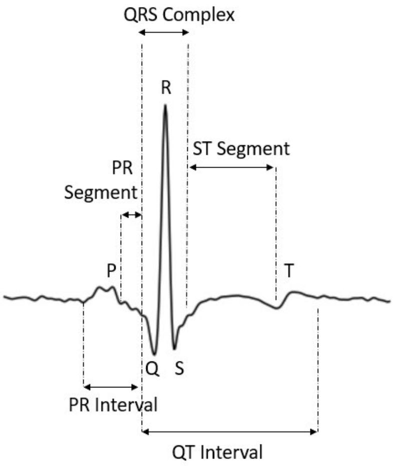


Fig. 1. A typical normal ECG signal

Arrhythmia is a condition in which the heartbeat is irregular, intermittent, fast, and sometimes slow. People with heart disease who have arrhythmias cause their heart cannot pump enough blood through the body. A heart rate of fewer than 60 beats per minute is an indication that a person is suffering from bradycardia arrhythmia. Meanwhile, a heart rate that exceeds 100 beats per minute is a tachycardia arrhythmia. Cardiologists analyze ECG signals to detect and classify arrhythmia. Usually, they detect arrhythmia by observing the distance between R-peak to the next R-peak of the QRS complex and classify the arrhythmias by observing the morphology of the QRS complex. The accuracy of the ECG signal analysis depends on the cardiologist's expertise.

Automatic arrhythmia detection has been studied by several researchers [3]–[12]. They used a heuristic [3]–[9] and machine learning [10]–[12] method to search for QRS waves. The algorithm proposed by Pan and Tompkins [3] is studied QRS complex detection based on a microprocessor with detection steps: noise removal using a bandpass filter, Derivative signal ECG, squaring signal, moving window integration, thresholding to find the region of interest (ROI) of QRS Complex. The authors [4] implement an adaptive threshold and step back to double-check the QRS complex using kurtosis coefficient. Kurtosis is a statistical parameter used to check the shape of the QRS complex. The use of kurtosis can reduce errors in detecting the QRS complex. They proved the superiority of their method compared to some previous research, such as Pan and Tompkins's method, by conducting experimental tests on the massachusetts institute of technology-beth israel hospital (MIT-BIH) Arrhythmia Database. Our previous research used a heuristic algorithm running on a computer [6], the algorithm is QRS complex detection based on variance analysis and adaptive threshold (QVAT). The QVAT has several steps in detecting QRS complexes and R-peaks, including noise removal using a bandpass filter, variance analysis, adaptive threshold, and R-peak detection. We used analysis of variance to find features of the QRS complex in the ECG range. We use an adaptive threshold to obtain the R wave slope, which varies due to the artifacts, noise and differences in the varying ECG signals.

Habib et. al. [10] used the convolutional neural network (CNN) deep learning method to detect the QRS complex. CNN Deep Learning has two input types, raw ECG and differentiated ECG. The CNN output proposed by Habib is classified into non-complex QRS signals and complex QRS signals. The use of hybrid machine learning for complex QRS detection was introduced by Yuen et al. [11]. The authors used WavletCNN to remove noise and artifacts and contrast the QRS complex features from other waves. Then the signal generated by WaveletCNN is input by ConvLSTM to get a QRS complex wave. The author claims that the proposed machine learning architecture is very suitable for ECG wearables that have ECG signal data acquisition with lots of noise.

Some research on arrhythmia classification classified it based on the morphology of the QRS complex waves [13]–[24]. Sharma and Dinkar [13] proposed a classification method based on the sine–cosine algorithm (SCA), a metaheuristic method to find optimal solutions. The authors start by reducing ECG noise using discrete wavelet transformation (DWT), which continued to find QRS complex features using the Linear Adaptive SCA (LA-SCA). Support vector machines (SVM) and deep neural network (DNN) use ECG data of complex QRS and RR intervals, to classify into 16 Arrhythmia classes. Hou et. al. [20] proposed long short-term memory (LSTM) and SVM to classify Arrhythmias. Input is QRS Complex which is processed by Auto Encoder (AE-LSTM). The AE-LSTM consists of an LSTM Encorder and Decorder that generate Complex QRS features. The features obtained by the autoencoder are used as SVM input to determine the arrhythmia class.

A machine learning input that uses 1 ECG segment consisting of several QRS complexes was proposed [17]–[19] Plawiak and Acharya [17] used a 10-second ECG as segment input to determine the class of Arrhythmia. This method has the advantage of detection speed because each segment consisting of about 10 or 20 QRS complexes is processed directly. ECG segment input is processed by the deep genetic ensemble of classifiers (DGEC). The methods are hybrid machine learning, which consists of ensemble learning, deep learning and evolutionary computation. Li et. al. [19] classified arrhythmia from overlapping ECG segments that segment is 5 s ECG. The author uses overlapping input to overcome the problem of class imbalances. The authors use CNN as a classifier and add the residual network structure to the convolution layer. They use the residual network to avoid saturation during training. The author claims his method is suitable for classifying arrhythmias for different patients.

Usually, health applications that use deep learning methods run on servers or cloud computing because deep learning processing requires a powerful processing unit. The input of the applications is from the sensor that collects patient data and then forwards it to the server. However, this technology has drawbacks, including a long delay in sending data and requires large bandwidth consumption.

Edge technology enables distributed computing across small devices. In addition, edge computing has low latency and bandwidth usage compared to computing on a server. Some research on telehealth technology for cardiology system analysis also uses edge computing technology [25]–[30]. Lu et al. [25] propose an ECG device consisting of a mobile phone, an ECG sensor, the AD8232 model, and a microcontroller. Cardiology patients check independently through the ECG sensor, and then the microcontroller processes the data to be sent to the mobile phone via Bluetooth. The patient's phone forwards ECG data to the server. Then, the cardiologist analyzes the ECG using his mobile phone. Devi et. al. [26] used Arduino to implement the PTK algorithm to find the peak value of R, RR interval, and heart rate variability (HRV). These results are used as input to classifier arrhythmias machines running on cloud computing or server computers. Scrugli [27] implements edge computing on internet of medical things (IoMT) to classify arrhythmias using the ARM processor on the raspberry pi. The author classifies five types of arrhythmias using 1D CNN.

Multi-class Arrhythmia detection is preceded by detection of QRS Complex waves followed by Arrhythmia classification based on QRS complex morphology. Previous research separated the detection of QRS complex waves and the classification of arrhythmias. In the implementation of cardiac test, it is important to know the arrhythmia class after it has been successfully detected. Arrhythmia classification based on the morphology of the QRS complex wave is generally processed using a powerful processing unit found in the hospital or the cloud. The powerful processing unit results in more costs or the detection of multi-class arrhythmias cannot be done by the patient independently.

The proposed system consists of 1 Lead ECG signal acquisition and intel neural compute stick (INCS) running on a single board computer (SBC) as an edge processing unit. QRS complex detection and arrhythmia classification are processed using edge device. Using computing on edge devices can overcome delay, bandwidth and cost problems compared to cloud computing. The proposed study uses an algorithm based on variance analysis of the ECG sample data to detect the QRS complex and R-peak called QVAT. The algorithm runs on an edge device which has the following steps: ECG filtering, variance analysis, adaptive threshold, QRS complex segmentation and the last step is the search for R-peak using local maxima. Furthermore, the QRS complex wave as a 1-dimensional matrix is converted into a spectrogram in the form of a 2-dimensional matrix. The spectrogram is input for CNN 2D deep learning to classify arrhythmias.

The main contributions of the study can be summarized as follows. A proposed heuristic-based QRS complex detection called QVAT is implemented on edge devices. Classifying arrhythmias based on the morphology of the QRS complex in the form of a 2D spectrogram matrix processed using an intel computing stick running on SBC as an edge device. The remainder of this paper is organized as follows. Section 2 of this paper is material and methods, covering the research description and methods used. Section 3 is the result and discussion. Section 4 is conclusions of the paper.

2. Method

The proposed system has several stages of procedures to get the results of detection and prediction of arrhythmia classification. Fig. 2 shows a block diagram of our proposed method. At the data acquisition stage, filtering of ECG values is needed before detecting the QRS complex using the QVAT method. The QVAT obtained the R-peak on the ECG signal that used the anchor point as input of deep learning CNN. R-peak is the median of the sample ECG data used as CNN input in the training process. We used the MIT-BIH arrhythmia database [31] and data acquisition from the volunteers for the CNN dataset. ECG data from the MIT-BIH arrhythmia database has been sampled at 360 Hz with an average recording duration of 30 minutes resulting in 648000 datas. The dataset of the proposed CNN model is divided into three parts in the training process, namely 80% data for training, 10% data for validation, and 10% data for testing. The data is carried out by a training process using CNN, which will produce a classification model of arrhythmias.

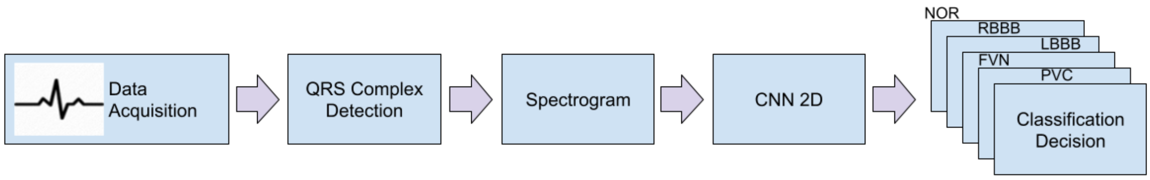
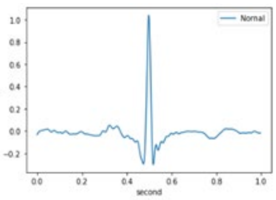
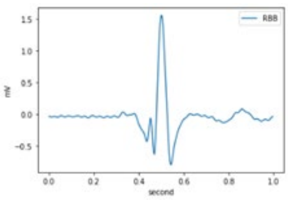


Fig. 2. Proposed methodology

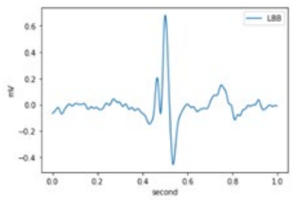
The result of deep learning CNN is classifying 5 classes of arrhythmias see Fig. 3, including: normal (NOR), right bundle branch block (RBBB), left bundle branch block (LBBB), premature ventricular contraction (PVC) and fusion of ventricular and normal (FVN).



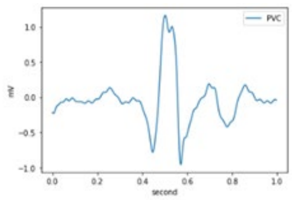
(a)Normal



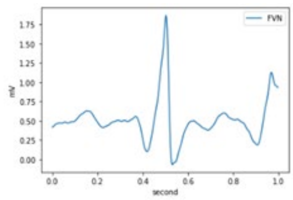
(b) RBBB



(c) LBBB



(d) PVC

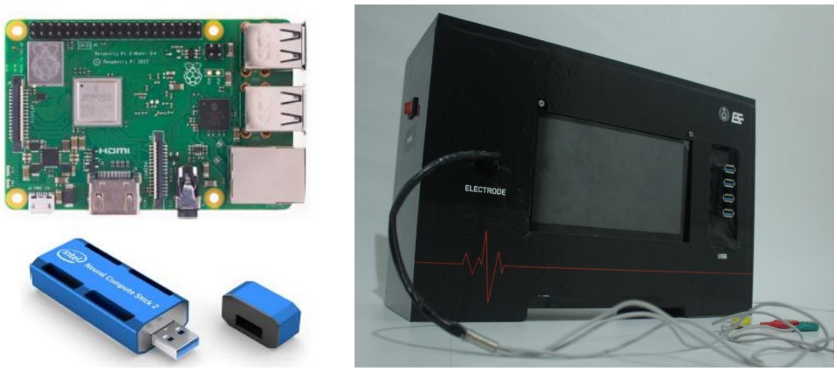


(e) FVN

Fig. 3. Class of arrhythmias

2.1. ECG Device

The ECG device consists of sensors, AD8232, ADC ADS1115, Raspberry Pi 3 Model B+ and intel compute stick as shown in Fig. 4. The ADS1115 converts the analogue value obtained by the AD8232 module into a digital value. This digital value has used an input of the Raspberry Pi 3 since it does not have analogue input pins. Intel neural compute stick speeds up the computational stage at the time of testing due to the limited ability of raspberries in computing. The power supply used in the device uses a 2S lithium-polymer battery using a regulator to lower the voltage to 5V with a maximum current of 5A. The output of the device is a visualization of the predictive results of arrhythmia disease classification as shown in Fig. 5. There is a record button for acquiring ECG data and an analysis button for analyzing data acquisition results.



(a) Main components (b) Device prototype

Fig. 4. Proposed ECG device

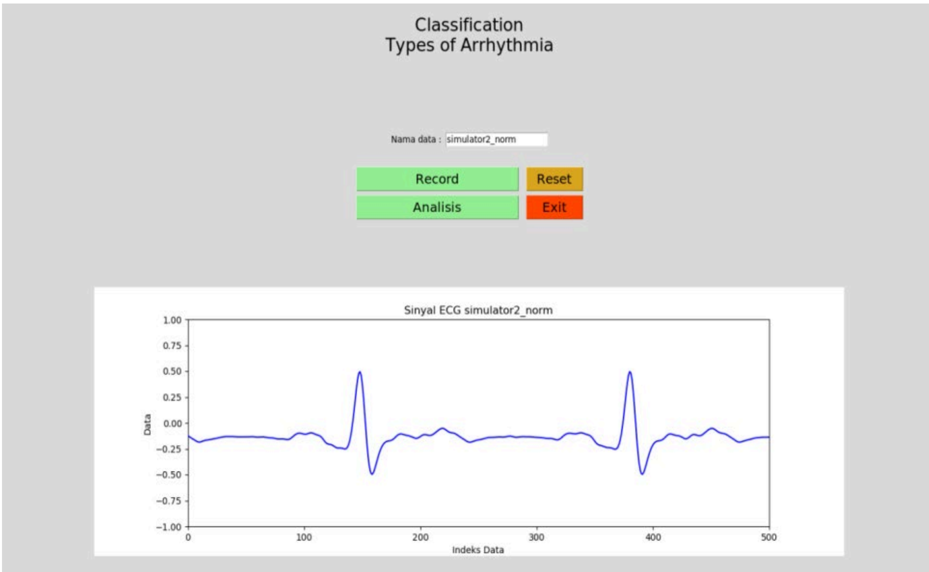


Fig. 5. User interface and ECG vizualization on edge device

2.2. DataSet

The data used in this study was taken from the MIT-BIH Arrhythmia Database, and primary data was taken from the proposed ECG data. The MIT-BIH Arrhythmia Database contains 48 recorded ECG signals taken from 47 patients. Each recording has a frequency of 360 Hz with an average recording duration of 30 minutes or 648000 data. Table 1 shows the dataset's samples of each type of arrhythmia. We balance the number of datasets of each class to have the same number by reducing the amount of data in the class that is too much, while the amount of class data is slightly augmented by using shifts from the existing data. So the total number of datasets in each class is 7129. The training, validation, and test datasets are 5703, 713, and 713.

Table 1. Arrhythmia Class of MIT-BIH

No.	Arrhythmia Class	Number of Samples
1	Normal	75011
2	RBBB	7211
3	LBBB	8071
4	FVN	802
5	PVC	7129

2.3. QVAT

The initial procedure for classifying arrhythmias is the output of QRS complex detection. Some of the difficulties and challenges of the QRS complex detection are: the number of QRS complexes on the ECG recorded is huge, has a small magnitude, short duration, T waves as large as QRS complex waves, noise due to power supply, and muscle movement noise. To solve it, we use QVAT, which has several steps in detecting QRS complexes: filtering ECG signal, variance analysis, the adaptive threshold to find the ROI of QRS complex and then local maxima to predict R-peak.

We use the bandpass filter to reduce noise that causes errors in detection. Noise that may occur includes interference of electromagnetic waves due to using an alternating current (AC) power supply and noise due to body muscles activity. The variance amplifies the QRS at positive coordinates, while the adaptive threshold used localizes the QRS complex. The interval of the QRS complex on a normal ECG is 0.12 seconds. In other words, the length of the QRS complex is 40 samples with a frequency of 360 Hz. Equation (1) represents the variance equation of the filtered ECG signal. Variance i is represented by var_i, y_(f_i) is the filtered ECG signal i and (y_f)̅ is the average from i-20 to i+19.

$$var_i = \sum_{i-20}^{i+19} \frac{\left(y_{f_i} - \overline{y_f}\right)^2}{40} \tag{1}$$

Localization of the QRS complex is used to find the position of the R-peak. We use the adaptive threshold because the ECG signal captured by the sensor has different characteristics. The result of this step is the ROI of the QRS Complex. Then, we continued to find R-peak in the ROI using the local maxima technique.

2.4. Spectogram

ECG is a time-domain-based signal, or ECG in discrete is a one-dimensional matrix function. We propose the classification of arrhythmias using a 2-dimensional (2D) CNN. Then, the 1-dimensional matrix of ECG is converted into using 2D matrix using short time fourier transform (STFT). The output of this method is the 2D matrix with time as the x-axis and frequency as the y-axis. This conversion is spectrogram. An ECG signal in continuous time with the window shifted all the time has an STFT according to (2).

$$X(\tau, \omega) = \int_{-\infty}^{\infty} x(t) w(t-\tau) e^{-jwt} dt \tag{2}$$

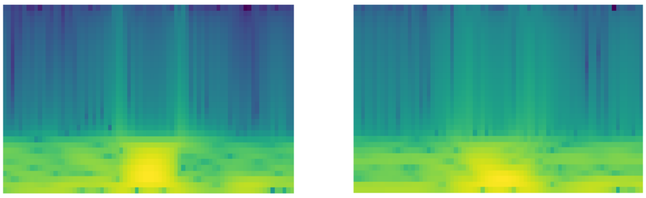
Where w(t) is a Hann or Gaussian window function based on a time function centered in zero, and x(t) is an ECG signal with a continuous function. ECG signals with discrete-time, the STFT equation according to (3).

$$\mathrm{X}(\mathrm{m}, \omega) = \int_{\mathrm{n}=-\infty}^{\infty} \mathrm{x}[\mathrm{n}] \mathrm{w}[\mathrm{n}-\mathrm{m}] \mathrm{e}^{-\mathrm{jwt}} \tag{3}$$

w(n) is the Hann window function based on a sample of ECG, and x(n) is the discrete ECG signal. Let x(n) be the ECG sample signal of length N. The hanning window w(n) has length m where $m \ll n$. In other words, the first, second, and third windows are x[0],x[1],x[2],...,x[m-1], x[1],x[2],x[3],...,x[m] and x[2],x[3],x[3],...,x[m+1], respectively. In our study, the windows size m is 64, and the overlap is 32.

We use the input matrix 2D spectrogram as the input to the proposed CNN. The spectrogram is converted from the sample ECG with a duration of 0.5 seconds before and 0.5 seconds after the R-peak.

The dataset of CNN deep learning is 360 samples with an R-peak located in the middle because the dataset is the MIT-BIH arrhythmia database, which has a frequency of 360 samples per second. In other words, our proposed place of the R-peak is the 180th from 360 sample data. Fig. 6 is an example of the result of converting an ECG signal as a function of time into a spectrogram. More specifically, the Normal beat, and Right Bundle Branch Block Beat shown respectively: Fig. 6a, and Fig. 6b. The spectrogram is ECG spectrums 258 ×347 red, green and blue (RGB) pixel image.



(a) (b)

Fig. 6. Spectrogram of arrhythmias: (a) Normal, (b) Right Bundle Branch Block Beat

2.5. CNN Architecture

Convolution neural network (CNN) is a type of deep learning generally used to classify two-dimensional data objects. The CNN architecture divides into input, feature learning, and classification. In the feature learning, CNN reduces the dimensions of the feature map using a pooling process whose output layer is called the pooling layer. The layer consists of filters of a specific size and stride. Stride determines the pooling shift has been done to the entire feature map area. Reducing the feature map size or downsampling to speed up computing and avoid overfitting. The pooling operation used in this research is max pooling. The output of the feature extraction process is converted into a 1-dimensional matrix known as flattening. The flattening matrix is used for the hidden layer, and the classification results are issued.

The parameter of the training process is the batch size, and epoch. Batch size defines the number of samples distributed to the neural network in one iteration. Epoch is when the entire dataset has gone through the training process on the neural network until it is returned to the beginning for one round. Several epochs are needed to get the error (loss) as small as possible in the training process. In this study, a batch size of 80, the epoch is 100 times. After the validation process is carried out, the next step is testing. The testing process is a process to predict the classification results through a weight model that has been built using the CNN architecture. We classify arrhythmias using a deep learning 2-dimensional convolutional network (2D CNN) with 23 layers. Table 2 is the proposed CNN architecture plus the input layer to become 24 layers. Input functions consists of an Input layer and two dimensions Zero Padding (ZeroPadding2D). The layer's input is an ECG spectrogram, an RGB image (3-dimensional array) with 258×347 pixels. Zero Padding adds a value of 0 to the input matrix so that it does not lose features when performing convolution with the kernel filter.

The feature learning function that we propose consists of 5 learning features. Each learning feature has 1 to 2 convolution layers and 1 pooling layer. We use 5 feature learning to get many features from complex QRS, which uses input for the fully-connected layer as classifier. The process for extracting learning features is as follows. Feature Learning #1 consists of a 2-dimensional convolution layer with 16 kernels, each with a size of 5×5 (Conv2D 16×5×5). The feature learning layer use Rectified Linear Unit (RELU) as an activation function. Therefore, we use 2 dimensions max pooling with size 2×2 as a pooling layer (MaxPooling2D 2×2). The result of Feature Learning #1 is a matrix measuring 129×173×16. Feature Learning #2 consists of 2 layers: Conv2D 32×3×3 and MaxPooling2D 2×2. The result of Feature Learning #2 is a matrix measuring 63×85×32. Feature Learning #3 consists of 3 layers: Conv2D 32×3×3, Conv2D 32×3×3, and MaxPooling2D 2×2. The result of Feature Learning #3 is a matrix measuring 29×40×32. Feature Learning #4 consists of 3 layers: Conv2D 32×3×3, Conv2D 32×3×3, and MaxPooling2D 2×2. The result of Feature Learning #4 is a 12×18×32 matrix. Feature learning #5 consists of 3 layers: Conv2D 64×3×3, Conv2D 64×3×3, and MaxPooling2D 2×2. The result of Feature Learning #5 is a 4×7×64 matrix.

The classification function of the architecture is fully-connected layer (FC Layer) or multi-layer perceptron (MLP) networks. The classification consists of 1 flaten layer, 7 dense Layer, 1 output layer. The layer that functions as a classification starts from the flatten layer, which converts the feature learning output from a 4×7×64 matrix to a 1-dimensional matrix of 1792 or 1792 nodes. The dense #1 layer to the dense #7 layer makes it a hidden layer on the FC layer with the relu activation function. The dense #1 layer uses the flatten layer's output as input and has an output of 512, repeating until the dense #7 layer has 8 output nodes. The output layer has 5 output nodes with the softmax activation function, which classify 5 arrhythmias.

Table 2. CNN 2D Model

No	Function	Layer	Filter/ Padding	Shape
1	Input	InputLayer		(258, 347, 3)
2		ZeroPadding2D	(2,2)	(262, 351, 3)
3	Feature Learning #1	Conv2D	(16,5,5)	(258, 347, 16)
4		MaxPooling2D	(2,2)	(129, 173, 16)
5	Feature Learning #2	Conv2D	(32,3,3)	(127, 171, 32)
6		MaxPooling2D	(2,2)	(63, 85, 32)
7	Feature Learning #3	Conv2D	(32,3,3)	(61, 83, 32)
8		Conv2D	(32,3,3)	(59, 81, 32)
9		MaxPooling2D	(2,2)	(29, 40, 32)
10	Feature Learning #4	Conv2D	(32,3,3)	(27, 38, 32)
11		Conv2D	(32,3,3)	(25, 36, 32)
12		MaxPooling2D	(2,2)	(12, 18, 32)
13	Feature Learning #5	Conv2D	(64,3,3)	(10, 16, 64)
14		Conv2D	(64,3,3)	(8, 14, 64)
15		MaxPooling2D	(2,2)	(4, 7, 64)
16	Classification	Flatten		1792
17		Dense		512
18		Dense		256
19		Dense		128
20		Dense		64
21		Dense		32
22		Dense		16
23		Dense		8
24		Output		5

2.6. Performance metrics

We measure the success of the proposed ambulatory ECG using metrics: accuracy (Acc), positive predictive (+P), sensitivity (Se), specificity (Spe), and F1-score. Our proposed device uses accuracy to measure the classification success rate in predicting the positive class. The calculation of accuracy according to (4). True Positive (TP) is the total number of class positives detected or classified correctly. True Negative (TN) is the number of negative classes correctly detected or classified by the algorithm. False Positive (FP) is the number of errors detecting the actual positive class. False Negative (FN) is the number of errors an algorithm detects the negative class, but the object is actually a positive class. Positive Predictive is the degree of reliability of the model or algorithm when providing a predictive value of the positive class. Percentage of +P is calculated using (5) which is the ratio of correct predictions in the positive class to all classification positive predictions. The +P metric is used if we measure the success of the classification in minimizing the false positive rate. The sensitivity is used to measure reliability or classification algorithm to correctly predict the data in the positive class. Sensitivity is defined as a comparison of the amount of data that is correctly classified in the positive class from all data in the positive class. Percentage of Se uses (6). The sensitivity is suitable if we measure the success of the classification in minimizing the false-negative rate. Specificity is reliability to predict data in the negative class correctly. In other words, Spe is the sensitivity in the negative class. This metric is appropriate when we want to maximize the true negative rate. The Spe calculate uses (7). We use the F1-score to measure the success of the classification at the false positive and false negative rates simultaneously according to (8).

$$Acc = \frac{TP+TN}{TP+FP+FN+TN} \tag{4}$$

$$Se = \frac{TP}{TP+FN} \tag{5}$$

$$+P = \frac{TP}{TP+FP} \tag{6}$$

$$Spe = \frac{TN}{TN+FP} \tag{7}$$

$$F1 - score = \frac{2\times(+P)\times Se}{(+P)+Se} \tag{8}$$

3. Results and Discussion

3.1. R-peak Detection

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

3.1.1. R-peak Detection using MIT-BIH Database

The QVAT algorithm detects R-peak after it finds the QRS complex. We classified arrhythmias using CNN with R-peak as the input reference. Our algorithm detects R-peak in the MIT-BIH Arrhythmia dataset in records 100, 101, 103, 105, 106, 107, 108, 109, 111, 112, 114, 115, 116, 117, 118, 119, 121, 122, 123, and 124 as a detection measure. The length of the ECG signal is 5 minutes (108,000 samples) on each record. The results of r-peak detection from QVAT can be seen in Table 3.

Table 3. Comparison result of QRS detection methods

No	Rec	TP	FN	FP	Se(%)	+P(%)
1	100	370	0	0	100	100
2	101	340	0	1	100	99.71
3	103	354	0	0	100	100
4	105	416	0	1	100	99.76
5	106	331	0	0	100	100
6	107	352	0	0	100	100
7	108	277	6	0	97.88	100
8	109	431	0	0	100	100
9	111	348	0	2	100	99.43
10	112	426	0	0	100	100
11	114	275	0	0	100	100
12	115	314	0	0	100	100
13	116	388	6	0	98.48	100
14	117	250	0	2	100	99.21
15	118	363	0	1	100	99.73
16	119	325	1	0	99.69	100
17	121	302	0	0	100	100
18	122	420	0	0	100	100
19	123	247	0	0	100	100
20	124	251	0	0	100	100
Total		6780	13	7	99.81	99.90

Under normal conditions, our proposed detection algorithm can detect various QRS complexes. However, there are several errors. It cannot detect the QRS signal because it has almost the same magnitude and shape as non-QRS signals. One of them is records 108 and 116. We have a significant error, namely six errors each. But the error in predicting complex QRS against non-QRS signals in this algorithm is quite good. There is a maximum of 2 errors in records 111 and 117. The sensitivity, and positive predictive are 99.81% and 99.90%, respectively. The performance of the methods for detecting the QRS complex and the R-peak compared to the other methods is shown in Table 4. All selected methods have good detection, sensitivity Se and positive predictive +P is relatively high, above 97.07% and 95.43%. The table shows that the complex QRS detection heuristic method has good Se and +P results when compared to the method using machine learning. The QVAT method implemented on the ECG device has a higher sensitivity Se and predictive positive +P than Pantomkins, Habib, and Yuen methods. However, the Rahul method has slightly better Se and +P than QVAT. Since Rahul method has a double-check process for the QRS complex using the kurtosis coefficient to reduce the error in detecting the complex QRS. This process is suitable for minimizing complex QRS errors but has an additional computational cost, increasing processing time. Double-check process for the verify QRS complex challenging to implement for real-time computations such as our algorithm running on an edge device.

Table 4. Comparison result of QRS detection methods

No	Method	Author	Method	***Se*** (%)	+***P*** (%)
1.	QVAT	This Study	Heuristic	99.81	99.90
2.	PTK [3]	Pan and Tompkins	Heuristic	99.54	99.74
3.	Rahul [4]	Rahul et.al.	Heuristic	99.90	99.94
4.	Habib [10]	Habib et.al.	CNN	99.22	-
5.	Yuen [11]	Yuen et. al.	CNN, LSTM	97.07	95.43

3.1.2. R-peak Detection using Volunteer Data

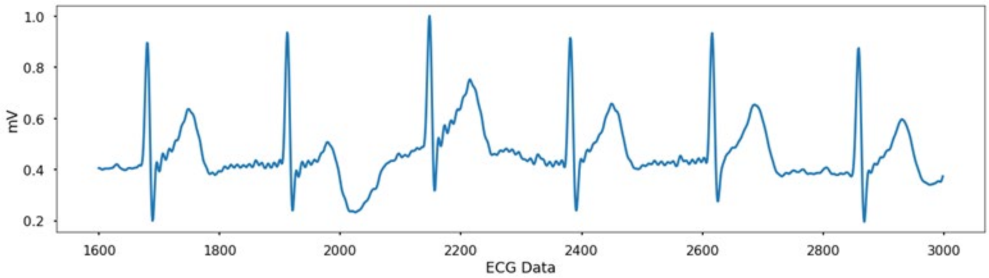
We used our device to analyze the ECG of volunteers for 10 seconds. Our device uses a sample rate of 100 Hz, so the amount of data generated is 3000 ECG data. The acquisition data value range is positive from 0 to 1 mV. The result of the volunteer test is shown in Fig. 7, and the R-peak is detected to determine the annotation point. Fig. 7a is voluntary ECG raw data recorded on the proposed device. The signal of which the noise is reduced using a bandpass filter. The cut-off frequency of the high pass filter is 3 Hz, and the cut-off frequency of the low pass filter is 45 Hz. The result of this process is shown in Fig. 7b. The following process is variance analysis. The process uses input from the filtered ECG according to (1). The output of this step is depicted in Fig. 7c. The local adaptive threshold is used to find the ROI of the QRS complex. The threshold selects a different threshold value for each sample of ECG based on the analysis of 1-second ecg data before the data. The output of the adaptive threshold is shown in Fig. 7d. The R-peak is searched based on the most significant value of the ECG signal with the limits according to the results of the adaptive threshold. We call this the ROI of the R-peak. The ECG signal, equipped with the peak notation of the R in each wave of the QRS complex, is shown in Fig. 7e.

3.2. Arrhytmias Classification

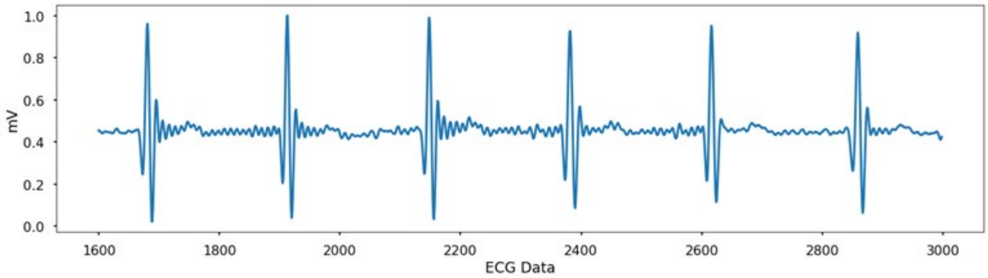
We classify arrhythmias using a deep learning 2-dimensional convolutional network (2D CNN). The classification dataset is the MIT-BIH Arrhythmia database with Modified Lead II (MLII) data. The dataset is divided into three sub-data: training, validation, and testing datang. The training, validation, and test data numbers are 5703, 713, and 713, respectively. This experiment requires a training process using 100 epochs. At the end of the training process the accuracy levels of the training and validation datasets are 100% and 99.58%. While the data loss from the training and validation dataset has a value of 4.835e-12 or close to 0 and 0.0482.

The accuracy result of the testing datasets was 99.82%. This result is obtained from a correct detection number (out of 713 data) for Normal (NOR), Right Bundle Branch Block (RBBB), Left Bundle Branch Block (LBBB), Fusion of Ventricular and Normal (FVN), Premature Ventricular Contraction (PVC) of respectively 713, 712, 711, 710 and 703, as depicted Table 5. Our classifier is 100 % in Accuracy (Acc), Predictive Positive (+P), Sensitivity (Se), Specificity (Spe), and F1-score in class

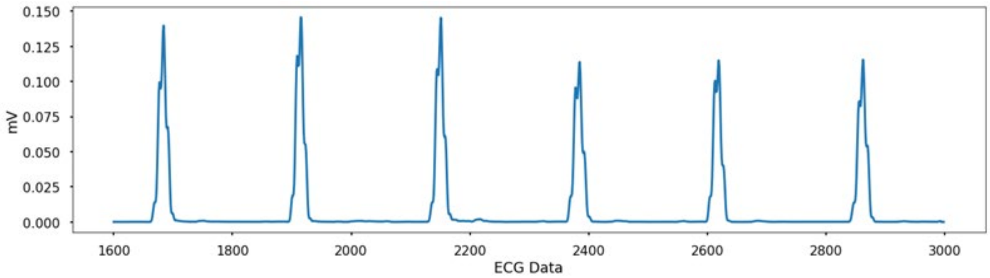
Normal. And a little error in the RBBB, LBBB, FVN, and PVC classes. The total Acc, Se, +P, Spe, and F1-score are 99.82%, 99.55%, 99.55%, 99.89%, and 99.55%, respectively.



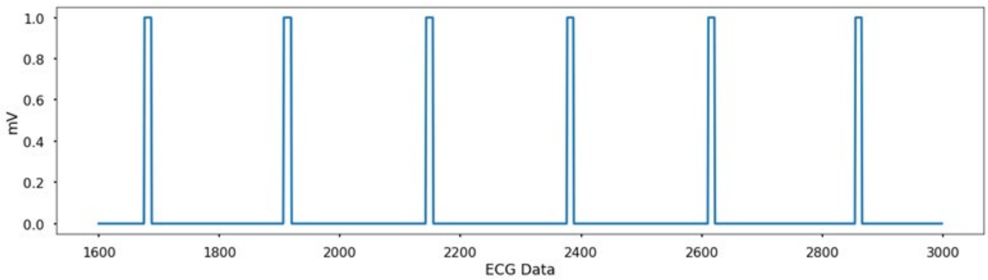
(a)



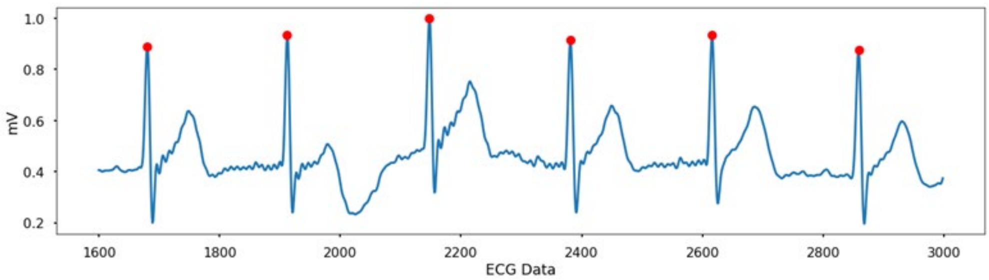
(b)



(c)



(d)



(e)

Fig. 7. Volunteer Data Test: (a) Raw ECG, (b) Filtered ECG, (c) Variance signal analysis, (d) Result of treshold, and (e) R-peak detected

A comparison of our work to the other arrhythmia classifier, including Sharma et. al. [13], Hou et. al. [20], Plawiak et. al. [17], and Li et. al. [19] has shown in Table 6. All methods were tested using the MIT-BIH arrhythmia database with different input segment lengths, number of classes, architecture, and methods. Configuration of the proposed that uses 2D CNN with 24 layers running on the raspberry PI edge device has better performance than other classier. The result shows that our proposed device can detect multiclass arrhythmias.

Table 5. Result of Arrhythmia Classification

No.	Class	TP	TN	FN	FP	Acc(%)	Se(%)	+P(%)	Spe(%)	F1-score(%)
1	Normal	713	2852	0	0	100	100	100	100	100
2	RBBB	712	2849	3	1	99.89	99.58	99.86	99.96	99.72
3	LBBB	711	2852	0	2	99.94	100	99.72	99.93	99.86
4	FVN	710	2844	8	3	99.69	98.89	99.58	99.89	99.23
5	PVC	703	2847	5	10	99.57	99.29	98.60	99.65	98.94
Total		3549	14244	16	16	99.82	99.55	99.55	99.89	99.55

Table 6. Comparison result of arrhythmia classification

No.	Author	Method	Input	Class	*Acc*	*Se*	*Spe*	*+P*
1	This Study	24 layer 2D CNN	2D ECG Spectrogram	5	99.82	99.55	99.89	99.55
2	Sharma and Dinkar [13]	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. [20]	LSTM	1D QRS Complex	5	99.74	99.35	99.84	-
4	Plawiak and Acharya [17]	DL + GA	10 s ECG	17	99.37	94.62	99.66	-
5	Li et. al. [19]	CNN	5s ECG	5	94.54	93.33	80.80	-

3.3. Execution Time

Our experiments were conducted using the same software implemented in Python running on different processing devices. The device used is the Personal Computer i7 with a 240 GHz CPU compared to the Intel Movidius compute stick running on the Raspberry Pi 3 Model B+, the processor, ram, storage and operating system specifications of the two devices tested are listed in Table 7.

Table 7. Specifications of Processing Unit

	Computer	Raspberry Pi
Processor	I7 CPU @2.40GHz GPU NVIDIA GeForce GTX 1050 Ti 2GB	Quad-core ARM Cortex-A53 CPU @1.40GHz Intel Movidius 4GB CPU @700 MHz
RAM	16 GB	1 GB
Storage	SSD 128 GB	microSD 16 GB
Operating System	Windows 10 64-bit	Raspbian 32-bit

The test scenario is QRS Complex detection and Arrhythmia classification from ECG with a total sample data of 1000, 1400, 1800 and 3600. The digital ECG signal has a sampling rate of 100 Hz. The order of execution as follows. QRS complex data to find R-peak using the algorithm proposed by QVAT. Transforming the Complex QRS ECG signal from a 1-dimensional matrix to a 2-dimensional spectrogram. CNN 2D Deep Learning in this test is used to predict arrhythmias from the QRS complex in the form of a spectrogram. The execution time of the training process is not included in this experiment. From the ECG processing experiment with a recording length of 36 seconds or 3600 ECG digital data, the I7 personal computer executed 3.16 times faster than the execution of the Raspberry Pi 3 Model B. The results of the overall execution time can be seen in Table 8.

Table 8. Comparison of Raspberry Pi and Computer Execution Time

Number of ECG Data	Execution Time (second)	
	Computer	*Raspberry Pi*
1000	5.88	16.01
1400	7.59	21.51
1800	9.65	27.37
3600	20.13	63.59

3.4. Future Works

In the future works, We can further improve the robustness of the proposed R-peak detection algorithm (QVAT). First, We add a double-check algorithm in QVAT based on historical RR intervals to decrease FN. And reduce the false detection of QRS complex in the non-QRS complex (FP) by adding 1 class of non-QRS complex in the classification process as a correction. The execution time using edge computing can be accelerated using the latest edge technologies. Our proposed model can be employed in a clinical scenario as shown in Fig. 8. The patient records his heart activity using the proposed ECG device. Arrhythmias are detected by the distance of one R-peak to the next R-peak. An arrhythmia is a heart abnormality if the distance from R to R is more than 1.67 seconds or less than 1.0 seconds since the normal heart rate beats between 60 to 100 beats per minute. We classified arrhythmias based on the morphology of the QRS complex. Furthermore, the ECG signal and arrhythmia classification are sent and stored in the Server. The doctor at the hospital diagnoses heart conditions based on the ECG graph and arrhythmia classification. He gives treatment or sends messages to the patient to meet him for further examination if he finds an abnormal ECG.

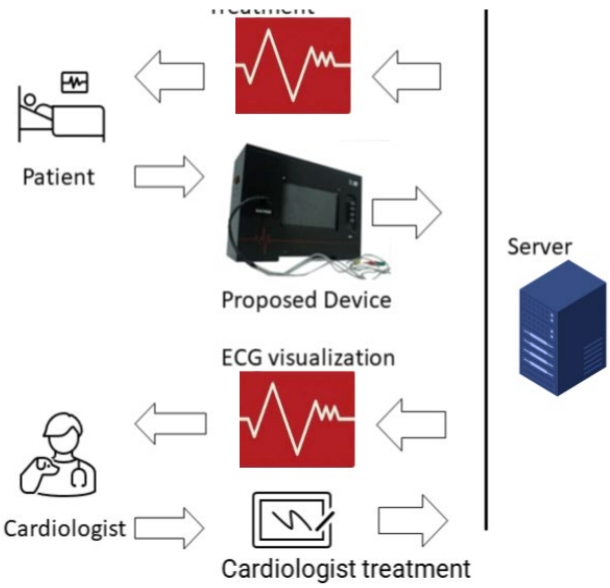


Fig. 8. An illustration of the application of the proposed ECG system

4. Conclusion

This study proposes an Edge device that detects and classifies arrhythmias using a heuristic algorithm and Deep Learning CNN 2D. Our edge device uses intel stick as deep learning processing running on a raspberry pi that detects and classifies arrhythmias smoothly in the test scenario. We tested the robustness of the detection and classification using the MIT BIH dataset. Our proposed heuristic algorithm is called QVAT. The average sensitivity and positive prediction of the detection test are 99.81% and 96.90%, respectively. Our proposed device classifies arrhythmias into five classes: Normal, RBBB, LBBB, FVN, and PVC. The classification is based on the QRS complex morphology. The input of Deep Learning 2D CNN is an ECG spectrogram. The classification accuracy, sensitivity, prediction positive, specificity, and F1-score consisting of Normal, RBBB, LBBB, FVN, and PVC are 99.82%, 99.55%, 99.55%, 99.89%, and 99.55%, respectively. The experimental result of arrhythmia classification shows that our method outperforms the method proposed by Sharma, Hou, Plawiak, and Li. Our edge device that implements QVAT as an R-peak detection is better than Pan Tomkins, Habib, and Yuen. However, the Rahul method is slightly better than QVAT. The execution test of our proposed methods is running the same ECG data and the script on the computer and the edge device. The ratio execution time of a personal computer's (processor I7) is 3.16 times faster than edge device.

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Declarations

Author contribution. The contribution or credit of the author must be stated in this section. Arief Kurniawan: conceptualization, methodology, hardware, software, formal analysis, and writing original draft. Eko Mulyanto Yuniarno: validation and formal analysis. Mochamad Yusuf: medical conceptualization and medical supervision. Eko Setijadi: supervision and writing review. G. J. Verkerke: supervision and writing review. I Ketut Eddy Purnama: supervision, conceptualization, formal analysis, and writing review.

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Conflict of interest. The authors declare no conflict of interest.

Additional information. No additional information is available for this paper.

Data and Software Availability Statements

The secondary data used in the experiment is public data, namely the MIT-BIH Arrhythmia Database downloaded from http://archive.physionet.org/cgi-bin/atm/ATM. We use tensor flow library which is an open source machine learning platform that runs on computers and raspberry pi.

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