R-Peak Detection of Beat Segmentation and Convolution Neural Network for Arrhythmia Classification

by Erwin Erwin

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R-Peak Detection of Beat Segmentation and Convolution Neural Network for Arrhythmia Classification

ANITA DESIANI[1], ERWIN[2,*], SRI INDRA MAIYANTI[1],
BAMBANG SUPRIHATIN[1], NAUFAL RACHMATULLAH[3],
ANNISA NUR FAUZA[1], INDRI RAMAYANTI[4]

[1]Department of Mathematics, Universitas Sriwijaya, Indonesia
Jl. Raya Palembang-Prabumulih KM.32, 30662, Indralaya, Indonesia
[2]Department of Computer Engineering, Universitas Sriwijaya, Indonesia
Jl.Raya Palembang-Prabumulih KM.32, 30662, Indralaya, Indonesia
[3]Department of Informatics Engineering, Universitas Sriwijaya, Indonesia
Jl.Raya Palembang-Prabumulih KM.32, 30662, Indralaya, Indonesia
[4]Medical Collage, Universitas Muhammadiyah
Jl. KH. Balqi, Talang, 16 Ulu, Palembang, Indonesia
*Corresponding Author: erwin@unsri.ac.id

Abstract

One of the abnormalities in cardiology is arrhythmia. The arrhythmia classification can use Electrocardiogram (ECG) signals. ECG has a large size because ECG should be recorded within a certain interval. The ECG arrhythmia can identify which beats have normal and abnormal patterns. The arrhythmia ECG data is provided by www.physionet.org which contains data from 47 patients in MIT-BIH that were recorded for 30 minutes. From the data, there are 650,000 signal points. The segmentation carried out in this study uses R-peak Detection. The segmentation results were 109,452 beats with 252 signals. In this study, R-peaks of ECG signals were combined with Convolution Neural Network (CNN) to detect and classify a normal and abnormal beat or beat that has arrhythmia. CNN is known as a robust classification method for data with large dimensions. The Accuracy result obtained from R-peak Convolution Neural Network (CNN) for arrhythmia classification on testing was 97%. The precisions for normal and abnormal beats are 99% and 91%. The sensitivities of normal and abnormal beats were 98% and 94%. These results indicate that the application of R-peak of ECG signals and CNN are excellent for arrhythmias detection on the ECG signals.

Keywords: Arrhythmia, Beat, Cardiology, CNN, ECG, R Peak

1. Introduction

Heart disease is one of the number one causes of death in the world [1]. Based on data from Health Research (Riskesdas) in 2018, the rate of the disease continues to increase significantly from year to year. There are at least 15 out of 1,000 people, or around 2,784,064 people in Indonesia suffering from it [2]. The disease is divided into three classes, namely electricity (arrhythmia), blood circulation (blood vessel disorders), and structure (heart muscle disease) [3]. Arrhythmia is a condition in which the heart beats faster, slower, or becomes irregular than a normal heartbeat [4]. Electrocardiogram (ECG) is a simple test to measure and record electrical heart activity. This test is used for an electrical impulse detection machine, it is called an electrocardiograph [5]. Electrocardiogram signals (ECGs) are able to use to diagnose irregular heartbeats especially arrhythmia [6]. ECG is a signal that serves to describe the electrical activity carried out by the heart [7]. An ECG can be obtained from an ongoing heart rhythm. The rhythm consists of many beats. A Beat has a duration of 0.7 seconds with a 252-point signal on rhythm [8]. Manually printed ECG paper is used to analyze the detection of heart abnormalities in the world of health [9]. However, this method takes a long time and needs high accuracy to detect cardiac abnormalities. In addition, ECG paper can experience problems with ink evaporation, fuzzy paper, folded paper, or torn paper [10]. This can make ECG interpretation in diagnosing arrhythmia inaccurate.

MIT-BIH dataset is one of the datasets that provide ECG Arrhythmia dataset. It can be accessed on ww.physionet.org. MIT-BIH stands for Massachusetts Institute of Technology - Beth of Israel Hospital. The dataset is obtained from 47 patients in the arrhythmia Laboratory research at Beth Israel Hospital. The data contains 47 arrhythmic patient data with a signal duration of 30 minutes and 650,000 signal points. Every signal is named rhythm and contained many beats. The beat is part of a rhythm consisting of one P wave, one QRS complex with R as the highest peak, and one T wave [11]. The top point of R is the highest point of a beat in the complex QRS region. Several methods are used to detect QRS complex areas such as wavelets, Daubechies decomposition techniques, sophisticated averages, median filters, adaptive filters, and Fourier transforms [12]. The method requires a mathematical model and special programming to detect R peaks in the QRS region, so it requires a certain amount of time to segment the ECG. According to Qin [13], not all beats can be used to detect arrhythmia heart failure, but only the beat that is recorded and lies on the QRS complex curve as a meaningful beat. The important beats have a duration of about 0.7 seconds which is divided into two groups of 0.25 seconds before the R-peak point and 0.45 seconds after the R-peak point [14]. Some studies use segmentation methods to get meaningful beats in one rhythm. Banerjee [15] used the Empirical Mode Decomposition (EEMD) ensemble technique in combination with a Butterworth filter and Wavelet filter to detect the meaningful beat of R peaks point. The results of the segmentation are evaluated for prediction of arrhythmic patterns by Naive Bayes with the accuracy was 85.5% and obtained the best improvement by KNN which the accuracy was up to 99.7%, but the paper does not explain the sensitivity and f1-scores for every label. Lee [16] tried Efficient Fiducial Point Detection of ECG QRS Complex using Polygonal Approximation to improve the quality of beat ECG but the technique is complicated and measured the performance by standard deviations and average scores. Banerjee [17] has detected beat ECG based on Biometrics for Human Identification using wavelet for segmentation and discrete orthogonal Stockwell Transform (DOST) for classification. The accuracy of the study was fairly high. The previous segmentation technique was monotonous, time-consuming, uncomfortable, requires expertise, and still needs other classification methods to recognize the pattern of data [18].

The conventional method sometimes doesn't always work well, takes a long time to converge, and only find minimum local solutions. This is caused by the combination of architectural parameters, the initial determination for the initial weight of each input, and bias, especially for large-sized or big data [19]. The arrhythmia signal data is a big data set because it has 650,000 signal points for one patient. Deep learning can be a solution to overcome the problem. The virtue of it is being able to analyze and learn from big data without supervision because deep learning can work in unsupervised conditions [20] and it can be used to interpret and classify the ECG signals [21-22]. It can improve all parts of artificial intelligence (AI), from natural language processing to machine vision, face recognition, and image classification [23-24]. CNN is one method in deep learning. CNN consists of an input layer, one or more convolution layers, one or more fully connected (FC) layers, and an output layer [25]. CNN has one or more convolution layers and a fully connected layer (FC). The input and output of each stage have several arrays which are commonly called feature maps [26]. CNN architecture consists of two parts, namely feature extraction, and classification. Convolution layers use for feature extraction and Fully Connected layers for classification which is based on features that have been trained in convolution layers. The classification part should be defined as the activation function in the end part of the CNN architecture, for example, a Softmax function to predict output target [27]. CNN can learn and manage by itself [28]. CNN has been applied in various applications such as object recognition [29], image classification [26], and handwriting classification [30]. CNN can also be used for image classification. Identification of Heart Rhythm Devices Using Artificial Neural Networks was carried out by [8]. The other predominance of CNN is powerful to handle data with big dimensions (big data) like image, signal, etc because CNN has the ability to reduce the dimension of data by itself [31].

Several researches have applied CNN to detect Arrhythmia. Yildirim [32] conducted a study to detect arrhythmia using the 1D-CNN deep learning method. The study only used the ECGs at the first ten seconds of rhythms for each patient with 17 class labels. The accuracy of the study is 91.33%. Zubair [33] has researched automatic ECG beat classification systems using the CNN without beat segmentation. The accuracy of the study is 92.7%. Wang [34] improved CNN based approach for automated heartbeat classification and got an accuracy of 99.06%, but the sensitivity and specificity did not evaluate. Acharya [35] used the CNN technique to automatically detect the different ECG segments. The study applied CNN in two experiments namely with and without Noise removal. The results of the two trials did not show a significant effect, where the accuracy obtained in the test without noise removal was 93.47%, while in the test with noise removal the accuracy only increased by 0.56%.

In this paper, the study conduct to combine the CNN with R-peak detection to classify arrhythmia beat. The motivation for this study is to propose a combination of methods to obtain important features of the ECG and provide accurate input on the classification of beat arrhythmia. The novelty in this study is to combine segmentation techniques and classification methods using a simple technique for beat segmentation, namely R-peak detection, but it can produce good input for the classification process using deep learning techniques, namely Convolution Neural Network (CNN). The contribution of this study is it can be an alternative method where the CNN method is not simple because it is based on deep learning combined with a simple beat segmentation method, namely R-peak detection so that the segmentation process does not add complexity for CNN training.

R-peak detection is used to obtain signals that are meaningful or that are the most important feature in recognizing or classifying beat arrhythmia beat so that signals that are not important or have no meaning in the beat arrhythmia beat are discarded and do not need to be trained by CNN. The findings obtained robust results for the classification of normal and abnormal R-peak detection with high accuracy, f1 score, and sensitivity. The proposed method is limited to detecting the R point of the ECG signal as input for classification using the CNN architecture. The CNN architecture for the study was implemented using a network architecture with 3 convolution layers and 2 FC layers.

The structure of the paper is organized as follows: Section 2 presents the proposed method, which includes collecting data, R-Peak detection for beat segmentation, build the CNN architecture, and evaluation. Section 3 describes the results and analysis. Section 4 concludes the paper.

2. Experimental Method

2.1. Collecting Data

The data are taken from the dataset of Beth Israel Hospital (MIT-BIH) from the Massachusetts Institute of Technology. In this study, data were used from 47 patients with arrhythmias. Each patient has a signal duration of 30 minutes and a signal point of 650,000. Each R-peak has an annotation or non-annotation symbol. The channel used is the MLII electrode channel (modified lead II).

2.2 R-Peak Detection for Beat Segmentation

The ECG consists of signals that describe the electrical activity carried out by the heart that is named rhythm. Every rhythm contains some beats. Every single beat has a P wave, a QRS complex with R as the highest peak, and a T wave.

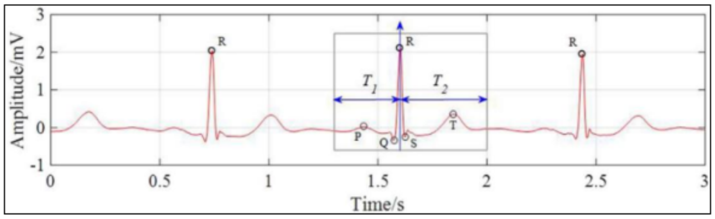

Fig. 1. The duration of the meaning signals on ECG according to the QRS complex [13]

Based on Fig 1, the meaningful beat has a time duration of 0.7 seconds where T_1 has a duration of 0.25 seconds before the R point and T_2 is 0.45 seconds after peak R [13]. Pre-processing data is the process to prepare data before the data is used in classification. Beats and labels are got from the process segmentation by finding the starting point and endpoint of the beat by using Eqs. (1) and (2) [32].

$$s = R - A_1 \text{ with } s \geq 0 \tag{1}$$

$$f = R + A_2 \text{ with } f < n \tag{2}$$

where A_1 is signal points on T_1 time (before R point) and A_2 is signal points on T_2 time (after R point), s and f are the starting and ending points for 1 beat, R as the highest peak point of each ECG signal, and n as the signal point length of 650,000.

2.3 Build The CNN Architecture

The signal obtained from the detection of point R will be used as input for classification using the CNN architecture. The CNN architecture for the study was implemented using a network architecture with 3 convolution layers and 2 FC layers. In the model, it needs to initialize the initial kernel value ($\boldsymbol{k_{p,q}^l}$) at the convolution layer, the weight ($\boldsymbol{w_{i,j}}$) on the FC layer with a random value, and bias with the initial value 0. It determines the number of filters for each convolution layer and the number of neurons for the layer FC. The convolution process is carried out in following with the number of filters in the convolution layer according to Eq. (3) [33]. The activation function used in this process is the ReLU activation function. The ReLU function has been used in hidden layers because the ReLU is a simple calculation. Process back and forth via ReLU only uses if condition, No exponential, multiplication, or division operations[34]. The advantages of ReLU will emerge when dealing with networks that have a large number of neurons. These reasons can significantly reduce training and testing time suitable on hidden layers [34], [35].

$$C_p^l = \sigma\left(\sum_{m=1}^{M} I_{i+m-1}^{0j} k_{p,q}^l + b_p^l\right) \tag{3}$$

with C_p^l is the *feature map* for next p value at the l layer, p as filter amount, M as the size of the kernel, σ is activation function, I as input, $k_{p,q}^l$ are the kernel for l layer in the feature map now (p) and next (q), b_p^l is the p-th feature map bias in the l-layer. If the CNN layer structure used is no longer a convolution layer after the convolution layer, then the next stage is the same as the previous stage, which is to carry out the re-convolution process [36]. The feature map obtained from the last convolution layer is the feature map that will be used at the FC layer as a feature for classification as a matrix [29]. The feature map in the form of a matrix will be combined into one column vector according to Eq. (4).

$$f = \text{Con}\left(C_p^l\right); p = 1, 2, 3, \ldots \tag{4}$$

where f is the merged feature map from concatenation operation of feature maps, C_p^l is the p feature map in the l layer. Next, the process is to calculate the features that enter the FC layer using Eq. (5) [37].

$$y_i = \sigma\left(\sum_{j=1}^{n} w_{i,j} f_j + b_i\right) \tag{5}$$

with y_i is the result *fully connected* i layer, $w_{i,j}$ is the weight from j neuron to I neuron, f_j is j input, b_i is I biased. In the end, the Softmax function gives decimal possibilities to each class in plural class problems. The total decimal probability must be 1.0. This additional limitation helps to convert training faster than it should [30]. The softmax function is the following Eq. (6) [38].

$$f_i(z) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \text{ , with } i = 1, 2, \ldots, k \tag{6}$$

where f_i is the result of the function for each i-i index and z is the prediction label given by the CNN architecture. The R-peak detection and CNN architecture used for the arrhythmia beat classification. It is shown in Fig 2.

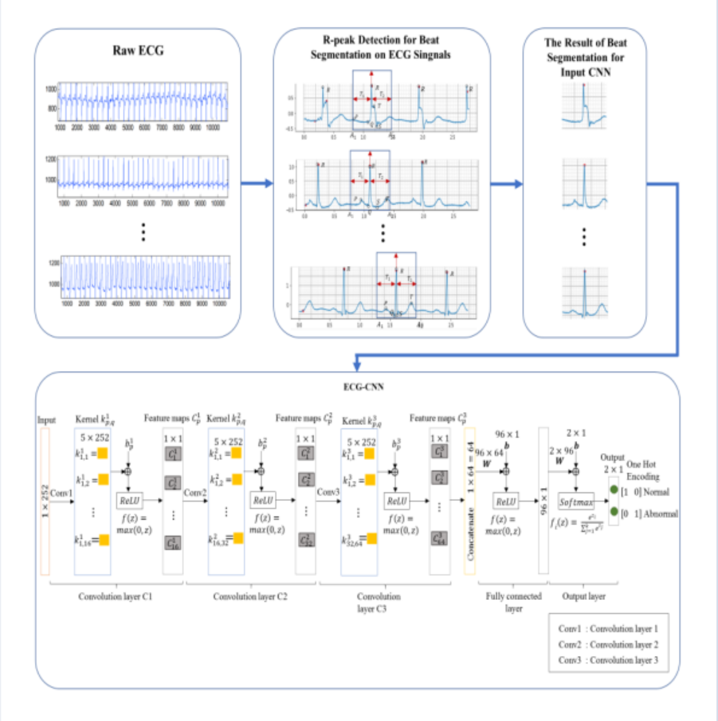

Fig. 2. The R-peak detection and CNN network architecture on ECG signals for MIT-BIH arrhythmia dataset

In Fig 2, the R-peak detection results to obtain beat arrhythmias on the ECG signal are combined with CNN Architecture for classification. The R-peak detection technique is used at the pre-processing stage to obtain important features of the ECG signal, which then the results will be processed into the CNN architecture to classify which signals are normal and which signals are not normal. The CNN architecture had 1 input layer, 3 convolution layers, 2 fully connected layers, and 1 output layer. The first step was initialization of the initial value of the kernel $\left(k^{l}_{p,q}\right)$ up to 5, weight $\left(w_{i,j}\right)$, bias $\left(b^{l}_{p}\right)$ with the random value. The padding was 2 and the stride was 1.

2.4 Evaluation

According to [26] determining the performance of the classification results can be seen from the performance measurement parameters namely the level of accuracy, sensitivity, and F1 score. The confusion matrix is used to calculate these factors. If the dataset consists of only two classes, then one class is considered a positive class and the other is a negative class. To calculate the accuracy, sensitivity, and F1 score are used Eqs. (7), (8), and (9) with TP as True Positive, TN as True Negative, FN as False Negative, and FP as False Positive, as follows:

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \times 100\ \% \tag{7}$$

$$F1\ score = \frac{TP}{TP+FP} \times 100\ \% \tag{8}$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100\% \tag{9}$$

3. RESULTS AND ANALYSIS

The dataset used is the ECG dataset downloaded from the MIT-BIH Arrhythmia Dataset on the page www.physionet.org. This dataset provides 47 arrhythmic patient data that consists of 23 series '100' and 25 series '200'. Each patient has a signal duration of 30 minutes and a signal point of 650,000. Each R peak has a symbol in the form of an annotation or non-annotation beat. The channel used is the MLII electrode channel (limb modification II). The amplitude point contained the arrhythmia patient for 30 minutes with several signal points of 650,000 (frequency 360 Hz). R-peak point is the location of point R on the ECG signal point. Each patient has a different number of R-peak points and R locations. Point R is used to determine the meaningful beat. R points for the 100th patients and the 101th patients are shown in Table 1.

Table 1. R-peak points location on ECG signal for the 100th and 101th arrhythmia patient

The patient number	Point R	1	2	3	4	⋯	2271	2272	2273	2274
100	**The location of the point R**	18	77	370	662	⋯	649232	649484	649734	649991
101	**The location of the point R**	7	83	396	711	⋯	648647	649004	649372	649751

The 100th Patient has 2274 R-peak points, which means the 100th patient has 2274 meaningful beats. The 101th patient has 1874 R-peaks points and it means the patient has 1874 meaningful beat. The Symbols for every beat can be in the form of Normal beat (N) and abnormal beat.

3.1. Beat Segmentation

The Beat segmentation in the study used R-peak detection. It finds the starting point (s) and endpoint (f) beat with point R using Eqs (1) and (2). The data on the 100th patient to find the starting point and endpoint are shown in Table 2.

Table 2. The starting and the ending point of R-peak point location on ECG signal of the 100th patient

No.	Point R	Endpoint
1.	18	180
2.	77	239
⋮	⋮	⋮
2273.	649 734	649 869
2274.	649 991	650 153

Table 2 showed that patient 100 for beats numbers 1 and 2 did not qualify because $s \leq 0$, and beat number 2274 did not meet the requirement because $f < 650{,}000$ so the total beats in patient number 100 were 2271. The same method will be performed for all patient data at MIT-BIH arrhythmia so that the total number of beat data for all arrhythmia patients after beat segmentation was 112,563 beats (Table 3).

Table 3. The number of beats on ECG signals for arrhythmia patients in MIT-BIH arrhythmia dataset

Patient number	Number of Patient Beats
100	2271
101	1872
⋮	⋮
234	2763
Total Number of Patient Beats	112 563

Beats (on Table 3) of all patients who have been obtained are recorded the electrical amplitude and transformed in the form of a matrix so that it becomes X (input). The variable X was the matrix 112,562×252. Each beat was labeled with annotated beats and is transformed into a matrix using Eq. (3) so that it is obtained as y (label). The variable y is the size matrix 112,563×1. Variable X with the non-annotation beat label is deleted because it does not have a meaningful label so the *X* variable used is a matrix of 109,452×252 where 109,452 is the total number of all beats and 252 is the signal length for one beat. The variable *y* is a matrix of 109,452×1 with a total number of all beats and 1 is the length of the label for each beat. Labels consisting of 15 beat annotations will be grouped into 2 major classes, namely normal and abnormal beat as shown in Table 4. The variable *y* in CNN must be in the form of one-hot encoding. The form is shown in Table 4. After being changed in the form of one-hot encoding, the size of the *y* variable has been changed in the form of a matrix with a size 109,452×2.

Table 4. One-hot-encoding for the labels and the classes of normal and abnormal arrhythmia beats on ECG signals

Label	Class	One-hot Encoding
N, L, R, e, j	Normal	[1 0]
/, A, E, F, J, Q, S, V, a, f	Abnormal	[0 1]

3.2. Build of CNN Model

On the step, the CNN process work based on Fig 2. In the first convolution layer, there were 16 filters, and the size of the kernel was 5×252. The convolution results were added to the bias and entered into the Relu activation function so it produced a feature map C_1^1 through C_{16}^1. Furthermore, the second and the third convolution processes followed in the same way but with different filters, namely

32 and 64. After producing the feature maps C_1^3 to C_{64}^3, the concatenation operation was performed to produce a matrix in one dimension that is used as a fully connected layer input. After that, the fully connected layers would process using the Relu activation function and 96 neurons. The last process should calculate the output layer by using a "softmax" activation function and it produced an output measuring 2x1. The Relu function is important because it is simple and does not need much time even it has large neurons without making a significant difference to the accuracy. The Softmax Activation was applied on the output layer because it allowed the CNN to run a multi-class function. The Softmax was used to map the non-normalized output of a network to a probability distribution over predicted output classes [38].

The number of filters and the number of biases used for the first, second, and third convolution layers were 16, 32, and 64. The use of filters on the CNN architecture 16,32,64 is based on references to several studies such as that conducted by Li (2018) [39] by adding 32 filters in the next layer and Hsieh (2020) [40] increasing the filter size by multiplying by 2 for each convolutional layer. The neurons used for the first and second FC layers were 96 and 2. The second step was to calculate the size of the feature map. The resulting output feature map size was a matrix 1×1. Each input, kernel, padding, and stride would affect the size of the resulting feature map. The third step was performed the convolution process following the filter in the convolution layer. The convolution layer consisted of 3 layers with 16, 32, and 64 consecutive filters respectively. The convolution process was carried out with Eq. (3).

On the architecture, the convolution process to get the value C_1^1 was to carry out a convolution operation between input (X) (using padding the same size as the kernel) and kernel $(k_{1,1}^1)$ which produced one value, then the value is added to the bias (b_1^1) to produce a new value, after that the value was substituted into the ReLU$= max(0, z)$ activation function. The calculation result of the activation function was the result of the convolution process for C_1^1. The same way was done for the calculation of the values C_2^1 to C_1^{16}.

For example, a simple calculation in the convolution process, for example, input by taking the first 5 beats from I, namely: $input(I) = [-0.45 \quad -0.55 \quad -0.50 \quad 0.1 \quad 0.04]$, the kernel given to the first layer is $k_{1,1}^1 = [1 \quad 0 \quad 0]$, bias $b_1^1 = 0.2$, the activation function used is ReLU $(\sigma) = max(0, z)$, stride = 1 and padding = 1, then the calculations for the feature map C_1^1 are illustrated in Fig 3.

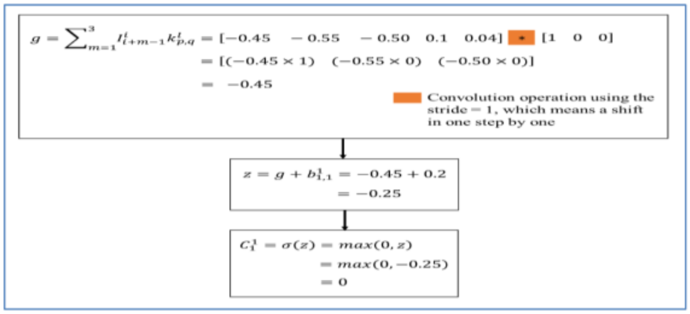

Fig 3. Illustration of the convolution process in the first layer and the first feature map with ReLU function

Illustration of the results of Fig. 3, the results obtained from the convolution process $C_1^1 = 0$ means that the value of the feature map on the first layer of the 1st filter is 0. The same way beat ECG performed on the data for each layer of convolution. In Fig 3, it shows that the use of the ReLU activation function in the hidden layer can reduce the complexity of time and calculations for each convolutional operation.

The feature map obtained from the last convolution layer was the feature map that would be used at the FC layer as a feature to classify. The feature map in the form of a matrix would be combined into one column vector (concatenation) according to Eq. (4). Furthermore, the process at the FC layer was carried out by calculating using Eq. (5). The first FC layer uses 96×64 weight and 96×1 for bias z_j to produce output 96×1.

3.3 Evaluation Results

The dataset used was divided into training data and test data using percentages split. The percentage distribution used was 33% which means 33% of data was taken as testing data, and 67% of data was taken as training data. The training data used in CNN modeling was 73,330 and the testing data used was 36,120. From the confusion matrix, True Positive (TP) was the amount of data included in the classification label that successfully predicted in Normal labels class as much as 29,303. False Negative (FN) was the amount of data included in the classification of the normal labels but it was predicted Abnormal labels as many as 606. False Positive (FP) is the amount of data included in the abnormal label but it was predicted as normal labels as many as 388. False Negatives (FN) is the amount of data included in abnormal labels and it was successfully predicted as abnormal labels as many as 5,823. From confusion matrix of the training, it could be calculated for accuracy, F1 score, and sensitivity. The accuracy was 98%. It means that the accuracy was excellent. The F1 score of Normal labels and abnormal labels were 99% and 91%. The sensitivity of normal labels and abnormal labels 98% and 94%. To see the performance advantages of the models that have been built, the results of accuracy, F1 score, and sensitivity will be compared with previous studies. It was shown in Table 5.

Table 5. The analysis and the comparison performance of the proposed method vs the previous studies on ECG signals in MIT-BIH arrhythmia dataset

Author	Method	Accuracy (%)	F1-Score (%)	Sensitivity (%)
Isin [41]	QRS Detection and Deep learning for Feature Extraction, Multilayers Neural Network for Classification	98.51	-	-
Hanun [42]	Deep Neural Network (DNN)	83.70	-	-
Rajendra [11]	using different intervals of tachycardia ECG segments with convolutional neural network	94.90	81.44	99.13
Mathews [43]	Restricted Boltzmann Machine and deep belief networks (DBN)	95.36	-	-
Yao [44]	using Attention-based Time-Incremental Convolutional Neural Network (ATI-CNN)	:	81.2 88.9	-
Banerjee[45]	using multiresolution wavelet analysis method for Delineation of ECG characteristic features	-	99.6	99.8
Lee, Y [16]	Using Polygonal Approximation for Efficient Fiducial Point Detection of ECG QRS Complex	-	-	-
Banerjee [17]	Cross Wavelet Transform for ECG Pattern	97.6	98.8	97.3
Raj [46]	Using discret orthogonal stockwell transform (DOST) for feature extraction of ECG signals, support vector machines (SVMs) and tuned using particle swarm optimization (PSO) technique	99.18	-	62.5
Wang[33]	Improved Convolutional Neural Network Based Approach for Automated Heartbeat Classification	-	81.3	83.2
Proposed Method	R-peak detection and CNN for classification	97.24	95	96

Table 5 was related to some research on arrhythmia using different methods. The study by Isin [41] was obtained a very high accuracy but the F1 score and the sensitivity were not displayed. The study by Raj [46] gave the highest accuracy but it had the lowest sensitivity. The other research by Hannun [42] applied deep neural network (DNN) and it obtained the lowest accuracy, but F1-Score and the sensitivity were also not displayed. Based on Rajendra results [11], it could be seen that using different intervals of the ECG segment of tachycardia with convolutional neural networks combined with k-fold Cross Validation gave the higher sensitivity but for accuracy and F1-Score were lower than the proposed method. Mathews [43] took into account the application of the Boltzmann Limited Machine and deep confidence network to the automatic classification of single-lead ECG signals. The experimental results were high at 360.590 Hz sampling rate but it could not show the performance of sensitivity and F1-Score. A model named ATI-CNN for the classification of arrhythmias of ECG signals of varying lengths was proposed by Yao [44]. This model extracted information from ECG signals in two steps: fusion of spatial information based on convolutional neural networks and fusion of temporal information based on LSTM cells and attention modules. ATI-CNN was compatible with inputs of varying lengths, which leads to superior classification performance, especially in detecting paroxysmal arrhythmias. The study did not evaluate the accuracy and the sensitivity, it only evaluated the F1-score of 8 types of arrhythmia and sinus rhythm.

In Table 5, the proposed method gave better accuracy than some previous studies [11], [17], [34], [37], [46–48]. For the F1-score, the best results were obtained by [45]. The highest sensitivity, was obtained by [17]. some study showed that they got the better accuracy than proposed method [17], [41], [46], even though the accuracy, F1 Score and Accuracy values are not the best, the results of the accuracy of the sensitivity and F1 score of the proposed method are very good, which is above 90%, this explains that the combination of R-peak detection and CNN techniques in the proposed method is reliable enough to be used in the classification of beat detection in arrhythmia. Some previous studies just took the accumulation of F1 score and sensitivity of all labels, so it was impossible to compare the performance model to predict for each label. The accuracy of the proposed method was good because it is above 90%. The average results of the F1 score and sensitivity of all labels are good cause above 90%. These results concluded the proposed method was quite reliable for classifying beat of arrhythmia.

4. CONCLUSION

The accuracy of CNN models to identify ECG beat patterns is 97.24%, which means that the CNN model is robust at introducing ECG beat patterns in arrhythmia. F1 Score of normal beats and abnormal beats were 99% and 91%. It described the model as excellent to find a normal beat or abnormal beat from all events. The sensitivity of normal beats and abnormal beats were 98% and 94%. The sensitivity score is highest than the previous method. This shows that the proposed method is effective for calling all beat labels from both normal and abnormal beats. Therefore, it is evident that the proposed method has the potential to be implemented in the medical field. The proposed method can function as an adjunct to the doctors cross-examine their findings. In addition, the doctor can recommend appropriate treatment right away and avoid further damage to the heart condition.

5. ACKNOWLEDGEMENT

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Nomenclatures

FC	Fully Connected
S	Starting Points
F	Final/ Ending points
T_1	Duration Signal before R-peak
T_2	Duration Signal after R-Peak
$k^l_{p,q}$	Kernel Value
$W_{i,j}$	Weight
C^l_p	Feature Map

I_{i+m-1}^{0j}	Input Layer
b_p^l	Bias Map
F	Merged Feature Map
F	The Result of Merged Feature Map
y_i	Fully Connected
Z	Neuron value
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative

Greek Symbols

σ	Activation Function

Abbreviations

ECG	Electrocardiogram
MIT-BIH	Massachusetts Institute of Technology-Beth Israel Hospital
CNN	Convolution Neural Network
EEMD	Empirical Mode Decomposition
KNN	k-Nearest Neighbour
AI	Artificial Intelligent
MLII	Modified Lead II

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