Application of convolutional neural network classifier for wireless arrhythmia detection

D E Kusumandari¹, M I Rizqyawan¹, M Yazir³, M Turnip², A Darma³ and A Turnip¹*

¹Technical Implementation Unit for Instrumentation Development, Indonesian Institute of Sciences, Bandung, Indonesia
²Faculty of Technology and Computer Science, Universitas Prima Indonesia, Medan, Indonesia
³jujhin@gmail.com

Abstract. The heart as the main system of blood circulation in our body can certainly experience abnormalities called arrhythmia. Information of the arrhythmia is very important in the field of health and electrocardiogram is one of the most commonly used tools to detect the heart abnormalities. A wireless monitoring of the heart activities has been developed. An application of convolutional neural network classifier for arrhythmia detection is proposed. Twenty four healthy subjects were tested in the three experiment methods. The classification accuracy about average 93.97% is obtained.

1. Introduction
Heart disease is the number one killer in the world. Every year, more than 2 million Americans die of heart disease/stroke [1-4]. Heart disease is a disorder that occurs in large blood vessel systems. So that causes the heart and blood circulation is not working properly. Heart disease is often known as Sudden Death. The high number of death caused by heart disease can be prevented and suppressed by increasing the public's knowledge of heart disease symptoms, improving the quality of equipment, medical examinations, and supported by a healthy lifestyle. Due to the large number of inpatients and increasing of the deaths, heart disease has become a special concern for the government. Cardiac arrhythmias or heart rhythm (i.e., abnormal changes in cardiac electrical activity) are a common feature of heart disease. Such abnormalities are identified from the heartbeats of too slow, too fast or even irregular. This condition can cause the heart is not able to pump the blood throughout the body well and can even result in an emergency of the heart failure. Each heartbeat will produce an electrical impulse that flows throughout the body to stimulate muscle contraction according to a particular pattern. The pattern of electrical activity of the heart or caused by the heartbeat can be measured using an electrocardiogram (ECG) which captures the time-series electrical activity of the heart. The information content present in the ECG signals can be used to identify various forms of cardiac arrhythmias. Therefore, the development and application of certain methods to classify ECG data has been of particular concern to the current researchers. With a reliable method, it is expected that built medical instruments can be used for the proper diagnosis, treatment and prevention of arrhythmias or abnormal heart conditions.
Various methods have been proposed in the past for the classification of ECG signals based on signal processing techniques such as frequency analysis [5], wavelet transforms [6-8], and band pass filters [3, 9-10], statistics [11] and heuristic approaches [12] hidden Markov model [13], supporting vector machines [2, 4, 14], artificial neural networks, and other mixed methods [15-20]. But overall each method is still not perfect, especially in the application. The problems often encountered in algorithm development are the variation of ECG signals between patients and limitations of accuracy when used to classify new patient ECG signals. This makes the method not widely used, especially for clinical, and tends to have a high degree of accuracy and efficiency for larger databases [21, 22]. To overcome these weaknesses, several methods with patient-specific designs of late have been developed [22, 23-25]. From the test results indicate that its performance has a significant increase in performance against the results of conventional classification methods. The classification method has a general approach with two main operations: feature extraction and classification of extracted features.

To minimize the deficiencies of previous methods and to improve the classification performance, an adaptive 1D convolutional neural networks (CNNs) classifier are used for ECG signal classification and its anomaly detection. The CNN consist of hierarchical neural networks with each layer of convolution alternating with a subsampling layer. The principle can be analogous to simple and complex cells in the human visual cortex. Basically the ECG signal consists of many waves, each wave representing one heartbeat (one heart electrical activity). The types of waves represent each combined segment form. In one wave the ECG signal consists of several wave points called intervals and segments. The point consists of points P, Q, R, S, and T. whereas te intervals consist of PR intervals, QRS intervals and QT intervals as well as the segments composed of PR segments, and ST segments. The applied algorithm is used to identify the intervals and segments.

2. Method
To evaluate reliability and ensure ease of operation, ECG signals from 24 subjects, aged 24 ± 3 years, were recorded. All subjects are healthy both physically and mentally. Next, each experiment is divided into two session conditions: relax (14 subjects) and type (10 subjects), respectively. Each is equipped with three channel sensors with each location relating to cardiac activity. Once completed, each electrode must be covered with an electrolyte gel to minimize the effect of noise. ECG data were collected from three Ag / AgCl electrodes embedded in a developed wireless ECG system.

The ECG signals processing methods consists of several stages including pre-processing, algorithm processing, and classification. In the preparing pre-processing the data set that used as input for processing is generated. 30 minutes length recording data with 360 Hz frequency at 48 two-channel with resolution of 11 bits per channel with a distance of 10 mV. Further process of algorithm processing is algorithm design which designed using Python programming and applied to convolutional neural network method for classification. The design of the algorithm is divided into three main parts which are generate data, skew data and run experiment while for data training optimizer used stochastic gradient descent model. The last process is classification which is the result of classification of the input and algorithm that has been designed. The output generated from this program is the accuracy of arrhythmia detection. This research method can be illustrated as in figure 1.
Classification is a process of arrhythmia grouping which is output is an average accuracy of the epoch process for each type of arrhythmia. These results will serve as an evaluation of the convolutional neural network method as a classifier. The first processing is the determination of RR-interval using Wavelet and DWT method. Then the results will be adjusted to the arrhythmia category and will be made into 1 batch file with arff format to further processed by using software WEKA.

3. Signal Processing
Band pass filter is used to reduce the effect of noise due to the muscle contraction. The design with a frequency of 60 Hz, used as an initial damping and T-wave interference. The bandpass is desirable to maximize QRS energy around 5-15 Hz that is quick and recursively applied in real-time with poles are located in z plane of the unit circles to cancel zeros. This approach results in a filter design with integer coefficients, this is because only integer arithmetic is required. The filter class that has the poles and zeroes only on the unit circle allows for limited passband design flexibility.

Convolutional neural networks use relatively less complex pre-processing, especially when performing the data labeling process and inputting input values compared to other classification algorithms. Convolutional neural network is divided into several layers: the input layer and the output layer and some hidden layers. Part of the hidden layer in this algorithm is convolutional, pooling and fully connected layer. Convolutional Layers apply convolution operations to data inputs and emulate individual neuron responses to be forwarded to the next layer. Pooling is a non-linear down-sampling whereas a fully connected layer connects each neuron in one layer to each neuron in another. This is in principle the same as the multi-layer perceptron neural network.

4. Results and Discussions
The problem encountered in the classification process of arrhythmia is feature extraction. Feature extraction is required to obtain R-R intervals from the recorded ECG signal. An applied of incorrect methods in feature extraction can lead to calculation delays in subsequent processes. If the extracted feature is not appropriate then it could be serious, where the result represent someone who has no arrhythmia (normal) detected as an arrhythmia (abnormal). Another problem is over fitting data, where the results will show good accuracy but when the data is applied to the real data then the result become less accurate.

At the time of testing the data is divided into two parts, namely 80% as a training file and 20% as a test file. By converting 2-dimensional convolution to 1-dimensional convolution as a representation of convolutional neural network algorithm, the program runs self learning to get the processing results that have been designed on the previous algorithm. The main provision in this process is that the epoch process will be done as much as 1500 times. During training, the selected learning rate and lamda were 0.01 and 0.9 with convolotional layers of 300 (using a batch stochastic gradient with batch size 256). The process is done with cross validation 4 times to avoid over fitting data. The output obtained from the algorithm is the final result of the signal processing. Cross entropy is used for loss function testing and regularization, where the regularized coefficient value is λ. Initial test showed that
choosing $\lambda$ with value more than 0.01 gave as significant performance degradation. Therefore, the uniform distance value test in the range of $[0,0.01]$ (0.0, 0.001, 0.002, ..., 0.01) is done. The obtained results with an average accuracy of 99.15% against the $\lambda$ test with a value of 0.01 as shown in figure 2 are achieved.

The classification result of WEKA software using convolutional neural network method is obtained as in figure 3. From figure 3 it can be explained that the confusion matrix obtained from each class is as follows: For class B arrhythmia detected 10 as class B and 1 as class T so that TP rate of 0.909; for N class arrhythmia detected 254 as N so TP rate of 1,000; for class T detected 1 as class T and 7 as class B and 4 as class N so TP rate of 0.083; and for the VT class is not detected at all. The results are obtained based on the classification process using WEKA program and convolution neural network as classifier.

In the analysis results into two experiments sheme that are in relaxed and typed conditions there are some differences in the results of QRS detection by applying the Pan-Tompkins algorithm. The difference occurs due to the activities of each groups such that affecting the detection value of desired QRS waves. The results are represented in the form of tables with outputs categorized based on the variables required for subsequent calculations. The required variables are as follows: True Positive (TP) ie the exact number of peaks which detected as a peak; True Negative (TN) ie the number of peaks that are not peaks and detected as non peak; False Positive (FP) ie the number of detected peaks as a peak but not peak; False Negative (FN) is the number of peaks that are not detected as peak but peak. As shown in table 1(relaxed) and table 2 (Typed), the average accuracy, sensitivity, and positive predictivity are 98%, 98%, 100% and 59%, 64% and 86%, respectively.

Figures 4 and 5 shows the results on each of the QRS detection stages using Pan-Tompkins algorithm for each experimental group. In the QRS detection, the length of the used raw data is about 2 minutes with the results as shown in figures 4(a) and 5(a). The upper part is the raw data, the second row is the filtered signals using bandpass and derivative filters, respectively, the third row is the average windowing and QRS detection which is characterized by red round point, respectively. The zooming results of figures 4(a) and 5(a) are shown as in figures 4(b) and 5(b) for each group which are the detected QRS are clearly shown.

Figure 2. Algorithm training test with Pyton.
Figure 3. Classification results with WEKA CNN algorithm.

Table 1. Relax condition: the QRS Detection using Pan-Tompkins algorithm for the average accuracy, sensitivity, and positive predictivity.

| NO | File | Original Peak | Detected peak | Undetected Peak | Non Peak | TN | TP | FN | FP | Accuracy (%) | Sensitivity (%) | PP (%) |
|----|------|---------------|---------------|----------------|----------|----|----|----|----|--------------|----------------|--------|
| 1  | 14.07.57 | 169            | 169           | 0              | 0        | 0  | 169| 0  | 0  | 100%         | 100%           | 100%   |
| 2  | 09.51.19 | 175            | 167           | 0              | 0        | 0  | 167| 0  | 0  | 100%         | 100%           | 100%   |
| 3  | 09.57.37 | 156            | 156           | 0              | 0        | 0  | 156| 0  | 0  | 100%         | 100%           | 100%   |
| 4  | 10.04.55 | 156            | 150           | 10             | 9        | 0  | 141| 0  | 9  | 88%          | 93%            | 94%    |
| 5  | 10.09.29 | 150            | 149           | 0              | 0        | 0  | 149| 0  | 0  | 100%         | 99%            | 100%   |
| 6  | 13.20.22 | 189            | 189           | 0              | 0        | 0  | 189| 0  | 0  | 100%         | 100%           | 100%   |
| 7  | 13.23.41 | 192            | 190           | 2              | 0        | 190| 2  | 0  | 2  | 99%          | 99%            | 99%    |
| 8  | 13.27.21 | 176            | 176           | 0              | 0        | 0  | 176| 0  | 0  | 100%         | 100%           | 100%   |
| 9  | 13.31.31 | 166            | 166           | 0              | 0        | 0  | 166| 0  | 0  | 100%         | 100%           | 100%   |
| 10 | 13.49.42 | 223            | 220           | 3              | 0        | 220| 3  | 0  | 3  | 99%          | 99%            | 99%    |
| 11 | 13.56.54 | 169            | 169           | 0              | 0        | 0  | 169| 0  | 0  | 100%         | 100%           | 100%   |
| 12 | 14.01.00 | 174            | 163           | 14             | 0        | 163| 14 | 0  | 14 | 92%          | 94%            | 94%    |
| 13 | 14.03.47 | 221            | 211           | 10             | 1        | 211| 10 | 1  | 1  | 95%          | 95%            | 95%    |
| 14 | 16.06.17 | 151            | 151           | 0              | 0        | 0  | 151| 0  | 0  | 100%         | 100%           | 100%   |
| 15 | Total    | 2467           | 2426          | 39             | 10       | 0  | 2417| 39 | 10 | 98%          | 98%            | 100%   |

Table 2. Typing condition: the QRS Detection using Pan-Tompkins algorithm for the average accuracy, sensitivity, and positive predictivity.

| NO | File | Original Peak | Detected peak | Undetected Peak | Non Peak | TN | TP | FN | FP | Accuracy (%) | Sensitivity (%) | PP (%) |
|----|------|---------------|---------------|----------------|----------|----|----|----|----|--------------|----------------|--------|
| 1  | Data 1 | 168           | 28            | 140           | 0        | 0  | 28 | 148| 0  | 100%         | 66%            | 93%    |
| 2  | Data 2 | 176           | 117           | 50            | 9        | 0  | 117| 50 | 9  | 100%         | 96%            | 93%    |
| 3  | Data 3 | 206           | 209           | 6             | 0        | 0  | 209| 6  | 0  | 100%         | 97%            | 100%   |
| 4  | Data 4 | 178           | 174           | 110           | 106      | 0  | 68 | 110| 106| 88%          | 38%            | 39%    |
| 5  | Data 5 | 198           | 186           | 22            | 10       | 0  | 176| 22 | 10 | 100%         | 89%            | 95%    |
| 6  | Data 6 | 187           | 172           | 29            | 14       | 0  | 158| 29 | 14 | 100%         | 84%            | 92%    |
| 7  | Data 7 | 214           | 191           | 67            | 44       | 0  | 147| 67 | 44 | 99%          | 69%            | 77%    |
| 8  | Data 8 | 165           | 157           | 14            | 6        | 0  | 151| 14 | 6  | 100%         | 92%            | 96%    |
| 9  | Data 9 | 202           | 113           | 110           | 21       | 0  | 92 | 110| 21 | 100%         | 46%            | 81%    |
| 10 | Data 10| 172           | 80            | 107           | 8        | 0  | 82 | 107| 8  | 100%         | 99%            | 91%    |
| Total | 1866       | 1428          | 655           | 218          | 0        | 0  | 1219| 663| 218| 98%          | 64%            | 86%    |
5. Conclusions
A wireless monitoring of the heart activities is developed. An application of convolutional neural network classifier for arrhythmia detection is proposed. Twenty four health subjects were tested in the two experiment methods. The average accuracy, sensitivity, and positive predictivity are 98%, 98%, 100% (for relax subjects) and 59%, 64% and 86% (for typing subjects), respectively. The arrhythmia classification accuracy of 93.97% with misclassification of 6,028 using weka algorithm based convolutional neural network classifier is obtained.

Acknowledgment
This research was supported by the Technical Implementation Unit for Instrumentation Development, Indonesian Institute of Sciences and, Insentif Riset Sistem Inovasi Nasional (INSINAS), Kementerian Riset, Teknologi, dan Pendidikan Tinggi (Ristekdikti), Indonesia.

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