

Implementation of mobile health monitoring system with ECG signal classification for arrhythmia detection

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Abstract

Cardiovascular disease is one of the leading chronic disease and has contributed to the increase in hospitalization cost in many country including Malaysia. The patient of heart disease require a continuous monitoring and close attention to their vital sign even after discharge from the hospital. In this work, we proposed a mobile health monitoring system for ECG signal classification to detect cardiac arrhythmia. Specifically, we use the Convolutional Neural Network (CNN) for classification of the signal which is to be implemented in mobile application. The ECG device transmit signal data via a Bluetooth communication to the mobile phone and the patient should be alerted for any abnormal sign. The result of this project should help the patient in monitoring their heart condition with better accuracy and help doctors to manage their patient. The result of this study is expected to produce and accurate prediction to detect Arrhythmia.

Keywords: Electrocardiogram, Classification, Arrhythmia, Heart disease

1. Introduction

Heart disease is one of the major cause of death and remain the leading chronic disease globally. Since the case of hospitalized heart failure and mortality is increasing, it has become a global issue that had imposed a huge economic burden to the health care and the government. Arrhythmia or the unusual rhythm of the heart is one of the common type of heart disease. This occur when there is any changes from the normal sequence of electrical activity of the heart. The heartbeat can be too slow, too fast or irregular that may cause the heart not able to pump blood properly and could result in a medical emergency condition called cardiac arrest. In each heart beats, an electrical impulse is generated by the heart constantly and travel through electrical pathway that eventually stimulate the heart muscle to contract in a certain pattern. These electrical activity pattern that occur in the heart can be measured using Electrocardiogram (ECG) which captures the time-series electrical activity of the heart. The information that present in the ECG data can be used to identify various form of cardiac arrhythmia. Therefore, the use of methods that classify the ECG data can be very important in the proper diagnostic, treatment and prevention of arrhythmia or abnormal heart condition.

2. Previous work

Detection of Bundle Branch Block (BBB) was proposed by Kumari & Kumar (2013) using an improved Multi-Layer Perceptron Neural Network (MLP NN) based on modular neural network. The proposed model was to classify three different class of instances which are Right bunch bundle block, Left bunch bundle block, and Normal RR interval.

The ECG feature that was selected for classifying arrhythmia is RR interval which was extracted using Continuous Wavelet Transform (CWT) and Symlets filters. Symmetric uncertainty technique was used for feature reduction. The ECG data were from the MIT-BIH arrhythmia database consists of 165 instances where 55 events were from each class. The classification process was done with 25 selected features. The performance of the classifier was evaluated based on four measure which achieved result is accuracy 95%, precision 95.1%, recall 95.1% and RMSE 0.1765.

Oussama, Saadi, & Zine-Eddine [2] have proposed an automatic supervised classification of heartbeat using Multi-Layered Perceptron Neural Network (MLPNN). The combination of respiratory signal and ECG signal that were recorded simultaneously has been used for the classification of heart beat into normal and abnormal class. Evaluation of the algorithm was done using ECG-respiratory signal obtained from MIT Physionet Apnea-ECG database which consists of 70 ECG recordings sampled at 100Hz with varying length from 7-10 hours. The pre-processing was done using high-pass filter and signal empirical mode decomposition to delineate the ECG wave, QRS onset, T wave and P wave definition. For the respiratory signal, the position of RQ and RS was detected based on the projection of Q and S point on the respiratory signal. Since the classification process consider both temporal and energy as the feature, energy was measured for both QRS complex and the respiratory signal. Then, feature vector was extracted from each of the ECG heartbeat which result in a total of 11 features (1). Vectors $X_1 - X_{11}$ were concatenated and result in only on vector X as the classifier input. The Principal Component Analysis (PCA) was used to reduce the size of the vector $[X]$. The result of the classifier achieved accuracy of 97.57%.

Table 1: Feature extracted with the assigned vector from ECG and respiratory signal [2]

| Designations | Description | Assigned vectors |
|--------------------------|---|------------------|
| R-R interval duration | Interval between two successive QRS | X_1 |
| Q-R interval duration | Interval between R peak and the beginning of QRS complex | X_2 |
| RS interval duration | Interval between the end of QRS complex and the peak R | X_3 |
| QRS complex duration | Interval between the end and the beginning of the QRS complex | X_4 |
| RR_S interval duration | Interval between the current R peak and the following R peak | X_5 |
| RR ratio | $RR_{ratio} = RR_S/RR_p$ | X_6 |
| E_{QRS} | Energy of QRS complex | X_7 |
| QT interval duration | Interval between T-end and the beginning of QRS complex | X_8 |
| ST segment duration | Interval between the beginning of T wave and the end of QRS complex | X_9 |
| ST interval duration | Interval between T-end and the end of QRS complex | X_{10} |
| ER_{QRS} | Energy of respiratory signal | X_{11} |

Although the previous approach produces a good result, they have not perform well in practice because they have not taken into account the inter-patient variation of the ECG signal when designing the classifier. In other words, the ECG data that were used to model the classifier has not been carefully separated that the data for the same patient is likely to appear in both the training and testing phase. This condition can result in a bias of the classification result and may not represent the realistic prediction of the ECG data. Therefore this open a new paradigm and challenge in ECG classification research.

Oresko et al. [3] has proposed a wearable Smartphone-based real-time cardiovascular disease detection via ECG processing. The approach consists of ECG signal pre-processing using Pan-Tompkins algorithm to detect and extract the QRS waveform. The classification method is performed using the Adaptive Artificial Neural Network (ANN)

based algorithm and has been implemented in an HTC Microsoft Windows Mobile 6 Smartphone using LabVIEW mobile module. The algorithm was initially trained using the MIT ECG database and retrained based on real ECG recording acquired using Alive Bluetooth ECG heart monitor. The overall accuracy of the proposed methods in average is 93.32%. This approach was modelled based on individual patient ECG waveform which is important in addressing the inter-patient variations of the ECG classification.

A patient-specific ECG classification approach that combine the two major process of ECG classification which is the feature extraction and feature classification into a single process has been proposed by [4]. This approach perform very well that the normal process of manual feature extraction and other pre- and post-processing is not required. The model was based on adaptive 1 Dimensional Convolutional Neural Network (1D CNN). The proposed model was adapted from the traditional 2D CNN with a small modification and the aim was to model simple CNN with only 3 hidden layers and easy to train. The 1D CNN was able to classify raw data of heart beats in any sampling rate directly. There were only few dozens of Back Propagation (BP) epochs was required for the training. The 1D CNN demonstrated a superior classification performance and processing speed with just few hundreds of 1D Convolutions.

3. Methods

Database used

In order to model the classifier, an existing database is needed. The MIT-BIH Arrhythmia database is the popular database that has been extensively used in the literature. Moreover the guideline of using such database for medical research has been recommended by the Association for the Advancement of Medical Instrumentation (AAMI) [5].



Figure 1: System architecture

System Architecture

The proposed system will be to implement a mobile application for classification of ECG signal. The system is intended to be used by mobile patient who wearing the ECG capturing device and transmit the ECG signal to the mobile application via Bluetooth communication (see Figure 1). Bluetooth is used because a mobile phone is usually placed in a close proximity with the patient where transmission range higher than the Bluetooth range is not necessary. We adapted the method proposed by [4], the 1-D Convolutional Neural Network (CNN) to implemented the working application in a mobile phone.

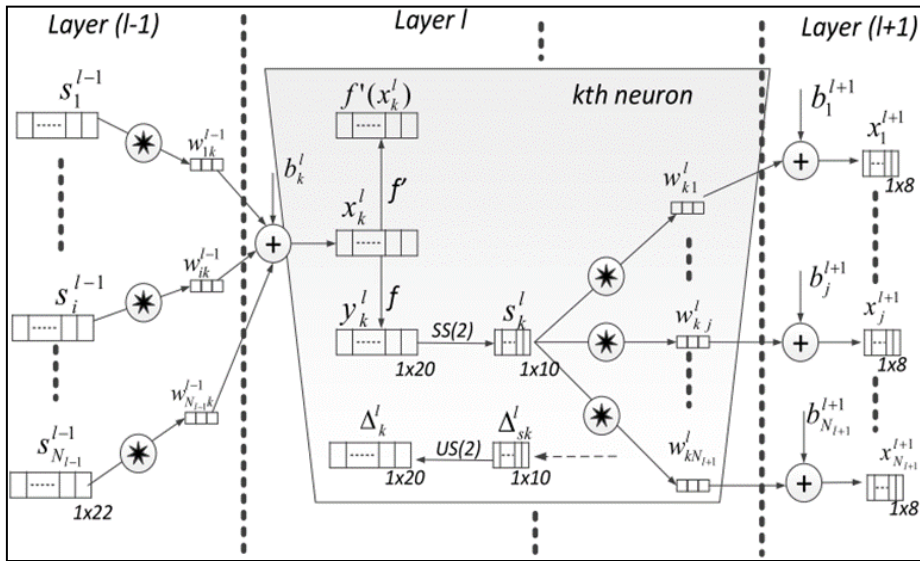


Figure 2: 1-D Convolutional Neural Network (CNN) [6]

4. Expected Result

The result of this project should help the patient in monitoring their heart condition with better accuracy and help doctors to manage their patient. The result of this study is expected to produce an accurate prediction to detect Arrhythmia.

5. Conclusion

In conclusion, a method for monitoring cardiac arrhythmia is needed to manage patient efficiently. The current work aims to implement a system to classify ECG signal and detect arrhythmia based on CNN algorithm. The performance of the method will be compared with the previous method to evaluate the accuracy. With the implementation of this mobile health monitoring system, heart disease patients should be able to monitor their vital signs at home. This would benefit the hospital in reducing the time of patient in ward as they are able to continuously monitor their heart condition without staying in the hospital.

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