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IOT Based ECG Monitoring System for Post-Operative Heart Disease Patients

Charu Gandhi[1*] Pratibha Luthr[1], Nikhil Kandwal[1], Nimit Garg[1]
[1] Department of CSE, Jaypee Institute of Information Technology, Noida, U.P. India
* Correspondence: pluthra97@gmail.com

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Abstract: In this paper we are proposing a model based on IoT wearable devices which can be used to detect the risk of heart attack in patients suffered from heart stroke. We have applied Support Vector Machine (SVM) machine learning algorithm on the ECG dataset from MIT-BIH and evaluate the accuracy of the model since the accuracy is not so good for this kind of case so, we approach to CNN model, in CNN we go with the 2D CNN so that we get the maximum features from ECG signals because many features lost during the time of noise filtration process. On comparing the accuracy of CNN model with SVM model we found that the accuracy of CNN model is far much better than SVM model.

Keywords: Support Vector Machine; CNN model; ECG dataset; MIT-BIH.

1. Introduction

Today, the modern era is advancing in technology but also brings enormous health risks along with it such as cardiovascular diseases (CVDs). According to the World Health Organization (WHO), cardiovascular diseases (CVDs) are the number one cause of death today. Over 17.7 million people died from CVDs which is about 31% of all deaths, and over 75% of these deaths occur in low- and middle-income countries. Abnormalities in heartbeat under critical circumstances, popularly known as arrhythmia, can be life-threatening and it requires immediate care. Nevertheless, most of the arrhythmias are harmless but even then, they may require critical care to prevent further health issues. A wrong diagnosis may risk a person's life.

Arrhythmias are of various types and its every type is associated with some kind of pattern. The arrhythmia can be classified into two main classes. The first one is associated with the arrhythmia formed by a single irregular heartbeat, called morphological arrhythmia. The other class of arrhythmia formed by the set of irregular heartbeats called, rhythmic arrhythmia. These heartbeats produce abnormalities in the morphology or wave frequency, and all of these abnormalities can be identified by the ECG analysis.

The process of identifying and classifying arrhythmia can be troublesome for a human being because, in the process of ECG analysis, we have to analyse each heartbeat of the ECG records acquired by the Holter monitor for instances, during hours, or even days. In the analysis, there is the possibility of human error which can be life-threatening. An alternative is to use computational techniques for automatic classification.

Early heart attack prediction in patients can be very useful in today's world. We see a lot of people die due to inability to get treated on time. But, by developing a model where person can be alerted beforehand in case of a near heart attack situation he/she can call an ambulance on time for the rescue. There are a variety of studies done before on this.[1] A prediction system based on Artificial Neural Networks and Naïve Bayes to predict the possibility of a heart disease and medication is provided accordingly. The author used a Body area network of sensors to get data from the patient and then pushed the data to the doctor via a Zigbee connection. [3] FC Chang et al. very briefly analysed variations of HRV analysis in different approaches. We can get a huge understanding of PPI, RRI and PPG signals from this which helped us in concluding That PPG signals will be most efficient to use for acquiring patient's data.[5] This gives us a widespread knowledge about Support Vector Machine algorithm and its benefits as a data mining algorithm in case of arrhythmia. In, this clinical data of hypertensive patients followed up for at least 12 months were collected ad hoc. Subjects who experienced a vascular event (i.e., myocardial infarction, stroke, syncopal event) were considered as high-risk subjects. They finally concluded that The HRV based classifier showed higher predictive values than the conventional echo graphic parameters, which are considered as significant cardiovascular risk factors.

SVM algorithm surely provided us with some good results but we faced a problem of noise in the ECG wavelets of arrhythmia patients. This made us compromise, but we can't compromise with a patient's life so it will be better if we can remove the noise. [6]Gler, Beyl ED et al gave us a perspective that combined neural networks might be a solution. They, decomposed the ECG signals into time-frequency distribution using discrete wavelet transformation and some statistical features were calculated to depict their distribution. We then focused on doing the same using [9] Convolutional Neural Networks and converted the wavelets into 2-D greyscale images. We have transformed ECG signals into ECG images by plotting each ECG beat. in case of 2-D images noise filtering and feature extraction is no longer required. 2D convolutional and pooling layers are more suitable for filtering the spatial locality of the ECG images. Data augmentation has been done using images as input data. When CNN is used as the classifier, data augmentation can effectively reduce over fitting and maintain a balanced distribution between classes. As a result, higher ECG arrhythmia classification accuracy can be obtained.

Several methods have presented in the literature survey section. We first came across a research paper in which Artificial Neural Networks and Naïve Bayes is used to predict the possibility of a heart disease and medication provided accordingly. They used a Boly area network of sensors to get data from the patient and then pushed the data to the doctor via a Zigbee connection. The components used by them are Lm35 temperature sensor, ECG sensor, Heartbeat sensor. They have used Arduino Uno which is a microcontroller connected to a power supply (PC), an electric buzzer to alert the care taker during extreme conditions, Bluetooth controller to establish a connection between MCU, PC to embedded project. They have used Glass Fish Server to host we service and SOAP API to be able to call we service at client side. They mainly intended to develop user-friendly system, that focused mainly on neural networks and Naive Bayes classification approach to solve a problem of prediction of heart disease in which the ANN approach overtook the Naive Bayes approach in terms of accuracy by having accuracy of 86% respectively even though we have reduction in attributes. The predictive power of ANN classification is also much advanced than Naive Bayes classification in terms of performance measures evaluated. This approach gave us a widespread knowledge about the whole procedure. But we were still not aware about the complications so we further studied about a a predictive model to develop a model to predict Atrial Fibrillation in different racial backgrounds. Also, several complications relating to atrial fibrillation are also predicted. The author of this research paper, goes beyond the clinical variables to racial and background factors such as genetics. They also proposed that although imperfect, available risk values may play a role in the identification of individuals who are more likely to develop AF. AF is responsible for a large share of the strokes, and the first clinical expression of AF in a number of cases is stroke. This research paper provided us a broader aspect of the problem. Then we have to study about HRV analysis and its variations. FC Chang et al. [3] author analyses the normal-to-normal interval from a continuous ECG (R-R interval) and also the data on the pumping action of the heart which is derived from a PPG (Peak to peak interval). To avoid distortion in the signals he passed them through DC-35Hz FIR filter then analysed it using HRV. The aim of the author is to check the variations of HRV obtained by these two methods. It was concluded that there is little difference between the RRI and PPI sequence and the prevalence of PPG interference was also reported due to the contact pressure of the PPG sensor and the relative movement during the measurement.

Therefore, we further proceeded with PPG signals as they were produced by most of the IoT wearable devices. Then we further moved on to the ECG classification. We have the data from MIT-BIH and it comprises of ECG wavelets of patients recorded for 12 minutes. There are many methods for the ECG classification, support vector machine (SVM) is one of them, and it is a widely applied experimental model for ECG arrhythmia classification. We came across a paper which applied this model. The ECG automatic classification method, which is based upon the time intervals between the subsequent beats and the morphological traits for ECG characterizations, was introduced by Eduardo José da S. Luz [2], with a Single SVM classification model. Various descriptors were used based on wavelets, local binary patterns and higher order statistics and several amplitude values, all of which were fed to a single SVM model, and the results were then computed according to the trained model. This was a fair approach but it also has some drawbacks. The MIT-BIH database is extremely unbalanced. However, authors ignored this and used intra-patient scheme. But if we follow a more realistic approach and don't mix heartbeats for training and testing, we will face a great difficulty in getting good results. Although a number of the literatures have proposed certain limits, they either have good ECG recording performance without cross validation, or ECG beat loss during noise filtering and extraction processes or the limited number of ECG arrhythmia classifications. Then we further continued our research in this direction. Then we came across such a research paper, Gler, Beyl ED et all [6] using combined neural network model to guide model selection for classification of ECG beats. Using discrete wavelet transformation, the ECG signals were decomposed into time frequency distribution and statistical characteristics were calculated to represent their distribution. Four types of ECG beats were obtained by the training of the model. They concluded that the combined neural network model achieved accuracy rates which were higher than that of the stand-alone neural network model. This further helped us in understanding use of Deep learning algorithms to overcome the problem of noise and filtration in database. Jun TJ et all proposed deep neural networks for the classification of premature ventricular contraction beat, which is an asymmetrical heartbeat. Multiple methods of machine learning for detecting PVC beats were proposed though they were low in precision. They evaluated on TensorFlow (an open source machine learning platform). We also researched about how to overcome the problem of large-scale image recognition for very deep convolutional networks. In the largescale image recognition setting, Simonyan et all studied how the CN depth affects its accuracy. Their work was mainly involved in the thorough evaluation of networks of increasing depth with very small convolution filters. They have made their two ConvNet models available to the public to support further research into the use of visual depth in computer vision. Then we implemented the work done by Jun, Nguyen et all [9] using CNN classifier on MIT-BIH database after converting the ECG wavelets into 2-D greyscale images. We have transformed ECG signals into ECG images by plotting each ECG beat. We first detected the R-peaks in ECG signals using Biosppy module of Python. Once the R-peaks have been found, to fragment a beat, we take the present R-peak and the last R-peak, took half of the distance between the two and included those signals in the present beat. Similarly, we did this for the next beat wavelet. By this we have convert the 1-D images of wavelets into 2-D because in case of 2-D images, the issue of noise filtering and feature extraction is not there. 2D convolutional and pooling layers are more appropriate for filtering the spatial section of the ECG images. Data augmentation has been done by feeding images which are converted into 2-D as input data for the classifier. Most previous ECG arrhythmia research could not physically add modified data to augment the training set as one biased ECG value could reduce the test set's performance. The reason for this is that, contrary to CNN, each ECG signal value is classified equally by other classifiers like SVM and a Tree-based algorithm. Our CNN model uses 2-D ECG image input data, however, changing the image with cropping and resizing does not reduce performance but increases the training data set. As a result, higher classification accuracy can be achieved.

2. Materials and Methods

2.1. System Architecture

This section describes the architecture of an IoT based health care system which monitors our cardiovascular health and predicts health risks based on the collected data. The system has following components: Sensors, android/iOS application, NodeMcu, patient's database, cloud server.

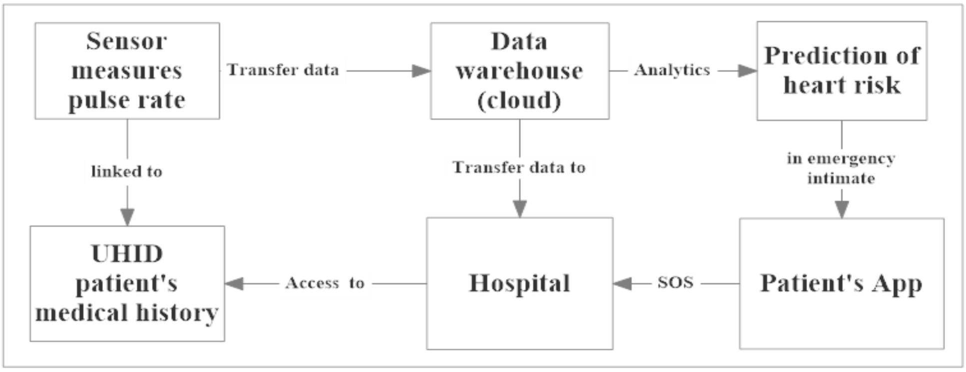

Figure 1. The proposed system.

2.2. System Analysis

This health monitoring system is designed for post operated cardiovascular disease. The system has ECG sensor and heart beat sensor, data will be collected through these sensors and then data will be transferred to the cloud. At cloud further processing will be done, we are using CNN based model for prediction. If there is any anomaly in the heartbeat of patient then an alert will be generated. In case of emergency one emergency alert will be sent to the nearby hospital and other alert will be sent to their family members.

2.2.1. Experimental Setup

ECG sensor- Heart rate monitor AD8232 and heartbeat sensor are connected to NodeMcu. Leads of ECG sensor and pulse sensor are connected to the body of the user. These sensors collect the data periodically or when initiated by the user and then that collected data will be transferred to the cloud server using NodeMcu. At cloud that data will be stored for further processing. Since this setup is also connected to the hospitals, so the doctors can evaluate their patient's data. At cloud our model will start doing computation on the received data and after computation calculated data will be updated in the user's mobile application. Every patient data linked to UHID so that in case of emergency a doctor can access patient's medical history more easily and quickly.

2.2.2. Data Source

The well-known Massachusetts Institute of Technology-Berth Israel Hospital (MIT-BIH) arrhythmia database was employed to train and test our classification model.

This database contains 48 ECG records of about 30 min, sample data of 360 Hz with 11-bit resolution from 47 different patients. Each record comprises two signals, the first one is, for all 18 the records, the modified-lead II (MLII), whereas the second one corresponds to V1, V2, V4, or V5, depending on the record. Therefore, only the MLII is provided by all the records. The database contains approximately 110,000 beats, all of them were independently annotated by two or more expert cardiologists and the disagreements were resolved. Following the Association for the Advancement of Medical Instrumentation AAMI recommended practice, the MIT-BIH heartbeat types are grouped into five heartbeat classes as shown in Table 1.

Table 1. Five heartbeat classes

AAMI	MIT-BIH
Normal (N)	N, L, R
Supraventricular ectopic beat (SVEB)	e, j, A, a, J, S
Ventricular ectopic beat (VEB)	V, E
Fusion (F)	F
Unknown beat (Q)	/, f, Q

2.2.3. Algorithm Applied

By coming across various research papers initially, it was concluded that SVM classifier model would be more applicable to start the research. The SVM model applied on MIT-BIH dataset is described below:

SVMs are maximum edge classifiers that map input vectors to a higher dimensional space where a maximal isolating hyper plane is built to separate two diverse classes. The principle disadvantage of SVMs is their confinement to twofold order issues. In the literature section, there are two basic choices to fathom that, in particular one against all (OAA) and one against one (OAO). Being N the quantity of classes, in the main option NSVM models are built, i.e., one for every class; though in the second option a SVM is developed between each pair of classes, resulting in N (N − 1)/2 models. At long last, a voting framework is required for the two options so as to get a final conclusion. In this work, the OAO approach was utilized, since it is increasingly reasonable to work with imbalanced information and requires less time for preparing than OAA when the quantity of tests is altogether substantial.

The first step in the process is the pre-processing step in which noise from the data was removed and then sampled the filtered data to convert the analog signal into a digital signal. Since SVM is a feature-rich classifier so, the next step is to extract the features from the data. Feature extraction is the key to success in the heartbeat classification. After the feature extraction step, the SVM model gets trained using the dataset. Now the model is ready for heartbeat classification for arrhythmia.

During the noise filtration process, most of the important beats are getting ignored that can vary the results and error rate should be very less for heartbeat classification so, the new model is approached. The model is Known as Convolution Neural Network in 2D (CNN-2D). The main advantage of this model in heartbeat classification is that this model does not use the feature extraction process so, the noise filtration is not required anymore.

In the process of model designing, the first step is ECG data pre-processing in which analog data transforms into 2D 128 X 128 grey image as a single beat. In the raw database, every wave is divided based on Q-wave peak time. In particular, each individually designated beat is marked at the Q-wave peak times. Hence, we have labelled the Q-wave peak signal to centre a single ECG beat plot, with the previous and the upcoming 20 signals excluded. The next step is the beat annotation process in which Six different classes of arrhythmia is defined. After the beat annotation step, the most important step here comes in i.e., Data Augmentation. In data augmentation step the six ECG arrhythmia beats with nine cropping methods: left top, centre top, right top, centre left, centre, centre right, left bottom, centre bottom, and right bottom. Each cropping method results in two of three sizes of an ECG image, i.e., 96 x 96 pixel and then, these augmented images are resized to the original size which is 128 x 128 pixel. It’s time to train the model for that keras sequential model is going to be used which is based on TensorFlow library. For ECG classification eleven-layer model is used in which output of one layer has been treated as input for another layer. Now the model is ready for classification.

3. Results and discussion

After the successfull deployment of CNN 2D model, its time to deploy it on the cloud server so that data can be monitored in real time. To deploy this model as a web app, flask framework has been used. After designing web app, the whole model is loaded as a docker image to the gcloud server. After successfull deployment the model is ready to serve. Data collected from AD8232 ecg sensor send to the cloud server through nodemcu module, on cloud further computation will be done and result will be generated.

4. Conclusions

The project initiated with applying SVM on the public MIT-BIH database. The accuracy of the SVM is 80-83%. But there were some irregularities with the database which made it difficult to carry on with SVM. Therefore, Convolutional Neural Networks is used for this purpose. For this, 1-D wavelets of ECG Dataset were converted into 2-D greyscale images. Then data is augmented so as to increase the accuracy of the prediction. By this, the accuracy of prediction is 91-93%.

Further, dataset was uploaded on the cloud and used on a web app designed to predict the possibility of a patient suffering through another heart attack.

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