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ECG Signal Classification Using Deep Learning

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***Abstract*: Heart arrhythmia is an irregular state of heart. This problem occurs when the electrical signals that coordinate the heart's beats don't work properly. Electrocardiography (ECG) is used to check the electrical activity and your heart rhythms. It records the electrical activities of the heart of a patient using electrodes attached to the skin. Electrodes are taped to the chest to record the heart's electrical signals, which cause the heart to beat. The signals are shown as waves on an attached computer monitor or printer. An electrocardiogram records the electrical signals in your heart. ECG signals reflect the physiological conditions of the heart, medical doctors use ECG signals to diagnose heart's normal and abnormal condition i.e., heart arrhythmia. Medical professionals use their most important skill of identifying the dangerous types of heart arrhythmia from ECG signals. However, ECG waveforms performed by professional medical doctor manually is tedious and time- consuming. As a result, the development of automatic techniques for identifying abnormal conditions from daily recorded ECG data is of fundamental importance. Moreover, timely first-aid measures can be effectively applied if such abnormal heart conditions can be detected automatically using health monitoring equipment which internally uses machine learning algorithms. Thus, machine learning will play an important role in this regard.**

***Keywords*: Electrocardiography (ECG), heart arrhythmia, CNN, machine learning algorithms.**

1. Introduction

Heart arrhythmia is a common symptom of heart diseases. There are different types of heart arrhythmia such as ventricular fibrillation, premature ventricular beats (PVCs), atrial fibrillation, ventricular escape and ventricular fibrillation. The rhythm of a heartbeat is controlled by an electrical impulse generated in the senatorial node. An arrhythmia beats occurs when electrical signals who coordinates heart beat don't work properly. Faulty signals cause heart to beat fast or too slow or irregular. There are different ECG patterns of arrhythmias. The arrhythmias such as ventricular as well as atrial fibrillations and flutters are life-threatening and may lead to stroke or sudden cardiac death. There are possibilities of arrhythmic beats for a patient who had previously suffered from a heart attack and also further the high risks of dangerous heart rhythms. Heart disease is the leading cause of death across the world in both urban and rural areas. The most common type of heart disease is a coronary heart disease, which results in killing nearly 380,000 people annually.

Simple time domain features-based technologies for identification of arrhythmia disease itself cannot provide good discrimination among normal and abnormal type. These difficulties can be solved by using proper machine learning techniques for an intelligent diagnosis system. Here we have compared the different techniques of machine learning and deep learning algorithms for classification of ECG signals.

2. Literature Review

In this study [1], ECG signals Multilayer perceptron and Support Vector Machine (SVM) classifiers were used because the SVM and MLP classifiers gave the most successful results during classification.

calculation time is the most important for feature extraction and classification operations. The performance of the classifiers is calculated by considering the time and other performance criteria. The work of this study was to apply some waves transformation techniques such as DCT, CWT, DWT to ECG signals in order to improve the classification performance by these wave transformations.

In [2] this study, the goal was to contribute to the diagnosis of ECG classification by introducing a new feature called amplitude difference to heart classification based on two processes:

1) Feature extraction and heartbeat detection; 2) To classify heartbeats by their features random forest classifier is used. Extensive experiments investigating the effects of adding a new feature in ECG classification using the MIT-BIH heartbeat database show that considering an amplitude difference feature can improve the performance of ECG classification by reducing false-positive and false-negative rates.

This [3] paper is concerned, Deep Neural Network (DNN) is implemented for this classification. It's clearly shows that the patient is suffering from arrhythmia or sinus rhythm and the results obtained shows that the DNN has the highest accuracy. The sensitivity, accuracy, specificity and error rate of the classifier are mentioned in the experimental result. 94% of accuracy is acquired from the DNN classifier, making it more accurate than the existing system.

The system proposed in [4] paper is concerned on the classification arrhythmia, here higher-order neural unit (HONU) is used i.e., a QNU, with error Backpropagation in Batch optimization by Levenberg-Marquardt technique. The

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goal of the paper is to present a method that uses the classifier to aid the physicians in the recognition of ECG arrhythmias, and to evaluate the performance of the QNU for ECG classification.

The [5] this paper has encouraged us do research that consists of differentiate between several arrhythmias by using deep neural network algorithms such as convolution neural network (CNN) and multi-layer perceptron (MLP). The ECG databases accessible at PhysioBank.com and kaggle.com. These were used for testing, training and validation of them CNN and MLP algorithms. The proposed algorithm in this paper consists of four different hidden layers with biases, weights in MLP. It also includes a four-layer convolution neural network which is used to map ECG samples to the different classes of arrhythmia.

In this paper [6] a different technique is introduced which is a coarse-to-fine ECG classification techniques that can be used for efficient processing of large Electrocardiogram (ECG) records. By quantizing the number of beats as well as by reducing size of the beats using Multi-Section Vector Quantization, this technique reduces time-complexity of ECG classification without compromising accuracy of the classification.

In [7], different neural networks are used in order to determine their accuracy in identification and separation of categories or classes. Among all neural networks Feed Forward back propagation has been chosen for classification. A proper balanced input is used for training the network, taking same number of patterns from each class. This trained network is then used for classification of a completely different dataset.

3. Proposed System

A. Problem Definition

ECG signals generally contain effects of noise and random fluctuations and they are extremely random in nature.

Smoothing out the effects of noise and fluctuations prior to feature extraction is challenging. Feature values play a decisive role in further classification of different ECG cases so they need to be critically computed. Due to the above reasons, serious challenge for ECG signals is to obtain a high value of sensitivity and accuracy.

B. System Architecture

The system architecture of this ECG signal classification system is as shown in figure. Raw ECG signal will be the input to the system. This raw signal contains noise. So, we need to preprocess the raw data ECG signal which will removes this noise. Three different denoising techniques which can be used are moving average filter, median filter and notch filter. After feature extraction then the next step is to filter ECG signal. Total nine features are extracted for each beat using discrete wavelet transform, namely area under QRS complex, R normal, R point location, RS, RR points, duration of QR, R peak, area under autocorrelation and SVD of ECG. Different techniques i.e., FFT, DWT and CWT etc. will be used for the extraction of different features from the denoised ECG signal.

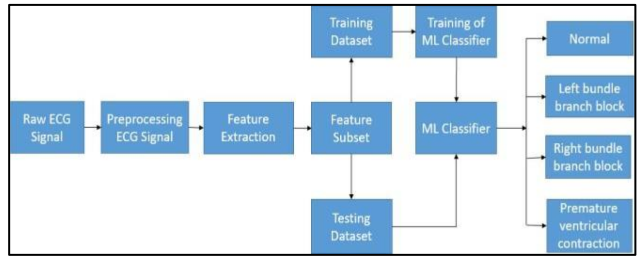

Fig. 1. The system architecture

The result of feature dataset will be divided into testing and training dataset. Training dataset will be feed to the different Machine Learning classifiers. In the proposed system a CNN classifier, SVM classifier, random forest classifier, logistic regression will be used. Different weight and hypothesis will be taken into consideration to increase the accuracy of classification. At the end, the best combination of the preprocessing and classification techniques resulting on conducting this study will be used which can most accurately identify the type of heart arrhythmia.

For performance analysis and evaluation, we used three standard metrics: sensitivity, specificity, and accuracy. These metrics are used to quantify the performance of the system. The sensitivity is measures of the capacity of test the positive samples.

Where,
TP is True Positive
TN is True Negative
FN is False Negative
FP is False Positive

$$\text{Sensitivity (Sn)} = (TP/\ TP + FN) * 100$$

Where TP that defines true positive and FN represents the false negative. The specificity that measures the capacity of test the negative samples.

$$\text{Specificity (Sp)} = (TN\ /\ TN + FP) * 100$$

Where TN that defines the true negative and FP represents the false positive. The accuracy is the ability of the test to correctly identify a classified type without and with positives. It reflects both sensitivity and specificity.

$$\text{Accuracy (Ac)} = (TP + TN)\ /\ (TP + TN + FP + FN) * 100$$

C. Algorithm Used

A convolutional neural network is a deep learning algorithm which can takes image as an input and assign importance (learnable weights and biases) to various objects in the image and to be able to differentiate one from the other.

It works similar as our brain works. In this way, the computer is able to perform image classification by considering or looking for low-level features such as curves and edges and then building up to more abstract concepts through a series of Convolutional layers. CNNs are used in different areas, including pattern recognition, natural language processing, speech recognition, and video analysis. CNN is becoming most popular because there are number of reasons.

4. Results

Table 1
Accuracy of algorithms

Algorithm	Accuracy
CNN	95%
Logistic regression	94%
Random forest	91%

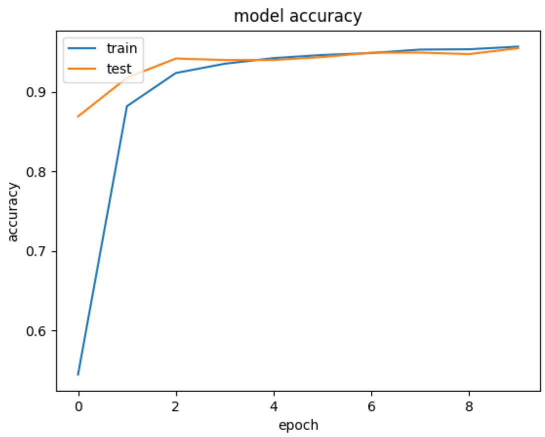

Fig. 2. CNN model accuracy

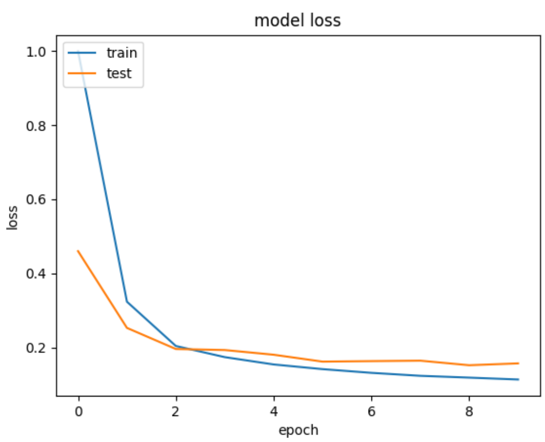

Fig. 3. CNN model loss

5. Conclusion

In the proposed system we are going to evaluate the various methods of classification techniques which can be used to identify the type of ECG. The proposed system can classify the type of ECG data with high accuracy and by comparing with different ML algorithms by using a proper combination of preprocessing and classification techniques. The system used supervised learning techniques that is CNN for classification.

Specificity, Sensitivity, f1 score and Accuracy will be used as a metric for performance evaluation.

6. Future Work

In future work, we are going to design an integrated system for classification of ECG signals, which will monitor and scan the patient's ECG by internal camera of the robot and it will predict the arrhythmia ECG signal and also diagnose the arrhythmia ECG signal to advise the medical expert. As a part of future work this method can be tested over some live ECG databases. More techniques can further be tested for data balancing and More refinement can be done in the down-sampled ECG database like PTBDDB database to achieve more accurate results.

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