Prediction of Cardiac Arrhythmia using Artificial Neural Network

V. Sai Krishna, A. Nithya Kalyani

Abstract--- Cardiac Arrhythmia is a condition in which the heartbeat is abnormal. Different medical data mining and machine learning techniques are being implemented to extract valuable information regarding heart disease prediction. But, the accuracy of the desired results is not yet satisfactory. The lack of specialist doctors and increase in wrong diagnosed cases has necessitated the need for building an efficient heart disease detection system. The aim of this paper is to classify the ECG signal data of a person into different types of Arrhythmia such as Bradycardia, Tachycardia etc. After appropriate feature selection, the plan is to solve this problem by developing a heart attack prediction system using Deep learning techniques, such as Recurrent Neural Networks to predict the likely possibilities of Cardiac Arrhythmia in a patient. This paper presents a survey of recent techniques for prediction of Cardiac Arrhythmia and their methodologies.

Keywords--- Cardiac Arrhythmia, ECG, Deep Learning, Recurrent Neural Network.

I. INTRODUCTION

Cardiac Arrhythmia represents an abnormal heartbeat. The heartbeats may be fast or slow than the normal ones or they may be fluctuating. The symptoms may be weakness, fainting, and pain in the chest area. Arrhythmia can be harmful or harmless depending on the type of it. The symptoms of all the types of arrhythmia are similar [1].

Electrocardiogram (ECG) is used to detect the Cardiac Arrhythmia. It is a graph of the electrical activity in the heart produced by an Electrocardiograph. As shown in the Figure-1 the graph is a periodic waveform composed of the P wave, the Q-R-S complex, and the T wave. The P wave represents atrial depolarization whereas the Q-R-S complex represents ventricular depolarization and the T wave represents the recovery of repolarization [2].

For the purpose of predicting Cardiac Arrhythmia, the Q-R-S signals need to be identified because this part of the signal is where we can identify the irregularity of a heartbeat. As irregularities in the Q-R-S complex represent arrhythmia detecting these waves is an important part of the prediction.

Predicting Cardiac Arrhythmia before-hand can save the lives of patients by treating it. Neural Networks are being used in many fields to solve complex problems. As the ECG signals are time series data, with large enough dataset, neural networks can give astonishing results in predicting cardiac arrhythmia.

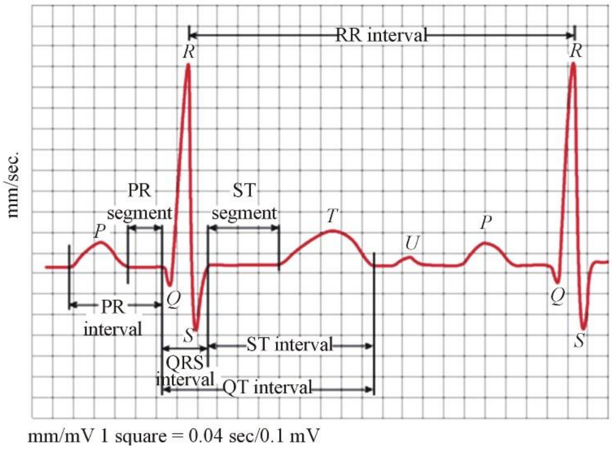

Figure 1: ECG Beats and Intervals

II. LITERATURE REVIEW

Different methods for prediction or classification of cardiac arrhythmia using machine learning techniques were proposed. The following study discusses briefly the proposed methodologies.

Andrew Y. Ng et al. [3] proposed an algorithm to detect different types of arrhythmias from ECG signals recorded with the single-lead wearable monitor. A 34-layer convolutional neural network was trained on a large dataset. This model maps the ECG signal sequences to a set of sequence of rhythm classes. It then classifies the noise and the rhythm which then learns to distinguish twelve different types of arrhythmia present in time series. This model is optimized using residual connections and batch-normalization. The proposed model achieved an accuracy of 97% in detecting cardiac arrhythmia.

Deshmukh Rohan et al. [4] has proposed a Neural Network model for the ECG signal classification. In this proposed methodology, Empirical Mode Decomposition was used to classify arrhythmia. The ECG signal data were interpreted as patterns and after feature extraction, the neural network was trained for classification. The Empirical Mode Decomposition is an adaptive time-space analysis used for processing non-linear, non-stationary series. The dataset was trained on a three-layered feed-forward neural network. The accuracy of this methodology in classifying the ECG signals was 95%.

Latha Parthiban et al. [5] proposed a Coactive Neuro-Fuzzy Inference System for arrhythmia prediction. This model uses a genetic algorithm with neural networks and fuzzy logic to detect the presence of the arrhythmia.

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The accuracy of this model was represented as a mean squared error with 0.00842.

Maedeh Kiani Sarkalehm et al. [6] proposed an expert system for ECG arrhythmia classification. The ECG recordings were processed using Discrete Wavelet Transform (DWT) and the feature extraction is also done with DWT. Then the classification is done using a Multilayer Perceptron. With this system, two types of arrhythmia are detected. The accuracy of this system is 96.5%.

Sean Franklin et al. [7] proposed the use of an Artificial Neural Network to classify the ECG waveforms into 6 different categories. They proposed a model to detect important characteristic points of ECG signals to determine if the patient's heartbeat is normal or irregular, accentuating one of several already pre-determined heart diseases. This was accomplished by acquiring various ECG signals from an online database, and feeding the signal's characteristic points through an artificial neural network which will train, test, and validate the ECG signal appropriately.

Mohd. Khalid Awang et al. [8] proposed a model for prediction of cardiac arrhythmia using artificial neural network mainly predicting angina in patients. They have built a Heart Disease Management Information System to collect data of patients and a Neural Network simulator with the activation function as a binary sigmoid. The accuracy of this model was 88.89%.

Argyro Kampouraki et al. [9] studied the heartbeat time series classification using support vector machines. Feature extraction was done using signal analysis and statistical methods. They have used leave-one-out cross-validation for the SVM classifier which resulted in low noise in the signals. A QRS detector was used to extract the RR features from the HRV signal and common HRV analysis methods were selected as features for the Gaussian kernel-based SVM classifier. The accuracy of the classification model was 97%.

Ali Sadr et al. [10] compared Multi-layer perceptron and Radial Basis Function in the classification of ECG signals. They have created a neural network model that is capable of non-linear mapping. In this way, they were able to predict a 20-second duration of ECG signal from a two Second recorded ECG wave. In this comparison the Radial Basis Function neural network reconstructions the ECG signals with an accuracy of 94% which was found to be 2% better than the MLP architecture.

Mehmet Engin et al. [11] proposed a fuzzy-hybrid neural network for classifying ECG signals. Higher order wavelet transform variances were used as features. The QRS signals were extracted by passing ECG signals through bandpass filters and then fed onto the fuzzy layer and artificial neural network. The efficiency of this classifier was 98%.

Yuksel Ozbay et al. [12] used Artificial Neural Networks to classify the types of cardiac arrhythmia. 10 different arrhythmias are used for training different structures of ANN separately and by mixing those 10 types of arrhythmias. Backpropagation was used as the loss-reducing algorithm. The accuracy of this model was turned out to be 96%.

Prathibhamol Cp et al. [13] developed a prediction system using clustering and regression. The dataset is divided into disjoint clusters using the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering algorithm. From this, the clusters with fewer instances are considered for training. Then Multiclass Logistic Regression has been applied. The dataset was chosen from the UCI Machine Learning Repository. The accuracy of this model turned out to be 80%.

Vasu Gupta et al. [14] have developed a model by combining SVM and Random Forests. After feature selection, SVM with a polynomial kernel of degree 2 and Random Forests were combined. First, the SVM was used as a one class classifier and then the random forest was applied. A confusion matrix was also presented. The accuracy of this model was found to be 77.4%.

Nachiket Tapas et al. [15] proposed an ensemble of classifiers consisting of random forest, LogiBoost and Multilayer Perceptron for the prediction of cardiac arrest. They have used boosting on the logistic regression classifier and bagging on the random forest classifier. The accuracy of the ensemble was found to be around 85%.

Ozal Yildirima et al. [16] presented a prediction system for cardiac arrhythmia using 1D CNN. The dataset used was obtained from the MIT-BIH arrhythmia database. The model used a 16-layer 1D CNN from ECG classification. The first 13 layers consisted of 1D CNN, Batch Normalization and MaxPooling and in the 14th layer the output from the 13th layer is flattened, and a normal dense layer is used. The final output layer is a SoftMax layer. The accuracy of this system turned out to be 91.33%.

Alka S. Barhatte et al. [17] developed an ECG signal analysis using wavelet energy histogram and Arrhythmia classification using Support Vector Machine. The model uses the wavelet energy histogram method to detect the Q-R-S complex. After the detection, the SVM with RBF kernel is used for Arrhythmia classification. The classification accuracy of this model was found to be 99.75%.

III. PROPOSED SYSTEM

The proposed system uses the dataset from MIT-BIH dataset [34]. As this dataset contain raw ECG signals, they need to be filtered first. Bandpass filters are used for filtering out noise data and Hilbert Transform is used as the QRS detection algorithm [2]. After retrieving the filtered data, the plan is to build an LSTM-RNN (Long Short-Term Memory - Recurrent Neural Network). The LSTM is used instead of a simple RNN because it eliminates the vanishing gradient problem.

A. Filtering the ECG signals

The ECG data obtained from MIT-BIH dataset contains raw signals and therefore they need to be filtered. Bandpass filters are used to filter out the noise signals from the ECG data. Butterworth filter was used as the bandpass filter. Figure-2 shows the original and filtered ECG signal.

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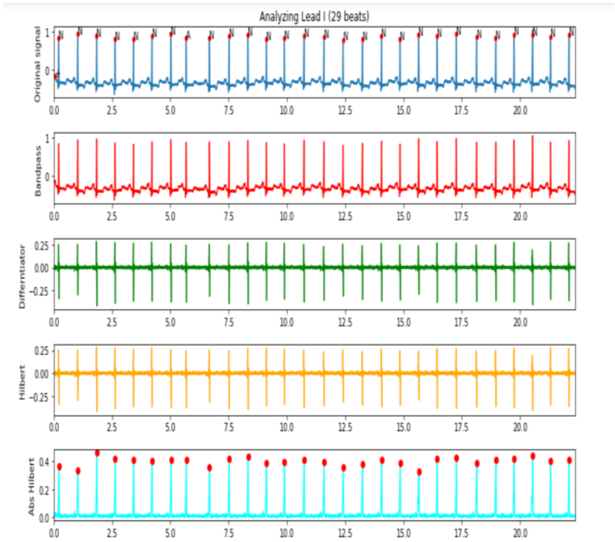

Figure 2: ECG signals obtained after applying Bandpass filter and Hilbert Transform.

B. Applying Hilbert Transform to detect Q-R-S complex

For a real-time function x(t), the Hilbert transform (H) is shown in the Figure-3.

$$\hat{x}(t) = H[x(t)] = \frac{1}{\pi}\int_{-\infty}^{\infty} x(\tau)\frac{1}{t-\tau}\,d\tau.$$

Figure 3: Equation of Hilbert Transform

Hilbert transform is applied on the filtered ECG signal to detect the Q-R-S complex wave. Figure-2 shows the Hilbert Transformed ECG signal. In the Figure-2, the "Abs Hilbert" with red marked points shows the 'R' peaks. An accuracy of 98.66% was achieved in detecting the Q-R-S complex using the Hilbert Transform.

Table 1: Comparison of different Methodologies used for classification/prediction of Cardiac Arrhythmia

APPROACH	INPUT DATASET	METHODOLOGY	ACCURACY
Arrhythmia Detection with Convolutional Neural Networks [3]	ECG samples	34-layer Convolution neural network	97%
ECG beat classification utilizing layered Neural Network [4]	ECG samples	Empirical Mode Decomposition	97%
Heart Disease Prediction System using CANFIS and Genetic Algorithm [5]	ECG samples	Coactive Neuro Fuzzy Inference System with Genetic Algorithm	Mean Square Error of 0.00842
Classification of ECG Arrhythmias using Discrete Wavelet Transform and Neural Networks [6]	ECG samples	Discrete Wavelet Transform and Artificial Neural Network	96.5%
Cardiac Condition Detection using Artificial Neural Networks [7]	ECG samples	Artificial Neural Networks	95%
Prediction of heart disease using Artificial Neural Networks [8]	ECG samples	Heart Disease Management Information System and Neural Network Simulator with binary sigmoid function	88.89%
Heartbeat Time Series Classification with Support Vector Machines [9]	ECG samples with HRV data	Gaussian Kernel-based Support Vector Machines.	97%
Prediction of Arrhythmia using Radial Basis Function and comparison with MLP [10]	ECG samples	Multiplayer Perceptron and Radial Basis Function	94%
ECG beat classification using neuro-fuzzy network [11]	QRS signals from ECG samples	Fuzzy logic with neural networks	98%
Arrhythmia identification Using Artificial Neural Networks [12]	ECG samples	Artificial Neural Networks	96%
Cardiac Arrhythmia Prediction using clustering and Regression [13]	ECG samples	DBSCAN and Multi class Logistic Regression	80%
Prediction and Classification of Cardiac Arrhythmia [14]	ECG samples	SVM and Random Forest	77.4%
Prediction of cardiac arrest recurrence using ensemble classifiers [15]	ECG samples	Ensemble of Random Forest, LogiBoost and MLP	85%
Arrhythmia detection using deep convolutional neural network with long duration ECG signals [16]	ECG samples	1D-CNN	91.33%
QRS complex detection and arrhythmia classification using SVM [17]	ECG samples	Wavelet Energy Histogram and SVM	99.75%

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IV. CONCLUSION

Prediction of Cardiac Arrhythmia can be performed using many Machine learning and deep learning techniques. In this paper, different types of Machine Learning and Deep Learning models on the prediction and classification of cardiac arrhythmia have been discussed. The ECG signal preprocessing using bandpass filters and Q-R-S signal detection using Hilbert transform [2] have also been discussed. It is inferred that the performance of Artificial Neural Networks is high compared to the usual machine learning models. Therefore, predicting arrhythmias using ANN will provide more accuracy. Various artificial neural network models such as Multi-layer Perceptron, Recurrent Neural Networks, Convolution Neural Networks and ensemble of neural networks have been proposed. Future work is to explore the accuracy of Recurrent Neural Networks on predicting arrhythmias using Long Short-Term Memory (LSTM) after appropriate noise removal from the ECG signals. LSTM is better than simple RNN as they avoid the vanishing gradient problem.

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