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Detection of Abnormal ECG Signal using DWT Feature Extraction and CNN

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Abstract - *Cardiovascular disease (CVD) is one of the important reasons of mortality in the worldwide. The main cardiovascular diseases are heart attack, Bigeminy, Trigeminy, left and Right Bundle Branch Block. ECG Signals can be used to predict the whether the patient is in normal or abnormal state. Visual analysis needs experience to identify the problems in ECG. This paves a way for Computerized ECG. In computerized ECG the automatic classification of heart disease into normal and abnormal is done in an automated manner. The Discrete Waveform Transform can be used to extract the features from the signal. Once the features are extracted in a numerical value, then it can be used to predict whether the signal is normal or abnormal. The convolutional Neural Network is used to predict the status of the signal. The goal of the project is to improve the efficiency of the prediction system for the early stage of cardiovascular disease by using DWT Feature extraction and Convolutional Neural Network.*

Key Words: CNN, DWT, Feature Extraction, ECG.

1. INTRODUCTION

Currently, the most effective practice for reducing human mortality rates caused by complicated diseases is to notice their symptoms at early stages. Through the first recognition of symptoms one will get the foremost effective clinical treatment for the most effective outcome [4]. The medical treatment has been supported by computerised processes. Signals recorded from the physique provided valuable data regarding the activities of its organ. Their characteristic form and spectral property will be related with a traditional or pathological perform [5]. Most of the previous analysis focuses on ECG signal processing in order to predict the upset in early stage. In this paper, we have a tendency to gift a review of the recent advancement in prediction of upset analysis victimization ECG signal analysis; in specific to the information used and therefore the designation of information acquisition, features extraction and classification methodologies. The goal of this review is to access and improve the efficiency of the prediction system for the early stage of cardiovascular disease with the knowledge of the current advancement in the technology.
The ECG (ECG) represents a recording of the changes occurring within the electrical potentials between totally different sites on the chest skin, wherever the electrodes are placed as a result of the cardiac activity [4]. Every beat of the heart will be ascertained as a series of deflections far from the baseline on the ECG. These deflections replicate the time evolution of electrical activity within the heart that initiates muscular contraction. the foremost vital options will be obtained from the ECG signal morphology are P wave, QRS complex, and T wave as shown in figure 1.1.

Usually, ischemia is expressed within the ECG signal as ST segment deviations and/or T wave changes. The automated identification of cardiac muscle ischemia, supported the ECG signal involves 2 phases that are ischemic beat classification and ischemic episode detection [4]. The ST segment morphology compatible with ischemia (ischemic changes) typically obtained by recording the ECG signal over long amount of time like a pair of hour 24 hour observation [3]. ischemia change the ECG signal often have an effect on the complete wave of ST-T complex as shown in figure 2, inadequately delineated by isolated feature like ST slope, ST-J amplitude and positive and negative amplitude of the T wave. heart rate Variability (HRV) is an analysis of variations within the instantaneous pulse rate time series exploitation the beat-to-beat RR-intervals (the RR tachogram) [2]. In spite of that, this project can focus additional on the ECG signal morphological than HRV, particularly in detecting the tiny changes in ECG signal.

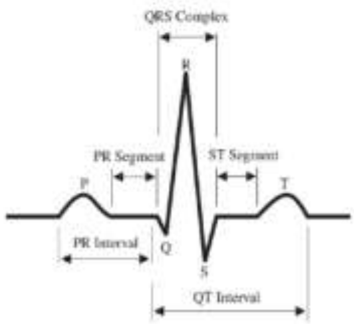

Figure-1.1 the Components of ECG Signal

2. LITERATURE SURVEY

2.1 Survey on the DWT Feature Extraction

There are several studies proposed for the analysis of the ECG beats. Gradient–based algorithm and time domain morphology was presented in [8]. Also, in [6] statistical method of comparison between relative magnitudes of ECG samples and their time domain slope has been described.

Another classifier based on ECG morphological features was reported in [7]. Wavelet transform finds application in ECG beats detection and feature extraction as reported in [9]. Also, Mahesh used wavelet and Pan-Tompkins algorithm to extract time-frequency features for ECG beat detection system [11]. In [12] they presented classification of normal and abnormal signal using R-R interval features of ECG waveform. In [13], the principal component of 4th-levels DWT with db4 mother wavelet is used to classify normal and arrhythmic beats with accuracy of 95.60%.

In the literature, it is observed that wavelet transforms have been frequently used to extract features from heart sounds [17]. The features of heart sounds have been determined by Andrisevic et al[20] with the help of wavelet transform and principle component analysis. The heart sounds were classified into two categories by a neural network with a specificity of 70.5% and a sensitivity of 64.7%. Gupta et al. determined the features of heart sounds by using wavelet transform [18].

Heart sounds were classified into three categories by Grow and Learn network with a total performance of 96%. Uguz et al. determined the features of heart sounds by using wavelet transform and short-time Fourier transform [19]. The heart sounds were classified into two categories by a hidden Markov model with a specificity of 92% and a sensitivity of 97%. Comak et al. analyzed the Doppler signals of heart valves by using wavelet transform and short-time Fourier transform [20]. The heart sounds were classified into two categories by the least-squares support vector machine with a specificity of 94.5% and a sensitivity of 90%.

The Wavelet transform is a two-dimensional timescale processing method or non-stationary signals with adequate scale values and shifting in time [11]. The wavelet transform is capable of representing signals in different resolutions by dilating and compressing its basis functions [12]. The results reached Cuiwei Li et al [4] by indicates that the DWT-based feature extraction technique[13] yields superior performance. Neuro-fuzzy is a hybrid of artificial neural networks and fuzzy logic [14].

Fuzzy Neural Network as in the literature [14] incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The fuzzy membership, fuzzy rule identification and supervised fine-tuning are the three phases in learning process of FNN. The input linguistic layer, condition layer, rule layer, consequent layer, output linguistic layer are the five layer neural network of neuro-fuzzy approach. In the input linguistic stage the defuzzification of the outputs and fuzzification of the inputs will take place. The output linguistic layers performed by fuzzy rule identification. The clusterization of the input data will be done by this self-organizing layer. The input vector to the second sub-network (MLP) is formed by the output of the membership values.

2.2 Survey on the CNN Prediction Technique

Automatic high-accuracy methods for R-peak extraction have existed at least since the mid 1980's [16]. Current algorithms for R-peak extraction tend to use ripple transformations to calculate features from the raw ECG followed by finely-tuned threshold based classifiers [10]. Because accurate estimates of heart rate and heart rate variability can be extracted from R-peak features, feature-engineered algorithms are often used for coarse-grained heart rhythm classification, including detecting tachycardias (fast heart rate), bradycardias (slow heart rate), and irregular rhythms. Such features alone won't be adequate to differentiate between most of the heart arrhythmias. These features based on the atrial activity of the heart as well as alternative features pertaining to the QRS morphology are needed. Much work has been done to automatize the extraction of alternative features from the ECG. For example, beat classification is a common sub-problem of heart-arrhythmia classification. Drawing inspiration from automatic speech recognition, Hidden Markov models with Gaussian observation probability distributions have been applied to the task of beat detection. Artificial neural networks have also been used for the task of beat detection. While these models have achieved high-accuracy for some beat types, they are not yet sufficient for high-accuracy heart arrhythmia classification and segmentation. For example, train a neural network to distinguish between Atrial Fibrillation and Sinus Rhythm on the MIT-BIH dataset. While the network can distinguish between these two classes with high-accuracy, it does not generalize to noisier single-lead recordings or classify among the full range of 15 rhythms available in MIT-BIH. This is in part due to insufficient training data, and because the model also discards critical information in the feature extraction stage.

The most common dataset used to design and evaluate ECG algorithms is the MIT-BIH arrhythmia database which consists of 48 half-hour strips of ECG data. Other commonly used datasets include the MIT-BIH Atrial Fibrillation dataset) and the QT dataset. While useful benchmarks for R-peak extraction and beat-level annotations, these datasets are too small for fine-grained arrhythmia classification. The number of distinctive patients is in the single digit hundreds or fewer for these benchmarks. A recently released dataset captured from the AliveCor ECG monitor contains about 7000 records [14]. These records solely have annotations for atrial Fibrillation; all alternative arrhythmias are classified into one bucket. The dataset we tend to develop contains 29,163 unique patients and 14 classes with hundreds of unique examples for the rarest arrhythmias.

Machine learning models supported deep neural networks have systematically been able to approach and infrequently exceed human agreement rates once massive annotated datasets are available. These approaches have additionally proven to be effective in healthcare applications, particularly in medical imaging where pretrained ImageNet models can be applied. We draw on work in automatic speech recognition for processing time-series with deep convolutional neural networks and continual neural networks, and techniques in deep learning to form the optimization of these models tractable.

3. OVERVIEW OF SYSTEM

3.1 Problem Definition

Visual analysis of ECG for doctors is complex and time consuming task. Visual analysis needs experience to identify the problems in ECG. This paves a way for Computerized ECG. In computerized ECG the automatic classification of heart disease into normal and abnormal is done in an automated manner.

3.2 System Model

In the proposed system, ECG signal for digital signal processing and prediction of normal/abnormal status of that signal was acquired by measurement card with sampling frequency fs = 500 Hz. The first ECG lead was measured. A simple amplifier circuit which is designated for ECG signal is used for analogue signal processing. The circuit with ECG amplifier is fully described in [7]. In Figure 3.5.1 there is shown raw ECG signal. The ECG Signals will be loaded into the system as the .mat file which will be digitalized. The Signal is Pre-Processed using Filters for Feature Extraction. The filters will separate the combined features in the original ECG signal. This separated features will contains the data which is used to predict the normal/abnormal status of the signal. In Feature Extraction Module, the required data is extracted from the signal in numerical form. The DWT (Discrete Wavelet Transform) is used to transform the processed signal into feature extractable form. The Discrete Wavelet Transform is designed to address the problem of non-stationary ECG signals. The translation and dilation operations are used in mother wavelet which is generating function. The varying window size is the main advantage of Wavelet Transform. This window size will be broad at low frequencies and narrow at high frequencies. This methodology leads to the optimal time-frequency resolution in all frequency ranges. Convolutional Neural Network is used to predict the ECG whether it is Normal or Abnormal by taking extracted data. CNNs consist of layers that are sequentially composed, each of which is itself the composition of convolution and pooling operations. The input to a layer is a multichannel signal composed of features extracted from the previous layer, or the input signal itself at the first layer.

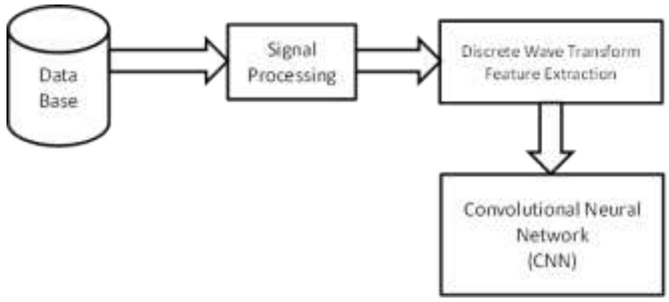

Figure- 3.2.1 Architecture Diagram for ECG Signal Prediction

3.3 DWT Feature Extraction Technique

The problem of non-stationary ECG signals have addressed by the wavelet transform (WT). The single generating functions called the mother wavelet are derived by translation and dilation operations. The varying window size is the main advantage of WT. It is because of the broadness in low frequencies and gets narrowed at high frequencies. This characteristic leads to an optimal time-frequency resolution in all frequency range. The WT of a signal is the decomposition of the signal over a set of functions obtained after dilation and translation of an analysing wavelet. By performing the spectral analysis of the signals with the WT, the data points in the ECG signals can be compressed into a few features. These features characterize the behaviour of the ECG signals. To recognize and diagnose [8] the ECG signals a smaller number of features is used. The discrete wavelet transform (DWT) is used to decompose the ECG signals into time-frequency representation.

In recent years, DWT technique is widely used in signal processing. The good time resolution is main advantage of DWT. It provides good frequency resolution at low frequency and good resolution at high frequency. The DWT can reveal the local characteristics of the input signal because of this great time and frequency localization ability. In terms of shifted versions of a low pass scaling function φ(t), DWT represents a 1-Decomposition signal s(t) and shifted and dilated versions of a prototype band pass wavelet function.

$$\psi(t).\ \Psi j,k(t) = 2(-j/2)\ \psi\ (2\text{-}j\ t - k) \quad (1)$$
$$\varphi\ j,k\ (t) = 2\text{-}j\ \varphi\ (2\text{-}j\ t - k) \quad (2)$$

where: j controls the dilation or translation
k denotes the position of the wavelet function

To utilize successive low pass and high pass filters to compute DWT, Mallet-algorithm can be used to calculate DWT at different resolutions.

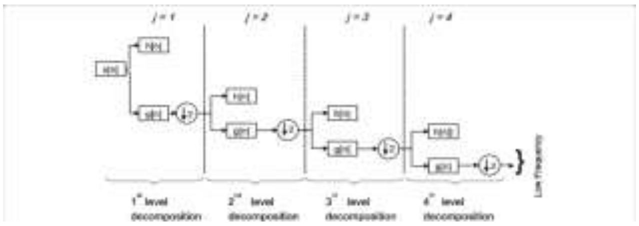

Figure-3.3.1 Decomposition of input signal by DWT

In the figure 3.3.1, the procedure for decomposition of input signal x[n] using DWT is schematically shown. In each stage there are two digital filters and two down samplers by 2 to produce the digitized signal. The first signal is represented as g[n], which is a discrete mother wavelet and also a high-pass filter. The second is h[n] which is low-pass filter. The details D1 and the approximation is provided by the down sampled outputs of first high pass filters and low-pass filters. The first approximation (A1) is iteratively decomposed again and again. The successive high pass and low pass filtering of the time domain signal will results in the decomposition of the signal into different frequency bands. The signal decomposition can mathematically be expressed as follows:

$$y_{hi}[k] = \Sigma\, x[n].g[2k - n] \quad (3)$$
$$y_{lo}[k] = \Sigma\, x[n].h[2k - n] \quad (4)$$

3.4 Convolutional Neural Network

Given a training set T := {(x,y)} formed by inputs x and outputs y, a learning algorithm produces an alternative representation that can estimate the output $\hat{y}$ that should be assigned to an input $\hat{x} \notin T$. Neural Networks (NNs) produce a representation using a stacked layered architecture in which each layer composes a linear transformation with a point wise nonlinearity. Formally, the first layer of the architecture begins with a linear transformation to produce the intermediate output $u_1 := A_1x_0 = A_1\hat{x}$ followed by a point wise nonlinearity to produce the first layer output $x_1 := \sigma_1(u_1) = \sigma_1(A_1x_0)$. This procedure is applied recursively so that at the lth layer we compute the transformation.

$$x_l := \sigma_l(u_l) := \sigma_l(A_l x_{l-1}) \quad (1)$$

In an architecture with L layers, the input $\hat{x} = x_0$ is fed to the first layer and the output $\hat{y} = x_L$ is read from the last layer [9]. Elements of the training set T are used to find matrices A_l that optimize a training cost of the form $\sum_{(x,y) \in T} f(y,x_l)$, where $f(y,x_l)$ measures the difference between the desired output y stored in the training set and the NN's output x_l produced by input x. Computation of the optimal NN coefficient A_l is carried out by the back propagation algorithm [9].

The Neural Network architecture is a multilayer perceptron composed of fully connected layers [10]. If we denote as M_l the number of entries of the output of layer l, the matrix A_l contains $M_l \times M_{l-1}$ components. This, likely extremely, large number of parameters not only makes training challenging but empirical evidence suggests that it leads to over fitting. The convolution and pooling are the two operations with which CNN will resolve this problem.

3.5 Input & Output

Input - The ECG Signal fragment of the Heart Patient is fed into the system as shown in Fig 3.5.1.

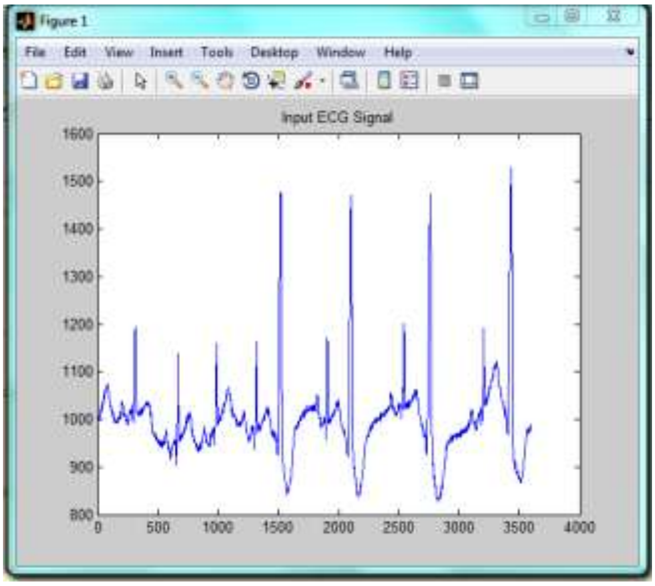

Figure 3.5.1 Fragment of ECG Signal of Heart Patient

Output - The Pop-up message stating the status of the Patient. The confusion matrix is generated to validate the results as shown in Fig 3.5.2

```
------------------------------------------
              Actual Classes
--------------1---------2-----
Predicted|
  Classes|
_________|________________
        1 |    22.0 |    0.0
        2 |    0.0  |    19.0
------------------------------------------
------------------------------------------
              Actual Classes
--------------1---------2-----
      TP |   22.00 |   19.00
      FP |   0.00  |   0.00
      FN |   0.00  |   0.00
      TN |   19.00 |   22.00
Preci. |   1.00  |   1.00
Sensi. |   1.00  |   1.00
Speci. |   1.00  |   1.00
------------------------------------------
Model Accuracy is 1.00
------------------------------------------

Cf =

    22     0
     0    19
```

Figure 3.5.2 Generated Confusion Matrix

3.6 Parameters Used For Implementation / Simulation

- **Accuracy (A):** the proportion of the total number of predictions that was correct. The accuracy can be expressed using following equation.

$$A = \frac{Tp + Tn}{Tp + Tn + Fn + Fp}$$

- **Sensitivity or Recall (St)**: the probability that a test will indicate 'disease' among those with the abnormal Pulse. The Sensitivity can be expressed using following equation.

$$S_t = \frac{Tp}{Tp + Fn}$$

- **Specificity (Sp):** the fraction of those without heart disease who will have a negative test result.

$$S_p = \frac{Tn}{Tn + Fp}$$

3.7 Complexity Involved In the Proposal

The complexity involved in the proposal is the features which should be extracted from the ECG signal. The particular feature which is required to predict the status of the patient should be extracted and which will be used to train the Neural Network.

4. CONCLUSIONS

ECG signal plays a vital role in case of cardiac disease detection as it contains all functional information about cardiac condition of a person. We proposed a cardiologist friendly approach for cardiac disease prediction using CNN classifier. The time domain features of ECG signal are capable of discriminating healthy signal and patient signal as well as can differentiate different types of cardiac diseases. Results have shown the advantages of DWT feature extraction technique over Fourier transform for ECG signal processing. The classification accuracy for cardiac disease detection is found 100% which can help to a more accurate early diagnosis of different cardiac diseases. As time domain features are used for the detection of cardiac diseases, this method would be very helpful for the medical professionals and will be a useful component for clinical decision support system to detect cardiac arrhythmia more precisely.

The DWT Feature extraction method can be improvised by using Principle Component Analysis method (PCA). PCA will reduce the Dimension of data extracted using DWT. Therefore, a very few features are sufficient to predict the abnormal signal. This efficient feature extraction method can be used to predict the probability of specific disease that cause the abnormality in the ECG signal.

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