

Automatic Detection of Cardiac Arrhythmia using Neural Network

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Abstract – Cardiac arrhythmia indicates abnormal irregular activity of heart beat that can be a great threat to human. So it need to be identified for clinical diagnosis and treatment. Analysing of ECG signal is an important role in determining cardiac diseases. An systematic method of analysing ECG signal and identifying the heart abnormalities have been proposed. Existing system uses the SVM classifier (support vector machine) for classification. K means clustering algorithm and dynamic time warping for detecting the values from the ECG . These methodologies provides less accuracy and faces high computational load is the main drawback. To overcome these drawbacks, we proposed a system, that uses the Feed Forward neural network method. This neural network has been selected for this system because it performs in One-way propagation. It computes the result fast and with high accuracy. At first QRS components have been extracted from the ECG signal. By rejecting the background noise from the ECG signals to improve the accuracy in results. From the extracted signals, transforming raw data into a readable format that is more suitable for further analysis. Data are given to the feature extraction process. Neural networks always perform supervised learning tasks, building knowledge from predefined data where the similar matching information are provided in advance. The final task is to classify the heart abnormalities by comparing the ECG and previously stored information. Here, data used for the analysis of ECG signal are from database.

Keywords – Dual-Tree Complex Wavelet Transforms, Wavelet transform, Multi scale analysis, Gray-Level Co-Occurrence Matrix, Multilayer Perceptron Networks.

I. INTRODUCTION

The automatic detection and classification of arrhythmias in electrocardiography-based signals (ECG) has been widely studied in the last years in order to aid the diagnose of heart diseases. One way to perform this type of test is to conduct a long-time recording of the cardiac activity of an individual in his/her normal routine in order to obtain a reasonable amount of information about the individual's heartbeats. However, the posterior task of analysing such data may be tiresome and more prone to errors when interpreted by human beings, since there is a huge amount of information to be processed. In order to cope with such problem, several works have been carried out arrhythmia. Classification in EEG signals by means of machine learning-oriented techniques . However, regardless of the classification algorithm used, some processing steps are crucial to design a reasonable approach to detect

arrhythmia. The quality of classification when dealing with ECG signals is directly dependent on the pre-processing phase, which aims at filtering noise frequencies that might interfere with ECG signal . After pre processing, it is required to detect and segment each heartbeat of the ECG signal. In order to perform this task, an important step is the detection of the QRS complex(three deflections from ECG signal), specifically the R wave, since most part of techniques for the detection and segmentation of heartbeats are based on the location of such deflection. Because of the steep angular coefficient and amplitude of the R wave, the QRS complex becomes more obvious than any other part of the ECG signal, being easier to be detected for later segmentation. The final step is the classification of ECG signals, which is usually accomplished in a supervised fashion. Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) [are among the most used machine learning techniques for this purpose. Other approaches such as Linear Discriminant Analysis and a hybridization of Support Vector Machines and Artificial

Neural Networks are also applied for heartbeat classification. However, one of the main shortcomings related to the aforementioned pattern recognition techniques concerns with their parameters, which need to be fine-tuned prior to their application over the unseen sample.

- **Related work**

Method for the automatic processing of the electrocardiogram (ECG) for the classification of heart beats[1], for the pre processing the ECG signal[8]. To study about the Hermitian Model of Higher-Order Statistics for Classification [2]. Data set results analysing and comparison [4]. Classifying the heartbeat rate from the ECG[3] is referred. To implementation of tree approach in detection of arrhythmia[5]. Multiple instance learning and Implementation study of Multi scale energy and eigen space approach to detection and localization of arrhythmia[6][7]. Grouping ECG Complexes Using Hermite Functions[9]. Implementation of power Line Interference Detection in ECG signal[10]. Template matching method[11] and wavelet transform[12].

- **ECG data description**

The ECG data are used in this paper is gathered from kaggle – MITBIH arrhythmia database. The dataset contains Non-ecotic beats (normal beat), Supraventricular ectopic beats, Ventricular ectopic beats Fusion Beats. This database was developed by collecting data from the various experimental results. These dataset contains 109446 ECG samples beats, we use only few samples for our experiments.

1. Method I

- **Digital Image Processing**

The identification of objects in an image is the main thing in image processing. It contain various techniques like noise removal, feature extraction, regions and possibly areas with certain textures. Manipulating data within the sort of a image through several possible techniques. These images are often in two-dimensional array of brightness values, and is most familiarly represented in some patterns. An image are often processed optically or digitally with a computer. To digitally process the image, it is necessary to reduce the image to a series of numbers which will be manipulated by the personal computer. A typical digitized image may have 512×512 or roughly 250,000 pixels, although much larger images are getting common. Once the image has been digitized, there are three basic operations will be performed within the computer. For some extent point operation, a pixel value within the output image depends on one single pixel value in the input image. For local operations, several neighbouring pixels within the input image determine the worth of an output image pixel. In a global operation, all the input image pixels produces an output image pixel value. These operations, taken singly or in together, are the means by which the image is enhanced, restored, or

compressed. An image is enhanced when it's modified in order that the knowledge it contains is more clearly evident, but enhancement can be include making the image more visually appealing. An example is noise smoothing. To smooth a noisy image, median filtering is applied with a 3×3 pixel window. The value of each pixel in the noisy image is recorded, along with the values of its nearest eight neighbours. These nine numbers are then ordered consistent with size, and therefore the median is chosen because the value for the pixel within the new image. As the 3×3 window are moved one pixel at a time across the noisy image, the filtered image is produced..

- **Classification of Images:**

Binary Image: A binary image be a digital image that has only two possible values for every single pixel. Typically two colours used for a binary image are black and white though any two colours are used. These colours are used for the objects within the image is the foreground colour while the other image is the background colour. Binary images is also called bi-level or two-level. Each pixel is stored as a single bit (0 or 1). This name white and black, monochromatic are often used for this project, and also designate any images that have only single sample per pixel, like grayscale images.

Gray Scale image: A grayscale Image is digital image in which the value of every pixel is a single sample, It carries only intensity information. These images is also known as black-and-white, are composed exclusively of shades of gray (0-255), varying from black (0) at the weakest intensity to white (255) at the strongest. Grayscale images are distinct from one bit black and white images, these are the context of computer imaging and images with only the two colours, black, and white (also called bi-level or binary images). Grayscale images have many different shades of gray in between. Grayscale images are known as monochromatic and in such cases they are monochromatic proper when only a given frequency is captured. It is synthesized from a full colour image, then the section about converting to grayscale.

Colour Image: A digital colour image may be a digital image that includes colour information for every single pixel. Each pixel has a feature value which determines it's appearing colour. This value is qualified by three numbers giving the decomposition of the colour within the three primary colours Red, Green and Blue. Any colour visible to human eye are represented in this way. The decomposition of a colour in the three primary colours is quantified by a range between 0 and 255. For example, white will be coded as $(R,G,B) = (255, 255, 255)$; black will be known as $(R,G,B) = (0,0,0)$; and say, bright pink will be : $(255,0,255)$. Images are in two-dimensional array of colour values, pixels, each of them coded on 3 bytes, representing the three primary colours. This allows the image to contain a value of $256 \times 256 \times 256$

= 16.8 million different colours. This technique is called as RGB encoding, and is specifically adapted to human vision. It is observable that our behaviour and interaction are highly influenced by emotions of people whom we intend to interact with. Moreover, there are a number of applications where emotion recognition can play an important role including biometric authentication, high-technology surveillance and security systems, image retrieval, and passive demographical data collections. It is unarguable that faces the most important feature that characterises among human. By only looking ones' faces, we are not only able to tell who they are but also perceive a lot of information such as their emotions, ages and genders. This is why emotion recognition by face has received much interest in computer vision research community over past 20 years.

2. Method II:

There are four main parts in an ECG arrhythmia recognition and classification system, containing: pre-processing, heartbeat segmentation detector, feature extraction and classifier construction.

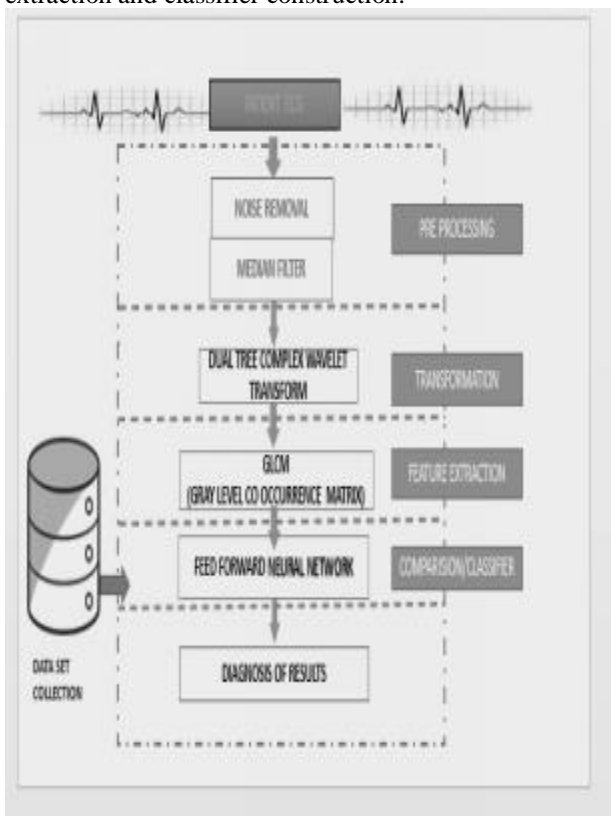


Fig.1. Architecture diagram of the proposed system.

• Pre-Processing

Median Filter is a non-linear digital filtering technique, it is widely used to remove noise from a signalled images. Noise reduction is an important pre-processing step to enhance the results of later processing. The major important role of the median filter is to perform through the signal entry by entry, restoring each entry with the median of neighbouring entries. The pattern of

neighbours is known as "window", which slides, entry by entry, over the signal. For 1D signals, the obvious window is simply the first few preceding and following entries, whereas for 2D (or higher-dimensional) data the window must include all entries within a given radius or ellipsoidal region. Median filters play a major role in reducing random noise, whenever the noise amplitude probability density has large tails, and periodic patterns. The median filtering process is efficient by sliding a window over the image. The filtered image is obtained by placing the median of the values within the input window, at the location of the middle of that window, at the output image. The median is that maximum likelihood estimator of location in the case of Laplacian noise distribution. For relatively uniform areas, the median filter estimates the grey-level value, with particular success in the presence of long-tailed noise. As an edge is crossed, one side or the opposite dominates the window, and therefore output switches sharply between the values. Thus, the edge is not blurred. Median filters of both recursive and non-recursive types are considered. Recursive median filters were more efficient than those of the non-recursive type. The median filter is that one sort of nonlinear filters. It is very effective at removing impulse noise, the "salt and pepper" noise, within the image. The principle of the median filter is to exchange the grey level of every single pixel by the median of the grey levels in a neighbourhood of the pixels, instead of using the average operation. Before beginning median filtering, zeros must be padded round the row edge and therefore column edge. Hence, edge distortion is introduced at image boundary. The nonlinear function of the median filter can be expressed as

$$Y(n) = \text{med}[x(n-k), x(n-k+1), \dots, x(n), \dots, x(n+k-1), x(n+k)]$$

• Transformation Dual-Tree Complex Wavelet Transforms(DT-CWT):

The dual-tree complex wavelet transform (CWT) could be a relatively recent enhancement to the discrete wavelet transform (DWT). The multidimensional (M- D) dual-tree CWT is a non separable but is predictable in computationally efficient, separable filter bank (FB). The study behind the dual-tree transforms shows how complex wavelets with good properties could be designed, and illustrates a wide spread of applications in signal and image processing. The real DWT produces both large and tiny wavelet coefficients. In contrast, the (approximately) analytic CWT produces coefficients whose magnitudes are more directly associated to their proximity to the edge. Here, the test signal can be a step edge at $n = n_0$, $x(n) = u(n - n_0)$. The figure shows the data of the wavelet coefficient $d(0, 8)$ (the eighth coefficient at stage 3 in "Real-Valued Discrete Wavelet Transform and Filter Banks, as a function of n_0 ". The top panel, the coefficient $d(0, 8)$ is computed using the real DWT method. The lower panel, the complex coefficient $(0, 8)$ is computed using the dual-tree CWT.

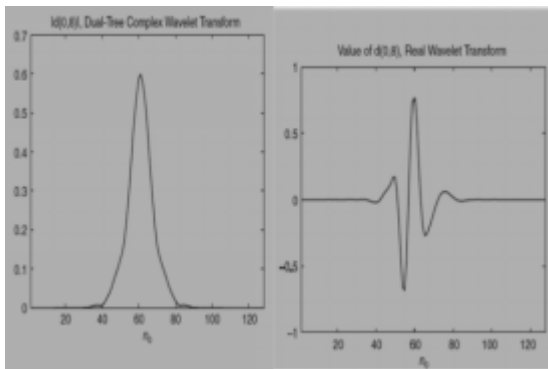


Fig.1.2. the value of the wavelet coefficient in “Real-Valued Discrete Wavelet Transform and Filter Banks.

The wavelet transform has implemented to increase the success across the gamut of signal processing applications. The DWT replaces the infinitely oscillating sinusoidal basis functions of the Fourier transform with a gaggle of locally oscillating basis functions called wavelets. Classical setting in the wavelets were stretched and shifted versions of a fundamental, real-valued band pass wavelet $\psi(t)$. When carefully chosen and combined with shifts of a real-valued low-pass scaling function $\phi(t)$, they form an orthonormal basis expansion for one-dimensional (1-D) real-valued continuous-time signals. That is, any finite energy analog signal $x(t)$ is decomposed in terms of wavelets and scaling functions via

$$x(t) = \sum_{n=-\infty}^{\infty} c(n) \phi(t-n) + \sum_{j=0}^{\infty} \sum_{n=-\infty}^{\infty} d(j,n) 2^{j/2} \psi(2^j t - n).$$

The scaling coefficients $c(n)$ and wavelet coefficients $d(j, n)$ are computed via the inner products,

$$c(n) = \int_{-\infty}^{\infty} x(t) \phi(t-n) dt,$$

$$d(j, n) = 2^{j/2} \int_{-\infty}^{\infty} x(t) \psi(2^j t - n) dt.$$

• **Feature Extraction:**

The gray co matrix function creates a gray-level co-occurrence matrix (GLCM) by calculating the pixel with the intensity (gray-level) value i occurs during specific spatial relationship to a pixel with the value j . By default, the spatial relationship is defined because the pixel of interest and the pixel to its immediate right (horizontally adjacent). But specify other spatial relationships between the two pixels. Each element (i,j) within the resultant GLCM is simply the sum of the number of times that the pixel with value i occurred within in the specified spatial relationship to a pixel with value j within the input image. Because the processing required to calculate a GLCM for complete dynamic range of an image is prohibitive, gray co matrix scales the input image. By default, gray co

matrix uses scaling to reduce the number of intensity values in gray scale image from 256 to eight.

The number of gray levels determines the dimensions of the GLCM. To control the amount of gray levels within the GLCM. To control the amount of gray levels within the GLCM and therefore the scaling of intensity values, using the Num Levels and therefore Gray Limits parameters of the gray co matrix function. The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of gray levels within the texture image. To create multiple GLCMs, specify an array of offsets to the gray co matrix function. These offsets define pixel relationships of varying direction and distance. Row_offset is the number of rows between the pixel of interest and its neighbour. Col_offset is the number of columns between the pixel of interest and its neighbour. This example creates an offset that specifies four directions and 4 distances for each direction. GLCMs can derive several statistics from them using the gray co props function. These statistics provide information about the texture of an image. Statistic such a as Contr, Correlation, Energy, Homogeneity gives information about image.



Fig.1.3. Glcm Comparison.

• **Feed Forward Neural Network**

Neural network is modern tool in recognition and discrimination between different sets of signals. To get best results using the neural network, it is necessary to settle on an appropriate architecture and learning algorithm. Based on the research in previous research papers, suitable consistent method is used to expand or shrink the neural network size until a reasonable output is obtained. In this work we tried different sizes for the neural network using python and we found that the best among them .It consists of an input layer with 2000 inputs, first hidden layer holds 11 nodes, and T ANSIG transfer function, second hidden layer holds 7 nodes, and T ANSIG transfer function, and output layer with transfer function holds 2 outputs. One of the two outputs is used for the detection of arrhythmia, and the other for the localization. T ANSIG transfer function is chosen to limit the signal between -1 and 1. For the output layer, PURELIN transfer function is chosen to give all the possible cases for the location of arrhythmia. This network consists of input layer (on the left) with three neurons, hidden layer (in the middle) with three neurons

and an output layer (on the right) with three neurons. An Neuron in the input layer for predictor variable. In the case of categorical variables, N-1 neurons represent the N categories of the variable.

Input Layer — A vector has predictor variable values ($x_1 \dots x_p$) is presented to the input layer. The input layer is to (or processing before the input layer) standardizes these values so that the range of each variable is -1 to 1. The input layer distributes the values to every neurons in the hidden layer. In addition to the predictor variables, there is a continuous input of 1.0, called the bias that is fed to every hidden layers; the bias is multiplied by a weight and added to the sum given into the neuron.

Hidden Layer — Neuron in the hidden layer, the input neuron is multiplied by a weight (w_{ji}) with the data from input neuron, and therefore resulting weighted values are added together producing a combined value u_j . The weighted sum (u_j) is fed into a transfer function, σ , which outputs a data value h_j . The outputs are collected and it is passed to the output layer.

Output Layer — Neurons in the output layer, the data from each hidden layer neuron is multiplied by a weight (w_{kj}), and resulting weighted values are added together producing a combined value v_j . The weighted sum (v_j) is fed into a transfer function, σ , which outputs a data value y_k and y data is the outputs of the network. If a multivariate analysis is being performed with a constant target variable, then there is a single neuron in the output layer, and it generates a single y value. For classification problems with endless target variables, there are N neurons in the output layer producing N values, one for every N categories of the target variable.

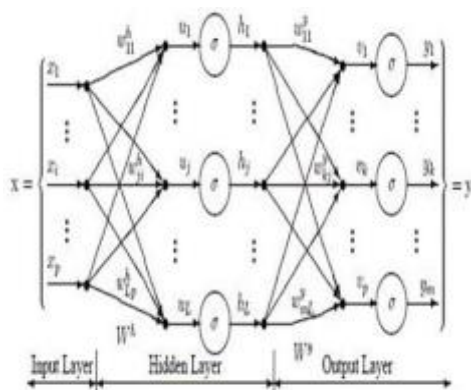


Fig1.4 Layers of Neural Network.

II. EXPERIMENT RESULTS

In these experiment, the results were based on using different ECG signals. Sensitivity and specificity are two parameters which are used to calculate the result efficiency of the classifier. Here we increased the efficiency of the system compares to the previous works. Results produced by this projects are verified with the experts. The sample signals are collected from the kaggle dataset, they provide exact results. These datasets are

trained during the development phase for producing the accurate results.

Metric / Datasets	No Of Datasets	Sensitivity	Specificity	Accuracy in Proposed Method	Accuracy in Existing Method
Normal	128	96	94	95	89
Abnormal	130	93	96	94.5	91

Fig 1.5. Comparison of proposed approach with existing methods.

III. CONCLUSION

The experiments show that the suggested algorithm has performed more accurate results in compared to the previous implemented algorithm. The specificity and sensitivity of arrhythmia detection obtained by the suggested algorithms better. The proposed method can be used for other application for comparing the ECG signals. Here experimental results produces the accuracy level of 95 % for the implemented algorithm. These results are improved compared to existing systems.

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