# Classification of Heart Disease

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**Abstract -** *worldwide heart disease is the main reason for human death. In general terms, abnormal functioning of heart known as heart disease. In women and men, the percentage of death due to heart disease is 48% and 46% respectively. Hence, proper diagnosis of heart disease is very important in practice for physicians. In this work, a system is design for diagnosis of heart disease named as murmurs. Probabilistic neural network classifier is use for heart murmurs.*

***Key Words*: Heart Disease, Probabilistic neural network, Diagnosis, murmers.**

## 1. INTRODUCTION

Improper functioning of heart leads to heart disease. For men and women, leading cause of death is heart disease, which is one in every four deaths. Worldwide heart disease is the second disease to cancer that causes death, hence proper diagnosis of heart disease is very important. In earlier days, prediction of heart disease is done by listening heartbeats, which is very uncertain. Poor clinical decisions can lead to dangerous consequences which are therefore unacceptable. Therefore, updated and accurate methodologies were discovered by researchers to predict heart disease. Technique, known as phonocardiogram, were heart sound are registered. With the help of phonocardiogram (PCG), it is possible to analyze the heart acoustic signal from timing, frequency and location point of view. In phonocardiogram's classification, neural network have shown proper and efficient result.

Neural networks used in pattern classification, time series forecasting applications and control systems; this is because of their non-linear modelling characteristics. To obtain 90% classification accuracy, as pre-processor Wavelet transform and as classifier neural network classifiers are used as input space feeders. In real applications, because of their advantages of information handling and fitting functions; high diagnosis accuracy and better fault tolerance to meet the complexity, nonlinearity, uncertainty in real-world systems, Neural networks, have been used as classifiers.

### 1.1 HEART ANATOMY AND MURMERS

Nutrients and oxygen are required for survival to the organs and cells throughout the body through blood. Continuous pumping of this blood is the main functioning of heart. Heart Disease can be stated as improper functioning of heart. The sound of blood flow turbulence in the heart is known as heart Murmurs. Stethoscope can be used to listen this sound.

Murmurs are of two types: harmless and abnormal. Harmless murmurs can happen during fast blood flow than the normal flow during fast growth in children, physical exercise or pregnancy. Abnormal murmurs may be a sign of a more serious heart condition, such as a congenital heart defect that is present since birth or heart valve disease. To physicians for accurate diagnosis of many heart diseases, the skill of cardiac auscultatory is very essential and important. Hence, training and experience is required to recognize and distinguish the primary symptoms of cardiac diseases based on the heart sound.

### 1.2 ECG SIGNALS

The ECG signal is periodic waveform. One cycle of the blood transfer process from heart to the arteries is represented by the one period of the ECG waveform. This part of the waveform is generated by an electrical impulse originated at sino-atrial node in the right atrium of the heart. The impulses causes contraction of the atria which forces the blood in each atrium to squeeze into its corresponding ventricle.

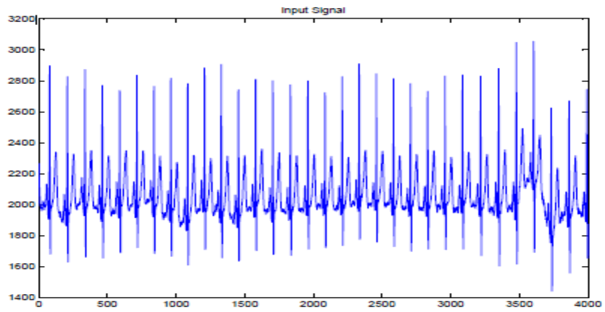
The resulting signal is called the P wave. The atrioventricular node delays the excitation impulse until the blood transfers from atria to the ventricles is completed, resulting in PR interval of the ECG waveform. The excitation impulse then causes contraction of the ventricles which squeezes blood into the arteries. This generates the QRS part of the ECG waveform. During this phase the atria are relaxed and filled with blood. The T wave of the waveform represents the relaxation of ventricles. The complete process is repeated periodically, generating the ECG trace.

## 2. LITERATURE SURVEY

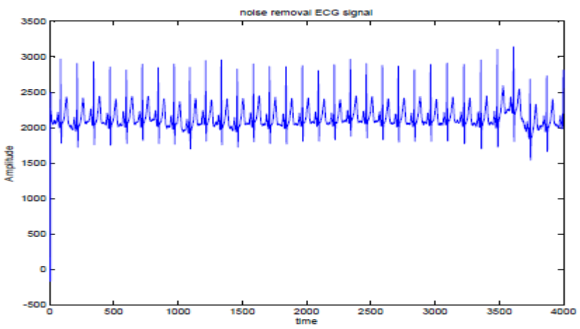
In 1995, D. Barschdorff, U. Femmer, and E. Trowitzsch, stated the model for ECG signal analysis using wavelet transforms and artificial neural network. This methodology is efficient and accurate for diagnosis of heart sound. In Multilayer perceptron, the learning speed is very low as it is back propagation through time is first order gradient descent method. Same with the Levenberg-Marquardt training algorithm. Hence, reliable training algorithm is required for analysis purpose.

## 3. PRE-PROCESSING

The electrocardiographic signals are disturbed by noise from different sources. External electromagnetic field interference, Power line interference, noise due to random body movements and respirational movements, instrumentation noise are the different sources of noise interference. These noises can be classified according to their frequency content. It is essential to reduce these disturbances in ECG signal to improve accuracy and reliability. To reduce his noise various filters are used. Here we have used low pass filter for pre-processing purpose. In low pass filters, all the high frequency amplitude signals are removed. On ECG signals low pass filters are used to remove high frequency external interference and muscle artifacts. Attenuation is done on typical high frequency ECG components. On QRX complex, effective noise removal can be done using analog low-pass filtering.




**Fig, No, 1**: - Input signal




**Fig, No, 2**: - Noise removal of ECG Signal

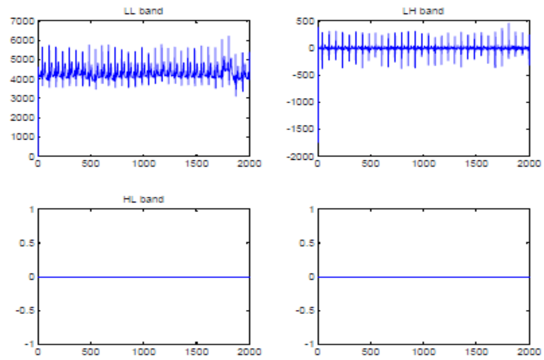
## 4. FEATURE EXTRACTION

Distinguishing feature from a given input signal is known as feature extraction. Itis about maintaining the uniqueness of ECG signal, reducing the dimensionality of the input-vector. Good features possess the attributes of being simple to extract, invariant against time translations and overall amplitude variation, and capable of discriminating different phonetic categories.

ECG measurement is now used both for monitoring and diagnosis as a detection method of vast range of anomalies. The most important values to be measured are regularity of the signal, the distances between characteristic points and interferences in the shape of single heartbeat. Once a cardiac register is acquired, different wavelet transform is applied.

Transform for which the wavelets are discretely sampled is known as discrete wavelet transform. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency *and* location information. A **wavelet** is a wave-like oscillation with an amplitude that begins at zero, increases, and then decreases back to zero. Discrete wavelet transform is given as,

$$W\varphi(jo,k) = \frac{1}{\sqrt{M}} \sum_{n} s(n)\, \Psi jo,k(n) \qquad (1)$$



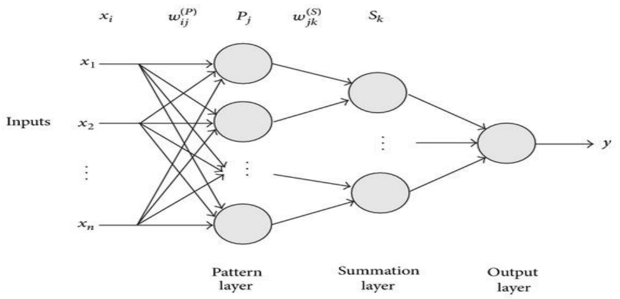

**Fig, No: 3:** Feature Extraction of Pre-Processed Signal

## 5. CLASSIFIER MODEL

Due to their nonlinear modelling characteristics, neural networks have been successfully implemented in control systems, pattern classification and time series forecasting applications. Wavelet transform has been used as signal pre-processor and in neural network classifiers as input space neural networks, have been used as classifiers in real applications due to their advantages of fitting functions and dealing with information feeders with 90% classification accuracy. Wavelet higher prediction accuracy and better fault tolerance to meet the uncertainty, nonlinearity, and complexity in real-world systems.

In a PNN, the operations are organized into a multilayered feedforward network with four layers:

- Input layer
- Pattern layer
- Summation layer
- Output layer




**Fig, No: 4** Probabilistic Neural Network

## 6. RESULT

Preprocessing is done using LPF and the chebishev filter in which noise is removed. Features are extracted using wavelet transform.Results are observed using two methods.Total 30 signals are used for the training in which 15 are negative and 15 are positive signals.

In order to evaluate the performance of pattern classification systems (developed using supervised machine learning techniques such as PNNs and SVMs), the binary classification performance has to be measured.

**Table no. 1:** Confusion Matrix

| Confusion Matrix | Positive($p^a$) | Negative($n^a$) |
|---|---|---|
| Positive($p^p$) | True positive(TP) | False Positive(FP) |
| Negative($n^p$) | False Negative(FN) | True Negative(TN) |

The performance of a binary classifier cannot be described by a single value and is usually quantified by its accuracy during the test phase, i.e., the fraction of misclassified points on the test set. The performance of a binary classifier can be best described in terms of its sensitivity and specificity, quantifying its performance to false positive (FP) and false negative (FN) instances.

Sensitivity is defined as the ratio of signal which are marked and classified as deficient, to all marked signals, given by:

$$\text{Sensitivity} = TP/TP + FN \qquad (1)$$

Specificity is defined as the ratio of signals which are not marked and also not classified as deficient, to all unmarked signals, given by:

$$\text{Specifity} = TN/TN + FP \qquad (2)$$

The overall accuracy is the ratio between the total number of correctly classified instances and the test set size, given by:

$$\text{Accuracy} = TP + TN/\ TP+FN+TN+FP \qquad (3)$$

## 7. CONCLUSION

Preprocessing is done using LPF and the chebishev filter in which noise is removed. Features are extracted using wavelet transform.Results are observed using two methods.Total 30 signals are used for the training in which 15 are negative and 15 are positive signals.

- ➢ Using Neural Network:
- From the confusion matrix following is the result:
- accuracy = 90.90%
- TPR = 94%
- TNR = 86.66%
- ➢ Using SVM:
- In this method following result is obtained.
- Accuracy = 54.54%
- TPR =100%
- TNR = 6.66%

Comparing both the methods accuracy using Neural network training is more than SVM. Thus proposed methodology is completely automatic and helps to diagnose the heart insufficiency with accuracy and precision.

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