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Detection of Heart Defects using Electrocardiogram (ECG)

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Abstract

Electrocardiogram (ECG) signals are vital to identifying cardiovascular disease. The numerous availability of signal processing and neural networks techniques for processing of ECG signals has inspired us to do research on extracting features of ECG signals to identify different cardiovascular diseases. We distinguish between a healthy person ECG data and person having disease ECG data using signal processing and neural network toolbox in Matlab. The data was downloaded from physiobank. To distinguish normal and abnormal ECG, Neural network is used. Feature extraction method is used to identify heart diseases. The diseases that are identified include Tachycardia, Bradycardia, first-degree Atrioventricular (AV) and a healthy person. Subsequently, ECG signals are very noisy; signal processing techniques are used to remove the noise impurity. The heart rate can be calculated by detecting the distance between R-R intervals of the signal. The algorithm successfully distinguished between normal and abnormal ECG data.

Keywords: ***Electrocardiogram (ECG), Cardiovascular Disease, Bradycardia, Tachycardia, atrioventricular, Neural Network, MATLAB, Physiobank***

1. Introduction

An Electrocardiogram is a signal used by a medical professional to detect human heart conditions. It measures the electrical activity of the human heart over a period of time. The electrical waves of the human heart can be measured at selectively placed electrodes in various points of the human body. An ECG displays the voltage between pairs of these electrodes and the muscle activity that they measure, from different directions by a specific instrument to show the result on the graph clearly. A normal ECG signal consists of a P wave, a T wave, and a QRS complex. A"P wave" is created by right and left atria, or upper chambers, following a flat line when the electrical impulse goes to the ventricles. The right and left ventricles make the next wave called "QRS Complex".[2] The final wave, or "T wave," represents electrical recovery. Numerous pattern recognition methods were developed for arrhythmia detection and classification. Typically, these methods are based on three main steps which are preprocessing, feature extraction, and classification. The ECG signals are enhanced by eliminating various kinds of noise and artifacts to produce ECG waveform.

The existing feature representation methods include morphology, temporal information, wavelet transform, high-order statistics, Hermite basic function, and hidden Markov modeling. Additionally, principal component analysis, independent component analysis, and linear discrimination analysis are usually applied to reduce dimensionally future representation. Finally, Resultant features are used to train the decision classifier like neural networks, support vector machines, path forest, and Gaussian processes. Despite these great determinations, it has been shown recently that automatic methods do not perform well and the outcomes obtained by such methods remain unsatisfactory.

This research paper is based on ECG signal is a use of pattern recognition. The technique used pattern recognition comprises of signal preprocessing, Peak detection (P, QRS peak detection), feature extraction and neural network for disease identification and signal classification. In this research, the discrete wavelet transform and neural network toolbox of MATLAB are used. The R peak detection gives information about heart rate abnormality. ECG is used to measure the rate and uniformity of heartbeats as well as the size and position of the chambers, the presence of any damage to the heart, and the effects of drugs or devices used to regulate the heart To acquire the signal, ECG devices with varying number of electrodes (3– 12) can be used.[1] Typical ECG waveform is shown in figure 1.

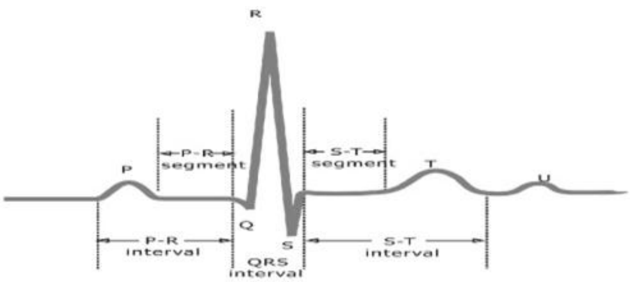

Figure 1. ECG waveform and Interval

The ECG can be divided into the phases of depolarization and repolarization of muscle fibers making up the heart. The depolarization phase corresponds to P-wave (atrial depolarization) and QRS-wave (ventricles depolarization). The repolarization phase corresponds to the T-wave and U-wave (ventricular repolarization).[2] Arrhythmia or dysrhythmia is a heart disorder representing itself as an irregular heartbeat due to malfunction in the electrical system cells in the heart.[2] It causes the heart to pump blood less effectively and causing disorders in the heart conduction process.[2] ECG signal comprised of P wave, PR segment, PR interval, QRS complex, ST segment, ST interval, RR interval and T wave in the ECG waveform shown in figure-1, for the analysis of amplitude and duration of wave's interval and segment to be used for arrhythmia classification. Typical features (amplitude and time duration) is shown in Table-1. If there is a change in amplitude, time or pattern of an ECG signal, the disease can be detected. Arrhythmia refers to any variation from the normal sequence of ECG signal. The electrical impulses may occur too fast, too slowly, or erratically- causing an irregular heartbeat. When the heart doesn't beat properly, it can't pump blood effectively which causes the lungs, brain and all other organs to shut down or be damaged.[2] Heart rate is directly proportional to number of peaks and sampling frequency and it is inversely proportional to length of signal. The normal range of heart rate is 60 to 100.[3] Two types of Arrhythmias are Tachycardia (Figure 2) and Bradycardia (Figure 3) can be found using the Heart rate. Tachycardia means the heart rate is above 100 beats per minute (BPM) in adults. This occurs when the electrical signals in heart's upper chambers fire abnormally.[3] Braycardia means that the heart rate is below 60 beats per minutes. Elderly people are more prone to problems with slower heat rate. A slower heart rate may cause insufficient blood flow to the brain with symptoms such as dizziness or lightheadedness.[4] Atrioventricular block (AV block, Figure 4) is a partial or complete interruption of impulse transmission from the atria to the ventricles. PR interval of First-degree AV block is longer than normal, typically greater than 0.20 sec. This paper describes an effective algorithm, that is used to extracts all features of ECG signal and based on that extracted features our algorithm provides an effective way to detect the cardiovascular diseases like tachycardia, bradycardia and First Degree AV Block.

Table 1: Normal ECG Feature and intervals

S.N.	Features	Amplitude(mV)	Duration(ms)
1	P Wave	0.1-0.2	60-80
2	PR segment		50-120
3	PR interval		120-200
4	QRS complex	0.5-1	80-120
5	ST Segment		100-120
6	T Wave	0.1-0.3	120-160
7	ST interval		320
8	RR interval		400-1200

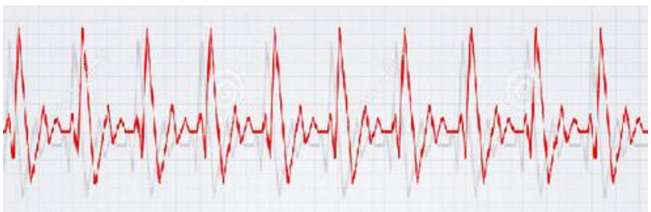

Figure 2. Tachycardia ECG signal[15]

Figure 3. Bradycardia ECG signal[15]

Literature Reviews

Recent advancement in science and technology has led to an unprecedented advancement in provision of technological solutions for the numerous problems facing mankind. Researchers are busy leveraging modern technology to provide better and improved solutions commensurate to the ever increasing demands. A heart rate monitor is a personal monitoring device that allows one to measure heart rate in real time. Early system consists of a monitoring box with a set of electrode leads which is attached to the chest. The first wireless electrocardiogram (ECG) heart monitoring was invented in 1977 as a training aid for the Finnish National Cross Country Ski team and as "intensity training" became a popular concept in athletic circles in the mid-80s, retails sales of wireless personal heart monitors started in 1983.[5] In older versions of the monitor, when a heartbeat is detected a radio signal is transmitted, which the receiver uses to determine the current heart rate. This signal can be simple radio pulse or a unique coded signal from the chest strap, the latter prevents one user's receiver from using signals from other nearby transmitters.[5] Newer versions of a heart rate monitor include a microprocessor which is continuously monitoring ECG and calculating the heart rate, and other parameters. Modern heart rate monitors usually comprise of two elements: a chest strap transmitter and a wrist receiver or any receivable device like mobile phone or laptop. In early plastic straps, water or liquid was required for good performance. Later components have used conductive smart fabric with built in microprocessors which examines the ECG signal to determine heart rate. More advanced models will offer measurement of heart rate variability, activity, and breathing rate to assess parameters relating to monitor and alert systems provides a more unique, effective and efficient means of real-time monitoring of patients' health parameters and has ever since witnessed an unprecedented tremendous advancement as researchers keep searching for better ways to make these monitoring and alert system more flexible, portable and efficient.

2. Methodology

For the processing of an ECG signal, the signal is obtained from Physio.net which has clinical data of patient ECG. The signal that is received from Physio.net contains noise. So to denoise ECG signal, Low pass filter, high pass filter and derivative base filter is used. Feature extraction (R peaks, P peaks detection) of that ECG signal is done using discrete wavelet Transform. Based on detected R peaks, we have found heart rates and disease from those heart rates like Tachycardia (faster heart rates) and Bradycardia (slower heart rates). From noticed P peaks and R peaks we found PR interval and from the value of PR interval we can decide whether a person has First Degree AV block disease or not. Finally we use deep neural network with 5 hidden layers to classify signals of healthy person and person having first degree AV block disease and find accuracy of the network from that.

2.1 Deep Neural Networks

The architecture of the neural network is simple. One of the neural networks techniques is feed-forward neural networks with many hidden layers, which are often called as deep neural network. In that network back propagation is used for learning parameters of the neural network. Neural Network can be thought of as a function $f": x \rightarrow y$ which takes an input $x \in \mathbb{R}^n$, and produces an output $y \in \mathbb{R}^n$ and whose performance is parameter by $\theta \in \mathbb{R}^n$.[2] Therefore, for instance, f_θ could be simply $y = f_\theta(x) = \theta.\, x$. A unit is parameter by a weight vector w and a bias term denoted by b. The first layer has p^1 units then each of the units has $w \in \mathbb{R}^n$ weights associated with them. The first layer gives an output $o_1 \in \mathbb{R}^{p1}$. The output of the unit can be described as, $o_i = [\sum_{i=1}^{n} x_k \cdot w_k + b_i]$. The index k corresponds to each of the inputs/weights (from1 to n) and the index i corresponds to the unit in the first layer (from 1 to $p0$).

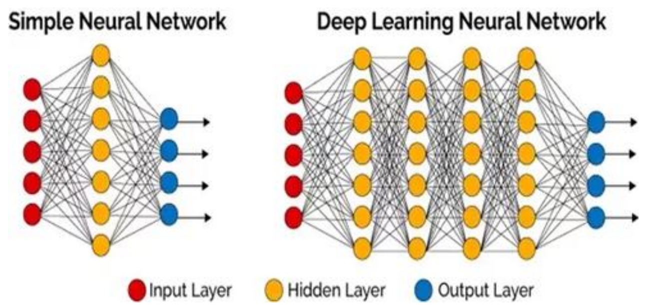

Figure 4. Comparison between simple neural network (NN) and deep NN; simple neural networks contain only one hidden layer as well as the input and output layers, while deep learning neural networks contain more than one hidden layer. In this case, there are four hidden layers between the input and output layers[5]

2.2 Discrete Wavelet Transform

To enhance signal characteristic, the wavelet Transform (WT) approach is applied to each 2-second window to obtain a multiresolution time-frequency representation for the raw ECG signal. Compared to Fast Fourier Transform (FFT) and short-term Fourier Transform (STFT) approaches, WT introduces new strategy to disclose spectral characteristic of signals. It is known that FFT can only give the frequency spectrum of the entire time series, which is enough for stationary signals but does not sufficiently represent the time-varying modes of non-stationary signals such as ECG. To support non-stationary signals, STFT presents the windowing tools to examine only a small section of the signal at a time. Conversely, because of the unaffected window, it is limited by both the dilemma of resolution and the Heisenberg uncertainty principle. The former one mean that it undergoes from a poor frequency resolution with a narrow window or a poor temporal resolution with a wide window, and the latter one indicate that it cannot give what frequency exists as what time interval.

An alternative approach to STFT to overcome the above stated limitations is WT, which analyzes the signal at different frequencies with different resolutions. Particularly, it can overcome the problem of resolution after introducing different window sizes for different frequency components, and thus provide a good temporal resolution at high frequencies and a good frequency resolution at low frequencies. Another contribution in overcoming Heisenberg uncertainty principle is that it can detect the sharp changes in spectral character, which is often the cases in ECG signals, such as the sharp R peaks and other shape changes due to the heart illnesses. A computation-effective algorithm of the WT is Discrete Wavelet transform (DWT), which has a recursive structure. DWT uses scale and position values based on power of two.[8]

3. Results

3.1 R peaks Detection

As a first step of an ECG signal Analysis, we need to detect R peaks of ECG signal. In this research paper, discrete wavelet transform technique of signal processing has been used to detect R peaks of an ECG signal. The R peaks of an ECG signal have largest amplitude. The high recognition of accuracy of the proposed method is especially significant because it is based on the wavelet transform. Previous studies using the wavelet transform did not show high performance, compared with non-wavelet transform-based methods. Below figure shows R peak detection of an ECG signal using discrete wavelet transform.

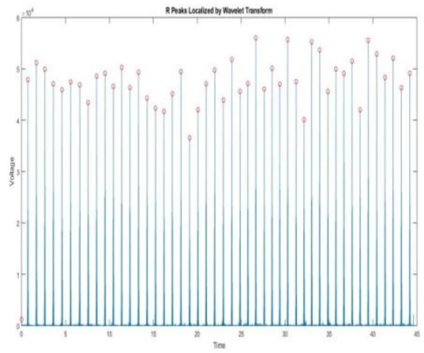

Figure 5. R peak Detection of ECG signal

3.2 Calculating Heart Beats

After detecting R-peaks of ECG signal, next step is to calculate heartbeats from that detected R peaks of an ECG signal. For calculation of heart rate, we need to find the number of peaks and Length of the signal. We can find that in MATLAB. For calculating heart rate, we need to multiply the number of peaks of an ECG signal, 60 and Sampling frequency of an ECG signal then divide it to the length of the signal.

3.3 Detection of Various Diseases from ECG signal

In this research, we have differentiated four types of ECG signals: Tachycardia, Bradycardia, First Degree AV block, and Healthy person. If the person has bradycardia that means the person's heart beat is slower than normal which would be slower than 60 BPM.[7] For most people, a normal heart rate is in range of 60 to 100 BPM while at rest. For some people, a slow heart rate does not cause any problems.[7] It can be a sign of being physically fit.[7] Healthy young adults and athletes often have heart rates of less than 60 beats per minute.[7] When electrical signals in the heart's upper chambers fire abnormally, which interferes with the electrical signals coming from the sinoatrial(SA) node [the heart's natural pacemaker], a series of early beats in the atria speeds up the heart rate.[7] For detecting Bradycardia, and Tachycardia, the heart rate which is calculated from ECG signal is used. For detecting First Degree Atrioventricular, we used the duration of PR interval. For Detecting Duration of PR, first we detect P and R peaks of the ECG signal using discrete wavelet transform, then by using those points we measured distance between PR points which is called as PR interval. When the PR interval is greater than 0.20 seconds it is called as a person has first-degree AV block disease.

3.4 Automatic Classification

As described earlier, we used deep neural network for classification whether an ECG signal is of healthy person or an ECG signal of person having First Degree AV block disease. The first Degree AV block and healthy person ECG signal is fed into Neural network. The output is defined by 1's and 2's so the network can understand that the healthy person data is corresponds to 1 and First Degree AV block data corresponds to 2.

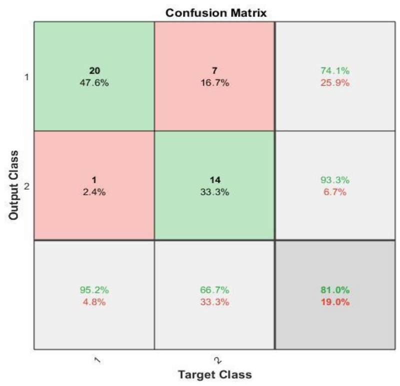

Figure 6. Confusion Matrix of neural netwok

In Figure 6, the confusion matrix from which we can see that network outputs are very accurate as green squares represent percentage of correct responses and low number of incorrect responses are represented by red square. The lower right gray square illustrates the overall accuracies. This means the network accuracy of classifying healthy person data and first degree AV block person data is 81.0%

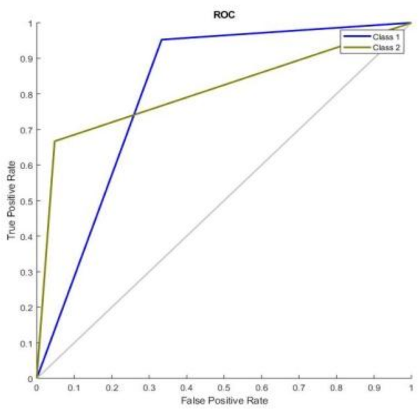

Figure 7. Receiver Operating Characteristic (ROC)

In figure 7, the colored line in both axes represents ROC curves. The ROC curve is a plot of the true positive rate versus the false positive rate as the threshold is varied [8]. A good test would show points in upper left corner. In the above figure 7 we have a good test because all the points are in upper left corner of the curve.

4. Conclusion

The algorithm proposed here was tested on MIT/BIH Normal Sinus Database and MIT/BIH Arrythmia Database obtain from physio.net ATM. The algorithm has successfully detected R-peaks, P- peaks, Q-peaks and PR interval of ECG signal using discrete wavelet transform. The algorithm could distinguish Normal and First Degree AV block ECG signal with accuracy of 81% using neural network to classify signal successfully. In additionally heart rate was calculated to detect disease like Tachycardia and Bradycardia.

Table 2: Disease Characteristics

Name of Abnormalities	Characteristics features
Bradycardia	Heart Rate < 60 BPM
Tachycardia	Heart Rate > 100 BPM
First Degree AV Block	PR interval > .20 Second (200 ms)

Appendix

1. Detection of live ECG using Arduino and AD8232

Live ECG has been detected using Arduino and AD8232 heartbeat sensor. It shows sequence of PQRST waves of ECG signal when three ECG leads are connected to a human body. The live ECG which we get from Arduino and AD8232 has lots of high frequency and contamination noise which is almost impossible to remove that so we have to use predefined data of physio bank to do ECG signal analysis.

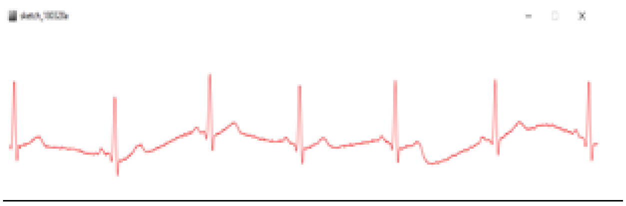

Figure 8. Live ECG signal using AD8232 heart beat sensor and Arduino

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