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A Review on: ECG Signal Analysis Using Artificial Neural Network

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Abstract: The most difficult task in cardiovascular disease diagnosis is doing precise electrocardiogram analyses (ECG). In order to classify and interpret ECG data automatically, numerous studies are being carried out. Wavelet Packet Decomposition (WPD) and Feature extraction are used to decompose the patient's raw ECG data. Artificial Neural Networks (ANNs) are used to refine the classification (ANN). A unique approach for the automatic analysis of ECG data has been developed that successfully distinguishes between abnormal and normal ECG signals. This bio-electrical signal is used to record the heart's electrical activity over time, and is known as an electrocardiogram (ECG). Detecting cardiac illness early and accurately is critical to a patient's recovery and treatment. Cardiac illnesses are detected using ECG signals, which are obtained mostly from PhysioDataNet and the MIT-BIH database. Wavelet toolbox is used for pre-processing the ECG signal and also for feature extraction from the ECG signal. The whole project may be done in MATLAB. The algorithm's efficiency is measured using the MIT–BIH Database. In this paper we are reviewing technique of ECG signal analysis and classification.

Keywords: ECG, ECG signal analysis, ECG Signal Classification, ANN

1.INTRODUCTION

Electrocardiogram, or ECG, is the abbreviation for Electrocardiogram, which is a medical term for a picture of the heart's electrical activity. It signifies that the heart's muscle is contracting and relaxing. Another phrase for electrocardiography is to provide or deliver the heart condition is utilized. The ECG waveform is analyzed to determine whether or not the heart is normal or abnormal. Electrocardiography measures the electrical activity of the heart's muscles and reports the results. Random bio-signals, which are frequently non-stationary signals, may occur. This is a possibility. As a result, correct diagnosis necessitates careful monitoring of the ECG signal pattern and heart rate variability throughout time. Long-term recording generates enormous amounts of data, making analysis tedious and time consuming.

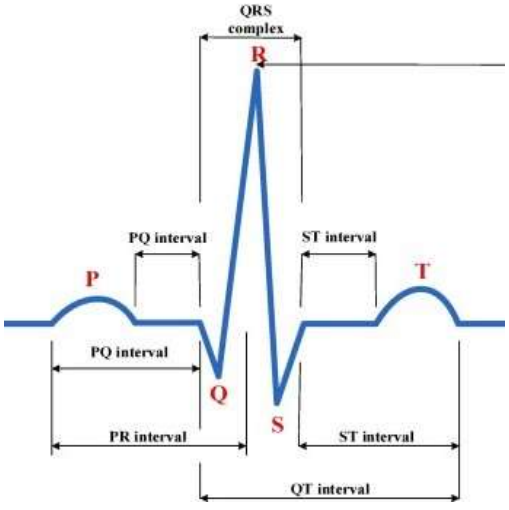

Figure: 1 ECG Signal

Heart and blood vessel disease is a leading cause of death worldwide. It is common practise to check a patient's cardiac electrical activity when they are suspected of having a cardiac condition. Bioelectric potentials are generated by cells, and the material that generates these potentials is ionic. The medical term for the recording of electrical heart activity is electrocardiogram (ECG) (ECG). The electrocardiogram (ECG) is a bioelectric event generator since it is a periodic, regularly repeated signal coordinated with the heart's beating. The waveforms' phase and amplitude relationships were defined to maintain uniformity. Whenever this value changes, it could be an indication that something is wrong with the heart's normal function. Because the heart provides the driving force for blood circulation, it's important to understand the electrical activity and mechanical activities it performs. SA node is a group of cells located in the right atrium that initiates electrical activity in the heart. The SA node has received the nickname "natural pacemaker" because to its extensive use. To generate electrical impulses, a healthy heart should beat at 72 beats per minute. Energy from the SA node is distributed throughout the body. Approximately 1 m/s of the wave goes through the left and right atria, causing the atrium to contract and the ventricles to contract in response to the created impulse. These electrical impulses on the skin's surface can be recorded with an electrocardiograph. It measures the electrical activity of the heart as a waveform on an electrocardiogram (ECG). The P wave, the first of the heart's four waves, is produced by atrial depolarization. Ventricular depolarization produces a QRS COMPLEX, which occurs after a P wave has occurred. The final wave to be seen is the T wave,

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which indicates ventricular repolarization. It takes about 0.8s for a PQRST wave to complete one PQRST cycle.

2. LITERATURE REVIEW

Poonam Sao et. All (2015) The most common application of the ECG is in the detection of cardiac disease. ECG signal feature extraction and categorization have been tackled using a variety of Artificial Neural Network models, both supervised and unsupervised. A neural network (ANN) classifier was used to classify data based on heart rate signals fed with three parameters: spectral entropy, Poincare plot geometry, and the greatest Lyapunov exponent (LLE). [1]

SaharH.El-Khafif et. All (2013) For the purposes of automatic ECG classification, multiple neural network-based classifiers were evaluated and used in this study. In order to train these classifiers, researchers used polyspectral patterns and information gleaned from higher-order spectral analyses of normal and ischemia electrocardiograms. They contain amplitude and phase information, as well as Gaussian noise-free spectral noise patterns. The polycoherence index slices as input features, the Extended Delta-BarDelta learning algorithm, and two hidden layers produced the best classification results. Slices from higher-order statistics reveal their power in analysing and classifying nonlinear ECG dynamics in the work given here. [2]

Ling Guo et. All (2013) EEG signals, for example, have long been studied using the wavelet transform as a valuable technique. When looking at the relative wavelet energy (RWE), you can see how much energy is linked with each of the EEG signal's frequency bands. A discrete wavelet transform was used to break down EEG signals into their component frequencies, and then two features indicating relative wavelet energies in the low and middle frequency bands were recovered from the energy distributions of normal and epileptic EEG signals. This was followed by classifying the data using a feed-forward ANN composed of three layers. This approach was shown to have a 95% classification accuracy rate, demonstrating its efficacy. Because of this, relative wavelet energy can be used to characterize EEG signal characteristics and be beneficial in other biomedical signal analyses. It's a technique worth learning about. [3]

Himanshu Gothwal et. All (2011) An ECG signal was analysed using Fast Fourier Transform to find distinct patterns. In order to build an Artificial Neural Network that can forecast diseases, these features created training and testing datasets. Even with significantly aberrant ECGs, the system is proven to be extremely resilient and can recognize and forecast many aspects. This is a huge advantage because the ECG pattern differs greatly from person to person. These variables include, but are not limited to, peak height, QRS width, peak occurrence or absence, heart rate, and so on. Once the QRS complex is identified, it can be used in other studies or systems. It is the most critical part of any ECG. Because of the system's high level of precision, it's extremely dependable and effective. [4]

Geir E. Oien et. All (1996) A neural classifier based on forward-connected multilayered neural networks classified ECG data from two different databases. Using the more interesting data source for the practically crucial "T/NT" task, three classifiers based on such networks were evaluated using different input feature vectors. An AR model may not be the best option for analyzing ECG data if the periodogram model surpasses the other 15-dimensional feature model, as shown by this research. However, merging two feature vectors into a single 30-dimensional vector allowed for a T/NT accuracy of 94.2% overall (at the cost of longer training sessions). So, one of the feature vectors is enriched with data the other does not possess. [5]

Muhammad Arif et. All (2010) According to the authors' findings, artificial neural networks may be taught to detect and pinpoint myocardial infarction using a 12-lead ECG. If a patient is confident in the accuracy of the MI classification, an acute myocardial infarction can be more correctly identified. Because there are increasingly more MI kinds to categorize, classifier localization performance suffers. As a result, classifiers have a hard time telling apart MIs that are almost identical (those MI types that have an identical main artery but different sub-arteries, such as anterior MI and antero-lateral MI). More time domain features can be used in future study to improve MI localization classification accuracy. This will allow future MI detection and localization to make use of the same time domain feature collection. [6]

S. Issac Niwas et. All (2005) The ECG signal is an effective diagnostic tool for detecting cardiac conditions. As a diagnostic tool to assist physicians in the investigation of heart disorders, neural network classifier is presented in this paper. The accuracy of event detection is the most critical component in determining the success or failure of an automatic ECG diagnosis system. For the tools' accuracy, various criteria matter, including the size and quality of their training set, how rigorous their instruction was, and what parameters they used to describe the input they were fed with. To begin, only data from the MIT/BIH database is being considered. For higher accuracy in diagnosing and classifying diseases, future expansion will include all 12 lead information. [7]

Abishek Santhosh Raj et. All (2014) As a result, the proposed methodology was used to perform a 99.7% accurate auto analysis of ECG data. Patients with conditions like Myocardial Infarction, Valvular Disease, and Pulmonary Embolism had their ECG data compared to that of healthy individuals. As a unique approach to the correct diagnosis of Cardiovascular Diseases, this algorithm has shown promise. Using a hardware-based

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system, the same technique can help analyse ECG data more quickly, accurately, and automatically. [8]

Gaurav Kumar Jaiswal et. All (2014) This study uses an ANN-based system to sort ECG waveforms into several categories. Most information concerning cardiac activity can be found in an ECG waveform, which is driven by the electrical activity of the heart. Only five characteristics of the ECG signal, P, Q, R, S, and T, are discussed in this study. This is accomplished by taking the P-wave, PR segment, PR interval, QRS complex, ST segment, T-wave, ST-interval, QTc, and QRS voltage from the ECG waveform and extracting various properties and durations. Most of the data originates from PhysioDataNet and the MIT-BIH data base, with the exception of ECG signal and heart rate as parameters for disease identification. The goal of this study is to discover the optimum neural network topology for classifying heart disease anomalies. Because the ECG waveform differs from person to person under various conditions, this technique also defines the normal zone for classifying anomalies. [9]

Wei Jiang et. All (2007) This study presents block-based neural networks (BbNNs) for the classification of individual ECG heartbeat patterns. With reconfigurable digital hardware like field-programmable gate arrays, you can build a BbNN from an array of 2-D modular component NNs with customizable topologies and internal configurations (FPGAs). It is the signal flow between blocks that determines the BbNN's internal configuration and overall structure. The network architecture and weights are optimized using local gradient-based search and evolutionary operators, with the rates changing adaptively based on their efficacy in the previous evolution phase.. This adaptive operator rate update strategy ensures a higher average fitness when compared to the established fixed operator rates. It. An ECG dataset with Hermite transform coefficients and an R-peak gap is fed into a BbNN. [10]

3. METHODOLOGY USED FOR ANALYSIS OF ECG SIGNALS

3.1 Artificial Neural Network

Logician Walter Pits and neurophysiologist Warren McCulloch created the first neural network in 1943. Artificial neural networks (ANNs) are useful in areas like pattern recognition, classification, and the like since they are biologically inspired networks. It is possible to classify biomedical data using the ANN's decision-making process because the input pattern features are holistic and based on them. Non-linear classifiers are frequently trained using the generalized back propagation approach (BPA). To minimize overall system error to an absolute minimum, the BPA uses supervised learning to lower the mean square error function. We start with a random connection weight and lower the overall system error by modifying it over time. The weights are updated in reverse order, starting with the output layer. Classification can be accomplished with the help of an ANN. Process neurons with the typical sigmoid activation function were employed in the succeeding hidden layers.

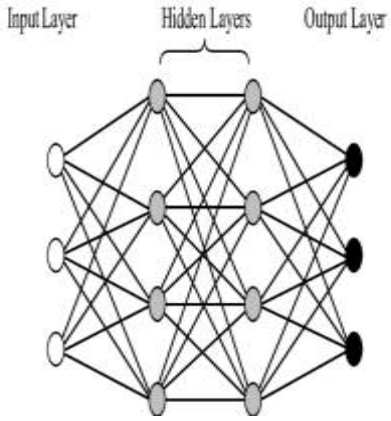

Figure: 2 Artificial Neural Network

3.2 Probabilistic Neural Network

With an artificial neural network (ANN), complex problems that are difficult to tackle with traditional rule-based programming can be handled. Classification was performed using a Probabilistic Neural Network in this instance. The Bayesian network and a statistical procedure known as KernelFisher Discriminant analysis are the foundations of a probabilistic neural network, which is a feed-forward neural network. One of the main advantages of a PNN is that the operations are organized into three distinct layers: the Input Layer, The Hidden Layer and The Decision Layer. Each predictor variable value is represented by a single neuron in the input layer. The hidden layer's neurons receive their values from the input neurons, which then distribute them to each one. Each case in the training data set is represented by a neuron in the hidden layer. In addition to the goal value, the neurons record the value of the predictor variable for the case.

3.3 Wavelet Transform

The wavelet transform is a convolution of the wavelet functions y(t) with the signal x(t). Discrete Wavelets are associated with scaling functions $\phi(t)$. Wavelet transform was utilised to retrieve ECG signal characteristics. Wavelet analysis analyses a signal by breaking it down into its component elements. To obtain approximation coefficients, run the scaling function across the signal once.

3.4 Wavelet Packet Decomposition

Since ECG signals are always changing, Wavelet Transform is an excellent tool for evaluating them. Decomposition of a signal into detail and approximation signals is accomplished using discrete wavelet transforms (DWTs). Wavelet function and number of decomposition stages are crucial in the analysis because they determine the final result. Actually, the choice of these parameters depends on the application type and the content of the frequencies. The Daubechies wavelet family, which has a form comparable to ECG signals, was shown to be the

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optimum wavelet for this strategy. As a wavelet transform, Wavelet Packet Decomposition (WPD) applies more filters than the discrete wavelet transform to the discrete-time (sampled) signal (DWT). When someone asks what Daubechies is, they usually reply with "db." A complete representation of discrete signals is provided by the Wavelet packet decomposition theory described above. To improve the signal-to-noise ratio (SNR), baseline drift and high frequency noise are removed using filters during the pre-processing step before feature extraction.

3.5 Feature Extraction

Entropy, frequency, and energy are just a few of the important features that are extracted during feature extraction. Ischemic episodes can be detected by alterations in ECG characteristics as QRScomplex shape, ST-segment deviation, and T-wave alternation. In wavelet analysis, a signal or image is broken down into a series of approximations and details that are then compared. Mother wavelet is Daubechies db4 because it looks like a heartbeat. The classifier classifies an ECG signal as normal or abnormal based on a few criteria. Skewness was identified in the data using average power, skewness, and entropy. The mean of a signal is defined as the average of all of its voltages, all taken together. A statistician is referring to the average value of a signal when they talk about the mean. To arrive at the average, sum together all of the samples and divide by N. When calculating variance, add all of the standard deviations together. There are no exceptions to this rule. It is possible to measure power in units called watt-seconds (W-sec). Periodic signals are dominated by power signals. Power signals are the most common type of periodic signal. The period of a periodic signal can be used to estimate its power. An input signal's entropy can be utilized to characterize the texture because it's a statistical measure of its randomness. A signal's randomness affects its compressibility, therefore more randomness means it's less compressible, and vice versa.

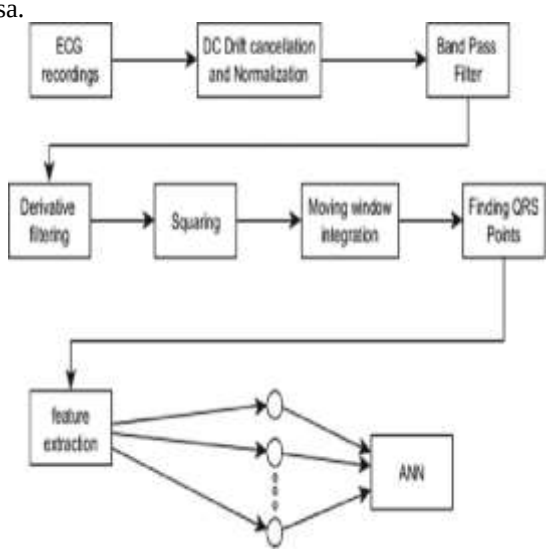

Figure: 3 Block Diagram for Pan Tompkins algorithm (gray dotted box) to derive features used as ANN inputs

3.6 Training and Classification

To train an artificial neural network, a typical way is to use back propagation, which is a generalization of the delta rule. The neural network can be trained using the Back Propagation method, which is detailed below. The Physionet database can be used to gather an ECG data set that includes both normal and pathological signals.

4. ECG PRE PROCESSING TECHNIQUE

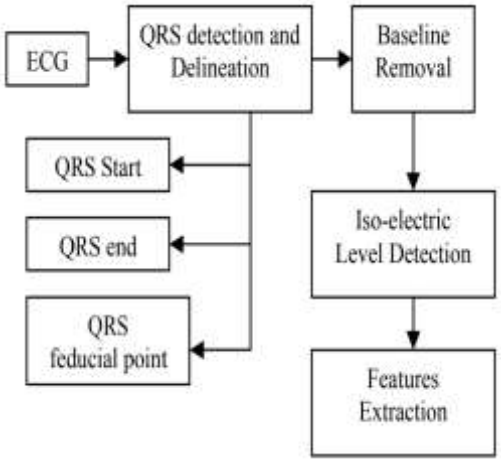

Figure: 4 ECG pre processing steps block diagram

It's impossible to appropriately analyze the ECG's properties when the baseline wanders since the iso-electric line isn't clearly defined. The frequency range of its spectral content is typically below 1 Hz, but it can contain higher frequencies on occasion. When describing an iso-electric level, the flattest region in the PQ interval is taken as the mean value. Electrocardiogram (ECG) at various times in a beat is evaluated against an iso-electric level, which must be detected.

5. CONCLUSION

An electrocardiogram (ECG) is a signal that shows the activity of the heart on a regular basis. ECG can provide a wealth of information about the heart's normal and abnormal physiology. However, due to the nature of non-stationary ECG data, visual analysis is extremely difficult. ECG signal analysis is in need of computer-based approaches. An ECG shows the state of the cardiac heart and hence serves as a guide to how healthy a person is. If the electrocardiogram (ECG) is properly evaluated, it can tell us about a variety of heart disorders. A non-stationary signal like an ECG has anomalies which appear at random intervals rather than being periodic. As a result, the technology described above can be used to do automatic analysis of ECG signals. Patients who have been diagnosed with diseases like Myocardial Infarction, Valvular Disease, and Pulmonary Embolism can have their ECG data distinguished from healthy individuals' data. Better information about cardiac problems can be gleaned from an ECG, especially while monitoring the

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cardiac system's postoperative health. Using a trained model to categorize and analyze diseases with feature values makes it feasible to better monitor cardiac disorders.

REFERENCES

[1.] Poonam Sao, Rajendra Hegadi, Sanjeev Karmakar "ECG Signal Analysis Using Artificial Neural Network" International Journal of Science and Research 2015.

[2.] SaharH.El-Khafif1, and Mohamed A.El-Brawany "Artificial Neural Network-Based Automated ECG Signal Classifier" Hindawi Publishing Corporation 2013.

[3.] Ling Guo, Daniel Rivero, Jose A. Seoane "Classification of EEG Signals Using Relative Wavelet Energyand Artificial Neural Networks" IEEE 2013.

[4.] Himanshu Gothwal, Silky Kedawat, Rajesh Kumar "Cardiac arrhythmias detection in an ECG beat signal using fast fourier transform and artificial neural network" J. Biomedical Science and Engineering, 2011.

[5.] Geir E. 0ien, Nils A. Bertelsen, Ef-testd, John H. Hus "ECG Rhythm Classification Using Artificial Neural Networks" IEEE 1996.

[6.] Muhammad Arif, Ijaz A. Malagore, Fayyaz A. Afsa "Automatic Detection and Localization of Myocardial Infarction using Back Propagation Neural Networks" IEEE 2010.

[7.] S.Issac Niwas, R. Shantha Selva Kumari, Dr. V. Sadasivam "Artificial Neural Network Based Automatic Cardiac Abnormalities Classification" IEEE 2005.

[8.] Abishek Santhosh Raj, Dheetsith N, Sainath S Nair, Debashree Ghosh "Auto Analysis of ECG Signals Using Artificial Neural Network" IEEE 2014.

[9.] Gaurav Kumar Jaiswal and Ranbir Paul "Artificial neural network for ecg classification" Recent Research in Science and Technology 2014.

[10.] Wei Jiang, and Seong G. Kong "Block-Based Neural Networks for Personalized ECG Signal Classification" IEEE 2007.