A Comprehensive Survey on ECG Signal Graph Interpretation

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Abstract - Some people can find it difficult to comprehend the ECG report (graph). It would be less complicated if there was a program that could interpret the ECG data and provide the patient advice on the best course of action to take right away. The patient's state is often classified as either "normal" or "abnormal" on an ECG report. However, it is not much simpler to grasp the graph after utilizing this little analysis. An ECG Graph Analyzer should come to the user's aid if they find themselves in a position where they are unable to visit a qualified doctor to analyze their findings. In this survey study, we examine numerous cutting-edge techniques applied to solve this problem**.**

Keywords - ECG, ANN, Deep Learning, Machine Learning, ECG Signals

I. INTRODUCTION

The ECG sector is flourishing with cutting-edge technologies and R&D initiatives. ECG readings provide as a visual representation of a human heart's electrical activity. The P, QRS, and T waveforms are among the several waveforms that make up an ECG signal. Several variables are presumed and examined in an ECG to identify cardiac problems in a person. Many software programs and algorithms have previously been developed to make the study of ECG data easier. A variety of findings were reached based on the analysis of databases from throughout the world. Studies that attempted to remove pointless noise from a digitalized ECG data in order to better grasp the heart rate frequency were effective in doing so. Cardiac rate frequency is crucial in determining a person's heart condition.

With regard to P, Q, R, and S peak values, the suggested method finds and examines anomalies. The proposed study is broken down into three steps, the first of which involves applying data capture to real-time ECG data. The ECG signal data is subjected to pre-processing in the second step. In the third step, features are extracted from the ECG signals, and then the aberrant peaks are identified from the extracted features to determine the abnormality of the ECG signals. Data is obtained from the appropriate database, pre-processed using Base Line Correction (BLC), inflection points are found using Powerline interference, features are extracted using the GLCM method, and then features are categorised and anomaly is detected using the SVM classifier.

An ECG graph contains many waves, intervals, segments, and joints. It is shown in the Fig.1, Fig.2 and Fig.3 below.

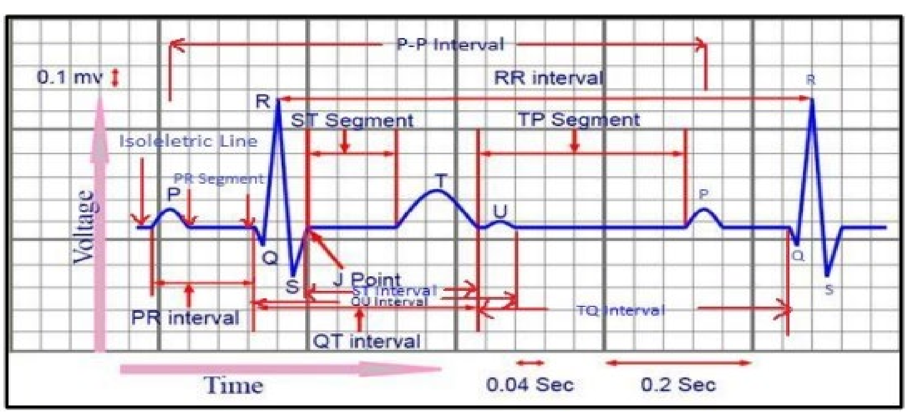

Fig 1. ECG Waveforms.

The following table explain the various features of an ECG graph Table 1.

Table 1. Parts of ECG Wave

Feature	Description
P Wave	Represents atrial depolarization.
Q Wave	Represents septal depolarization.
R Wave	Represents early ventricular depolarization.
S Wave	First negative deflection after the R wave.
T Wave	Represents ventricular repolarization.
P-R SEGMENT OR PQ SEGMENT	Between the conclusion of the P wave and the beginning of the QRS complex, it is the flat, typically called the isoelectric region.
P-R INTERVAL OR PQ INTERVAL	The amount of time it takes for electrical activity to transfer between the ventricles and atria.
R-R INTERVAL	It reflects the interval between two QRS complexes and starts at the peak of one R wave and finishes at the peak of the following R wave.
QRS COMPLEX	Represents the depolarization of the ventricles.
QT INTERVAL	the time taken for the ventricles to depolarize and then repolarize.
ST SEGMENT	It is an isoelectric line that represents the time between depolarization and repolarization of the ventricles.
J-POINT	The junction between the termination of the QRS complex and the beginning of the ST segment.
Q-U INTERVAL	The QU interval is a measure of the length of time it takes for an electrical current to travel from one part of the body to another.

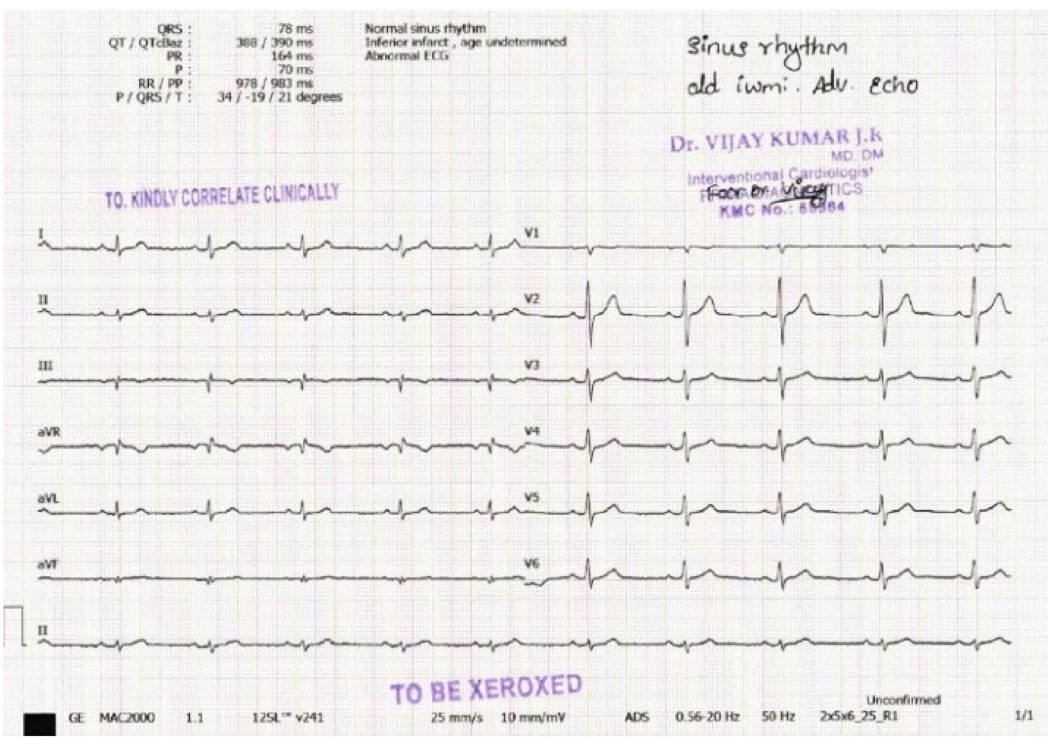

Fig 2. Real Time Example of ECG Graph.

The horizontal axis of the ECG printout represents time and the vertical axis is the amplitude of the voltage.

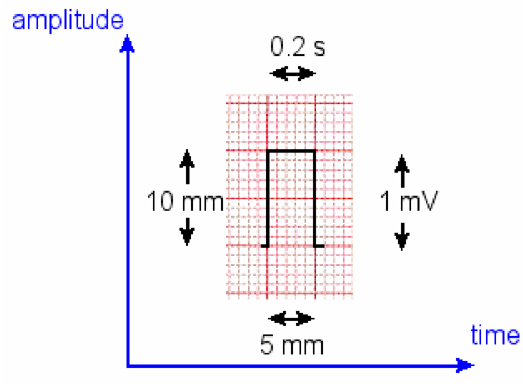

Fig 3. Interval Reading.

On the graph, 1 mV = 10 mm high. Amplitude units are millivolts (mV).
On the graph, 25 mm = 1 second applies to the time scale (or 1mm per 0.04 seconds).

Using the ECG graph, we can identify the characteristics of each individual. Based on which we can differentiate the features which can be used as input for the machine learning algorithm.

II. LITERATURE SURVEY

In the proposed article by Saria, it is possible to see the processes involved in the diagnosis of cardiac arrhythmia using ECG signals where Classification of Heart Diseases was carried out after ECG acquisition, pre-processing, peak identification, feature extraction, and classification. To determine whether algorithm was more dependable and accurate, the TERMA and FrFT based algorithms were applied to two separate databases, MIT-BIH (48 patients) and Shaoxing People's Hospital (SPH) Database (More than 10,000 Patients). In comparison to the other algorithms, the model that was trained using the FrFT approach provided more accurate results. [1]

In the study article Jakub Parak and Jan Havlik have proposed, the three ECG heart rate frequency identification methodologies are detailed, as well as the use of digital signal filtering on ECGs. In order to streamline data processing, the model was trained using ANN and Heart Rate Frequency Detection Algorithms to filter out unnecessary sounds. The algorithms were created using statistics-based methods, and metrics from statistical testing were used to evaluate and contrast each tactic. The technique makes it simple to determine the heartbeat's frequency. This method speeds up computers and is especially effective for processing ECG signals. [2]

A weak signal and the approach that may be used to denoise it is presented in the research article with the title "Denoising of weak ECG signals by employing wavelet analysis and fuzzy thresholding" in order to get to a more accurate diagnosis and analysis of cardiac problems. Noisy signals have been retrieved using signal processing methods. The fuzzy s-function is then utilized to calculate the threshold value of the decomposed weak ECG signals. ECG signal reconstruction is done using inverse wavelet packet transform. The accuracy rate was used in several trials to demonstrate the effectiveness of the suggested strategy. In the article, it was presumed that the White Gaussian noise, which weakens the signal, had distorted the ECG signal. The signals were recorded and subsequently digitalized using the Harvard-MIT Division Datasets. To reach a decision, several outcomes from tests were compared. The new approach performed very well when compared to the current methods, it was subsequently concluded. [3]

Priyanka Mayapur's work, Classification of Arrhythmia from ECG Signals using MATLAB, attempts to offer methods for categorizing ECG Signals created from Lead- 11 ECG setup, which is effective in identifying arrhythmias using MATLAB as it makes the classification simpler and easier. The suggested technique divides signals into normal and abnormal, as well as other types of abnormalities. This paper also includes a comparison of several practices already in use. The American Heart Association ECG Database, The European Society of Cardiology STT Database, UCI, and the MIT-BIH arrhythmia database were used to train the model (Machine Learning Repository). However, because MATLAB requires more time to categorize heartbeats, the approach method is not compatible for bigger databases Table II. [4]

Table 2. Existing Algorithms and Databases

S. No	Objectives	Algorithms	Database	Year
1	Classification of Heart Beat Using Machine Learning Algorithms	Artificial Neural Networks Algorithm, FrFT-Based Algorithm	MIT-BIH, Shaoxing People's Hospital Database	2021
2	Signal Processing and Heart Rate Frequency Detection Methods	Artificial Neural Networks Algorithms	Dataset not specified	2011
3	Denoising of weak ECG Signals using wavelet analysis and fuzzy thresholding	Basic Search Algorithms, Loop Based Algorithms	Harvard-MIT Division of Health Sciences and Technology	2012
4	Arrhythmia Classification from ECG Signals using MATLAB	Naïve Bayes, Decision Tree Classifiers, SVM	AHA, ESC, UCI, MIT-BIH	2019
5	Digitization of ECG Paper Record using Deep Learning	K-Means Algorithms	Saidhan Hospital, STEM1 Global	2021
6	Heart Diseases Classification using Machine Learning Algorithms	CNN (Convolutional Neural Network)	Mayo Clinic (44,959 Patients' Data)	2019

The research article published under the Journal of Medical and Biological Engineering titled "ECG Paper Record Digitization and Diagnosis Using Deep Learning" examines how to accurately diagnose heart-related disorders by digitalizing an ECG graph into a 1-D signal. Datasets from Saidhan Hospital and STEM1 Global were utilized to process images using ANN, DNN, and other methods. According to the suggested study article, converting an ECG graph to a 1-D digital signal makes the data easier to use and analyze, simplifying and streamlining medical operations. This study uses the mentioned dataset to evaluate an ECG graph and turn it into a 1-D signal in an effort to highlight the value of digitization in today's society, particularly in the medical industry. [5]

In their study titled "Analysis and Classification of Heart Diseases using Heartbeat Features and Machine Learning Algorithms," authors Fajr and Mamoon employed machine learning technology to categorize the anomalies in an ECG signal. Thus, waveforms from distinct ECGs were taken into consideration, and subsequently, they were distinguished by certain traits. Spark-Scala is preferable if the dataset supplied is huge. ML Libraries, Discrete Wavelength Transform, Decision Tree Algorithms, Random Forests Algorithm, and Gradient Boosted Trees Algorithm were some of the approaches used in addition to Spark-Scala. This study has the benefit of being more precise and effective in classifying the cardiac signal, among other benefits. This research analyses an intelligent model that can categorize the data into a certain type of heartbeat. Additionally, it makes use of bigger datasets and big data techniques to improve the effectiveness of classifying heartbeat signals. This model has a great deal of promise to be used to help the medical community read ECG signals. [7]

The article "Cardiac arrhythmia detection using deep learning" briefs that the volume of daily ECG data gathered in homes and hospitals may make it impossible for general practitioners or operators to evaluate the information. Traditional techniques of machine learning focuses on manually constructed feature extraction, which necessitates in-depth subject expertise and pre-processing. The advances in deep learning technology facilitates to perform high-level automatic feature extraction and classification. Datasets from MIT-BIH Arrhythmia (MITDB), Creighton University Ventricular Tachyarrhythmia (CUBD), MIT-BIH Atrial Fibrillation (AFDB) and Physio Net/CinC Challenge 2017 were utilised for classification and feature extraction/selection using Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) Algorithms, Deep-Belief Network (DBN) and Auto-encoder methodologies under deep network architecture. Deep learning model interpretation, however, is difficult and necessitates access to substantial datasets. While developing of deep learning algorithms there will always be a need to identify the correct size of training and test datasets. [8]

The absence of appropriate datasets for training the models and for further evaluation processes to validate the developments of computerized ECG analysis was noted in a research study titled "Deep Learning for ECG Analysis: Benchmarks and Insights from PTB-XL [9]." The authors put up a system in which the publicly accessible dataset (12-Lead ECG Dataset PTB-XL) would get first benchmarking results from a variety of ECG statements. Convolutional neural networks, Res-Net, and Inception-based architectures were among the many types of architectures employed. The work ends by providing many paths for further investigation into the dataset, including the investigation of co-occurring illnesses, the connection between human-provided diagnosis and model uncertainty, and the use of interpretability tools. [10]

III. Conclusion

The different methodologies and methods used to train models to recognize waveforms in an ECG signal are compared in this research review paper. Depending on the datasets and range of designs examined, the accuracy varies for various models. The predictivity rate is only 33.8% when a model is created using convolutional neural networks to detect patients with ventricular dysfunction. It was determined that ECG is a reliable screening technique. To analyze the heart's dysfunctions, a variety of AI and deep learning models were trained. In order to monitor, analyze, and transform an ECG Graph into 1-D signals, a study work that employed STEM1 Global Dataset, different Deep Learning, and K-Means Algorithm enhanced the significance of digitization in today's society. An intelligent model was used to classify the signals into different types of heartbeats, which boosted the model's effectiveness and accuracy. These methods of ECG analysis may be combined with a variety of technologies and used in hospitals to improve patient care and prevent delays in that care.

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