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AI tools for prediction and analysis of neurological disorder using ECG data

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Abstract : Neu**rological diseases (ND) are illnesses linked to the peripheral and central nervous systems (CNS). They place a significant strain on global health, which is expanding exponentially. Even though ND has a significant negative impact on patients and societies, people still know very little about its epidemiology, including the variations in disease frequency over space and time and the associated risk factors and outcomes. Due to physical, cognitive, and psychological impairments, patients with ND frequently require extensive social and financial support, making early prediction and diagnosis of the ND crucial.In this study, we first evaluate the literature on AI methods for ECG data analysis in relation to ND. The dataset for this investigation includes normative and Tilt Table Test (TTT) ECGs as per the traditional methods for the detection of POTS. It contains ECG data from patients with and without ND from Bangalore's neurophysiological AFT Lab (NIMHANS). In order to identify the recorded dataset as normative or ND data and forecast ND using this ECG data, we preprocess the data using common approaches like filtering and feature extraction. We then train and evaluate a number of machine learning (ML) models. Our test results show that AI algorithms can predict neurological disorders with given ECG data. We also predict the neurological disorder POTS from the normative ECG data without performing TTT. Finally, we suggest a future study in this field. Overall, this study indicates the potential of AI technologies for ECG analysis in relation to ND. As a result of our research, it is possible to anticipate and monitor ND using ECG data, and AI techniques can assist in realizing this possibility**

***IndexTerms* - —Neurological Disorder, Electrocardiogram, Postural orthostatic tachycardia syndrome, Machine learning, Tilt Table Test.**

I.INTRODUCTION

ND refers to any disorders that affect the CNS which includes the nerves brain and spinal cord. These disorders can cause discomforts like headaches, tingling, muscle weakness, numbness, tremors, and seizures and affect memory speech, or movement. These diseases can have a major impact on an individual's physical and mental health, the quality of life. Some common examples of ND include POTS, Epilepsy, Parkinson's disease, Alzheimer's disease, Stroke, and migraines. ND can be due to a variety of factors like traumatic injuries, genetic mutations, infections, and exposure to toxins. The symptoms broadly rely on the specific condition and its severity but may include seizures, tremors, difficulty in speaking, understanding language, memory loss, and loss of motor function. Diagnosis of ND typically involves a combination of medical history, physical examination, and diagnostic tests such as MRI or CT scans, ECG, and blood tests. Treatment options vary depending on the specific disorder but may include medication surgery, physical therapy and counseling. Research in the field of ND is ongoing, with a focus on understanding the underlying causes of these conditions and developing new treatments to improve outcomes for patients advances in technology such as artificial intelligence and machine learning are also being explored for their potential to improve the diagnosis and treatment of ND.

A. Postural orthostatic tachycardia syndrome:

The main focus of the study pertaining to our research is PoTS. PoTS is a type of neurological condition that affects the ANS specifically the system that modifies the Heart Rate and Blood pressure. PoTS is characterized by a significant rise in the hr upon standing which can cause symptoms such as lightheadedness, fatigue, dizziness and fainting. The exact root of pots is not yet fully understood but it is thought to be related to a malfunction in the ANS it often affects young women and can be triggered by various factors including infection, surgery, trauma, or hormonal changes. There are several ways in which POTS can be detected and diagnosed. Diagnosis of pots involves monitoring HR and BP while changing positions from lying down to standing up and ruling out other potential causes of symptoms such as heart disease or dehydration. One of the efficient ways of diagnosing POTS is through TTT. TTT is performed on the patient by making them lie on a table that is then tilted to a certain angle to record the patient's BP and HR and they are observed throughout the examination if the HR increases by a minimum 30 bpm or exceeds 120 bpm within 10 minutes of standing POTS may be diagnosed.

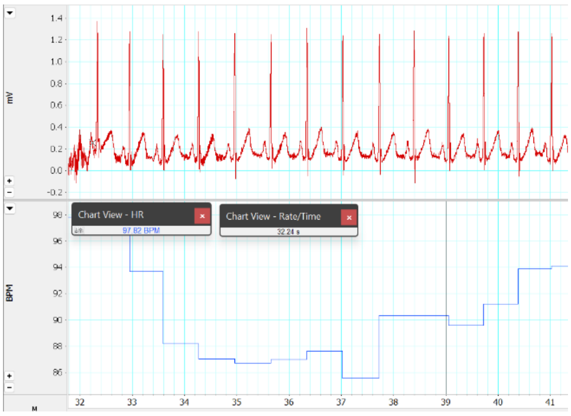
Fig. 1. NORMAL ECG DATA


FIG. 2. POTS ECG DATA

B.Electrocardiogram (ECG):

ECG data is essentially a time series of electrical signals that are generated by the heart's electrical activity. By analyzing this data, healthcare professionals can gain insights into a patient's heart function and detect abnormalities that may be indicative of certain neurological conditions, such as POTS. The common approach to predicting neurological disorders is by the traditional techniques performed by neurophysiologists, hence our work aims to build a suitable AI model which helps in early prediction of ND and classifies them accordingly.

C.Artificial Intelligence:-

In Healthcare AI tools can help to automate the analysis of ECG data, making it faster for prognosis and more accurate than traditional manual methods. AI tools are becoming increasingly important in the prediction and analysis of neurological disorders using ECG data. There are several AI tools that can be used for the prediction and analysis of ND using ECG data. In addition to improving the accuracy of ECG analysis, AI tools can also help to make healthcare more accessible to people who may not have access to specialized medical facilities or healthcare professionals. For example, smartphone applications that use AI algorithms to analyze ECG data are becoming increasingly popular as a way for patients to monitor their heart function from home. ECG data provides important information about the electrical activity of the heart and can be used to diagnose a wide range of ND, including arrhythmias, heart failure, and coronary artery disease. AI tools can help analyze and interpret ECG data more accurately and efficiently than traditional methods and can aid in the prediction and diagnosis of neurological disorders. In our work, we are using AI tools for a variety of tasks with ECG data analysis, such as preprocessing and feature extraction, classification, and prediction. Preprocessing and feature extraction involve cleaning and transforming the raw ECG data into a format that can be used for our further analysis. The AI algorithms are used to extract features from the ECG signal, such as heart rate variability, frequency, and time duration, which are used as inputs to the machine learning model developed for classification and prediction. Our developed model performs classification and prediction involving the usage of AI algorithms to categorize ECG data into different classes, normative or neurological disordered, and to predict the occurrence of a particular neurological disorder based on the input clean ECG data. We are using machine learning algorithms such as logistic regression, decision trees, and artificial neural networks that are being used for these tasks. These algorithms are trained on large datasets of ECG data retrieved from the AFT Lab, allowing the model to learn patterns and make accurate predictions. Overall, AI tools have gained the potential to revolutionize the analysis and prediction of ND using ECG data rather than traditional methods. Hence our model aims to provide a more accurate and efficient analysis of ECG data and predict POTS from the normative ECG data to help in the early prediction and treatment of neurological disorders, leading to better patient outcomes and improved quality of life.

The establishment of large hospitals where hundreds to thousands of patients are treated , it has created a serious problems of biomedical waste management. The seriousness of improper biomedical waste management was brought to the light during summer 1998. In India studies have been carried out at local / regional levels in various hospitals, indicate that roughly about 1-5 kg/bed/day to waste is generated. Among all health care personnel ,ward boys , sweepers, operation theatre & laboratory attendants have come into contact with biomedical waste during the process of segregation , collection, transport, storage & final disposal . The knowledge of medical , paramedical staff & ward boys , sweepers about the biomedical waste management is important to improve the biomedical waste management practices. The biomedical waste requiring special attention includes those that are potentially infectious , sharps ,example needle , scalpels , objects capable of puncturing the skin , also plastic ,pharmaceutical & chemically hazardous substances used in laboratories etc.

II. LITERATURE REVIEW

In [1] Neurological disorders(ND) are described as a substantial challenge in healthcare systems, and their prevalence is growing exponentially in low and middle-income nations. Given the considerable impact of ND on both individuals and society, insight into their epidemiology, including disease frequency variation over location and time, as well as knowledge of associated risks and outcomes, is considered inadequate. Medically speaking in [2], ND encompasses those that impact not just the brain itself but also the nervous system(NS). Many NS disorders have been shown to be extremely complicated to diagnose and cure when compared with other kinds of diseases. Different symptoms may well be linked to structural, metabolic, or physiological anomalies in the NS. Fatigue, lack of coordination, loss of sensation, paralysis, convulsions, confusion, discomfort, and unconsciousness are a couple other impacts.

The abnormality of the ECG shape is called cardiac arrhythmia. During a cardiac arrhythmia, the heartbeat is too swift, too relaxed, or irregular. In a typical ECG waveform, each beat contains P,QRS complex and T wave. [3]At crucial levels, these abnormalities are divided into two categories such as ventricular fibrillation and tachycardia that could stimulate cardiac arrest and sudden death, thus it is utmost important for immediate treatment. Tachycardia specifically refers to a HR that is exceeding 100 per minute for an adult as they are categorized as regular or irregular, and narrow complex or wide complex. The primitive problem of automatic ECG analysis arises from the non-linearity generated ECG signals and the massive variation in ECG of different patients.

In [4], most cases, these signals are corrupted by background noises, such as electromyogram generated noise and electrode motion artifacts, which also amplifies the complexity of automatic pattern recognition in ECG.

At the stage of preprocessing [3], the main objective is to reduce such artifacts to determine the points (P, Q, R, S, T). This stage uses a filtering block to remove artifacts from an ECG signal. Conventionally, an ECG signal is primarily bandpass filtered with various ranges of frequencies before analysis. This filtering is extensively used to remove baseline wander, power line interference, muscle noise and low- high frequency noise components. The two other widely used ECG signal filters are two median filters that have 200 and 600 ms widths respectively to delete the baseline wander [58,59], P and T waves.

In [5] the authors explained that these tests may be used for the evaluation of unexplained recurrent fainting and syncope , POTS (Postural Orthostatic Tachycardia Syndrome), Autonomic failure, Neurogenic orthostatic hypotension(NOH), Orthostatic intolerance(OI), Small fiber nerve function.

The various Maneuvers that are performed during the recordings are mentioned in [6].

1. Valsalva maneuver is a breathing technique that influences HR, evaluates the changes in baroreflex arc and its responses. The ratio is calculated as the ratio of the highest HR during expiration to the lowest HR during the initial 20 secs post the expiratory strain.

2.Deep Breathing, a Metronomic technique. The expiratory–inspiratory difference (E-I difference) is determined from the highest and lowest HR from six cycles of respiration per minute.

3.Sustained handgrip test where the handgrip is maintained at one-third of the maximum contraction strength for 3–5 minutes.

4.Orthostatic test also known as active standing , the Heart Rate Variation(HRV) is performed during the initial stage of orthostasis adaptation. The ratio is calculated as a quotient of the maximal to minimal RR interval. The 30/15 ratio should be at least 1.04, but it decreases with age.

In [7] Tilt table testing is described and it is used because temporary loss of consciousness is a common phenomenon in various clinical settings. Involuntary motor activity often raises suspicion of epilepsy. However, syncope may also be accompanied by convulsions that resemble epileptic seizures. Because only epilepsy can be treated with antiepileptic drug (AED) therapy, it is important to distinguish between syncope and epilepsy. The head-up tilt-table test was performed according to the European Society of Cardiology (ESC) protocols and guidelines. The incline was performed at her 60° angle, with a maximum duration of 45 minutes in the upright position.

[8]Machine learning, an application of artificial intelligence (AI) techniques, combines statistics and computer science to enable machines to automatically learn something new and improve their performance through meaningful data without explicit instructions. Supervised learning is an approach that trains on labelled data. It is primarily used for classification or regression purposes, and its algorithms include k-nearest neighbors (k-NN), linear/logistic regression, naive Bayes, random forests, and support vector machines (SVM). [9]An effective electrocardiogram (ECG) arrhythmia classification method using a deep two-dimensional convolutional neural network (CNN) is being used. Each ECG beat was transformed into a two-dimensional grayscale image as input data for the CNN classifier. The experimental results show that the proposed CNN classifier using transformed ECG images has excellent classification accuracy without manual preprocessing of ECG signals, such as noise filtering, feature extraction and feature reduction. was confirmed to be achievable.

[10]POTS is defined as a clinical syndrome with frequent symptoms that occur within 10 min of standing, an increase in heart rate of at least 30 bpm when moving from a recumbent to a standing position. Head-upright tilt table testing (TTT) is commonly used for the evaluation of POTS . The purpose of the present study was to determine the prevalence of ST changes during TTT in a young, otherwise healthy population of patients with POTS. During tilt testing, the QT interval was found to be significantly shorter in patients with POTS with significantly flattened T-waves.

In [11], the researchers have compared the HR and HRV of POTS patients with those of healthy people. It is hypothesized that compared to healthy participants, the POTS sample had significant higher HR, greater LF/HF ratio, and lower mean RR-Interval.[12]Movement is impaired by Parkinson’s disease, a chronic and progressive disease of the nervous system.

[13]Audio signal analysis is a diagnostic of Parkinson’s disease considered an important non-invasive method for Clinicians and neuroscientists interested in techniques for noninvasive PD detection and prediction. Detection of heart abnormalities using ECG may provide diagnostic signs for brain dysfunctions namely stroke. In [14], Authors used 98 ECG data sets, including normative and stroke data, in their work. They applied CNN to create a model with Batch Normalization (BN), Rectified Linear Units (ReLU), and Convolution layers. DenseNet was used to cope with overfitting since it reduces network parameters without compromising accuracy. Finally, the Adam optimizer is employed because it can handle sparse gradients on noisy inputs and reduce the convergence to local minima while consuming little memory.

Recurrent Neural Networks (RNN) were used in [15] to categorise normal and anomalous beats. When applied to an ECG, CNN cuts the beats to specific length chunks, curbing classification performance.. Here, the authors use RNN to input the current beat and the last beat to acquire the associated key aspects of the beats precisely and automatically. The study demonstrated that long short-term memory(LSTM) generates the greatest outcomes in binary categorization of ECG arrhythmia. The results reveal that RNN LSTM has a high degree of accuracy.

[16]The primary objective of this narrative review is to highlight the emerging AI technologies that focus on unsupervised aspects of machine learning. The authors have described various forms of AI available for use for implementation in smart devices. The authors also mention Self organising maps which help in concussion, epilepsy detection and neuroimaging using adaptive boosting(AdaBoost) algorithms in smart devices. [17]This research has spotted a few machine learning techniques on the basis of various measures of accuracy that helped in diagnosing three basic ND. The Kappa statistics is used to measure the accuracy level of classifiers, when it was applied to classifiers like SVM, KNN, and random forest signified higher values with all attributes. [18]This study has explored different state-of-the-art AI-based CAD systems. The authors state that the 3D CNN and CNN – Recurrent neural network (RNN) are more recent networks used in the diagnosis of epilepsy with high performance.

III. SYSTEM ARCHITECTURE OVERVIEW

Flowchart for Neurological disorder detection starts with collecting data from the nearest neurological center. After Data cleaning and Data preprocessing, the Refined data is fed to the data classification model which decides whether that person has a neurological disorder or not. development with the training data and subsequent classification on the test data. Multi Classification model is applied to determine the type of Neurological disorder.

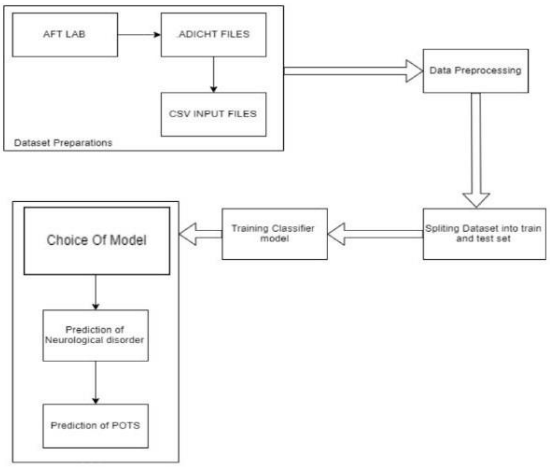

Fig. 3. Framework Model

IV. ASSUMPTIONS AND DEPENDENCIES

The proposed project deals with the prediction and classification of neurological disorders which typically assumes the following:

State of the art of recording devices: The proposed project model requires Bio Amp(Amplifier), Heart Rate Variability Machine, and BP Machine, and the dataset collected includes both lying down ECG and Tilt ECG data as the resources. The data collection depends on the ECG Machine which is received from BIOAMP where amplification and noise filtration of ECG signals takes place.

State of the art of machinery: BP machine and passive electrodes are required for ECG to be recorded.

Fig. 4. BioAmp

Adicht instrument software: The input data being used is in Adicht file format which will be viewed using LabChart Reader for analysis. This software supports several input data formats for electrocardiogram (ECG) data and beat-to-beat RR interval data. It includes an adaptive QRS detection algorithm and tools for artifact correction, trend removal, and analysis sample selection. The software computes all the commonly used time-domain and frequency-domain HRV parameters and several nonlinear parameters.

guidance and consultation from doctors: This project depends on the guidance of doctors for performing ECG in lying down and tilt table testing. The recorded values under consideration are evaluated according to the knowledge received from the doctors.

A clear distinction between POTS and normative ECG data: The Data is collected from the neuroscience center include tilt table test and normative ECG data for the analysis and prediction of abnormalities. In terms of dependencies, the proposed project depends on various libraries such as Kera's, NumPy, Sklearn, SciPy, TensorFlow for classification of the model. It also depends on various choice of Neural networks like CNN, LSTM, RNN and combination of one another.
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V. METHODOLOGY

A. DATA COLLECTION

In our project the data collection workflow starts with collecting ECG data from the nearest neurophysiological centre. The ECG data is being collected from the AFT lab with the help of an HRV machine and BP machine which are connected to the Bio Amp(Amplifier). ECG data is typically collected using electrodes placed on the skin at various points on the body, such as the chest, arms, and legs. These electrodes detect the electrical signals generated by the heart as it beats and transmit the information to an ECG machine. This machine then records and displays the data as a series of waveforms on the computer in the form of a graph. There are several different types of ECG data that can be collected, including resting ECGs i.e. normative ECG, exercise ECGs, and Tilt Table Test ECGs. In our project we mainly focus on normative resting ECGs and Tilt Table Test ECGs.The resting ECGs are typically performed while the patient is lying down at rest to record the base heart rate values.While recording the normative resting ECGs, the patient is asked to perform few maneuver to track the heart rate variability. Whereas the tilt table testing ECG is performed by tilting the patient at a certain angle to record the variation in the heart rate during the tilt. We consider the normative resting and tilt table testing ECGs in our project by the guidance of neurophysiologists. Our primary focus, under the direction of the neurophysiologists, is training our model with the data from healthy individuals and patients with neurological disorders from the neurophysiological centre to do prediction and classification.Overall, the data collection process for the classification of neurological disorders using ECG data involves careful patient selection, data preprocessing, feature extraction, machine learning model development, and evaluation.

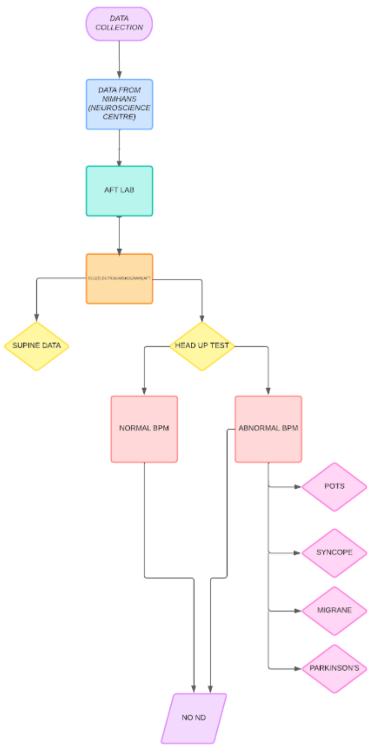

Fig. 5. Data Collection

B. DATA PREPARATION

The data obtained from the Neurophysiological Centre is raw data present in the ADICHT file format. The ADICHT file software stores the recorded biological signals of patients.The ADICHT file format is not supported by many programs[no need to put this.hence we convert this file to the CSV format in the easy readable form to input it into our model. The collected ECG recordings contain normative and PoTS (Posturaorthostatic tachycardia syndrome) ECG data chosen from the patients age range of 24-38 years old. The duration of ECG recording of the patient takes upto 30 minutes which includes lying down , maneuver and tilt ECG. The entire 30 minutes range contains artifacts which are caused due to unwanted movements like cough, shaking, and other disturbances. Due to which we choose the best 5 minutes for normative lying down and tilt table test recordings respectively.

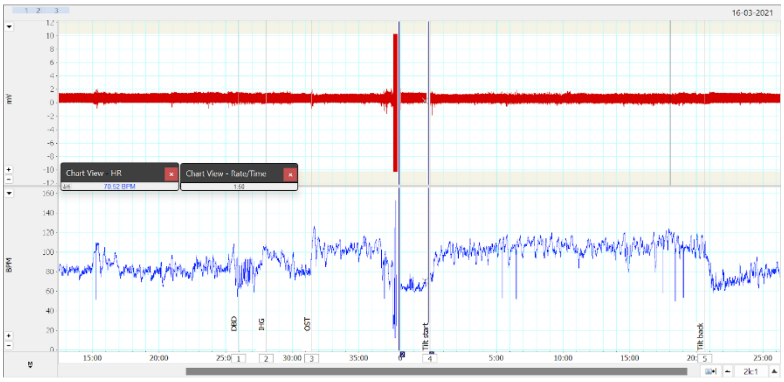

Fig. 6. ECG Recording

C. DATA PREPROCESSING

An ECG signal denoising is a significant pre-processing step that reduces noise and emphasises characteristic waves in ECG data. Noise reduction in ECG data is an important step to improve the quality and accuracy of ECG signal processing and scrutiny. Unnecessary signals/noise in ECG signals disrupt the clinical information contained within them. To ensure the accuracy of data analysis we performed few data cleaning techniques such as removing unwanted data by dropping the null values. The data format received from the neurophysiological AFT Lab was in adicht file format which was then converted into csv file format. We used LabChart Reader for analysis and evaluating adicht file format.

D. DATA LABELLING

Our data is being labelled using ID. The process of generating unique identifiers to each data point or sample in a dataset is done with the help of data labelling(DL) using ID. Each data point is allocated an ID using a basic numbering strategy in which each data point is assigned an ID. After tagging the data points with IDs, they are being used to train and evaluate ML models. DL using ID is especially beneficial for our data which is complicated and individual data points must be tracked and referenced over time. It helps to assure data accuracy and consistency by standardising the labelling and reference of each data point.

E. DATA CLASSIFICATION

Data classification is the process of arranging the data into discrete categories or classes based on specific characteristics or features. In the context of our project, our model detects neurological disorders using AI from the collected ECG data of the patients. Data classification involves categorising ECG signals based on their waveform patterns, which can be indicative of specific neurological disorders. The ECG (electrocardiogram) data is the measure of the electrical activity of the heart, and abnormalities in this electrical activity can be associated with neurological disorders such as POTS, Epilepsy or Parkinson's disease. Machine learning algorithms are trained on large datasets of ECG signals to identify patterns that are associated with these disorders and are used for the classification purpose. The process of classifying ECG data involves several steps. First, the raw ECG signals are pre-processed to remove noise and the artefacts that interfere with the classification process and obtain cleaned data. This involves filtering, noise reduction, and smoothing techniques. Patient ecg data is used to train the machine learning system.
We are using decision trees and logistic regression in our project. A statistical model called logistic regression is used to examine and forecast binary outcomes, where 0 and 1 re resent normal and neurological disease, respectively. Logistic regression is mostly employed in our constructed model to characterize the data and provide insight into the relationships between the variables. Additionally, these variables may be nominal or disordinal. The logistics function is used in the developed model to simulate the likelihood of a binary response, which is a fundamental design variable. By fitting a function to the data that converts the continuous values of the independent variables into probabilities between 0 and 1, the likelihood ratio is used in our project to model the probability of a specific outcome, in this case, the probability that a patient will have a neurological disorder as a function of the independent variables. Our dataset contains characteristics that can be separated linearly, hence lr performs extremely well.
The decision tree is utilised in our project since it is the most potent algorithm and is frequently used to find solutions to classification and regression difficulties. It is a type of supervised learning in which the model makes predictions about the results based on a collection of input variables. This particular algorithm was based on a tree's node-and-edge structure, where each node denoted a particular choice or test to be made about one of the input variables. The purpose of using a decision tree in our project is to create a model that learns from the training data and is then applied to the prediction of the normal and nd by using learning decision rules derived from the training data that can be applied to predict a class label of 0 or 1 for a record it initiates from the root of the decision tree. The values obtained by the root attributes are then compared to those provided by the records attribute to forecast the normative or ND. In order to progress to the next node, we monitor the branch that corresponds to that value using this comparison as our base. This algorithm finishes when all the data points in a branch belong to the same class, either normative or ND, respectively. Since the decisions made by the model can be easily understood and visualized, the decision tree algorithm is used in our project. In this instance, the input data would be the ECG readings of patients with and without neurological problems. The algorithm would

then evaluate the ECG data to find patterns and develop criteria for determining whether a patient has a neurological disorder based on their ECG readings.

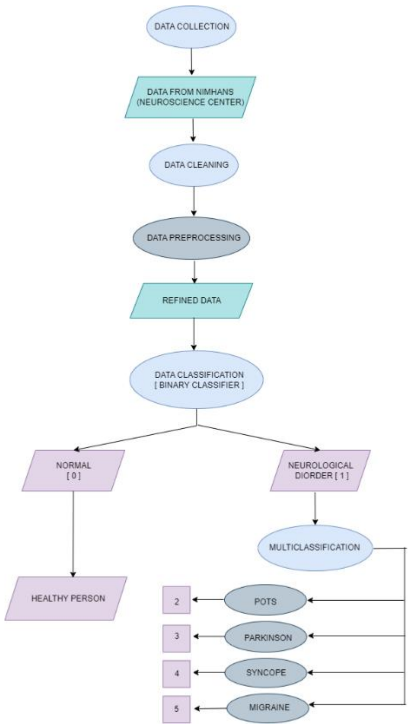

Fig. 7. Flowchart Model

E.EVALUATION OF MODEL

We examine the efficiency of our model using metrics that indicate accuracy and precision, such as the roc curve and confusion matrix. The performance of our classification model at various classification thresholds is shown graphically in our proposed model through the use of the roc curve. This metric specifically depicts the true positive rate (TPR) and false positive rate (FPR), which are two crucial metrics. The method of predicting the chance of a patient having a neurological problem based on their ECG reading and the area under the roc curve would involve training the model on a dataset of ECG readings and neurological disorder diagnoses. In general, the roc curve aids in the development of a strong performance measurement of our binary classification model for predicting neurological illnesses using ECG data and can aid in the choice of an appropriate classification threshold for a particular use case.

A ROC curve can be used to assess the effectiveness of a binary classification model when attempting to categorise neurological illnesses using ECG data. This is how it goes: How to build a binary classification model A machine learning model is first developed using a dataset of ECG measurements and diagnosis of neurological disorders. Create probability ratings: The model creates a probability score for each patient in the validation set that indicates the likelihood that the patient has a neurological condition. A continuous value between 0 and 1 represents this score.

Analyze the performance of the model at various thresholds: The patients are then classified as having a neurological illness or not using various categorization thresholds based on the probability scores. For illustration, a 0.5 threshold may be implemented.

The true positive rate (TPR) and false positive rate (FPR) should be calculated. The TPR and FPR are computed for each threshold. The TPR measures the percentage of real positive cases—patients with neurological disorders—that the model properly classifies as positive. The FPR measures the percentage of real negative cases—patients without a neurological disorder—that the model misclassified as positive.

Create a ROC curve plot: Then, a graph with the TPR on the y-axis and the FPR on the x-axis is created using the TPR and FPR pair data. The ROC curve is the plot that is produced. Use the measurement of the area under the ROC curve (AUC) to measure model performance: The area under the ROC curve (AUC) is a metric used to measure model performance. An AUC of 1 would indicate a perfect model, whereas an AUC of 0.5 would indicate a model that performs no better than random chance.

It is helpful to visualize and assess the effectiveness of a binary classification model for predicting neurological illnesses using ECG data using the ROC curve and AUC. The ROC curve can be used to pick an acceptable classification threshold for a given use case by illustrating the trade-off between the model's sensitivity (TPR) and specificity (1-FPR) as a function of the classification threshold. A training set and a validation set are separated from the dataset. The model gains the ability to forecast whether the patient has ND or not.

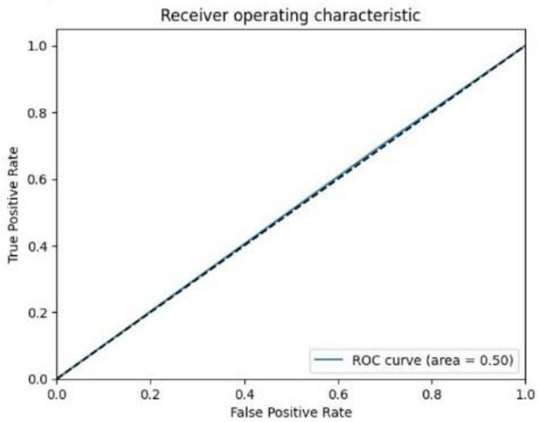

Fig. 8. ROC Curve

F. CONFUSION MATRIX

A confusion matrix is a helpful tool for assessing how well a binary classification model performs when used to predict neurological illnesses from ECG data. Here is an example of how it is used in our project.

Create a binary classification model first: Using a dataset of ECG readings and neurological condition diagnoses, a machine learning model is first created. There is a training set and a validation set for this dataset. Based on the ECG data, the model develops the ability to identify neurological disorders in patients.

Create predictions: Based on the ECG data, the model creates a prediction for each patient in the validation set as to whether or not they have a neurological condition. Create confusion matrix: The number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions made by the model are displayed in a 2x2 table called the confusion matrix.

TP: The proportion of individuals with neurological conditions that the model properly recognized as such.

TN: The proportion of individuals without a neurological illness who were accurately classified as such by the model.

FP: The number of patients who the model mistakenly classified as having a neurological illness even when they did not.

FN: The percentage of patients with neurological disorders which the model misdiagnosed as not having neurological disorders.

Analyze the confusion matrix. The F1 score, accuracy, precision, and recall may all be determined using the confusion matrix. These measurements can shed light on the model's advantages and disadvantages as well as point out areas that want improvement.

Accuracy: The percentage of patients who were properly diagnosed by the model, calculated as (TP + TN) / (TP + TN + FP + FN).

Precision: The percentage of patients who were expected to have a neurological illness and really had one, computed as TP / (TP + FP).
Recall, also known as sensitivity, is the percentage of individuals with neurological disorders that the model correctly detected (TP / (TP + FN).
The harmonic mean of recall and precision, computed as 2 * (recall * precision) / (recall + precision), is the F1 score. On overall, the confusion matrix is an effective tool for assessing how well a binary classification model predicts neurological illnesses from ECG data. The metrics derived from the confusion matrix can be used to analyse the model's performance and make adjustments to improve accuracy and usefulness.

Detecting ND using ECG data requires a well-designed methodology to ensure accurate diagnosis and minimize false positives. In our project study, we investigated the use of ECG data for detecting neurological disorders. We collected ECG data from a sample of patients diagnosed with ND and a control group of healthy individuals from the nearest neuroscience center NIMHANS, Bangalore. We then preprocessed the data to remove noise and artifacts and extracted features that are relevant to the detection of ND from the retrieved data. We used machine learning algorithms, including logistic regression and decision trees, to train models on the extracted.

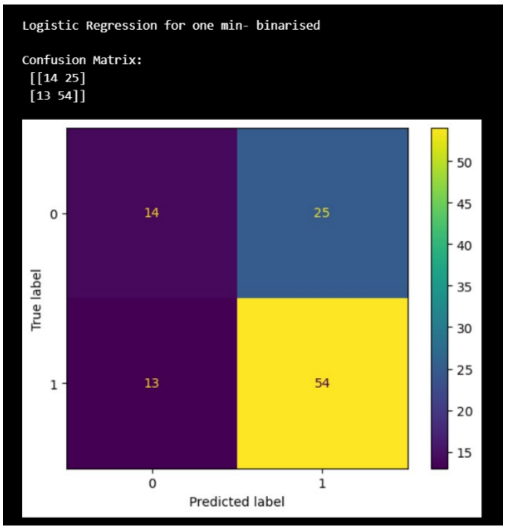

Fig. 9 . Confusion Matrix

VI. CONCLUSION

In conclusion, AI tools for prediction and analysis of Neurological Disorders using ECG data project have shown promising results in predicting whether the person has Neurological disorder or not, and also the model is able to predict POTS disorder. This means to predict the POTS, Normal Lying down ECG data is enough. By analyzing the features of ECG data, the model is able to make accurate predictions. Person's safety is ensured by performing early detection of POTS without the tilt table testing

VII. FUTURE WORKS

In future work, we will perform Multi-classification for the prediction of other neurological disorders such as epilepsy, Alzheimer's, Syncope and Migraine. We also look forward to integrating our model with ADI instruments to prognosticate the neurological disorder for the early prediction.

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