Classification of ECG data using non-linear time series analysis

MSc Data Science, University of Aberdeen 2024

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Abstract

Introduction

ECG analysis in recent times has always played an important role as it helps in efficient diagnosis and in providing valuable information for clinical applications. This thesis will give an overview about the PTB-XL dataset being used and the results which are obtained after intensive data analysis including data collection, data preprocessing, data exploration and time series analysis, and lastly creating a model for classification of healthy and unhealthy patients.

Method

The method to achieve our goal is to first collect and import the raw ECG signals from the PTB-XL dataset into the system. On the imported ECG signals, baseline correction is performed using a high pass filter and then we perform standardization to compute the statistical quantifiers. The signals then undergo frequency domain analysis through the Fast Fourier Transform (FFT) method to identify key spectral components from the power spectrum. This is followed by peak detection on the time series which provides with RR intervals. Machine learning algorithms are then applied which gives insights regarding the patient health.

Results

The T test which has been performed on the ECG signals of healthy and unhealthy person shows a significant difference between the groups. The T value obtained for Mean RR interval is 4.48 and P value obtained is $7.59\times10{-}9$ also the T-statistic for standard deviation of RR intervals is -9.18and the P-value is 5.50e-20. After applying the machine learning algorithm of Random Forest classifier which gave the best accuracy of 0.70 while the Support Vector Machine gave an accuracy of 0.65.

Conclusion

We have been able to get a detailed overview about how different machine learning algorithms classifies between healthy and unhealthy patients. As more research work and advanced neural network methods are done, may lead to better accuracy and help in clinical diagnosis of ECG.

Introduction

Imagine a world where Electrocardiography (ECG) is so advanced where in no time the cardiologists can predict any clinical diagnosis. This thesis thrives to explore innovative machine learning algorithms in reaching the desired goal. We have been able to provide an approach in this thesis where we can differentiate between a healthy and unhealthy person on performing analysis of the ECG signals of the PhysioNet dataset which have been the source of research in recent years. Our focus has centered around the Lead II signal of the ECG signal. The reason for choosing this signal as it gives a good view of the P wave and provides us with useful information about the heart's activity which is used for the classification of cardiac abnormalities like arrhythmias, ischemia, and conduction disorders. This thesis will focus on the classification of ECG signals using supervised machine learning.

Literature

ECG data analysis has been used to classify and predict illness for many years. Many researchers have worked on ECG analysis and used machine learning algorithms to have an understanding and help in clinical diagnosis. The work done by one researcher [i]is using long-short term memory (LSTM) networks for arrhythmia classification, and obtained an accuracy (ACC) of 0.6. [ii]Apart from this one study has shown a computer-aided diagnosis system for automatically diagnosing four types of serious arrhythmias using entropy measures, fractal dimensions, or Lyapunov exponents to classify the irregular nature of arrhythmic ECG signals These features were classified using analysis of variance (ANOVA) and automated using K-nearest neighbor (KNN) and decision tree (DT) classifiers, resulting in ACC scores of 93.3% for KNN and 96.3% for DT. Moreover, different deep learning models have been performed to detect atrial fibrillation which achieved a accuracy of 0.992. [iii]Research have also combined CNN and nonlocal convolutional block attention modules (NCBAMs) which achieved an accuracy of ACC pf 0.93 for arrhythmia detection.

[iv]Another work which has been performed by one of the researchers is classifying ECG signals using nonlinear analysis and machine learning, which can help in the automatic diagnosis of cardiovascular disorders. The proposed methodology is using Recurrence plot, autoencoders, CNN classifier and machine learning algorithm which is stacked classifier. The Physikalisch-Technische Bundesanstalt (PTB) dataset from the PhysioNet1 is employed in this study. This dataset comprises 549 recordings of standard 12-lead ECG signals from 290 subjects aged between 17 and 85 years. The stacked classifier was a combination of three algorithms which is Support Vector Machine, XGBoost, and RUSBoost. This classifier gave a peak accuracy of 97.05%. The result of such high accuracy in classifying was obtained as the sample set on which the model was trained is comparatively very low. [v]One more comparative study was done on wavelet and Fourier Transform using Neural Networks classification of Myocardial infarction work has been done. ANN classifier and MATLAB software has been used for the training and classifying the data. Back Propagation Algorithm (BPA) is the algorithm was used to train the network and the performance goal was met at 2300 epochs with a training span of 45 sec. The accuracy and sensitivity obtained is 0.95 and 0.90 respectively.
The amount of research and work particularly on the PTB-XL dataset have been particularly very less but have often been used in combination with other datasets for obtaining insights on the heart's functionality and ECG

Dataset

The ECG data which has been used in this thesis to analyze and classify is collected from the Physikalisch-Technische Bundesanstalt (PTB) XL dataset which is a large and publicly available collection of ECG recordings. PTB-XL comprises of 21,837 clinical 12-lead ECG records from 18,885 patients, spanning a broad range of diagnostic categories. The dataset contains patients aged between 2 and 89 years. Male and female sex have been represented by 0 and 1 The data is sampled at two different rates: 100 Hz and 500 Hz. Metadata and waveform annotations are present too providing data of patients age, sex and the recording environment. The 12 different lead of ECG signals are divided into 3 groups as follows: -

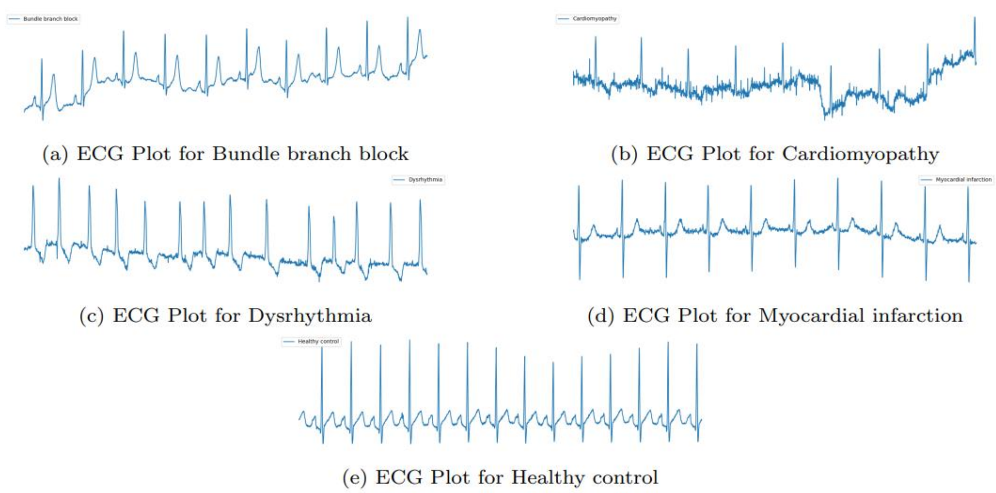
- Limb Leads: I, II, III
- Augmented Limb Leads: aVR, aVL, aVF
- Chest Leads: V1, V2, V3, V4, V5, V6

There are diagnostic levels which are affiliated with the SCP-ECG standard and the two levels of granularity are detailed below: -

1. **Superclasses**: There are broadly divided into five categories: -
    - Normal ECG
    - Conduction Disturbance
    - Myocardial Infarction
    - ST/T Change
    - Hypertrophy

2. **Subclasses**: Under superclass there are 71 more detailed diagnostic labels, namely:
    - Atrial fibrillation
    - Inferior myocardial infarction
    - Non-specific ST/T abnormalities
    - Left bundle branch block
    - Right ventricular hypertrophy

The below figure shows different plots of cardiac disorders which have been down sampled at 250Hz.iv



(a) ECG Plot for Bundle branch block

(b) ECG Plot for Cardiomyopathy

(c) ECG Plot for Dysrhythmia

(d) ECG Plot for Myocardial infarction

(e) ECG Plot for Healthy control

Fig 1***: ECG Plot showing various heart diseases and Healthy Person***

Methodology

The below flowchart Fig 2 gives an overview of the methodology and the steps which have been performed on the ECG data of the patients. Here we have focused on the lower sampling rate of 100 Hz and Lead II signal.

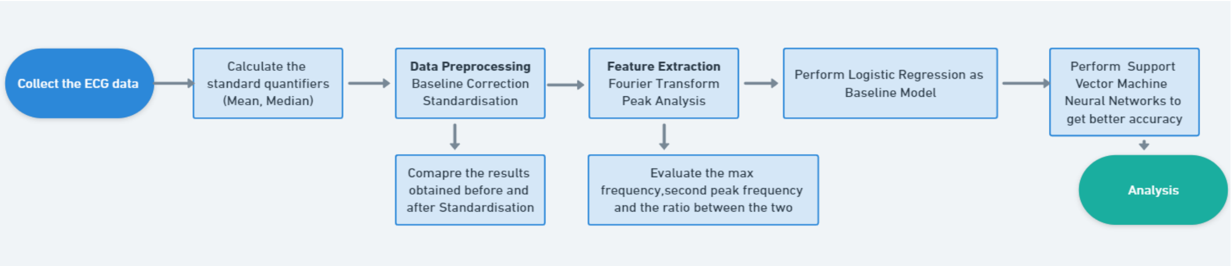


Fig 2: ***Flowchart for ECG data classification***

Below are the details of the preprocessing steps which have been performed on the ECG signals. These steps are detailed below:

- **Standard Quantifiers:** The mean and median have been calculated for the ECG Lead II signal where the mean indicates the baseline level and the overall amplitude level of the ECG signal. On the other hand, the median will help to identify any abnormalities in the signal and will be less affected to outliers as compared to the mean.

- [vi]**Baseline Correction**: Baseline correction is a process of minimizing or removing the low-frequency components from the ECG signal and in the process to yield the true cardiac activity. Baseline drift can take place due to patient movement while taking the reading/chest movements while breathing/improper way of placing electrodes with the skin/ electromagnetic interference of nearby electronic devices.

  Baseline Correction can be achieved in different ways such as using a high pass filter or polynomial fitting or moving average technique. These techniques will enhance the overall signal quality, give accurate measurements and a consistency across samples will be observed making the analysis more reliable and achieving a higher accuracy. In this thesis we have used the high pass filter method to achieve the same.

- **Standardization**: Standardization is performed on the baseline signal to achieve a mean of zero and a standard deviation of one. This step standardizes the signals which will allow for comparison between different patients records. After Standardization is performed cross verification of the data obtained with the previous so that we can observe how much change we are able to obtain and whether the technique used is giving any benefit and clarity is observed.

  Feature extraction which mainly comprises Fourier Transform and Peak Analysis both in Frequency domain and Time domain. We will mainly focus on RR intervals while performing this task which in

- **Fourier Transform:** The Fourier Transform is a mathematical technique that transforms a time-domain signal into its constituent frequencies. The Fast Fourier Transform (FFT) is an algorithm used to compute the Fourier Transform, which allows us for rapid spectral analysis of ECG signals. After baseline correction and standardization, the FFT is applied to the ECG signals to identify key spectral components. This transformation gives the frequency content of the signals which is used for further analysis. This method will help to recognize the primary frequency component and the second frequency component consecutively and the ratio of these frequencies will provide insight into the overall cardiovascular health of the patient.

- [vii]**Time Domain Peak Analysis:** Peak analysis in the time domain helps to identify the peaks in the ECG signal which helps doctors to understand about any heart rate variability in the patient. The RR interval has been the focus area in this thesis as it will give information on one complex heart cycle. We can also evaluate metrics such as peak amplitude and peak time. In ECG analysis this technique is used to detect QRS complexes which correspond to heartbeats.

- **Logistic Regression:** [viii]Logistic Regression is of two variants were estimating the parameters of a logit model and binary classification where a single binary dependent variable which is encoded as “0” and “1”, while the independent variable can be continuous or binary variable. As our aim is to classify into two groups of between healthy and unhealthy people we have chosen the diagnosis column as the dependent variable.

  Logistic Regression has been applied as a baseline model in the analysis work to gain insights into how the model is performing. We have used various classification models as use cases to get the best accuracy and prediction.

- **Classification:** After performing Logistic regression, we use classification techniques such as Support Vector Machine (SVM), Random Forest Classifier, Stacking classifier and neural network techniques to achieve higher accuracy on the dataset. SVM algorithm divides the available data points into two classes which for our case in healthy and unhealthy people, using a hyperplane which solely maximizes the distance from the closest points. We have used more than one classification technique to understand and see how the dataset responds to

- **Neural network** which is basically a deep learning process about designing the model as per the human brain with designing of neurons in layered manner. We have used neural networks to check if we can get better results as compared to logistic regression.

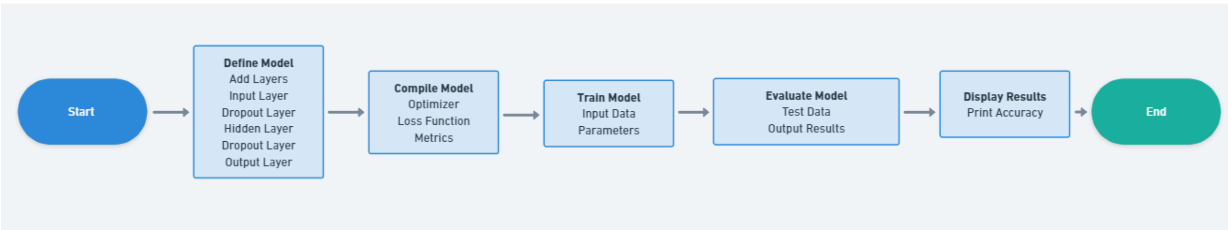


Fig 3: ***Neural network model working flowchart***

To verify how efficient our machine learning algorithms are we have used the confusion matrix and the different related metrics to have a clear understanding about the classification between the two groups. The confusion matrix and the related metrics are listed below:

- Confusion matrix: This gives us an overview about how many predictions have been done correctly and incorrectly.

		Actual class	
		P	N
Predicted class	P	TP	FP
	N	FN	TN

Fig 4: ***Confusion Matrix***

where TP = True Positives TN = True Negatives FP = False Positives FN = False Negatives
True Positives: Model correctly predicts that a patient has a disease and has the disease.
True Negatives: Model correctly predicts that a patient has no disease and doesn't have the disease.
False Positives: Model predicts that a patient has a disease but the patient actually does not have the disease
False Negatives: Model predicts that a patient does not have a disease (negative) but the patient actually does have the disease.

These definitions have been defined in respect to ECG.

The general formula for calculating Accuracy, Precision, Recall, AUC score are defined below:

Accuracy: Accuracy measures the proportion of correct predictions (both true positives and true negatives) among the total number of cases.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + FN}$$

Precision (Positive Predictive Value): Precision measures the proportion of true positive predictions among all positive predictions.

$$Precision = \frac{TP}{TP + FP}$$

Recall (True Positive Rate): Recall measures the proportion of the model to correctly identify all the positive instances in the dataset.

$$Recall = \frac{TP}{TP + FN}$$

AUC (Area Under Curve): AUC is the area generated by the Receiver Operating Characteristic (ROC) which is calculated as below in mathematical terms:

$$AUC = \int_0^1 \{TPR\}(t), d\big(\{FPR\}(t)\big)$$

where TPR is True Positive Rate, FPR is False Positive Rate

Implementation

Workflow Overview

The implementation of Classification of ECG data using nonlinear time series analysis consists of a series of important steps which are data loading, data preprocessing, feature extraction, and data analysis. All the process has been implemented using Python programming language and the platform used in Jupyter. Each step is very important to ensure we obtain our desired accuracy and they are described briefly below:

Data Loading: The PTB-XL dataset contains of 28 columns with 12-lead ECG records for 21837 patients. In this step we will import the PTB-XL dataset onto the system.

Data Preprocessing: Here we will perform baseline correction and then standardization will be applied to the ECG signals.

Feature Extraction: Fourier Transform, time domain peak analysis and frequency domain peak analysis will be performed to obtain insightful features from the ECG data.

Analysis: Analyzing the extracted features to classify the ECG signals and identify health conditions.

Implementation

Data Loading: The PTB-XL dataset is available in the public domain for research purpose which has records from a diverse patient population and makes it perfect in having in in-depth analysis of ECG data. The dataset which has the data of the patients is imported and loaded using a WFDB (WaveForm DataBase) Python library. The PTB-XL dataset is accessed and stored locally. Each ECG record is stored in a pair of files: a header file (.hea) that contains metadata and a data file (.dat) that contains the actual signal data.

Data Preprocessing

Preprocessing is a critical step to ensure the quality and consistency of the ECG signals before feature extraction. It involves several sub-steps:

Baseline Correction: Once the signal is loaded baseline correction is performed by first calculating the Nyquist frequency which is 0.5 times the sampling frequency. After this normalization of cut off frequency is done by dividing the cut off by the Nyquist frequency and finally the final signal is passed through a Butterworth high pass filter which will help to remove the low frequency components from the ECG signals.

The reason for choosing Butterworth filter as smoother ECG signals is easily obtained and its mathematical design is very simple as compared to another high pass filter. Moving average doesn't provide such flexible approach but polynomial fitting does provide almost the same results as Butterworth filter.

Standardization: After baseline correction the average value is calculated and also the standard deviation. Once these metrics are computed we minimize the mean from each ECG signal and divide the standard deviation to get a desired mean of 0 and a standard deviation of 1. This helps to have consistency and comparability features across signals.

Standard Quantifiers: Obtain the mean, median and standard deviation of the ECG signals using the available built-in functions which are present in the *numpy* library of Python.

Feature Extraction: Feature extraction provides us the foundation for doing analysis which involving the identification of relevant characteristics from the ECG signals that can aid in classification. Several techniques are employed which are described below:

Frequency Domain Peak Analysis: The standardized signal with a default a sampling frequency of 100Hz is used to compute the amplitude and the phase of each frequency component of the signal and the process is called a as Fast Fourier transform where the original time domain signal is converted into a frequency time signal. The dominant features and relevant values are extracted where we normalize the FFT and find out the amplitude values corresponding to the detected peak. In the end we will get the maximum peak frequency, second peak frequency and the ratio between the highest peak to the second highest peak for each and every patient record.

Time Domain Peak Analysis: We have first set a threshold with respect to the maximum amplitude to obtain the most significant peaks. Further we have estimated metrics such as the peak distances and standard deviation of distances which signifies the consistency of the heartbeats. We also obtained statistical metrics to analyze the degree of heart variability.

The extracted features are now applied to a machine learning algorithm which is Logistic Regression, SVM and neural network further for a detailed analysis of the ECG signals and identify potential health conditions. The analysis involves several steps:

[ix]**Logistic Regression:** We have first handled the missing value if any present and then define the dependent and independent features. After this standardization, fitting the logistic regression model to the training data is performed. We evaluate the model performance by confusion matrix and classification report.

Support Vector Machine: To get more accuracy we have used the Standard Scaler, SVC and GridSearchCv machine learning algorithms. Here we train the data using the regression model and evaluate the model performance which do have performed better than logistic regression. Further Hyperparameter tuning have also been applied to get more refined results.

We have used different techniques of classification such as Random Forest Classifier for achieving better accuracy and also used hyper parameter tuning methods to fine tune the model as much as possible. Different classification techniques gave a comprehensive overview about how the model performs if we add or change the value of the parameters.

Neural Networks:

- Till now we did achieve some significant accuracy when we implemented Logistic Regression classification techniques but we wanted to have a look about how better the model would perform if we build a Neural network method.

- We used a standard neural network which comprises of two hidden layers and dropout layers to prevent overfitting. The model undergoes training using the training dataset and is then evaluated using the test data. We evaluated the model accuracy and performance to determine its classification accuracy.

Results

This section will showcase a detailed overview of the various results which have been obtained while performing and implementing the various steps on the PTB-XL dataset to have better ECG classification between healthy and non-healthy patients. We will first showcase few graphs about how the ECG data changes while implementing the techniques such as bassline correction, standardization, Fast Fourier transform and time domain peak analysis for a single patient to have a understanding how efficient this techniques are for ECG analysis. After this we will show the results which have been obtained using Logistic Regression and deep learning techniques.

1. First, we import, read the dataset onto the system and plot the reading for the 12- lead channels. The below figure shows the different channels.

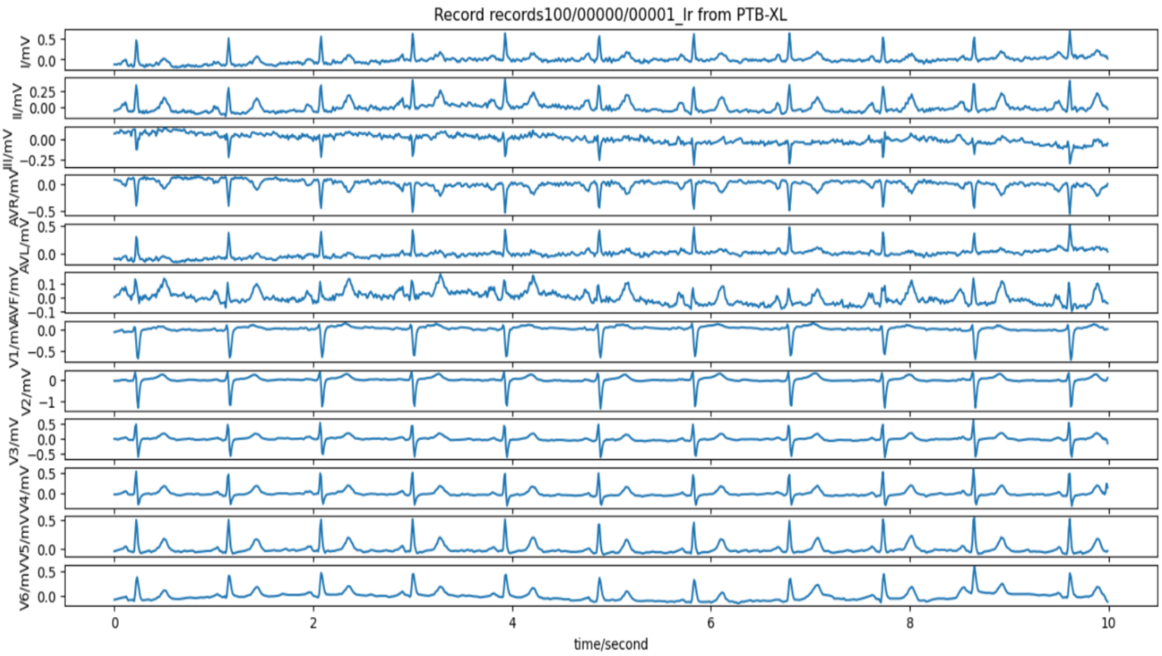


Fig 4: Plot showing *12 lead ECG signal of a patient*

2. Baseline removal and standardization has been applied and we obtain the below result of the mean and standard deviation distribution. From the below figure we can see the baseline removal has ensured everything around the zero ECG reading. Standardization made the standard deviation to 1.

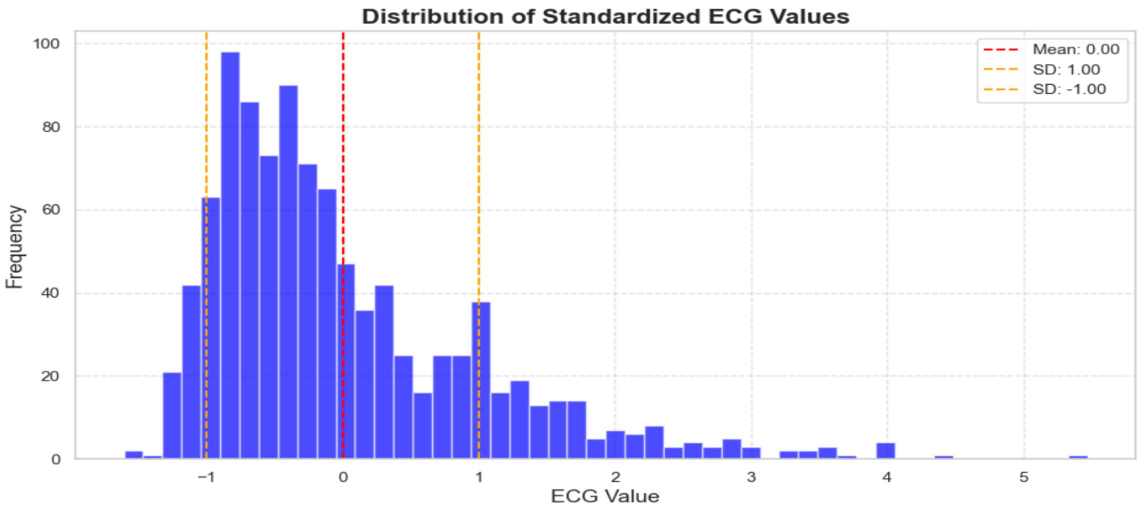


Fig 5: *Plot showing standardization of ECG*

3. After standardization fast Fourier transform has been applied to have an analysis on the frequency components. Here we can see the dominant frequency and other frequency components which can give some insights about the heart activity. The below figure shows amplitude as a function of frequency.

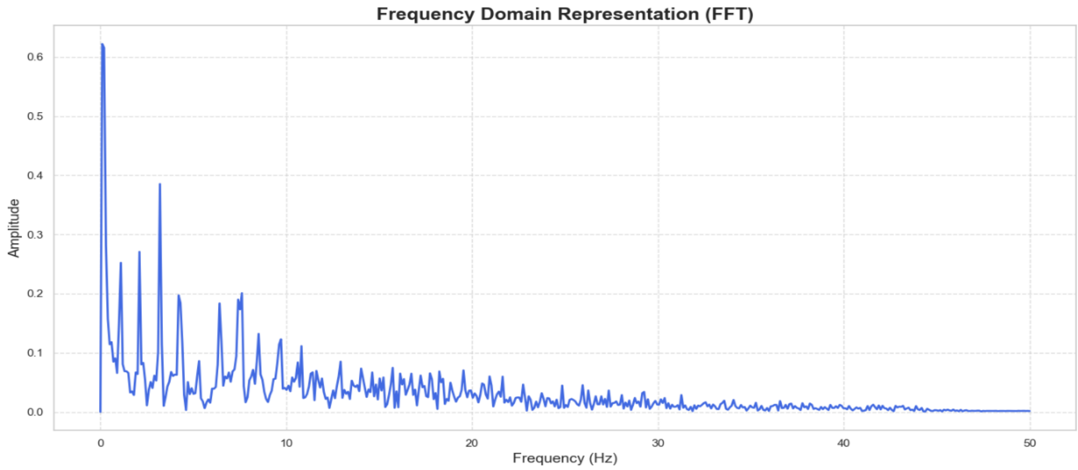


Fig 6: ***Plot showing Frequency Domain Representation***

4. When we perform the time domain peak analysis, we get the below plot denoting the peaks which corresponds to heartbeats. Here the red 'x' symbols denote the detected peaks and the height denotes the amplitude of each detected peak. Along with it we obtain the statistical metrics to have a clear understanding about the RR intervals.

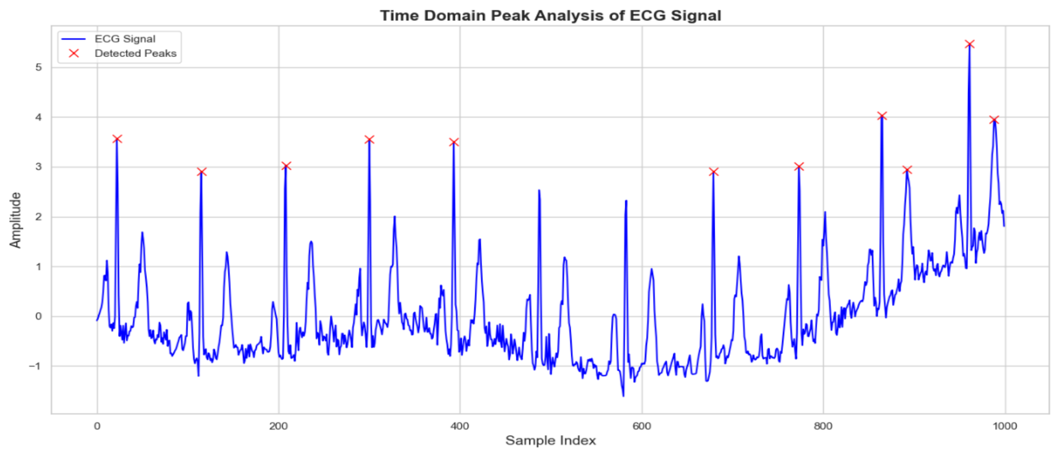


Fig 7: ***Peaks detected after performing time domain peak analysis***

Mean RR Intervals: 0.1932 sec

Median RR Intervals: 0.1850 sec

Standard Deviation of RR Intervals: 0.1361 sec

A mean RR interval of 0.1932 seconds suggests an average heart rate of approximately 310 beats per minute (bpm), assuming normal sinus rhythm. A Standard Deviation of RR Intervals of 0.1361 seconds reflects the degree of variation in time between heartbeats. The greater this variation will indicate irregularities in the heart rhythm.

Till now we have shown what are the results obtained during the pre-processing steps in the next section we will see what are the results obtained when machine learning algorithms and deep learning is applied on the training and test dataset. Our training dataset and the test dataset have been trained on and tested on 6549 and 2199 records of patients of the PTN-XL dataset. The below table shows the mean and standard RR interval for T test which tells us there is significant difference between the two classes.

Table showing the Mean RR interval and Standard Interval

T Test	Mean RR interval	Standard RR interval
T statistic	4.48	-9.18
P value	7.59E-06	5.50E-20

5. Logistic Regression gave an accuracy (ACC) of 0.68 and a precision of 0.64 for normal patients and a value of 0.70 for patients with a heart disease. The below figure of Receiver Operating Characteristic (ROC) illustrate how well does the model is performing in classifying between the two classes as Area Under Curve (AUC) value of 0.72 indicating the same. The more the value of AUC closer to 1 will signify the better performance.

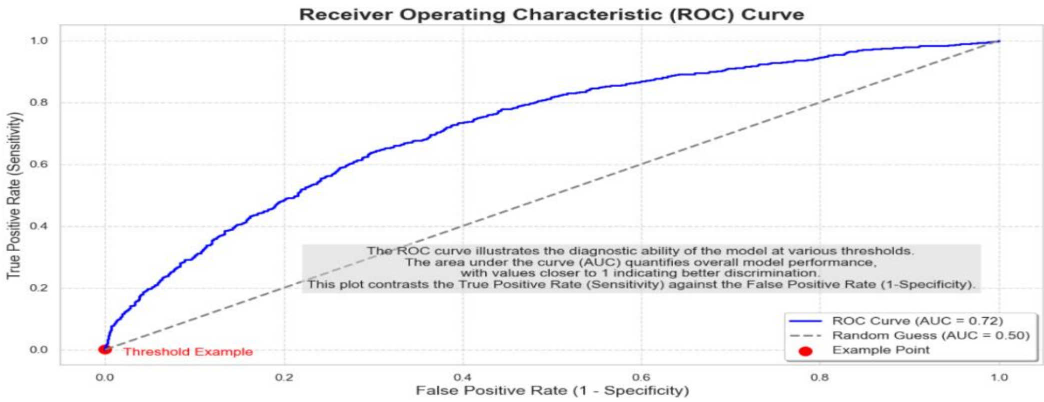


Fig 8: ***ROC Curve for Logistic Regression model***

6. [x]Radom Forest Classifier machine learning classification gave an accuracy (ACC) of 0.71 and a precision of 0.68 for normal patients and a value of 0.73 for patients with a heart disease. Also, a Recall value of 0.64 and 0.76 for normal patients and disease patients respectively. The below figure of ROC illustrates how well the model is performing in classifying between the classes. 0

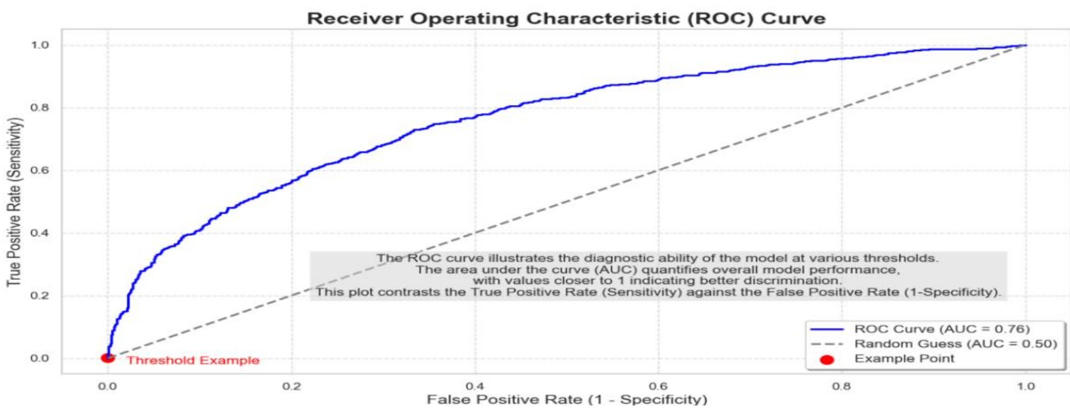


Fig 9: ***ROC Curve for Random Forest Classifier***

7. [xi]Support Vector Machine classification model gives a accuracy (ACC) of 0.68 and a precision of 0.64 for normal patients and a value of 0.72 for patients with a heart disease. Also, a Recall value of 0.66 and 0.71 for normal patients and disease patients respectively. The below figure of ROC illustrates how well the model is performing in classifying between the classes.

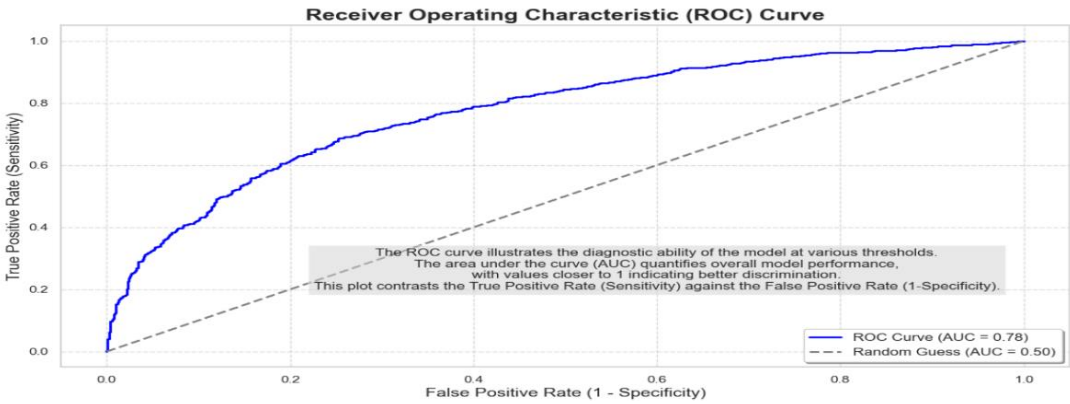


Fig 10: ROC Curve for Support Vector Machine

8. Neural Network provides a accuracy of 0.69 and a precision of 0.64 for normal patients and a value of 0.73 for patients with a heart disease. Also, a Recall value of 0.68 and 0.70 for normal patients and disease patients respectively. The below figure of ROC illustrates how well the model is performing in classifying between the classes.

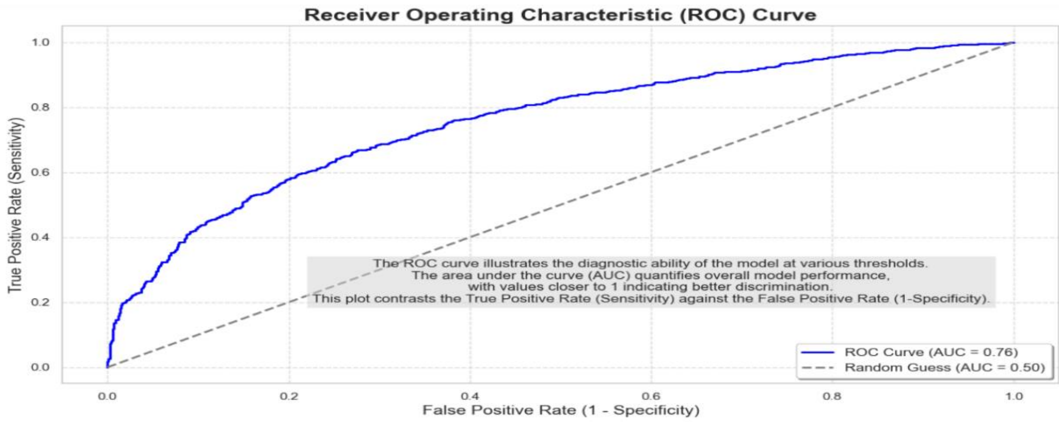


Fig 11: ROC Curve for Neural Network

9. We have also tried other classification algorithms such as [xii]Stacking classifier machine learning algorithm to have a better understanding how the model classifies and whether this classifier will give a reasonable accuracy than other classification models. The accuracy (ACC) of 0.69 with precision of 0.68 for normal patients and a value of 0.69 for patients with a heart disease was obtained after training and testing with the test dataset. Also, a Recall value of 0.60 and 0.76 for normal patients and disease patients respectively.

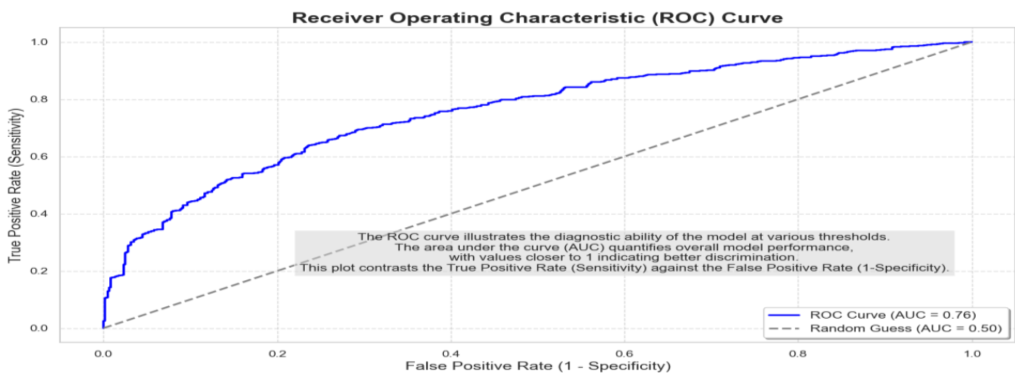


Fig 12: ROC Curve for Stacking Classifier

The below table summarizes the value obtained the accuracy, precision, recall, and F1-score for the different classifiers.

Table summarizing the Accuracy, Precision, Recall, AUC for Healthy (Class 0) and Unhealthy (Class 1)

Classifier	Accuracy	Precision (Class 0)	Precision (Class 1)	Recall (Class 0)	Recall (Class 1)	AUC
Logistic Regression	0.68	0.64	0.70	0.60	0.74	0.72
Random Classifier	0.71	0.68	0.73	0.64	0.76	0.78
Support Vector Machine	0.68	0.64	0.72	0.66	0.71	0.78
Stacking Classifier	0.69	0.68	0.69	0.60	0.76	0.65
Neural Network	0.69	0.64	0.73	0.68	0.70	0.76

Discussion

The analysis and classification of ECG signals is a tedious process as it involves various steps to make the signal worthy of classifying before reaching conclusions. Here we did perform very important steps such as data preprocessing in which baseline correction was performed to remove the low-frequency components from the signal and this was achieved with the help of a Butterworth High pass filter. Then standardization was done on the signal so that statistical metrics can be evaluated and comparisons can be done with other patient's readings. Feature extraction was done in the next step which involved Fast Fourier Transform and Time domain peak analysis. In both the process where we extracted the essential features such as the frequency components, peaks, mean RR and median RR intervals. These features help in clinical diagnosis of the patients and get a brief understanding about heart rate variability (HRV). The RR intervals is one of the most important features as it talks about the QRS complexes which corresponds to the depolarization of the right and left ventricles of the heart and contraction of the large ventricular muscles. As a large QRS complex means increased risk of ventricular arrhythmia.
We then performed a few machine learning algorithms such as support vector machine, random forest classification, statistical classifier to classify between healthy and unhealthy patients. The accuracy obtained after applying these techniques indicates that Random Forest gives the best accuracy out of all three algorithms with accuracy of 0.70. The other classification methods after using Hyperparameters gave a moderate performance in comparison to Random Forest. The AUC values and ROC graphs also indicate the same and give a clear picture and understanding about these models and the performance. The Neural Networks model was also used to classify the classes and it did perform decently. It does give an understanding that deep learning techniques in recent times might have given advanced results as it performs like a complex human brain but not in this case as the accuracy is less than Random Forest

Conclusion and Future Work

We were able to demonstrate the use of machine learning techniques and neural networks for classifying between healthy and unhealthy patients and got reasonable accuracy. While performing this process we had to take care of low -frequency components which if taken more care and if other advances are used will yield better results in the analysis. The second challenge encountered was that the model accuracy changes very less as we reach a certain limit. Fine tuning the neural network model by varying the size of each layer and number of layers could possibly improve accuracy. Improvements of the random forest, such as gradient boosting methods may also improve the classification accuracy achieved. Also, non-linear dynamic methods will help to reach better accuracy which in turn will help the clinical diagnosis. Combining several machine learning algorithms with non-linear methods such as Chaos Theory, such as fractal dimensions or recurrence qualifications or metrics from information theory such as, Approximate Entropy (ApEn) will help in effective diagnosis and better results.

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