**A**

**Minor Project Report**

on

**CLASSIFICATION OF EPILPETIC SEIZURES USING MACHINE LEARNING**

Submitted for partial fulfillment for the degree of

**Bachelor of Technology**

(Information Technology)

in

Department of Information Technology

by

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(June-2020)

**SCHOOL OF COMPUTING AND INFORMATION TECHNOLOGY**

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**CERTIFICATE**

Date

This is to certify that the project titled **Neuro-Analyzer** is a record of the bonafide work done by **Anamay Deshpande** (179302016) & **Harshit Koodi** (179202060 )submitted in partial fulfilment of the requirements for the award of the Degree of Bachelor of Technology (B.Tech) in **(Information Technology)** of Manipal University Jaipur, during the academic year 2019-20.

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**ABSTRACT**

Seizures are aberrations in the brain’s normal electrical activity that produce disruptive physical symptoms. To diagnose and characterize seizures, clinicians measure the brain’s electrical activity using electroencephalography (EEG), a method that involves placing electrodes on a patient’s scalp to measure voltage differences across the brain. Due to the variety of seizure types and different presentations between people, no general model has been made to identify seizure from non-seizure EEG data. The goal of this project is to build such a general recognition model. To do so, we used a data set of 500 patients recorded at Stanford children’s Hospital over the last number of years. We examined the performance of regression models such as knn, naive bayes, logistic regression, random forest, gradient boosting and decision tree. We found that the gradient boosting performed best with an accuracy of 99%.

**LIST OF TABLES**

|  |  |  |
| --- | --- | --- |
| **Table No** | **Table Title** | **Page No** |
|  |  |  |
| 1. | KNN | 13 |
| 2. | Logistic Regression | 13 |
| 3. | Naïve Bayes | 13 |
| 4. | Random Forest | 13 |
| 5. | Gradient Boosting | 13 |
| 6. | Decision Trees | 13 |

**LIST OF FIGURES**

|  |  |  |
| --- | --- | --- |
| **Figure No** | **Figure Title** | **Page No** |
|  |  |  |
| 1. | Block Diagram | 11 |
| 2. | Random Layout | 12 |
| 3. | Confusion Matrix (KNN, Logistic Regression) | 14 |
| 4. | Confusion Matrix (Naïve Bayes, Random Forest) | 14 |
| 5. | Confusion Matrix (Decision Tree, Gradient Boosting) | 14 |
| 6. | Bar Graph and Learning Curve | 15 |
| 7. | ROC\_AUC\_Curve | 15 |

|  |  |
| --- | --- |
|  | **Contents** |
|  |  |
|  | Page No |
|  |  |
|  |  |
| Abstract | 3 |
|  |  |
| List of Figures | 4 |
|  |  |
| List of Tables | 4 |
|  |  |

**Chapter 1 INTRODUCTION**

**1.1** Introduction to work done/ Motivation (*Overview, Applications & Advantages*) 6

**1.2** Project Statement / Objectives of the Project 7

**1.3** Organization of Report 7

**Chapter 2** **BACKGROUND OVERVIEW**

**2.1** Conceptual Overview (*Concepts/ Theory used*) 8

**2.2** Technologies Involved 9

**…**

**Chapter 3** **METHODOLOGY**

**3.1** Detailed methodology that will be adopted 10

**3.2** Circuit Layouts / block diagrams 11

**…**

**Chapter 4** **IMPLEMENTATION AND RESULTS 14**

**4.1** Predictions 14

**4.2** Confusion Matrices 15

**…**

**FUTURE WORK AND CONCLUSION 16**

**Chapter 5**

**5.1** Progress Chart/Time Line Chart 16

**5.2** Future Work and Conclusion 17

**REFERENCES**

**ANNEXURES (OPTIONAL)**

**INTRODUCTION**

*1.1 Introduction to work done:*

Epilepsy is one of the most common neurological diseases that affects about 70 million persons all over the world. 85 percent of the persons that are affected belongs to the developing countries and 2.4 million new cases of the disease occur every year. At least half of all the epileptic cases commence during childhood or adolescence, and the disease can affect any person at any age. The study of epilepsy has always been of importance in the biomedical research field, and one reason is because people with the disease are two or three times more likely to die prematurely when compared to someone without the disease.

Epilepsy is characterized by recurrent, unprovoked seizures, which are classified depending on if the onset is partial or generalized. A partial onset means that the epileptic activity begins in one hemisphere of the brain, and a generalized onset is when there is initial involvement of both hemispheres. Depending on where in the brain the epileptic activity begins and how far it spreads, the various seizure types differ. Hence, the seizures alter from brief lapses of attention to severe and long-lasting convulsions. The properties of an epileptic brain are hard to understand, and the human knowledge is still insufficient to understand them. Loss of mindfulness, small abnormalities in the movement pattern, twitching of muscles and many others are examples of temporary symptoms of epilepsy. Further, the epileptic seizures often occur spontaneously and without any external interference, causing them to sometimes remain unnoticed. Therefore, the measuring of the seizures should be a continuous process, which means several engineering challenges.

Epilepsy can be assessed by the electroencephalogram (EEG). EEG is one method for measuring electrical activity of the brain, and lately there has been a huge rise of interest in the decoding of brain states based on the underlying EEG. EEG records the electrical signals sent by the brain through electrodes attached on the head of the subjects and are then sent to a computer for interpretation. Diagnosis of epilepsy based on EEG signals can be troublesome and slow, especially for long-duration EEG signals. It could also be difficult to characterize and interpret the EEG signal, since it is highly non-linear and non-stationary. Nevertheless, it is a well-established technique with low costs associated with it. One important aspect of epilepsy research includes analyzing and classifying EEG-data in order to detect seizures in early stages. If a seizure is detected in its early stages, then neurostimulation can be applied to prevent the seizure from developing and spreading to other parts of the brain. Therefore, it is essential to find an efficient method for automatic seizure detection. Many researchers have for a long time attempted to automate the detection of epilepsy in order to simplify the epileptic treatment. The time taken to review the EEG recordings is greatly reduced by automation, which means that more patients could be treated.

A lot of work has been done on patient-specific classifiers, but building subject-independent models is a more difficult problem due to the high EEG variability between the subjects. Patient-specific classifiers have shown to be successful while patient-independent classifiers still have not performed as well. This project is aimed at tackling an inter-subject detection of EEG correlates of epileptic seizures. A lot of computational work could be saved if patient-independent classifiers were sufficiently accurate. Such a method would be more financially feasible to incorporate into automated detection devices.

*1.2 Project Statement:*

Several studies have applied different machine learning algorithms to detect seizures in EEG-data. However, most of the work has been done on patient-specific classifiers. A previous study achieved high accuracy in a patient specific setting where different methods were compared. To our best belief, no other studies in the patient-independent domain have compared regression methods specifically. Therefore, this project is concerned with a comparative analysis of different regression algorithms employed for EEG based epileptic seizure identification.

*1.3 Objective:*

|  |  |
| --- | --- |
| **PROS** | **CONS** |
| 1. The computational time taken will be much faster than that of a human. | 1. Without a medical professional, the data which is evaluated cannot be 100% verified. |
| 1. The values computed will help in determining which prediction model has better accuracy. | 1. The software and hardware requirements of the system are high due to which most personal computers might face difficulty in working. |
| 1. It will result in significant reduction of cost in detection and prediction of epilepsy. | 1. If in a case, there are inaccuracies in the classification algorithm, it may result in inaccuracies and lossy data. |
| 1. It will result in significant reduction of human error in the detection of AD. | 1. Without a complete dataset, the machine will face the difficulties in giving accurate results   and analyzing patterns. |

*1.4 Organization of Report:*

This report is divided into 5 chapters. The first chapter introduces the subject, project statement, scope and objective of the project. In chapter 2, background information on the subject is presented, such as the machine learning methods compared and related work. The third chapter explains the methods used including the feature extraction and classification. The results are presented in the fourth chapter. At last, the findings are concluded in chapter 5.

**BACKGROUND OVERVIEW**

*2.1 Epileptic seizures*

A seizure corresponds to the event and the primary clinical encumbrance of an active epileptic condition. It could be hard to give an elaborated specification of subjective and objective clinical phenomena during an epileptic seizure, because of the broad range of possible appearances. How the seizure present depends, among other things, on the location of onset in the brain, sleep-wake cycle and the maturity of the brain.

*2.2 Epilepsy detection using EEG*

By analyzing recorded EEG signals, it is possible to study the characteristics of epileptic seizures. The EEG signals recorded during seizures contains patterns that differ from the EEG signals recorded from a non-epileptic person. Hence, the EEG analysis enables to differentiate epileptic from normal data, and to distinguish the different phases of a seizure. By detecting EEG changes preceding a seizure, it is possible to predict the onset of epileptic seizures. That type of prediction system requires an automated system that can clearly distinguish normal, pre-ictal, and inter-ictal stages. The normal stage is EEG-data from a healthy person, the pre-ictal stage refers to the EEG changes preceding a seizure, and the inter-ictal stage refers to the EEG changes during a seizure. For this detection system, there are two main considerations. The first consideration is the type of features to be extracted from the EEG signal, i.e. the feature extraction techniques. The second consideration is the type of analysis techniques to be utilized on the extracted features to detect the stage, i.e. the classification techniques.

*2.3 EEG Channel Selection for Epileptic Seizure Detection*

When performing EEG on scalp, the voltage difference between two specified electrodes forms a channel. There are five brain waves distinguished by their different frequency bands that contains most of the useful information about the state of the human brain. The frequency bands are delta, theta, alpha, beta and gamma. All of them are related to different states of the mind, and unexpected disturbance of the waves occurs for instance during an epileptic seizure. To classify these signals, you can choose to either work on a subset of work on all the channels or channels based on a selected criterion. During seizure detection the channel reduction is of a potential value. Generally, EEG recordings have different channels for signals received from different placings on the scalp. Working with many channels sometimes lead to an overfitting effect, especially when working with channels that are redundant. The channel selection can be used to cut down the feature pattern size, and thereupon decrease the computational cost of the feature extraction and classification. A study published in 2015 concluded that it is possible to make use of a small set of EEG channels ranging from 10 to 30 percent of the total channels, without losing much performance in the classification tasks. The study also mentions that signal statics such as entropy and variance could be used for channel selection during EEG seizure detection.

*2.4 Technologies Involved*

HARDWARE

* Intel Core (TM) i5-6300HQ
* CPU @ 3.40GHz x 4
* 8GB of DDR4 RAM
* NVIDIA GeForce GTX 960M 4GB DDR5

*SOFTWARE*

* Python 3.7
* Anaconda Navigator
* Jupyter
* Python Libraries (NumPy, Pandas, Matplotlib, SciPy)

**Methodology**

This section starts with describing and motivating the data used in the project. The selection of EEG-channels is also discussed, followed by an explanation of how the feature extraction was performed. The last two subsections include the performance metrics used in the study, and details about how the classification was done.

***3.1 Detailed Methodology that will be adopted***

*3.1.1 Data*

The existing data is preprocessed EEG recording provided by Boston children’s Hospital. The dataset includes 4097 electroencephalograms (EEG) readings per patient over 23.5 seconds, with 500 patients in total. The 4097 data points were then divided equally into 23 chunks per patient; each chunk is translated into one row in the dataset. Each row contains 178 readings that are turned into columns; in other words, there are 178 columns that make up one second of EEG readings. All in all, there are 11,500 rows and 180 columns with the first being patient ID and the last column containing the status of the patient, whether the patient is having a seizure or not.

*3.1.2 Feature Extraction*

All features have the same importance as each of them represent one EEG reading so no need for feature extraction.

*3.1.3 Dataset Splitting*

The dataset is divided into training, validation and testing sets in the ratio of 70:15:15. After splitting the data, we balance the data in the training set using sub-sampling method. This is done because of the higher number of non-seizure output label cases and by not balancing the data, our model is trained on a biased dataset, leading to inaccurate results. Lastly the data is transformed so that it will have a mean value of 0 and a standard deviation of 1.

*3.1.4 Parameter Calculation*

We have used 6 parameters to evaluate the performance of each classification model. All parameters are calculated by using the number of true positives and negatives & false positives and negatives the model has predicted. These values are obtained through a confusion matrix. The parameters are:

1. Accuracy- It is the ratio of number of correct predictions to the total number of input samples.

Accuracy = (TP+TN)/(TP+TN+FP+FN)

1. Precision- It is the fraction of retrieved documents that are relevant to the query.

Precision = TP/(FP+TP)

1. Recall- is the fraction of the relevant documents that are successfully retrieved.

Recall = TP/(FN+TP)

1. F1-Score- s a measure of a test's accuracy and is the harmonic mean of precision and recall.

F1-score = 2\*(precision\*recall)/(precision+recall)

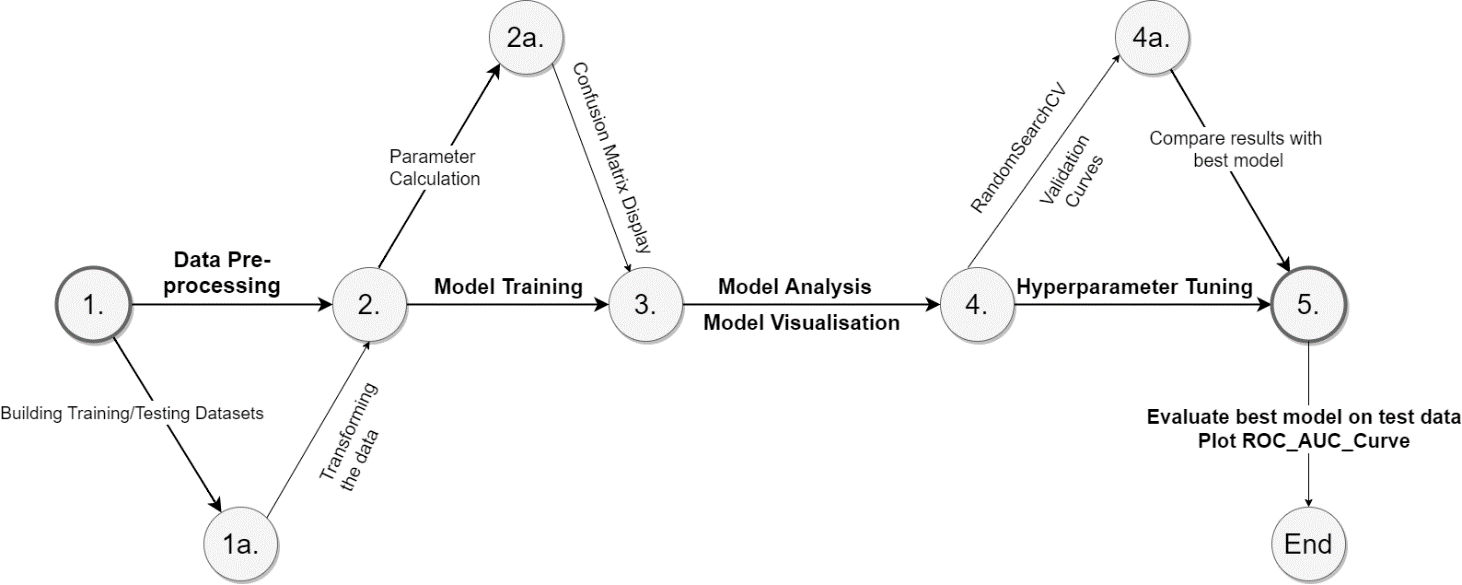
1. Specificity- is defined as the proportion of actual negatives, which got predicted as the negative.

Specificity = TN / (TN + FP).

1. Matthews’ Correlation Coefficient- It is a measure of the quality of binary classifications.  The MCC is a correlation coefficient between the observed and predicted binary classifications; it returns a value between −1 and +1. A coefficient of +1 represents a perfect prediction, 0 no better than random prediction and −1 indicates total disagreement between prediction and observation.

MCC= ((TP\*TN)-(FP\*FN))/sqrt((TP+FP)\*(TP+FN)\*(TN+FP)\*(TN+FN))

***3.2 Block Diagram-***



***3.3 Classification Models-***

In this project, we have used 6 classification models to evaluate the prediction on our datasets. The models used are-

* K-Nearest Neighbors
* Logistic Regression
* Naïve Bayes
* Random Forest
* Gradient Boosting
* Decision Trees

To evaluate each model, we have defined a function that calculates the 6 parameters and returns the result. We have also defined a function that displays the confusion matrix for each model on the training and validation datasets and shows the number of true positives, true negatives, false positives and false negatives. The classifier for each model is trained and the predicted values are sent to the confusion matrix function where the results are calculated and displayed.

***3.4 Hyperparameter Tuning-***

Looking at the results achieved, we see that the 3 best models are- Decision Tree, Random Forest and Gradient Boosting. The effectiveness of the Decision Tree model is a bit low as compared to the other 2 models, so we perform hyperparameter tuning on it to try and increase the effectiveness. With hyperparameter tuning, our goal is to set the optimal combination of hyperparameters that minimizes the loss. We try to achieve this using 2 methods- Validation Curves and RandomSearch.

Using validation curves, we visually see the optimal value for each hyperparameter and then manually set the hyperparameter in the model to try and improve the accuracy. RandomSearchCV is a technique where random combinations of the hyperparameters are used to find the best solution for the built model. The function is called and after entering the desired arguments, the function gives the optimal solution for each hyperparameter.

![A drawing of a person

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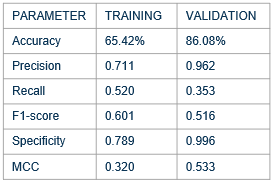
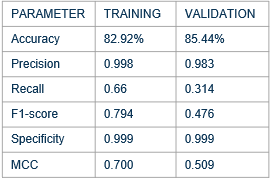
***3.5 Model Evaluation-***

We see that after hyperparameter tuning the Decision Trees model, the effectiveness of that model is still not as good as our best model i.e. Gradient Boosting. So now we evaluate our model on the test data. This step is crucial to determine whether the model is effective or not as it will try and predict the outcome on data is has never seen before.   
After evaluating it on the test dataset, we plot a roc\_auc\_curve to display the results of the model on all 3 datasets. A receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. The ROC curve is created by plotting the true positive rate against the false positive rate. The AUC tells us the area under the curve and the more the area, the better the model is at correctly classifying the output.

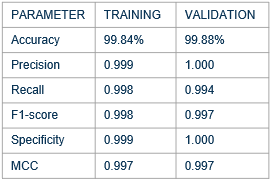
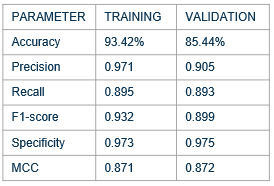
**Chapter 4 IMPLEMENTATION AND RESULTS**

*4.1 Performance:*

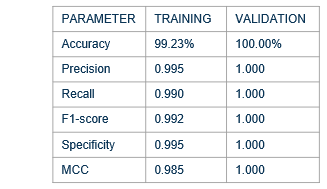
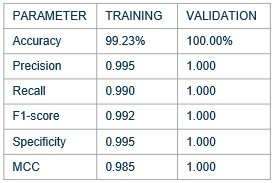
KNN Model Logistic Regression



Naïve Bayes Random Forest

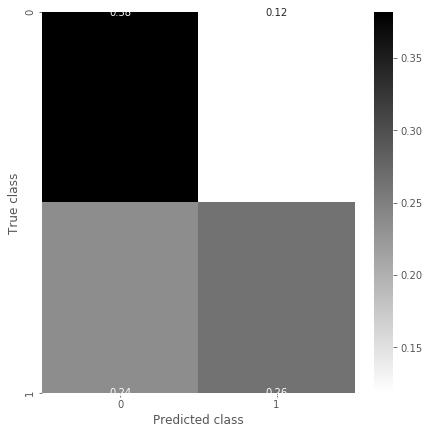
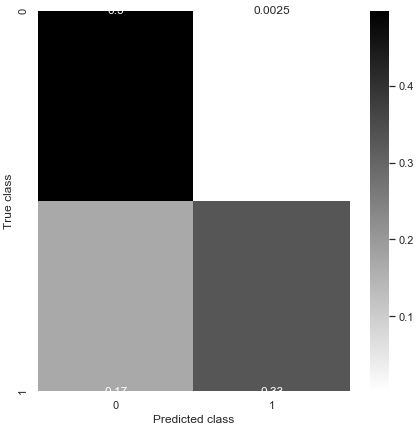


Decision Trees Gradient Boosting

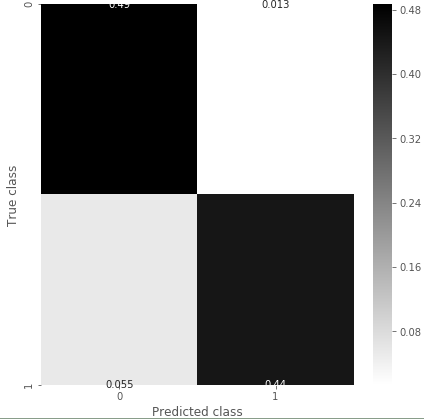
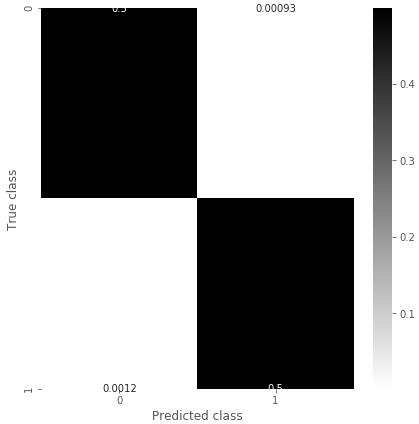


*4.2 Confusion Matrices:*

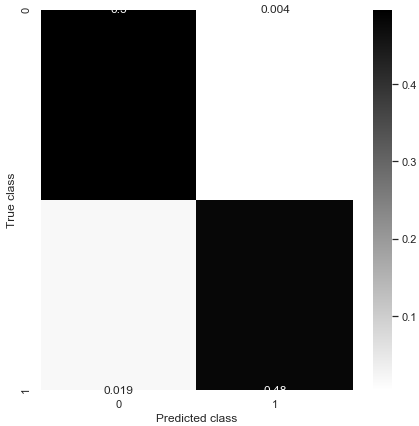
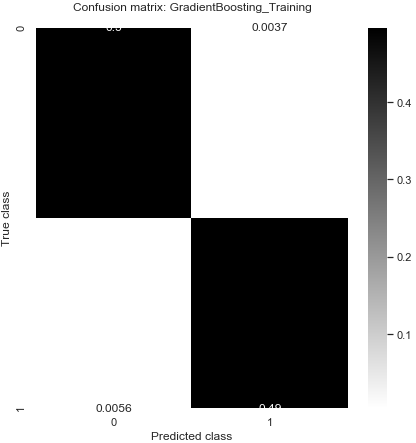
KNN Logistic Regression



Random Forest Naïve Bayes

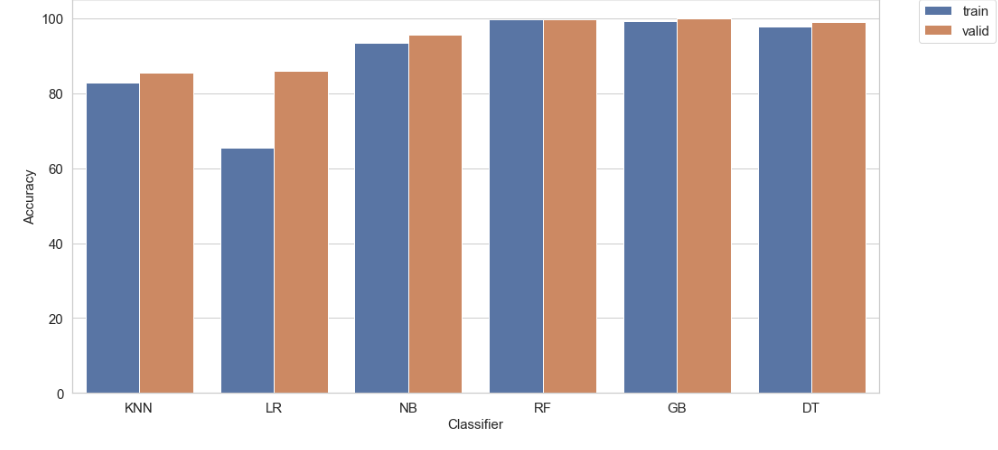


Gradient Boosting Decision Trees



*4.3 Model Analysis:*

Bar graph comparing accuracies of every model



Learning Curve for Decision Trees Model

A screenshot of a social media post

Description automatically generated

*4.4 Model Evaluation:*

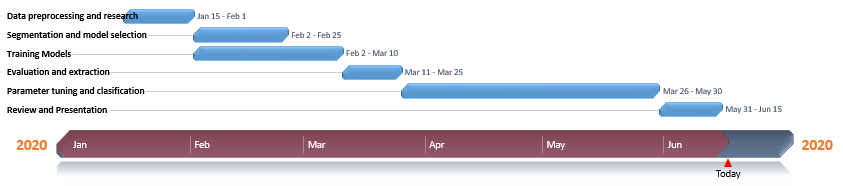
ROC\_AUC\_Curve for Gradient Boosting Model

A picture containing white, black, table, large

Description automatically generated

**Chapter 5 FUTURE WORK AND CONCLUSION**

***5.1*** *Progress Chart/Timeline Chart*



*5.2 Future work and conclusion*

*5.2.1 Future work*

To further enhance the research, the amount of data and number of patients could be increased. The amount of data used in this project is quite limited from a machine learning perspective and therefore the classifiers would probably benefit from more data to train on. Due to the variability and differences regarding epileptic seizures, having data from more patients could lead to a more complete and accurate detection method.

Also, more classifiers could be tested in order to find a detection method with better performance. To reduce the possibility for the classifier to be bias due to unevenly scaled data, a future consideration could be to apply a proportion of 1:1 between the two classes (non-seizure and seizure).

*5.2.2 Conclusion*

Out of all the methods the two methods, Gradient Boosting and Random Forest performed very similar in terms of accuracy. Gradient Boosting was statistically significantly better than other models with an accuracy of 99.065% on data that had been scaled for more even proportions between non-seizure and seizure samples. So, we can conclude that as far as regression models are taken in account for seizure detection Random Forest classifier performed better than other classifiers.

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