An Approach to Detect Epileptic Seizure Using XAI and Machine Learning

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Declaration

It is hereby declared that

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2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

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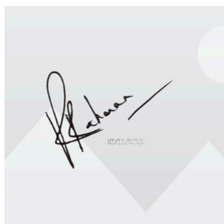

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Abstract

One of the most common neurological disorder in health sector is Epileptic Seizure (ES) which is occurred by sudden repeated seizures. Hitherto more than 50 million people in the whole world are suffering from Epileptic Seizures. The abnormal brain activity of the central nervous system often causes unusual behavior, losing awareness and psychological problems etc. Moreover, many risks associated with epileptic seizures include sudden unexpected death in epilepsy (SUDEP) which is really a concerning problem discussed in this article. For abstaining from adverse consequences of epileptic seizure-like this health sector focuses more on the early prediction and detection of epilepsy. The complex signals of brain activity are reflected as swift-passing exalted peaks in Electroencephalogram (EEG). Initially, the specialist inspects the EEG signals over a few weeks or months to identify the presence of epileptic seizures, which is a very time-consuming and challenging task. Hence, Machine learning (ML) based classifiers are capable to categorize EEG signals and detect seizures along with displaying related perceptible patterns by maintaining accuracy and efficiency. In order to detect epileptic seizures, EEG-based signal recognition algorithms had been shown in this paper by applying both Multi-Class Classification and Binary classification. The algorithms were Decision Tree Algorithm, Random Forest Algorithm, Multi-Layer Perceptron (MLP) and K-Nearest Neighbor (KNN), Gradient Boosting Classifier, Gaussian Naïve Bayes, Complement Naïve Bayes, SGD Classifier, Explainable Artificial Intelligence (XAI), LIME Algorithm etc. However, K-Nearest Neighbor appears with pretty higher accuracy in certain conditions.

Keywords: Machine learning (ML), Multi-Class Classification, Binary classification. K-Nearest Neighbor (KNN), Decision Tree Algorithm, Random Forest Algorithm, Multi-Layer Perceptron (MLP), Gradient Boosting Classifier, Gaussian Naïve Bayes, Complement Naïve Bayes, SGD Classifier, XAI, LIME Algorithm, Sudden Unexpected Death in Epilepsy (SUDEP), Epileptic Seizure (ES), Electroencephalogram (EEG).

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Table of Contents

List of Figures

Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

ϵ Epsilon

$\in$ Belongs to

π Pi

υ Upsilon

$ADAM$ Adaptive Moment Estimation

AR Auto Regressive

DL Deep Learning

EEG Electroencephalogram

f Function of

i index

$LIME$ Local Interpretable Model-Agnostic Explanations

ML Machine Learning

MLP Multi Layer Perceptron

XAI Explainable Artificial Intelligence

Chapter 1

Introduction

An epileptic seizure is one of the most usual brain disorders at this present time which is considered a chronic condition. According to the survey of WHO it is estimated that nearly 50 million-60 million people are dealing with epileptic seizures [1]. Usually, this disorder happens when the electrical activity of the brain gets hampered by some causes like – malformations of some things in the brain, oxygen shortage during birth, molecular mutation etc. In most cases, epileptic seizures occur in neonatal and the adolescence period. People of any ages can be attacked by this chronic disease. In the research field as well as in the biomedical sector, the study of epileptic seizures is a new scopes and opportunities to work on. For this reason, it has immense significance in the research field. A patient with an epileptic seizure attack may have premature death which is not a good sign as well as genuinely a threat to the health sector for any country [5].

Epilepsy is usually a chronic condition which is classified by reclining on the onset. This is distinguished by recurrent unprovoked seizures. It can be either generalized or partial. A generalized onset means the abnormal electrical activity in both of the left and right hemispheres. On the other hand, a partial-onset means the epileptic activity in only one hemisphere which can be either in the left or right portion. There are different types of epileptic seizures which are usually categorized by their capability of spreading. Moreover, the category also depends in which part of the brain abnormal activity is detected. Generally, the functions of the brain with abnormal electric signals are arduous and there is inadequate knowledge to understand the types of epilepsy. The most common symptoms of an epileptic seizure's patient are abnormal behavior, unconsciousness, unawareness of self-movement, severe headache, and muscle hitching. Moreover, the seizure attack can happen anytime and cause a serious hamper to a patient. To understand the types and their consequences proper measuring is much needed for a patient.

Electroencephalogram (EEG) is one of the most renowned methodologies by which abnormal electrical signals can be detected and examined properly [8]. EEG can decode the electrical signals of the brain and interpret them. Initially, the electrodes are fitted to the scalp which mainly generates different types of signals. After that, the EEG records these emitted signals and interprets them accordingly [9].However, EEG signals recording is a time-consuming process that may needs weeks or months which is a matter of concern. Furthermore, it is also a slow and lengthy process.

Sometimes it can provide wrong interpretation even after a long period of EEG recordings, which may hamper a patient life [5]. However, Electroencephalogram has adequate frameworks and reasonable cost management. Sometimes it has not sufficient capacity to detect and predict epilepsy at a very early age. If a patient can have prior knowledge about his epilepsy at the early stages, it can be helpful for him to take the necessary steps to prevent the further development of seizures. That is why an automated epileptic seizures prediction and detection algorithm are inevitable and highly required [4] [7].

1.1 Problem Statement

There is a lot of research work related to Epileptic Seizure Detection. Various Machine Learning (ML) based algorithm was used in many studies. The major concern of most studies is tangible patient classifiers. As EEG interpretation is a lengthy process and sometimes inefficient, an automated detection methodology is essential. CNN (Convolutional Neural Network) and RFC (Random Forest Classifier) algorithm have relatively higher efficiency than the traditional EEG interpretation. However, a study compared that K-Nearest Neighbor (KNN) has pertinently more efficiency and accuracy than any other ML-based algorithm [7]. In this paper, our major concern is proposing a digitalized epileptic seizures detection which will have comparatively higher accuracy and efficiency and as well as less time-consuming. We believe no other studies have done the comparative analysis of seizure detection systems individually. Hence, this paper will mainly focus on the pertinent analysis and exploration of the RFC, KNN and other algorithms. Also, the patient-specific classifiers will be another area where this paper will contribute with some innovative and supervised landmarks. Furthermore, the clinical process of decoding the EEG signals and classifying the electrical activity is neither simple nor efficient for the expert. This study will also focus on the further development of minimizing troublesome issues like this. Finally, we will interpret the results using Explainable Artificial Intelligence (XAI).

1.2 Research Objective

The key objective of this study is to establish a discriminative framework that will have higher accuracy and efficiency in detecting epileptic seizures at the very early stage. Training and testing of the mentioned algorithms will be used in the EEG recordings to increase the potentiality and classify a patient into seizure and non-seizure classes. Moreover, this study will also focus on identifying different types of seizures and their functionality to have a transparent idea about epilepsy. We will use an EEG Database to incorporate our proposed methodology. As this paper will survey several patients, we need a profuse amount of data to synchronize them for reaching higher accuracy. The result will vary on the types of data set and the volume of data. This study also explored the ML-based algorithm and extracted the feature vectors from every single EEG signal under the time and frequency domains. Furthermore, this study will also help the researcher of the biomedical field to determine which algorithm of the Machine Learning classifier is more pertinent in detecting and predicting seizures. This paper is also useful for the reader to comprehend the EEG data sets.

1.3 Thesis Outline

The layout of this study is categorized into 6 chapters. In chapter 1, this study is about the introduction, which has the problem statement, purpose, and objective of this study. In chapter 2, the background information and the related works that we had gone through for research are presented. In chapter 3, we analyzed the background of the models we used. Chapter 4 is about the methodology and experiment that we used for the early detection of epilepsy along with data set description and data pre-processing. Chapter 5 contains the result and discussion of our model implementation. Finally, this paper is concluded in chapter 6 with some findings and references.

Chapter 2

Literature Review

An article published in 2020 [16] was introduced aiming to detect epileptic seizures from EEG by two different feature extraction methods and compare the performance of various machine learning algorithms. Discrete Wavelet Transform and Auto-Regressive (AR) models were used as the parametric methods to adjust the EEG signal into the mathematical model here. After these transformations, the extracted data were used as input for ML-based classifiers. For example, K-Nearest Neighbor (k-NN), Naive-Bayesian Algorithm and Back-propagation, etc. In addition, the performance of these machine learning algorithms was compared to both feature extraction methods. There was one possible consequence of the identification of epileptic seizure which was logic 0 if the person had an epileptic seizure, otherwise logic 1. The dataset which was taken from the department of the Medical Faculty Hospital of Dicle University included 400 records of people from where 200 were normal and the other 200 were epilepsy. Therefore, wavelet transforms vector size was 400x129 and autoregressive extraction input vector size was 400x15 considering both of their datasets was 129 and 15 respectively. In the study, for EEG signals, it was found that wavelet transform performed better than the AR method. Moreover, these outcomes showed, their proposed detection of epileptic seizure by using K-NN and ANN had better accuracy than literature studies and faster as well. On the contrary, the k-means algorithm performed the lowest compared to others in terms of results. In the case of early detection, this study showed both faster and more feasible results than the former studies.

Research work presented that [6] Epilepsy is the most usual neurological disorder that can occur at any age. A person with epilepsy can face many problems along with recurrent and unpredictable seizures. It would be a relief for the patient if they could somehow predict these unpredictable seizures in advance. It would be alleviation for the patient if they would some way or another anticipate these contingent seizures in advance. The EEG signal of an epileptic seizures patient can be categorized into 4 states which are: pre-ictal, ictal, post-ictal, and inter-ictal. EEG is an effective tool widely used in predicting epileptic seizures. The normal and abnormal brain function can be detected by the analysis of EEG measurements. It is important to decode the EEG signals for several weeks which is really not only time-consuming but also difficult for an expert. In this case, a machine learning-based prediction method can be an alternative. In this paper, the primary aim is to implement ML methods for epileptic seizure prediction. The Deep Learning (DL) model can interpret patterns extracted from the EEG raw data. The DL model will follow

some steps like signal processing, feature extraction and selection, classification and checking performance.
A related work [20] mainly focuses on the identification of epileptic seizures centered on Electroencephalography (EEG) signals and convolutional neural network (CNN). At present time, Epileptic seizure is considered as one of the most usual neurological disorders stated in this paper. EEG signals can be used to detect epilepsy very broadly by monitoring the differences in voltage changes along the brain's surface. Moreover, they also provide spatial and temporal information about the brain. In this topic, we would talk about various techniques that are used to extract feature extraction from EEG signals. Like frequency domain, time domain, time-frequency domain, nonlinear signal analyses etc. Moreover, the outcomes for the frequency domain signals and the time domain signals as well as a comparison between the frequency domain signals and the time domain signals centered on the results from the Freiburg database and the CHB-MIT database have also been discussed in this article. In addition, there is also a short discussion about the comparison of other techniques rather than the frequency domain signals and the time domain signals. We can notice that frequency-domain signals function far better than the time domain signal for both the Freiburg database and the CHB-MIT database which has been stated in the conclusion.
[23] This article focuses on and discusses different methods and models of machine learning and their accuracy and precision in the recognition of epileptic seizures. According to the International League against Epilepsy (ILAE), Epilepsy is called a "chronic condition stated in this article. Moreover, a lot of risks associated with epileptic seizures include sudden unexpected death in epilepsy (SUDEP) which is really a concerning problem discussed in this article. EEG can help to detect and diagnose epileptic seizures. In this article, five steps have been taken in the proposed methodology which are – a collection of raw data, statistical feature extraction, training of dataset, machine learning model implementation, model evaluation. In the machine learning model implementation step, basically, two models of machine learning have been used which are – logistic regression and decision tree model. In conclusion, it is stated in the paper that the logistic regression model has a higher accuracy rate than the decision tree model but in the precision sector, the decision tree model provides better outcomes than the logistic regression model.
[24] A research work discusses the prediction of epileptic seizures by applying some machine learning methods. According to this article, an epileptic seizure is the third most usual brain disorder. Some reasons behind epileptic seizure-like – molecular mutation, etc have been said in this paper. Moreover, it is stated in this paper that there are four distinguishing states which are – pre-ictal state, ictal state, postictal state, inter-ictal state. Basically, the goal of this study is to give prognosis of the epileptic seizure by examining the EEG signals at the start of the pre-ictal state's necessary time before the starting time of the ictal state. Furthermore, there are a lot of steps like – data acquisition, surrogate channel, feature extraction training data, etc. in the proposed method of this paper. Besides, some techniques and machine learning models have been utilized in different steps of the proposed method like – averaging filter, large laplacian filter used in surrogate channel step, statistical moments and spectral moments used in feature extraction step, and so on. To conclude, the provided framework by the author was more efficient and sensible in predicting epileptic seizures with an average time of 23.6 minutes. By this proposed

method, a patient can have a prior idea about his seizures, which may save his life. Another research paper [12] reflects the uses of machine learning in EEG signals for the prediction of epileptic seizures. An epileptic seizure is a chronic illness that affects the central nervous system particularly. It occurs when a sudden electrical discharge hits the cerebral networks. We can predict early and diagnose the function of the brain during epileptic seizure attacks by Electroencephalography (EEG) very effectively. Moreover, some methods of classical ML approaches like – time domain, frequency domain, etc. used in feature extraction step, reduce dimensions in feature selection step, and so on have been discussed in this paper. Furthermore, deep learning (DL) which is an advanced idea of machine learning and some of DL's models like – CNN, LSTN, etc. have also been discussed in this paper to predict epileptic seizures. In conclusion, this paper has basically highlighted the necessity of early prognosis of epileptic seizures as well as the way of using ML and DL techniques to predict epileptic seizures.

[21] A research article presented that EEG signals are mostly adjuvant in identifying many psychological disorders of the central nervous system like Epileptic Seizures, Schizophrenia, Cerebral Aneurysm, etc. An epileptic seizure occurs from the instant electrical release of a part of brain cells which causes short-term disquiet of brain. Specific analysis of epileptic in the EEG signal can divulge useful facts about this frequent brain disorder. As the signal of EEG is very composite, it needs the analysis of various factors. Manual visual testing of EEG signals has been discovered convenient in detecting patterns. Nevertheless, this method needs distinguished analytical and technical skills along with diverse signal-processing techniques. So, automated analysis of EEG signals becomes more convenient with the advancement of technology. The automated system can interpret EEG data by giving a digitized seizure detection system. In this paper, they discovered machine learning methodology in the recognition of epileptic seizures. Here, the most important classification systems are KNN and SVM. Resolving the EEG signals under the time and frequency domains the experts focuses on the extraction. In this phase, neurologists started the extraction of the features of all the EEG signals. Then the maximal indicative features have been selected from the extracted EEG signals. Here, the author used two different methods which are T-test and SFFS. In conclusion, the SVM and KNN annexed the most significant feature from the extracted individual signals.

Similar research work shows that [3] EEG is a confined measurement of the cerebrum's electrical activity. In this study, Support Vector Machine (SVM) has been implemented by analyzing EEG signals to determine the epileptic seizure. Categorizing the brain's electrical activity emerged as a major concern because of the excessive complexity. For this reason, the significance of an adequate Machine Learning (ML) based methodology is much congenial. Only an efficient and high-performing algorithm can detect and predict epileptic seizures dexterously. Because an algorithm with high efficiency can classify the extracted features which originated from the EEG signals. The brain's electrical activity is classified into seizures and non-seizures periods under a supervised and discriminative framework by this detection. Within the discriminative framework, there will be a solution to the binary classification problem with high accuracy. The classifier's high accuracy is a completely automated process. It demonstrates a feature vector that integrates into a single feature space of the brain's electrical activity. In addition, this feature vector can

be widened with information derived from the brain's other electrical signals.
Research article [13] published in 2012, discusses Epilepsy as one of the most usual neurological disorders that affect a huge amount of people at any age all over the world. This disorder can harm an individual with sudden, unpredictable seizures which may injure terribly. Through the advancement of technology, we can predict epileptic seizures in advance by the electroencephalogram (EEG).EEG evaluates the electrical activity of brain function. In order to detect seizures at a very early age, the expert needs to decode the EEG signals which were originated from the brain's electrical activity. However, plenty of research work has been done focusing done on patient-specific classifiers, this paper focuses on the cross-patient view. In order to detect epileptic seizures, EEG-based signal recognition algorithms had been shown in this paper. The algorithms were SVM and KNN. These two methods perform almost similarly. But K-Nearest Neighbor appears with pretty higher accuracy in certain conditions.
Research work presented that [18] Epileptic seizure is the most usual neurological disorder that has affected almost 65 million people across the world. The detection of epileptic seizures is a complex process that takes a lot of effort and time. The electroencephalography (EEG) records brain activity later which is inspected by a neurologist over time. Sometimes a neurologist needs to inspect the brain activity for a few months which is a lengthy process. In this case, an automated approach is time befitting as it can detect and predict epileptic seizures within less time. Deep learning, Machine Learning, Image processing are some of the approaches to detect seizures. In the Machine Learning approach, the aim is to demonstrate a framework that will take the feature vectors of EEG signals as input and classify it into a seizure and non-seizure classes. This Binary classification is conducted by an SVM (Support Vector Machine) Classifier. The features were excerpted from each EEG signal of the EEG channel. Later all these features were merged together to configure a feature vector. In this approach, they showed frequency domain features, time-domain features, and brain connectivity along with graph features. There is some classification model such as Quadratic Discriminant Analysis, Support Vector Machine, K-Nearest Neighbors, Random forest, Radial Basis Function, Kernel, Multi-Layer Perceptron etc. Among them, the SVM classification model shows 100% accuracy in detecting and classifying patients into the Seizure and non-seizure classes.

Chapter 3

Background Analysis

3.1 Decision Tree Algorithm

A decision tree actually is a machine learning algorithm where data is divided in some phases according to some parameters and conditions. This tree is kind of supervised learning technique which is frequently used in solving Classification problems [22]. Decision Tree is usually like the thinking process of a human being how a human think step by step while making a decision. This algorithm's main goal is to create a model that can predict the outcome results depending on some conditions and parameters. In order to build a tree, we use Classification and Regression Tree algorithm.

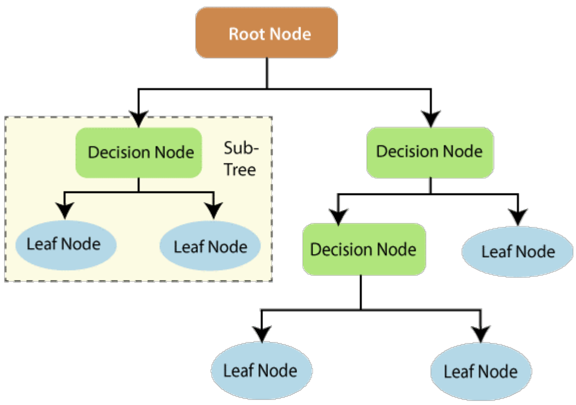


Figure 3.1: Process of Decision Tree Algorithm

A decision tree has two types of nodes which are the Leaf Node and Decision Node. Decision nodes are used for making the decision and Leaf nodes are used as the output or results. Decision Nodes have multiple branches but Leaf Node does not have any. The algorithm starts from the root node of the tree. According to the given data set it predicts the classes. For this the algorithm compares the values of the root property from the data set attributes. For the next nodes, the method uses Attribute Selective Measure (ASM) to compare the attribute value with the other sub-nodes based on the best attribute in the data set. That's how it keeps processing nodes until it reaches the tree's leaf node.

3.2 Random Forest Algorithm

Random Forest Algorithm is basically a ML based algorithm where a set of decision trees is selected arbitrarily from the training set. This learning method is used for classification, regression and other tasks [27]
Random Forest algorithm contains lots of decision trees on different subsets. It takes the average for predicting the accuracy of that dataset. It does not depend on one tree for the result. Rather than it determines the ultimate output by calculating the majority votes of predictions. The more number of tree we have in dataset the more is probability of the correct prediction. [Fig:3.2]

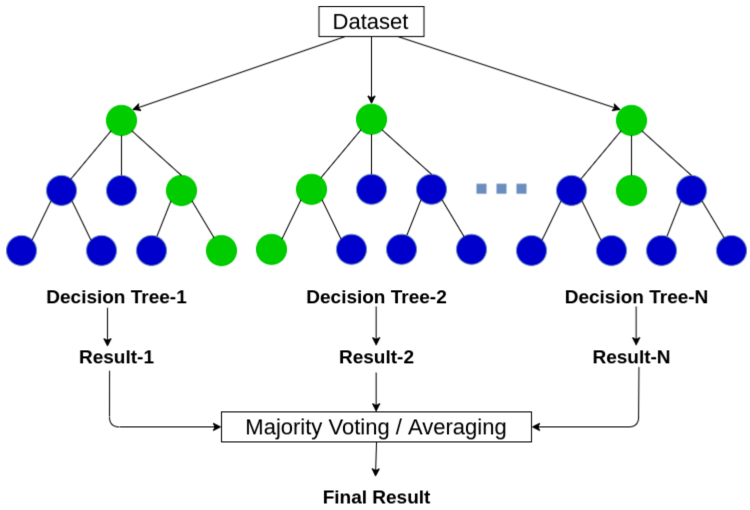


Figure 3.2: Process of Random Forest Algorithm

Random Forest algorithm is more reliable because it gives higher chances of correct prediction even if the dataset is too large. In some cases it can have higher accuracy when there is large amount of data missing. That is a huge advantage. Moreover, this system takes less training time comparing other algorithms. For the output initially it creates random forest by combining N decision tree. After that it makes predictions for each tree it has created. Every decision tree provides a prediction result in the training phase. Whenever there arises a new data point, the algorithm predicts the final decision based on the majority of results.

3.3 MLP Classifier

Multi-layer Perceptron is a supervised and feedforward algorithm that propagates group of outputs from inputs. [19] An MLP is structured by three different layers. Such as input layer, output layer and hidden layer [Fig:3]. First of all, the input layer processes the data from the received input signals. The major implementation such as classification and prediction is operated by the output layer. A random amount of hidden layers works as the primary algorithmic engine of the MLP. It lies between input and output layers of the MLP. MLP always allows the data to move forward from input layer to output layer as it is a feed forward network. The back propagation learning algorithm are widely used by MLP for training the network. MLPs are schematic in such a way that it can approximate several continuous function and resolve linearly inseparable problems. Along with that MLPs are used in approximation, pattern classification, recognition and prediction.

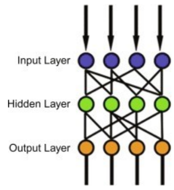


Figure 3.3: MLP with single hidden layer

The computation of MLP is based on a function

$$f(\cdot) : R^m \rightarrow R^0 \tag{3.1}$$

here m is the numeral digits of quantity of input number and o is the numeral digits of quantity for output number. In the [Fig:3.3], the left layer is called input layer.It contains a set of neurons

$$\{x_i | x_1, x_2, x_3 .... x_m\} \tag{3.2}$$

which represents the input features. As the hidden layer lies in between input layer and output layer, every single neuron in the hidden layer transfigure the values from the preceding layer. After that the linear summation is structured along with its weight

$$\{w_1 x_1 + w_2 x_2 + w_3 x_3 + ... + w_m x_m\} \tag{3.3}$$

The hidden layer follows a non-linear activation function

$$g(\cdot) : R \rightarrow R \tag{3.4}$$

which is a hyperbolic $\boldsymbol{tan function}$. Finally the output layer which lies in rightmost side, accepts the values from the previous hidden layer and transfigure them as output values.

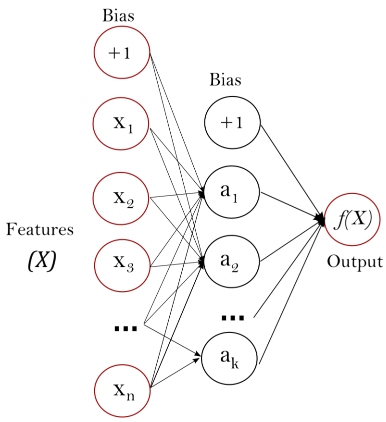


Figure 3.4: Different layers of MLP

The module contains some weight matrices and bias vectors, where the matrix of index i illustrates the weight in between layer i and i+1. On the other hand, the vector in the index i represents the bias value which is summed up to layer i+1.

3.4 KNN Classifier

K-Nearest Neighbors is a simple and supervised ML based algorithm which is used in regression and classification related problems. Though it is mainly used for classification problems. [28] The KNN algorithm works on the basis of 'feature similarity' for assuming the value of every single data from the dataset. It usually represents that every single data will be attributed an assumed value on the basis of how near it is to its neighbors. The two properties of KNN makes this algorithm more transparent. These are Lazy learning algorithm and Non-parametric learning algorithm. KNN is often called a lazy learning algorithm because specialized training phase is absent here. Also it performs action and stores the dataset while classifying by not learning from the training set. Moreover, it is also known as non-parametric learning algorithm because of not using any training data points for generating model. In the training phase, KNN algorithm saves the dataset whenever it gets newer data. After that the algorithm classifies all the data in a category which is almost similar to the renewed data. The KNN algorithm is very easy to implement. But the algorithmic cost is a bit higher because of scanning all the data points in the same sample. Also it requires more memory space for storing the data in testing phase.

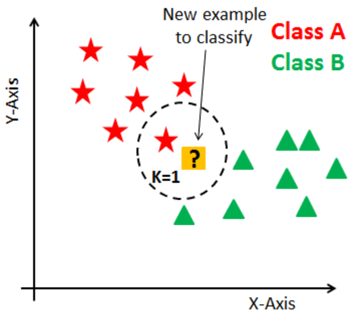


Figure 3.5: Starting of KNN Algorithm Process

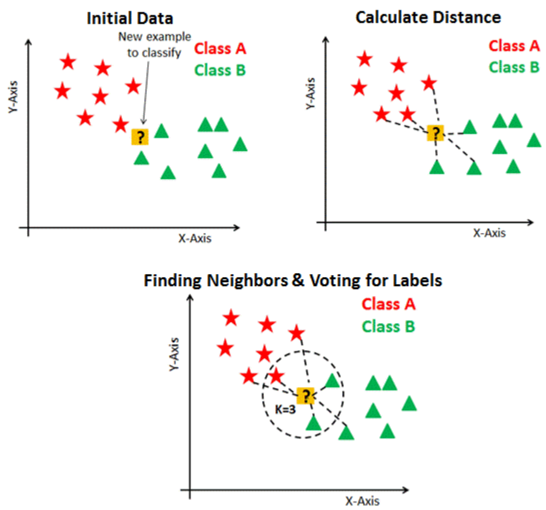


Figure 3.6: Measuring Distance and Deciding the labels

The "K" in KNN, refers the number of nearest neighbors and the key deciding factor is the number of neighbors. The KNN start its working process by identifying it's

all neighbors and measuring the distances between the quest and all the data points in the data set. After that this algorithm votes for the most manifold label. Along with that this algorithm fixed a number which is marked as "K" and appoint them a value on the basis of its neighbors. If the data is appointed with the value of k=1, it is called the nearest neighbor algorithm [Fig:3.5]
The label can predict the point "new example" shown in the previous example [Fig:3.5]. The KNN will start its working process by searching the "K" nearest point to "new example." After that each data point will vote for their nearest class. Then the highest voted class will be used to generate predictions. [Fig:3.6]

3.5 Gradient Boosting Classifier

Gradient Boosting Classifiers are an aggregation of ML based Algorithms which join numerous weak learning models simultaneously to make a strong model. Recently Gradient Boosting Models are getting renowned for its viability in classifying complicated data sets. It is an AdaBoosting Method attached with weighted minimization where the classifiers and the weighted inputs are rechecked. The key purpose of Gradient Boosting Classifiers is to reduce the loss of the class value and the tentative class value.
In this algorithm, each weak learner is joined to the model. Thus the loads of the past learners are congealed or commenced in their position so that the fresh layers can present here without changing the past layers. [26] This is particular from the methodologies utilized in AdaBoosting where the values are changed when the new layers of learners are added. Another capacity of Gradient Boosting Classifiers is they can be utilized on beyond Binary Classification problems, even they can be applied on both Regression problems and as well as Multi-Class problems. Gradient

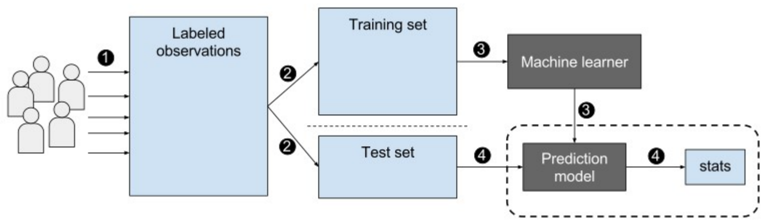


Figure 3.7: Gradient Boosting Classifiers Model

Boosting has 3 major part. These are: Loss Function, Weak Learner and Additive Model. This ML based algorithm always focus on reducing the errors and loss of the classifiers by optimizing various loss functions [14]. Also it can be used in many real life Machine Learning challenges like penalized learning, tree constraints, randomized sampling, and shrinkage etc.

3.6 Gaussian Naïve Bayes

Gaussian Naïve Bayes is a predictive and generative Machine Learning based algorithm which is useful for many classification functions. It provides results with high accuracy even if the information is inadequate. Also this model can smoothly work with unstructured large data with complex problems. GNB model does not require huge time on classifying training data and generate efficient performance by excluding insignificant specification. The formula of Gaussian Naïve Bayes is,

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{3.5}$$

Where, P(A|B) represents posterior probability of presumption A on the executed event B. P(B|A) is Likelihood probability of the proof given that the presumption is true. P(A) is Prior Probability of presumption before observing the proof. P(B) is Marginal Probability which is the probability of proof or evidence [10]. [29]

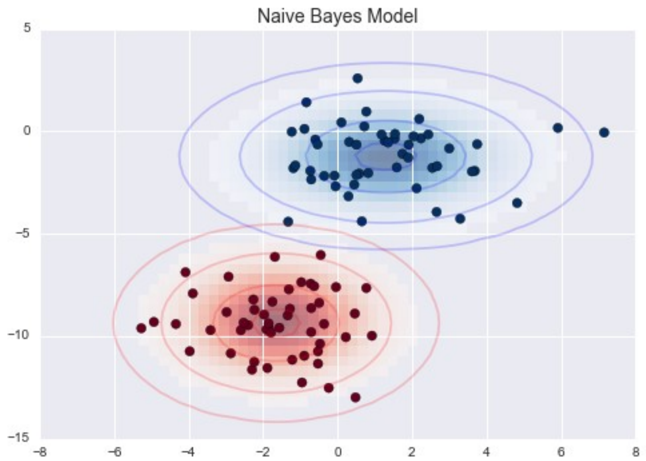


Figure 3.8: Gaussian Naïve Bayes Model

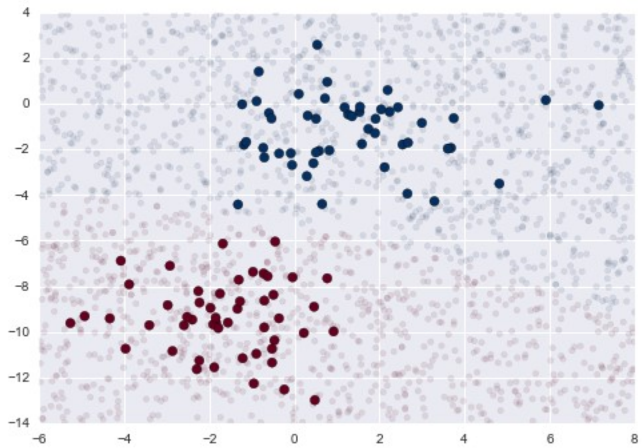


Figure 3.9: Gaussian Naïve Bayes Model

The Gaussian Naive Bayes classifiers inclined to execute efficiently in one of the following circumstances: 1.When the naive prediction actually matches the data. 2. When the datasets are structured in an organized way with having less complexity. 3. When the Datasets are high-dimensional in structure and there is less model complexity.

3.7 Complement Naïve Bayes

Complement Naïve Bayes is a process of calculating probability of possible outcomes. But there is a slight difference in this process. Instead of measuring the probability of an item which belong to a specific class we measure the probability of that item to be found to every classes we are using for calculation.
[2] Complement Naive Bayes is evolved from the standard Multinomial Naive Bayes algorithm. This classifier is designed such a way that it can correct severe assumptions. This is a popular and commonly used Machine Learning algorithm which is used for classification.
The calculation process is each class calculate the probability of the given instance which does not belongs to it. After completing calculation for all the available classes, we analyze all the calculated values and select the smallest value from there. The smallest value is to be selected. The reason is it has the lowest probability that will not be found on that particular class. This indicates that it consumes the highest probability to be present in that class. That's why this class is selected. That is how probability is calculated on Complement Naive Bayes.

3.8 Stochastic Gradient Descent

Stochastic Gradient Descent or SGD is an iterative method which optimize to fit linear classifiers and regression under convex loss functions. Support Vector Machines and Logistic Regression is a field where SGD works. It changes actual gradient which is measured from the data set by an estimation which is calculated from a randomly selected subset of the data.

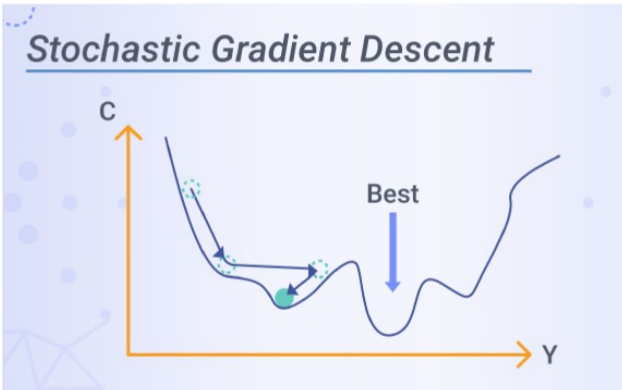


Figure 3.10: Stochastic Gradient Descent Model

SGD is a faster method. But comparing to ADAM it is a quite unstable. SGD is comparatively noisier than typical Gradient Descent. This generally takes lots of iterations to reach the minima since its randomness in its descent. Although it requires a higher number of iterations but it is much less expensive than usual Gradient Descent.

3.9 Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence (XAI) is a group of methods and tools that approves human users to perceive and fidelity of the resultant outcome made by Machine Learning based Algorithm. Mainly this algorithm is used to represent an Artificial Intelligence (AI) Model. [15] XAI also helps to provide model accuracy, integrity, subtlety and results in the decision making of AI. Also it can help users to comprehend and explain neural networks, deep learning and as well as other ML based algorithms.

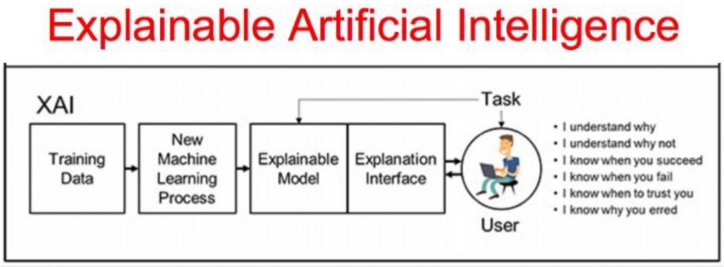


Figure 3.11: Work flow of Explainable Artificial Intelligence

Also the key objective of Explainable Artificial Intelligence (XAI) is to contribute in algorithmic accountability. [25] XAI generates some comprehensive facts about how Artificial Intelligence comes up with a decision. These are-

- Strength and weakness analysis of the program.
- Tangible conditions used by the program to make a decision.
- How programs changes decision by analyzing particular criteria.
- Variance of fidelity for different types of decisions.
- Inclination towards different types of error by the program.
- Ways of solving errors.

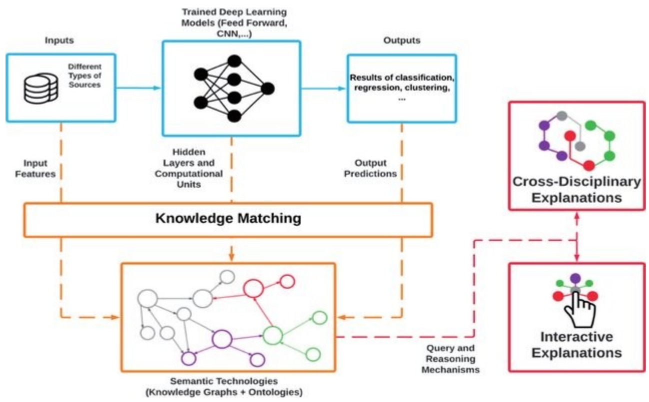


Figure 3.12: Semantic Knowledge Matching for XAI Model

3.10 LIME Algorithm

One of most used Explainable Artificial Intelligence method is LIME Algorithm. LIME stands for Local Interpretable Model-Agnostic Explanations. This is a special method by which it can predict any Machine Learning based model with a local and illustrated model to explain certain approximation.

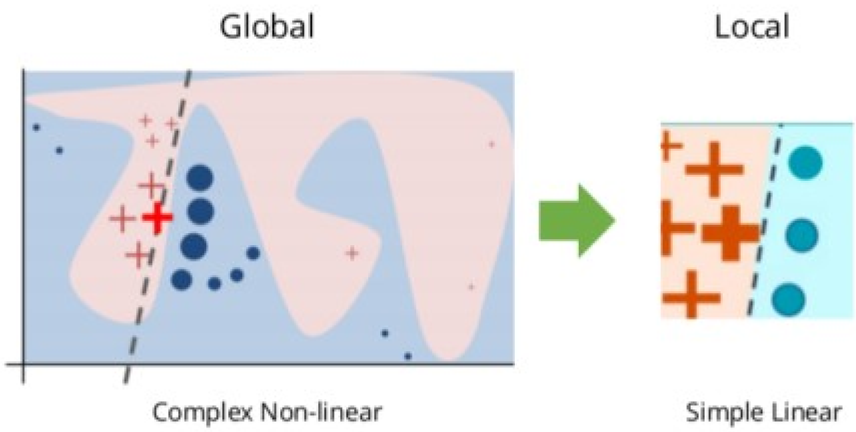


Figure 3.13: LIME Algorithm

Moreover, LIME algorithm has more fidelity to human users for various reasons such as Model Bias, information crack, toughness etc. [11] It provides a specific method to unfold black boxes and the solid reasons of LIME predictions and assumptions. LIME explains the results in such a way that even a normal person can realize the comparison and understand the prediction. Also LIME uses a generic representation of data which is interpretable to the human users. [17] The equation that represent LIME is following:

$$\xi(x) = \underset{g \in G}{\operatorname{argmin}} \quad \mathcal{L}(f, g, \pi_x) + \Omega(g)$$

Figure 3.14: LIME Model Equation

Here f represents the original predictor,x represents original features,g represents XAI model which is a linear model, π represents the approximated measure between z to x to allocate locality around x. LIME algorithm is widely acceptable because of its interpret ability, local trustworthiness, model agnostic and global perspective features.

Chapter 4

Methodology

4.1 Work Flow Overview

In our paper, we used different machine learning models. For instance, Decision Tree Classifier, Random Forest Classifier, Multi-Layer Perceptron, K-Nearest Neighbor which can analyze EEG signals to determine the epileptic seizure efficiently. As we all know that brain's electrical activities have a very complex structure. This methodology will use a high-performing algorithm that can provide early prediction and detection by maximizing efficiency. First of all, our ML-based algorithm will take all the raw data as input. These raw data will be the data set of EEG signals which is the collection of all the electrical activities. After taking as an input this algorithm will classify the data under time and frequency domain extraction.

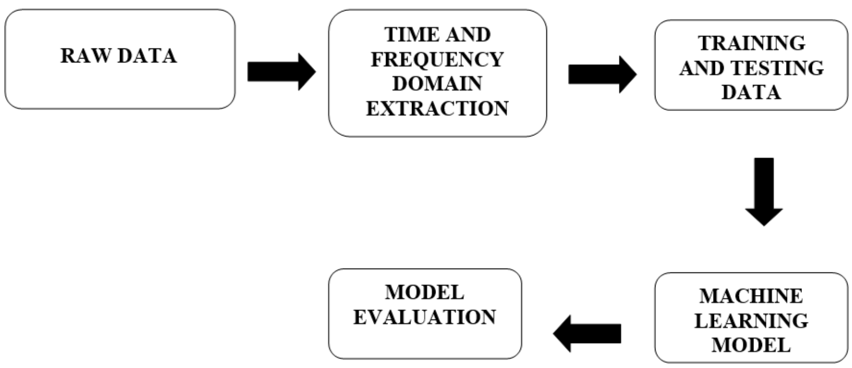


Figure 4.1: Blocked Diagram of the Proposed Methodology

The extracted features mainly originated from the EEG signals. In the third phase, after the feature extraction, the brain's electrical activity is classified into seizures and non-seizures. Within the proposed Machine Learning model, there will be a solution to the multiclass classification problem with high accuracy. The classifier's high accuracy is a completely automated process. Decision Tree Classifier, Random Forest Classifier, Multi-Layer Perceptron and K-Nearest Neighbor will be used to classify and extract the features from the EEG signals. We choose these models because KNN can be thought of as an automatic feature extractor. Moreover, MLP is simple, and it is mainly used because of its high accuracy level. In addition, Decision tree and Random forest classifier also provide high accuracy.

4.2 Dataset Description

Our dataset is collected from an online source UCI Machine Learning repository. The dataset represents the conditions of a person while EEG recording going on. There are 5 individual folders and 100 files in it. Each file represents a person which has the data of brain activity for 23.6 seconds. The amount of data point is 4097 and it represents the EEG recordings of the patient at various point of time. These data points are of 23.5 seconds for each 500 people. To make our analysis easier we have divided the data points into 23 chunks. A single chunk consists of 178 data points per second. So we got 11,500 pieces of information in total which is in the row, 178 data points per second which is in the column. The last column represents the label y. This label is categorized with 178 dimensional input vector in 5 different categories 1, 2, 3, 4, 5.Here, 5 indicates eyes were open of the patient while EEG signal was recording, 4 indicates eyes were closed at that time, 3 indicates they could locate the position in the brain where the tumor was as well as signal was recorded from the sound brain area, 2 indicates EEG signal was recorded from the tumor area, 1 indicates seizure activity Patients having epileptic seizure are in class 1 and who does not have epileptic seizure goes in class 2, 3, 4 and 5. This classification makes work easier for us to identify which patients have epileptic seizure or not.

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X22
X21.V1.79	135	190	229	223	192	125	55	-9	-33	-38	-10	35	64	113	152	164	127	50	-47	-121	-138	-125
X15.V1.92	386	382	356	331	320	315	307	272	244	232	237	258	212	2	-267	-605	-850	-1001	-1109	-1090	-967	-746
X8.V1.1	-32	-39	-47	-37	-32	-36	-57	-73	-85	-94	-99	-94	-96	-104	-103	-92	-75	-69	-69	-53	-37	-14
X16.V1.60	-105	-101	-96	-92	-89	-95	-102	-100	-87	-79	-72	-68	-74	-80	-83	-73	-68	-61	-58	-59	-64	-79
X20.V1.54	-9	-65	-98	-102	-78	-48	-16	0	-21	-59	-90	-103	-84	-43	-9	3	-21	-60	-96	-103	-75	-29
X14.V1.56	55	28	18	16	16	19	25	40	52	66	81	98	111	122	105	85	66	51	34	19	16	8
X3.V1.191	-55	-9	52	111	135	129	103	72	37	0	-38	-77	-113	-128	-121	-105	-71	-27	13	44	60	64
X11.V1.27	1	-2	-8	-11	-12	-17	-15	-16	-18	-17	-19	-18	-16	-15	-14	-21	-19	-24	-24	-24	-17	-20
X19.V1.87	-278	-246	-215	-191	-177	-167	-157	-139	-118	-92	-63	-39	-11	14	36	60	70	78	79	69	27	-45
X3.V1.491	8	15	13	3	-6	-8	-5	4	25	41	48	44	34	16	-2	-11	-24	11	33	43	48	42
X3.V1.6	-5	15	28	28	9	-29	-41	-19	14	30	22	-6	-30	-40	-42	-48	-50	-55	-58	-66	-49	-20
X21.V1.72	-167	-230	-280	-315	-338	-369	-405	-392	-298	-140	27	146	211	223	214	187	167	166	179	192	190	168
X7.V1.162	92	49	0	-32	-51	-65	-37	-19	-25	-29	-52	-62	-85	-107	-97	-69	-46	-37	-48	-59	-58	-61
X1.V1.211	15	12	0	-17	-28	-31	-39	-51	-44	-35	-20	1	16	24	22	26	27	22	16	14	26	34
X1.V1.615	-24	-15	-5	-1	4	3	6	10	11	7	8	12	10	10	5	-1	-11	-13	-24	-39	-44	-52
X22.V1.24	-135	-133	-125	-118	-111	-105	-102	-93	-94	-90	-82	-75	-71	-69	-69	-69	-61	-59	-57	-64	-66	-65
X1.V1.863	39	41	41	42	43	43	46	47	49	50	52	52	53	59	58	63	62	64	59	57	55	50
X9.V1.302	9	4	-5	-10	-22	-30	-33	-43	-41	-40	-42	-46	-47	-52	-50	-51	-43	-34	-23	-6	4	10
X7.V1.541	-21	-5	1	7	19	20	13	2	-1	-3	-3	-14	-18	-21	-2	17	39	56	65	58	31	19
X9.V1.915	4	24	51	76	92	102	104	101	90	80	53	32	9	5	17	42	72	94	103	106	107	106
X23.V1.96	410	451	491	541	581	641	736	757	692	435	61	-387	-823	-1107	-1188	-1110	-947	-765	-600	-471	-376	-301
X1.V1.614	-24	-27	-23	-28	-34	-40	-47	-43	-38	-23	-1	7	18	7	11	-1	-18	-22	-21	-2	15	35
X11.V1.13	-264	-189	-117	-45	20	70	111	143	161	179	194	200	193	164	128	92	67	57	38	-21	-141	-239
X18.V1.54	-4	40	78	123	149	185	197	189	167	141	129	140	167	183	182	154	124	102	85	63	34	1
X19.V1.29	593	328	88	-106	-456	-732	-921	-782	-522	-248	-68	89	221	342	336	219	82	-32	-83	-114	-134	-134
X21.V1.80	-16	-15	-19	-16	-14	-5	0	-1	-3	-5	-7	-6	-6	4	15	16	25	32	32	33	33	34
X2.V1.72	-20	-38	-53	-58	-66	-66	-69	-77	-87	-84	-82	-72	-58	-47	-50	-65	-81	-98	-105	-102	-97	-95
X3.V1.744	-340	-381	-376	-336	-275	-204	-131	-70	-16	20	46	60	68	76	80	85	87	88	86	77	63	44
X12.V1.73	-30	15	61	80	72	41	-11	-31	-47	-63	-53	-48	-41	-49	-51	-48	-47	-52	-57	-60	-81	-82
X8.V1.614	-1	18	35	36	29	17	10	1	-3	-2	8	22	33	24	15	9	3	-14	-17	-9	4	21

Figure 4.2: Epileptic Seizure Recognition Data Set

4.3 Data Pre-processing

As we stated earlier, we used a dataset collected from UCI Machine Learning Repository. In this dataset, there were no missing or null values available to handle. Moreover, there were no categorical values which is why we didn't have to do any label encoding here. We selected some features in order to minimize the computational time and optimize the model's performance. Moreover, feature selection helps with interpretation and visualization of data while overcoming the problem of various dimensionality for the enhancement of our model's performance. It can also decrease the duration of utilization, training time and need of storage. In feature selection, we basically selected the values of corresponding signal in our dataset as features. We selected the final column "Y" as our label which has 5 categories in total. We used Scikit-learn's train test split() function in order to split our dataset. For splitting the dataset we applied 8:2 ratio along with random-state equal to 1. As a result, our dataset got divided into two parts where first part consists of 80% data and worked as the training dataset. On the contrary, the rest 20% of the dataset worked as testing set. All of them were chosen randomly as we applied random-state during splitting and both the features and labels were separated according to the provided ratio. We assessed several Machine Learning models such as Decision Tree Classifier, Random Forest Classifier, Multi-Layer Perceptron and K-Nearest Neighbor using Scikit-learn library for our supervised regression tasks and examined the data to see which performed better. We trained our machine learning models by using the model-fit-generator function and observed the accuracy score of all the models accordingly.

4.4 Experiment

We used Google collaborator for our python programming stuffs. First of all, we uploaded our dataset in the Google Collaborator so that we can read it. Then we preprocessed the data as it is required for further prosecution. For testing and training purpose we choose 80% data randomly to be trained and rest of the data to be tested. Next we applied the machine learning models mentioned above and found out accuracy score for each of the models. We used scaled data for some models to find out the accuracy score. We also plotted confusion matrix for each of the models individually to understand the performance of the models more elaborately. Moreover, we plotted a bar chart including accuracy score of all the models. Confusion matrix and bar chart were plotted for both binary and multi-class classification of our dataset so that we can compare the results. Last but not the least, we used explainable artificial intelligence (XAI) to interpret the results of our models. For this purpose, we installed LIME in Google Collaborator. We used prediction generated by Random Forest Classifier in the LIME algorithm as it provided the best accuracy score among all the models we used. Finally, we interpreted two cases, one for the presence of seizure and another for the absence of seizure with the help of LIME algorithm.

Chapter 5

Result and Discussion

5.1 Confusion Matrix for Multi-Class Classification

Confusion matrix is mainly the summary of predicting results of a classification problem. It helps to visualize the summary results with analytic like accuracy, definite points and precision etc. Moreover, confusion matrix provides contiguous analogy of values like True Positives negatives and False Positives Negatives. It is generally a table which provides a clear idea about the performance of the proposed model. In this paper we have shown the individual confusion matrix for each algorithm for multi-class classification.

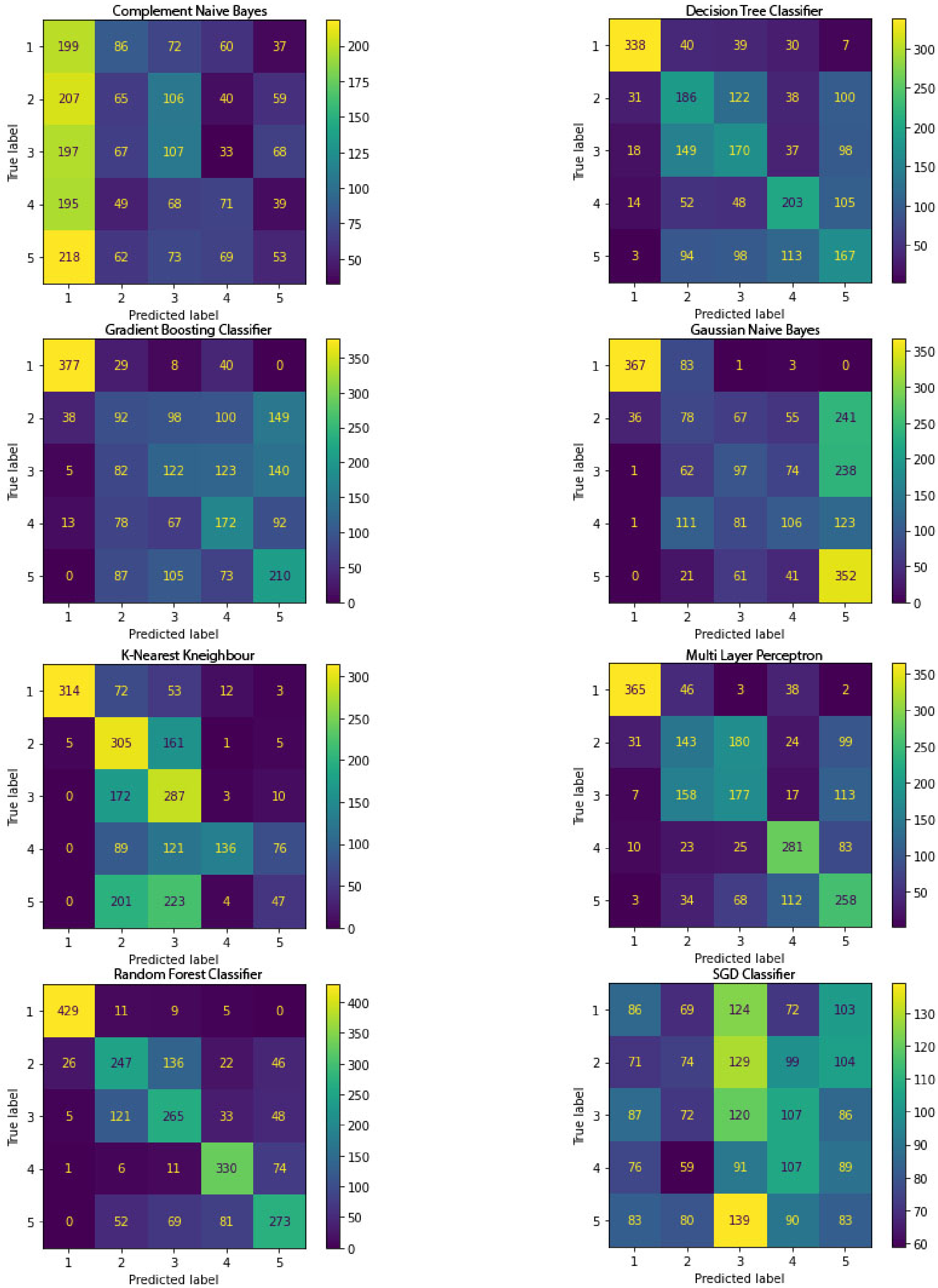


Figure 5.1: Confusion matrix of all the model for multi-class classification

From the above figures we can easily notice that, the Random Forest Classifier provides the highest true prediction rate compare to other algorithms and classifiers. Then, the MLP algorithm provides the second best true prediction rate. However, KNN classifier, Gaussian Naïve Bayes, Decision tree classifier and Gradient Boosting Classifier have the moderate true prediction rate. On the other hand, Complement Naïve Bayes and SGD classifier has the lowest true prediction rate according to the above figures.

5.2 Confusion Matrix for Binary Classification

In this paper we have also shown the individual confusion matrix for each algorithm for binary classification.

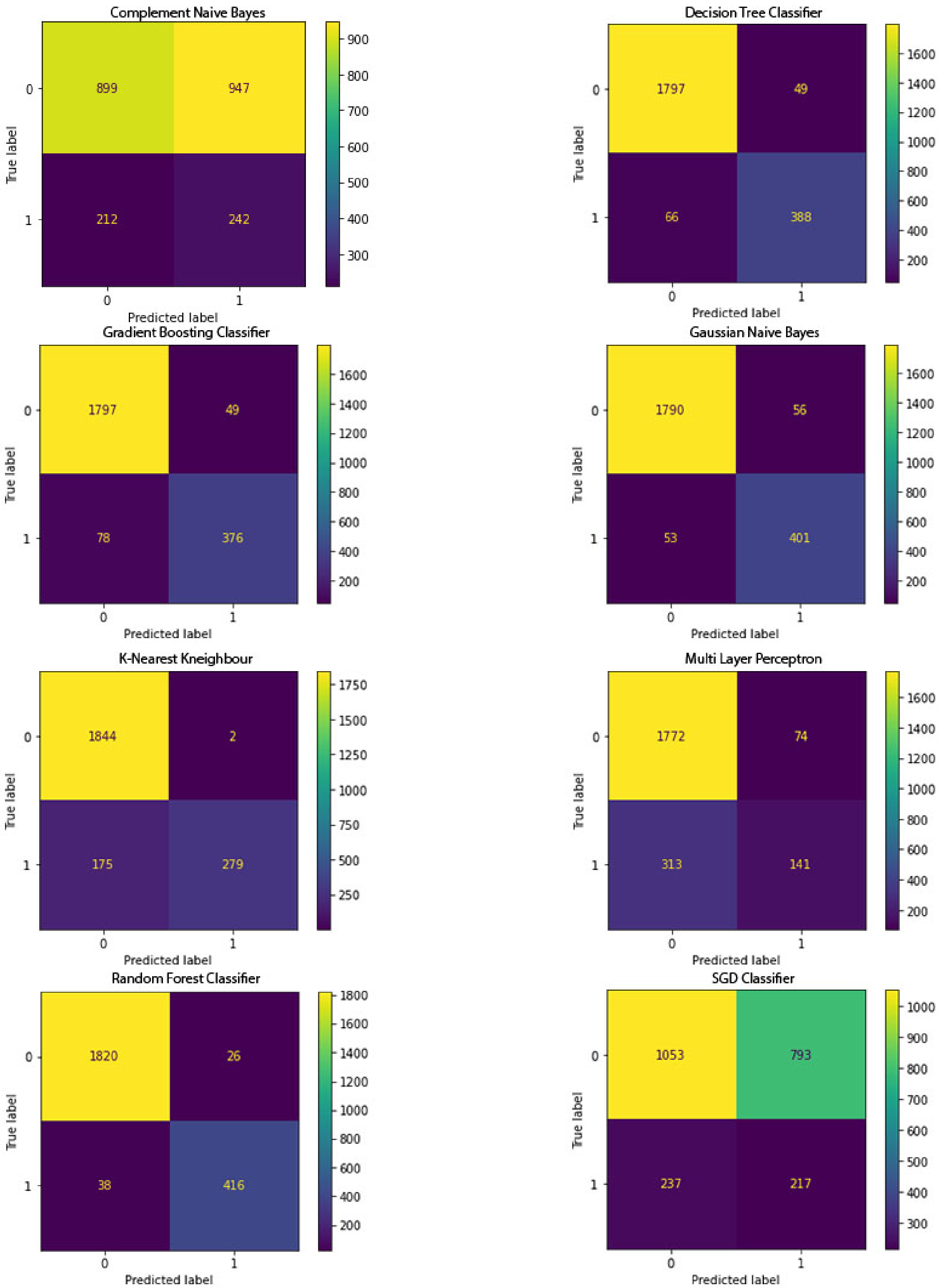
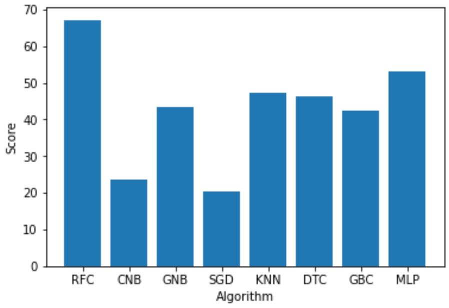


Figure 5.2: Confusion matrix of all the model for Binary classification

From the above figures we can easily see that, the RFC gives the highest true prediction rate compare to other algorithms and classifiers like multi-class classification. Then, the Gaussian Naïve Bayes has the second highest true prediction rate. Moreover, MLP algorithm, KNN Classifier, Decision Tree Classifier and Gradient Boosting Classifier have the moderate amount of true prediction rate. However, Complement Naïve Bayes and SGD classifier has the lowest true prediction rate according to the above figures like multi-class classification.

5.3 Comparative Analysis



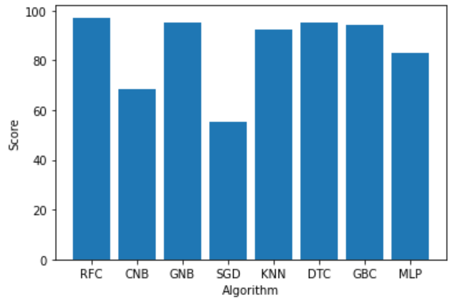


Figure 5.3: Accuracy of the applied classifiers in bar chart for Multi-Class & Binary Classification

In this section we have done a comparative analysis between the accuracy score of different Machine Learning models for both Multi-Class Classification and Binary Classification.
We have used Decision Tree, Random Forest, Multi-layer Perceptron, K-Nearest Neighbor, Gaussian Naïve Bayes, Complement Naïve Bayes, Gradient Boosting Classifier and SGD Classifier for applying in our proposed model. From the bar chart we can see that all the algorithms which are used for this research, provides distinguished accuracy. Among the algorithm the accuracy percentage differ from one another.
From the bar chart we can see that all the algorithms which are used for this research, provides distinguished accuracy. Among the algorithm the accuracy percentage differ from one another. Let's discuss about the accuracy rates of the applied models in binary classification first. From the above chart, we can easily see that the Random Forest Classifier has the highest accuracy rate among all other applied algorithms. Moreover, the accuracy rate of Random Forest Classifier is 97.30%. Furthermore, the accuracy rate of the Decision Tree Classifier in binary classification is 95%. Besides, from the above charts we can see that the accuracy rates of Gaussian Naïve Bayes, Gradient Boosting Classifier, MLP Classifier, KNN classifier are 95.26%, 94.48%, 95.35% and 92.30% respectively in binary classification. However, the accuracy rates of Complement Naïve Bayes and SGD Classifier are too much lower in both binary classification and multi-class classification. The accuracy rate of Complement Naïve Bayes is 68.39% and the accuracy rate of SGD Classifier is 56.09%.

Now, let's discuss about the accuracy rates of the applied models in multi-class classification. Here, the Random Forest Classifier has also the highest accuracy rate among all other applied algorithms. In the sector of multi-class classification the accuracy rate of Random Forest Classifier is 67.13% which is lesser than the obtained accuracy rate in binary classification. Moreover, the accuracy rate of the Decision Tree Classifier in multi-class classification is 46.26% which is also lower than the obtained accuracy rate in binary classification. Furthermore, the accuracy rates of Gaussian Naïve Bayes, Gradient Boosting Classifier, MLP Classifier, KNN classifier are 43.48%, 42.30%, 53.22% and 47.35% respectively which are similarly lesser than

the obtained accuracy rate in binary classification. On the other hand, the accuracy rate of SGD Classifier is 20.43% which is too much lesser than the obtained accuracy rate of SGD Classifier in binary classification. Besides, the accuracy rate of Complement Naïve Bayes is 23.61% which is also too much lesser than the obtained accuracy rate of Complement Naïve Bayes in binary classification.
From the bar chart and above description we can see that, the Random Forest Classifier has the highest accuracy rate among all other applied algorithms in both binary classification and multi-class classification. There are many reasons behind of having a higher accuracy rate of this Random Forest Classifier into a data model. The versatility of the random forest classifier usually keeps a great role for obtaining a higher accuracy rate as we can use this classifier for regression as well as classification tasks both.

Moreover, over fitting problem usually occurs in a less amount in machine learning due to the usage of the Random Forest Classifier in a data model. Decision Tree Classifier works very fast as well as interpretation and visualization of nonlinear data patterns is very easy by using the Decision Tree Classifier. These are some reasons behind getting high accuracy rate after usage of the Decision Tree Classifier. On the other hand, we can see that, SGD classifier gives lower accuracy rate in both binary classification and multi-class classification and there are also some reasons behind this. In the time of using SGD Classifier, most of the times it does not work and perform well as some type of hyper parameter tuning need to be done to make it perform well.

Moreover, we can see the above bar charts that we are getting lower accuracy rates in almost every data models in multi-class classification rather than binary classification. There may be some reasons behind this. Let's talk about these reasons. Maybe some irrelevant features may be present in the data set and for these features the applied models may gain lower accuracy rates. Moreover, classes may be remained imbalanced which may also be a reason to obtain lower accuracy rate in multi-class classification. Furthermore, there could be some problems in normalizing the data set which may also be a reason to obtain lower accuracy rates.

5.4 Classification Report

Generally, we apply a lot of classification algorithms in our data set. If we want to do the measurement of the quality of predictions of these classification algorithms then we can use classification report. We can see two charts of classification report have been given. Let's describe the chart for the case of binary classification first. Here, we can see the term precision which indicates the percentage among the whole predictions were correct. For RFC classifier the precision rates are 0.98 for "No seizure detected" and 0.94 for "Seizure Detected". Moreover, for MLP the precision rates are 0.95 for "No seizure detected" and 0.92 for "Seizure Detected".

Classification Report for RFC (Binary classification)

	precesion	recall	f1-score	support
0	0.98	0.99	0.98	1846
1	0.94	0.91	0.33	454
accuracy			0.97	2300
macro avg	0.96	0.95	0.95	2300
weighted avg	0.97	0.97	0.97	2300

Classification Report for MLP (Binary classification)

	precesion	recall	f1-score	support
0	0.95	0.98	0.97	1846
1	0.92	0.78	0.85	454
accuracy			0.94	2300
macro avg	0.94	0.88	0.91	2300
weighted avg	0.94	0.94	0.94	2300

By recall term expresses the true proportion of the correct and actual positives that were classified. In RFC the recall rates are 0.99 for "No seizure detected" and 0.91 for "Seizure Detected" and for MLP the recall rates are 0.98 for "No seizure detected" and 0.78 for "Seizure Detected". By f1-score a value is expressed by combining of precision and recall. By accuracy term the accuracy of the model is usually expressed which is 0.97 for RFC and 0.94 for MLP. By support term we understand that the number of samples used in each metric which is 2300 for both RFC and MLP classifier. By the term macro average we understand the average precision rate, recall rate and the f1-score between classes which is 0.95 for RFC and 0.91 for MLP. By the term weighted average we understand that calculation of metric in terms of how many samples were in each class which is 0.97 for RFC and 0.94 for MLP.

Classification Report for RFC (Multi-class classification)

	precesion	recall	f1-score	support
1	0.92	0.94	0.93	454
2	0.56	0.51	0.53	477
3	0.53	0.54	0.54	472
4	0.68	0.78	0.72	422
5	0.61	0.56	0.58	475
accuracy			0.66	2300
macro avg	0.66	0.67	0.66	2300
weighted avg	0.66	0.66	0.66	2300

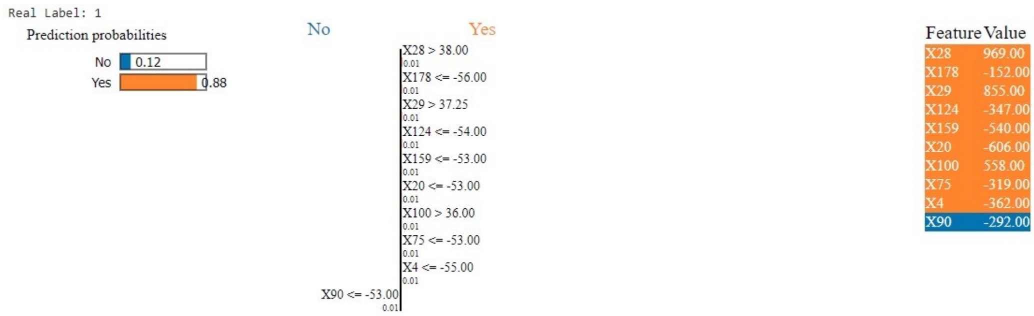
Classification Report for MLP (Multi-class classification)

	precesion	recall	f1-score	support
1	0.87	0.87	0.87	454
2	0.37	0.18	0.24	477
3	0.39	0.56	0.46	472
4	0.60	0.53	0.56	422
5	0.42	0.50	0.46	475
accuracy			0.53	2300
macro avg	0.53	0.53	0.52	2300
weighted avg	0.53	0.53	0.51	2300

Now, let's discuss about the classification report for multi-class classification. We can see different precision rates, recall rates and f1-scores for five classes in the above chart. For RFC the accuracy rate is 0.66 and for MLP classifier the accuracy rate is 0.53. Moreover, the macro average rate is 0.66 for RFC classifier and 0.52 for MLP classifier. Furthermore, the weighted average is 0.66 for RFC classifier and 0.51 for MLP classifier. Here the value of the support is also 2300.

5.5 Interpretation of the results using XAI

In this section, we interpreted two cases, one for the presence of seizure and another for the absence of seizure with the help of LIME algorithm.



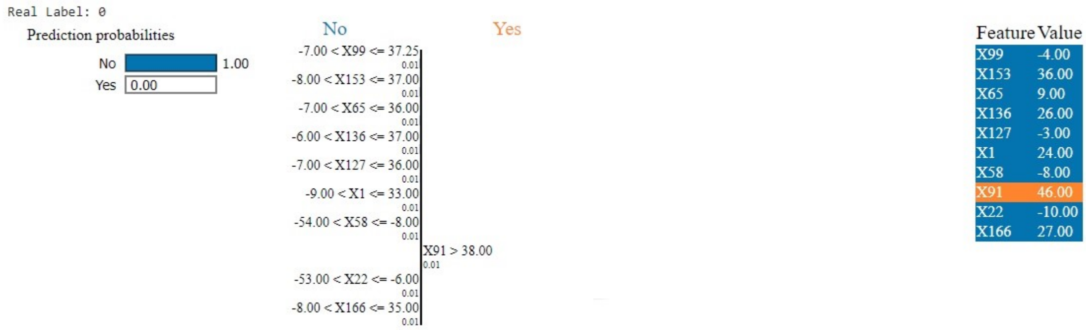


Figure 5.4: LIME Algorithm Result (Presence & Absence of seizure)

Here we can see the prediction probabilities of epileptic seizure for some values. Real Label is 1. In addition, the ratio of yes and no is 0.88 and 0.12. On the process we have used RFC score on Lime Algorithm. For detecting whether there is epileptic seizure or not we have taken some features that cause a great impact on result. The values are respectively X28, X178, X29, X124, X159, X20, X100, X75, X4, X90. We can observe that except X90 every other value indicates positive. Value of X90 is -53 that indicates negative which means there is not any epileptic seizure for the feature X90. For all the other feature X28, X178, X29, X124, X159, X20, X100, X75 and X4 the value is 969.00, -152.00, 855.00, -347.00, -540.00, -606.00, 558.00, -319.00, -362.00 which lies between the range of positive result. So, for these values the system detects epileptic seizure for the patient.
In this figure we can see the prediction probabilities of epileptic seizure for some more values. The ratio of yes and no is 0.00 and 1.00 and Real Label is 0. Like previous in the process, we have used RFC score on Lime Algorithm. For detecting whether there is epileptic seizure or not we have taken some features that cause a great impact on result. The values are respectively X99, X153, X65, X136, X127, X1, X58, X91, X22, X166. We can observe that except X91 every other value indicates negative. Value of X91 is 46, there is detection of epileptic seizure for the value X91. For all the other value X99, X153, X65, X136, X127, X1, X58, X22, X166 the features value is -4.00, 36.00, 9.00, 26.00, -3.00, 24.00, -8.00, -10.00, 27.00 which lies between the range of negative result. So, for these values the system detects no epileptic seizure for the patient.

Chapter 6

Conclusion

In this paper different types of Machine Learning models have been used to detect Epileptic Seizure by recognizing EEG signal. In order to enhance the efficiency and potentiality of the EEG recognition, Random Forest Classifier (RFC) performs the best output for both Multi-Class Classification and Binary Classification. Along with Random Forest Classifier, Decision Tree Classifier, MLP Classifier and Gaussian Naïve Bayes performed comparatively well. Moreover, Gradient Boosting Classifier and KNN Classifier generated a moderate output. On the contrary SGD Classifier and Complement Naïve Bayes could not meet up the expected accuracy level. However, Random Forest appears with pretty higher accuracy in certain conditions. As we have said earlier, there had been a lot of related work in analyzing the EEG recordings and there has been proposed some methodology with an accuracy range of 50% to 70%. To our best belief, Random Forest can originate the accuracy range up to expected range which is really noteworthy in the research field. Finally, the reasons behind getting these results were interpreted by LIME algorithm of Explainable Artificial Intelligence (XAI). As a consequence, the features that affected the prediction score most were detected which can be used for future purposes in the field of Epileptic Seizure detection.

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