Seizure Activity Monitoring System

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March 14, 2024

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I. ABSTRACT

Epilepsy stands as one of the prevailing neurological disorders. This enduring ailment, marked by recurrent, unforeseeable, and unprovoked seizures, impacts a substantial global population. The transitory disruption in typical brain activity induced by this persistent condition can significantly impact the health of individuals affected by it. Detecting epileptic seizures before their onset proves invaluable. To streamline such diagnostic processes, contemporary research has put forth machine learning methodologies that amalgamate statistical principles with computer science.

Machine learning, a facet of artificial intelligence, empowers machines to autonomously acquire new knowledge. This technology, fueled by actionable data, enhances efficiency. Within the realm of healthcare, machine learning, along with computational techniques, is employed to forecast epileptic seizures based on electroencephalogram (EEG) recordings.

To study or predict a scenario, however, analyzing this data on its own is insufficient. This study's objectives include providing full versions of machine learning prediction models for detecting epileptic seizures as well as identifying various types of predictive models and their applications in the field of healthcare.

II. KEYWORDS

seizure,epilepsy,ECG,Machine-Learning,Algorithm, Blood,Random-Forest,Feature-Selection, Electroencephalography(EEG),Neurological-Disorders, Realtime Detection,seizure prediction,

III. INTRODUCTION

An epileptic seizure, also known as a seizure or epilepsy, is a short neurological disease of the brain that can be caused by an unexpected spike in the activity of the brain's nerve cells. This widespread neurological condition affects people of all ages. One percent of the world's population has this ailment. Epilepsy can be brought on by a range of disorders, such as vascular, brain infections, brain tumors, nutritional deficiencies, pyridoxine deficiency, and abnormalities with calcium metabolism. To accurately diagnose epilepsy, research is necessary to fully understand the mechanisms that result in epileptic illnesses[17].

There are various diagnostic techniques, such as electroencephalogram, computed tomography, positron emission tomography, ultrasonography, and magnetic resonance imaging (MRI) (EEG). MRI, CT scans, and ultrasounds are pricy and not suit- able for long-term detection. Nonetheless, the EEG is a low-cost test that can be used for long-term detection. Hence, the most accurate technique to diagnose epilepsy is with an EEG. The EEG provides a wealth of physiological and pathological information that is useful when treating epileptic cases, such as identifying the epileptogenic zone for presurgical evaluations. Currently, the primary method for EEG diagnosis is a physical inspection of the EEG recordings by neurologists. Long-term EEG visual scoring is laborious and time-consuming. So, neurologists might gain from the automatic recognition technique when analyzing EEG records or data. Over the past 20 years, machine learning (ML), a branch of artificial intelligence (AI), has advanced significantly. By utilizing algorithmic, mathematical, and computer science tools, ML reveals the fundamental features of the data as well as internal relationships. Today, it plays a significant role in the science of disease diagnosis. Nowadays, machine learning algorithms are used to predict or identify a number of severe conditions, such as thyroid, cancer, diabetes, heart disease, and epilepsy. Epilepsy is one condition that can be treated early to save a person's life.

It is challenging to anticipate possible seizures, though. As most seizures occur rapidly, it is challenging for researchers to predict potential seizures before they occur. The method outlined in this article will make it simpler to determine whether or not someone is having a seizure.

There has been a lot of research done on epileptic seizure detection. Several Machine Learning (ML)-based algorithms were used in many investigations. Concrete patient classifiers are of special interest in the majority of investigations. Since EEG interpretation is a time-consuming and oftentimes ineffective process, an auto-mated detection system is required. Several categorization methods perform better than the traditional EEG interpretation. K-Nearest Neighbour (KNN) surpassed all other machine learning-based algorithms in a comparison study in terms of relevance, effectiveness, and accuracy[1].

Our main goal in this research is to propose a digitalized method for identifying epileptic seizures that will be more precise, effective, and time-saving than present approaches. Our investigation indicates that no prior studies have specifically compared seizure detection technologies. As a result, the main focus of this effort will be on the analysis and research of the RFC, KNN, and other algorithms. The patient-specific classifiers are another area where our research will contribute with some new and supervised landmarks. A specialist cannot easily or effectively decode the EEG readings and classify the electrical activity. This study will also pay close attention to how these types of annoying problems are being reduced over time. Eventually, the results will be interpreted using explainable artificial intelligence.

This project's primary objective is to develop a discriminative framework that will be better able to identify epileptic episodes in their very early phases. We will use an EEG database to put our recommendations into practise. To increase accuracy, we need a lot of data to synchronise the data gathered from the surveys of different patients in this paper. In this study, the ML-based approach was also studied, and the temporal and frequency domains of each and every EEG data set were used to reconstruct the feature vectors. Also, this research will help biomedical scientists decide which machine learning classifier algorithm is better at spotting and predictingseizures. By employing this study, the reader can comprehend the EEG data sets.

IV. Literature Review

The Internet of Things (IoT) is rapidly automating the healthcare industry. The IoMT, which is the sector of the IoT devoted to medical research, uses data collecting and processing to improve patient care. Machine learning (ML) algorithms are being used in IoMT applications to make predictions and improve decision-making. One of the challenges in healthcare is the early detection of epileptic seizures.[5].

The authors proposed a machine learning-based computational imaging analysis pipeline for fully automated and quantitative evaluation of tertiary lymphoid structures (TLSs) in routine H&E-stained whole-slide images. They first used a convolutional neural network with deep residual learning (ResNet18) to segment tumor vs normal tissue in whole-slide images. Next, they performed single-cell imaging analysis by a mask region-based convolutional neural network (R-CNN) to segment and classify individual nuclei into 3 cell types: lymphocytes, tumor cells, and other nonmalignant cells. Given the lymphocyte density map, they performed image processing and trained a machine learning model to obtain segmentation and classification for TLSs.[3].

To provide a comprehensive analysis of the field, this review examines different machine learning approaches employed in epilepsy seizure detection. These approaches include classical machine learning algorithms such as support vector machines (SVM), decision trees, random forests, and more recent deep learning techniques like convolutional neural networks (CNN) and recurrent neural networks (RNN). Each approach is evaluated based on its performance metrics, computational efficiency, and ability to handle the complexity of EEG data[8].

Epilepsy is a neurologic condition that impacts the central nervous system, resulting in atypical brain activity and giving rise to periods of aberrant behaviour or seizures, occasionally accompanied by a loss of consciousness. Individuals diagnosed with epilepsy face several everyday obstacles, mostly related to the necessary measures they must take to adapt to their illness. This is especially true while participating in tasks that involve the operation of heavy machinery, such as driving.The assessment of brain activity during seizures in epilepsy research mostly depends on the use of electroencephalography (EEG) recordings. However, the process of manually identifying the exact site of seizures within electroencephalogram (EEG) data is found to be arduous and time-consuming. An autonomous detection framework is proposed as a viable alternative, serving as a crucial tool to support healthcare professionals and patients in implementing essential preventive measures.. [4].

Wearable seizure detection devices are important for patients with intractable epilepsy, who have uncontrolled and unpredictable seizures. Current methods for tracking seizure frequency, such as seizure diaries, are unreliable. Wearable devices based on electromyography (EMG), accelerometry, and multimodal recordings have been validated for detecting convulsive seizures, but not nonconvulsive seizures. Changes in heart rate (HR) and heart rate variability (HRV) have been suggested as biomarkers for detecting focal nonconvulsive seizures. A recent study used HRV-based seizure detection algorithms to detect both convulsive and focal nonconvulsive seizures. The best algorithm had a sensitivity of 93 percentage [7].

Epileptic seizure is a neurological disorder that can be detected by analyzing brain signals. EEG is a non-invasive, non-painful, and efficient way to record electrical activity of the brain. Different machine learning and statistical techniques can be used to identify patterns in EEG signals that are associated with epileptic seizures. Some of the most common machine learning algorithms used for EEG signal classification include neural networks, fuzzy inference systems, wavelets, and statistical methods[9].

Nocturnal Frontal Lobe Epilepsy (NFLE), a type of epilepsy where seizures primarily occur during sleep. Traditional diagnosis involves manually inspecting EEG signals, which is time-consuming and often requires multiple experienced neurologists. Recent advances in machine learning, particularly a proposed Convolutional Neural Network (CNN) architecture, show promising results in automating seizure detection for NFLE patients. The CNN model outperforms previous literature in terms of accuracy, sensitivity, and specificity. Additionally, the model's ability to predict seizure onset times aligns well with neurologists' assessments, offering encouraging results[10].

The passage discusses the use of Electroencephalography (EEG) in monitoring the brain activities of patients with epilepsy. Reading and analyzing long EEG recordings manually is time-consuming, so there's a need for automatic seizure detection. However, the diverse nature of EEG signals from different patients makes this task challenging for both humans and automated methods. The authors propose three deep transfer convolutional neural networks (CNN) based on VGG16, VGG19, and ResNet50, using the CHB-MIT scalp EEG dataset[12].

The passage discusses the importance of automated epileptic seizure detection in advancing epilepsy diagnosis and aiding medical professionals. It introduces a new methodology using Tunable Q-wavelet Transform (TQWT) for extracting nonlinear features from Electroencephalogram signals. The study includes data from non-seizure, pre-seizure, and seizure EEG activity. The methodology involves three steps: decomposing EEG activity into time-frequency sub-bands, extracting three nonlinear features, and using soft computing techniques for classification. Experimental results show that the proposed methodology effectively detects epilepsy, demonstrating its efficiency and suitability for the task[15].

The methodology outlined entails the application of a deep learning architecture to identify epileptic episodes. The innovative framework in question possesses the ability to acquire knowledge straight from the data without the necessity of extracting particular traits. The approach being suggested is founded on a deep learning model specifically designed for the classification of electroencephalogram (EEG) recordings. The electroencephalogram (EEG) data is partitioned into discrete segments of 4 seconds in duration. These segments are subsequently employed to train neural networks that are capable of encoding and retaining information over extended and brief time intervals. It is important to acknowledge that during the process of capturing EEG signals, it is possible to catch and record actions such as eye movements and blinking.[16].

Nowadays, the mobile healthcare industry is prospering due to the increase in computer processing power, improvement of next-generation communication technologies, and high storage capacity. Mobile multimedia sensors can acquire healthcare data, which can be processed to make decisions on the health status of users. In line with this, we propose a mobile multimedia healthcare framework in this paper, where an automatic seizure detection system is embedded as a case study. In the proposed system, electroencephalogram signals from a head-mounted set are recorded and processed using convolutional neural networks. A classification module determines whether the signals exhibit seizure. Experimental results show that the proposed system can achieve high levels of accuracy and sensitivity. The Children's Hospital Boston-Massachusetts Institute of Technology database indicates the system accuracy and sensitivity to be 99.02 percentage and 92.35percentage[18] .

The passage discusses a study aimed at identifying effective techniques for early seizure detection. The primary objective is to find a method that offers high sensitivity and specificity. The study explores various approaches, including feature extraction from raw EEG signals, encompassing both time and frequency domains, and leveraging wavelet parameters. Different classifiers like RNN, Artificial Neural Network, Modified Neural Network, and Support Vector Machine are utilized for classification. The results indicate that utilizing DT-CWT as a feature set combined with a Support Vector Machine as a classifier achieves a remarkable classification accuracy of 100%, with an impressively low false alarm rate of 0. This underscores the significant improvement in accuracy that can be achieved through the integration of wavelet decomposition and comprehensive feature extraction in early seizure detection. These techniques hold promise for providing timely alerts to epileptic patients, allowing for more effective diagnosis and intervention before the onset of a seizure.[19].

Epileptic patients endure chronic, unprovoked seizures, which can lead to a wide range of debilitating medical and social consequences. The development of a system for early seizure detection holds the potential to create novel intervention methods aimed at either controlling or shortening the duration of these seizure events. In this context, we propose the implementation of a deep learning framework utilizing Gated Recurrent Unit (GRU) Recurrent Neural Networks (RNNs) for the purpose of seizure detection. These algorithms function by analyzing recorded EEG signals, extracting pertinent information, and ultimately distinguishing an episode of epileptic seizure from the background EEG activity[20].

V. METHODOLOGY

A. A Framework for seizure detection

Using an EEG/ECoG seizure dataset, we give in this section a visual frame- work of the model utilized for seizure identification. Data collection, data preparation, applying machine learning classifiers, and performance evaluation are the four processes that make up the process.

B. Data Collection

The collection of the brain signals dataset is a prerequisite. Several monitoring tools are employed for this. EEG and ECoG are frequently utilised because their electrodes or channels are glued into place on the scalp's surface in accordance with the 10-20 International system at various lobes. Each of them is wired to the EEG equipment, which transmits immediate information about voltage variations as well as temporal and geographical information. The EEG channels are applied to the subject's scalp as shown in Figure, and the EEG monitoring tool reads the electrical impulses to display the raw signals on the screen. Additionally, the analyst has care- fully observed these raw signals and divided them into "seizure" and "non-seizure" stages.

C. Data Transformation

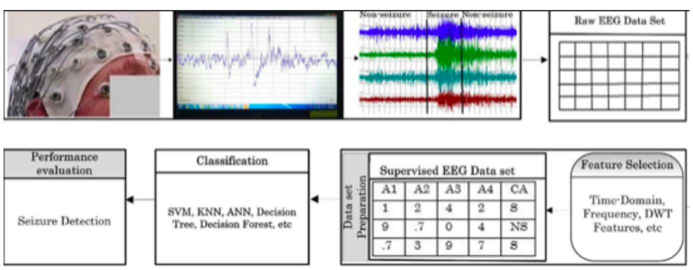

Fig. 1. Basic Model of epileptic seizure detection[7]

The conversion of the signal data into a 2-D Tabular format is the critical next step after data gathering. This facilitates analysis and provides crucial information, such as seizure detection. Because it hasn't been processed yet, this data is raw. Hence, providing pertinent information won't be appropriate. Several feature selection methodologies have been used for the processing. In this step, the dataset is also presented as supervised, which means that it offers potential class-values for the class attribute.

D. Dataset Description

Our data set was gathered from a UCI machine learning repository online. The conditions of a person while an EEG recording was taking place are depicted in the dataset. There are 100 files and five separate folders in it. Each file, which contains 23.6 seconds' worth of data on brain activity, represents a single individual. 4097 data points total, representing the patient's EEG recordings at various points in time. 23.5 seconds are the data points for each 500 people. The data points were separated into 23 chunks to facilitate our research. There are 178 data points in each chunk every second. Hence, the row contains 11,500 total data points, and the column contains 178 data points every second. The label y is shown in the final column. This label is divided into five different categories—1, 2, 3, and 4—with 178-dimensional input vectors. Here, 5 indicates that the patient's eyes were open while the EEG signal was being recorded, 4 that they were closed at the time, 3 that they were able to identify the tumour's location in the brain and that the sound brain area was where the signal was coming from, 2 that the signal was coming from the tumour area, and 1 that seizure activity was occurring. Individuals with epileptic seizures go into class 1, while those without them fall into classes 2, 3, 4, and 5. We can more easily determine which patients are experiencing epileptic seizures thanks to this classification.

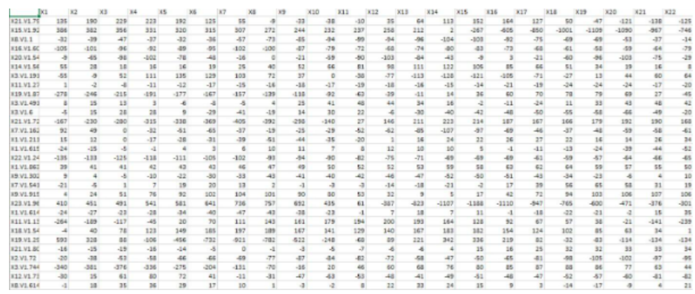

Fig. 2. Dataset presentation

E. Dataset preprocessing/preparation

We used a dataset obtained from the UCI Machine Learning Repository, as we previously mentioned. There were no available null or missing values in this dataset. We didn't need to perform any label encoding in this case because there were no categorical data. To cut down on computation time and improve the performance of the model, we chose a few features. Also, feature selection aids in data interpretation and visualization while resolving the issue of multidimensionality to improve the performance of our model. Also, it can cut down on training time, storage requirements, and utilization times. We essentially chose the values of the appropriate signals in our dataset as features during the feature selection process. We chose the final column, "Y," which has a total of five categories, as our label. To divide our dataset, we utilized Scikitlearn's train test split() tool. We used an 8:2 ratio and a random-state equal to 1 to divide the dataset. As a result, our dataset was split into two parts, the first of which served as the training dataset and contained 80percent of the data. Nonetheless, the remaining 20percent of the sample served as a testing set. All of them were selected at random since we used random-state splitting to separate the features and labels in accordance with the suggested ratio. For our supervised regression tasks, we evaluated a number of machines learning models, including Decision Tree Classifier, Random Forest Classifier, and K-Nearest Neighbor, using the Scikit-learn package, and we looked at the data to determine which performed better. Using the model-fit-generator function, we trained our machine learning models, and then we looked at the accuracy score of each model in turn.

F. Applying machine learning classifiers and performance evaluation

Several supervised machine learning techniques have been applied to attain a high accuracy of seizure detection rate and discover pertinent knowledge from the EEG processed dataset[8].

1) Decision Tree Classifier: In reality, a decision tree is a machine learning technique where data is segmented into stages based on various criteria and situations. This tree is a supervised learning method that is widely employed to address classification issues. While making decisions, people typically think in decision trees in the same way that they would in real life. The basic objective of this technique is to build a model that can forecast results based on various inputs and situations. We utilize the Classification and Regression Tree technique to create a tree. The Leaf Node and Decision Node

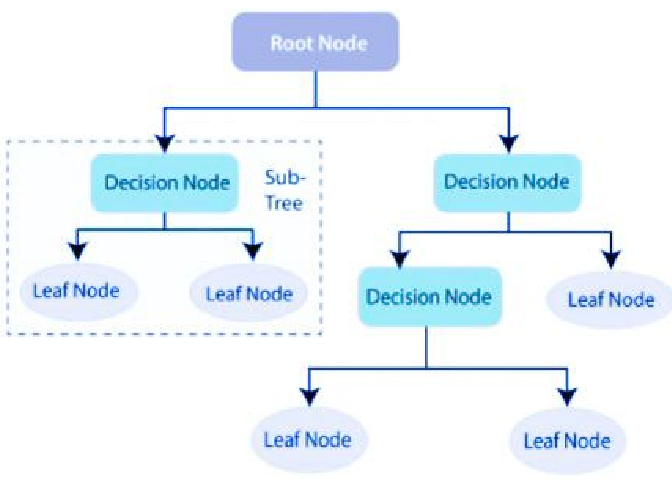

Fig. 3. Decision tree

are the two different sorts of nodes in a decision tree. Leaf nodes are utilized as the output or results after a judgement has been made using Decision nodes. While Leaf Nodes do not have any branches, Decision Nodes do. The algorithm begins at the tree's root node. It predicts the classes based on the provided data set. The method does this by comparing the values of the root property from the attributes of the data set. The approach compares the attribute value with the other sub-nodes for the following nodes using Attribute Selective Measure (ASM), which is based on the best attribute in the data set. It proceeds in this manner to process nodes until it reaches the leaf node of the tree[2].

2) Random Forest Classifier: A series of decision trees are randomly chosen from the training set in the Random Forest Algorithm, which is essentially a machine learning-based technique. This technique for learning is utilised for problems like classification and regression. Many decision trees on various subsets are included in the Random Forest algorithm. For estimating the dataset's correctness, the average is used. The outcome is inde- pendent of any particular tree. Instead, it calculates the predictions' majority votes to determine the final result. The likelihood of a good prediction increases with the number of trees in the dataset. Because the Random Forest algorithm increases the likelihood of a successful prediction even with a big dataset, it is more dependable. In some circumstances, it may be more accurate when a significant

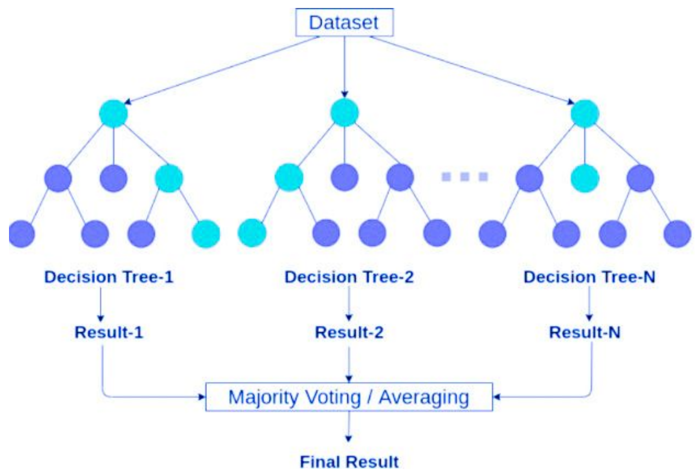

Fig. 4. Random Forest

quantity of data is absent. That is a significant benefit. In addition, this system needs less time to train than existing methods. By mixing N decision trees, it first builds a random forest for the output. Then, for each tree it has produced, predictions are made. At the training stage, every decision tree offers a prediction result. The algorithm predicts the outcome based on the majority of findings whenever a new data point is available[6].

3) KNN Classifier: K-Nearest Neighbors is a straight-forward and supervised machine learning technique that is applied to problems in regression and classification. Despite the fact that classification issues are its primary purpose. The KNN method relies on "feature similarity" to estimate the worth of each and every piece of data in the dataset. It typically means that each piece of data will be given an assumed value based on how close it is to its neighbours. This technique is more transparent thanks to KNN's two characteristics. They are the non-parametric learning algorithm and the lazy learning algorithm. Because there is no specialized training step in KNN, it is frequently referred to as a lazy learning algorithm. Additionally, it classifies without using the training set while taking action and storing the dataset. Furthermore, because it does not create a model using any training data points, it is sometimes referred to as a non-parametric learning algorithm. Every time it receives updated data during the training phase, the KNN algorithm saves the dataset. The algorithm then groups all the data into a category that is almost identical to the newly updated data. Implementing the KNN algorithm is relatively simple. However, be- cause all the data points in the same sample are being scanned, the algorithmic cost is a little higher. Moreover, extra RAM is needed to store the data during testing. The “K” in KNN stands for the number

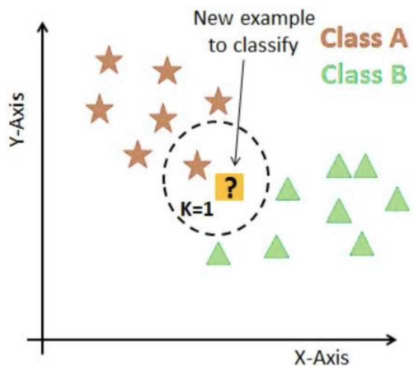

Fig. 5. starting KNN classification

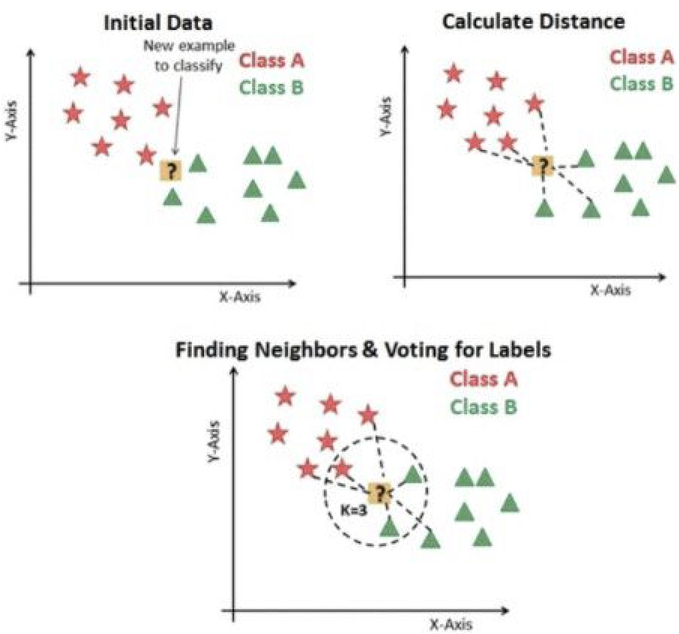

Fig. 6. Measuring Distance and Detecting the labels

of closest neighbors, and this is the main determining factor. The KNN begins operation by locating all of its neighbors and calculating the separations between the search and each individual data point in the data set. The system then selects the label with the most variety. Also, this tech- nique set a number that is designated as “K” and assigned them a value based on their neighbors. The nearest neighbor algorithm is used when the data is assigned the value of k=1. The label can foresee the “new example” point that was demonstrated in the prior example. The KNN will begin working by looking for the “K” closest point to the ”new example.” Each data point will then cast a vote for the class that is closest to them. Predictions will then be made using the class with the highest number of votes.

4) Gradient Boosting Classifier: Gradient Boosting Classifiers are a collection of machine learning (ML) based algorithms that combine many weak learning models at once to create a strong model. Gradient Boosting Models are becoming more and more well-known recently for their success in identifying challenging data sets. The classifiers and the weighted inputs are tested again in this AdaBoosting Method with weighted minimization. Reduce the loss of the class value and the tentative class value is the main goal of gradient boosting classifiers. Each weak learner is connected to the model in this algorithm. In order for the new layers to exhibit themselves here without altering the previous layers, the loads of the previous students are congealed or started in their positions. This differs specifically from the AdaBoosting approaches where the values are modified as new layers of learners are added. Gradient Boosting Classifiers also have the ability to be applied to challenges involving Regression and Multi-Class problems in addition to Binary Classification issues. Three main components make up gradient boosting.

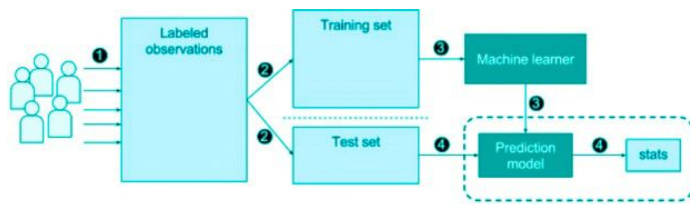

Fig. 7. Gradient boosting classifier model

They are: Additive Model, Weak Learner, and Loss Function. By optimising several loss functions, this ML- based approach constantly focuses on lowering the mistakes and losses of the classifiers. Additionally, it can be applied to a variety of real-world Machine Learning problems, including penalized learning, tree restrictions, randomized sampling, shrinkage, etc.

5) Logistic Regression: A generalization of the ideas and capabilities of regular linear models, logistic regression is a sort of generalized linear model. Instead of predicting something continuously, the model in logistic regression predicts if something is true or false. The model is sent via a sigmoid function to translate from the log of odds to the likelihood that the sample belongs to the positive class after fitting a linear decision boundary for each class using the model. This model performs effectively when the data separation is apparent because it seeks to identify the best separation between the positive class and the negative class. One of the models requires that the dependent variable be dichotomous and that all features be scaled.

6) Support Vector Machine: Support vector machines display training data as a set of points in space divided into groups by a distinct gap that is as wide as possible. In terms of sensitivity, SVM performs better for epileptic seizure prediction. Effective in high-dimensional spaces and memory-efficient due to the decision function’s usage of a subset of train- ing points With minimal pre-processing, this system achieves 90, 90, and 94SVM displays good performance outcomes in a variety of application domains. SVM pro- vides accurate responses for the attributes or features used. A binary

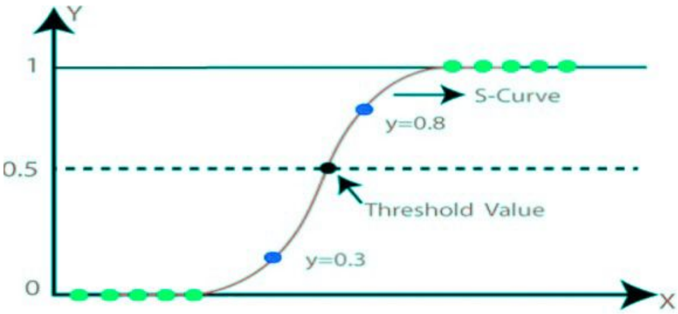

Fig. 8. Logistic regression

classifier is used. Pair-wise classification can be used for multi-class classification. Support Vector Ma- chines (SVM), a cutting-edge machine learning method, have been used to effectively present potential solutions for prediction Models.

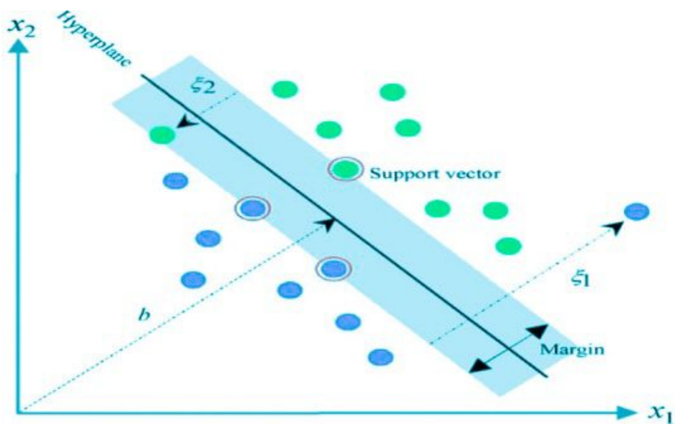

Fig. 9. Support vector machine

7) Classification: A dataset D in classification has a collection of ‘non-class attributes” and a “class attribute”. These are the main parts, and as they are both strongly associated with prospective classification, their relevant information is crucial. The term “target attribute” refers to the “class attribute” C, which includes multiple class values, such as seizure and non-seizure. On the other hand, “non-class attributes” or predictors are defined as attributes A = A1, A2.A3... An. The classifiers listed below have been employed frequently in seizure detection. The processed EEG dataset is subjected to the application of common classifiers for seizure identification, including SVM, decision tree, and decision forest.

8) Performance Evaluation: The accuracy of the findings obtained is used to compare various approaches. Tenfold cross-validation is the most widely used raining method, where each fold, or one horizontal slice of the dataset, is seen of as the testing dataset and the other nine segments as the training dataset. The performance of classifiers is typically evaluated using metrics like precision, recall, and f-measure in addition to accuracy. These are based on the four categorization outcomes that are shown in Table: True-Positive (TP), True-Negative (TN), False-Positive (FP), and False-Negative (FN). Precision (TP+FP) is defined as the ratio of true positives to all cases recognized as positive[11]

Acronym	Detection Type	Real World Scenario
TP	True positive	It a person suffers to seizure and also correctly detected as a seizure
TN	True Negative	The person is actually normal and the classifier also detected as a non-seizure'
FP	False Positive	Incorrect detection, when (ho classifier detects the normal patient as a seizure
FN	False Negative	Incorrect detection, when the classier detects the person with seizures, as a normal person

Fig. 10. confusion table

$$TP = \frac{TP}{TP + FP} * 100 \tag{1}$$

According to Eq. 1, it is the proportion of chosen situations that are right. The low rate of false positives indicates high precision.

$$RECALL = \frac{TP}{TP + FP} * 100 \tag{2}$$

Recall is the proportion of true positive cases to actual positive cases. The proportion of corrected cases that are chosen is shown in Equation 2.

$$F - measure = 2 * \frac{Precision * Recall}{Precision + Recall} * 100 \tag{3}$$

Although the classifier’s findings showed a high Recall, this does not mean the classifier performed well in terms of precision. The weighted harmonic mean of Precision and Recall, often known as the F-measure score and represented in Eq. 3, must therefore be calculated. Both false-positive and false-negative results are taken into consideration. In most cases, it is more beneficial than accuracy, particularly when the dataset is unbalanced.

9) Experiment: For our Python programming tasks, we used Google Collaborate. In order to read our dataset, we first submitted it to Google Collaborator. The data was then pre- processed because further prosecution would demand it. We randomly select 80percent of the data for training, and the remaining data is used for testing. The accuracy score for each of the machine learning models was then determined by applying the afore- mentioned models. To calculate the accuracy score for some models, we used scaled data. To further fully comprehend the performance of the models, we additionally presented confusion matrices for each of the various models. Also, we created line charts and scatter plots with the accuracy rating of each model. For both binary and multi-class classification of our dataset, confusion matrix and bar chart were created so that we could compare the outcomes. Last but not least, we classified seizures using predictions produced by the Random Forest Classifier and other algorithms[13].

VI. RESULTS AND DISCUSSION

Adding to it this process was taken further for experimental purpose by testing it on super computer. Here epoch size is increased in order to test how accurate will the output be generated if done so. This was done on Super Computer ”PARAMSHAVAK” with the specifications 96gb ram 16 TB rom, processor ”Intel®65039; Xeon®65039; Gold 6145” with 16 GB NVIDIA QUADRO RTX 5000 Graphic card Epilepsy is a dynamic condition with a wide variety of seizure types, symptoms, and presentations. As a result, there are many different ictal and interictal EEG data to examine. Researchers have started using a variety of signal processing methods, including both univariate and multivariate tools, to comprehend these data. The richness of the data sets has prevented these techniques from having any success in seizure prediction, even with these tools. These imitations may have some roots in the fact that we don’t fully comprehend the process that causes seizures. Because the initial set of trials was a victim of overtraining, it has frequently been challenging to reproduce the early success of a particular metric. No method has been able to consistently and reliably predict seizures with a high degree of specificity and sensitivity up to this point. However, there are situations when the distinctions between seizure prediction, early detection, and detection become hazy. Many machine-learning techniques perform excellently for early seizure prediction. According to the literature already in existence, SVM and the multi model approach both give greater accuracy when compared to other algorithms.

VII. CONCLUSION

Accurate epilepsy detection is becoming more crucial as the condition spreads. Correctly identifying seizures from a vast volume of data is a significant difficulty. Machine learning classifiers are appropriate for precise seizure identification since EEG signals in such datasets are complicated. Nonetheless, choosing the right classifiers and features is essential. In light of this, this work has evaluated machine learning strategies for seizure detection in great detail. We conclude that decision forests, which are a collection of decision trees, are the most effective “non-black-box” classifiers. This is because it can produce a number of logical rules that are understandable and effectively explain situations. Also, it can help in learning important information such as seizure types and seizure localization. On the other hand, “black-box” classifiers have high projected accuracy but are unable to construct logic rules. We should choose acceptable features that can lead to reasonable conclusions when making our selections. According to a survey of the literature, including variables like entropy, line length, energy, skewness, kurtosis, and standard deviation can produce classifiers that are 100percent accurate. As the size of the data rises, we advise against using the irrelevant features. This is due to the classifier’s rising computation costs and potential for producing illogical patterns. The low-dimensional dataset will be created if only one or two features, such as line length and energy, are used. Nevertheless, the knowledge discovery process will not be successful using this dataset. We think that this review study will give data scientists working on epileptic seizure detection using EEG signals fresh insights. In conclusion, this study focuses on a review of choosing appropriate features and machine learning classifiers[14].

VIII. REFERENCES

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