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Early and Accurate Diagnosis of a Neurological Disorder Epilepsy Using Machine Learning Techniques

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Abstract: An epileptic seizure is a type of seizure induced by aberrant brain activity caused by an epileptic condition, which is a brain Central Nervous System disorder (CNS). CNSs are relatively prevalent and include a wide range of symptoms, including loss of awareness, and strange behaviour. These symptoms frequently result in injuries as a result of walking imbalance, tongue biting, and hearing loss. For many researchers, detecting a prospective seizure in advance has been a difficult undertaking. In this research work we have used non-imaging data and applied supervised learning algorithms to determine the classification of epilepsy and try to improve the efficiency of the model, compared to the existing ones. Random Forest algorithm was found to have highest accuracy compared to other machine learning models. The paper can be helpful in diagnosing high-risk brain diseases and predicting diseases such as Alzheimer's with symptoms challenging to predict and diseases with overlapping symptoms and overlapping symptoms and attribute values. The scope of the research work can be further extended to determine at which stage the epilepsy is present in a patient, in order to provide a correct diagnosis and medical treatment.

Index Terms: Random Forest, SVM, Logistic Regression, Epilepsy, Convolutional Neural Network, Decision Tree, k Neural Network.

1. Introduction

Increasing neurological disorders worldwide are causing a heavy burden to society, families, and healthcare. The early detection of these disorders is of utmost importance. One of the prevalent diseases engulfing humanity is epilepsy. The word epilepsy is associated with the Greeks and Latins. It ranks fourth among the most common neurological illnesses, affecting almost 50 million people worldwide. Epilepsy accounts approximately 1% of worldwide sickness burden; 80 percent of epilepsy burden is in the developing world, where 80–90% of people with epilepsy receive no care at all in some places.

Repeated seizures are a symptom of this brain illness caused by a disruption in the brain's nerve cell function. The proportion of the general population with active epilepsy is estimated to be between 4 and 10 for every 1000 people at any particular time. A seizure can be caused by anything that disturbs the usual connections between nerve cells in the

brain. A person experiencing two or more seizures is considered to suffer from epilepsy. Epilepsy can be caused by various factors, including an imbalance of nerve signalling chemicals known as neurotransmitters, tumors, strokes, and brain damage caused by sickness or injury, or a combination of these factors. In most circumstances, there may be no known etiology for epilepsy. People who have epilepsy are more prone to physical injuries. They tend to suffer from psychological conditions like anxiety and depression. There is a risk of premature death as well.

Electroencephalography (EEG) is an essential tool for monitoring and diagnosing epilepsy patients' brain activity. An electroencephalogram (EEG) uses electrodes connected to the scalp to detect electrical activity in your brain. Electrical impulses are used to communicate between brain cells. The EEG measures voltage fluctuations in the brain's neurons induced by ionic current.

Machine learning has significantly evolved in the field of health care. This paper analyses the dataset taken from the EEG by using specific machine learning classifiers. The train and test data set ratio are 70% and 30% respectively. The accuracy of each technique is measured, and the confusion matrix is displayed. The methods used are Logistic Regression, Random Forest, SVM, Naive Bayes, Decision Tree, Gradient Boost Classifier, and K-nearest neighbours. Each model's accuracy is calculated before and after the normalization of the dataset values. This paper highlights the model with the best accuracy on the testing and training.

2. Literature Survey

Shoeb and Guttag [1] performed training on 2 seizures per patient and performed testing on 24 patients for 196 hours. The database used was the CHB-MIT database. The team classified the feature vector of a seizure or non-seizure activity using a support-vector machine. A function f(x) was constructed which mapped the feature vector x taken from the datasets using the EEG to the label y= ±1. The paper concluded that 96% of the seizures were detected out of the 173 test seizures.

Sandeep and Satchidananda [2] used a publicly available EEG dataset to perform experimental evaluations in the analytical study. Their paper focuses on machine learning techniques like neural networks and support vector machines to classify the EEG signals and label the patients suffering from epilepsy. The efficiency of various ML techniques like MLPNN, RBFNN, RNN, PNN, and SVM was used. They concluded that SVM was the most powerful technique for classification purposes.

In [3], the authors Temujin Gautama, Danilo P. Mandic, and Marc M. Van Hulle developed a strategy for improving signal categorization by enabling the complete categorization of E.E.G time-series signals. They have also described the basis of the analysis's statistical framework and two established nonlinearity analysis methods. The third-order autocorrelation function and the asymmetry due to time-reversal are briefly addressed. The dataset was taken from the publicly available website.

In paper [4], the authors proposed an epilepsy detection technique based on a neural network method. The data was segmented into 17 sub-segments, and these sub-segments were decomposed to W.P. trees with distinct mother wavelets to identify epileptic episodes from E.E.G. signals. They used E.E.G. data from a center for epilepsy research at Born University.

In paper [5,6], the authors studied the classification of E.E.G signals using wavelet coefficients. They combined a neural network’s adaptive capabilities with the quantitative fuzzy logic approach and the invariant transformation of the probability density function; analysed the sub bands of E.E.G. signals in terms of the delta, alpha-beta, and gamma, and applied multiresolution decomposition and an artificial neural network.

The authors of [7] developed a multilayer perceptron neural network-based classification technique for epilepsy therapies, as well as a multidomain feature extraction.

In addition, as mentioned in ref [8,] the authors accomplished automated epileptic seizure detection and prediction utilising the discrete wavelet transform and wavelet packet decomposition, as well as provided a technique for the categorization of E.E.G. signals to identify epileptic seizures.

Paper [9] introduced hybrid machine learning approaches for detecting epileptic seizures, while paper [10] proposed robust machine learning classification techniques for detecting epileptic seizures using diverse feature extraction methodologies, and [11,12] advocated convolution for epileptic seizure prediction.

The authors of [13] employed a variational autoencoder to perform unsupervised seizure recognition on raw EEG.EEG artifacts were suppressed using a sparsity-enforcing loss function. Three freely available EEG datasets were used to confirm this. With up to 0.83 AUC, non-seizure vs. seizure periods were successfully identified. The techniques in machine learning become less outstanding when compared to deep learning, as the detection of seizure becomes fast. The researchers interested have trained models using deep neural networks with multi-channel and high-resolution EEG data [14,15]. CNN model is used to detect tumors which lead to epilepsy in the EEG data.

The authors of [16] suggested using the 2-5 Hz power as a feature in a one-class SVM outlier identification algorithm to identify epileptic seizures on the human EEG. The probability distribution of the 2–5 Hz EEG power was heavily tailed in the majority of patients, indicating the existence of severe events. They got 100% sensitivity and 12% accuracy with one-class SVM. 88% of detections with low precision reflect the questionable non-seizure activity that requires manual classification by a professional. The one-class SVM proved stable against between-subject variability since it was trained using data from just one person. The findings show that extreme value theory, a physical idea, and outlier

identification techniques, a machine learning concept, effectively combine to address the important problem of medicine.

The authors of [17] provide researchers in this field with a thorough analysis of the various elements and difficulties in identifying and forecasting epileptic episodes using DL approaches. DL and ML research on various datasets, neuroimaging modalities, DL model implementation tools, DL model types, classifier approaches, and their popularity are compared. There are issues that must be fixed so that DL models to function correctly. Finally, potential future possibilities for enhancing datasets, DL models, rehabilitation tools, and hardware resources are discussed in light of the debate and difficulties. Additionally, it is projected that in the future epileptic seizure detection and prediction on cutting-edge platforms would make use of the most successful medical sector technologies, such as IoT and cloud computing.

3. The State of Art

The objective of this study is to classify epilepsy using machine learning models related to non- image data in the form of EEG data. Many researchers have already applied different types of ML models obtaining different efficiencies based on the characteristics they have taken. Here we have attempted to improvise the efficiency of the model in classifying the epilepsy. The epilepsy dataset has to be filtered and modified to reduce errors in the result.

The dataset should not be trained too frequently i.e., overfitting to maintain the accuracy after training. Also, the dataset should be properly trained on the entire dataset and should not lead underfitting. The epilepsy dataset should be collected from different sources for better accuracy. The diagnosis of epilepsy is done majorly by the MRI, ECG data done on the patient to detect unusual electrical impulses of damaged brain. The work done on classification of epilepsy is based on image processing of MRI scans and identification by the model (Pictorial data). The paper mainly focuses on classification of epileptic seizures using EEG done in the field which contains many classifiers of machine learning and neural networks (Numerical data).

4. Methodology

The epileptic data is taken in the form of EEG as the dataset [12]. The dataset gives the data of EEG taken at different points of the brain. In this dataset, there are 5 types of labels where only one of the labels specifies about the epilepsy causing tumour. The machine learning models are trained on this dataset such as Random Forest, Decision Tree, SVM, KNN, Logistic Regression, CNN and Naive Bayes. Flow of Implementation of the work carried out is depicted in figure 1. The steps followed are listed below:

Step 1: A relevant dataset consisting of the measurements from the EEG was taken and was made 0 and 1 for seizure and non-seizure cases, respectively.

Step 2: Apply data manipulation techniques to clean the data. Normalization is converting the values of numeric columns in a dataset to a similar scale without distorting the ranges of values. A min-max feature scaling was used for normalization.

Step 3: The test and train size of data was made 30 % and 70% respectively

Step 4: The various ML models like Logistic Regression, Random Forest, SVM, Naive Bayes, Decision Tree, Gradient Boost Classifier, K-nearest neighbours were implemented before and after the normalization of the dataset. These models were implemented using Scikit-Learn.

Step 5: A deep learning model multi-Layer perception was implemented.

Step 6: The accuracy of each model was compared and an analysis was performed to conclude the most suitable model for the seizure detection.

The various machine learning approaches used to carry out this project work is discussed in the following sections.

4.1. Decision Tree

The decision tree has two parts, decision nodes, and leaf nodes used when classes are not linearly separable. It is a binary tree that recursively splits the dataset until we are left with pure leaf nodes – that is, the data with only 1 type of class. By maximising the entropy gain, it determines the optimal split. A data sample travels to the left if it, else it moves to the right and finally reaches a leaf node where a class label is assigned to it. Decision trees are susceptible to the training data, resulting in high variance. The model may fail to generalize it. Hence the need for random forest classifier.

4.2. Random Forest Classifier

The name random is used since two random processes bootstrapping and random feature selection are used. Bootstrapping ensures that the same data is not being used for every tree, therefore helping the model to be less sensitive to the original training data. The random feature selection helps to reduce the correlation between the trees. If every feature is used, then most of the trees will have the same decision nodes, and there will be a lot of similarities, which in turn increases the variance. Another advantage of random feature selection is that – few trees will be trained on more minor essential features and give dire predictions. Few give wrong predictions in the opposite direction, thus ensuring balance.

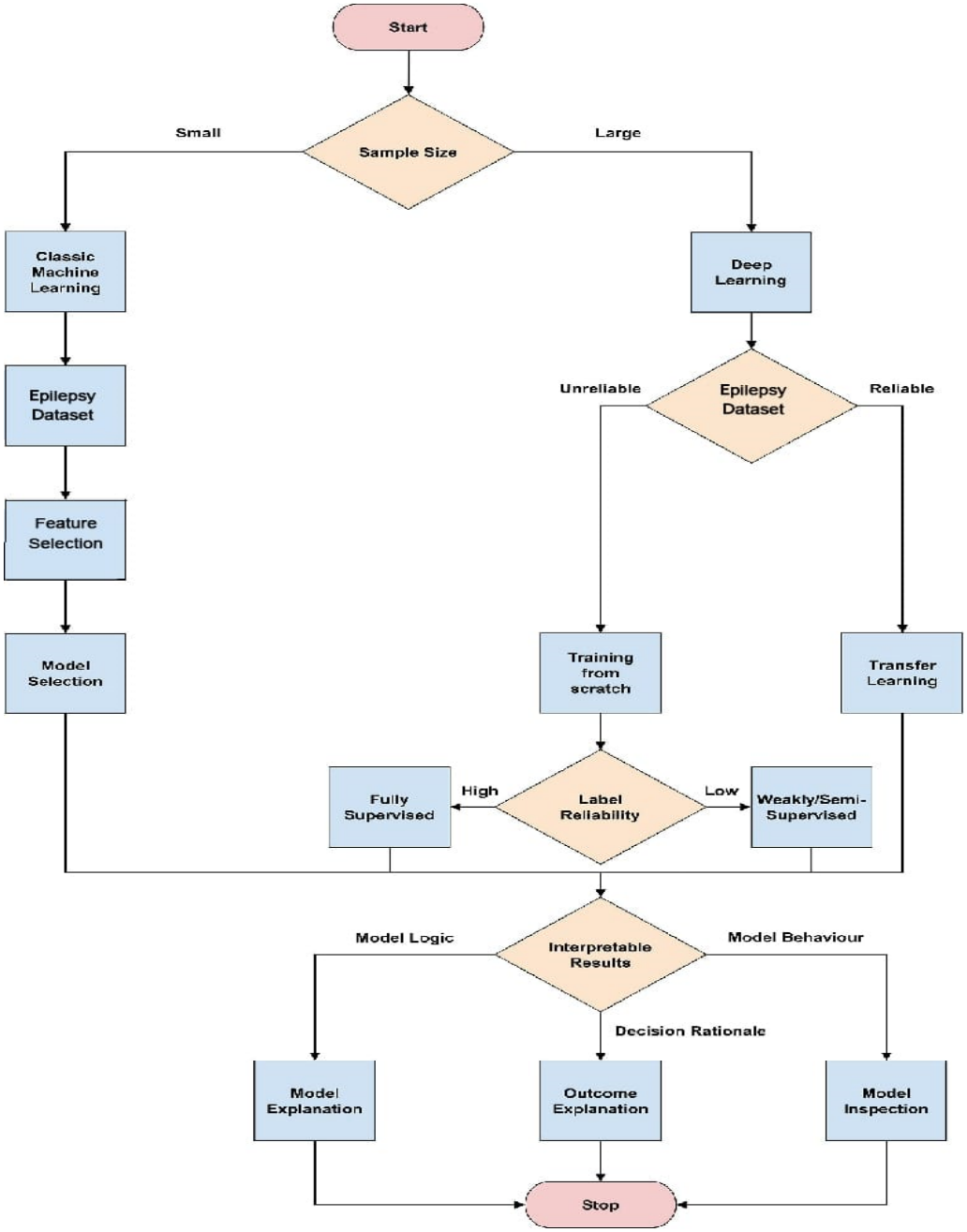

Fig.1. Flow of implementation of the project work.

The target variable y has two values in our dataset, 0 and 1. Therefore, it is a binary classification problem. It is made up of several different decision trees. It is less sensitive to the training data. Steps for Random Forest Classifier are to build normalized data form of given dataset. Then perform training on the decision tree on each of the bootstrapped data sets independently. For each tree, choose a subset of features at random and use only them for training. Consider a new data point. This data point is passed through each tree one by one, and the predictions are noted. A majority voting is taken as it is a classification problem.

$$ni_j = w_{jC_j} - w_{left(j)}C_{left(j)} - w_{right(j)}C_{right(j)} \quad (1)$$

Decision trees are extremely sensitive to the data used to train them, and even slight changes to the training set can result in dramatically different tree designs. Random forest takes use of this by enabling each tree to sample from the dataset at random with replacement, resulting in unique trees. Bagging is the term for this procedure. The training data is not split into smaller chunks; neither is each tree trained on a distinct chunk whenever bagging is used.

Considering a sample of size N, each tree is given a size N training set—a random sample of size N with the replacement is used instead of the original training data. The decrease in node impurity is weighted by the likelihood of accessing that node to compute feature significance. The node probability is computed by dividing the total number of

pieces by the number of samples that reach the node. The more significant the feature, the higher the value.

Consider a training set given by, A=$a_1, a_2, \ldots\ldots.., a_n$, with responses, B = $b_1, b_2, \ldots\ldots b_n$, being bagged repeatedly(k times) . The algorithm replaces the training set with a random sample, and fits trees to these samples: For k =1, 2, 3, ... K

N training instances from X, Y are sampled with replacement; they are referred to as A_k and B_k. On A_k and B_k, train a classification or regression tree f_k. After training, summing the predictions from all the various regression trees on x' can be used to make predictions for unseen samples a'

$$\hat{f} = \frac{1}{B}\sum_{b=1}^{B} fb(x') \tag{2}$$

The standard deviation of all the predictions from all the various regression trees on a' can be used to measure the prediction's uncertainty.

4.3. Gaussian Naive Bayes

Bayes' theorem generates the Naive Bayes classifiers. These classifiers are a set of methods of classification. The principle on which the group of algorithms work is as follows: each pair of features is not dependent on others for classification purposes.

Consider n features given by X = (X_1, X_2, X_3, ... X_n) and assume the correct label is given by Y. Y and X are considered random variables to tackle the problem in a probabilistic view.

The expression below is a conditional probability. A particular value of y must be found for which the conditional probability should become maximum so that the class label is found.

$$P(Y = y|X = (x1, x2, x3, \ldots., xn) \tag{3}$$

To solve the expression mentioned above, the Bayes theorem is used.

$$P(Y|X) = \frac{P(X|Y)*P(Y)}{P(X)} \tag{4}$$

In our project, we have implemented the Gaussian Naive Bayes classifier. Continuous values linked with each feature are dispersed according to a Gaussian distribution in this algorithm. A Gaussian distribution is another name for a normal distribution. When plotted, it provides a bell-shaped curve which is symmetric about the mean of the feature values, as shown below:

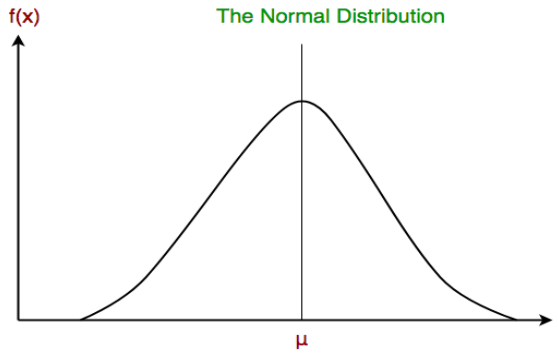

Fig.2. Naive Bayesian normal distribution graph.

Since the possibility of the features is assumed to be Gaussian, conditional probability is as follows:

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_i - \mu_y)2}{2\sigma_y^2}\right) \tag{5}$$

4.4. Logistic Regression

A logistic function is widely used to describe a binary dependent variable in a mathematical model. The sigmoid function is another term for logistic activity, and it is supplied by:

$$F(X) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1} \tag{6}$$

This function aids the logistic regression model in condensing data from (-k,k) to (0,1). Most of the time, logistic regression is used for binary classification jobs. However, it may also be utilized for multiclass classification.

4.5. K-nearest Neighbour Algorithm

KNN is one of the supervised machine learning models. The model is given the dataset with labelled features (x,y) and the model finds a link between features and labels. Here the main objective is to find the function h: X→Y so that an unknown feature tuple x when given as an input, h(x) can predict identical output y. The algorithm plots the graph of all values and plot a value based on K nearest neighbours of unseen data out of all classes of K neighbours.

For determining distance, we will use the Euclidean metric.

$$d(x, x') = \sqrt{x_1 - x_1' \ )2 + \cdots + (x_n - x_n')2} \tag{7}$$

Finally, the input feature x is predicted based on highest probability and given as a result. The input feature x is predicted based on highest probability and given as a result.

$$P(y = j|X = x) = 1/K \sum_{i\epsilon A} I\left(y^{(i)} = j\right) \tag{8}$$

For Regression the technique will be the same, instead of the classes of the neighbours we will take the value of the target and find the target value for the unseen datapoint by taking an average, mean or any suitable function you want.

4.6. Convolutional Neural Network

It is a method in which we take a tiny number matrix (called a kernel or filter), apply it to our picture, and then transform it using the values from the filter. The following formula is used to determine subsequent feature map values, where the input picture is indicated by f, and our kernel is denoted by h. The result matrix's row and column indexes are denoted by m and n, respectively.

$$G[m, n] = (f * h)[m, n] = \sum_j \quad \sum_k h[j, k] f[m - j, n - k] \tag{9}$$

Here for classification purpose, here the dataset is reshaped and passed into conv1D dimensional data.Then the data subsequently mapped by different layers in convolutional neural network.

4.7. Gradient Boost Classifier

Gradient Boost Classifiers are a collection of machine learning algorithms that combine many weak learning models to create a more robust prediction model. The goal of "gradient boosting" is to enhance the strength of a weak hypothesis or learning algorithm through a sequence of adjustments.

The Gradient Boosting Classifier uses a loss function. The loss function must be differentiable. Logarithmic loss is widely used in classification methods. Two essential parts - weak learner and additive component are present.

Since the dataset is a binary classification, we consider yes as 0 and no as 1. We start with a single leaf node that predicts X's initial value. log(odds) is utilized for the classification problem, and it is converted to probability.

$$P(yes) = \frac{e^{\log(\text{odds})}}{1 + e^{\log(odds)}} \tag{10}$$

If the probability of yes exceeds a certain threshold (0.5), all items in the training dataset are classed as yes. The pseudo residual is then computed (the difference between the observed value and the predicted value.

The residual is utilized to obtain the next tree.

$$\frac{\sum Residual}{\sum [PreviousProb * (1 - PreviousProb)]} \tag{11}$$

The numerator represents the sum of residuals in a specific leaf. The denominator is the sum of (previous prediction probability for each residual) * (1 - same previous prediction probability). We can now combine our old lead with our new tree, which has the following learning rate:

$$Older\ Tree + Rate\ of\ Learning * NewerTree \tag{12}$$

4.8. Multi-Layer Perceptron

Multi-Layer Perceptron (MLP) is an enhancement of feed forward neural networks. MLPs are neural organization models that work as general approximators, i.e., they can generalize any continuous functions. For example, they can be utilized as SEE models. MLPs are made of neurons and also known as perceptrons. A perceptron gets n features as information/inputs ($x = x_1, x_2, \ldots, x_n$), and every one of these elements is related to a weight. The input layer, the hidden

layer, and the output layer are the three layers that make up the system. The information streams in the forward course from input to output layer in an MLP, similar to a feed forward network. The back propagation learning algorithm is used to prepare the neurons in the MLP. The following are the calculations that occur at each neuron in the result and secret layer:

$$o(x) = G\big(b(2) + W(2)h(x)\big) \tag{13}$$

$$h(x) = \emptyset(x) = s(b(1) + W(1)x)) \tag{14}$$

We have utilized the model with the 'lbfgs' as a solution for weight optimization, an optimizer in the family of quasi-Newton techniques, alpha with a value of 1e-5, for epilepsy classification. It has three hidden layers, each with 13 neurons, 10 neurons, and 5 neurons, with a maximum number of iterations of 1000 and for each hidden layer we have used the relu activation function.

5. Results and Discussion

The dataset is classified into data containing epilepsy and one doesn't. The data was divided into training and testing sets, with test size as 30% and train size as 70%. The fit() method is used to train the algorithm. The predictions on test data are made. The regression techniques need to be rounded off to give the result either 0 or 1. For the neural network training, the data was reshaped to 1D and then used conv1D method for regression.

For Normalization of data, min-max feature scaling is used to rescale the features between 0 and 1 by subtracting the minimum value of the feature and then dividing by the range.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{15}$$

From the results, Random Forest has performed better compared to other models, Naive Bayes has second only to random forest with higher prediction accuracy when predicting epileptic seizure prediction. The accuracy in this paper uses the accuracy score in scikit implementation.

$$Accuracy = \frac{Total\ number\ of\ corrected\ predictions}{Total\ \ number\ of\ predictions} \tag{16}$$

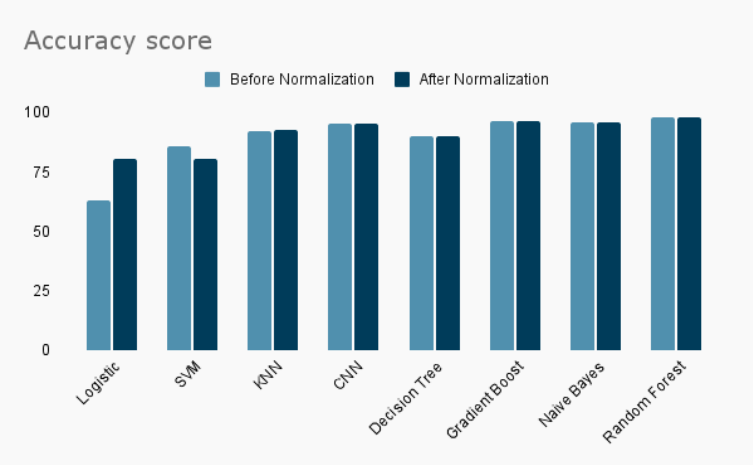

Fig.3. Comparison of accuracies of ML models.

The results before and after normalization is mentioned in table 1 below.

From the results, we can see that, min-max normalization has increased the accuracy except for SVM. After results, Random Forest algorithm's accuracy has decreased, but has highest accuracy compared to other machine learning models.

Table 1. Accuracy of different Machine Learning models.

ML Models	Accuracy	
	Before Normalization	After Normalization
Logistic Regression	62.84	80.69
SVM	85.9	80.66
KNN	92.43	92.66
CNN	95.28	95.28
Decision Tree	90.26	90.26
Gradient Boost classifier	96.57	96.57
Naive Bayes	96.02	96.03
Random Forest	98.02	97.91

6. Conclusions

This project focuses on machine learning techniques such as random forest, SVM, Logistic Regression, Decision Tree, and others to diagnose epilepsy using EEG data. This diagnostic procedure, which employs machine learning models, allows neurologists and patients to receive a timelier diagnosis. The result of implementation shows almost 100% accuracy with the Random Forest methods.

This implementation is based on epileptic disease data. Similarly, we may further detail on detecting brain illnesses like Alzheimer's. These disorders have no symptoms in the early stages, but a neurologist may discover them after an MRI and the third internship. As a result, machine learning techniques may diagnose such illnesses with greater accuracy. Such efforts may save a patient's life, and neurologists can then diagnose properly.

The paper can be helpful in diagnosing high-risk brain diseases and predicting diseases such as Alzheimer's with symptoms challenging to predict and diseases with overlapping symptoms and overlapping symptoms and attribute values. This paper examines and proposes a diagnosis model for brain disorders such as epilepsy and other diseases like FTD disease using a combination of multiple feature selection algorithms and classification algorithms. The best technique to detect the condition with better accuracy and acquire a high performance by trying various combinations is determined. This helps the community by allowing for early diagnosis, which benefits the neurologist. The results tend to be more accurate when using a large dataset.

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Author Contributions

All the four authors have equally contributed towards the completion of the work and documentation.

Conflict of Interest

The authors declare no conflict of interest.

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