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Comprehensive Evaluation Of Machine Learning Algorithms For Epileptic Seizure Categorizationn With PCA

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Abstract:
One of the most dreaded disorders of the central nervous system, epilepsy is linked to abnormal activity that explodes in the brain. Neurologists employ a well-known method called electroencephalography (EEG), which records the electrical anomalies emerging from the brain, to diagnose this illness. Due to the large volume, complexity, and nondeterministic nature of the obtained signal data, interpreting these recordings requires an expert, who is hard to come by in developing nations. Therefore, in order to improve computer aided diagnosis (CAD) solutions, a comprehensive comparison of four crucial machine learning (ML) algorithms—Logistic Regression (LR), K-Nearest Neighbour (K-NN), Decision Tree (DT), and Naive Bayes (NB)—for seizure categorization is offered. Using the Time frequency domain (TFD) approach, which is a member of Cohen's distribution class, pertinent properties are chosen from the EEG dataset. Model efficacy is analysed both pre- and post-introduction of principal component analysis (PCA) to the dataset. Our results indicate that as the complexity of the dataset is reduced, the classification accuracy enhances. The NB classifier performs better than the other classifiers, which makes it the most appropriate for classifying epileptic instances.

Keywords: *Time frequency distribution, Epilepsy, Computer Aided Diagnosis, EGG.*

1. INTRODUCTION

A neurological condition that affects both the brain and the nervous system is epilepsy. It is a well-known neurological condition that affects roughly 1% of people in general. A sign of epilepsy, seizures are brought on by aberrant electrical activity in the brain. Normal brain activi[1]ty is temporarily impaired during an epileptic seizure, which interferes with the brain's ability to communicate with other body parts. Epileptic patients are more prone to experience severe bodily harm, which can occasionally result in death [1]. Due to the unpredictability of these seizures and the patient's ignorance of this abrupt development, injuries have resulted. Consequently, a prior alert could be generated so that the patient can take preventative measures if a system is able to precisely forecast the pre-seizure phase, or the cognitive transition time before to seizure development. Even though a thorough history and evaluation of seizures and epileptic syndromes are the main methods used for diagnosis, EEG is still a valuable investigative tool. In addition to helping to distinguish between seizures and epilepsy, the EEG is beneficial for seizure disorders. There is a multitude of data in the EEG that needs to be processed for accurate investigation. As a consequence, precisely the most crucial features will be chosen and supplied to the classifier, rather than all of the EEG data. [2].

The TFD approach, which is a member of Cohen's distribution class, is used to this extraction function. The PCA technique is used to minimise the dimensionality of the data without sacrificing much information because the vast number of characteristics in the epileptic dataset utilised here could cause overfitting and jeopardise the efficacy of the model that is suggested. Here, we provide an organised comparison of various classifiers

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for the categorization of epilepsy. We evaluate the classification accuracy of epilepsy with and without PCA using different approaches. Here, the classifiers are evaluated using conventional effectiveness criteria. The organization of the paper is as follows. A brief description of the previous work is presented in section 2. In Section 3, the data used is described and also the proposed method with the TFD and PCA methods is discussed. Results are discussed in section 4, finally in Section 5, we conclude.

2. RELATED WORK

In this area, there are a lot of intriguing research that employ ML techniques to extract valuable information from a vast body of medical data regarding the diagnosis and classification of epilepsy. An automated seizure detection system can aid medical professionals in the diagnosis and treatment of epileptic patients. Numerous scholars have examined the application of diverse ML classifiers in the categorization and forecasting of epileptic episodes. Some of the ML classifiers that are used are the extreme learning machine (ELM), support vector machine (SVM), and different kinds of artificial neural network (ANN) models, such as probabilistic neural networks (PNNs), radial basis neural networks (RBNNs), and recurrent neural networks (RNNs). This study does a very fast epileptic seizure detection with the EEG signal using the classification approach DWT based SVD-Fuzzy-KNN [3]. Comparing SVD-Fuzzy KNN to numerous other known algorithms, it offers a high learning speed and a decent accuracy of 93% based on DWT. Many patient-specific classifications have been made, but creating patient-independent systems is more challenging.

This report presents comparative study using pattern recognition algorithms for epileptic seizure identification based on EEG. Due to the complexity of the EEG disagreement among the different individuals, the cross-patient assessment was the focus. The comparison techniques were SVM and KNN. The investigation reveals that the KNN, with an accuracy of 79%, is statistically considerably stronger than the SVM for data that are comparable in size to non-seize and seizure sample proportions. EEG data processing plays a major role in epileptic seizure prediction and identification approaches. It is challenging to diagnose and forecast these epileptic seizures since a thorough examination of the EEG data is necessary. This work introduced a novel approach for discovering epileptic seizures using EEG. The analytical DWT technique is used in conjunction with PCA and linear discriminant analysis (LDA) to identify epileptic episodes [4]. The experimental findings show that the PCA and LDA with NB classifier have accuracy of 98.6% and 99.8% respectively. Furthermore, the goal of studying lengthy and complex EEG data was to make signal processing easier. Using non-linear independent component analysis (ICA), the dimensions and dimensional decreasing values were then classified using the LR classification [8]. A 95% accuracy rate is indicated by the findings.

An alternative method to the rigorous EEG schedule of analysis is described in this study [9]. To reduce the size of the results, sparse principal component analysis (SPCA) and soft decision tree (SDT) are employed. The data indicates a 96% accuracy rate on average. 1D multi-level wavelet decomposition was used in conjunction with a multivariate EEG signal independent component analysis (ICA) to detect epileptic seizures [13]. Initially, Lyapunov's largest exponents (LLE) were prepared and classified using vectors. The purpose of this work was to develop an automatic rest (RSN) mechanism that provides quick marking and the clinical importance of operations in fMRI mapping of spatial maps in functional networks [14].

3. PROPOSED WORK

Here, we go through the dataset's structure, the TFD method, and the PCA methodology while addressing different ML methods for epilepsy classification, including KNN, NB, LR, and DT. The flowchart for the epilepsy model is depicted in the corresponding picture, and a thorough description of each step is provided below.

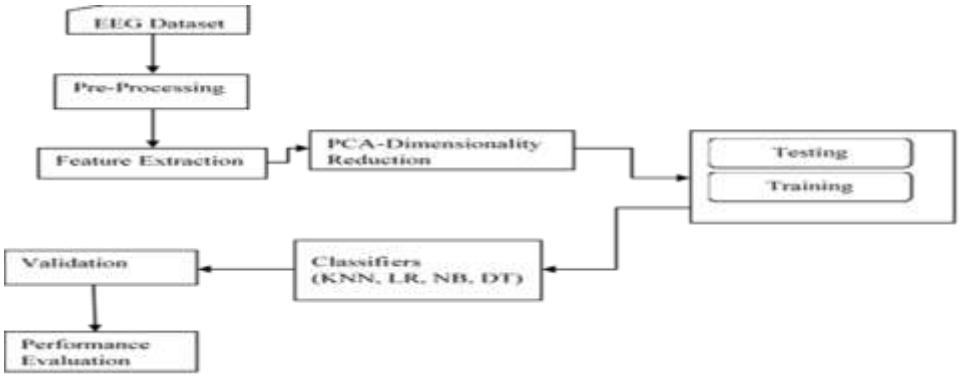


Figure-1. Proposed Classification Model

a) We have taken the epileptic seizure dataset, i.e. used in this paper, from the UCI machine learning repository to support our learning. This dataset consists of 4097 EEG recordings for 23.5 seconds in 500 patients. Each patient is divided into 23 chunks by data points. The translated information sequence is grouped into 178 columns that represent a second of the EEG readings in the rows of datasets. The patient ID and last column contain either a seizure or no. A total of 11,500 rows with 180 columns are detailed.
[https://archive.ics.uci.edu/ml/datasets/Epileptic+Seizure+Recognition] [15].

b) Feature Extraction

By identifying distinct features that set one input pattern apart from another, feature extraction minimises the original data. An algorithm's input data is condensed to a smaller set of features when it becomes too big to handle or appears to be essentially redundant. It is believed that feature selection will use this condensed representation of original data to obtain the details required to carry out the intended activity if the resulting characteristics are deliberately selected. The t-f representations are quadratic, and the TFD implemented pertains to the Cohen's class of distributions.

$\rho(t, f) = \int\int\int e^{i2\pi\upsilon(u-t)} g(\upsilon,\boldsymbol{\tau})\, x^{*}(u-1/2\,\boldsymbol{\tau})\, x(u+1/2\boldsymbol{\tau})\, e^{-i2\pi f\tau} d\upsilon\, du\, d\boldsymbol{\tau}$…… (1)

where ‘t’, ‘f’, x(t), x∗(t) and g (υ, τ) are time, frequency, signal, complex conjugate and kernel function respectively. Table-1 depicts the TFDs used in our work, as well as the kernels that go with them. The most common TFDs from Cohen's class have been used.

	Distribution	**Kernel (g(υ, t))**
1.	Margenau Hill (MH)	$\cos(\pi\upsilon\boldsymbol{\tau})$
2.	Wigner-Ville (WV)	1
3.	Rihaczek (RIH)	$e^{-i\pi\upsilon\tau}$
4.	Pseudo Margenau Hill (PMH)	$h(\boldsymbol{\tau})e^{-i\pi\upsilon\tau}$ ($h(\boldsymbol{\tau})$: window function)
5.	Pseudo Wigner-Ville (PWV)	$h(\boldsymbol{\tau})$ ($h(\boldsymbol{\tau})$: window function)
6.	Born-Jordan(BJ)	$\sin(\pi\upsilon\tau)/(\pi\upsilon\tau)$
7.	Butterworth(BUT)	$1/\left[1+\left(\frac{\upsilon}{\upsilon_1}\right)^{2N}\left(\frac{\tau}{\tau_1}\right)^{2M}\right]$ (N, M , $\upsilon_1, \tau_1 > 0$)
8.	Choi-Williams(CW)	$e^{(-\pi\upsilon\tau)^2/2\sigma^2}$
9.	Generalized rectangular (GRECT)	$\sin\left(\frac{2\pi\sigma\upsilon}{\lvert\tau^{\alpha}\rvert}\right)/(\pi\upsilon)$ (σ: scaling factor, α: dissemmetry ratio)
10.	Reduced Interference (RI)	$\int_{-\infty}^{+\infty} h(t)e^{-j2\pi\upsilon\tau t}\, dt$ ($h(\boldsymbol{\tau})$: window function)
11.	Smooth Pseudo Wigner-Ville (SPWV)	$G(\upsilon)\, h(\boldsymbol{\tau})$ ($h(\boldsymbol{\tau})$: window function)
12.	Zhao-Atlas-Marks(ZAM)	$h(\boldsymbol{\tau})\sin(\pi\upsilon\tau)/(\pi\upsilon\tau)$ ($h(\boldsymbol{\tau})$: window function)

Table-1. Cohen's Distribution Class

Using t-f analysis, which depicts the signal's energy distribution over the t-f plane, one can determine the signal's Power Spectrum Density (PSD). Several features are taken out of the PSD. For both the time and frequency axes, a partition-based grid is employed. Three equal-sized windows were selected for the time domain, and five subbands were selected for the frequency domain based on medical information of EEG, they are 0–2.5 Hz, 2.5–5.5, 5.5–10.5, 10.5–21.5, and 21.5–43.5 Hz, in these subbands specific features are expected to be found. Each feature f (i, j) is calculated as:

$$f(i,j) = \int \int PSD_x(t,w)\,dw\,dt \quad \text{.....(2)}$$

PSDx is the PSD of the signal x calculated with one of the methods above, t_i (i^{th} time window) and w_j (j^{th} frequency band). The feature set shows the signal's energy distribution along the t-f plane since each feature represents the fractional energy of the signal in a particular frequency band and time window. The feature set should have sufficient details about the nonstationary characteristics of the signal in order to be transferred to the following stage of the model [16].

b) Principal Component Analysis

It is clear from the dataset presented in the preceding section that we are dealing with high-dimensional data obtained by appropriate medical instruments, which normally conceals low-dimensional information. The acquired data will also be contaminated with a variety of noises, rendering the data inefficient and, as a result, failing to meet the model's primary goal. For such high-dimensional data, storage space and computational cost are a major concern, causing undue strain in data analysis. As a result, we try to reduce data dimensionality and extract only meaningful and relevant features from the original high-dimension data for dealing with it accurately and efficiently [17]. PCA is a widely used technique for extracting relevant feature information from noisy or multidimensional data. Therefore, PCA was chosen in this study to efficiently deal with the complex dataset and to better analyze the results. The PCA algorithm is defined below.

Algorithm

Step1. Get the Data from m*n Matrix A.

Step2. Covariance matrix.

Step3. Compute Covariance Matrix's Eigenvectors and Eigenvalues.

Step4. Choose Principal components and form feature vector.

Step5. Derive New Dataset.

Figure-2. PCA Algorithm

The covariance matrix is determined for the given dataset and a new dataset with a medium value of zero is computed for each dimension/variable. For the construction of the covariance matrix, we should have at least two dimensions. There is also a provision here to have more than two dimensions of the covariance matrix if a need exist. The following formula is given for the computation of covariance.

$$Cov(X, Y) = \frac{\sum_{i=1}^{n}(Xi-\overline{Xi})(Yi-\overline{Y}i)}{(n-1)} \quad \text{(eqn.1)}$$

Next, for a dataset of 'n' dimensions we define the covariance matrix, as shown below.

$$C^{n\times n} = (C\ i, j,\ C\ i, j = cov\ (Dim\ i, Dim\ j)) \quad \text{(eqn.2)}$$

where $C^{n\times n}$ is the matrix with 'n' rows and 'n' columns and Dim_x is the x^{th} dimension. Below shown is an example of covariance matrix for three dimensions x, y, z.

$$C = \begin{pmatrix} cov(x,x) & cov(x,y) & cov(x,z) \\ cov(y,x) & cov(y,y) & cov(y,z) \\ cov(z,x) & cov(z,y) & cov(z,z) \end{pmatrix} \quad \text{(eqn.3)}$$

We begin by determining the covariance matrix, as well as its eigenvectors and eigenvalues. These are crucial because they provide us with useful information. We can order them from highest to lowest and make them a functional vector. The components are listed in order of importance. We won't lose a lot of data, but the less important values will be overlooked. If these elements aren't included, the final dataset will be smaller than the original. Finally, we have a dataset with only the most important attributes and values. After choosing the components the transposition of the vector is performed and then multiplied to get transposed dataset.

FinalData=RowFeatureVector×RowDataAdjust
(eqn.4)

RowFeatureVector is a matrix of eigenvectors transposed into the columns with the most important eigenvectors at the top. RowDataAdjust contains data items that have different dimensions for each row and columns. FinalData is the final data collection of column data objects and row sizes.

c) K-Nearest Neighbor

The KNN algorithm is based on the supervised learning technique. The algorithm assumes that the new data and the existing data are similar, and it assigns the new data to the category that is closest to the existing categories. The algorithm can be used for both regression and classification, but classification is the most common application. KNN is a non-parametric algorithm, meaning it doesn't make any assumptions about the data. The algorithm is also known as a lazy learner algorithm because it does not immediately learn from the training set; instead, it saves the dataset and then uses it to classify the new data into a category that is very similar to the old data [18].

Algorithm
Step1. ‘K’ Number of the neighbors selected
Step2. Euclidean distance is calculated
Step3. Nearest ‘K’ neighbors selected
Step4. From each category compute number of data points
Step5. New data points to be assigned to the maximum category
Step6. Model ready.

Figure-3. KNN Algorithm

d) Logistic Regression

A logistic regression algorithm forecasts the probabilities of a target variable. The presence of the target or dependent variable is dichotomous, implying that there are only two possible classes. In simple terms, the dependent variable is binary, with 1 (success/yes) or 0 (failure/no) as the options. It is one of the most basic machine learning algorithms for a wide range of problems. Logistic regression can be grouped by the number of categories into the following forms. A dependent variable in binary classification only has two possible forms 1 or 0 i.e. like success or failure, yes or no, win or lose, etc. The next is a multi-independent variable where 3 or more unordered types can be used and the last being the ordinal classification where 3 or more ordered types can be added to the dependent variable. The following points should be taken into account during the implementation of logistic regression. If the regression is binary, the target variables always have to be binary and factor level 1 should be the desired outcome. The independent variables must be genuinely independent and significant variables should be included in the model [19].

e) Naive Bayes

A probabilistic machine learning model called a NB classifier is used to perform classification tasks. The main element of the classification is based on the Bayes theorem. The theorem of Bayes finds the possibility of an occurrence due to the probability of another event that has already occurred. The theorem is mathematically stated as:

P (A/B) = (P (B/A) P (A))/(P (B))
(eqn.5)

The probability of ‘A’ occurring can be found using the Bayes theorem given that ‘B’ has occurred. In this case, ‘B’ is the proof and ‘A’ is the hypothesis. The prediction/features

here are independent. The assumption is, if one feature doesn't affect the others, it is considered naive. We have the following form of Naive Bayes Classifiers. The first is the Multinomial Naive Bayes classification method. The second group is Bernoulli Naive Bayes, which resembles the multinomial Naive Bayes, but is Boolean. Finally, if the predictors are continuous and are not discrete, we have the Gaussian Naive Bayes classification model.

f) Decision Tree

DT is a supervised learning tool for solving classification or regression problems, but mostly to address classification problems. The classifier is tree-structured, with internal nodes and branches representing attributes and outcome respectively. In all decision-making processes, the decision nodes are used and have several branches, while leaf nodes are the output and have no branches. The general structure of a decision tree is explained in the diagram below.

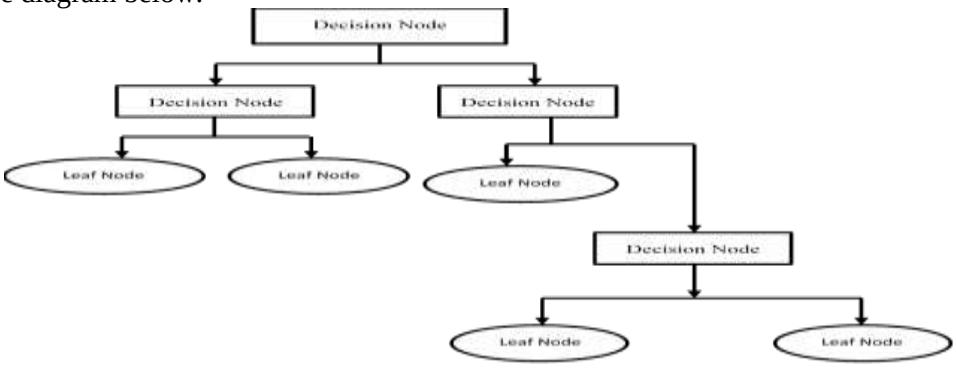


Figure-4. Structure of Decision Tree

The popularity of the decision tree is that it normally mimics human ability in decision making. Hence, a clear understanding of the logic behind the decision-making tree is known since it displays a tree-like structure. Another important element is the selection of attribute measures for the root node and the sub-nodes, for this the best attribute is selected. We have two techniques for selection attribute measures, the Information Gain (IG) method where tree is built based on the amount of information a feature provides about the class and Gini Index (GI) method is the measure of impurity or purity used while creating a tree preferring the attribute that has low GI value.

Algorithm
Step1. Begin the tree with the root node ‘S’.
Step2. Using Attribute Selection Measure (ASM) select best attribute.
Step3. Subdivide S into subsets containing the best possible values for each attribute.
Step4. Create a decision tree node with the best attribute.
Step5. Using the subsets of the dataset, create new decision trees in a recursive manner until there are no more trees to be created.
Step6. Model ready.

Figure-5. Decision Tree Algorithm

g) Prediction Performance Indices

The most common performance metrics used to evaluate a model are precision, specificity, sensitivity, accuracy & F-measure in machine learning. An accuracy is a tool used to measure the accuracy of the classification model, i.e. the total number of correct model predictions. The specificity is a metric that tells how many epileptic and non-epileptic patients the model was anticipated to be. Sensitivity shows the number of epileptic patients once known with the help of an epilepsy model. Precision is a measure that tells us honestly how many people have epilepsy. The F-measure is a method of combining model accuracy with recall and is described as the harmonic mean of model accuracy and recall that is used in determining model accuracy in particular for the test for binary classification models.

Parameter	Mathematical Expression	Definition
Accuracy	$\frac{(TN + TP)}{(TN + FN + FP + TP)}$	The number of correct predictions made by model across all types of predictions.
Precision	$TP/((TP + FP))$	The model's total number of correct predictions.
Recall	$TP/((TP + FN))$	The model's total number of positive results.
Specificity	$TN/((TN + FP))$	The number of negatives that the model has returned.
F-measure	$2.(\text{Recall}.\text{Precision})/(Recall + Precision)$	Combines the precision and recall value to give a single score.

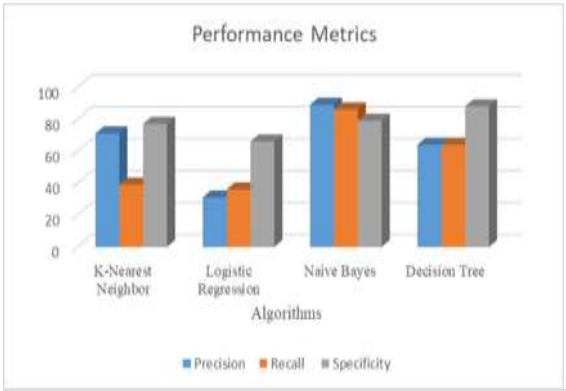
4. EXPERIMENTAL SETUP AND RESULTS

The model is checked, compared and validated with the results of the most commonly used epilepsy dataset. It is a part of the dataset from UCI repository that analysts can use for machine learning. The above paragraph describes the details. Either "1" or "0" is the outcome of the model. 0 is taken for 'Non-Epileptical' and 1 for 'Epileptic.' Next, the output measurements, such as precision, specificity, sensitivity, accuracy, and F-measure are used to determine the classifier's efficiency. From the experimentation that we carried out we found the following results as depicted in the table below, the performance of the classifiers is been drastically affected due to the corrupt and imbalanced dataset. The results below show that the performance of the classifiers is not satisfactory.

Classification Algorithm	Precision	Recall	Specificity	Accuracy %
K-Nearest Neighbor	0.713	0.399	0.772	85.71
Logistic Regression	0.310	0.363	0.661	69.10
Naive Bayes	0.887	0.868	0.799	87.09
Decision Tree	0.644	0.641	0.885	80.11

Table-2. Performance of Classifiers without PCA

The above classifiers performance is significantly defined by the data representation, which is largely uncorrelated. This is because correlated data reduces the significance of data representation, causing the classifier model to be confused during the learning process. The results showed that removing correlated information positively affected the classification performance of the classifiers.Table 2 shows increase in classifier performance when the dataset is trimmed and only important features and necessary values are processed and fed, except for the LR model. From the results it is evident that the NB classifier’s performance outperforms the other algorithms in classifying the epilepsy dataset with 96% accuracy. As a result, dimensionality reduction is critical in machine learning, particularly when working with thousands of features.



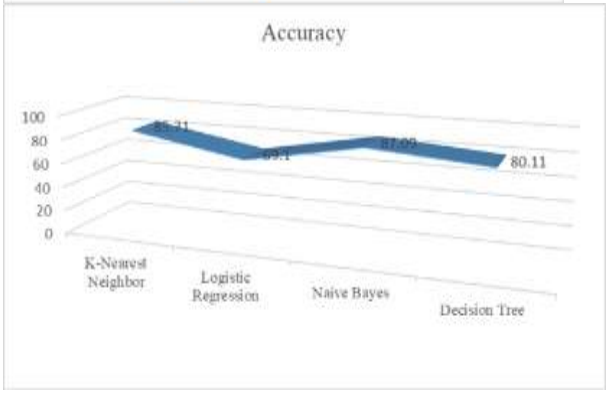


Figure-6. Performance metrics of classifiers

Figure-7. Classifiers Accuracy

Table 2 provides the performance of various classifiers in consideration. The performance measurements are determined on the basis of the incorrect and correctly identified instances from a total number of cases. It is evident from Table 2 that the NB Classifier shows the maximum accuracy and hence the classifier can predict epilepsy more accurately than other classifiers. The significant performance metrics such as precision, recall and F-measure of all the classifiers undertaken for analysis is shown in figure-9. Accuracy another important metric of the classifiers is plotted through a graph shown in figure-10.

Classification Algorithm	Precision	Recall	Specificity	Accuracy %
PCA+ K-Nearest Neighbor	0.911	0.590	0.973	94.71
PCA+ Logistic Regression	0.355	0.455	0.791	72.62
PCA+ Naive Bayes	0.921	0.787	0.997	96.25
PCA+ Decision Tree	0.749	0.873	0.915	91.02

Table-3. Performance of Classifiers with PCA

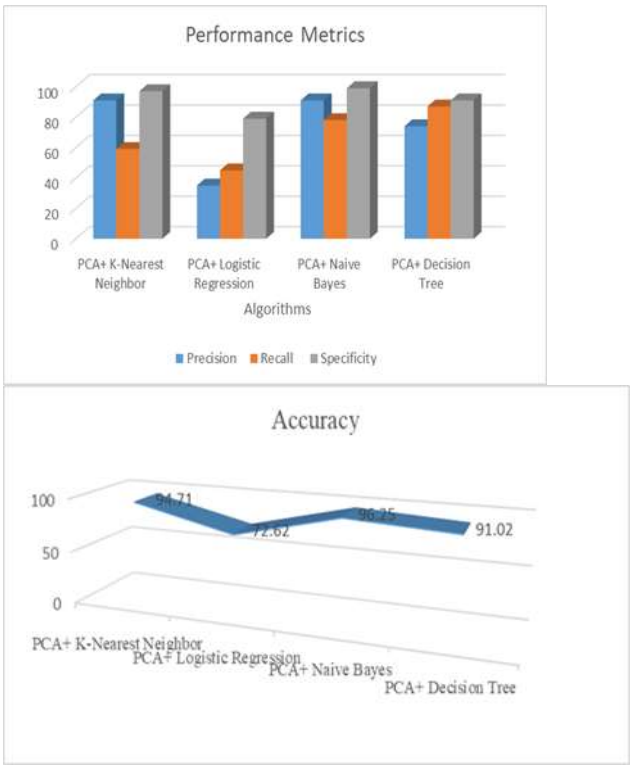


Figure-8. Performance metrics of classifiers after (DR)

Figure-9. Classifiers Accuracy (With PCA).

Figure11 reflects the ROC region of all classification algorithms such as NB, LR, KNN and DT with 0.982, 0.487, 0.964 and 0.870 AUROC scores, respectively. We infer from the above discussion that the NB outperforms other algorithms and is the ultimate choice for supervised classification for the complex information and gives solid accuracy of 96.25% in comparison with other classification algorithms.

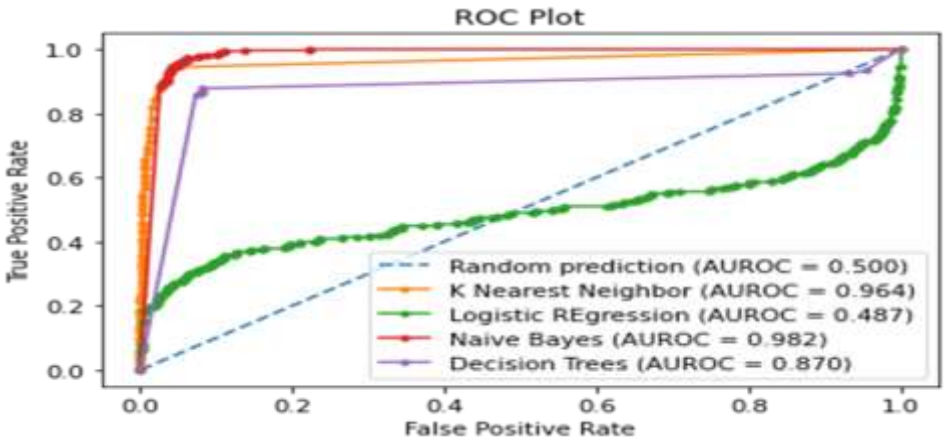


Figure-10. ROC of Classifiers.

5. CONCLUSION

From this study it is evident that there is a need to understand the complex nature of EEG signals. Epilepsy is a disease where the normal life of an individual is devastated. Therefore, here a model using 'PCA + classifier' to classify epilepsy seizures among the patients was presented in the paper. In order to test the classification accuracy using PCA, we introduced four machine-learning techniques. The test results show that if PCA extraction is done, the classification rate is higher than the usual procedure. The Naive

Bayes model, after reducing the size of the dataset, achieves the highest precision of 96.25% among our tested classifiers. Another observation here is that when we have huge, complex, and varied data, logistic regression performance is very poor. When the performance metrics of the classifiers used in this study are compared, the NB classifier outperforms the other classifiers in every way, making it particularly appealing when compared to other epileptic data classification strategies.

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