Detection of Epilepsy based on EEG Signals using PCA with ANN Model

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Abstract. Epilepsy is a chronic neurological illness that affects millions of people throughout the world. Epilepsy affects around 50 million people globally. It is estimated that if epilepsy is correctly diagnosed and treated, up to 70% of people with the condition will be seizure-free. There is a need to detect epilepsy at the initial stages to reduce symptoms by medications and other strategies. We use Epileptic Seizure Recognition dataset to train the model which is provided by UCI Machine Learning Repository. There are 179 attributes and 11,500 unique values in this dataset. MLP, PCA with RF, QDA, LDA, and PCA with ANN were applied among them; PCA with ANN provided the better metrics. For the metrics, we received the following findings. It is 97.55% Accuracy, 94.24% Precision, 91.48% recall, 83.38% hinge loss, and 2.32% mean squared error.

1. INTRODUCTION

It is a severe neurological condition with distinct features, such as recurring seizures. Over 3000 years ago, the context of epilepsy was written in a Babylonian medical text. According to estimates, 70 million people worldwide suffer from epilepsy [1]. Epilepsy is more frequent in the elderly than in the young, and it is a primary cause of death in individuals who have it. Patients take antiepileptic medicines on a daily basis in the treatment of epilepsy. However, approximately 25% of them experience seizures once again. Surgery is the most important and widely adopted method of treatment for these patients. Surgery can only be performed if the epileptogenic focus is accurately identified. Different trace types are used for this purpose when seizure begins. This is why it is extremely important to detect seizures. So, the goal of this project is to create an Epileptic Seizure Detection System [2].

One application of Machine Learning in healthcare is digital diagnosis. In patient electronic healthcare data, machine learning can detect patterns of specific diseases and warn clinicians to any abnormalities. Artificial Intelligence can be compared to a second set of eyes that can evaluate a patient's health based on knowledge acquired from enormous datasets by aggregating millions of observations of diseases that a patient may have [3]. Feature removal and EEG classification are the two most critical processes in an EEG-based epilepsy detection system. Temporal and spectral properties can't extract useful information from EEG signals because they're non-stationary in nature and both temporal, spectral representations of the signal are non-localized [4, 5].

In this research, we put an efficient machine learning model to the test, specifically to see which one
has the best accuracy for detecting multi-category EEG signals [6, 7]. PCA is a dimensionality reduction method that turns a big to small number of variables, lowering the complexity of huge datasets. This component will be used to send our data into the PCA. We feed the input data to the ANN model after converting high dimensional to low dimensional data. A three-layer biological neural network known as an Artificial Neural Network (ANN) is made up of nodes known as Neurons. Weights, biases, learning rate, batch size, and other parameters are included. The input layer feeds data to all hidden nodes.

2. LITERATURE SURVEY

Wu J, et.al, [8] proposed a Machine Learning Model by combining the CEEMD and XGBOOST models to predict the ES by using EEG signal dataset collected from the Bonn and CHBMIT Universities. The dataset is divided into five subsets, each with 100 single channels at 173.6Hz and 23.6s duration. To obtain the multi-domain features, the raw EEG signals were decomposed using the (CEEMD) technique. The XGBOOST model used these features to accurately distinguish epileptic and non-epileptic seizures with 99% accuracy. Matin A, et.al, [9] implemented a Machine Learning Hybrid Model namely PCA, ICA and SVM to predict the Epileptic Seizures. They used the EEG signals dataset that contains 5 subsets each with 100 single channel of 173.6 Hz sample and 23.6s duration. These features were then processed by the SVM classifier. The proposed model's accuracy in classifying and detecting epileptic seizure patterns is stated to be 99%, which is higher than that of other models.

Raghu S, et.al, [10] proposed REN Model and applied it on the dataset collected from Bonn University to predict the Epileptic Seizures. The dataset contains 5 subsets each with 100 single channel of 173.6 Hz sample rate and 23.6s duration. WPNormEn and WPLogEn features were extracted from EEG signals using the Wavelet Packet Decomposition technique. The REN classifier was then used to process the extracted features. Sharmila A, et.al, [11] presented a DWT model with Naïve Bayes and k-NN classifiers to predict the ES. They used EEG signals dataset which contains 5 sets and 500 single-channels of 173.6Hz sample rate with 23.6s duration and these are collected from the Bonn University, Germany. For feature extraction 3 statistical features were used namely MAV, AVP, SD which are derived from DWT coefficients. In comparison to the k-NN classifier, the proposed DWT and Naive Bayes classifier model achieves 96.47% accuracy with 9 data set combinations in classifying the two types of epileptic seizures (normal and seizure active).

Wang G, et.al., [12] Using the EEG signals dataset of 10 patients with a 200 Hz sample rate, a Directed Transform Function (DTF) Machine Learning Model was constructed to detect Epileptic Seizures. The data was gathered at Xi'an Jiaotong University's Hospital. The DTF algorithm is utilized to segment the EEG signals using the sliding window technique, and information outflow is assigned as EEG signal characteristics, which are then categorised using the SVM classifier with 5-fold cross validation. They proposed a DTF model that, when compared to the Auto Regression (AR) model, recognises epileptic seizure cycles in diagnosis with a greater accuracy of 98.4 percent.

Li P, et.al, [13] proposed a FE and DE models to detect the ES by using the EEG signals dataset which is collected from the Bonn University. The dataset contains 5 subsets with 500 segments of 173.61 Hz sample rate with duration of 23.6 s. For feature extraction, used sliding window techniques such as the Single Window Protocol (SP) and the Multiple Window Protocol (MP). Individually, FE performed better than DE, with an accuracy of 90.40%. However, combining both the DistEn and FuzzyEn models yields the best accuracy of 93% for both normal and ictal interictal EEGs.

Wang L, et.al., [14] presented a Multi-Domain Feature Extraction, Non-Linear Analysis and Discrete Wavelet Transform (DWT) models to predict the ES by using the EEG signals dataset. The dataset
consists of 5 subsets with 500 segments of 173.61 Hz and 23.6 sec duration. They suggested a multi-domain FE and non-linear analysis model that can identify and categorise epileptic and non-epileptic seizures with 99.2% accuracy, compared to single domain feature extraction and non-linear analysis models. Aldana L, et.al., [15] proposed a Multiway Data Analysis model with k-NN, RBSVM and LDA classifiers to predict the Epileptic Seizures. They used the EEG signals dataset of 14 patients with 200 Hz sample rate. The dataset is collected from the CIREN and Clinical Surgical Hospital Hermanos Ameijeirasin. For feature extraction CPD, BTD and Wavelet or HHT techniques are used. The proposed RBSVM model gives a better accuracy of 98% in the classification of normal and seizure EEGs, compared to k-NN and LDA classifier models.

Wang X, et.al, [16] implemented a RF model combined with GSO model along with time-frequency analysis and PCA analysis to detect the ES. They used the EEG signals dataset of 25 patients from Bonn University, which includes 5 subsets of 500 single channels with 173.61Hz. To obtain the time-frequency features from EEG signals, they used the Fourier transform, Multitaper spectral analysis, Partial Auto Correlation Function (PACF), and Short-Time Fourier Transform (STFT) techniques. They proposed the Novel RF-GSO model, which has 96.7 percent accuracy. Ullah I, et.al, [17] proposed a P-1D-CNN to predict the Epileptic Seizures. They used an EEG signal dataset from ten patients, which is divided into 5 subsets, each with 100 single channels. With an accuracy of 99.1%, the proposed P-1D-CNN model performs better in identifying both binary and ternary epileptic problems (ictal vs. normal vs. interictal).

Peachap A B, et.al, [18] presented a Laguerre Polynomial Wavelets, ANN, and SVM models to detect ES. They used a 5 class EEG signal dataset with 500 single-channel signals and a length of 23.6 seconds. To obtain the best feature set, they used the CWT to decompose the EEG signals in the time and frequency domain. In comparison classification methods, the proposed model (LPV, CWT, ANN, and SVM) classified and the 8 different condition classes of EEG signals with 3, 5, and 10 fold cross-validation, yielding a classification accuracy of 99 %. Subasi A, et.al, [19] proposed an Auto Regression (AR) model with Maximum Likelihood Estimation (MLE) to detect the ES. They used the EEG signals dataset of several patient's which is obtained from the NDMFHDU. For feature extraction, signal analysis and ANN were used. The proposed AR with MLE model has a higher accuracy of 92.3% in classifying two different types of epileptic seizures (normal and active seizure) compared to the Fast Fourier Transform (FFT) with MLE model.

Sriraam N, et.al., [20] implemented a multi-features and MLPNN classifier model to predict the ES by using the EEG signals dataset of 20 patients. The dataset has a sampling rate of 128Hz and a period of 20 minutes. They used the extracted features of power spectral density (Yule–Walker method), entropy (Shannon and Renyi entropy), and Teager energy to improve seizure recognition efficiency. In comparison to other models, the proposed MLPNN model has 97% accuracy and is well suited for real-time seizure detection identification. Sharmila A, et.al, [21] presented a DWT model with PCA, LDA by using NB and k-NN classifiers to detect the ES. They used an EEG signals dataset obtained from Bonn University, which consists of 5 sets, each with 100 segments and duration of 23.6 seconds. The statistical features were extracted using the WT, and the features were reduced using the PCA and LDA. As compared to DWT, LDA with Nave Bayes, and DWT, PCA with k-NN (or) Nave Bayes models, the proposed DWT, LDA with k-NN classifier models performs the best in classifying normal and epileptic condition patients with 99% accuracy.

Pakistan K, et.al, [22] proposed a CCA and ANN model to detect the ES. They used an EEG signal dataset of 24 patients with 256 sample rate obtained from the Boston Hospital's Physio Net Online Data Base. The CCA was used to extract feature vectors, which were then used as input by the ANN. To classify the occurrence of non-epileptic and epileptic seizures, the proposed CCA-ANN model shows better accuracy of 92.5% compared to other referenced techniques. Wei X, et.al, [23] proposed a 3D CNN model to detect the Epileptic Seizures. They used the data from the Department of
Neurology at Xinjiang Medical University's First Affiliated Hospital, which included EEG signals from 13 patients with a sample rate of 500Hz. Sliding Window Analysis was used to isolate the characteristics, which separates the raw EEG signals into segments. In comparison to 3D CNN with single-channel EEG signals, the proposed 3D CNN model with multi-channel EEG signals achieves an accuracy of 92.3% by demonstrating the effectiveness of 3D kernels in classifying epileptic and non-epileptic seizures. Ahmadi A, et.al, [24] implemented a Wave Packets (WP) and SVM classifier models to predict the Epileptic Seizures. They used EEG signals of 10 patients, which consist of 5 sets, each with 100 segments, obtained from Bonn University in Germany. They used the WPT to decompose EEG signals and obtain statistical features like SD and RMS. They proposed a model that provides an accuracy of 97.8 percent in identifying real-time seizure detection between stable and active seizure, outperforming other binary classification models.

Samiee K, et.al., [25] proposed a Rational DSTFT model to predict the ES by using the EEG signals dataset. The dataset was collected from Bonn University which consists of five subsets, each with 100 single-channel and a period of 23.6 seconds. They used the DSTFT technique to extract feature vectors, which were then processed using the MLP. When compared to other techniques, the proposed model has an accuracy of 98.1 percent in classifying seizure epochs and seizure-free epochs. Satapathy S K, et.al., [26] implemented the NN (MLP, PNN, RBF, RNN) and SVM classifier models to detect the ES by using the EEG signals dataset. The dataset was collected from Bonn University and consists of five subsets, each with 100 single-channels and a length of 23.6 seconds. They used the Discrete Wavelet Transform (DWT) to derive statistical features such as the MIN, MAX, MEAN and SD by decomposing the EEG signals. They proposed an SVM with RBF model that outperforms MLP, PNN, and RNN models in classifying healthy and active seizure conditions with an accuracy of 98 percent.

Swami P, et.al., [27] proposed a WPT and SVM classifier models to predict the ES by using the EEG signals dataset. The dataset was collected from Bonn University and the Neurology & Sleep Centre in New Delhi, and it consists of five subsets, each with 100 single-channels and sample rates of 173.61 Hz and 200 Hz. They used the WPT technique to extract time-frequency features from EEG signals by decomposing them. They proposed a WPT and SVM model with 10-fold validation that improves the accuracy of classifying the epileptic and non-epileptic seizures by 99%.

3. METHODOLOGY
A. Objectives
Machine Learning is now widely used in the area of medical diagnosis to provide an accurate assessment of a patient's health status. ML models for predicting epileptic seizures assist doctors in providing effective care. The tasks/objectives that must be completed in order to attain this are as follows:-
1.) To improve the effectiveness of the epileptic seizure detection in the field of medical diagnosis of a brain an automated epileptic seizures detection system is introduced to accurately detect the epileptic and non-epileptic seizures of a patient.
2.) To enhance the performance of the classification and identification of the epileptic seizure an optimal model is selected from the set of various models by using different metrics.

B. Dataset
The dataset was obtained from the UCI Repository to detect the Epileptic Seizure. The dataset is divided into five subsets, each of which contains 100 single channel recordings with a sample rate of 173.6Hz and duration of 23.6 seconds. These EEG signals were recorded by placing the electrodes on the surface of the scalp as per 10–20 International system. The dataset contains 179 attributes and 11500 instances which are unique values, each with 5 target variables. The 178 attributes are called as the Explanatory variables which are \{X1, X2, X3, .........., X179\}, the last 179th column is the target variable which is labeled as \(y= \{0, 1\} \) where
0 - Seizure is not recorded.
1 - Seizure activity is recorded.

C. Dataset Description

| Attributes  | Description                                                                 |
|-------------|-----------------------------------------------------------------------------|
| X1 to X178  | These are the explanatory variables that contain the patient's EEG data,    |
|             | with values ranging from -1415 to 2047.                                    |
| X179        | It is the response variable in which if the output is 0 then there is no    |
|             | seizure or if it is 1 then there is an active seizure.                    |

3.1 Architecture of PCA with ANN Model

![Architecture Diagram](image)

The Figure 1 is an Architecture which shows the combination of the PCA and ANN models that processes in such a way that the EEG signal dataset is taken as input by the PCA algorithm. After that we calculate the Covariance matrix for the EEG dataset. Both Eigen values and Eigen Vectors were calculated for the covariance matrix in order to generate Feature Vector from those values. Finally we achieve the optimal feature set by multiplying the transpose of the feature vector by the transpose of the scaled matrix. The optimal feature set from the PCA is fed as input to the ANN input layer that duplicates the each data value and transfers it to the hidden layer. In the hidden layer the received data is processed by using the weighted system connections and after that the data is transferred to the output layer which returns a value that corresponds to the prediction of the response variable.
3.2. Applied Models

A. Linear Discriminant Analysis (LDA)

LDA is a Dimensionality reduction technique. It is primarily concerned with projecting features from higher-dimensional space to lower-dimensional space. We feed the dataset into the LDA model, and the model calculates class separability, which is defined as the distance between the means of distinct classes. The term for this is between-class variance, and then it computes the distance between each class’s mean and sample, which is known as within-class variance. It generates a lower-dimensional space (lds) in which the variance between classes is optimized while the variance within classes is minimized. Predictions on the training dataset of EEG signals can be made by plugging the statistical properties into the LDA equation. The information is used to calculate the attributes. The LDA model classifier can effectively classify a patient's epileptic seizure and provides an accurate result.

\[ S_b = \sum_{i=1}^{g} N_i (\bar{x}_i - \bar{x}) (\bar{x}_i - \bar{x})^T \]

Where \( S_b \) is called as Between-Class Variance, \( N \) is Number of Instances, \( x \) is an Input class.

\[ S_w = \sum_{i=1}^{g} (N_i - 1)S_i = \sum_{i=1}^{g} \sum_{j=1}^{N_i} (x_{ij} - \bar{x}_i) (x_{ij} - \bar{x}_i)^T \]

Where \( S_w \) is known as Within-Class Variance, \( N \) is Number of Instances, \( x \) is an Input class.

\[ P_{lda} = arg_{P} \max \left| \frac{P^T S_b P}{P^T S_w P} \right| \]

\( P_{lda} \) is called as Prediction for LDA model, \( P \) is called as lds projection, also known as Fisher’s criterion.

![Fig.2. Classification of data before and after implementing LDA](image)

Figure 2 shows that the classes can contain several characteristics, employing just one to classify them may result in some overlapping of variables; hence there is a need to increase the number of features to avoid this, resulting in accurate classification.

B. Quadratic Discriminant Analysis (QDA)

QDA is also a Dimensionality reduction technique which is similar to linear discriminant analysis LDA, in which the measurements from each class are considered to be regularly distributed. It gives the covariance matrix greater flexibility, which tends to suit the EEG signal dataset better than LDA, but it also has more parameters to estimate. With QDA, the number of parameters grows significantly. Because each class will have its own covariance matrixes shown in Eq (1). This can be a problem if you have a lot of classes but not a lot of sample points. We will estimate the covariance matrix \( \Sigma_k \) separately for each class \( k \), \( k = 1, 2, \ldots, K \) as shown in Eq (2). The QDA model analyses the EEG signal dataset and more accurately identifies a patient's epileptic seizure than the LDA model.

\[ \delta_k(x) = -\frac{1}{2} \log|\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log \pi_k \quad \text{--------> Eq (1)} \]
Where $\delta_k(x)$ is the Quadratic Discriminant function, $\Sigma_k$ is known as the Covariance matrix, $x$ is an Input class, $\mu_k$ is called as Mean of the input class.

Likelihood ratio=$\frac{\sqrt{2\pi}^{\Sigma_{y=1}} \exp(-\frac{1}{2}(x-\mu_y=1)^T \Sigma_{y=1}^{-1}(x-\mu_y=1))}{\sqrt{2\pi}^{\Sigma_{y=0}} \exp(-\frac{1}{2}(x-\mu_y=0)^T \Sigma_{y=0}^{-1}(x-\mu_y=0))} < t \text{----------> Eq (2)}$

Where $x$ is an Input class, $\mu_y=0, \mu_y=1$ are the mean of the Input classes, $\Sigma_{y=0}, \Sigma_{y=1}$ are the mean of the covariances.

The Figure 3 depicts a random example that was chosen at random and resulted in this sort of graph, which is an example of QDA.

C. Principal Component Analysis with Random Forest Classifier (PCA with RF)

PCA is a statistical methodology for converting high-dimensional data to low-dimensional data by identifying the most essential characteristics that capture the most information about the EEG signal dataset. The features are chosen based on how much variance they introduce into the result. The feature that causes highest variance is the first principal component. Random Forest is a Supervised Machine Learning method that produces many decision trees and blends them together to get a more accurate and trustworthy forecast. As a result, it leads to a better model. But when we combine both models and examine the "feature importance's" of our Random Forest model, PCA can make analyzing each feature a little more difficult. On the other hand, it performs dimensionality reduction on the EEG signal dataset, reducing the number of features that the Random Forest must process. As a result, PCA aids with the training of your Random Forest model. Combining PCA and RF models gives higher accurate result in detecting and classifying the epileptic seizure of a patient.

$$Z^1 = \phi^1 X^1 + \phi^{21} X^2 + \phi^{31} X^3 + \ldots + \phi^{p1} X^p$$

Where $Z^1$ is the First Principal Component Analysis, $\phi^{p1}$ is the loading vector comprising of loadings ($\phi^1, \phi^2, \ldots$) of first principal component, $X^1, X^2, \ldots X^p$ are normalized predictors.

D. Multi-Layer Perceptron (MLP)

There will be two components to the EEG signal dataset: training and testing. We've set aside 20% of the dataset to see how accurate the trained model is. Each layer of an MLP is fully coupled to the one before it. The nodes of the layers, with the exception of the input layer's nodes, are neurons with nonlinear activation functions. Each neuron in the hidden layers receives the output data of the EEG
signals from every neuron in the previous layers and uses a weighted linear summation to turn these values into an output value. Thus the final output value of the MLP model shows a higher effectiveness in predicting the epileptic seizure that is much higher than the previous models.

\[ \sum_{i=0}^{n-1} w_i x_i = w_0 x_0 + w_1 x_1 + \cdots + w_{n-1} x_{n-1} \]

Where \( n \) is the number of neurons of the layer, \( W_i \) corresponds to the \( i^{th} \) component of the weight vector. The output layer receives the values from the last hidden layer.

![Diagram of multi-layer perceptron learning](image)

**Figure 4: The diagrammatic representation of multi-layer perceptron learning**

**E. Proposed System**

The proposed model is a Principal Component Analysis with Artificial Neural Networks. PCA is a dimensionality-reduction technique for lowering the dimensionality of large data sets by transforming a large collection of variables into a smaller set that preserves the bulk of the information in the larger set. We feed the input EEG (Electroencephalography) dataset into the PCA model for identifying the most essential characteristics that capture the most information about the EEG signal dataset. The features are chosen based on how much variance they introduce into the result. The feature that causes highest variance is the first principal component. After that we feed the input data to ANN model. The data from the input layer is sent to all the hidden nodes as it duplicates each value. After that the data is processed in the Hidden layer by the weighted system. Weights are a set of predetermined numbers stored in the program that are multiplied by the values entering a hidden node. Finally the processed data is fed to the output layer that corresponds to the prediction of the response variable.

**Step:-1**

We take the EEG signal dataset as an input for the PCA model and divide it into two halves, X and Y, with X being the training set and Y representing the validation set.

\[ Z = \frac{x - \mu}{\sigma} \]

Where \( z \) is the scaled value, \( x \) is the initial input, and \( \mu \) and \( \sigma \) are mean and standard deviation.

**Step:-2**

Before using the PCA algorithm, the EEG signal dataset must be normalized. After normalizing the EEG signal dataset, we find the covariance across multiple dimensions and arrange them in a covariance matrix.

\[ \text{Cov}(X,Y) = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y}) \]

Where \( \text{cov}(X, Y) \) are the two variables of the covariance matrix, \( n \) is the number of inputs, \( \bar{X} \) and \( \bar{Y} \) are the mean of the X, Y variables.

**Step:-3**

After determining the covariance matrix of the EEG data, we must compute the eigenvalues and eigenvectors for the covariance matrix, which represent data variability in the plot on an orthogonal
basis, as well as the direction of maximum variance among the data.

**Step:-4**
The higher eigenvalues selected will define the size of the new feature set. A feature vector is also generated, which a vector matrix is made up of eigenvectors of relative chosen eigenvalues. To identify the primary components of the EEG signal dataset, we employ the feature vector.

**Step:-5**
To obtain a matrix containing principal components, we multiply the transpose of the feature vector by the transpose of the scaled matrix.

**Step:-6**
After the dimensionality reduction of the EEG signal dataset the optimal feature set is chosen and fed as input to the ANN.

**Step:-7**
The input layer duplicates each data value after obtaining it from the PCA method and sends it to all of the Hidden layer's hidden nodes. The hidden layers take the input and use a system of weighted connections to process the best featured EEG data and then transfers the processed data to the output layer.

\[ y = g_3(W_3g_2(W_2g_1(W_1x))) + [b_3+...] \]

Where \( g \) is the activation function, \( W \) is called as weights and \( b \) is the bias term.

**Step:-8**
The hidden layers provide the processed EEG data to the output layer.

The data in the image showed in figure 5, which has the greatest variation along the red line in two-dimensional space, which is an example of PCA.

### 4. RESULT ANALYSIS

**Accuracy:**
It is defined as the percentage of correct predictions given the test data. Divide the number of right predictions by the total number of predictions to get the answer.

\[ \text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \]

Where TP = True Positives, TN = True Negatives, FP = False Positives and FN = False Negatives.
Precision:
It is defined as the proportion of relevant cases (true positives) among all those projected to belong to a particular class.

\[
\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}
\]

Recall:
It is defined as the proportion of examples predicted to belong to a class compared to all of the examples that genuinely belong to the class.

\[
\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}
\]

Hinge Loss:
It is a loss function used to train classifiers in machine learning and is used for "maximum-margin" classification, most notably for SVMs. The prediction of y is defined as for an expected output t = 1 and a classifier score y.

\[
1(y) = \max (0, 1 - t \cdot y)
\]

Mean Squared Error:
The average of squared differences between the predicted and true outputs is known as the mean squared error. The squared error is widely used because it does not care whether the prediction was too high or too low; it simply reports that it was incorrect.

\[
\text{MSE} (y_{\text{true}}, y_{\text{pred}}) = \frac{1}{n_{\text{samples}}} \sum (y_{\text{true}} - y_{\text{pred}})^2
\]

4.1 Results Obtained

Table 1. The results of the different algorithms are as follows.

| Algorithms                                      | Accuracy   | Precision  | Recall     | Hinge Loss | Mean Squared Error (MSE) |
|------------------------------------------------|------------|------------|------------|------------|--------------------------|
| Linear Discriminant Analysis (LDA)             | 82.91%     | 94.91%     | 12.55%     | 97.69%     | 17.8%                    |
| Quadratic Discriminant Analysis (QDA)          | 92.47%     | 78.85%     | 83.63%     | 88.13%     | 7.52%                    |
| Multi Layer Perceptron (MLP)                   | 97.21%     | 95.09%     | 89.46%     | 83.39%     | 2.78%                    |
| Principal Component Analysis with Random Forest(PCA with RF) | 92.69%     | 94.13%     | 64.34%     | 87.91%     | 7.69%                    |
| Principal Component Analysis with Artificial Neural Network(PCA with ANN) | 97.55%     | 94.24%     | 91.48%     | 83.38%     | 2.32%                    |

Figure 6 is used for comparison of accuracy of different models and Figure 7 is used for comparison of different metrics between different algorithms.
5. Conclusion and Future Work

Epileptic Seizure detection is primarily investigated using a variety of traditional and cutting-edge technologies. EEG signals are typically used to monitor it. Many algorithms were proposed earlier to detect Epileptic Seizure. Our algorithm can outrun these algorithms in terms of evaluation metrics. The algorithm employed is Principal Component Analysis (PCA) with Artificial Neural Networks (ANN) that converts high-dimensional data to low-dimensional data, retaining required data from the dataset. The output of PCA is fed to the ANN which processes the optimal features set received from PCA that gives an output value corresponds to the response variable. The proposed algorithm gives better performance in terms of Accuracy with 97.55%, Precision with 94.24%, Recall with 91.48%, Hinge Loss of 83.8% and Mean Squared Error of 2.32%, which are better than the previous algorithms. We met the objective of increasing the effectiveness of epileptic seizure detection in the field of medical diagnosis of a brain by introducing an automated epileptic seizures detection system to accurately detect the epileptic and non-epileptic seizures of patients by improving the performance of the classification and identification of the epileptic seizure from a set of various metrics.
In the future, if we have other forms of seizures, this model can be utilized, and we can use different datasets if we wish. This model is producing better results than prior models, and we believe it can be used to identify seizures in the future.

6. References

[1] Siddiqui, M. K., Morales-Menendez, R., Huang, X., & Hussain, N. (2020). A review of epileptic seizure detection using machine learning classifiers. Brain informatics, 7, 1-18.

[2] Fergus, P., Hussain, A., Hignett, D., Al-Jumeily, D., Abdel-Aziz, K., & Hamdan, H. (2016). A machine learning system for automated whole-brain seizure detection. Applied Computing and Informatics, 12(1), 70-89.

[3] Hussein, R., Palangi, H., Ward, R., & Wang, Z. J. (2018). Epileptic seizure detection: A deep learning approach. arXiv preprint arXiv:1803.09848.

[4] Hussain, L. (2018). Detecting epileptic seizure with different feature extracting strategies using robust machine learning classification techniques by applying advance parameter optimization approach. Cognitive neurodynamics, 12(3), 271-294.

[5] Upadhyay, R., Padhy, P. K., & Kankar, P. K. (2016). A comparative study of feature ranking techniques for epileptic seizure detection using wavelet transform. Computers & Electrical Engineering, 53, 163-176.

[6] Murugavel, A. M., & Ramakrishnan, S. (2014). An optimized extreme learning machine for epileptic seizure detection. Int. J. Comput. Sci, 41(4), 212-221.

[7] Kabir, E., & Zhang, Y. (2016). Epileptic seizure detection from EEG signals using logistic model trees. Brain informatics, 3(2), 93-100.

[8] Wu, J., Zhou, T., & Li, T. (2020). Detecting epileptic seizures in EEG signals with complementary ensemble empirical mode decomposition and extreme gradient boosting. Entropy, 22(2), 140.

[9] Matin, A., Bhuiyan, R. A., Shafi, S. R., Kundu, A. K., & Islam, M. U. (2019, May). A hybrid scheme using PCA and ICA-based statistical features for epileptic seizure recognition from EEG signal. In 2019 Joint 8th International Conference on Informatics, Electronics & Vision (ICIEV) and 2019 3rd International Conference on Imaging, Vision & Pattern Recognition (icIVPR) (pp. 301-306). IEEE.

[10] Raghu, S., Sriraam, N., & Kumar, G. P. (2017). Classification of epileptic seizures using wavelet packet log energy and norm entropies with recurrent Elman neural network classifier. Cognitive neurodynamics, 11(1), 51-66.

[11] Sharmila, A., & Geethanjali, P. (2016). DWT based detection of epileptic seizure from EEG signals using naive Bayes and k-NN classifiers. Ieee Access, 4, 7716-7727.

[12] Wang, G., Ren, D., Li, K., Wang, D., Wang, M., & Yan, X. (2018). EEG-based detection of epileptic seizures through the use of a directed transfer function method. Ieee Access, 6, 47189-47198.

[13] Li, P., Karmakar, C., Yearwood, J., Venkatesh, S., Palaniswami, M., & Liu, C. (2018). Detection of epileptic seizure based on entropy analysis of short-term EEG. PloS one, 13(3), e0193691.

[14] Wang, L., Xue, W., Li, Y., Luo, M., Huang, J., Cui, W., & Huang, C. (2017). Automatic epileptic seizure detection in EEG signals using multi-domain feature extraction and nonlinear analysis. Entropy, 19(6), 222.

[15] Aldana, Y. R., Hunyadi, B., Reyes, E. J. M., Rodriguez, V. R., & Van Huffel, S. (2018). Nonconvulsive epileptic seizure detection in scalp EEG using multiway data analysis. IEEE journal of biomedical and health informatics, 23(2), 660-671.

[16] Wang, X., Gong, G., Li, N., & Qiu, S. (2019). Detection analysis of epileptic EEG using a novel random forest model combined with grid search optimization. Frontiers in human neuroscience, 13, 52.
[17] Ullah, I., Hussain, M., & Aboalsamh, H. (2018). An automated system for epilepsy detection using EEG brain signals based on deep learning approach. *Expert Systems with Applications, 107*, 61-71.

[18] Peachap, A. B., & Tchiotsop, D. (2019). Epileptic seizures detection based on some new Laguerre polynomial wavelets, artificial neural networks and support vector machines. *Informatics in Medicine Unlocked, 16*, 100209.

[19] Subasi, A., Kiymik, M. K., Alkan, A., & Koklukaya, E. (2005). Neural network classification of EEG signals by using AR with MLE preprocessing for epileptic seizure detection. *Mathematical and Computational Applications, 10*(1), 57-70.

[20] Srirmaam, N., Raghu, S., Tamanna, K., Narayan, L., Khanum, M., Hegde, A. S., & Kumar, A. B. (2018). Automated epileptic seizures detection using multi-features and multilayer perceptron neural network. *Brain Informatics, 5*(2), 1-10.

[21] Sharmila, A., & Mahalakshmi, P. (2017). Wavelet-based feature extraction for classification of epileptic seizure EEG signal. *Journal of medical engineering & technology, 41*(8), 670-680.

[22] Pakistan, K. (2016). Canonical correlation analysis and neural network (CCA-NN) based method to detect epileptic seizures from EEG signals. International Journal of Bio-Science and Bio-Technology, *8*(4), 11-20.

[23] Wei, X., Zhou, L., Chen, Z., Zhang, L., & Zhou, Y. (2018). Automatic seizure detection using three-dimensional CNN based on multi-channel EEG. *BMC medical informatics and decision making, 18*(5), 71-80.

[24] Ahmadi, A., Shalchyan, V., & Daliri, M. R. (2017, April). A new method for epileptic seizure classification in EEG using adapted wavelet packets. In 2017 Electric Electronics, Computer Science, Biomedical Engineering' Meeting (EBBT) (pp. 1-4). IEEE.

[25] Samiee, K., Kovacs, P., & Gabbouj, M. (2014). Epileptic seizure classification of EEG time-series using rational discrete short-time Fourier transform. *IEEE transactions on Biomedical Engineering, 62*(2), 541-552.

[26] Satapathy, S. K., Jagadev, A. K., & Dehuri, S. (2017). Weighted majority voting based ensemble of classifiers using different machine learning techniques for classification of EEG signal to detect epileptic seizure. *Informatica, 41*(1), 99.

[27] Swami, P., Godiyal, A. K., Santhosh, J., Panigrahi, B. K., Bhatia, M., & Anand, S. (2014, December). Robust expert system design for automated detection of epileptic seizures using SVM classifier. In 2014 International Conference on Parallel, Distributed and Grid Computing (pp. 219-222). IEEE.