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Neural network based seizure detection system using statistical package analysis

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ABSTRACT

Due to the unpredictable interruptions within the functions of the human brain, disturbance occurs and it affects the behavior of the human and is equally laid low with the frequent occurrence termed as seizures. Therefore, the proposed system detects the seizure using machine learning algorithms. The electroencephalogram (EEG) contains information of the brain to detect the seizure. The objective is to evaluate the performance of machine learning classifiers K-nearest neighbors (KNN), artificial neural network (ANN), support vector machine (SVM) and principal component analysis (PCA) by comparing the accuracy of the classifier. This work uses total of 11,500 EEG samples from the UCI machine learning repository. The seizure detection was done in two ways. First method, features extracted from the EEG signal and classification techniques are done to classify the seizure. The second method uses the principal component analysis algorithm to improve the significant selections of features from the dataset. The outcomes are analyzed using the statistical package for the social science (SPSS) tools. ANN with extracted functions achieved 96% of accuracy and significant efficiency of ($p<0.05$) in comparison with different machine learning classifiers. It would be prudent to conclude that the ANN demonstrated the best accuracy, sensitivity, and specificity.

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1. INTRODUCTION

Seizure is a serious brain illness and a chronic neurological disorder of all age groups. Seizure occurs as sudden uncontrolled electrical disturbance in the human brain and causes change in behavior and movement in the human body. The continuous occurrence of seizure leads to epilepsy. If the seizure occurs during night hours and the person is unattended, it will lead to a dangerous scenario where extreme illness may cause death. This detection process needs to be carried out with the help of neurologists and considered to be a time-consuming process and decreases the chance of prediction rate [1].

Seizure disorders are of two specific categories, such as unprovoked and provoked seizure. The natural causes such as genetic factors or metabolic imbalances in the body will lead to unprovoked seizure, whereas brain related injury or stroke will lead to the provoked seizure. Also, seizure can be generally categorized as long-term seizure and short-term seizure based on the frequency of occurrence. Seizure may last for five minutes to 10 minutes or even longer, this will lead to more complications and cause permanent brain damage. It is highly preferred to detect and predict the long/short term seizure prior to avoiding critical situations. The statistical report was discussed in Table 1 to prioritize the importance of early detection of seizure. The survey has proved that around 3.4 million people in the world suffer from seizures. Around 30 to 40 percent of the people suffer from epilepsy that is due to genetic disorder [2].

Table 1. Percentage of seizure affected person based on age group and seizure type

Seizure types	Percentage (%)	Age group	Percentage (%)
Long Term	50	0 to 17	60
Short Term	20	18 to 50	30
Generalized	30	above 55	10

Seizure occurs for all age groups from newborn-children-adults-senior citizens. The reasons for the seizure occurrence are high fever, lack of sleep, stroke, genetic even autism disorder may also lead to seizure. Stress is the major cause of seizure occurrence in working women and men [3]. The major applications of the machine learning techniques were used in medical applications for early detection and prediction of the disease without human intervention [4], [5]. Kumar *et al*. [6] proposed the application to detect epilepsy seizures more predominantly using electroencephalogram (EEG) signals and can be embedded into the real-time diagnosis of disease. Michielli *et al*. [7] proposed a deep learning architecture for automatic sleep scoring detection using EEG signals. A novel detection algorithm proposed for epilepsy monitoring and also applicable to personalized drug titration, and determining the duration of pharmacotherapy applications.

2. LITERATURE SURVEY

Several researches had been done in detecting epilepsy using machine learning techniques. 720 research articles published in Google Scholar and 121 articles were published in IEEE Xplore. Kumar *et al.* [8] proposed an intelligence system using variational mode decomposition and Hilbert transform for extracting features from EEG signals and stacked neural networks for epilepsy detection and achieved difference in accuracy for neurology and sleep center-New Delhi (NSC-ND) and Bonn University dataset. Tang *et al.* [9] developed an automated wearable sensor device for long term seizure monitoring with customized machine learning algorithms for identifying 9 different types of seizures. Eight out of 9 seizure types can be identified accurately by the customized convolutional neural network (CNN) algorithm.

Chang *et al.* [10] proposes an EEG signal classification method for identification of epilepsy and autism spectrum disorder based on a machine learning algorithm. In combination with discrete wavelet transform (DWT), Shannon entropy and K-nearest neighbors (KNN) for the detection of epilepsy and autism parameters. However, this work uses machine learning which deals with mathematics, and it is not suitable for real time progress.

Liu and Woodson [11] proposes an EEG signal classification method for identification of epilepsy based on a machine learning algorithm. Wavelet decomposition method used for pre-processing of the EEG signal to remove the artifact. One dimensional convolution neural network used to detect the focal and non-focal epilepsy condition. However, this system fails to provide the accuracy for the focal seizure detection, with an error rate of 20%.

Liu *et al.* [12] proposes an EEG signal classification method to detect the frequent occurrence of seizure based on a machine learning algorithm. Discrete wavelet transform used for pre-processing of the EEG signal. In combination with Shannon entropy as a feature and KNN classifier is used for classification and detection of seizure. The major drawback in this approach is data preprocessed with different sampling frequencies to remove the artifacts.

Ibrahim *et al.* [13] proposes an EEG signal classification method for detection of epilepsy based on Slantlet transform and sparse coding to monitor the seizure occurrence. In combination with the sparse representation coding and support vector machine used for classification and detection of seizure. The major drawback in this approach is that it uses complex pre-processing methods to remove the artifact from the EEG signal.

Yıldırım *et al.* [14] proposes a classifier in combination with genetic algorithm and hybrid support vector machine (SVM) to detect epilepsy based on a machine learning algorithm. A particle swarm optimization-based (PSO-based) approach used to optimize the SVM parameters. However, this system fails to predict the occurrence of seizure to the patient prior. Singh *et al.* [15] proposes an epilepsy detection system using EEG signal classification. In combination with harmonic wavelet packet transform (HWPT) as a preprocessing method and fractal dimension (FD) as the feature to monitor the occurrence of seizure. However, the author fails to reduce the false detection rate and this system increases the false detection rate up to 2 per hour and also increases the complexity.

Almustafa [16] proposed an epilepsy classification technique using different classifiers. Random forest classifiers outperformed when compared to other classifiers and achieved better detection accuracy. However, the author fails to analyze the classification algorithm with respect to the change in different features. Zhang *et al.* [17] proposed a deep neural network based pyramidal one-dimensional convolutional neural network for classification of focal and non-focal seizure using EEG signal. The algorithm produces 60% better classification accuracy when compared to the traditional CNN algorithm. However, this system focused on patient specific classifiers and it fails to provide accuracy when tested for another person.

Metternich *et al.* [18] proposed different techniques for extracting the feature from the non-stationary, nonlinear and non-Gaussian EEG signals. Wavelet based entropy, nonlinear, and higher order spectra-based features are extracted and given as input to the KNN and SVM classifiers. However, the author fails to reduce the false detection rate and this system and also increases the complexity.

Hou *et al.* [19] proposes a 5-stage classification algorithm for the detection of epilepsy using EEG signals. More relevant features extracted from the EEG signal and applied as an input to the: random case testing and continuous case testing classifiers, which minimize the error detection rate to 2-3%. However, the author fails to produce the accuracy in a random case testing classifier. Faust *et al.* [20] reviewed the signal of EEG, electrocardiogram (ECG), electromyogram (EMG), evidence of coverage (EOC) for healthcare applications, and concluded that deep learning algorithms produce significant results for a large dataset of physiological signals and also increases the accuracy of diagnosis. However, the author concluded that advanced deep learning algorithms are required for early detection of disease.

Acharya [21] developed a computer aided diagnostic system to identify the normal and abnormal activities using the optimal number of features in classifiers and found that non-linear features are used to capture the chaotic behavior in the EEG signals. However, the author fails to address the non-stationary characteristics of the EEG signal. Wang and Zheng [22] propose a weighted k-nearest neighbor classifier to identify the detection of epilepsy and fast Fourier transform used for preprocessing of the EEG signal. K-fold cross-validation techniques used to improve the accuracy of the classifier.

Subasi *et al.* [23] proposed a hybrid model classification for epileptic seizure detection using genetic algorithm and particle swarm optimization to identify the optimal parameter for the support vector machine classifier. The proposed classifier achieves the optimal result whereas the classifier performance will be degraded if the selected features are not optimal. The issues faced by the existing systems are that it fails to address the occurrence of seizure caused by stress and also increases the false detection rate as well as fails to detect the seizure signal accurately. To overcome these challenges, the proposed system tries to implement a system to detect seizure a priori and accurately that occurs due to stress.

3. METHODS AND MATERIALS

The EEG dataset collected from the UCI machine learning repository [24] for detection of epilepsy. The dataset contains 11,500 rows of data with 178 attributes. The database provides long-term EEG recordings of both focal and non-focal data [25]. EEG datasets selected with 178 attributes of 500 persons, which included long-term recordings for each second. The data set is divided into five classes and it is used for training and testing purposes. The class 1 dataset is taken during the seizure occurrence and class 2 to class 5 taken during the normal condition. Since identification of the focal and non-focal recording will be the goal, at least two hours of recordings prior to a seizure occurrence are taken for analysis. The required samples for this analysis are done using G power calculation. Minimum power of the analysis is 0.8 and maximum accepted error is 0.5.

4. PROPOSED SYSTEM

Seizure detection system under stress developed using ANN classifier. It can be categorized into four modules. Data acquisition module, data processing module, decision-making module, and alert generation module.

4.1. Data acquisition module and data processing module

The EEG datasets used were obtained from the UCI repository epilepsy EEG databases that were to be processed before applying it to the machine learning model. The processed EEG data classified as testing and training of 75% and 25% respectively. The processed data with obtained features given as input to the classifier. In this module data processed to extract the useful features from the dataset and the processed data can be given as an input to the classifier to detect the seizure occurrence. The following features are extracted from the signal, and it can be given as an input to the classifier to classify the focal and non-focal data mean, variance, standard deviation, maxima, minima, entropy, skewness, and kurtosis [26]. These features can be categorized into two types: training feature and testing feature. The desired classifier such as KNN, ANN, SVM, and decision tree trained with features and obtained the accuracy performance.

4.2. Decision making module and alert generation module

The classified features can be trained with ANN, SVM, and KNN based on the accuracy of this classifier the best classifier can be selected to detect the seizure. Once it is detected without a false detection rate and alert message can be given to the neurologist and the family members.

4.3. Artificial neural network

The ANN is one of the efficient machine learning algorithms used for the classification and prediction of data. It has three layers: input layer, hidden layer, output layer. The extracted features such as mean, variance, standard deviation skewness and entropy can be given as the input. In this layer the useful feature can be converted as an activation function and it can be given to the hidden layer. Here, the sigmoid activation function can be selected to identify the non-linear relationship between the inputs. The hidden layer can be selected depending on the size of the data used, and it can also be called a multilayer perceptron (MLP), here one hidden layer with 3 hidden neurons used. The sigmoid activation function used to convert the output to be 0's to 1 's. The activation function for hidden layer given by:

$$y1 \ = \ 1 \, / \, (1 + exp(-F)) \tag{1}$$

where, y1 denotes the output of the neurons in hidden layer. Feuler's number to distribute the output between 0's and 1's:

$$F \ = \ w1 * x(1) \ + \ w2 * x(2) \ + \ w3 * x(3) \tag{2}$$

where, w1, w2, and w3 denotes the weight coefficient of the neuron in hidden layer and x(1), x(2), and x(3) is the predictor variable of the corresponding neuron in input layer. Similarly, the hidden layer leads to the final prediction at the output layer:

$$y2 \ = \ 1 \, / \, (1 + exp(-F \,)) \tag{3}$$

$$F\,1 = \ W4 * y1 \ + \ W5 * y2 + W6 * y3 \tag{4}$$

where, y2 denotes the output of the neurons in output layer w4, w5, and w6 represents the weight coefficient of the neuron in hidden layer y1, y2, and y3 represents the output of the sigmoid activation function in (1) to (4). The feed forward network architecture has been used to classify the data to detect the seizure condition.

5. SPSS STATISTICAL TOOL

The IBM statistical package for the social science (SPSS) statistical software [27] is used for the analysis of classifier performance. Group 1, group 2, group 3, and group 4 represent the KNN, ANN, SVM, and decision tree respectively. In this epileptic seizure detection system group 1, group 2, group 3 and group 4 are considered to be the independent variables and the accuracy, sensitivity and specificity considered as dependent variables. One-way Anova tests are done to compare the accuracy, sensitivity, and specificity among the groups. The test setup used the spyder as a free integrated development environment (IDE) [28]. In (5) to (7) used for calculation of accuracy, sensitivity, and selectivity for seizure detection.

$$Accuracy = \left[\frac{TP+TN}{TP+FP+TN+FN}\right] \tag{5}$$

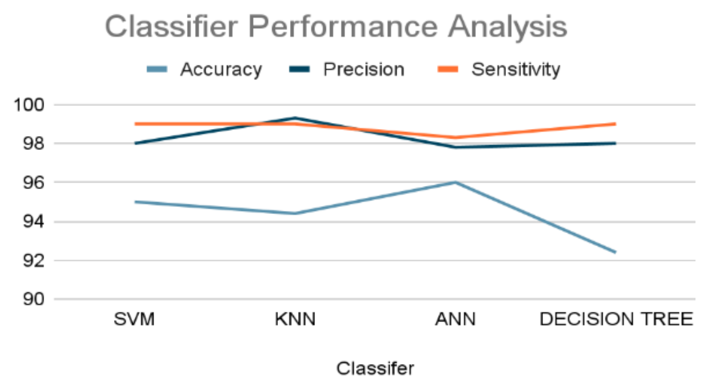
$$Specificity = \frac{TN}{TN+FP} \tag{6}$$

$$Sensitivity = \ TP/(TP + FN) \tag{7}$$

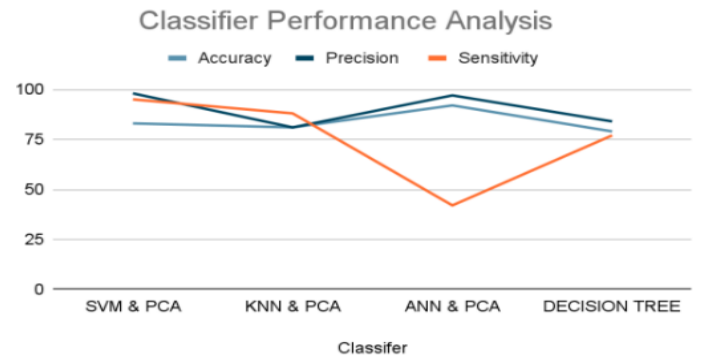
where, TP=true positive, TN=true negative, FP=false positive, and FN=false negative

6. RESULT

Several parameters used to analyze the performance of the classifier, which were discussed in this proposed method. Accuracy, precision and sensitivity of the classifier obtained using feature extraction method discussed in Figure 1(a). The classifiers accuracy, precision and sensitivity for principal component analysis methods discussed in Figure 1(b) among this feature extraction method achieved better accuracy



(a)



(b)

Figure 1. Performance analysis of the classifiers (a) feature extraction method and (b) PCA analysis

6.1. SPSS analysis results

The machine learning classifiers are statistically analyzed using the spss tool with 25 iterations where mean, standard deviation and standard error are analyzed for the classifier accuracy obtained using feature extraction method is represented in Table 2 whereas Table 3 represents the mean, standard deviation and standard error for PCA analysis method. Figure 2(a) and Figure 2(b) represent the standard deviation and standard mean analysis of the feature extraction method whereas Figure 2(c) and Figure 2(d) represent the standard deviation and standard mean analysis of PCA analysis method.

Table 2. Statistical analysis of SVM, KNN, ANN, and decision tree classifier for feature extraction method. Mean accuracy value and standard error mean for ANN compared with other classification algorithms are performed for 25 iterations

	Group	N	Mean	Std.Deviation	Std. Error mean
Classifier	SVM	25	93.8	.8408	.37603
	ANN	25	94.6	1.078	.48229
Classifier	KNN	25	93.0	.9165	.40988
	ANN	25	94.6	1.078	.48229
Classifier	Decision tree ANN	25	91.7	.5856	.26192
		25	94.6	1.078	.48229

Table 3. Statistical analysis of SVM, KNN, ANN, and decision tree classifier for PCA analysis method. Mean accuracy value, standard deviation standard deviation and standard error mean for ANN compared with other classification algorithms are performed for 25 iterations

	Group	N	Mean	Std.Deviation	Std. Error mean
Classifier	SVM	25	92.6	.7302	.376
	ANN	25	91.6	1.025	.482
Classifier	KNN	25	95.2	.7185	.409
	ANN	25	94.3	1.165	.482
Classifier	Decision tree ANN	25	90.5	.8614	.261
		25	91.6	1.154	.482

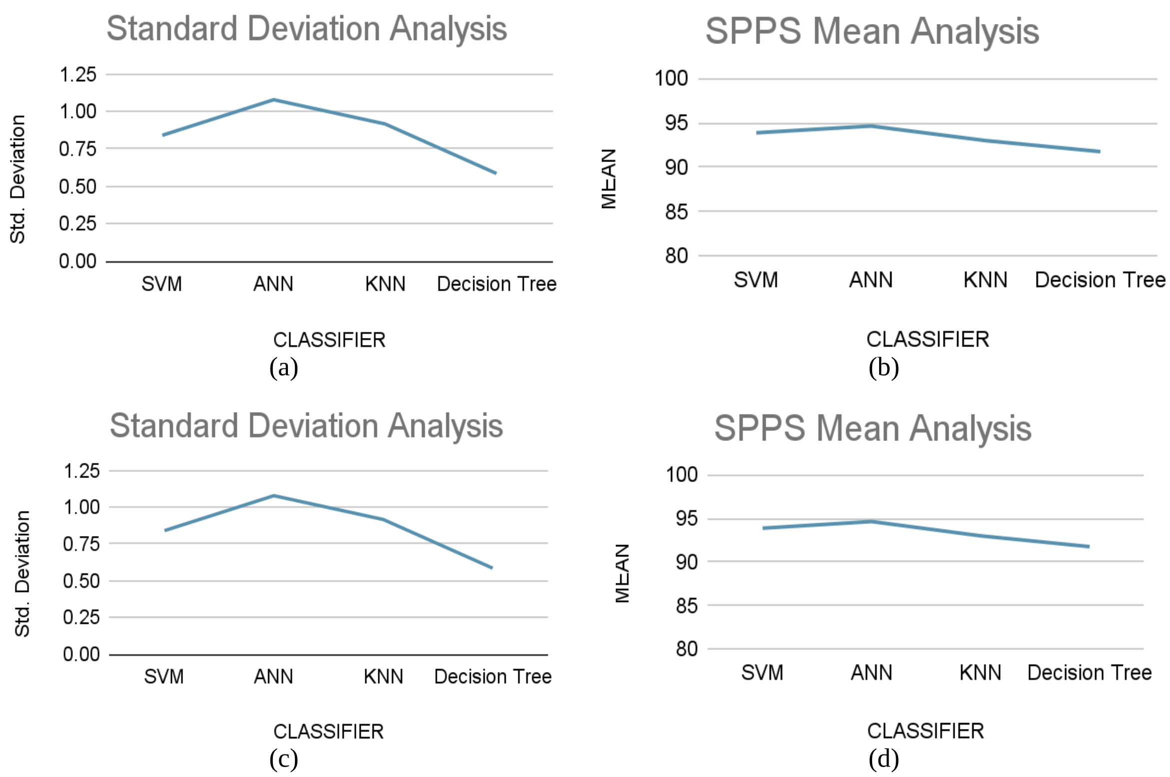


Figure 2. Performance analysis SPSS tool (a) mean analysis, (b) standard deviation analysis using feature extraction method, (c) mean analysis, and (d) standard deviation analysis using PCA analysis

7. DISCUSSION

In this proposed work, it is observed that ANN algorithm using feature extraction method provides better accuracy. Table 4 and Table 5 represents the accuracy, sensitivity, and specificity of KNN, SVM, ANN, and decision tree algorithms using feature extraction method and PCA analysis. ANN achieved the accuracy of 96% when compared to the other machine learning classifiers specified in Table 6. ANN with PCA provides an accuracy of 46% in comparison with other classifiers. The similar finding and this similar finding for the related study discussed as, proposed the patient-specific real-time automatic epileptic seizure detection system using long term scalp and short-term scalp data and achieved the accuracy of 96% sensitivity, 0.1 per hour median false detection rate using ANN algorithm. Hou *et al.* [29] proposed the epilepsy detection system for locating the epileptic foci in the brain using random forest classification model using locally linear embedding algorithm and the optimization improved 0.95 of effective result when compared with SVM, decision tree, KNN, and random forest.

Table 4. Performance analysis-accuracy, precision, and sensitivity of different classifiers SVM, KNN, ANN, and decision tree for feature extraction method

Classifier	Accuracy	Precision	Sensitivity
SVM	95	8.6	99
KNN	94.4	12.4	99
ANN	96	15.3	98.3
DECISION TREE	92.4	98	99

Table 5. Performance analysis-accuracy, precision, and sensitivity of different classifiers SVM, KNN, ANN, and decision tree for PCA analysis

Classifier	Accuracy	Precision	Sensitivity
SVM & PCA	83	98	95
KNN & PCA	81	81	88
ANN & PCA	92	97	42
DECISION TREE	79	84	77

Table 6. Comparison between performance analysis of feature extracted dataset and PCA analyzed dataset. Accuracy, precision, sensitivity, and specificity values obtained for SVM, KNN, ANN, and decision tree algorithms

Classifier	Performance analysis of classifier using extracted feature	Classifier	Performance analysis of classifier using PCA algorithm
SVM	Accuracy=95 Sensitivity=99 Specificity=98	SVM & PCA	Accuracy=83 Sensitivity=95 Specificity=98
KNN	Accuracy=94.4 Sensitivity=99 Specificity=99.3	KNN & PCA	Accuracy=81 Sensitivity=88 Specificity=81
ANN	Accuracy=96 Sensitivity=98.3 Specificity=97.8	ANN & PCA	Accuracy=92 Sensitivity=42 Specificity=97
DECISION TREE	Accuracy=92.4 Sensitivity=99 Specificity=98	DECISION TREE & PCA	Accuracy=79 Sensitivity=77 Specificity=84

8. CONCLUSION

The proposed method focused on different EEG feature extraction techniques and classification algorithms to identify the focal and non-focal condition of seizure. This proposed system detects the 178 attributes of both focal and non-focal EEG data. In the feature extraction method, the SVM classifier with extracted features given 95% accuracy and KNN classifier with accuracy 94.4%, decision tree algorithm with accuracy of 92.4% and ANN with 96%. In the PCA analysis method the SVM and PCA classifier was given 83% accuracy and KNN & PCA given 81% accuracy, decision tree algorithm and PCA with accuracy of 79% and ANN & PCA with 92%. From the above discussion, ANN classifier with feature extraction method gave better results in terms of accuracy, precision, and sensitivity. The detection and prediction of epilepsy at an early stage done with this analysis. In SPSS analysis the machine learning classifier ANN algorithm with feature extraction method gives significantly better accuracy and significance results in terms of standard deviation with 1.0, mean of 94 and acceptable error bias of +/- 2 SD. The future works will be carried out with the prediction of seizure related to stress with live dataset.

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