Classification of Seizure Types Based on Statistical Variants and Machine Learning

Anand Shankar
Department of Electronics and Communication Engineering
Indian Institute of Information Technology
Guwahati, India
Email: anand.shankar@iiitg.ac.in

Samarendra Dandapat
Department of Electronics and Electrical Engineering
Indian Institute of Technology
Guwahati, India
Email: samaren@iitg.ac.in

Shovan Barma
Department of Electronics and Communication Engineering
Indian Institute of Information Technology
Guwahati, India
Email: shovan@iiitg.ac.in

2021 IEEE 18th India Council International Conference (INDICON) | 978-1-6654-4175-9/21/$31.00 ©2021 IEEE | DOI: 10.1109/INDICON52576.2021.9691717

***Abstract*— The majority of the research works are successfully applying advanced machine learning algorithms to classify epileptic seizures using electroencephalograms (EEG). Certainly, the accurate classification of epileptic seizure types can play a significant role in the prognosis and treatment of epileptic patients' conditions. In this work, machine learning classifiers — artificial neural network, decision tree, *k*–nearest neighbor, random forest, and eXtreme boosting gradient have been employed to classify complex partial seizure, focal non-specific seizure, generalized non-specific seizure types, and seizure-free. For this purpose, statistical variants — mean, skewness, kurtosis, standard deviation, approximate entropy, and energy have been extracted from EEG segments. Thenceforth, machine learning algorithms performed multi-class epileptic seizure type classification based on these variants. Furthermore, using the principal components analysis methodology, the classification of epileptic seizure types has been analyzed using the lower dimensions of statistical variants sets. For evaluation of the proposed method, a publically available EEG dataset contributed by the Temple university hospital (TUH, v1.5.2) has been taken into consideration. The classification accuracy of multi-class epileptic seizure types has achieved up to 100%. The experimental performances demonstrated that the proposed work can efficiently and accurately classify the seizure types.**

Keywords*— *electroencephalogram, statistical variants, seizure types, machine learning.

I. Introduction

In most studies, electroencephalogram (EEG) is employed to characterize epileptic seizures activities [1–2]. The majority of current research works focused on the classification of epileptic seizures [3–4]. Certainly, accurate classification of seizure types is very crucial in the diagnosis of epileptic patient's conditions [5–6]. Furthermore, the classification of epileptic seizure types has hardly been explored [6–8]. As a result, automatic analysis of EEG signals to classify epileptic seizure types is very significant for improving patient care [9–10].

The advancement in machine learning (ML) algorithms has efficiently improved automatic classification and detection approaches in the field of biomedical signal processing and pattern recognition [1–3]. In recent years, most studies have employed ML to interpret epileptic seizures based on features extracted from EEG [2–3]. Commonly, relevant feature sets are retrieved from EEG signals that are evaluated in different domains — time, frequency, time-frequency, and non-linear [4–5]. Till now, most works have focused to classify epileptic seizures and seizure-free using EEG, although the detection and classification of epileptic seizure types have hardly been analyzed [6–10]. Certainly, automatic analysis of epileptic seizure type can improve recognition of the disease, diagnosis, and selection of appropriate drugs [8–9]. Nonetheless, a few studies on seizure type classification have been carried out [6–10]. For example, in [6] work, statistical features — mean, standard deviation, variance, skewness have been extracted from EEG. After that, these features fed into a support vector machine (SVM) model to classify four types of seizures (focal non-specific seizure (FNS), generalized non-specific seizure (GNS), simple partial seizure (SPS), and tonic seizure (TNS)). The classification accuracy has been reported up to 95.0%. In [7] work, 2D spectrogram images have been constructed from one-dimensional (1D) EEG. Subsequently, images of multiple channels have been vertically concatenated. Thereafter, four different deep neural network architectures have been employed to classify eight seizure types based on these images. The classification accuracy achieved by basic CNN, VGG19, VGG16, and AlexNet model up to 82.14%, 76.81%, 79.71%, and 84.04% respectively. In [8] work, the different machine learning classifiers have been used to classify seven types of seizures – complex partial seizure (CPS), FNS, GNS, absence seizure (ABS), SPS, TNS, and tonic–clonic seizure (TCS). The classification weighted $F1$–score recorded in the case of k–nearest neighbor (k–NN), stochastic gradient descent, eXtreme boosting gradient (XGBoost), and convolution neural network (CNN) are 90.1%, 80.7%, 86.6%, and 72.2% respectively. In [9] work, several machine learning algorithms have been employed to analyze and classify seven types of seizures (ABS, CPS, FNS, GNS, SPS, TNS, and TCS) using EEG. The highest $F1$–score has been achieved by plastic neural memory network (P–NMN), which is 94.5%. In [10] work, the author has constructed spectrogram images from raw EEG signals using saliency–encoded spectrogram (SES) approach. Thereafter, a deep convolution neural network (DCNs – SeizureNet) model has been employed to classify eight types of seizures. The proposed work has achieved a weighted $F1$–score of 94.0%. In this context, most works focused on tasks such as seizure detection and prediction, but seizure type classification is unexplored.

Motivated from the aforementioned works, five ML algorithms have been employed to classify three seizure types and seizure-free based on statistical features. Additionally, the classification has been also analyzed with reduced feature dimension by employing the principal components analysis (PCA) approach. The experimental results demonstrated that the proposed work can efficiently classify different seizure types.

The framework of this paper is as follows: introduction detailed in section II, followed by the experimental setup in Section III. Next, experimental results analysis in section IV. Finally, the conclusion of the proposed work in section V.

II. Proposed Method

The layout of the proposed idea has been shown in Fig. 1. First, pre-processing and segmentation of long recorded EEG of seizure types have been conducted, followed by statistical features extraction. Finally, based on features, different seizure types have been categorized by employing different machine learning classifiers. The details of the idea are described below.

A. Signal Processing

In this context, the recorded EEG signals need to be cleaned to eliminate the artifacts and noise [21]. Next, to reduce the trivial information at a higher frequency band, a band pass filter has been applied to obtain EEG in the range of 0.5-30 Hz, as most of the seizure activities occur in this range [11–12]. The EEG recording of each seizure type has been chosen relatively the same to generate balanced samples. Following that, the signal has been segmented based on a specific duration in order to extract statistical features.

B. Statistical Varinats

In the field of biomedical and pattern recognition, ML classifiers are utilising multiple statistical variants as important aspects of data for analysis [13–14]. In this work, six statistical variants — mean, skewness, kurtosis, standard deviation (*SD*), approximate entropy (*AE*), and energy have been taken into consideration. In this view, consider s_t $\{t = 1, 2, 3, \ldots, n\}$ is a time series with n number of samples, then statistical variants;

1. Mean

A well-known statistical variant — mean is used to analyze the central tendency of time series, which is calculated by (1);

$$\mu = \frac{1}{n}\sum_{t=1}^{n} s_t \tag{1}$$

where, μ depicts the mean of s_t. Moreover, it reduces errors when predicting sample values for data.

2. Standard deviation (SD)

The *SD* (2) is a measure that provides accurate information about the distribution of samples around the μ.

$$\sigma = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(s_t-\mu)^2} \tag{2}$$

where, σ represents the *SD*, and the low and high value of *SD* denotes less and more spread of samples around μ of data respectively.

3. Energy

The energy provides details about the strength of times series and is used as a key characteristic in the detection task of activities. It is evaluated by (3);

$$E = \frac{\sum_{t=1}^{n} |s_t|^2}{n} \tag{3}$$

where, E denotes the energy of s_t, and it is used as a feature that contributes significantly to the classification of epileptic seizures [4], [13].

4. Kurtosis

The kurtosis expresses the distribution and illustrates that samples are heavy-tailed or light-tailed relative to normal distribution. The low value of kurtosis expresses the lack of tails, while high value shows heavy tails in sample distribution and measured by (4);

$$K_t = \frac{\sum_{t=1}^{n}(s_t-\mu)^4}{n\sigma^4} \tag{4}$$

where, K_t indicates the kurtosis value. Indeed, heavy and light tails of samples mean that distribution is flattened and less flatten compared to normal distribution.

5. Skewness

The skewness (5) provides details about the symmetry or lack of symmetry of sample distribution around the μ.

$$S_k = \frac{\sum_{t=1}^{n}(s_t-\mu)^3}{n\sigma^3} \tag{5}$$

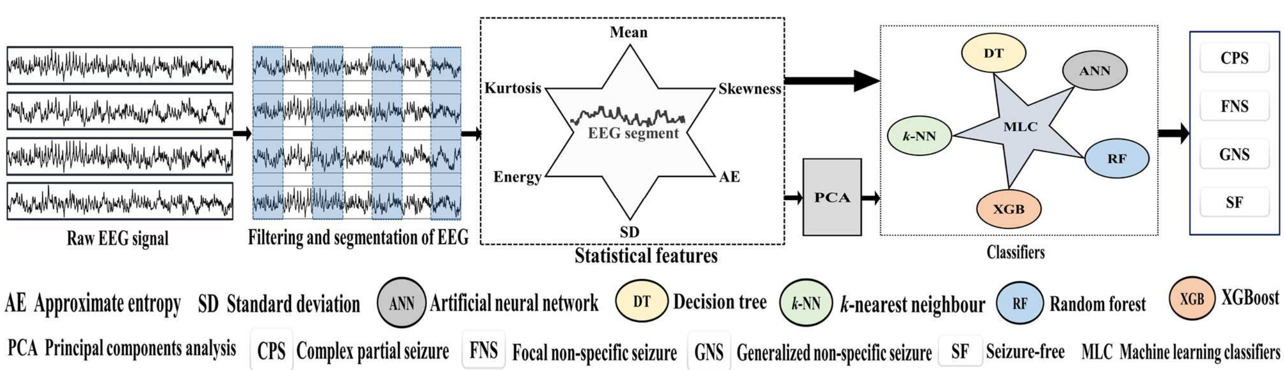

Fig. 1. The outline of the proposed idea for the classification of seizure-free and different seizure types from EEG recordings.

where, S_k represents skewness of s_t. The negative and positive skewness illustrates the left-skewed and right-skewed distribution relative to normal distribution respectively.

6. Approximate entropy (AE)

The *AE* provides information relative to correlation, symmetry, persistence, and uncertainty of variability within the time series [15–16]. The *AE* is computed by reconstructing the time series in phase space based on embedding dimension (m) and time delay (τ) parameters. For the s_t, the phase space reconstructed of vectors v_i and v_j is computed by (6),

$$\left.\begin{aligned} v_i &= s_i, s_{i+\tau}, s_{i+2\tau}, \ldots, s_{i+(m-1)\tau} \\ v_j &= s_j, s_{j+\tau}, s_{j+2\tau}, \ldots, s_{j+(m-1)\tau} \end{aligned}\right\} \quad (6)$$

where, $i, j = \{1, 2, 3, \ldots, (m\text{-}1)\tau\}$ are points in phase space. Next, the distance between vector v_i and v_j is calculated. Thereafter, C_i has been measured by (7), which is the number of j.

$$C_i = \left(n - m + 1\right)^{-1} \sum_{i=1, i\neq j}^{n-m+1} \left(\left\| v_i - v_j \right\|\right) < r \quad (7)$$

where, r represents the radius of similarity. Finally, *AE* (ϕ_m-ϕ_{m+1}) is computed, where ϕ_m is measured by (8);

$$\phi_m = \left(n - m + 1\right)^{-1} \sum_{i=1}^{n-m+1} \log\left(C_i\right) \quad (8)$$

The appropriate values of τ and m are determined by using average mutual information and the false nearest neighbour approaches [16]. Empirically, in this work, the appropriate values of τ and m have been tuned to 1 and 2 respectively. In addition, the value of r has been set to 0.2*variance of data.

C. Machine Learning Classifiers (MLC)

Next, five machine learning classifiers — artificial neural network (ANN), decision tree (DT), *k*–nearest neighbor (*k*–NN), random forest (RF), and eXtreme boosting gradient (XGB) have been employed to classify seizure types. The basic architecture of the classifiers has been discussed below.

1. Artificial Neural Network (ANN)

The ANN is one of the efficient and widely used algorithms of ML in the field of data analysis, and pattern recognition [17–18]. Indeed, each linked neuron of the ANN network is allied with some weights, which keep modifying and updating as the training proceeds [18]. The proposed ANN architecture has depicted in Fig. 2, having one input, four hidden, and one output layer. The non-linear activation function rectified linear unit (ReLU), and softmax function have been applied in hidden and output layers respectively. Finally, the softmax function in the output layer has computed the relative probability distribution of the outcome.

2. Decision Tree (DT)

The DT is an efficient, easy to interpret, and anticipated ML algorithm. Basically, it can regulate high dimensional data with promising performance. The DT is a tree-structured pipeline having internal nodes, branches, and leaf nodes that depict

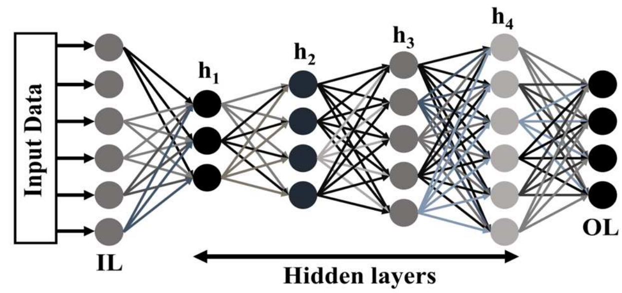

Fig. 2. The proposed architecture of ANN for classification of seizure types — CPS, FNS, GNS, and SF.

features, decision rules, and outcome respectively. Generally, it learns and selects appropriate features using feature selection measures. Following that, recursively tree-structured is partitioned based on features and appropriate outcomes are produced.

3. k-nearest neighbor (k–NN)

The *k*–NN is simple, non-parametric, easy to implement, and widely adopted ML algorithm in various fields [18]. Indeed, it is based on the feature resemblance technique. The *k*–NN algorithm, first evaluates the nearest neighbors based on distance metrics and further using those neighbors to categorize the proper classes. The *k* is a crucial hyper-parameter that depends on input data. In addition, it depicts the number of the nearest numbers considered in making an outcome decision.

4. Random Forest (RF)

The RF algorithm is based on a resemblance learning technique and is efficiently used on a large and complex dataset. Indeed, it consists of many classification trees, and the input vector passes through each of the classification trees [17]. Finally, RF predicts the outcome based on higher votes of prediction provided by classification trees. In addition, the large number of classification trees in RF leads to promising performance and reduces the overfitting problem of the model.

5. eXtreme Gradient Boosting–XGBoost (XGB)

Currently, XGB achieved great success in the field of data analysis and pattern recognition [18]. The XGB algorithm is a fast, scalable, and efficient application of the scalable gradient boosting tree technique. Indeed, it efficiently handles large datasets, as well as improves the execution time and performance of the model. Moreover, it supports parallel processing and has several regularization techniques that reduce the overfitting issue.

D. Principal Component Analysis (PCA)

The PCA is a multivariate approach to analyze the high-dimensional dataset. Certainly, a dataset has a substantial number of inter-correlated dependent observations which cannot be easily analyzed [3], [20]. Indeed, PCA minimizes the complexity of the dataset by transforming it to lower dimensions while preserving characteristics and patterns [20]. Primarily, PCA technique creates a new collection of principal

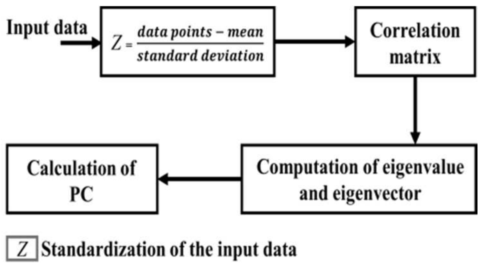

Fig. 3. The stages involved in computing principal components (PCs) using the principal components analysis (PCA) technique.

components (PCs) and expresses the data in terms of them. Certainly, it is significantly easier to decipher and analyze the dataset with small sets of relevant observations. In Fig. 3, steps used to obtain the PCs have been displayed. First, the value of observations is scaled within a certain range, after that, a correlation matrix is obtained, followed by a calculation of the eigenvalue and eigenvector of the matrix. Finally, using these eigenvalues and eigenvectors, PCs are computed.

III. Experiemntal Methodology

A. Data

For experimental validation, a publically available EEG database contributed by the Temple University Hospital (TUH, v1.5.2) has been taken into consideration [21]. In this work, the EEG signals having a sampling rate of 250Hz and recorded through the unipolar average reference montage technique have been used. The common 19 unipolar channels — C3, C4, Cz, F3, F4, F7, F8, FP1, FP2, Fz, O1, O2, P3, P4, Pz, T3, T4, T5, and T6 of EEG recordings have been taken into action. The dataset provides the details of the intervals of seizure types and has been labeled accordingly. In this context, EEG recording of seizure types — CPS, FNS, GNS, and seizure-free (SF) have been considered. The duration of SF recording has been chosen relatively the same as other seizure types. This study has used the EEG recordings of 18 patients in total. Table I, contain the summary of the dataset. The first and second columns, respectively, illustrate seizure types and EEG duration.

B. Experiment Setup

The filtered EEG signal of each seizure type and seizure-free have been decomposed into segments based on the duration of 1s. However, there is no overlapping between consecutive segments. The number of segments constructed for each seizure type is relatively the same. The EEG segments of the T3 channel from CPS, FNS, and GNS have been shown in Fig. 4. Next, statistical features have been extracted from each segment and labeled accordingly. Hereafter, feature sets have been standardized (Z_{data}) before feeding into classifiers by (9).

TABLE I. Description of dataset

Seizure type	Duration (s)
CPS	510.44
FNS	540.14
GNS	567.59
SF	500.00

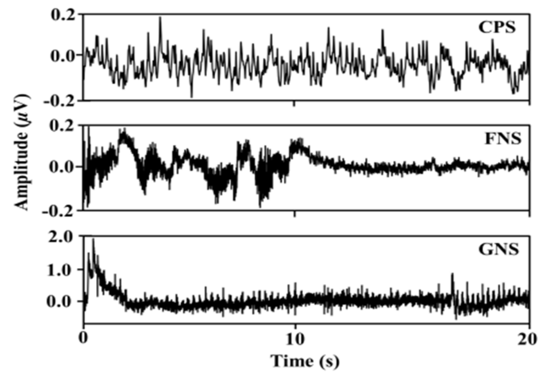

Fig. 4. The EEG signal of three seizure types — complex partial seizure (CPS), focal non-specific seizure (FNS), and generalized non-specific seizure (GNS) has been exhibited (top to bottom) respectively.

$$Z_{data} = \frac{smaple\ value - mean}{standard\ deviation} \tag{9}$$

Subsequently, one-way analysis of variance (ANOVA) testing has been evaluated for each feature to analyze the significance level. The value of p (≤ 0.005 is significant) for kurtosis, skewness, mean, *SD*, energy, and *AE* have been found ≤ 0.001. After that, features have been directly fed into different ML classifiers to discriminate seizure types and seizure-free. Now, the hyper-parameters of classifiers have been tuned properly to achieve promising performance. For ANN, batch size, the number of epochs, and learning rate have been set to 20, 100, and 0.0001 respectively. Besides, Adam (*beta*_1=0.9, *beta*_2=0.999, decay=1e-06) optimizer has been employed to minimize categorical cross-entropy loss. Next, the GridSearchCV technique has been used to tuned parameters of ML classifiers [1–3], [18]. The parameters of classifiers set for which the classification performance demonstrated promising results are — for *k*–NN, the value of *k* set in the range of 5 to 19 and the Euclidean distance metric has been used; in the case of XGB the gamma, the maximum depth, and minimum child weight have been tuned to 1.5, 9, and 11 respectively, while other parameters set to default; for RF the number of trees (estimators) and the maximum depth of tree has been set to 1000, and 10 respectively and other parameters as default; for the splitting of nodes in DT classifiers entropy criterion has been used, while the range is set from 3 to 20 for the maximum depth. Additionally, the classification of seizure type has been also analyzed with different combinations of feature sets. Consequently, the PCA has been used to reduce the dimension of the feature set. Each classifier has performed multi-class classification on the following groups — CPS–FNS–GNS, and CPS–FNS–GNS–SF. For evaluation of the proposed idea, each dataset has been split into training and testing samples in the ratio of 80:20. In addition, for ANN, 20% of training samples have been considered for validation testing.

IV. Results and Discussion

Therein, multi-class classification tasks have been performed on the above discussed groups. For analysis of experimental results performance — accuracy (A_{cc}) (10), and weighted $F1$–score (11) of classification have been verified.

$$A_{cc} = \frac{tn+tp}{tn+tp+fn+fp} \times 100\% \tag{10}$$

$$F1-score = 2 \times \frac{P_r \times R_l}{P_r + R_l} \quad \begin{cases} P_r = \dfrac{tp}{tp+fp} \\ R_l = \dfrac{tp}{tp+fn} \end{cases} \tag{11}$$

where, tp, fp, tn, and fn display true positive, false positive true negative, and false negative respectively. The $F1$–score shows the ability to compute the incorrectly categorized classes.

The classification A_{cc} has been achieved by different classifiers up to 100% with different combinations of PCs obtained by PCA technique. The variance of features (PCs) has been shown in Fig. 5, in which the vertical and horizontal axis shows the percentage of variance and PCs respectively. Now, it can be observed that the highest variance among these features is up to 35%, while the lowest variance of features is ≤ 7.5%. The first component shows the most variance among all PCs, whereas, first three and four PCA components (features) together have explained the variance ≥ 70% and ≥ 80% of total features respectively. Next, in Fig. 6, the classification A_{cc} achieved by ANN, DT, k–NN, RF, and XGB to categorise seizure types (STs) and seizure-free — CPS–FNS–GNS, and CPS–FNS–GNS–SF has been displayed. The horizontal and vertical axis depicts different classifiers and performance metrics (A_{cc}) respectively. It can be noticed that the k–NN performance is superior to other classifiers. In Fig. 7 (a) and (b), the A_{cc} recorded by classifiers when using different combinations of PCs has been displayed. In Fig. 7 (a), the left and right parts show the A_{cc}, when using two and three PCA features respectively. Similarly, in Fig. 7(b) the recorded classification A_{cc} has been shown when four and five PCs have been used as features. From both figures (Fig. 4, and 5), it can be been observed that k–NN can efficiently classify seizure types and seizure-free from EEG. In addition, other classifiers have shown promising performance while using different combinations of PCs as features. The classification results have reached up to 96% and 100% for CPS–FNS–GNS, and CPS–FNS–GNS–SF respectively, when using five PCs as features. However, using two PCs as features, the ANN, DT, k–NN, and RF have achieved classification accuracy ≥ 80%. Besides, XGB has shown promising performance when using three or more PCs as features.

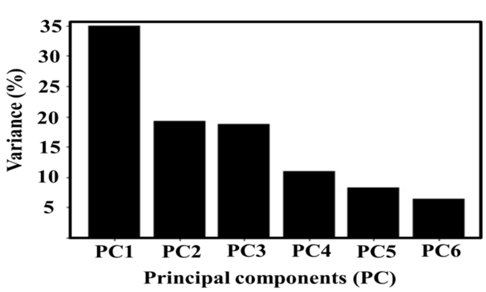

Fig. 5. The PCs (features) obtained by the PCA technique and their fraction of variance have been shown.

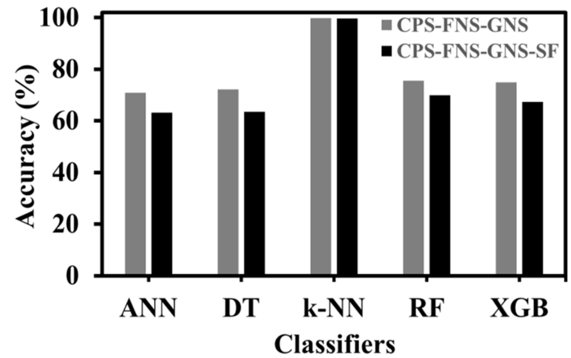

Fig. 6. The recorded classification accuracy by different machine learning classifiers in the classification of seizure types and seizure-free.

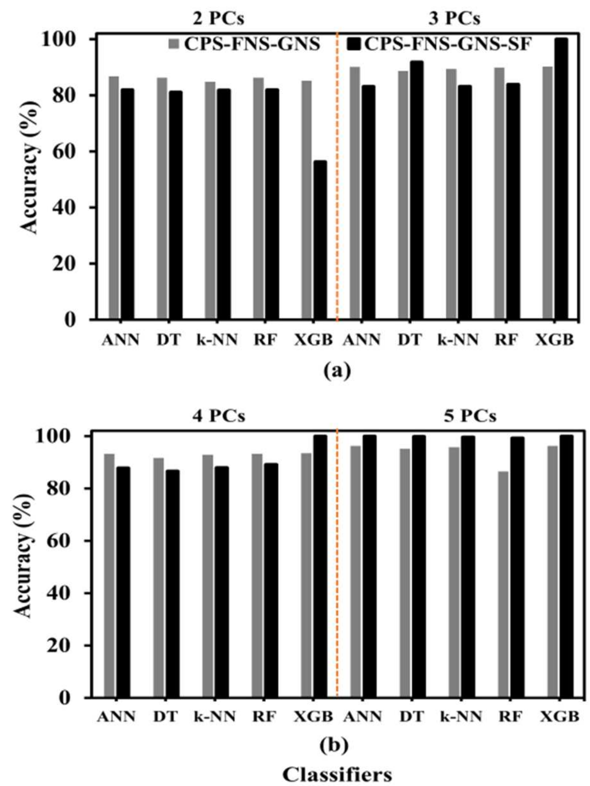

Fig. 7. The accuracy achieved in the classification of seizure types and seizure-free by different machine learning classifiers when using different combinations of PCs (features) (a) two and three PCs, and (b) four and five PCs have been displayed.

The other performance metric, the $F1$–score recorded for the classification tasks, has been summarized in Table II. The classification results recorded with different combinations of PCs have been displayed in the lower section of Table II. It can be realized that all machine learning classifiers have achieved $F1$–score ≥ 81.0% when employing three or more PCs as features. The classification performance metrics indicated that the proposed idea has the potential to efficiently classify different seizure types and seizure-free from EEG. Next, a comparative study with recent works has been summarized in Table III, in which the first, second, and third columns depict recent works, methods, and number of seizure types

TABLE II
CLASSIFICATION PERFORMANCE ACHIEVED BY MLCs

STs	*F*1–score				
	ANN	**DT**	***k*-NN**	**RF**	**XGB**
CPS-FNS-GNS	70.9	71.7	99.8	75.3	74.7
CPS-FNS-GNS-SF	63.2	63.1	99.7	69.4	67.3
PC1+PC2					
CPS-FNS-GNS	86.6	86.1	84.7	86.1	85.1
CPS-FNS-GNS-SF	81.9	81.2	81.9	82.1	56.2
PC1+PC2+PC3					
CPS-FNS-GNS	90.0	88.5	89.3	89.9	90.1
CPS-FNS-GNS-SF	83.4	81.9	83.1	84.0	99.9
PC1+PC2+PC3+PC4					
CPS-FNS-GNS	93.1	91.6	92.8	93.1	93.3
CPS-FNS-GNS-SF	87.7	86.5	87.8	89.0	99.9
PC1+PC2+PC3+PC4+PC5					
CPS-FNS-GNS	96.1	95.0	95.7	96.4	96.1
CPS-FNS-GNS-SF	99.7	99.8	99.8	99.9	99.9

respectively. The experimental results have validated that the proposed work could be helpful in the analysis of seizure types.

V. Conclusions

In this work, three seizure types —complex partial, focal non-specific, generalized non-specific seizures, and seizure-free have been distinguished by machine learning classifiers based on statistical variants extracted from EEG recordings. The different statistical features have been extracted from decomposed segments of long recorded EEG signals and directly fed into machine learning classifiers to categorize seizure types and seizure-free. In addition, classification performances with different combinations of features set have also been analyzed by employing the principal components analysis technique. With favorable and promising experimental results, the proposed work expresses the ability to efficiently classify seizure types and seizure-free from EEG recordings.

TABLE III. A COMPARATIVE STUDY

Works	**Methods**	**MLCs**	**NST**	**PM (%)**	
				A_{cc}	***F*1**
Inung, *et al*., [6]	EEG, S_F	SVM	4	95.0	-
Nataraja *et al*.,[7]	EEG, STFT	CNN	8	84.1	-
Roy *et al*., [8]	EEG, FFT	*k*–NN	8	-	90.1
		XGB		-	86.6
		CNN		-	72.2
David *et al*., [9]	EEG	P–NMN	7	-	94.5
Umar *et al*., [10]	EEG, SES	Deep CNN	8	-	94.0
Raghu *et al*., [22]	EEG, S_P	Pre-trained Deep NNs	7	88.3	-
This work	**EEG, S_F**	**MLCs**	**3**	**99.7**	**99.6**
		PCA, MLCs		**99.9**	**99.9**

Note: NST: number of seizure types, PM: performance metrics, S_F: statistical features, STFT: short-time Fourier transform, FFT: fast Fourier transform, SES: saliency–encoded spectrogram, P–NMN: plastic neural memory network, S_P: Spectrogram, NNs: neural networks.

Acknowledgment

The authors acknowledge Eureka/Sunrise/Early career Project with Ref: NECBH/2019-20/118] under North East Centre for Biological Sciences and Healthcare Engineering (NECBH) Twinning Outreach Programme hosted by Indian Institute of Technology Guwahati (IITG), Guwahati, Assam funded by Department of Biotechnology (DBT), Ministry of Science and Technology, Govt. of India with number BT/COE/34/SP28408/2018 for providing necessary financial support.

References

[1] A. Shoeibi, *et al*.,“Epileptic seizure detection using deep learning techniques: A Review,” *International Journal of Environmental Research and Public Health*, vol. 18, no. 11, pp. 5780, 2021.

[2] Rasheed, Khansa, *et al*., “Machine learning for predicting epileptic seizures using eeg signals: A review,” *IEEE Reviews in Biomedical Engineering*, vol. 14, pp. 139–155, 2021.

[3] M. Zubair, *et al.,* “Detection of Epileptic Seizures from EEG Signals by Combining Dimensionality Reduction Algorithms with Machine Learning Models, ” *IEEE Sensors Journal*, 2021.

[4] Alam, *et al*., “Detection of seizure and epilepsy using higher order statistics in the EMD domain,” *IEEE Journal of Biomedical. Health and Informatics*, vol. 17, pp. 312–318, 2013.

[5] C. Mahjoub, *et al*., “Epileptic seizure detection on EEG signals using machine learning techniques and advanced preprocessing methods,” *Biomed. Eng./Biomedizinische Technik*, vol. 65, no. 1, pp. 33–50, 2020.

[6] Inung, *et al*., “Seizure type detection in epileptic EEG signal using empirical mode decomposition and support vector machine,” *IEEE International Seminar on Intelligent Technology and Its Applications* (*ISITIA*), pp. 314–319, 2019.

[7] Natarajan, *et al*., “A convolutional neural network based framework for classification of seizure types,” 41*st* *Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (*EMBC*), 2019.

[8] Roy, Subhrajit, *et al*., “Seizure type classification using EEG signals and machine learning: Setting a benchmark,” *IEEE Signal Processing in Medicine and Biology Symposium* (*SPMB*), 2020.

[9] David, *et al*., “Neural memory networks for seizure type classification,” 42*nd* *Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (*EMBC*), 2020.

[10] Asif, Umar, *et al*., “SeizureNet: Multi-spectral deep feature learning for seizure type classification,” *Machine Learning in Clinical Neuroimaging and Radiogenomics in Neuro-oncology*, *Springer*, pp. 77–87, 2020.

[11] Tsipouras M. G., “Spectral information of EEG signals with respect to epilepsy classification,” *Journal on Advances in Signal Processing,* vol. 1 , pp. 1–17, 2019.

[12] Al Ghayab, *et al*., “Epileptic seizures detection in EEGs blending frequency domain with information gain technique,” *Soft Computing*, vol. 23, no. 1, pp. 227–239, 2019.

[13] Frolov, N.S *et al*., “Statistical Properties and Predictability of Extreme Epileptic Events,” *Sci. Rep.*, vol. 9**,** 2019.

[14] Elghamry, Hossam, *et al*., “Comparative Analysis of Various Machine Learning Techniques for Epileptic Seizures Detection and Prediction Using EEG Data,” *IEEE Novel Intelligent and Leading Emerging Sciences Conference*, pp. 175–180, 2020.

[15] Waqar, Hussain, *et al*., “Towards classifying epileptic seizures using entropy variants,” *IEEE Fifth International Conference on Big Data Computing Service and Applications*, pp. 296–300, 2019.

[16] Delgado-Bonal *et al*., “Approximate entropy and sample entropy: A comprehensive tutorial,” *Entropy* 21, no. 6, 2019.

[17] Slimen, I. B., *et al*., “Automatic Recognition of Epileptiform EEG Abnormalities Using Machine Learning Approaches,” 5th *International Conference on Advanced Technologies for Signal and Image Processing*, pp. 1–4, 2020.

[18] Mardini, Wail, *et al*. “Enhanced detection of epileptic seizure using EEG signals in combination with machine learning classifiers,” *IEEE Access*, pp. 24046–24055, 2020.

[19] Torla, *et al*., “Machine learning–XGBoost analysis of language networks to classify patients with epilepsy,” *Brain Informatics*, pp. 159–169, 2017.

[20] Jolliffe, Ian T., and Jorge Cadima, “Principal component analysis: a review and recent developments,” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 374, no. 2065, 2016.

[21] Obeid, Iyad, and Joseph Picone., “The temple university hospital EEG data corpus,” *Frontiers in Neuroscience*, 2016.

[22] Raghu S, Sriraam N, Temel Y, Rao SV, Kubben PL. “EEG based multi-class seizure type classification using convolutional neural network and transfer learning,” *Neural Netw*., vol. 124, pp. 202–212, 2020.