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A Hybrid Scheme Using PCA and ICA Based Statistical Feature for Epileptic Seizure Recognition from EEG Signal

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***Abstract*—Epilepsy is one of the most common neurological disorders which can be characterized by repetitive unprovoked seizures. Electroencephalogram (EEG) is the neuro-physiological measurement of the brain's electrical activity recorded by electrodes placed in the cerebral cortex. The EEG signals play an essential role in the diagnosis of epilepsy. This paper proposes an approach for classifying the epileptic seizure patterns that carry significant indications regarding chronic neurological disorders. In this proposed scheme, a hybrid dimension reduction model utilizing Independent and Principal Component Analysis (ICA, PCA) is developed followed by the extraction of statistical features for epileptic seizure identification. The original EEG signals are split into several windows and considered as the input of dimension reduction process. After performing the ICA and PCA, the different components of ICA and PCA are utilized for feature extraction. Finally, the supervised Support Vector Machine (SVM) classifier is employed for the classification purpose. To evaluate the raised method, the publicly available EPILEPTIC dataset is used. According to the experiments and result analysis, the proposed model shows significant performance using the first components of ICA and PCA algorithms.**

***Index Terms*—Epilepsy, Electroencephalogram (EEG), FICA, ICA, KICA, PCA, Support Vector Machine (SVM).**

I. Introduction

Epilepsy is a recurrent disorder of central nervous system (CNS) characterized by the cause of epileptic seizures in which neurological activity of CNS ends up in unusual stages such as sensations, loss of mindfulness, times of surprising conduct etc. At present, particularly a portion of the worldwide population is suffering from this unusual disorder. Moreover it is indeed a tough job to identify epileptic seizures and to diagnose without the cooperation of an expert in case of emergency. Currently the existence of an automated framework which can precisely classify epileptic seizures from Electroencephalogram (EEG) signals has become a highly essential demand to facilitate the experts for easy and fast diagnosis of epileptic seizure patients. Therefore, this problem has received a great attention for the researchers in quest of precise solutions. In [1], two essential feature extraction methods are proposed that mostly rely on the transformation of local patterns, namely the local neighbor descriptive pattern (LNDP) and one-dimensional local gradient pattern (1D-LGP). These computationally simple local pattern transformation based techniques have shown to possess better feature extraction ability than the usual 1-D local binary pattern (1-D LBP) based transformation. In [2], a two-stage classification model using principal component analysis (PCA) and enhanced Neural Network (NN) is proposed for robust identification of epileptic seizures and non-seizure signals.

The two pertinent properties of EEG signals are nonlinearity and dynamism. It is really challenging to decode the slightest variations in EEG signals by means of any visual supervision. To overcome the problem, a Recurrence Quantification Analysis (RQA) method is introduced in [3]. To detect seizures from EEG signal, an ad-hoc technique is described in [4]. In [5], a tunable-Q Wavelet Transform (TQWT) technique is presented for exposing epileptic seizure from scalp EEG signals. Various versatile techniques are suggested in frequency domain [6], [7] and wavelet transforms [8]–[11] analysis of epileptic EEG signals (E-EEGS) detection. In [12], statistical features are used by using wavelet transform for each sub-band of EEG signals followed by PCA and ICA based feature reduction scheme and LDA based classification scheme. In [13], an automatic scheme is presented for diagnosing epilepsy by a complex-valued neural network. The dual-tree complex wavelet transformation (DTCWT) is used for extracting features from EEG signals, followed by the construction of statistical feature vectors for classification. A hybrid SVM classifier proposed in [14] using a genetic algorithm (GA) and particle swarm optimization (PSO) for optimizing the parameters of SVM for diagnosing epileptic seizure. However, finding the discriminant feature from countless EEG time series signal is an extreme assignment.

In this paper, dimension reduction models are exploited to classify epileptic EEG patterns. The PCA and ICA are utilized for dimensionality reduction purpose from the EEG time series data, and factual highlights are separated from the components of ICA and PCA. Later, statistical features

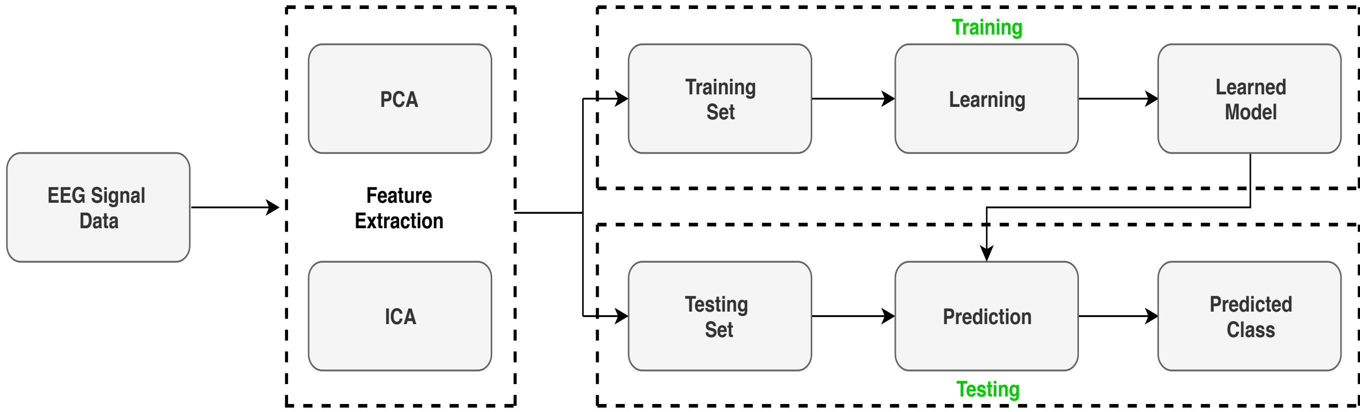

Fig. 1. General block diagram of the proposed hybrid scheme.

are extracted from the selected principal and independent components. The extracted features demonstrate a significant amount of class separation features for classifying the epileptic patterns. Finally, the supervised SVM classifier is utilized in the mentioned hybrid scheme for classifying the epileptic patterns.

The organization of this paper is as follows: Section II presents the methodology of the proposed framework, Section III provides the detailed description of experiments and analysis of the results, and Section IV presents the concluding remarks of the paper.

II. Proposed Method

The basic outline of the raised scheme for classifying the epileptic patterns from the EEG signal is presented in Fig 1. The proposed scheme consists of three major stages. These stages are presented in details in this Section. Typical examples of given EEG signals of 5 different classes are presented in Fig. 2.

A. Dimension Reduction

Dimension reduction is essential for extracting important information from a large signal. In this Section, the dimension reduction algorithms, such as PCA and ICA are utilized for discarding the less important information from the signal. For performing PCA and ICA, the original signal is split into p windows, where $p \in \{2, 4, 6, 8, 10\}$.

1) Principal Component Analysis (PCA): PCA is one of the most popular and important techniques for dimension reduction and feature selection. PCA identifies and expresses the key features from the data in such a way that the whole data is represented in a lower dimension. The features in a time series data are hard to find where the time series is really high dimensional. Therefore, PCA is a powerful tool for analyzing the data [16], [17]. This dimension reduction tool is appropriate when measurements are obtained from a huge number of observed variables. The smaller number of extracted variables is named as principal components (PC). PCA is accountable for most of the variance in the observed variables. It is typically applied to data that are generated from an experimental procedure. In this paper, PCA is applied on one dimensional EEG signal to identify the key features of the given signal by reducing its dimension. The basic algorithm of applying PCA is given below:

1) Let, there is a set of data vectors $X = x^1, x^2, .., x^n$ each consisting of m observations. Now, the data vectors are set up as the columns of an $m \times n$ data matrix X.
2) The mean vector or data average vector are defined as
$$\overline{\mathrm{X}} = \frac{1}{n}\sum_{k=1}^{n} x^k \tag{1}$$
3) Next, the covariance matrix is computed as
$$C = \frac{1}{n-1}\sum_{k=1}^{n}(x^k - \overline{\mathrm{X}})(x^k - \overline{\mathrm{X}})^T \tag{2}$$
4) The computation of the Eigen values and the eigen vectors are performed by applying the eigenvalues decomposition of C. The order of Eigen vectors should be sorted according to their eigenvalues in descending order to form a matrix S.
5) For each $x^1, x^2, .., x^n$ compute $Y^k = S^T x^k$.

For performing PCA on the EEG time series data, firstly the given EEG signal is split into p windows. Then, they become p number of time series of smaller length. These smaller time series are grouped together to form a matrix in order to perform the PCA operation. After performing PCA, the first PC is extracted for each class. For example, the first PC from each class with $p = 4$ is shown in Fig. 3.

2) Independent Component Analysis (ICA): ICA is a non-linear computational feature extraction technique for subdividing the signal into its statistically independent components (ICs) [18]. In the paper, ICA is utilized for reducing the dimension of the original EEG signal and extracting the key independent features of the given signal. ICs of an Epileptic EEG signal are computed by executing the following mathematical computation.

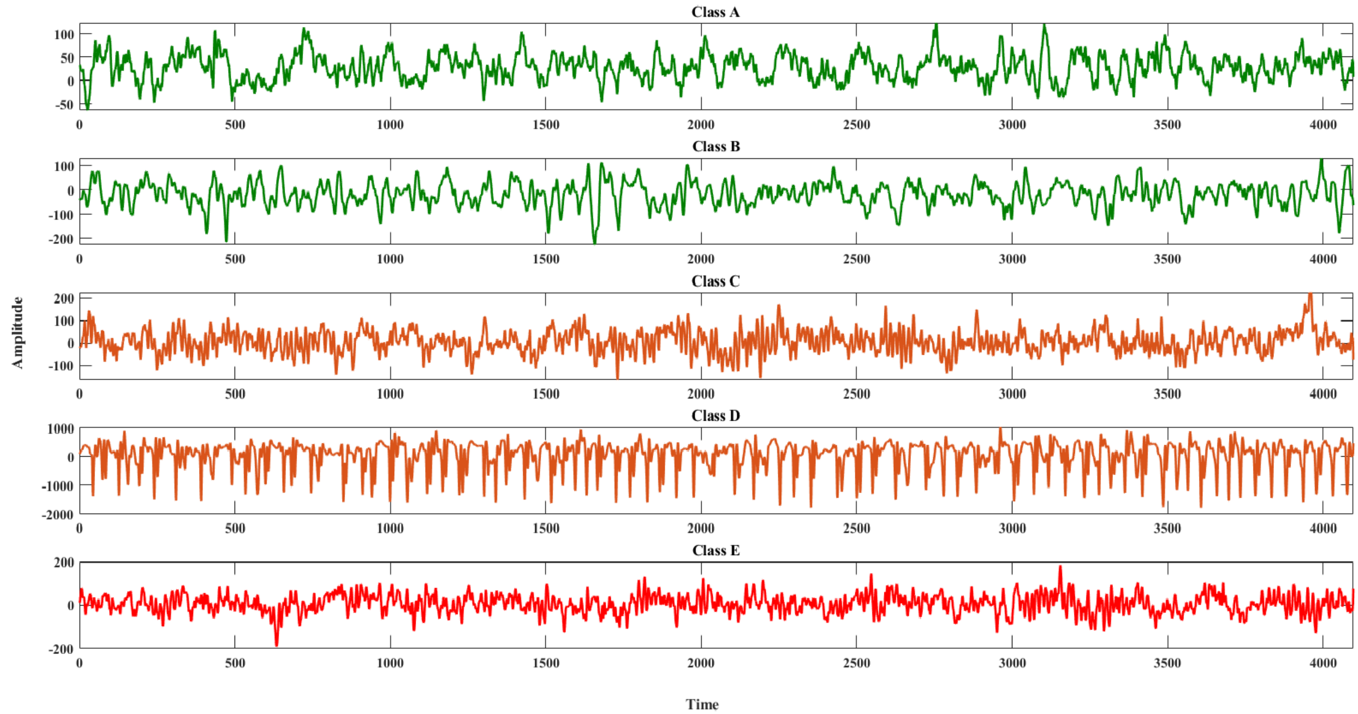

Fig. 2. Typical examples of given EEG signal from each of the 5 class. Class A and Class B are prepared on healthy volunteers based on awake states, such as eyes open and eyes closed respectively. Class C and Class D are prepared by diagnosing the patients before an epileptic attack from the stage of the opposite hemisphere of hippocampal formation of the brain. Class E is prepared during the epileptic seizure attack. The data-set is collected from the Department of Epileptology at Bonn University, Germany [15].

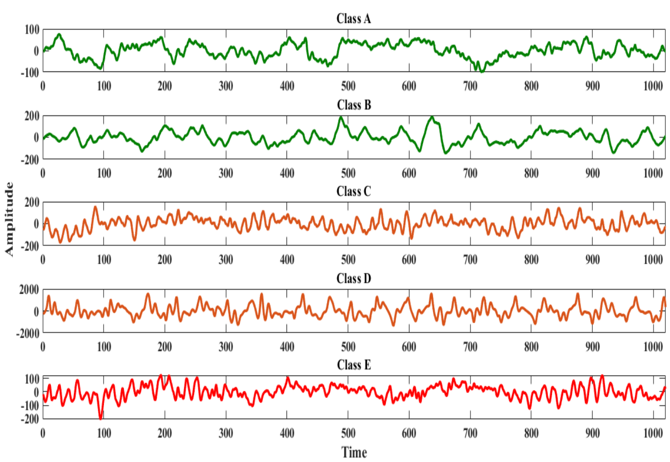

Fig. 3. The sample first principal components of each class.

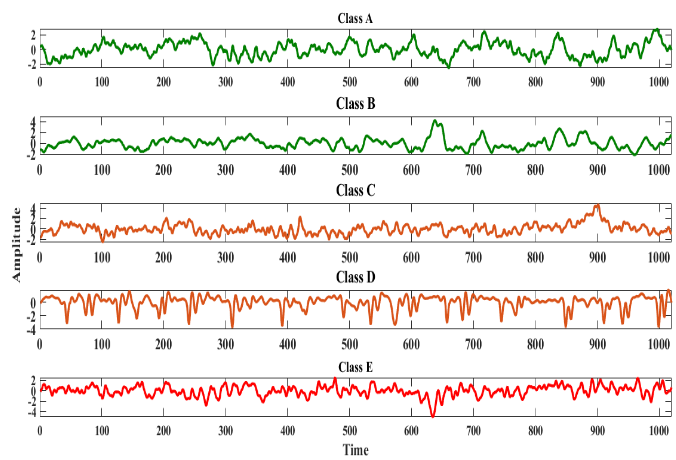

Fig. 4. The first independent components for each class using FICA.

1) Let, there exists n linear vectors computed by mixtures of $N_1, N_2, ..., N_k$ by consisting of k observations. Similarly, x is the source vector formed with $x_1, x_2, ..., x_k$. Then, the weighted matrix is denoted by W with components $a_{i,j}$. Finally the mixing model can be written as

$$N = Wx \tag{3}$$

At times, we need the segments of matrix W; signifying them by a_j the model can likewise be composed as

$$N = \sum_{i=1}^{n} a_i x_i \tag{4}$$

The factual model in Eq. (3) is called ICA. It demonstrates that ICA is a generative model. This implies that it depicts how the watched information are created by a procedure of blending the components x_i.

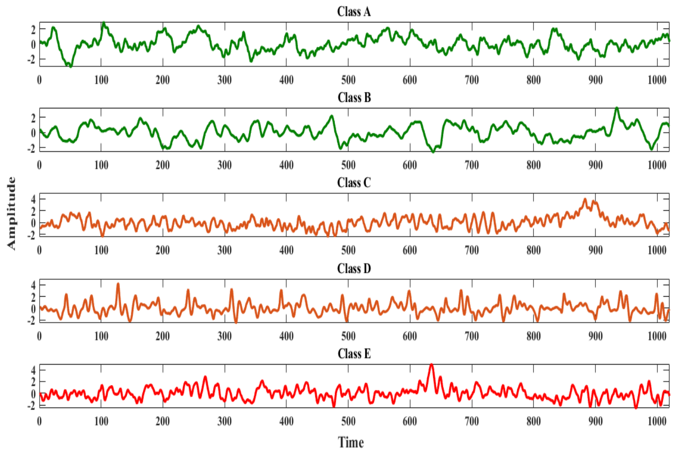

Fig. 5. The first independent components for each class using KICA.

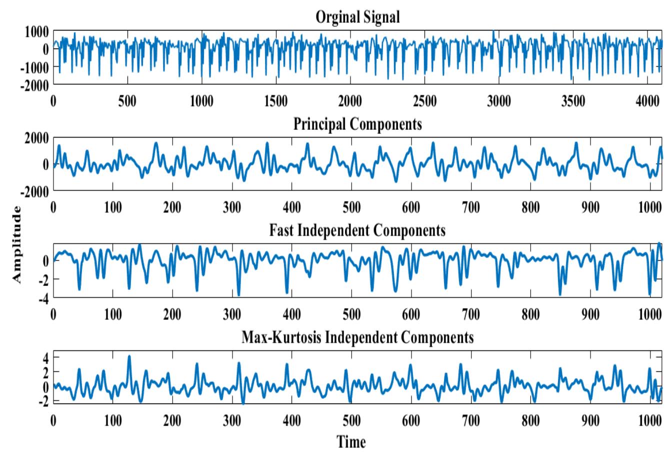

Fig. 6. First components of PCA, FICA and KICA from a given EEG signal.

2) Then, by evaluating the matrix W, we can process its reverse, say A, and acquire the IC defined by:

$$N = Ax \tag{5}$$

where, W and A are the reverse of each other.

In this research, for performing the ICA, the Fast ICA (FICA) and Kurtosis Maximization ICA (KICA) are used. After performing the FICA and the KICA on the matrix mentioned in Section II-A1, first IC of FICA and KICA are extracted for each class. Fig. 4 and 5 represent only the first components using FICA and KICA of EEG signal of each class respectively with $p = 4$. Fig. 6 shows the first components of PCA, FICA and KICA regarding a signal.

B. Feature Extraction

For feature extraction, the statistical features, such as mean, standard deviation (SD), median, energy, and entropy are extracted for the final classification of E-EEGS. After performing the FICA, KICA, and PCA, the statistical features are extracted individually from the first PC of PCA and the first IC of FICA, and KICA. From Fig. 3, 4, and 5, it is observed that the first components extracted from PCA, FICA, KICA of each class are significantly distinguishable. Moreover, it is demonstrated in Fig.6 that the first components of PCA, KICA and FICA from a given EEG signal show significant differentiable characterized nature in terms of their fluctuation. Hence, if features are extracted from all the three first components of a given signal, better classification performance is achievable. Hence, the extracted statistical features from PCA, FICA and KICA are cascaded in order to acquire the final feature vector for the classification.

C. Classification

Support Vector Machine (SVM) is a machine learning algorithm that classifies a given dataset into two classes and even into multiple classes using a hyperplane called margin. SVM is widely known to perform better in feature based approaches than other supervised classifier for two class problems. It has the potential for analyzing data and recognizing patterns and also learning in spaces having high-dimensionality. Unfortunately, there remain the existences of some datasets in numerous applications that can never be separated linearly. More specifically, there is no such hyperplane that can divide nonlinear datasets into two proper categories. To deal with these scenarios, the necessity for a kernel functional raises that can be utilized mostly to specify the diversified relationships between the existing datasets. Polynomial functions, the hyperbolic tangent and the Gaussian radial basis function can be referred to as examples of nonlinear kernel functions. The technique proposed in view of this literature operates on the Gaussian radial basis function kernel. This kernel provides support to the nonlinear classification of attributes of faults. The function is as follows:

$$k(sv_i, sv_j) = \exp\left(\frac{||sv_i, sv_j||^2}{2\delta^2}\right) \tag{6}$$

As parameter, the capacity k forms two separate sources of info sv_i, sv_j. To compute the width of compelling premise, the information parameters or highlight vector are prepared with another free factor, likewise indicated as δ.

III. Result Analysis

A. Description of the Data-set

For the evaluation of hybrid model, the EPILEPTIC dataset is widely used which is developed by the Department of Epileptology at Bonn University, Germany [15]. The data-set contains five different types of subsets, namely A, B, C, D, and E. Every subset contains 100 single channel EEG time series. Each signal is recorded for 23.6s consists of 4097 samples. A 12 bit A/D converter is used for digitizing these EEG signals and the frequency is 173.6 Hz. The subset A and B are prepared on five healthy volunteers based on awake states, such as eyes open and eyes closed respectively. The EEG signals of subset C and D are prepared by diagnosing the patients before an epileptic attack from the stage of the opposite hemisphere of hippocampal formation of the brain. The subset E is prepared during the epileptic seizure attack.

TABLE I
PERFORMANCE (%) OF THE PROPOSED SCHEME FOR VARIOUS COMBINATIONS.
(TRAINING AND TESTING RATIO: (5:5))

S/N	Group	Group Description	PCA			FICA			KICA			Hybrid (PCA+FICA+KICA)		
			Sen.	Spe.	Acc.	Sen.	Spe.	Acc.	Sen.	Spe.	Acc.	Sen.	Spe.	Acc.
1	A-E	Healthy (Eyes Open) - Seizure	69.50	70.50	70.00	62.30	62.90	62.60	62.10	61.90	62.00	100	100	100
2	B-E	Healthy (Eyes Close) - Seizure	67.90	69.10	68.50	48.37	49.30	48.80	61.92	62.08	62.00	98.92	99.04	98.98
3	C-E	Before Epileptic - Seizure	63.92	64.88	64.40	51.30	51.50	51.40	60.52	60.28	60.40	99.70	99.50	99.60
4	D-E	Before Epileptic Attack - Seizure	69.20	70.80	70.00	53.46	53.74	53.60	61.32	61.48	61.40	99.22	99.14	99.18
5	A-C	Healthy - Before Epileptic Attack	64.20	63.00	63.60	47.10	47.30	47.20	62.30	62.10	62.20	99.00	99.04	99.02
6	A-D	Healthy - Before Epileptic Attack	61.30	61.10	61.20	51.00	51.20	51.10	58.30	58.50	58.40	99.00	99.04	99.02
7	CD-E	Before Epileptic Attack - Seizure	64.30	64.50	64.40	46.30	46.50	46.40	59.70	59.50	59.60	97.10	97.30	97.20
8	AB-CD	Healthy - Before Epileptic Attack	59.00	61.00	60.00	48.90	48.70	48.80	59.18	59.22	59.20	97.52	97.28	97.40
9	ABCD-E	Non Seizure - Seizure	60.10	59.10	59.60	50.63	50.57	50.60	59.67	59.93	59.80	98.02	97.98	98.00

TABLE II
PERFORMANCE (%) OF THE PROPOSED SCHEME USING DIFFERENT TRAINING AND TESTING RATIO.

S/N	Group	Hybrid Scheme (PCA+FICA+KICA)+SVM					
		Training and Testing Ratio (6:4)			Training and Testing Ratio (7:3)		
		Sen.	Spe.	Acc.	Sen.	Spe.	Acc.
1	A-E	100	100	100	100	100	100
2	B-E	99.12	99.24	99.18	99.72	99.48	99.60
3	C-E	99.98	99.94	99.96	100	100	100
4	D-E	99.42	99.22	99.32	99.86	99.60	99.73
5	A-C	99.22	99.14	99.18	99.73	100	99.87
6	A-D	99.22	99.14	99.18	99.73	99.47	99.60
7	CD-E	97.96	98.08	98.02	99.33	98.54	98.93
8	AB-CD	99.00	99.00	99.00	99.16	99.24	99.20
9	ABCD-E	98.96	98.76	98.86	99.47	99.73	99.60

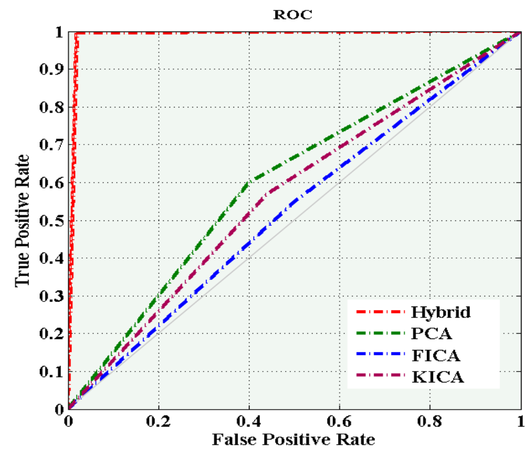

Fig. 7. The receiver operating characteristic (ROC) curves of PCA, FICA, KICA and the hybrid scheme for case ABCD-E.

The whole dataset is randomly branched into two parts by taking 50%, 60%, and 70% of EEG signals for training and the rest of 50%, 40%, and 30% respectively are used for testing purpose. In this way, all the experiments are done by 250 times and their mean accuracy is reported in Table I and Table II.

B. Parameters of Performance Evaluation

To evaluate the proposed scheme, the standard performance measures, such as Sensitivity (Sen.), Specificity (Spe.) and Accuracy (Acc.) are described below in equations (7-9):

$$Sen. = \left(\frac{T_p}{T_p + F_n}\right) \times 100\% \tag{7}$$

$$Spe. = \left(\frac{T_n}{T_n + F_p}\right) \times 100\% \tag{8}$$

$$Acc. = \left(\frac{T_p + T_n}{TotalTestPatterns}\right) \times 100\% \tag{9}$$

where, T_p and F_p represent the correctly classified positive patterns and falsely classified positive patterns respectively. Similarly, T_n and F_n represent true negative patterns and false negative patterns respectively.

C. Epilepsy Classification Performance

In order to show the performance of the proposed scheme, the five classes of data are grouped differently for classification. $p \in \{2, 4, 6\}$ is used for experimentation and similar performance is found in all cases. Hence, $p = 4$ is employed for reporting the results in the rest of the paper. The results are demonstrated in Table I and Table II, which are shown the experimental results for 5:5, 6:4 and 7:3 training and testing ratio. For example, the first row of the Table presents the performance of Class A versus Class E (A-E) problem with sensitivity, specificity and accuracy in term of training and testing ratio 5:5. Similarly, the performance of B-E, C-E, D-E, A-C, A-D, CD-E, AB-CD and ABCD-E problems are also reported in Table I. Moreover, features are individually extracted using PCA, FICA and KICA and their performance is also reported in the Table for comparing the performance with the raised hybrid scheme. From the Table, it is observed that the result of the proposed hybrid scheme outperforms than the results of individual PCA, KICA and FICA features. Fig. 7 shows the receiver operating characteristic (ROC) curves of PCA, FICA, KICA and the hybrid scheme for case ABCD-E. It is observed from the figure that the hybrid scheme shows significantly better performance than individual features.

For evaluating and comparing the performance of the proposed method with other state-of-the-art, the accuracy and corresponding feature dimension are reported in Table III. In the comparison Table, third (7:3) experimental results are

TABLE III
ACCURACY (%) COMPARISON OF THE PROPOSED SCHEME WITH OTHER STATE-OF-THE-ART METHODS.

Authors	Feature Number	Methods	A-E	B-E	C-E	D-E	A-D	CD-E	ABCD-E
[1]	256	LNDP+ANN	99.82	99.25	99.02	98.18	99.90	98.88	98.72
[13]	5	DTCWT+CVANN	99.30	–	–	99.30	99.30	98.28	99.15
[19]	2300	Permutation entropy+SVM	93.55	82.88	88.00	79.94	–	–	–
[20]	252	DTCWT+GRNN	100	100	100	98.50	–	98.67	–
[1]	256	1D-LGP+ANN	99.80	98.92	99.10	99.07	99.37	98.78	98.95
[21]	58	1D-LBP(all)+BayesNet	99.50	–	–	95.05	97.00	95.66	–
[21]	58	1D-LBP(u2)+BayesNet	98.00	–	–	95.50	99.50	97.00	–
[22]	6	DWT+SVM	100	100	99.6	95.85	–	–	97.39
Proposed Method	15	(PCA+FICA+KICA)+SVM	100	99.60	100	99.73	99.60	98.93	99.60

shown. It is illustrated that the proposed scheme performs significantly well than other state-of-the art.

IV. CONCLUSION

An efficient and robust classification scheme is introduced for diagnosing epilepsy from EEG signals. In the proposed hybrid framework, different dimension reduction algorithms, such as PCA, FICA and KICA are exploited for extracting efficient features of EEG signals. After performing the dimension reduction models, the different components of ICA and PCA are analyzed for feature extraction. For feature extraction, various statistical parameters are calculated. Finally, the SVM classification algorithm is employed for identifying the epileptic patterns. It is found that taking features from different dimension reduction schemes provide better performance than to take features from individual models. To validate the proposed model, a publicly available dataset is used. By introducing the dimension reduction scheme based on PCA and ICA, the proposed model shows satisfactory performance in comparison to the other state-of-the-art methods.

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