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Epileptic EEG signal classification using optimum allocation based power spectral density estimation

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Abstract: This study proposes a novel approach blending optimum allocation (OA) technique and spectral density estimation to analyse and classify epileptic electroencephalogram (EEG) signals. This study employs the OA to determine representative sample points from the original EEG data and then applies periodogram (PD), autoregressive (AR), and the mixture of PD and AR to extract the discriminative features from each OA sample group. The obtained feature sets are evaluated by three popular machine learning methods: support vector machine (SVM), quadratic discriminant analysis (QDA), and *k*-nearest neighbour (*k*-NN). Several output coding approaches of the SVM classifier are tested for selecting the best feature sets. This scheme was implemented on a benchmark epileptic EEG database for evaluation and also compared with existing methods. The experimental results show that the OA_AR feature set yields better performances by the SVM with an overall accuracy of 100%, and outperforms the state-of-the-art works with a 14.1% improvement. Thus, the findings of this study prove that the proposed OA-based AR scheme has significant potential to extract features from EEG signals. The proposed method will assist experts to automatically analyse a large volume of EEG data and benefit epilepsy research.

1 Introduction

The human brain is made up of a huge number of brain cells that are connected to each other. These links help transform the tiny electric signals generated by their activities and any defect in these connections can lead to a disorder in the brain. Electroencephalograms (EEGs) are the recordings of tiny electrical signals from the electrodes placed on the scalp. The EEG signals are affected by the neural activities. One of the abnormal activities is caused by epilepsy. Epilepsy is a neurological disease that affects the human brain. It causes seizures of involuntary activity that may involve parts or all of the body. Once the seizures appear, they impair patients' daily lives [1]. It is easy to treat the epileptic seizures with inexpensive medication when diagnosed early. However, it is not efficient to identify epileptic EEGs through visual examination by a specialist [2]. In order to detect epileptic seizures, a variety of methods have been developed to analyse and classify the EEG signals. Those methods can be grouped based on feature extraction. There are methods from time domain, frequency domain, time–frequency domain, traditional non-linear method, and graph theory [3].

One of the methods in time domain is the principal component analysis (PCA). This approach is used to reduce the large number of data and select the most important components as the features. The researchers in [4–6] applied the PCA to classify the epileptic EEG signals.

In terms of frequency domain, power spectral density (PSD) estimation methods are widely used to extract features in EEG signals. These methods can be grouped into categories of non-parametric approaches and parametric approaches. Periodogram (PD) is a non-parametric method and used to determine the estimate of the PSD [7]. An autoregressive (AR) model is a parametric approach [8]. So far much research work has been done by using the AR method for classifying EEG data [7, 9–11].

A wavelet transform is often employed to extract the features, the wavelet coefficients, in EEG signals. These coefficients represent EEG signals in time and frequency domain. A variety of wavelet transforms have used the time–frequency domain to analyse and classify the EEG signals [11–13].

Complex networks based on graph theory were developed to classify EEG signals, as reported by [14]. To reduce the dimensionality of the EEGs, a statistical model was employed in that study. The statistical features were mapped into undirected complex networks to extract the representative features. The attributes of the structural networks were extracted and fed to different classifiers. Zhu *et al.* [15] used a horizontal visibility graph to estimate alcoholic EEG signals. A statistical method was employed to select the best channels and detect the abnormal EEG signals. The selected channels were forwarded to two different classifiers [support vector machine (SVM), and *k*-nearest neighbour (*k*-NN)].

Nicolaou and Georgiou [16] provided a technique to detect epileptic seizures automatically. This technique employed a permutation entropy method to extract the key features from epileptic EEG recordings. Those features were utilised as the input to a SVM classifier. An average of 86.10% accuracy was achieved with the SVM and a permutation entropy. Song and Zhang [17] detected epileptic seizures using EEG signals based on a discrete wavelet transform. This approach decomposed EEG signals into five EEG sub-bands and extracted non-linear features, which are permutation entropy, sample entropy, and Hurst exponent. These features were extracted and used as the features set. An extreme learning machine was applied to evaluate the extracted non-linear features. The approach attained an 85.9% classification accuracy. In order to enhance the accuracy, they developed a genetic algorithm technique to select the most significant features from the extracted features. This method obtained a 94.2% classification accuracy with the extreme learning machine.

Samiee *et al.* [18] used the conception of an adaptive and localised time–frequency for the epileptic seizure detection. A rational discrete short-time Fourier transform was implemented to extract the features from multichannel EEG signals. The extracted features were forwarded to a multilayer perceptron classifier. A 98.1% overall classification accuracy was achieved in that study.

In 2016, Alcin *et al.* [19] applied a time–frequency image based on a grey-level co-occurrence matrix and filter vector method to extract the key features for epileptic EEG classification. The obtained features were utilised as the input into an ELM classifier. A 96.4% overall classification accuracy was achieved. Al Ghayab *et al.* [20] employed a simple random sampling technique combined with a sequential feature selection method to represent different combinations of epileptic EEG features. The extracted features were evaluated by applying a LS-SVM classifier. This technique gained a 99.9% accuracy from the most discriminative epileptic EEG features. A complete ensemble empirical mode decomposition with noise was developed by Hassan and Subasi [21]. From this model, six spectral moment features were extracted and forwarded to a classifier. The researchers applied a linear programming boosting classifier to perform classification and the method achieved 99.2 and 100% accuracy for E versus (A, B, C, D) and E versus A cases, respectively. In the same year, Djemili *et al.* [22] proposed an empirical mode decomposition method to extract features from the epileptic EEG data. Those features were fed to a multilayer perceptron neural network classifier and yielded 100 and 97.7% classification rates between A versus E and D versus E classes, respectively.

More recently, Patidar and Panigrahi [23] presented a new technique to discriminate the seizure-free segments from the epileptic seizure EEG signals by using the tunable *Q*-factor wavelet transform and Kraskov entropy. The approach achieved 97.75% accuracy with a least square SVM (LS-SVM) classifier. Satapathy *et al.* [24] used an integration of the best attributes of the artificial Bee colony and a radial basis function network in order to analyse EEG signals, and to classify the epileptic seizures. A 98% of average accuracy was gained with the method and an inverse multi-quadric kernel. Bhati *et al.* [25] designed a time–frequency localised three-band wavelet filter bank to classify the epileptic EEG signals based on a multi-layer perceptron neural network. The designed method was yielded 99.33% classification rate. Also, two techniques were used to extract the key features, which were local neighbour descriptive pattern and one-dimensional local gradient pattern by Jaiswal and Banka [26]. In order to select the most accurate classifier, the researchers applied different classifiers, such as *k*-NN, the SVM, the decision tree, and an artificial neural network. The best accuracy gained was 99.82 and 99.8% with the two techniques and the artificial neural network, respectively.

From our team's work, Zhu *et al.* [27] proposed a multi-scale *K*-means approach to detect the epileptic seizures from EEG signals. In order to find these seizures, the researchers extracted six key features by using sample entropy method and yielded 100, 99, and 99.1% classification accuracies for three cases (A versus E, B versus E, and AB versus CDE), respectively. In 2014, Zhu *et al.* [28] provided a fast weighted horizontal visibility graph to differentiate the epileptic patients from healthy people. They obtained 100, 93, and 95.4% accuracies for A versus E, D versus E, and ABCD versus E, respectively.

In the same year (2014), a combination of simple random sampling technique with J48 algorithm was implemented and achieved 100, 95.6, and 97.3% classification accuracy for three group: A versus E, B versus E, and C versus E, respectively, by Wang *et al.* [29].

Also, in 2014, Siuly and Li [30] introduced an optimum allocation (OA) technique to select the most represented samples from all EEG samples. A multiclass LS-SVM classifier was employed to classify the features by the OA technique. The study investigated four output coding techniques for the multiclass LS-SVM. The techniques were one versus one (1vs1), one versus all (1vsA), minimum output codes, and error correcting output codes being applied with the multiclass LS-SVM for classifying the multichannel epileptic EEG signals. An average of 99.9% classification accuracy was obtained in that study. Moreover, a clustering technique based on a LS-SVM was proposed by Siuly *et al.* [31]. A 99.9% classification accuracy was yielded by using clustering technique.

In this paper, an automatic feature extraction scheme is proposed based on OA and PSD estimate for extracting discriminative patterns from epileptic EEG data. First, the OA technique is used in two stages: (i) to determine sample size; and (ii) to partition data. The OA technique is used to reduce the huge number of EEG signals and to extract the most relevant features. Second, the extracted features are mapped into PSD estimation methods to reduce the high dimensionality. These methods are the PD and the AR. The obtained features from the proposed scheme are denoted as OA_PD, OA_AR, and OA_PD_AR sets. Then, the feature sets are fed to three popular classifiers, which are a SVM, quadratic discriminant analysis (QDA), and *k*-NN. For further investigation several output coding schemes for the SVM classifier, including 1vs1, all pairs (AP), 1vsA, binary complete (BC), ternary complete (TC), ordinal (OR), sparse random (SR), and dense random (DR), are tested for selecting the best parameters.

From the above discussion of the existing methods, there are several challenges in the epileptic EEG classification techniques. One of the challenges is their limited effectiveness. For example, some techniques do not work effectively for big data. Second, all the methods that applied the SVM classifier did not apply any of the eight output coding techniques: namely 1vs1, AP, 1vsA, BC, TC, OR, SR, and DR. In this research, the OA combined with a PSD estimate method is proposed to classify EEG signals.

The organisation of the rest of the paper is as follows. In Section 2, the data used in this study are described. In Section 3, the methodology of the proposed method is illustrated. The performance measurements are introduced in Section 4. Section 5 discusses the experimental results. Finally, the conclusion is presented in Section 6.

2 Epileptic EEG data

In this study, popular datasets have been used which were utilised in many research studies [16, 18, 20, 30, 32]. The datasets are open source and available in [33]. They were collected by Bonn University, Germany. The datasets include five classes of EEG recordings and are noted as: class A and class B from five healthy volunteers with eyes open and closed, respectively, while classes C, D, and E from another five epileptic patients. Classes C and D were recorded from five epileptic subjects during inter-ictal time periods (free of seizures). Class E was taken from five patients through ictal duration (seizures activity). Each class has 100 channels of EEG signals with each having 4096 data points. The EEG time duration for each class was 23.6 s, as explained in [34].

3 Proposed methodology

This study proposes a dynamic method to classify EEG epileptic data. Fig. 1 clarifies the structure of the proposed method. The sample size is calculated to determine the size of the selected samples (data points) in each class. This study divides EEG signals into *k* segments for making the signal quasi-stationary. The OA technique is applied to reduce the big data of EEG signals and select the most significant samples in the set of OA_sample. This study also investigates whether the PSD estimation methods are suitable for the OA technique for reducing the dimensionality of epileptic EEG signals.

Based on a PD and an AR, these estimation methods of PSD are conducted to generate three distinct feature sets which are denoted as OA_PD, OA_AR, and OA_PD_AR. The features sets with various classifiers are extracted and tested. The classifiers are a SVM, QDA, and *k*-NN, which are popular and widely used. All details of the proposed scheme are explained in the following sections.

3.1 Feature extraction

EEG signals normally contain a huge number of data points. Feature extraction techniques are applied to reduce the data size, and to achieve better performance. In this framework, the feature extraction stage includes several phases in this paper. Those phases are explained in the following subsections. The diagram of the methodology is shown in Fig. 1.

3.1.1 Sample size calculation (SSC): In this study, we need to calculate the sample size from each class of the EEG data (classes

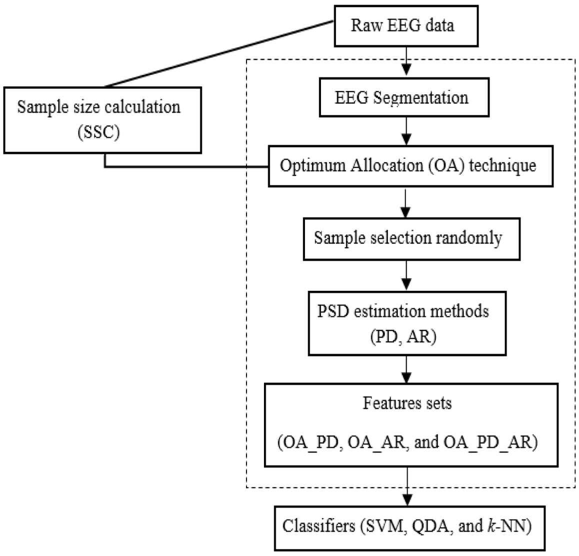


Fig. 1 *Block diagram of the proposed scheme for the automatic epileptic EEG signals classification*

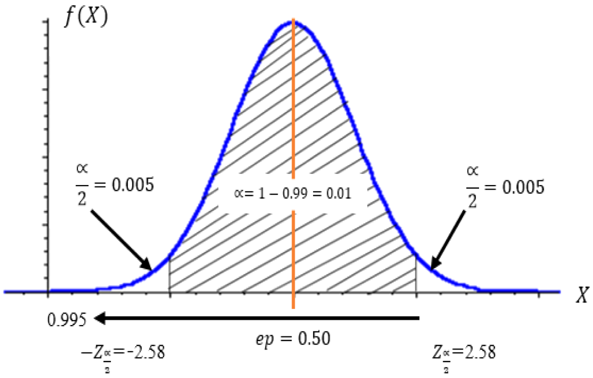


Fig. 2 *Curve of the standard normal distribution to calculate Z-score of confidence level 99%*

A–E of EEG recordings as mentioned in Section 2). The samples are a part of a statistical population whose properties are studied to obtain the information about the whole data. In this study, a number of samples are chosen from each class to extract key features. Thus, the sample size is the number of the key features that are included in the sample. It is determined by using sample size calculator software [35]. The formula of the SSC is presented below [6, 36]:

$$\mathrm{SSC} = \frac{Z^2 \times \mathrm{ep} \times (1 - \mathrm{ep})}{\propto^2} \tag{1}$$

where SSC is the calculated sample size; Z refers to the value of confidence level (Z-score); ep is the estimated proportion of a feature in the whole EEG data (if ep is not known the biggest sample size needs to be created). The value of ep is set at 0.5; $\propto$ is the confidence interval (margin of error).

In order to select the appropriate Z-score and $\propto$ when the confidence level is 99%, the $\propto = 0.01$ and $\propto$ is split evenly into two parts as shown in Fig. 2. From Fig. 2 the calculated Z-score is (Z = 2.58) [37]. Based on (1), the SSC is calculated for the whole dataset for the five epileptic EEG classes. This research used (2) to calculate the SSC for each class [6]

$$\mathrm{SSCoC} = \frac{\mathrm{SSC}}{1 + (\mathrm{SSC} - 1)/C} \tag{2}$$

where SSCoC is the calculated sample size for each class (refer to Section 3.1.1 for details); C is the size of an EEG class ($C = 4097$). From (2), we obtain the sample size of each class as SSCoC = 3288.

3.1.2 EEG segmentation: EEG signals are non-stationary, having a random distribution or pattern that can be analysed statistically but cannot be predicted accurately [30]. To make a signal more stable for obtaining better classification results, the signal was split into smaller segments, with a short time period.

The signal becomes quasi-stationary within the small period of time. In this study, the EEG recordings were divided into a number of small units called segments ($S_1, S_2, \ldots, S_k$) as shown in Fig. 3. K segments are chosen experimentally in this paper. The formula of the k-segment determination is presented below:

$$K = \mathrm{floor}\left(\frac{\mathrm{DS}}{P}\right) \quad P = S_1, S_2, \ldots, S_n \tag{3}$$

where K is the number of segments, DS is the data size in each class, and P is the number of data points per segment. In this scheme, each class of the EEG signals is partitioned into four k-segments and each segment has 5.9 s, when the data size of each segment is $S_1 = 1024$, $S_2 = 1024$, $S_3 = 1024$, and $S_4 = 1025$, respectively. This technique has an ability to analyse the EEG signals in real time. As the proposed algorithm splits the EEG signals into smaller segments with a shorter time period, that makes it easier to apply in real time.

3.1.3 Optimum allocation: The OA is an approach used in stratified sampling to allocate the numbers of sample units to different segments to provide the best accuracy [17]. In this framework, the OA is applied to randomly select the number of samples from different segments for each class as appeared in Fig. 3. This technique can predict the number of samples from each class by using (4) [6], based on the SSC as mentioned in Section 3.1.1

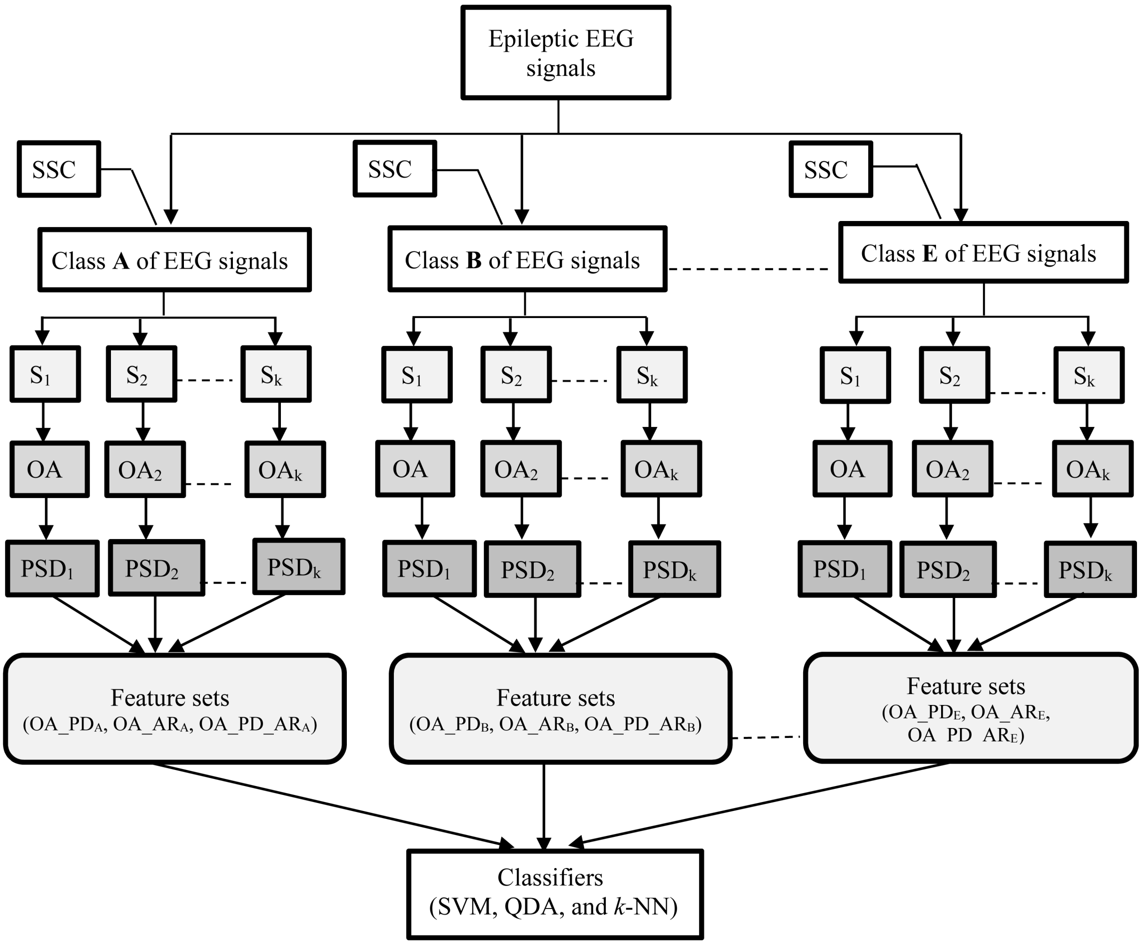


Fig. 3 *Extracted feature sets based on the OA and PSD methods. SSC, sample size calculation; S_k, the number of segments; OA_k, optimum allocation in k segment; PSD_k, power spectral density methods (PD, AR) in k segments*

$$\mathrm{SSC}(i) = \frac{S_i\sqrt{\sum_{j=1}^{p} E_{ij}^2}}{\sum_{i=1}^{k}\left(S_i\sqrt{\sum_{j=1}^{p} E_{ij}^2}\right)} \times \mathrm{SSCoC} \qquad (4)$$

where SSC(i) refers to the number of samples selected from each segment, S_i is the data size of each segment, $E_{ij}{}^2$ is the variance of the jth channel of the ith segment, SSCoC is the sample size of each epileptic EEG class calculated by (2). The sum of SSC(i) from each segment of the EEG class is 3288 samples.

In this schema, the EEG data of each class contains 4096 observations and 100 channels. Each class was divided into four k segments ($k = 4$) (refer to Section 3.1.2 for details) and p is the number of channels in each EEG class ($p = 100$). The size of the four segments of S_1, S_2, S_3, and S_4 are 1024, 1024, 1024, and 1025, respectively. The OA technique is used to choose the number of samples from each segment of that epileptic EEG class.

3.1.4 Power spectral density estimate method: In this study, two estimate approaches of PSD are utilised. One of these methods is PD. The PD is basically equal to the Fourier transform of the biased autocovariance, which is a non-parametric method. This method can detect the EEG power density of the frequency components in a signal. The formula of the PD is presented in the following equation [7]:

$$\widehat{\mathrm{PD}}(f) = \frac{\Delta t}{N}\left|\sum_{n=0}^{N-1} x_n \mathrm{e}^{-\mathrm{i}2\pi f n \Delta t}\right|^2, \quad -1/2\Delta t < f \le 1/2\Delta t \qquad (5)$$

where $\widehat{\mathrm{PD}}(f)$ is the estimated value (PD), Δt is the sampling interval, N is a number of samples in a signal, x_n denotes the signal, and f is the sampling frequency. In this study, after the OA technique is applied to select the most discriminative sample from each segment, the PD is used to extract the power density values from the selected samples as in Fig. 3.

Also an AR method is used in this investigation. The AR model is a linear prediction method to predict an output of a signal based on the previous outputs. The AR method is a spectral density estimation method, which is a parametric method for the PSD estimation [8]. The AR is used to determine the features of an EEG signal in this paper. The order p of the AR is presented below [9]:

$$\mathrm{AR}_t = -\sum_{m=1}^{p} \alpha_m \mathrm{AR}(t-m) + \epsilon_t \qquad (6)$$

where AR_t is a time series to be modelled, p refers to the number of time points in the past, α_m is modelling coefficients, and ϵ_t is a white noise (error term) which is selected best on the previous points, respectively. From the data $p + 2$ parameters, which are the coefficients, expected sample value, and variance of error term, are estimated in model 1. There are a set of equations, which are used to resolve the estimation problem of these parameters. The AR power spectral estimation of data from the order p is given in the following equation [7]:

$$p(f) = \sigma_p^2 \Delta t / \left| 1 + \sum_{m=1}^{p} \alpha_{pm} \exp(-j2\pi f m \Delta t)\right|^2 \qquad (7)$$

where $a_{p0} = 1$. In order to estimate the AR parameters, only p number of α_{pm} and $\sigma_p{}^2$ parameters are appropriate AR coefficients, which can be used to identify the amplitude rates, and can be calculated using the Burg method. The Burg algorithm, which is the most popular algorithm for estimating parameters, has been applied in this research [7, 38–40]. The initial values of the

Table 1 Results of the model selection of p for AR technique

	Accuracy, %		
P order	$p = 6$	$p = 7$	$p = 8$
Classifier	OA_AR	OA_AR	OA_AR
SVM	100	100	100
QDA	99.92	99.94	99.84
k-NN	100	100	99.96

algorithm for computing the parameters of the AR for order p are chosen as appeared in formulas (8)–(14)

$$\alpha_{11} = \frac{-R_{xx}(1)}{R_{xx}(0)} \tag{8}$$

$$\sigma_1^2 = \left[1 - \alpha_{11}^2\right] R_{11}(0) \tag{9}$$

For $k = 2, 3, 4\ldots$

$$\alpha_{kk} = -R_{xx}(k) + \sum_{m=1}^{k-1} \alpha_{k-1,m} R_{xx}(k-m) / \sigma_{k-1}^2 \tag{10}$$

$$\alpha_{ki} = \alpha_{k-1,i} + \alpha_{kk}\alpha_{k-1,k-i}, \quad i = 1, 2, 3, \ldots, k-1 \tag{11}$$

$$\sigma_k^2 = \left[1 - \alpha_{kk}^2\right] \sigma_{k-1}^2 \tag{12}$$

where $R_{xx}(k)$ refers to the estimation of the eigen relationship function of the process. When the processes are finished

$$\alpha_i = \alpha_{pi}, \quad i = 1, 2, 3, \ldots, p \tag{13}$$

$$\sigma^2 = \sigma_p^2 \tag{14}$$

Equations (8)–(14) are used to determine the parameters of the AR method. In this method, it is very important to select the order of the model. If the order of the AR method is low, their specific peak does not exist. If the order of this model is very high, misleading and wrong peaks would occur and spectra degenerate. In order to select the order of the AR method, the Akaike information criterion, which is a well-known criterion for selecting the model order [39], is used in this study. The order p is selected as 7 [7] as shown in Table 1.

3.2 Classification methods

After the features extraction, three different feature sets (OA_PD, OA_AR, and OA_PD_AR) were extracted by applying the OA technique and PSD estimation methods and forwarded into different classifiers as shown in Fig. 3. In this study, the SVM, QDA, and KNN classifiers were employed to select a suitable classifier for the obtained feature sets. All details of these classifiers are explained below.

3.2.1 Support vector machine: The SVM was developed by Cortes and Vapnik [41] and has become one of the most widespread classification methods. Generally, the SVM is used to separate the extracted feature sets into two classes through finding an optimal hyperplane. A study by Dagher [42] presented a quadratic kernel-free non-linear SVM which was used in this research. The quadratic function was utilised to split the feature sets non-linearly as can be found in [42]. Furthermore, various output codes are examined to solve the multiclass categorisation problem [43]. In this paper, eight output coding approaches: 1vs1, AP, 1vsA, BC, TC, OR, SR, and DR, are used to reformulate the problem into a set of binary classification problems. The best output coding is selected for the extracted feature sets.

3.2.2 Quadratic discriminant analysis: The QDA is a common supervised classification method [44] and is closely related to a linear discriminant analysis. The QDA presumes the covariance matrix can be different for each class and uses a simple max gate function as a classification rule [45]. The equation of the QDA is given below [46, 47]:

$$f_i(X) = -\frac{1}{2}(X - \mu_i)^{\mathrm{T}} \mathrm{Cov}_i^{-1}(X - \mu_i) + \log \pi_i \tag{15}$$

where X is a member of class i, μ refers to the mean value of each class, T is a transpose operator, and Cov_i is a covariance matrix for the ith class.

3.2.3 K-nearest neighbours: The k-NN is one of the most commonly used classification algorithms as it is among the simplest ones of all machine learning algorithms. The k-NN is a non-parametric method. This algorithm classifies the extracted key features based on the nearest training features [48]. It aims to classify an unlabelled input to its k-NN within the training set [35]. One important parameter (k) in the k-NN classifier should be chosen correctly. In this study, the number of the neighbours k is selected as $k = 1$. For details of this algorithm readers may refer to [6, 32, 38, 48–50].

4 Classification performance measurements

There are several types of classification measurement methods. One of these assessments is the n-fold cross-validation method [6]. In this study, a five-fold cross-validation is used as the training and testing processes to achieve the assessment of the classification execution. As can be seen in Table 2, this work obtains a total of 10,260, 2580, and 12,840 feature sets from OA_PD, OA_AR, and OA_PD_AR, respectively. The cross-validation technique divides the input datasets into five parts. From each partition, one part is used as a testing set for the classification and the remaining parts (four folds) are utilised as classifier training. This process is iterated five times, with each time a different fold being used as the testing set. The training parameters are obtained from the training process, which are used for the testing process to evaluate the algorithm. In each iteration, the training set consists of 8208, 2064, and 10,272 features from the total of feature sets, respectively. Whereas, the testing set consists of 2052, 516, and 2568 features from the same feature sets, respectively, as can be seen in Table 3.

In this procedure, the five classification accuracies can be obtained from each testing set. In the end, the average classification accuracy is obtained as the final performance measurement. Table 4 shows the results from each testing set by the cross-validation technique and their overall classification accuracy.

The performance of this proposed method is also evaluated by using different statistical methods. One of these measurements is the accuracy or the recognition rate, which is the percentage of the correctly classified ones by a classifier for the testing data. The second assessment is sensitivity, which is the proportion of the correctly identified positive set. The other statistical method is specificity, which is the percentage of the correctly identified negative set [20].

5 Experimental results and discussions

In this part of study, the experimental results were yielded based on the epileptic EEG signals described in Section 2. The datasets include five classes (class A, B, C, D, or E). The OA technique was used to extract the most discriminative samples based on the following three steps.

Table 2 Total number of the extracted features from each class of epileptic EEG signals

Methods	Dataset					
	Set A dimension	Set B dimension	Set C dimension	Set D dimension	Set E dimension	Total dimension
raw datasets	4097 × 100	4097 × 100	4097 × 100	4097 × 100	4097 × 100	20,485 × 100
OA	3288 × 100	3288 × 100	3288 × 100	3288 × 100	3288 × 100	16,440 × 100
OA_PD	2052 × 100	2052 × 100	2052 × 100	2052 × 100	2052 × 100	10,260 × 100
OA_AR	516 × 100	516 × 100	516 × 100	516 × 100	516 × 100	2580 × 100
OA_PD_AR	2568 × 100	2568 × 100	2568 × 100	2568 × 100	2568 × 100	12,840 × 100

Table 3 Number of the training and testing sets are used in this study

Methods	Total	Training	Testing
OA_PD	10,260	8208	2052
OA_AR	2580	2064	516
OA_PD_AR	12,840	10,272	2568

Table 4 Accuracies of the three features sets by using different classifiers

Classifiers	Feature sets		
	Overall accuracy of OA_PD, %	Overall accuracy of OA_AR, %	Overall accuracy of OA_PD_AR, %
SVM (1vs1)	99.8	100	99.9
SVM (AP)	99.8	99.9	99.8
SVM (1vsA)	97.7	99.9	98.2
SVM (BC)	99.6	99.9	99.7
SVM (TC)	99.8	100	99.9
SVM (OR)	99.1	99.9	99.3
SVM (SR)	99.6	100	99.8
SVM (DR)	99.7	99.9	99.7
QDA	98.5	99.9	99.2
k-NN	96.2	100	97.4

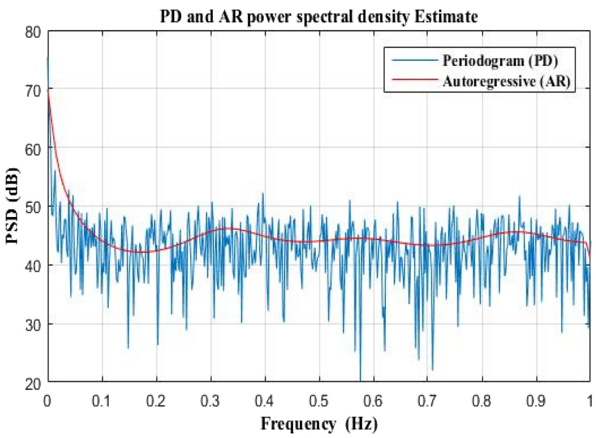


Fig. 4 *Example of PD and AR for a single-channel EEG*

First, the sample size calculator is used to determine the required sample size. Second, in order to make the EEG signals quasi-stationary, this study divided the signal of each class into smaller segments. From each segment, the representative samples were extracted by using the OA technique based on the determined sample size and named as OA_sample set. The OA_sample for each class of EEG signals contains 3288 observations with 100 channels. While the whole OA_sample set, which is obtained from five classes of the epileptic EEG signals, consists of 16,440 observations of 100 channels. The features went through two PSD methods (PD and AR) for reducing the dimensionality of the extracted features from each segment in an EEG class. The obtained features from the two methods are denoted as OA_PD, OA_AR, and OA_PD_AR sets as seen in Table 2. The OA_PD set was yielded when using the OA technique and the PD estimation method on each segment, respectively. On the other hand, the OA_AR set was extracted by employing the OA and AR techniques on each segment. While, the OA_PD_AR set was obtained by implementing the OA technique and the two PSD estimation methods (PD and AR) together as the features extraction technique on each segment.

Fig. 4 shows an example of the PD and AR estimates for a single-channel EEG. As shown in Table 4, the highest accuracies are obtained by using the SVM classifier with 1vs1 and TC output coding for three feature sets, which are OA_PD, OA_AR, and OA_PD_AR (complex feature set). The accuracies were 99.8, 100, and 99.9% for the OA_PD set, OA_AR set, and OA_PD_AR set, respectively, by applying the SVM classifier with two output codings of 1vs1 and TC.

Further, the second highest accuracies for the three feature sets were obtained through the implementation of the SVM with the AP, and the SVM with the SR gained the third highest classification accuracies. Also, the SVM with other output coding of 1vsA, BC, OR, and DR yielded a 97.7, 99.6, 99.1, and 99.7% overall classification accuracies, respectively, for the OA_PD set.

Table 5 Accuracies from each testing set by the cross-validation technique and the average accuracies

Classifiers	Methods	Accuracy, %					Average accuracy, %
		$Fold_1$	$Fold_2$	$Fold_3$	$Fold_4$	$Fold_5$	
SVM	OA_PD	100	99.7	100	99.8	99.7	99.84
	OA_AR	100	100	100	100	100	100
	OA_PD_AR	100	99.7	99.9	99.8	100	99.88
QDA	OA_PD	99.6	97.4	95.6	99.8	100	98.48
	OA_AR	100	100	100	99.5	100	99.9
	OA_PD_AR	99.4	98.8	97.9	99.8	100	99.18
k-NN	OA_PD	98.9	89.2	94.6	98.5	99.8	96.2
	OA_AR	100	100	100	100	100	100
	OA_PD_AR	99.2	92.4	96.3	99.1	100	97.4

Table 6 Results of sensitivity, specificity, overall accuracy, and overall error for each of the proposed classifiers with the extracted features sets

Classifier	Feature sets	Sensitivity, %	Specificity, %	Overall accuracy, %	Overall error, %
SVM	OA_PD	98.89	99.98	99.8	0.2
	OA_AR	100	100	100	0.0
	OA_PD_AR	99.23	99.98	99.9	0.1
QDA	OA_PD	93.10	99.94	98.5	1.5
	OA_AR	99.61	100	99.9	0.1
	OA_PD_AR	96.53	99.89	99.2	0.8
k-NN	OA_PD	84.35	99.82	96.2	3.8
	OA_AR	100	100	100	0.0
	OA_PD_AR	88.95	99.91	97.4	2.6

In the SVM with the same output techniques, an accuracy of 99.9% was achieved for the OA_AR set as presented in Table 4.

On the other hand, with the OA_PD_AR set, the SVM obtained a 99.2, 99.7, 99.3, and 99.7% accuracy with the same output coding, respectively. Although the *k*-NN classifier only achieved the lowest classification accuracy of 96.2 and 97.4% for the two features sets of the OA_PD set and the OA_PD_AR, respectively, it achieved 100% classification accuracy for the OA_AR set.

In order to see more details about the fold cross-validation, Table 5 illustrates the obtained accuracy from each testing fold of the cross-validation technique and overall classification accuracy for the proposed approach with three different classifiers, such as SVM, QDA, and *k*-NN. Clearly, from Table 5, the SVM and *k*-NN classifiers achieved 100% classification rates for each testing fold by the OA_AR scheme.

In addition, Table 6 shows the results of sensitivity, specificity, overall accuracy, and the overall error. Those results were obtained and compared with the proposed classifiers of the SVM with 1vs1 and TC output techniques, QDA, and k-NN classifiers. As appeared in Table 6, the best performances with the lowest errors were obtained by the SVM classifier for different feature sets. The QDA classifier yielded the second highest accuracies of 98.5 and 99.2% for the OA_PD set and OA_PD_AR, respectively. For OA_AR set, the QDA achieved a 99.9% overall accuracy and 0.1% overall error.

In the feature sets of the OA_PD set and the OA_PD_AR set, the lowest results with a high overall error were from the *k*-NN classifier. Obviously, from Tables 4–6, the performance of the SVM classifier is better than the performances of the QDA and *k*-NN classifiers.

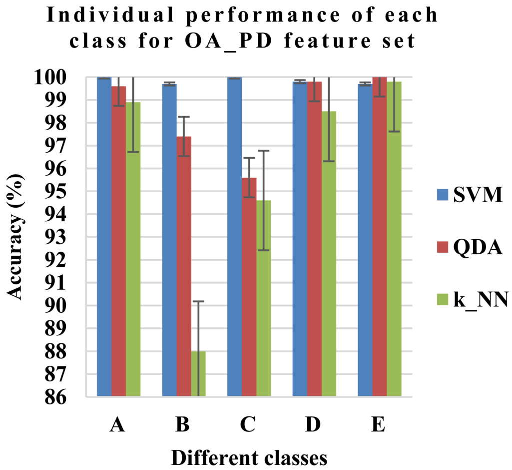
In addition, to investigate a suitable selection of order *p*, this research implemented the AR algorithm in different order of *p* as shown in Table 1. Table 1 shows that, a high classification accuracy was achieved when the *p* value was equal to 7.

Figs. 5*a–c* present a clear picture of individual performance for the three extracted features from each class. The figures show the classification accuracies from the three different classifiers for each EEG class. The error bars in Fig. 5 represent the standard errors, which indicate the error rates in the performances by the classifiers. As can be seen from Fig. 5, the accuracies from the SVM classifier are significantly better than the accuracy from the other two classifiers with the extracted features from each class.

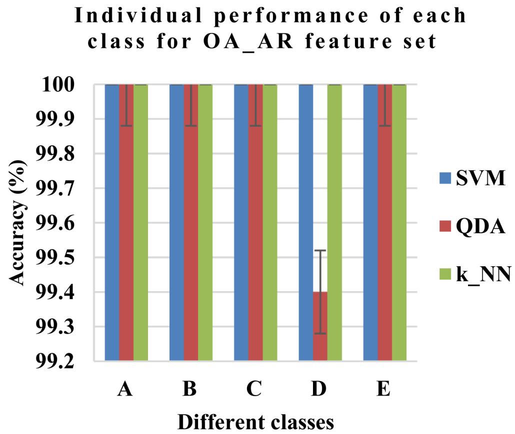
In addition, this study investigates the effectiveness of the used classifiers with the extracted feature sets. Table 7 illustrates a comparison of the overall accuracy among the classifiers using the proposed scheme and some existing methods from the related work with the same epileptic EEG database. From Table 7, Nicolaou and Georgiou [16] developed an epileptic detection method based on permutation entropy and SVM. Overall, they gained an average of classification accuracy of 86.1%. However, our proposed method achieved higher accuracy than those by Nicolaou and Georgiou [16]. Song and Zhang [17] employed wavelet transform pattern recognition and extreme learning machine and same method with genetic algorithm. These two methods achieved 85.9 and 94.2% average accuracies, respectively. Based on the obtained results, the proposed method outperformed Song and Zhang [17]. Another study was made by Samiee *et al.* [18] in which rational discrete short-time Fourier transform and multilayer perceptron classifier were used. The authors reported a 98.3% classification accuracy for **A**, **B**, **C**, **D**versus **E** case. The obtained results in our technique were higher than those by Samiee *et al.*[18].

Alcin *et al.* [19] used time–frequency image based on filter vector and extreme learning machine to detect epileptic seizures. An overall classification accuracy of 96.4% for all sets was yielded. Their result was lower than the proposed scheme. Al Ghayab *et al.* [20] classified two classes (**A** versus **E**) using simple random sampling technique and sequential feature selection method with LS-SVM. They achieved 99.9% accuracy rate for class **A** versus class **E**. Their result was lower than the proposed method. Hassan and Subasi [21] obtained 100% accuracy for only **A** versus **E** sets by using complete ensemble empirical mode decomposition and adaptive noise with a linear programming boosting compared with our method, which used all datasets and yielded 100% accuracy. Although the achieved results by the authors of [22, 27, 28] were 100% accuracies, they used part of datasets that was **A** group versus **E** group. The detection performance of the proposed technique was also higher than those by the authors of [24–26, 30, 31].

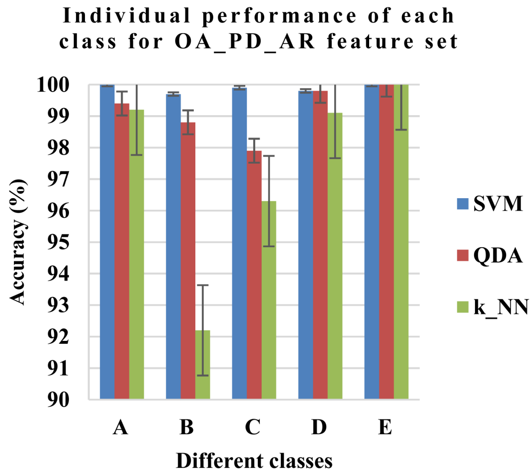
The existing methods were conducted with two sets and achieved an average of accuracy between 99 and 100% compared with the proposed method which was tested using the whole datasets. The highest overall classification accuracies are highlighted in bold font. The best performance was obtained from the OA technique combined with the AR estimation method as



a



b



c

Fig. 5 *Individual performance for each class with*
(a) OA_PD feature set, ***(b)*** OA_AR feature set, ***(c)*** OA_PD_AR feature set, using different classifiers

well as SVM classifier, compared with the results obtained by the authors of [16–31].

Even though the extracted features by using the OA combined with the mentioned spectral methods were scored the second highest accuracy with a 99.9%, it is considered acceptable in the research of epileptic seizures detection. The results affirmed that the proposed method has achieved a more accurate classification rate than the other existing methods which were conducted with the same datasets.

The advantages of this method are: (i) most of the research that applied the SVM classifier did not apply the eight output coding techniques, which are: 1vs1, AP, 1vsA, BC, TC, OR, SR, and DR. The proposed method tested these output coding techniques to select the best parameters of the SVM. (ii) The outcomes of this research can help physicians and doctors to better diagnose brain disorders. The main advantage of this method is: our proposed OA_AR technique can reduce big size EEG data into a small set selection the best representative data points from every segmentation of a dataset considering the variability of the observations. Due to the reduction of data, this approach can handle massive size of data with less computation cost compared to the existing methods. One of the limitations of the proposed method is that the delay time could be increased when it implements with a real-time application. However, the proposed method was implemented with off-line datasets collected by Bonn University, Germany.

6 Conclusions

In this study, a novel method was developed to classify the epileptic EEG signals. It presented an OA technique combined with two PSD estimation methods: PD and AR, for extracting and reducing the high dimensionality of EEG recordings. The feature sets were gained and denoted as OA_PD, OA_AR, and OA_PD_AR sets from the OA technique with the PD estimation method, OA technique with AR method, and OA technique with two PSD estimation methods (PD and AR) together as a features extraction technique, respectively, on each segment of each class from the epileptic EEG data. This paper also investigated the best matching classifier for the extracted features sets by implementing three well-known classifiers: SVM, QDA, and *k*-NN. The experimental results showed that the OA_AR set achieved better performances with the SVM classifier with 1v1 and TC output coding for the epileptic EEG signals, with an overall classification accuracy of 100%. On the other hand, the OA_PD_AR set yielded a 99.9% overall accuracy, which is the second highest accuracy with the SVM.

The proposed algorithm was compared with six existing methods. It was proved that the proposed scheme outperformed the other methods in terms of the accuracy. Also, the proposed method had a possibility to analyse other EEG signals, which can lead to assist physicians to diagnose and treat brain disorders. As a follow-on study, the proposed method will be implemented in real time and applied to other EEG recordings, such as the EEGs from Alzheimer, sleeping disorder, and alcoholic subjects.

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Table 7 Comparisons to the previous studies with the epileptic EEG data

Authors	Techniques	classes	Overall accuracy, %
Nicolaou and Georgiou [16]	• permutation entropy + SVM	A versus E, B versus E, C versus E, D versus E	86.10
Song and Zhang [17]	• wavelet transform pattern recognition + extreme learning machine	A, B versus C, D, E	85.9
	• wavelet transform pattern recognition + genetic algorithm + extreme learning machine	A, B versus C, D, E	94.2
Samiee *et al.* [18]	• rational discrete short-time Fourier transform + multilayer perceptron classifier	A, B, C, D versus E	98.1
Alcin *et al.* [19]	• time–frequency image + filter vector + extreme learning machine	All sets (A – E)	96.4
Al Ghayab *et al.* [20]	• simple random sampling technique + sequential feature selection method + least square support vector machine	A versus E	99.9
Hassan and Subasi [21]	• complete ensemble empirical mode decomposition + adaptive noise + a linear programming boosting	A, B, C, D versus E	99.2
		A versus E	100
Djemili *et al.* [22]	• empirical mode decomposition + multilayer perceptron neural network	A versus E	100
		D versus E	97.7
Patidar and Panigrahi [23]	• tunable *Q*-factor wavelet transform + Kraskov entropy + least square support vector machine	C, D versus E	97.75
Satapathy *et al.* [24]	• integrating the best attributes of artificial Bee colony + radial basis function network	A versus E	72.5
		D versus E	98
		A, D versus E	82.3
Bhati *et al.* [25]	• time–frequency localised three-band wavelet filter banks + multi-layer perceptron neural network	C, D versus E	99.33
Jaiswal and Banka [26]	• local neighbour descriptive pattern + artificial neural network	A versus E	99.82
	• one-dimensional local gradient pattern + artificial neural network	A, B, C, D versus E	98.72
		A versus E	99.80
		A, B, C, D versus E	98.65
Zhu *et al.* [27]	• sample entropy + multi-scale *K*-means	A versus E	100
		B versus E	99.0
		A, B versus C, D, E	99.1
Zhu *et al.* [28]	• fast weighted horizontal visibility graph + *k*-NN	A versus E	100
		D versus E	93.0
		A, B, C, D versus E	95.4
Wang *et al.* [29]	• simple random sampling + J48	A versus E	100
		B versus E	95.6
		C versus E	97.3
Siuly and Li [30]	• OA + multiclass least square support vector machine	multiple classes	99.9
Siuly *et al.* [31]	• clustering technique + LS-SVM	A versus E	99.9
proposed scheme	• OA_PD + SVM	all sets (A–E)	99.8
	• OA_AR + SVM	all sets (A–E)	100
	• OA_PD_AR + SVM	all sets (A–E)	99.9

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