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Robustified principal component analysis for feature selection in EEG signal classification

R. Martin
Faculty of Computer Science & Information Technology, Jazan University, KSA
* Corresponding author e-mail：jmartin@jazanu.edu.sa

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Abstract

Feature engineering is an important step in data analysis, especially for machine learning applications. A wide range of feature selection methods are being used in Electroencephalography (EEG) signal processing applications. Principal Component Analysis (PCA) is considered an ideal method for feature selection whenever high dimensional data is obtained, especially in signal processing applications. Following an examination of various EEG signal processing frameworks, PCA emerged as the winner in the battle to reduce dimensionality. Despite its widespread use, it has been found to be ineffective for EEG signal processing problems like epileptic seizure detection due to the nonlinear nature of the signal properties. Traditional methods for solving PCA are insufficient in this case, so suggest a novel technique. In this paper, PCA is explored with an EEG classification model. The proposed work demonstrates how PCA is robustified for an EEG signal processing scenario by applying kernel functions. Statistical features are extracted from EEG data after preprocessing by the Desecrate Wavelet Transform (DWT). Initially, the classical PCA algorithm is applied for feature selection by reducing the dimensionality. Later, the algorithm is robustified by applying a Gaussian kernel in a nonlinear, high-dimensional feature space. In an EEG classification of epileptic seizure detection, the adoption of robustified PCA outperforms conventional PCA in terms of accuracy.

Keywords: PCA, Dimensionality Reduction, Electroencephalography (EEG), Feature Engineering, Signal Processing

1. Introduction

Feature dimension is one of the challenging factors in machine learning based signal processing frameworks. Larger number of features makes it harder to process and visualize the data sets and work on them (F. Heydarpour et al., 2020 and Rahiminasab et al., 2020). As most of the features are correlated with one another, they may appear redundantly. This is the significance of adopting dimensionality reduction techniques in machine learning frameworks as stated in (R. John Martin, 2018). Wide ranges of feature reduction algorithms are being used for biomedical signal processing applications, especially in Electroencephalography (EEG). Principal Component Analysis (PCA) is the commonly used dimension reduction algorithm in EEG based frameworks of epileptic seizure detection. The main characteristic of PCA is to express the data by reducing the number of dimensions without much loss in the required data. It is a process of reducing the number of variables under consideration by setting a set of principal variables.

The purpose of PCA is to identify the subset of features in our dataset that best capture information on the entire dataset, allowing us to minimize dimensions with minimal information loss. For example, one can reduce the dimension of training data before feeding it to a ML model for classification to reduce computation time (R. John Martin, 2022). High correlation filters, random forests, and backward feature elimination are some of the strategies for dimensionality reduction. PCA effectively handles this problem by determining principal components, which are linear combinations of the original features. These components are extracted in such a way that the first captures the most variance in the dataset; the second collects the remaining variance while staying uncorrelated to the first, and so on.

Using the PCA can result in some information loss if we do not choose the right number of principal components for our data set and its variance. When we apply Principal Component Analysis to our data set, the original features are transformed into principal components: linear combinations of original data features. But which features, variables or

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characteristics in the data set are the most significant? After performing the PCA, answering this question can be difficult. The loss of information is caused by a nonlinear relationship between the features, which is also supported by a wide range of studies on EEG classification frameworks as stated in table 1. It is essential to keep the significant feature components in the dataset that will play a crucial role in the classification frameworks. This is the prime motive of this research.

The core objective is to minimize the data loss in the EEG classification models by enhancing the classical PCA. After extensive research, it was discovered that the PCA technique may be utilized to extract the necessary single or multiple EEG feature frequencies from an EEG input. Each signal's characteristic frequency yields just two valid eigenvalues. The number of effective eigenvalues is proportional to the number of raw signal frequencies and has no bearing on the size of signal sub-bands. Hence, the wavelet method of signal sub-band is obtained using DWT and applied to PCA. Now, the major challenging factor in this process is nonlinearity. Abnormalities in a multi-channel EEG must have nonlinear properties, so its signal sub-bands must be processed and the significant features retained using nonlinear kernel based analysis using robustified PCA (Cao, H et al., 2022).

In this attempt, the classical PCA is robustified by using a nonlinear kernel (Katayama H et al., 2022) to avoid the loss in cumulative EEG signal feature dimension, which will lead to accurate disease diagnosis. The contributions of this research include:

Study the existing EEG based epileptic seizure detection frameworks using classical PCA as the feature selection method.

Propose an enhanced PCA with a nonlinear kernel

Experiment with Classical PCA and Nonlinear PCA, and compare their performance.

The following sections of this paper review and exhibit the use of PCA and its variants in EEG signal processing with the application of epileptic seizure detection frameworks. Section two of this paper provides a comprehensive analysis of dimensionality reduction techniques used with EEG signal processing applications. Section three presents the concepts of conventional PCA and robustified PCA with an experimental framework of epileptic seizure detection. An EEG signal classification is used for validating how best the robustified PCA responds. The outcomes of the experiments are given in section four and the conclusion in section five.

Table 1 Summary of feature selection methods used in EEG **classification problems**

Reference	Feature Selection Method Adopted
Gajic et al. (2014, 2015)	Scatter Matrix
Ozan Kocadagli et al. (2017)	Fuzzy Relations
Ming-ai Li et al. (2016)	P. t-SNE
Hadi et al. (2016)	SFS
Elahi et al. (2013)	SFS & LDA
Ahmad M. Sarhan (2017)	Statistical moments
Satchidanada et al.(2013) Benzy V.K. et al. (2015)	Wavelet coefficients
Gopika Gopan et al. (2015)	Channel reduction
Edras Pacola et al. (2017)	LDA
Kavita Mahajan et al.(2011) Bugli C et al. (2007)	ICA & PCA
Harikumar et al. (2015)	PCA, ICA and SVD
Sharmila et al.(2017)	PCA & LDA
Paulo Amorim et al. (2017)	PCA, LDA & ICA
Xiao-Wei Wang et al. (2014)	PCA, LDA & CFS
Lina Wang et al. (2017) Rajendra Acharya et al. (2012)	PCA & ANOVA
John Martin R et al.(2021) Aminion et al. (2010) Xie et al.(2011, 2014) Noertjahjani et al. (2016) Chunchu R et al.(2014) Manisha Chandani et al.(2017) Sabeti M. et al.(2011) Hashem et al. (2017) Esma Sezer, et al (2012) Harikumar R.et al. (2015) Williamson JR et al. (2012)	PCA
Li-Chen Shi et al. (2017)	L1 norm PCA, sparse PCA and robust PCA

2. Related works

Different approaches are adopted for feature selection processes in EEG signal data analysis. Many works used non-linear statistical methods for reducing the feature dimension. Gajic et al. (2014) adopted scatter matrix method of feature reduction in epileptic seizure detection problem. In an Alzheimer's disease detection problem, Trambaiolli et al. (2017) used eight different algorithms for reducing features. Ozan Kocadagli et al. (2017) reported that they have employed fuzzy relations for reducing the features of epileptic seizure classification.

Ming-ai Li et al. (2016) extracted features using DWT and used an approach called parametric t-Distributed Stochastic Neighbor Embedding (P. t-SNE) for extracting reduced nonlinear features from MI-EEG. Edras Pacola et al. (2017) used Linear Discriminant Analysis (LDA) for obtaining distinctive features for binary classification by reducing the extracted features using wavelets. In a comparative study by Bugli C et al. (2007), Independent Component Analysis (ICA) and PCA were analyzed for efficient event detection. Similarly, Kavita Mahajan et al. (2011) also employed PCA and ICA for dimensionality reduction for their EEG classification problem. For evaluating the performance of various dimensionality reduction techniques, Harikumar et al. (2015) applied PCA, ICA, and SVD to an epileptic seizure detection problem. Sharmila et al. (2017) used PCA and LDA to dimension reduction of extracted features using DWT for the classification of epileptic EEG. Paulo Amorim et al. (2017) adopted PCA, LDA, and ICA to reduce the feature space for an EEG classification problem. Xiao-Wei Wang et al. (2014) used PCA, LDA, and correlation-based feature selector (CFS) for dimensionality reduction in an emotional state classification problem using EEG.

Hadi et al. (2016) inducted the Sequential Forward Feature Selection (SFS) algorithm for the selection of features and to reduce the dimensionality for the classification of epileptic EEG. Elahi et al. (2013) employed two methods such as SFS and LDA for feature reduction in order to maximize classification accuracy. According to Ahmad M. Sarhan (2017), statistical moments are applied in an epileptic seizure detection problem to reduce the dimensionality of input and to choose the features. Wavelet coefficients are used manually to reduce feature dimension after wavelet analysis in the works reported by (Satchidanada Dehuri et al., 2013) and (Benzy V.K. and Jasmin E.A., 2015).

In a multi-channel EEG data analysis by Gopika Gopan et al. (2015), feature reduction is achieved by limiting channel dimension. The extracted features from different domains are reduced by using PCA and Analysis of Variance (ANOVA) methods as reported in (Lina Wang et al., 2017). Similarly, Rajendra Acharya et al. (2012) used PCA for feature dimension reduction and ANOVA for feature selection in a wavelet framework for seizure detection problem.

A recent seizure detection framework by John Martin et al. (2021) used kernel PCA for feature optimization to enhance the classification accuracy and it is claimed that the kernel PCA is working well with SVM for EEG classification. To attain maximum separability extracted features are reduced in dimension using PCA as reported by M Aminion et al. (2010). Similarly, Xie et al. (2014) attain dimensionality reduction by removing insignificant components using PCA for epileptic EEG classification. In another work by Xie et al. (2011) used multi-scale PCA by combining WT and PCA to obtain reduced features. Noertjahjani et al. (2016) used PCA as an effective feature extraction method for the epileptic EEG classification using SVM.

Roozbeh Z et al. (2017) applied a robust feature extraction method by combining PCA and cross-covariance technique (CCOV) to reduce the feature dimension of EEG. In an EEG based vigilance estimation problem proposed by Li-Chen Shi et al. (2013), tried three other PCA variants for feature dimension reduction as L1 norm PCA, sparse PCA, and robust PCA along with standard PCA. Williamson et al. (2012) stated that principal components are obtained by reducing extracted features for their SVM classifier. “Table.1” shows the diversified approaches used for feature selection in the recent EEG classification frameworks of seizure detection. PCA is frequently employed for feature selection in the EEG signal classification frameworks of epileptic seizure detection, according to the referenced literature. When comparing PCA to one or more alternative feature selection methods such as ICA, SVD, LDA, CFS, and ANOVA [Harikumar et al. (2015), Kavita Mahajan et al.(2011), Bugli C et al. (2007), Sharmila et al.(2017), Paulo Amorim et al. (2017), Xiao-Wei Wang et al. (2014), Lina Wang et al. (2017) and Rajendra Acharya et al. (2012)], it is clear that PCA is the best method for reducing feature dimension. According to John Martin R et al.(2021), Hashem et al. (2017), and Xie et al. (2011, 2014), PCA significantly improves classification performance over other feature selection approaches.

Though PCA would identify the highly significant features in an EEG classification problem, it is critical to maintaining every required feature to avoid misclassification, especially in epileptic seizure detection applications. This is the driving force for using kernel approaches to improve the PCA's robustness.

3. Methods

Principal Component Analysis (PCA) is a feature reduction method which transforms a high dimensional dataset into a low-dimensional orthogonal feature space while retaining the maximum variance of the original high dimensional dataset. In the framework of EEG classification, PCA is inducted for feature dimension reduction, which will consolidate the most significant feature vectors into one or more principal

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components. Initially, wavelet domain feature extraction is materialized using the multiscale approximation principle of DWT as stated in (R. John Martin, 2018). Extracted high-dimensional features in DWT are further subjected to analysis in order to obtain compact dimensions in size to enable the classification process effectively and efficient. The proposed research is carried out in two stages: first, traditional PCA is implemented for EEG classification (Sec. 3.1), and then, using the kernel function, robustified PCA is developed (Sec. 3.2).

The assumptions that are used to approach PCA for optimum productivity include Linearity: The principle components (PCs) are a linear combination of the original features. PCA may not provide expected results if this is not true. Large variance implies more structure: Variance is an important measure in PCA that indicates how significant a particular dimension is. Hence high variance vectors will have emerged as principal components. Orthogonality: In PCA, principle components are considered orthogonal.

3-1.Feature dimension reduction using classical PCA

Each orthogonal feature vector is referred to as a Principal Component (PC). Eigen values are scalar factors of the degree of variance within the particular PCs. Principal components are graded by their corresponding Eigen values, and accordingly, the first PC captures the most significant variance in the dataset. The second one is perpendicular to the first and gets the next significant variance. The two major steps in PCA include i) Perform mean normalization and find the covariance matrix: The mean of the original signal data in all dimensions is first subtracted to produce a data set with a zero mean. Consequently, the covariance matrix is calculated. And ii) Compute eigenvalues and eigenvectors: The covariance matrix decomposition to obtain a matrix of eigenvectors in a n-dimensional space (n PCs) and their corresponding eigenvalues. This will be done with the help of the following algorithm:

Reducing data from n-dimensional to k-dimensional space. Computing the covariance matrix S:

$$S = \sum_{i=1}^{n} (x_i - m)(x_i - m)^T \qquad (1)$$

S is an [n x n] matrix.

Compute eigenvectors and eigenvalues of matrix S [U, V] = eigs (S), where eigs provides eigenvector. U and V are matrices, where U matrix is an [n x n] matrix, turns out the columns of U are the u vectors, so to reduce a system from n-dimensions to k-dimensions to take the first k vectors from U (first k columns).

$$U = \left[u^{(1)} \quad u^{(2)} \; \ldots\ldots u^{(n)}\right] \in R$$

It needs to find a way to change ‘x’ (which is n dimensional) to z (which is k dimensional). Thus reducing the dimensionality.

Take the first ‘k’ columns of the ‘u’ matrix and stack them in columns, where n x k matrix - call this Ureduce

(a) Calculate ‘z’ as follows,

$$z = (U_{reduce})^T \times x \qquad (2)$$

so, [k x n] * [n x 1] Generates a matrix which is k * 1.

Features are extracted through DWT based multiresolution analysis (MRA). The conventional method of PCA is materialized by applying features. The feature matrix X is in dimension 300 x 54 (100 samples each from F, N & S segments and each with 54 features). The input feature space is normalized by de-mean of the feature matrix. As the first step, the covariance matrix of the feature matrix is obtained. The eigenvalues and eigenvectors are then calculated by using a covariance matrix. This has been achieved by using the following Matlab code:

[coeff,score,latent,~,explained] = pca(X); Where "coeff" are the eigenvectors of the covariance matrix called principal component vectors, "latent” is the output, and are the eigenvalues of the covariance matrix. Multiply the original data by the principal component vectors to get the projections of the original data on the principal component vector space. This is also the output "score".

The features now in principal component space with variations specified in a vector “explained” is in “Table 2”. The feature variations obtained after conventional PCA is represented by using a scree plot in “Fig. 1”. From the scree plot it is noticed that the first 3 principal components (PC1, PC2, and PC3) together explain 98.1% of the variation. Thus the feature dimension is reduced to three and the remaining is considered insignificant.

Table 2 Vectors in principal component space during classical PCA

Principal Components	Variation
PC1	76.56131087
PC2	16.82612710
PC3	4.71003453
PC4	1.90019686
PC5	0.00232034

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PC6	0.00000449
PC7	0.00000420
PC8	0.00000101
PC9	0.00000028
PC10	0.00000019
PC11	0.00000010
PC12	0.00000003
PC13	0.00000001
………………. Upto PC54	

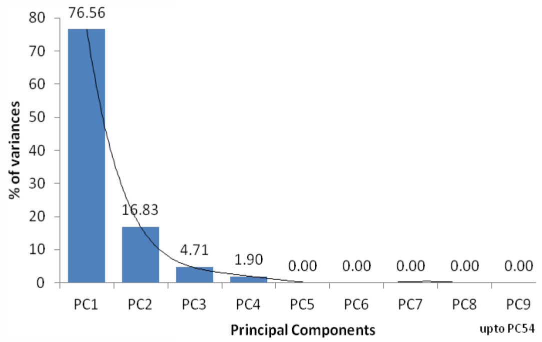

Fig. 1 Scree plot showing the percentage of variances among PCs in Classical PCA

3.2 Feature dimension reduction using robustified PCA

In high dimensional biomedical data like EEG, PCA is best used for expressing linear variability. But the characteristic of the high dimensional EEG data set is that it has a non-linear nature. In those circumstances, PCA cannot determine the variability of data accurately. To address this issue of non-linear dimensionality reduction, kernel based PCA can be recommended. Some improvisations are recommended with the usage of kernel functions for nonlinear mapping so that the principal components are computed efficiently in high dimensional feature spaces.

In general, non-linear methods (Harikumar R et al., 2015) are being applied to robustify the classical PCA. The extended form of a classical PCA is called Kernel Principal Component Analysis (Chenouri S et al., 2015; Schölkopf Bernhard et al., 1998) by adopting kernel methods. Some innovative approaches applied towards classical PCA which may enhance the dimension reduction process are termed robust PCA.

The linear transformation of PCA functionalities is carried out in a reproducing kernel Hilbert space with a nonlinear mapping. In kernel-based method, the mapping carried out by Kernel PCA depends on the choice of the kernel function K, probably may include the linear kernel; and the nonlinear kernel functions such as the polynomial kernel and the Gaussian kernel. In this method, principal components are computed efficiently in a high-dimensional feature spaces that are related to the input space by some nonlinear mapping.

Kernel PCA chooses the principal components which are nonlinearly related to the input space by performing PCA in the high dimensional input space obtained through nonlinear mapping, where the low-dimensional latent structure is, expected to be found easily.

Consider a feature space Φ such that:

$$x \rightarrow \Phi(x) \qquad (3)$$

Let's suppose $\sum_i^t \Phi(x_i) = 0$; it will formulate the kernel PCA objective function as follows:

$$\min \sum_i^t \left\| \Phi(x_i) - U_q U_q^t \, \Phi(x_i) \right\| \qquad (4)$$

Where U represents the eigenvectors of Φ(X)Φ(X)T. Note that if Φ(X) is n × t and the dimensionality of the feature space n is large, then U is n × n which will make PCA impractical.

To reduce the dependence on n, it is assumed that a kernel K(·, ·) will compute K(x,y) = Φ(x)TΦ(y). Given such a function, compute the matrix Φ(X)TΦ(X) = K efficiently, without computing Φ(X) explicitly. Significantly, K is t × t here and does not depend on n. Thus it can be computed in a run time that depends only on t. And also, it is observed that the PCA can be formulated fully in terms of dot products between data points. Replacing dot products by kernel function K, which is equivalent to the inner product of a Hilbert space yields the Kernel PCA algorithm. To attain optimum classifier performance in this proposed model, Gaussian kernel is inducted to robustify the conventional PCA.

On implementation of robustified PCA using Gaussian kernel function, the features of the input data are mapped into the principal components space. The variations of the principal components expressed in a vector "explained" are given in "Table 3". Observing the concentrated principal components in PC1, PC2, and PC3 obtained from robustified PCA, it is clear that the three principal components mentioned above can identify 99.13 percent of the variations in the input data. This is 1.03% ahead of the classical PCA. The scree plot in "Fig.2" illustrates the concentrations in the principal components of robustified PCA.

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Table 3: Vectors in principal component space during robustified PCA

Principal Component	Variation
PC1	77.25931087
PC2	16.99712710
PC3	4.86903453
PC4	0.87319686
PC5	0.00132034
PC6	0.00000449
PC7	0.00000420
PC8	0.00000101
PC9	0.00000028
PC10	0.00000019
PC11	0.00000010
PC12	0.00000003
PC13	0.00000001
…………….. Upto PC54	

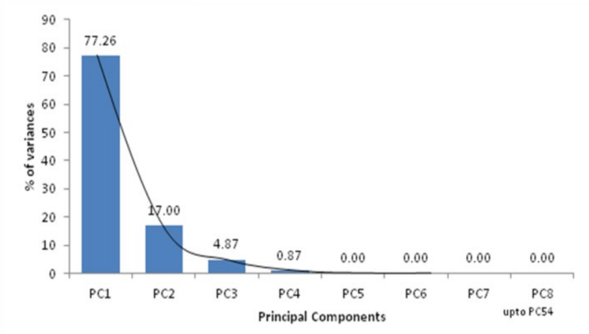

Fig 2: Scree plot showing the percentage of variances among PCs in Robustified PCA

4. Results and discussions

The major objective of this research was to improve the classical PCA to avoid the loss of important feature dimensions which are contributing towards accurate classification. In the proposed method, two variants namely Classic PCA and robustified PCA are implemented towards the EEG classification problem.

In the first phase of the research, classical PCA is adopted to identify the most significant features which are concentrated in the principal components. The percentage of variances in the data set concentrated in the principal components PC1, PC2, and PC3 together as 98.1% as represented in table 1 and figure 1, which means 1.9 % of the feature properties remain withthe rest of the principal components. Eliminating the remaining 1.9% of the feature properties may lead to misclassification.

As a second experiment, robustified PCA is implemented with the dataset. While looking at the percentage of variances in scree plots, it's evident that robustified PCA can explain 99.13 percent of the features, which is 1.03 percent ahead of classical PCA in the first phase. This is a clear indication of the enhanced performance of the robustified PCA over classical PCA. Thus, it is presumed that this enhancement will lead to a perfect classification of EEG signals.

To verify this enhancement in an EEG classification framework, the reduced feature matrix is prepared as training and test sets from the pool of 300 signal feature inputs representing ictal and interictal EEG samples of different subjects named Z, O, N, F, and S (R. John Martin et al, 2022). The most significant features concentrated in the first three principal components (PC1, PC2, and PC3) are applied to the classifier for epileptic EEG detection in both scenarios. The SVM nonlinear Polynomial kernel based classifier is used to classify the signal inputs on two subjects namely seizure (ictal) and seizure-free (interictal). To perform a 5-fold cross validation, 5 sets of training and corresponding test samples are prepared from the reduced feature matrix.

"Table.4a" demonstrates the performance of the classifier on the selected feature dimensions using classical PCA. It should be noted that the SVM-based classifier demonstrated 98.9% accuracy, implying that the classifier may exhibit a 1.1% error in EEG signal classification, which is a cause for concern in disease diagnostics.

Subsequently, the classification model is used with robustified PCA using its three principal components PC1, PC2, and PC3. It is observed that the robustified PCA using Gaussian kernel is doing better in the EEG classification framework of epileptic seizure detection which is 0.7% ahead of classical PCA as stated in “Table 4b”. This clearly shows that by identifying the most important EEG signal feature properties using the first three principal components, the robustified PCA significantly improves classification performance, resulting in accurate disease diagnosis.

Table 4: a) Classifier Performance with Features selected using Classical PCA

Classifier	Kernel Parameters	5-fold Cross Validation		
		SEN	SPE	ACC
SVM-Polynomial Kernel	d=2	0.937	0.967	0.938
	d=5	0.965	0.996	0.989

Table 4: b) Classifier Performance with Features selected using Robustified PCA

Classifier	Kernel Parameters	5-fold Cross Validation		
		SEN	SPE	ACC
SVM-Polynomial Kernel	d=2	0.927	0.989	0.975
	d=5	0.989	0.994	0.996

5. Conclusion

In this paper, a methodology has been proposed to enhance the classical PCA in EEG classification frameworks. The article began by reviewing the literature on EEG signal classifications for epileptic seizure detection utilizing classical PCA as a feature selector. As has been mentioned, the majority of authors employed traditional PCA in their frameworks, and who established that the EEG machine learning frameworks responded well to PCA combinations with only mediocre accuracy. Though PCA is a popular approach for reducing feature dimensions when there are a large number of features in classification problems, its performance is questionable when there is a nonlinear relationship between the data variables. This was the inspiration for the proposed research to enhance the classic PCA by incorporating a nonlinear kernel. Initially, the classical PCA is experimented with and tested with SVM based nonlinear classifier. After that, the classical PCA is enhanced with a Gaussian kernel, implemented, and tested with EEG signal classification. On comparing the feature variations with selected principal components, it is noted that the kernelized PCA performed better. Thus, the classical PCA is enhanced. The EEG classification model performed better than classical PCA when the reduced features from robustified PCA were applied. As a result, the proposed PCA enhancement significantly improves disease diagnosis by eliminating the misclassification of EEG signals. Furthermore, this research experiment yields significant outcomes that will be beneficial for future signal processing researchers.

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AUTHOR BIOGRAPHIES

Dr. John Martin has over 25 years of experience as an academic in the field of Computer Science. Dr. John Martin earned his Ph.D. in Computer Science from Bharathiar University in India and specialized in Machine Learning with an application to biomedical data analytics. He has vast experience in higher education as an educator and administrator in India and the Middle East. Currently, he is working in the School of Computer Science and Information Technology at Jazan University (Ministry of Education), KSA. He has published extensively in the fields of machine intelligence and biomedical data analytics and has served as editor and reviewer for refereed journals. His research was patented both nationally and internationally. His accomplishments as an educator, mentor, author, researcher, adjudicator, and consultant are acknowledged by the global community. His research interests include Machine Intelligence, Signal Processing, and Healthcare Data Analytics.