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Canonical Correlation Analysis and Neural Network (CCA-NN) Based Method to Detect Epileptic Seizures from EEG Signals

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Abstract

In this research, a novel method based on Canonical Correlation Analysis (CCA) and Artificial Neural Network (ANN) to detect epileptic seizures from EEG signals is proposed. CCA was applied on EEG signals and feature vectors corresponding to Eigen values were extracted. These Eigen values were fed as input to Artificial Neural Network (ANN)'s widely explored model Multilayer Perceptron Neural Networks (MLPNNs) for classification between occurrence of non-epileptic seizures and epileptic seizures. The extracted Eigen values using CCA proved to be a better epileptic seizures detector and provide average classification accuracy, sensitivity and specificity as 92.583%, 93.25% and 91% respectively.

Keywords: *Electroencephalography (EEG), Epilepsy, Epileptic Seizure Detection, Canonical Correlation Analysis (CCA), Artificial Neural Network (ANN)*

1. Introduction

The electroencephalography (EEG) is associated with electric potentials of cerebral activity which is recorded non-invasively using electrodes placed on human scalp [1-3]. EEG is an important tool which is used to diagnose neurological disorders such as; sleep disorder, tumor and epilepsy [1-3]. Previously, the EEG was analyzed by physician or neurologist through visual inspection. Recently, numerous computerized algorithms have been introduced to examine the energy contents of different frequency bands of EEG signals which carries very significant information about the several types of brain disorders. These computerized algorithms also prepare automatically a report to help the physicians in investigating the patients having several types of brain disorders [1-2].

The abnormal cerebral electrical potentials lead to unmanageable paroxysm in the human body and is a major cause of a critical neurological disorder called Epilepsy. 1-3% world's population are suffering from epilepsy disease and majority are from developing countries. Among them mostly are deprived to have an access of its proper treatment facilities. Hence, precise epileptic seizures detection has become very important subject for the neurologists worldwide [4-5]. EEG signals are mostly used to diagnose epilepsy and to detect epileptic seizures, as EEG signals can provide valuable information on disorders of human cerebral activity [6]. The non-stationary EEG signals consist of sinusoidal components of various frequencies which are interconnected through trillions of neurons. This complex nature of the EEG signals has made its visual analysis impossible. Hence, an automated techniques to analyze these EEG signals for the diagnosis purpose have been introduced [5, 7-10].

In recent decades, several non-linear time series methods were applied to detect epileptic seizures from EEG and also from other physiological signals i.e. electrocardiogram signals (ECG).

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Liu *et al*. [11] presented an algorithm to detect neonatal epileptic seizure using autocorrelation analysis. The performance of the algorithm was assessed using Autocorrelation Moment (SAM). The sensitivity of the system was 84% whereas, the specificity was 98%.

Gotman *et al*. [12] introduced 3 different methods for feature extraction for rhythmic activity in neonatal EEG; it is a patient independent algorithm. The three methods include calculating the frequency of the dominant peak, multiple spike detection and detection of extremely slow cerebral rhythmic activities. Pre-processing step contains Low pass filtering. The average detection rate of this algorithm was 71%.

Hassanpour *et al*. [13] implemented an algorithm to detect epileptic seizures from EEG. This algorithm extracts left and right singular values from time-frequency analysis of the signals. After that these singular values were squared to be considered as density functions. The main features obtained from the histograms were fed to a neural network for classification. The algorithm gave a Good Detection Rate of 92.5 % while False Detection rate is reported as 3.7%.

Wilson *et al*. [14] introduced an algorithm called as Reveal. The algorithm uses two seconds EEG epochs and calculates matching pursuit decompositions from them. This decomposition was characterized by its maximum amplitude and its overall RMS amplitude individually. The sensitivity obtain by this algorithm was 76% while false detections/hour is reported as 0.11.

Alkan *et al*. [15] implement a seizure detection algorithm in which power spectrum density is calculated by different techniques including autoregressive (AR), multiple signal classification (MUSIC) and periodogram. They used two different classifiers including Multilayer Perceptron Artificial Neural Networks (MLPNN) model and Logistic Regression (LR) for classification and decision making purpose. In this paper, classification results achieved with MLPNN are better than logistic regression (LR) when both classifiers were trained with estimated EEG power spectrum density using MUSIC technique. The classification accuracy, sensitivity and specificity results with MLPNN were obtained as 92%, 90%, and 93.6% respectively.

Greene *et al*. [16] presented an algorithm in which the combination of EEG and ECG recordings are incorporated to detect epileptic seizures. The proposed algorithm extracts six different features from each EEG signals including line length, power ratio, nonlinear energy, dominant spectral peak and its bandwidth and spectral entropy. Similarly, the algorithm extracts six features for ECG including "mean R-R interval, standard deviation between R-R intervals, mean spectral entropy, mean change in the R-R interval, coefficient of variation and the power spectral density" [16].

In this study, statistical classifier models are used considering a patient-specific and patient-independent system. These extracted features from both electroencephalography and electrocardiography recordings were then combined for each premature integration and late integration individually. In this work, the results achieved in terms of accuracy, specificity and sensitivity with premature integration combination in patient-specific mode were obtained as 86.32%, 88.77% and 76.37%, respectively, whereas Good Detection Rate (GDR) of 95.82% with False detection Rate (FDR) of 11.23% were also reported. However, with EEG and ECG late integration combination, the classification accuracy, sensitivity, specificity, GDR and FDR were obtained as 84.66%, 74.08%, 86.82%, 97.52% and 13.18%respectively. Furthermore, the classification accuracy, sensitivity, specificity, GDR and FDR for patient independent mode with premature integration combination were achieved as 71.51%, 71.73%, 71.43%, 81.44% and 28.57%, correspondingly. On the other hand, the classification accuracy, sensitivity, specificity, GDR and FDR for patient independent mode with late integration combination were achieved as 68.89%, 74.39%, 66.95%, 81.27% and 68.89%, respectively.

Aarabi *et al*. [17] implemented a method for detection of epileptic seizure in newly born babies. The proposed method was based on six multistage: 1) Collection of EEG data and preprocessing using band pass filter 2) Detection and removal of artifacts automatically 3) extraction of features for epileptic seizures and non-epileptic seizures 4) Selection of features 5) Classification and 6) Decision making. In this study, Artificial Neural Network (ANN)'s widely explored Back Propagation Neural Network model with 3 hidden layers has been employed here for classification and decision making. The trained classifier gave results for selectivity and sensitivity as 70.1% and 74% respectively, whereas FDR was reported as 1.55/hour.

Temko *et al*. [18] present a method to detect neonatal seizure based on Support Vector Machines (SVM). In this work, SVM is employed as a classifier to differentiate non-epileptic seizure and epileptic seizure activity. In order to enhance temporal precision and effectiveness of the method, two post processing steps were proposed in this work. 55 various features were extracted from entropy measures, frequency domain and time domain and those were used for classification purpose. The average classification results revealed that the method achieved GDR of 89% with only single FD per hour while GDR of 96% with 2 FD. Similarly, with 100% GDR the 4 FD per hour were reported.

In this research work, a novel technique based on CCA-NN to detect epileptic seizure is introduced. Other methods as discussed above generally use various types of features while the proposed method uses only one type of feature that is Eigen vectors corresponding to Eigen values. These Eigen values are extracted from EEG signals using Canonical Correlation Analysis and used to detect behavioral changes related to epileptic seizures. MLPNN classifier is used for classification in this work.

2. Material and Methods

2.1. EEG Data Sets

In this research, EEG data sets with epileptic seizures collected from the PhysioNet Online Data Base [19] were used. The EEGs recorded at the epilepsy monitoring unit of children's hospital Boston. These EEGs were recorded from 24 pediatric patients having 198 epileptic seizures. The EEG data was recorded with sampling frequency of 256 samples/second using standard 10-20 electrode placement systems and has 18 bipolar montage channels.

2.2. CCA Based Method for Epileptic Seizures Detection

The CCA solves the basis problem. It finds two basis vectors, one for each set of variables, in which cross correlation matrix become diagonal that should be maximized over correlation [20]. For example, in the case of EEG, the estimation of sources is pondered as blind source separation (BSS) problem. Considering BSS problem, the CCA tries to make the sources to be maximally correlated and mutually uncorrelated with their one sampled delay version of the original EEG signals [20]. Suppose $\mathbf{X}(k)$ be the observed EEGs random matrix with N number of samples and $\mathbf{S}(k)$ is a set of unknown sources which are mixed with mixing matrix $\mathbf{A}$. Let $\mathbf{Y}(k)$ be one sample temporally delayed version of $\mathbf{X}(k)$, i.e. $\mathbf{Y}(k)=\mathbf{X}(k\text{-}1)$. CCA tries to solve basis vectors to find the linear relationship between the variables of two sets, in the way these basis vectors are projected on the variables to mutually maximize the correlation between them. Suppose that $\hat{\mathbf{X}}$ and $\hat{\mathbf{Y}}$ be the corresponding vectors. These vectors can be achieved by eliminating the mean from each row of $\mathbf{X}(k)$ and $\mathbf{Y}(k)$, respectively. Suppose $x_1, x_2, x_3, \ldots\ldots, x_N$ be the random variables with mean zero, if we write the vector $\hat{\mathbf{X}} = [x_1, x_2, x_3, \ldots\ldots, x_N]^T$, then its covariance matrix will be $\mathbf{C}_{xx} = \hat{\mathbf{X}}\hat{\mathbf{X}}^T$. Similarly,

$y_1, y_2, y_3, \ldots, y_N$ be the random variables of $\hat{\mathbf{Y}}$ with mean zero, then we write $\hat{\mathbf{Y}} = [y_1, y_2, y_3, \ldots, y_N]$ and its covariance matrix will be $\mathbf{C}_{yy} = \hat{\mathbf{Y}}\hat{\mathbf{Y}}^T$.

Now, let's consider that we have k realizations for $x_1, x_2, x_3, \ldots, x_N$ and $y_1, y_2, y_3, \ldots, y_N$ that are contained in matrices $\mathbf{X} \in \mathbb{R}$ and $\mathbf{Y} \in \mathbb{R}$, respectively, then we have the covariance estimators,

$$\mathbf{C}_{xx} = \hat{\mathbf{X}}\hat{\mathbf{X}}^T,\ \mathbf{C}_{yy} = \hat{\mathbf{Y}}\hat{\mathbf{Y}}^T \text{ and } \mathbf{C}_{xy} = \hat{\mathbf{X}}\hat{\mathbf{Y}}^T$$

where $\mathbf{C}_{xy} = \hat{\mathbf{X}}\hat{\mathbf{Y}}^T$ or $\mathbf{C}_{yx} = \mathbf{C}_{xy}^T$ is the cross-covariance matrix between $\hat{\mathbf{X}}$ and $\hat{\mathbf{Y}}$.

Let's consider the linear combinations of random variables of vectors $\hat{\mathbf{X}}$ and $\hat{\mathbf{Y}}$ are as,

$$u = \mathbf{a}^T \hat{\mathbf{X}} \tag{1}$$

$$v = \mathbf{b}^T \hat{\mathbf{Y}} \tag{2}$$

Where $\mathbf{a} = [a_{x1}, a_{x2}, \ldots, a_{xN}]^T$ and $\mathbf{b} = [b_{y1}, b_{y2}, \ldots, b_{yN}]^T$ are known as weight vectors of $\hat{\mathbf{X}}$ and $\hat{\mathbf{Y}}$, correspondingly.

Later CCA procedure estimates $\mathbf{a}$ and $\mathbf{b}$, such that the correlation ρ between u and v is maximized, i.e.

$$\max_{a,b} \rho(u,v) = \max_{a,b} \frac{\mathbf{a}^T \mathbf{C}_{xy} \mathbf{b}}{\sqrt{\mathbf{a}^T \mathbf{C}_{xx} \mathbf{a}} \sqrt{\mathbf{b}^T \mathbf{C}_{yy} \mathbf{b}}} \tag{3}$$

After some manipulation in [21], we get solution of the Eq. (3) as,

$$\mathbf{C}_{xx}^{-1} \mathbf{C}_{xy} \mathbf{C}_{yy}^{-1} \mathbf{C}_{yx} \tag{4}$$

$$\mathbf{C}_{yy}^{-1} \mathbf{C}_{yx} \mathbf{C}_{xx}^{-1} \mathbf{C}_{xy} \tag{5}$$

While $\mathbf{a}$ is proportional to $\mathbf{C}_{xx}^{-1} \mathbf{C}_{xy} \mathbf{b}$ and similarly $\mathbf{b}$ is proportional to $\mathbf{C}_{yy}^{-1} \mathbf{C}_{yx} \mathbf{a}$ [21].

As $\mathbf{X}(t)$ and $\mathbf{Y}(t)$ are related, so the solutions of both equations Eq. (4) and Eq. (5) are similar. Hence, only one equation either Eq. (4) or (5) is chosen to find the specific weight vector; either $\mathbf{a}$ or $\mathbf{b}$. Here Eq. (3) is considered to find the weight vector $\mathbf{a}$.

By applying Eigen Value Decomposition (EVD) on Eq. (4) we obtain,

$$\mathbf{C}_{xx}^{-1} \mathbf{C}_{xy} \mathbf{C}_{yy}^{-1} \mathbf{C}_{xy} \mathbf{a} = \lambda \mathbf{a} \tag{6}$$

where λ represents the Eigenvalues in descending order ($\lambda_1 > \lambda_2 >, \ldots, > \lambda_N$) and $\mathbf{a} = [a_{x1}, a_{x2}, \ldots, a_{xN}]^T$ represents the eigenvectors analogous to the largest Eigenvalues. These eigenvectors are known as normalized canonical correlation basis vectors. The sequence of these eigenvectors analogous to the largest Eigenvalues is associated with maximal and minimal energy of the signal. This demonstrates that sudden changes in the EEG signals will affect the Eigen values. This feature of sudden change in Eigen values will be used to detect epileptic seizure in the EEG signal.

2.3. Classification

In this paper, multilayer perceptron neural networks (MLPNNs) is employed to classify epileptic seizures in the EEG Signals. MLPNNs having two or several layers are frequently put into practice feed-forward neural network because of their swift operation, constraint-less to implement, minor preparation training requirement [22]. There are tri chronological layers of MLPNN namely, input layer, hidden layer and output layer. The quantity of input neurons is identical to quantity of chosen features. The regulation of anticipated output classes is the function of output layers and amount of output neuron is in contingent to amount of anticipated classes. The system is quite compatible to intermediate layers, which can be incorporated to enhance the capability of the network, however such alteration is mostly handy for nonlinear system [7].The processing and transmitting the input information to the output layer is the domain of hidden layer. MLPNN may have several hidden layers, but generally, single hidden layered MLPNN is ideal as classifiers. It may not be essential, to have prior intelligence for the quantity of neurons required for hidden layers. The hidden layer with larger number of neurons is vulnerable to multiply the computational complications and delayed processing. Small number of neurons can cause the classification errors.

A MPLNN model, having inadequate or abundant hidden layer neurons almost certainly lead to the serious issues of excessive-fitting and generalization. Due to lake of authenticated analytical approach to determine the amount of neurons ideal for hidden layer, the required quantity can be found by trial and error [7, 22].

2.4. Proposed Method

The proposed method CCA-NN is depicted and summarized in Figure 1. Canonical Correlation Analysis (CCA) is applied on raw EEG data to extract feature vectors. Subsequently, these extracted feature vectors are incorporated to train Multilayer Perceptron Neural Network (MLPNNs). In this work, a single hidden layer MLPNN model is designed. This single hidden layer utilizes 20 hidden neurons. Whereas hyperbolic tangent function is utilized to activate MLPNN. MLPNN model was then trained by the widely explored and commonly used Levenberg–Marquardt back-propagation algorithm [22]. In order to avoid the over-fitting in MPLNN classifiers, the frequently used method namely 10 fold cross-validation is employed to generalize the outcomes of classifier. In this study, the classifier MPLNN is trained with epileptic seizure and non-epileptic seizure features. MPLNN compares extracted features using CCA with trained features on the basis of eigenvectors corresponding to the greatest Eigen values is associated with maximal and minimal energy of the signals. If the extracted features contains characteristic of epileptic seizures then trained classifier alerts the occurrence of epileptic abnormality and vice versa.

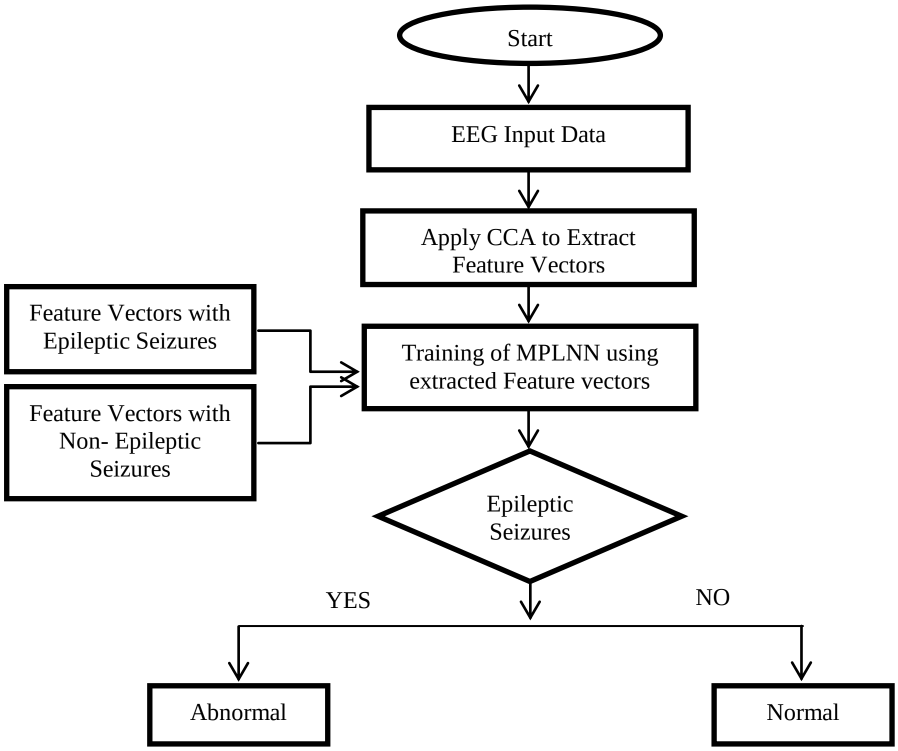

Figure 1. Flow Chart of Proposed Methodology

3. Results and Discussion

The performance and effectiveness of the proposed method CCA-NN in detection of epileptic seizure is assessed with regard to accuracy, specificity and sensitivity. These performance attributes including accuracy, specificity and sensitivity are formulated from confusion matrix define in Table 1 and described as follows:

Table 1. Confusion Matrix for Detection of Epileptic Seizure

		Predicted	
		Abnormal (Epileptic Seizure)	Normal
True (Actual)	Abnormal (Epileptic Seizure)	True Positive	False Positive
	Normal	True Negative	False Negative

Accuracy: The accuracy is defined as a percentage of total number of true epileptic seizure predictions and mathematically given as,

$$Accuracy = \frac{(True\ Positive + True\ Negative)}{(True\ Positive + True\ Negative + False\ Positive + False\ Negative)} \quad (7)$$

Sensitivity: Sensitivity gives true positive rate of predicted seizures. It is percentage of correctly detected epileptic seizures compared to the total number of true recorded seizures. Mathematically given as,

$$Sensitivity = \frac{True\ Positive}{(True\ Positive + False\ Negative)} \tag{8}$$

Specificity: Specificity gives true negative rate of predicted seizures. It is percentage of correctly detected non-seizures when truly there is no epileptic seizure. Mathematically given as,

$$Specificity = \frac{True\ Negative}{(False\ Positive + False\ Negative)} \tag{9}$$

An average classification accuracy for all 24 pediatric patients was 92.58%achieved using proposed method CCA-NN. Likewise, the average sensitivity and average specificity were obtained with CCA-NN as 93.25% and 91% respectively, while the false detection rate was reported with CCA-NN as 8.1%. Theses accuracy, sensitivity and specificity results for 24 patients are individually shown in Figure 2, 3, and 4 respectively.

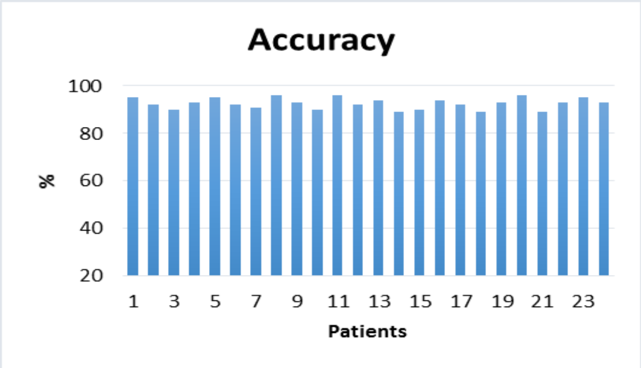

Figure 2. Individual Accuracy Result for 24 Patients

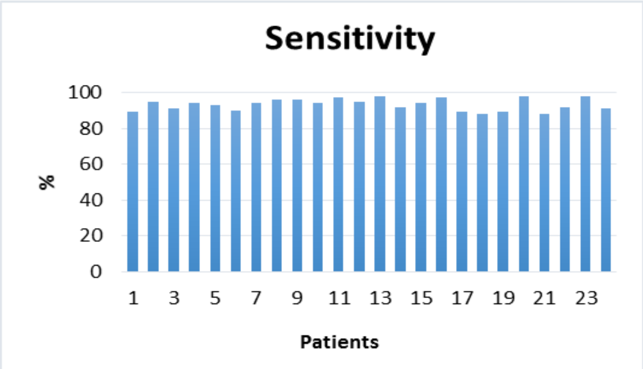

Figure 3. Individual Sensitivity Result for 24 Patients

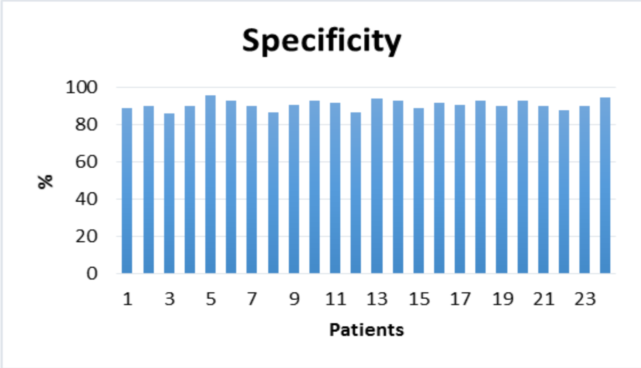

Figure 4. Individual Specificity Result for 24 Patients

Furthermore, the proposed method CCA-NN is also compared with other eminent epileptic seizure detection methods. Table 2 shows the comparative results. The classification results for accuracy and sensitivity achieved by CCA-NN are higher than other methods. However, the specificity obtained by proposed method is reasonably comparable but higher accuracy and sensitivity by CCA-NN demonstrates that this method is capable for detection of epileptic seizures. However, the results still propose that the proposed method can be modified further to improve its effectiveness and performance.

Table 2. Comparison of Proposed method CCA-NN with Related Eminent Methods

Method	Evaluation Criteria		
	Accuracy	Sensitivity	Specificity
Liu *et al.* [11]	N/S	84%	98%
Gotman *et al.* [12]	71%	N/S	N/S
Hassanpour *et al.* [13]	92.5%	N/S	N/S
Wilson *et al.* [14]	N/S	76%	N/S
Alkan *et al.* [15]	92%	90%	93%
Greene *et al.* [16]	86.32%	76.37%	88.77%
Aarabi *et al.* [17]	N/S	74%	70.1%
Temko *et al.* [18]	89%	N/S	N/S
CCA-NN	**92.583%**	**93.25%**	**91%**

4. Conclusion

This research work presents Canonical Correlation Analysis (CCA) and Artificial Neural Network (ANN)'s widely explored model Multilayer Perceptron Neural Networks (MLPNNs) based method to detect epileptic seizures from EEGs. The prime purpose of this research work is to detect epileptic seizures from recorded EEG data. First of all, feature vectors are extracted using CCA and these feature vectors are then used as input to the classifier MLPNN for training and decision making purpose. The classification results of accuracy, sensitivity and specificity reveals that CCA provides better features for epileptic seizure detection. In this work proposed method CCA-NN is also compared with other available techniques. The comparative results reveals that CCA-NN has achieved better accuracy and sensitivity than others while specificity is reasonably comparable. Others widely explored methods generally use different kind of EEG features from frequency domain or time domain. Nevertheless, the proposed method utilizes a single kind of feature only i.e. Eigen values which makes it less computational complex algorithm. Furthermore, the proposed method can be optimized to improve the specificity as well as sensitivity using different intelligent and efficient combination of classifiers which make it more efficient and effective for clinical applications.

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