Research Article

Efficient Automatic Seizure Detection Algorithms to Classify Epilepsy from EEG Signals Using Certain Post Classifiers

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ABSTRACT

Nearly 1% of entire human population suffers from epilepsy and around 80-90% is prevalent in the developing economies only. Due to the abnormalities in the electrical activity of the brain, epilepsy occurs and it results in sudden body movement and sensation accompanied by abnormal perception and behaviour. In the cerebral cortical regions of the brain, the firing of neurons is in a hyper synchronous state and is visualized as epileptic seizures. The three important characteristic features of seizures are that it is highly recurrent in nature, random and brief. The exact diagnosis of epilepsy is a tough task to perform because the symptom of epilepsy and the symptoms of other brain disorders are more or less similar and overlapping. Also, there is no clear knowledge about the progression of seizure. For treating the epileptic patient, diagnosis has to be done and for that it is essential to recognize the affected area in the brain. With the advent of Electroencephalogram (EEG), it serves as a great boon for the analysis of the dynamic and complex behaviors of the brain and it is helpful to learn about the various physiological states of the brain. For recognizing and diagnosing epilepsy, EEG has become a versatile tool. The clinical EEG data obtained is highly complex, difficult to interpret and multi-dimensional in nature. The extraction and interpretation of the useful information from the raw data is a very challenging task. The amount of data generated by EEG is massive and only with an expert it can be interpreted. In this paper, dimensions of the EEG data are reduced with the help of Linear Discriminant Analysis (LDA) and Isomap. The dimensionally reduced values are then classified with the aid of automated seizure prediction models in the form of post classifiers like Singular Value Decomposition (SVD), Cascaded Forward Back Propagation Network (CFBPN), Multi Layer Perceptron (MLP) and Radial Basis Function (RBF). The result analysis shows that when both the dimensionality reduction techniques are classified with RBF, a perfect classification and accuracy of 100% is obtained.

Keywords: EEG, Epilepsy, LDA, Isomap, CFBPN, MLP, RBF.

INTRODUCTION

One of the most common neurological disorders occurring in the brain is epilepsy and it troubles more than 40 million people worldwide[1]. The standard hallmark symptom of epilepsy is seizure and it has a wide range of both social and medical effects. Many patients do not respond to the intervention of the pharmacological methods and so to treat majority of patients, antiepileptic drugs cannot help. So to understand this dynamic disease, various new methodologies and possibilities for treatment are rising. Developing suitable devices that can incorporate versatile algorithms for early detection of onset of seizures is the need of the hour. With the help of such techniques, the severe physical manifestations starts in the patient, the seizure of the patient's can be easily detected and prevented. When the neuronal networks in the cortical regions of the brain synchronize excessively, this same problem occurs[2]. So the epileptic patients experience a lot of abnormal bursts in the electrical activity discharges of the brain. A lot of temporary changes in behaviour and perception are observed in a lot of patients who suffer from epileptic seizures. Due to the various structural malformations in the cerebral cortex, various kinds of brain injuries, genetic and physiological defects, the epilepsy occurs.

With the help of EEG, epileptic seizures can be analyzed in the human brain. Thus EEG serves as an important means to identify the seizure activity in brain of human. A great amount of information about the activities and function of the brain can be analyzed through EEG. To analyze the complex electrical fields of the activity of brain, EEG helps the clinician greatly. The electrodes are placed directly on the scalp and the cortical regions are analyzed in the brain. The EEG specialist tries to determine and understand the location and nature of the various EEG patterns, like corresponds to normal and abnormal neural activity from all the types of recordings. The EEG signal of epileptic patients display patterns which is very different when compared to the patterns of the normal state of brain. The varieties are shown with respect to time, frequency and space. When the electrodes are placed on the scalp, the potential differences between electrodes are detected by EEG. Depending on the synchronization of the involvement of neuronal activity, the patterns are displayed. With the aid of skilled visual encephalography professionals, the epileptic EEG signal can be identified in majority of the cases but it is quite time consuming and it is hard to find such experts and therefore automated seizure detection algorithms are important and its rise came into existence[3]. Some of the most important recent literature is discussed as follows: The automatic detection of seizure onset in pediatric EEG was done by Khan et al[4]. An algorithm for

seizure onset detection using intracranial EEG was performed by Kharbouch et al[5]. The comparison of Short Time Fourier Transform and wavelet transform methods in determining epileptic seizure activity in EEG signals for real-time applications was found by Kiymik et al[6]. The network mechanism of the spread of paroxysms, typical versus atypical absence seizures was performed by Perez Velazquez et al[7]. A system to detect the onset of epileptic seizures in scalp EEG was developed by Saab and Gotman[8]. The application of machine learning to epileptic seizure detection was performed by Shoeb and Gutterg[9]. With the help of matching pursuit, automatic epileptic seizure onset detection was done by Sorensen et al[10]. The continuous analysis of EEG's alpha wave by morlet wavelet transform was done by Wang et al[11]. Fuzzy support vector machine for classification of EEG signals using wavelet-based features was performed by Qi Xu et al[12]. The best basis-based wavelet packet entropy feature extraction and hierarchial EEG classification for epileptic detection was done by Deng Wong et al[13]. In this work, as the recordings of the EEG are quite long, the dimensions of it are initially reduced by using LDA and Isomap and later classified with SVD, CFFNN, MLP and RBF. The block diagram of the paper is given in Figure 1. The paper is organized as follows: The methods and materials are given in section 2 followed by the application of dimensionality reduction techniques in section 3. Section 4 gives the classification details of the employed post classifiers and section 5 gives the results and discussion followed by conclusion in section 6.
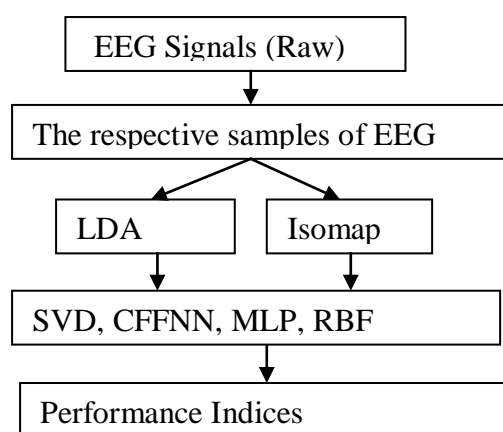

Figure 1: Overall Block Diagram of the Work

MATERIALS AND METHODS

Acquiring the EEG Data

The system employed to place the electrodes on the scalp of the brain to record EEG is the standard International 10-20 system. The EEG is recorded continuously for totally 16 channels. The reference of one electrode is done with respect to its adjacent electrode. For periods like resting, deep sleep, fast and slow movements, eyes open, semi closed, fully closed, the recording are done. Siemens Minograph Universal, a versatile EEG machine is used for the amplification purpose. Before the help of electrode paste, the electrodes are washed well and then placed on the scalp. The contact impedance is of the range less than $10 \ k\Omega$. 30 mm/s is the recording speed of EEG signals. Umax 6696 scanner is used for scanning purposes here. For totally 20 patients, with the help of experience neurologists, the readings had been obtained at Sri Ramakrishna Hospital, Coimbatore, India in European Data Format. For 30 minutes duration, the EEG recordings are done continuously and then it is divided into equal epochs which have 2 second duration. Later it is scanned to a small bitmap image size which contains nearly 400 x 100 pixels. To trace the vital changes in the signal, the 2 second epoch is pretty good.

Mitigating the Dimensions of the EEG Data

As 50 Hz is the maximum frequency of EEG, to obtain its samples, based on the Nyquist criterion the sampling frequency obtained is about 200 Hz. The amplitude values of the signal which are highly instantaneous in nature represent the sample values and ultimately for a single epoch there are totally 400 values. As there are totally 16 channels and each channel comprises of 3 epochs, the total number of samples to be processed is around 25,500 samples and this number is too massive for computation. The dimensionally reduced values are more sufficient to deliver the exact calculation in mean and variance. For the quantification of EEG, the different parameters are computed by utilizing the amplitude values with the help of appropriate programming codes. For both the training and testing purposes, EEG recordings of twenty patients are used.

LDA AND ISOMAP AS DIMENSIONALITY REDUCTION TECHNIQUES

The two important dimensionality reduction techniques utilized here are LDA and Isomap.

LDA

It is very common to implement a feature extraction technique as a basic pre-processing step while solving pattern classification problems. It not only reduces the computational complexity performance but also enhances the classification performance to a great extent. A particular class of feature extraction procedures is defined by a particular transformation

$Y = T(X)$, where $X \in R^D$ and $Y \in R^d$.

By optimizing the necessary objectives, the transformation T is obtained. Thus, there are two important parts to a feature extraction, firstly, the suitable objectives must be formulated well and secondly, the respective optimal solution of the transformation should be determined. One of the most famous linear dimensionality reduction algorithms is LDA[14]. Suppose a D-dimensional data set X is considered as follows $\{X = x_1, x_{2,....;}x_n\}$, with

totally C classes, the actual Fisher criteria implemented in LDA is given as follows

$$J = \frac{wS_B\omega^T}{wS_w\omega^T}$$

Where S_w denotes the average within class scatter matrix and S_B indicates the in between-class covariance matrix of X.

An Eigen value decomposition of $S_w^{-1}S_B$ is performed now and then the rows of ω is made equal to totally 'd' Eigen vectors which represents or belongs to the $d(d \le C-1)$ largest eigen values. Then a condition $d-by-D(d \le D)$ transformation matrix ω is examined so that the Fisher criterion is satisfied. The exact set X is mapped from $D-$dimensional space which is original to the newly found $d-$dimensional space with the help of function $Y = \omega X$. The newly formed space maintains all the discriminative information and content contained in X so that good classification rate can be obtained.

Isomap

It is a recently developed approach in the field of non linear dimensionality reduction and is based primarily on Multi Dimensionality Scheme (MDS)[15]. It is a type where non linear generalization is done to classical MDS. The main plan is to implement MDS in the geodesic space of the given non linear data manifold. Isomap is generally not applied in the input space. The shortest path in the curved surfaces of the non linear data manifold is measured by the geodesic distances. If short steps are initiated in between the adjacent sample points, then it can be easily approximated. Isomap then implement the MDS to the geodesic spaces rather than the distances which are in the form of straight line in order to trace a very low-dimensional mapping scheme. The Isomap has three steps; Firstly, in the high dimensional data space, the adjacent neighbors of each and every data point are found out. In between all the points, the geodesic pair wise distances are computed. Finally to preserve the distances, use MDS to embed the data. Similar the Local Linear Embedding (LLE), it can be proceeded as follows: The K nearest neighbour are identified by choosing all the points within a particular fixed radius ε. In a graph G, the representation of those neighborhood relations are done, so that each data point is connected to its adjacent and nearest neighbor with edges of weight $d_x(i,j)$ in between the neighbor. Between all the pairs of points of data manifold M, the geodesic distances $d_M(i,j)$ is estimated. In the graph G, the Isomap approximates the $d_M(i,j)$ as the shortest path distance $d_G(i,j)$. The shortest path is computed using Dijkstra's algorithm or Floyd's algorithm. The matrix of graph distances $D^{(G)}$ is found out which tells the shortest path distance in between the pairs of points in the manifold. Finally classical MDS is applied to $D^{(G)}$ so that embedding of data is generated in a $d-$dimensional Euclidean space Y. By managing the coordinates of y_i to the top 'd' Eigen vectors, the g_{min} of the cost function is obtained.

I CLASSIFYING EPILEPSY FROM EEG SIGNALS

The dimensionally reduced values are then fed inside the post classifiers to classify the epilepsy from EEG signals. The post classifiers used here are SVD, CFFNN, RBF and MLP.

SVD

The generalization of the eigen-decomposition yields the SVD and is primarily used to analyze rectangular matrices. In eigen decomposition, a matrix is decomposed into 2 simple matrices, whereas in SVD, a rectangular matrix is decomposed into three simple matrices, namely, a diagonal matrix and 2 orthogonal matrices. The SVD is more or less equivalent to PCA and metric MDS because a least square matrix for a particular matrix is obtained by a lower rank matrix which has similar dimensions. Therefore SVD serves as an important tool for multivariate analysis[16]. If A is a positive semi-definite matrix, the Eigen decomposition of it is expressed as

$$A = U\Lambda U^T$$

Where the ortho normal matrix is represented as U (i.e.) $U^TU = I$, Λ represents the diagonal matrix which contains the eigen values of A. To obtain a similar decomposition this is implemented to all the rectangular matrices comprising of real numbers, the SVD employs the eigen-decomposition of a positive semi-definite matrix. The idea is to simply decompose any matrix into 3 simple matrices into one diagonal matrix and second orthonormal matrices, the SVD becomes equivalent to the Eigen decomposition if it is applied to a positive semi-definite matrix.

If B is a rectangular matrix, the SVD of it is decomposed as follows

$$B = E\Delta F^T$$

Where E represents the normalized Eigen vector of the matrix BB^T (i.e) $E^TE = I$. The left singular vectors of B represent the columns of E. Q represents the normalized eigen vector of the matrix B^TB (i.e) $F^TF = I$. The right singular vectors of B represent the columns of F. Δ represents the diagonal matrix containing the singular values, $\Delta = \Lambda^{1/2}$ where Λ

represents the diagonal matrix of the Eigen values of both the matrices BB^T and $B^T B$. For a positive semi-definite matrix, if eigen-decomposition is performed, then SVD is obtained.

Cascaded Forward Back Propagation Network

A fundamental mathematical model of the human brain is Artificial Neural Network (ANN). A lot of interconnection in between the neurons is required to get a good performance in the real time neural network scenario. Through learning process, the Neural Networks can get the knowledge of the surrounding environment, so that the attainment of the desired design objective is done by changing the synaptic weights of the network analytically. Generally an ANN comprises of 3 and more neuron layers, one input layer, one hidden layer and one or more output layers. For restricting the building time of the model, only a single hidden layer is used in some cases. Various types of architecture are used in ANN. The architecture in Figure 2 explains the number of layers. The architecture explains the number of layers a network should have, the total number of neurons in each layer, the connection in between the layers and the transfer function of the layer. In this case, there are 2 main architecture involved namely, Feed forward back propagation and cascade forward back propagation[17]. The figure is shown here as one input layer of 3 neurons, one hidden layer of 2 neurons and one output layer. In feed forward back propagation, there is one input layer, one or more hidden layers and one output layer. The hidden layer consists of sigmoid neurons and it is followed by the output layer which consists of linear neurons. Cascaded Forward Back Propagation Network is similar to Feed Forward Back Propagation Network which utilizes Back Propagation Algorithm for the weight updation process. In this architecture the neurons in each layer relates itself to the neurons in the previous layer. The architecture of the cascade neural networks is dynamic in nature. In the context of cascade networks, only with the help of one neuron, learning is started and during the training phase, the learning algorithm adds new neurons automatically thereby creating a multilayer architecture. If the training error decreases, it implies that the total number of hidden layer neurons increases in a step by step fashion. The growth of the network is determined by the learning algorithm. For the updation of the weights in the network, two training algorithms such as Levenberg-Marquardt and Bayesian regulation back propagation algorithms are used. If the connectivity is controlled inside the network, then it can lead to a very fast learning rate.

Multi Layer Perceptron (MLP)

It is capable of learning nonlinear decision surface. This type of feed-forward network is normally directed and acyclic[18]. This type of feed-forward network is normally directed and acyclic as shown in Figure 3.
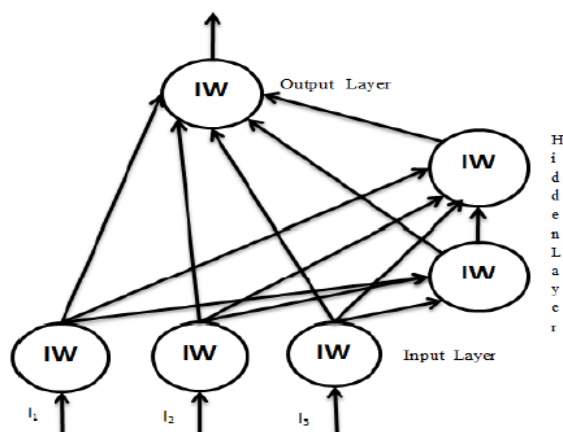

Figure 2: Architecture of CFBPN

It is based on a sigmoid unit and resembles much like a perceptron but based on a smoothed, differentiate threshold function represented as $\sigma_{(net)} = \dfrac{1}{1 + e^{-net}}$

Where $\lim_{net \to +\infty} \sigma(net) = 1$ and $\lim_{net \to -\infty} \sigma(net) = 0$
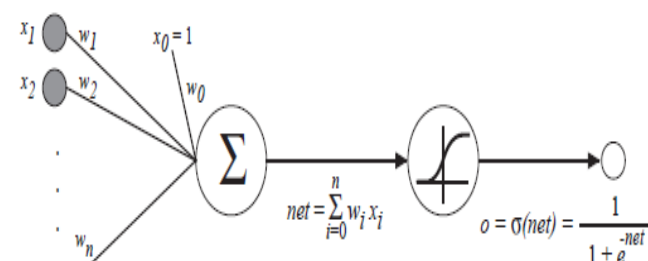

Figure 3: Multi Layer Perceptron (MLP)

To update the weights, Back propagation algorithm is used. The weights are learnt thoroughly for a feed-forward multilayer network with a particular set of fixed neurons of interconnection. To minimize the error, gradient descent is employed. The back propagation (training_examples, $\eta, \eta_{in}, \eta_{out}, n_{hidden}$) is carried out as follows. The input from unit i to unit j is represented as x_{ji} and the weight from unit i to unit j is represented as w_{ji}. A feed-forward network with η_{in} inputs, n_{hidden} units and n_{out} output units is created initially. The network weights are all initialized to very small random numbers. Till the achievement of the termination condition, the following steps are repeated.

For all $< \vec{x}, \vec{t} >$ in training samples,

a) The propagation of the input in the forward direction through the networks is done

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1) The input $\vec{x}$ is given to the network and then compute o_u for every unit u .

   b) The errors are propagated back through the network

2) For each network output unit k , its respective error term δ_k is calculated as follows

$$\delta_k \leftarrow o_k(1-o_k)(t_k-o_k)$$

3) For each hidden unit h , its error term δ_h is calculated as follows

$$\delta_h \leftarrow o_h(1-o_h)\sum_{k\in outputs} w_{kh}\delta_k$$

4) Each weight w_{ji} is updated as follows

$$w_{ji} \leftarrow w_{ji} + \Delta w_{ji} \text{ Where } \Delta w_{ji} = \eta\delta_j x_{ji}$$

The termination conditions are set as with fixed no of iterations, the error value falls below some threshold values. A function is said to be radial basis if the output is dependent on the distance of the input from a particular stored vector and it is shown in Figure 4.

Radial Basis Function (RBF)

A function is said to be radial basis if the output is dependent on the distance of the input from a particular stored vector. They generally represent local receptors, where each and every point is a stored vector applied in a single RBF[18]. In the context of a RBF network, one hidden layer implements neurons with RBF activation functions and as a result it explains the local receptors in detail. Also an output node used here is implemented to combine all the output of the hidden neurons in a linear fashion.
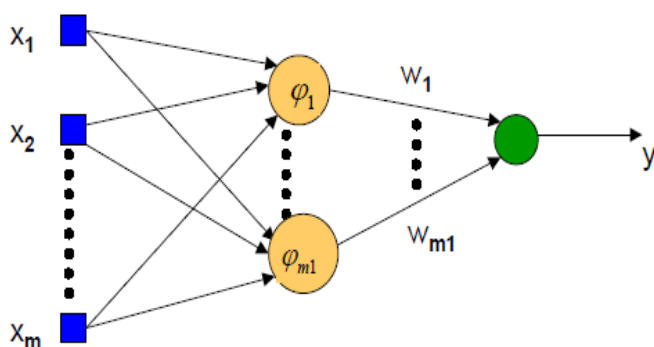

Figure 3: RBF

One hidden layer with RBF activation functions is represented as $\varphi_1,....,\varphi_{m1}$. The output layer with linear activation function is produced as follows

$$y = w_1\varphi_1(\|x-t_1\|) + ... + w_{m1}\varphi_{m1}(\|x-t_{m1}\|)$$

where $\|x-t\|$ represents the distance of $x = (x_1,...,x_m)$ from a vector t . Here the hidden units use the radial basis function $\varphi_\sigma(\|x-t\|)$, where t represents the centre and σ represents the spread. Here the centre and spread are the parameters. The output is mainly dependent on the distance of the input x from the centre point t . Only near its centre, the hidden neurons will be more sensitive to data points. In the case of Gaussian RBF, if the spread σ is adjusted, then the sensitivity can be tuned easily. If the spread is large, then it implies less sensitivity.

RESULTS AND DISCUSSION

When LDA and Isomap are effectively utilized as dimensionality reduction techniques and classified with post classifiers like SVD, CFBPN, MLP and RBF, based on the parameters like Performance Indices, Accuracy, Specificity, Sensitivity, Quality values and Time Delay the average results are computed in Tables 1 and 2 respectively. The mathematical formulae for the terms like Performance Index (PI), Sensitivity, Specificity and Accuracy are given as follows

$$PI = \left(\frac{PC - MC - FA}{PC}\right)\times 100$$

The Perfect Classification is indicated by PC, the Missed Classification is indicated by MC and the False Alarm is indicated as FA. The Sensitivity, Specificity and Accuracy measures are mentioned by the following formulae:

$$Sensitivity = \frac{PC}{PC + FA}\times 100$$

$$Specificity = \frac{PC}{PC + MC}\times 100$$

$$Accuracy = \frac{Sensitivity + Specificity}{2}\times 100$$

The Quality Value Q_v is defined in a significant manner as

$$Q_v = \frac{C}{(R_{fa} + 0.2)*(T_{dly} * P_{dct} + 6*P_{msd})}$$

Here the scaling constant is mentioned as C,

The number of false alarm per set is mentioned by R_{fa},

The average delay of the onset classification (seconds) is indicated by $T_{dly,}$. The percentage of perfect classification is mentioned by P_{dct}. The percentage of perfect risk level missed is identified by $P_{msd,}$. The time delay is mathematically expressed as follows

$$Time\ Delay = \left[2\times\frac{PC}{100} + 6\times\frac{MC}{100}\right]$$

If the Table 1 is considered for analysis, if LDA is utilized as a dimensionality reduction technique and classified with SVD, an average accuracy of 91.77 % is obtained with a perfect classification rate of 83.54%.

Table 1: Average Results Analysis for LDA

PARAMETERS	LDA + SVD	LDA + CFBNN	LDA + MLP	LDA + RBF
PC (%)	83.54	94.30	88.05	100
MC (%)	2.01	1.73	0	0
FA (%)	14.44	3.95	11.95	0
PI (%)	78.81	93.72	86.42	100
Sensitivity (%)	85.55	96.04	88.05	100
Specificity (%)	97.98	98.26	100	100
Time Delay (sec)	1.79	1.99	1.76	2
Quality Values	17.57	21.65	17.77	25
Accuracy (%)	91.77	97.15	94.03	100

If LDA-CFBNN combination is used, an average accuracy of 97.15% along with a perfect classification rate of about 94.30% is obtained, for LDA-MLP combination a perfect classification rate of about 88.05% and LDA-RBF combination, an accuracy of 100% is obtained.

Table 2: Average Results Analysis for Isomap Analysis

PARAMETERS	Isomap+ SVD	Isomap+ CFBNN	Isomap + MLP	Isomap + RBF
PC (%)	85	95.30	95.83	100
MC (%)	1.45	1.63	0	0
FA (%)	13.54	4.75	4.16	0
PI (%)	81.32	95.72	95.65	100
Sensitivity (%)	86.45	97.01	95.83	100
Specificity (%)	98.54	100	100	100
Time Delay (sec)	1.78	1.82	1.91	2
Quality Values	17.75	21.98	21.58	25
Accuracy (%)	92.5	97.52	97.91	100

If the Table 2 is considered for analysis, if Isomap is utilized as a dimensionality reduction technique and classified with SVD, an average accuracy of 92.5 % is obtained. If Isomap-CFBNN combination is used, an average accuracy of 97.52% is obtained, for Isomap-MLP combination, an average accuracy of 97.91% is obtained and Isomap-RBF combination, an accuracy of 100% is obtained.

CONCLUSION

Thus with the help of EEG signals, the electrical activity of the brain is easily indicated. The most important information about the state of the brain is given by the EEG. For the extraction of features, to reduce the dimensions of the EEG data and for the application of various advanced signal processing techniques to it, EEG is of great utility. Thus in this paper, two dimensionality

reduction techniques such as Isomap and LDA was utilized efficiently and then classified with four classifiers such as SVD, CFBNN, MLP and RBF. The result analysis shows that the best perfect classification rate is obtained when both the dimensionality reduction techniques are classified with the RBF Classifier with an average performance Index of 100 % and an average accuracy of 100%, with a very less time delay and a good quality value. Apart from the RBF classifier, the next best technique is the combination of Isomap-MLP which gives an average performance index of 95.65% along with an average accuracy of 97.91%. Future works may incorporate the usage of different modifications in the post classification techniques.

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