International Journal of Grid and Distributed Computing
Vol. 14, No. 1, (2021), pp. 2030 - 2049

Optimal Feature Selection using Plant Grow Optimization for Motor Imagery EEG Classification Based on Cascaded Neural Network

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Abstract

The complex state of electroencephalogram signal features deflects the predication rate of the brain-computer interface. The extraction of features from the EEG signal using stationary wavelet transforms function. The stationary wavelet transform function decomposed the layers of sub-bands of EGG signals. The extracted features are a combination of real signal and noise signal and the noise-signal degraded the performance of the EEG classification. For the removal of noise signal form extracted features using plant grow optimization algorithm, the plant grows optimization algorithm filter the noise feature from extracted data. The nature of the plant grows optimization algorithm is impulsively related to the nature of the EEG signal. Various authors proposed an EEG classification algorithm for the prediction of human diseases related to the control system of the brain. The classification algorithm faced a challenge of optimal feature selection and mapping of assign class for the predication. In this paper proposed cascaded neural network models for the classification of EEG signals. The cascaded neural network model is a combination of a Self-organized map network and a radial biased function. The RBF neural network is a supervised network model, and the SOM model is unsupervised. The SOM model performs the task of a grouping of signals, and RBF neural network model works for the predication of pattern for the classification process. The proposed algorithm simulates in EGG LAB with MATLAB 2016Ra. For the validation used sampled data of EEG signals from the reputed data source.

Keywords: - EEG classification, PGO, SOM, RBF, Feature, BCI, Motor Imagery

Introduction

The human brain is a dynamic network that continually changes the function and behavior of a control system. The behaviors of the human brain electrical signal recorded in from the EEG signal, the EEG signal nature is a time series of human activity[1]. The recoded electrical signal is a composite form of real signal and noise signal. The major dominated features of EEG signals are maximum frequency and maximum power and some other features of signal related to statically property of signal. The extraction of features from composite EEG signals is a challenging task for certain and estimated features for the process of classification. In the current research trend in

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brain-computer interface (BCI) used time and frequency dominated function for the extraction of features from EEG signals. Various authors used wavelet transform function for the extraction of features[2, 3]. The wavelet transform function extracts the feature of energy and frequency. Serval feature selection methods have been proposed, including PCA, ICA, and kernel-based approach. Some authors used swarm-based feature selection algorithms such as particle swarm optimization, firefly algorithm, genetic algorithm, and many more for the process of feature selection. The selection of features is an essential phase of EEG classification [5]. The better selection of features enhances the efficacy of the EEG classification algorithm. The increasing efficiency of classification supports critical disease detection and restores the disordered brain function. The huge dimension of feature vector, the complexity of process of classification increases[6, 7]. The unwanted features of EEG signals decrease the classification ratio and creates bottleneck problem for the classifier. Minimization of this bottleneck problem used plant grow optimization algorithm for the selection of feature vector[8]. The energy and frequency band features select from vector of features and boost the performance of classification. In this paper proposed cascaded neural network-based classification algorithm, cascaded neural network classifier enhance the classification ratio of $EEG\ signals$ data. The cascaded neural network is mutual combination of SOM neural network and RBF neural network model. The process of cascading algorithms describes in two mode of operation, one is clustering of feature vector and other is predication and classification of EEG features vector. By the nature of SOM network is unsupervised neural network model and RBF neural network is supervised neural network model[9, 10, 11]. The cascaded algorithm compares with other classification algorithms used for EEG classification. In consequence of classification used $machine\ learning$ and $deep\ neural\ network$ algorithm for the validation of proposed algorithm. The proposed algorithm simulates in MATLAB software and used reputed EEG classification dataset[12, 13]. The remaining part of paper brief as in $section\ II$. Process of feature extraction and feature optimization, in $section\ III$ discuss proposed methodology, in $section\ IV$ simulation and description of dataset and finally conclude in $section\ V$.

II. Related Work

Nourhan Wafeek categorize arm and finger developments acquired through $EEG\ signals$. The $EEG\ signals$ have been changed to frequency space using DWT as a component extractor. These removed features are then feed into a standard PSO based classifier to arrange the individual's improvements of arm and fingers. The $SOC\ initialization\ method$ based on multiple parameters, the issue of long-standing time required by $open-circuit\ voltage\ method$ to determine the initial value of SOC is solved. The real-time correction of battery capacity according to temperature improves the accuracy of SOC prediction[1]. Sabrina Ammar introduces a new patient-specific system with genetic and PSO algorithms. The results show that the discussed system is able to reach acceptable performances. the genetic algorithm and the practical swarm optimization were used for the parameter's adaptation. The aim is to analyses the exhibitions of these 2 techniques.

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simulation results represent that the genetic technique can reach better sensitivity value [2]. Jyoti Singh Kirar talked about four univariate include determination techniques, for example, Euclidean distance, relationship, shared data and Fisher discriminant proportion and two understood classifiers ($LDA\ and\ SVM$) are examined. The talked about strategy has been affirmed using the transparently available $BCI\ contention\ IV\ dataset\ Ia$ and $BCI\ Competition\ III\ dataset\ IVa$. Exploratory outcomes exhibit that the talked about strategy essentially beats the current techniques as far as classification error[3]. Minmin Miao characterized channel choice strategy dependent on straight discriminant criteria is utilized to naturally choose the channels with high discriminative forces. Exploratory outcomes exhibit that this plan can adjust to client explicit examples and discover the moderately ideal channels, recurrence band and time interim for highlight extraction [4]. Vasilisa Mishuhina Et al. examined a standard FWR strategy that uses all CSP highlights to keep away from data leases. The optimization procedure can be applied in all CSP-based methodologies. Simulations of this work represent the effect of the discussion about technique applied in the standard CSP and its two expansions, basic spatio-unearthly examples and regularized CSP [5].

N. Satheesh Kumar introduced the Adaptive Neuro-Fuzzy Inference System classifier got together with PSO that is named as PSO-ANFIS for ordering the diagnosing sign of EEG. To begin with, using Savitzky Golay (S-G) channel pre-prepared the information signal, after that by variational mode deterioration (VMD) broke down the sign. Highlights are removed; furthermore, these are prepared and furthermore portrayed using PSO-ANFIS, which orders whether the sign appears to be ordinary or else chemical imbalance signal. The examined procedure ordered the anomalous other than typical sign, even more absolutely, when appeared differently in relation to the present ones are built up through the investigation [6]. Sachin Taran Et al. $TQWT$ based component extraction technique is talked about for the arrangement of various MI assignments $EEG\ signals$. The $TQWT$ parameters are tuned for the rot of $EEG\ signal$ into sub-groups. Time zone extents of sub-bunches are considered as features for MI disintegration EEG signals. The $TQWT-set\ up$ together features are attempted as for least-squares reinforce vector machine classifier for the game plan of $right-hand$ and $right-foot\ MI$ undertakings [7]. Luis A. M. Pereira portrayed utilized an outstanding EEG benchmark dataset made out of five classes of EEG signals. Generally, the outcomes confirm the heartiness of the talked about BMOA and its variations [8].

Grega Vrbancic structured another technique that utilizations spectrogram pictures to encourage them with no element choice/extraction system legitimately into a profound convolutional neural system engineering and train it for the grouping of engine hindrance neural issue in an individual. The examined strategy was tried on a lot of (un)impaired subjects, where it beat the conventional AI techniques. The outcomes, got with no human intercession and by utilizing all the default parameter esteems, turned out not to linger much behind a built up best in class technique, that exploits utilizing area information for the investigation of EEG chronicles [9]. Bahareh Nakisa tackle the high-dimensionality issue, the talked about another structure to naturally look for the ideal subset of EEG highlights utilizing transformative calculations. The talked about system has

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been broadly assessed utilizing two open datasets and another dataset gained with a portable EEG sensor[10]. Ranran Zhang talked about another strategy $FB - TRCSP + RF$ dependent on CSP and irregular woods. The $FB - TRCSP$ is consolidated by the eighth request Butterworth bandpass-channels and the CSP with $Tikhonov\ regularization$. At that point, the model is applied to a test informational index gathered from 14 $subjects$ and is contrasted and the non-regularization strategy $FB - CSP + RF$. The outcomes show that the technique talked about yields moderately higher middle characterization exactness's and shows a more grounded capacity in $subject - to - subject$ learning contrasted with winning methodologies [11]. Asmaa Hamad et al. a modified classification architecture utilizing GOA and $SVMs$ for programmed automatic recognition in EEG is talked about called $GOA - SVM$ approach. Different parameters were extricated and utilized as the highlights to prepare the $SVM\ with\ RBF\ kernel\ function$ $(SVM - RBF)\ classifiers$. GOA was utilized for choosing the compelling element subset and the ideal settings of $SVMs$ parameters so as to acquire a fruitful $EEG\ classification$[12].

Hanan A. R. Akkar is to execute as of late developmental calculations for advancing neural loads, for example, GRO, $ABC, CSA\ what's\ more, PSO$. This ANN was investigated to arrange three classes of EEG signals sound subjects, subjects with interictal epilepsy seizure, and subjects with ictal epilepsy seizures. The above planning counts are stood out concurring from portrayal rate, getting ready and testing mean square mistake, normal time, and greatest iteration[13]. $F\ Lotte$ gives a complete overview of the latest classification calculations utilized in $EEG - based\ BCIs$, presents the standards of these strategies and rules on when and how to utilize them. It additionally recognizes various difficulties to additionally propel $EEG\ characterization\ in\ BCI$ [14].

Md Rabiul Islam et al. Offline investigation exhibits the talked about MTSMS approach outflanks best in class techniques. It accomplishes the most elevated normal order precision for all datasets. The expanded order exactness of MI errands with the talked about MTSMS approach can yield successful execution of BCI. The common data based sub-band choice strategy is executed to tune activity recurrence groups to speak to real engine symbolism tasks[15]. Shiu Kumar examined another automated filter tuning approach for motor imagery EEG signal grouping, which naturally and deftly finds the channel parameters for ideal execution. At that point assessed the exhibition of our talked about strategy on two open benchmark datasets [16].

III. Feature Extraction and Optimization

Wavelet Transform

Wavelet transform widely used in computer vision and pattern recognition. Wavelet transform analyzed the biomedical signal concerning time. The nature of the EEG signal is dynamic, now for findings of feature coefficient of EEG signal used wavelet transform and frequency dominated methods[17, 18, 26]. The recoded signal of EEG is the time sequence frame of the window, so the mapping with wavelet transform to get a significant feature coefficient for the classification of

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EEG signals[19, 27]. The multipoint resolution of a feature point of EEG signal required discrete wavelet transform (DWT) the layer of feature point decomposition of transform shown in figure 1. the process of layer decomposition proceeds in the manner of approximate coefficient and detail coefficient[21, 28]. The approximate coefficient is further decomposed into another layer of dissolution, the level of decay of transform up to five levels. Thus, the EEG signal is decomposed into D1-D5. The sampling frequency of the DB2 transform of DWT is 256hz, and the sample value range is distributed according to their coefficient value. The process of extraction measures mainly two features maximum power and energy of EEG signals. Focus on the minimization of the standard deviation of sub-bands for the better selection of feature coefficient[22, 25].

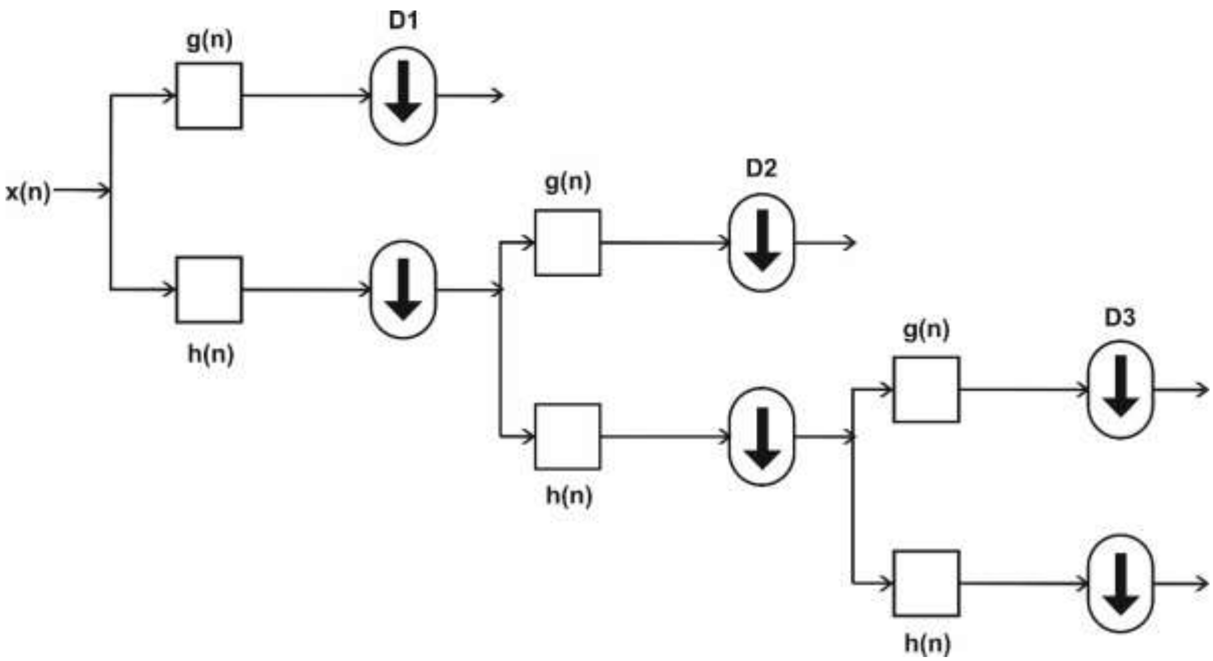

Figure 1: Process of layer decompaction of wavelet transform at level 3 using DB2.

Feature optimization is important phase of EEG data classification and disease predication. For the optimization of features various algorithms are used by research scholar such as GA $(genetic\ algorithm)$, PSO $(particle\ swarm\ optimization)$, ACO $(ant\ colony\ optimization)$ and many more. The mapping and selection of EEG data raised new feature level of EEG sample data. The sampling of all these data mapped with corresponding bands of frequency[22]. For the optimization of EEG data used plant grow optimization (PGO) algorithms. The principle of plant grow optimization algorithm is fight of competition for the successor of life. The process of plant grows optimization algorithm describe in three section given below[23, 24].

1 initialization

This phase defines the initial value of parameter for the growing the plant[22]

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$Set\ \ NG = 0\ \{NG\ is\ the\ generations\ counter\}$

$Set\ \ NC = 0\ \{NC\ is\ the\ convergence\ counter\}$

$Set\ \ NM = 0\ \{NM\ is\ the\ Mature\ points\ counter\}$

$Set\ the\ upper\ limit\ of\ the\ branch\ points\ N\ and\ initialize\ other\ parameters.$

$Select\ N0\ branch\ points\ at\ random\ and\ perform\ leaf\ growth.$

Assign morphogen

Calculate the eligibility of the leaf point.

Assign the concentration of the morphogen of each branch point.

Branching

Select two critical values between 0 and 1 randomly and dispose.

Produce new points by branching in four modes.

Selection mechanism

Perform leaf growth in all the points.

Pick out the mature branch points, the number of which is $k\ (0\ \leq k\ \leq\ N)$, by the maturity mechanism.

Set NM = NM + k

Produce a new point in the center of the crowded area and select the best point to substitute the crowded points.

Eliminate the lower competition ability branch points and select N branch points for next generation.

2. **Competition**

Compare the current points with the mature points and get the best fitness value

f_{max}

Set: $NG\ =\ NG\ +1$

$If\ \left(f_{max} <\ f_{\max_{old}}\ \right) Set\!: f_{max} =\ f_{\max\_old}$

If $\left(\left|f_{max} - f_{\max_{old}}\right| <\ \varepsilon\right) Set\!: NC = NC + 1$

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else

Set: NC = 0

else

Set: NC = NC+1

4. $termination$

$If\ (NG < NG_{max}\ \&\& NC < NC_{max} \&\& NM < NM_{max})$

$Goto\ step\ 2$

$else$

$Exit$

IV. Proposed Algorithm

The proposed algorithm focuses on the classification of EEG data accuracy and sensitivity. The algorithms follow the concept of cascading process of neural network. The cascading process of neural network enhanced the capacity of classification of data in concern of biomedical signal. the proposed algorithms used two neural network models, self-organized (SOM) map neural network and radial biases neural network (RBF)[17, 18]. The process of model work on the basis of unsupervised and supervised. The process of working algorithm describes here.

Xi= sample of optimal feature data

N =size of sample data

V= vector of feature data process.

O = mapped data of cluster

G=Group of patterns,

SM=successor matrix

Wn= winner matrix

Bf =final pattern of classification.

D = dimension of data

R = relation of feature data

S= sample of set

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$B^{\emptyset}$= adjust matrix

Ac = learning factor

The process of training sample as $(X_i \in R^D, y_i \in R)$,i=1……………….m

$sample\ of\ input(p)$ if $*= V$

$$[s^1, \ldots \ldots s^k] \leftarrow [rand(1,k) \times (p-w)] + 1$$

$V \leftarrow n$ vector of neuron

For $i \leftarrow 1\ \ to\ N\ do$

$O^{\cdot} \in C^D \leftarrow S *= V$

$N_*^i \in R^D \leftarrow biase\ of\ O$

$G \in R^D \leftarrow pattern\ N$

End for

Input sample of BF $g_*^1, \ldots \ldots \ldots g_*^m$

$F_{RBF} \in R^{D \times m} \leftarrow \emptyset([g_*^1, \ldots \ldots \ldots g_*^m])$ $\quad Adjust\ W$

$W \in R^D\ \leftarrow BF^{-1}$

$F \in R^{d.;,} \leftarrow W^T\ \emptyset(G)$

For $C \leftarrow 1\ to\ A_c\ do$ $\qquad training\ of\ class\ Cb$

Adjust the weight factor of cascading process

$CC \in R^{d^{\sim}}$ $\leftarrow$ relative feature process of SOM

Call kernel function

$$k(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{\gamma}\right), \gamma \in R_+$$

End for

Adjustment matrix $B^{\emptyset}$ of space F mapping of same class

$$B_{ij}^{\emptyset} = \{ \begin{matrix} e^{\left(-\|x_i - x_j\|^2\right).} \\ e^{\left(-\|x_i - x_j\|^2\right).} \end{matrix} \quad .$$

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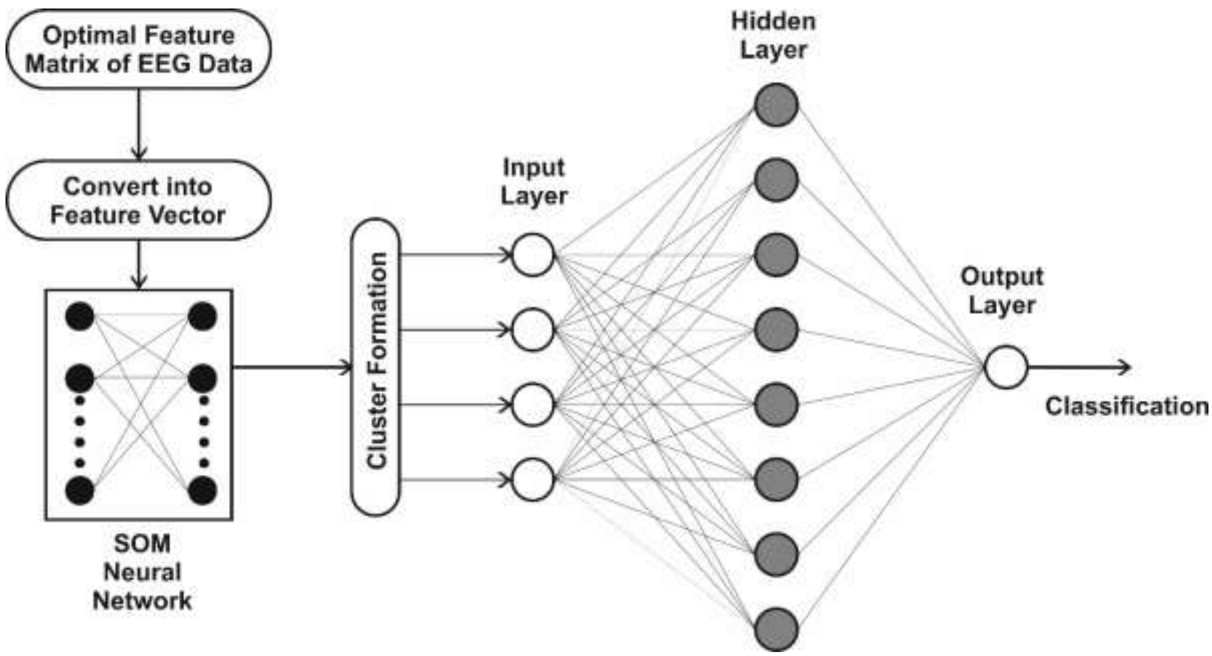

Figure 2: Process block diagram of proposed algorithm of cascaded model for classification of EEG data.

V. Dataset and Result Analysis

DATASET

In clinical diagnosis, the total EEG spectrum for all 20 participants, 14-Male(M) and 7-Female(F), participant's age, condition (ALS and Control) and ALSFRS-R value. With their significant accuracy of participants. Used representation in the table.

Applicant	Gender	Age	Position	$ALSFRS - R$
1	M	45	ALS	41
2	M	58	ALS	24
3	M	55	ALS	28
4	M	68	ALS	37
5	M	62	ALS	38
6	M	78	ALS	29
7	M	55	ALS	26
8	M	63	ALS	20
9	M	61	ALS	25
10	M	66	ALS	18
11	M	70	ALS	25

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12	M	66	Control	-
13	M	57	Control	-
14	M	70	Control	-
15	M	79	Control	-
16	M	57	Control	-
17	M	65	Control	-
18	M	56	Control	-
19	M	46	Control	-
20	M	57	Control	-

Table 1: Participant characteristics like sex, age condition and ALSFRS-R **(Stefanie Blain-Moraes, 2013).**

RESULT ANALYSIS

Signal	EBL		DNN		CASCADED	
	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	76.68	77.65	79.78	82.69	85.65	92.78
Delta	83.45	84.26	85.36	87.44	89.37	94.59
Theta	82.64	85.17	88.94	89.87	92.49	96.45
Alpha	77.14	79.86	82.65	85.88	90.28	95.36
Beta	76.02	80.64	81.82	83.62	89.34	93.15

Table 2: Result analysis of Accuracy parameter using EBL, DNN(Deep Neural Network) and Cascaded Neural Network with both DF (8, 16). The simulation process proceeds with all five types signal bands. The accuracy of the Cascaded neural network technique is more efficient in the comparison of Ensemble learning machine and deep neural network. The accuracy of cascaded technique 8-10% more efficient with respect to Ensemble technique and 5-8% more efficient with respect to deep neural network.

Signal	EBL		DNN		CASCADED	
	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	67.78	72.29	74.86	77.63	80.45	87.28
Delta	74.47	78.37	80.57	81.14	85.98	92.94
Theta	75.54	78.18	81.68	82.52	85.19	93.67
Alpha	79.63	80.28	82.19	84.47	88.37	94.53

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Beta	70.15	75.67	79.89	83.52	90.46	96.81

Table 3: Result analysis of Precision parameter using EBL, DNN(Deep Neural Network) and Cascaded Neural Network with both DF (8, 16). The simulation process proceeds with all 5 types signal bands. The Precision of the Cascaded neural network technique is more efficient in the comparison of Ensemble learning machine and deep neural network. The Precision of cascaded technique 9-13% more efficient with respect to Ensemble technique and 6-7% more efficient with respect to deep neural network.

Signal	EBL		DNN		CASCADED	
	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	80.65	83.47	86.74	88.23	89.25	92.83
Delta	81.36	82.25	84.52	88.75	91.67	94.49
Theta	80.41	83.63	85.36	86.72	89.55	96.86
Alpha	83.85	84.44	87.34	88.86	91.42	97.41
Beta	79.74	82.18	86.81	87.43	92.81	95.39

Table 4: Result analysis of Sensitivity parameter using EBL, DNN and Cascaded Neural Network both DF (8, 16). The simulation process proceeds with all five types signal bands. The Sensitivity of the Cascaded neural network technique is more efficient in the comparison of Ensemble learning machine and deep neural network. The Sensitivity of cascaded technique 8-12% more efficient with respect to Ensemble technique and 3-9% more efficient with respect to deep neural network.

Signal	EBL		DNN		CASCADED	
	16DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	78.67	83.36	85.25	88.69	91.25	94.27
Delta	79.49	84.11	86.39	89.26	91.87	95.18
Theta	77.26	85.84	88.44	89.73	90.62	94.49
Alpha	80.74	83.37	85.81	88.42	93.85	95.37
Beta	82.31	86.76	88.64	89.18	92.16	96.22

Table 5: Result analysis of Specificity parameter using EBL, DNN and Cascaded Neural Network with both DF (8, 16). The simulation process proceeds with all 5 types signal bands. The Specificity of the Cascaded neural network technique is more efficient in the comparison of Ensemble learning machine and deep neural network. The Specificity of cascaded technique 10-

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18% more efficient with respect to Ensemble technique and 4-7% more efficient with respect to deep neural network.

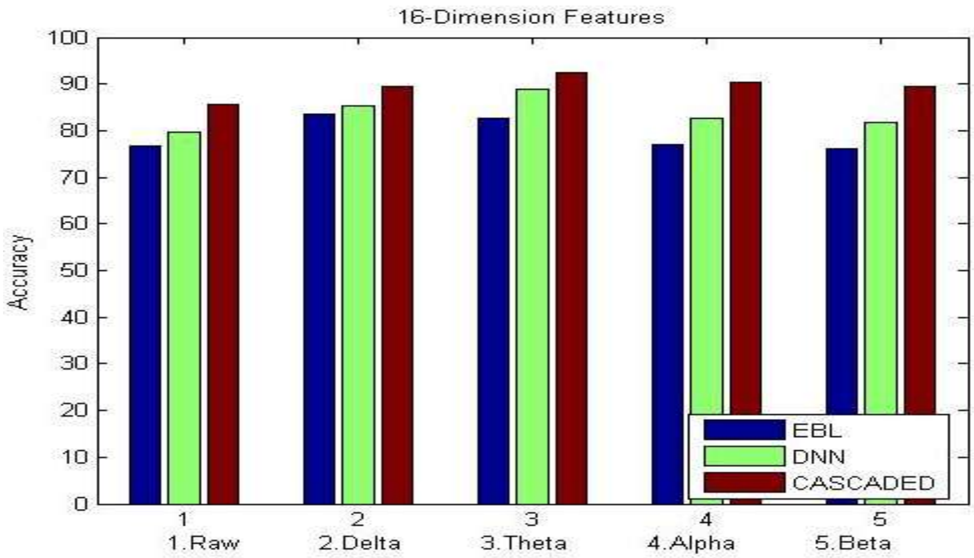

Figure 3: Performance of Accuracy parameter using EBL, DNN and Cascaded Neural Network with $16\ DF$ and all signal bands. Blue color bar represents the ensemble learning machine technique, green color represents the deep neural network technique and red color represent the cascaded neural network technique. In the perspective of signal bands raw, delta, theta, alpha, beta have cascaded technique have better accuracy performance comparison of remaining techniques. EBL have accuracy 76.68, 83.45, 82.64, 77.14, 76.02 with Raw, Delta, Theta, Alpha, Beta sequence and DNN have increased percentage 3, 2, 6, 5, 5 but CASCADED have better performance compare of DNN increased percentage 6, 4, 4, 7, 8.

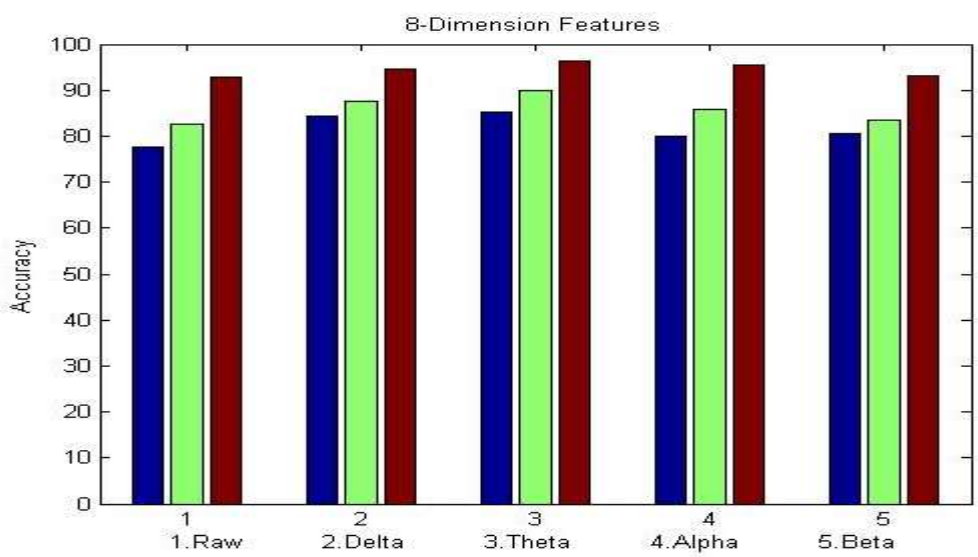

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Figure 4: Performance of Accuracy parameter using EBL, DNN and Cascaded Neural Network with $8\,DF$ and all signal bands. Blue color bar represents the ensemble learning machine technique, green color represents the deep neural network technique and red color represent the cascaded neural network technique. In the perspective of signal bands raw, delta, theta, alpha, beta have cascaded technique have better accuracy performance comparison of remaining techniques. EBL have accuracy 77.65, 84.26, 85.17, 79.86, 80.64 with Raw, Delta, Theta, Alpha, Beta sequence and DNN have increased percentage 5, -3, 4, 6, 3 but CASCADED have better performance compare of DNN increased percentage 9, 7, 7, 10, 9.

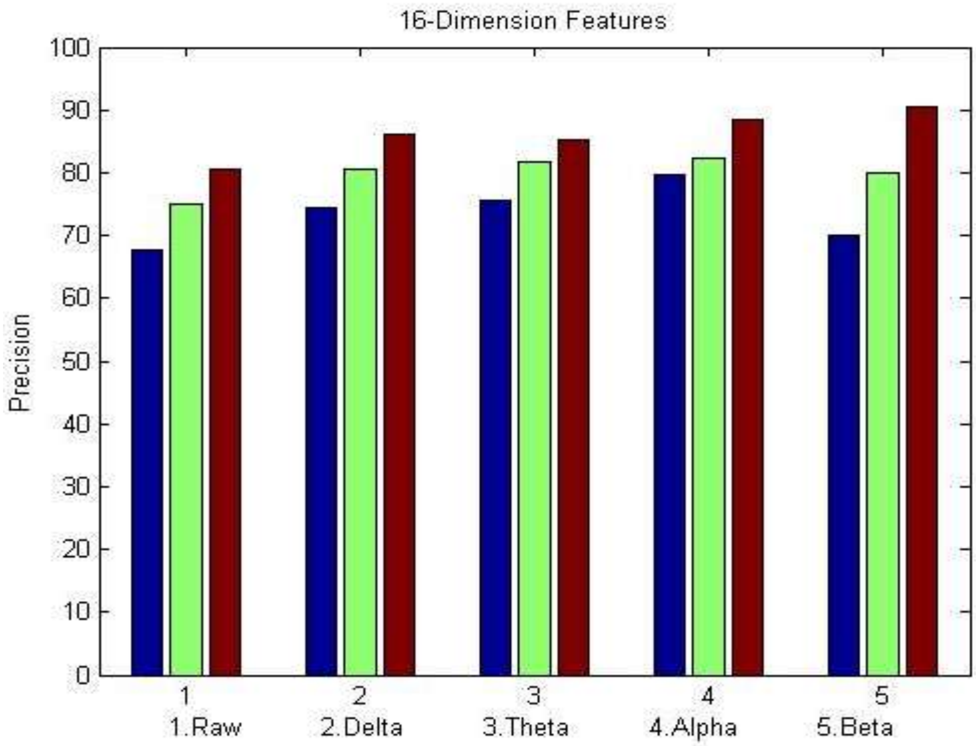

Figure 5: Performance of Precision parameter using EBL, DNN and Cascaded Neural Network with $16\,DF$ and all signal bands. Blue color bar represents the ensemble learning machine technique, green color represents the deep neural network technique and red color represent the cascaded neural network technique. In the perspective of signal bands raw, delta, theta, alpha, beta have cascaded technique have better precision performance comparison of remaining techniques. EBL have precision 67.78, 74.47, 75.54, 79.63, 70.15 with Raw, Delta, Theta, Alpha, Beta sequence and DNN have increased percentage 6, 6, 6, 3, 9 but CASCADED have better performance compare of DNN increased percentage 6, 5, 4, 6, 10.

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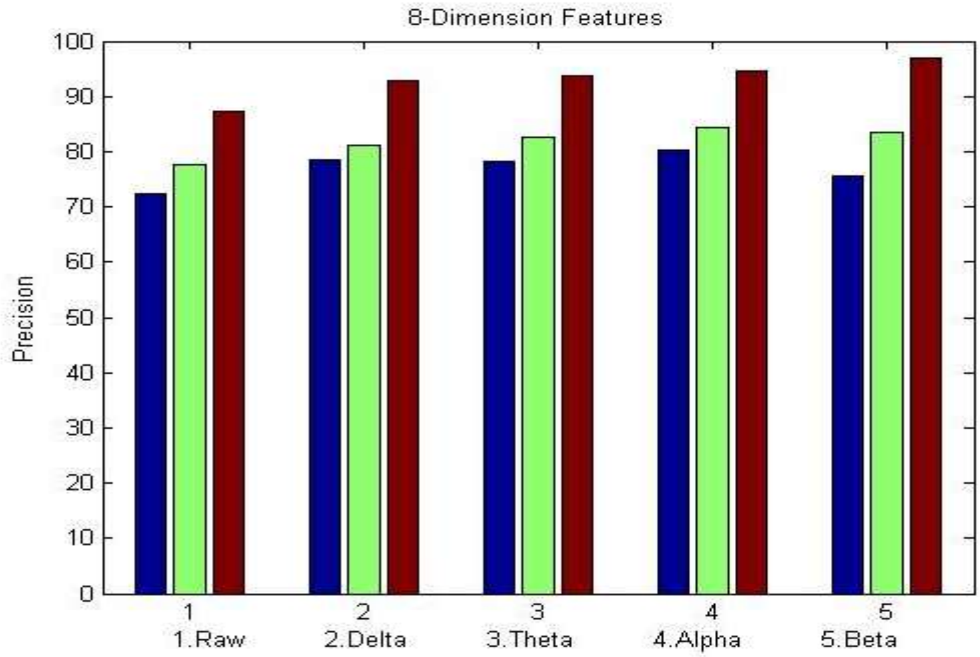

Figure 6: Performance of Precision parameter using EBL, DNN and Cascaded Neural Network with 8 DF and all signal bands. Blue color bar represents the ensemble learning machine technique, green color represents the deep neural network technique and red color represent the cascaded neural network technique. In the perspective of signal bands raw, delta, theta, alpha, beta have cascaded technique have better precision performance comparison of remaining techniques. EBL have precision 72.29, 78.37, 78.18, 80.28, 75.67 with Raw, Delta, Theta, Alpha, Beta sequence and DNN have increased percentage 5, 3, 4, 4, 7 but CASCADED have better performance compare of DNN increased percentage 9, 13, 11, 9, 12.

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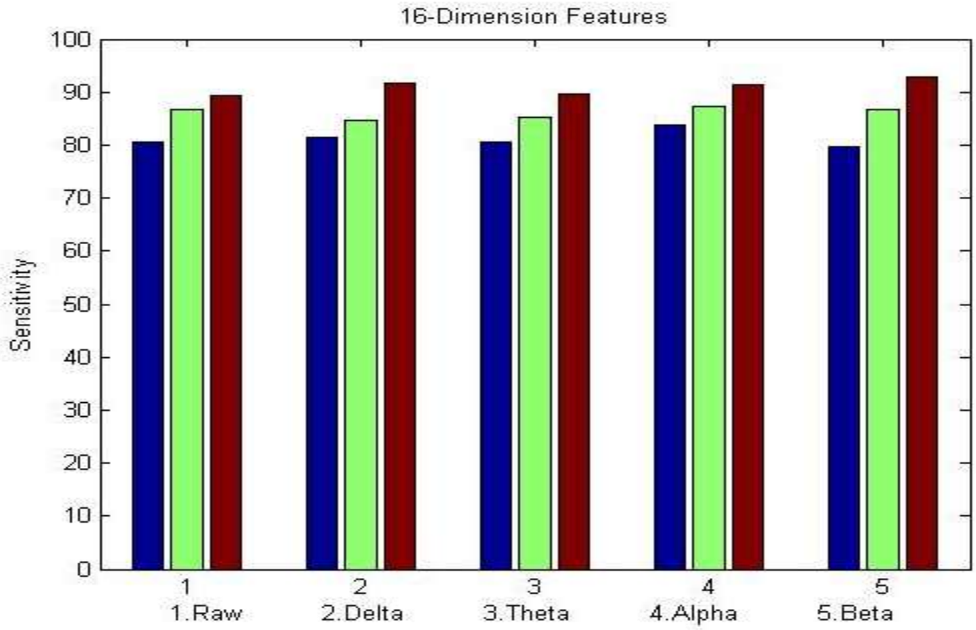

Figure 7: Performance of Sensitivity Parameter using EBL, DNN and Cascaded Neural Network with 16 DF and all signal bands. Blue color bar represents the ensemble learning machine technique, green color represents the deep neural network technique and red color represent the cascaded neural network technique. In the perspective of signal bands raw, delta, theta, alpha, beta have cascaded technique have better sensitivity performance comparison of remaining techniques. EBL have sensitivity 80.65, 81.36, 80.41, 83.85, 79.74 with Raw, Delta, Theta, Alpha, Beta sequence and DNN have increased percentage 6, 3, 5, 4, 7 but CASCADED have better performance compare of DNN increased percentage 3, 7, 5, 4, 6.

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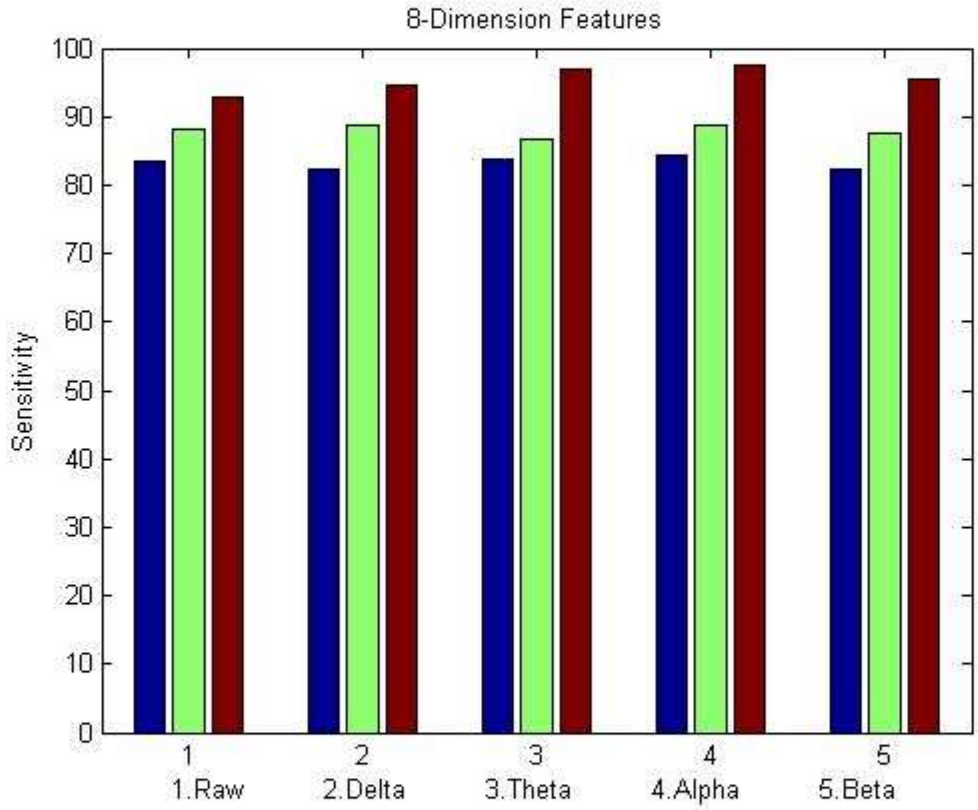

Figure 8: Performance of Sensitivity parameter using EBL, DNN and Cascaded Neural Network with $8\,DF$ and all signal bands. Blue color bar represents the ensemble learning machine technique, green color represents the deep neural network technique and red color represent the cascaded neural network technique. In the perspective of signal bands raw, delta, theta, alpha, beta have cascaded technique have better sensitivity performance comparison of remaining techniques. EBL have sensitivity 83.47, 82.25, 83.63, 84.44, 82.18 with Raw, Delta, Theta, Alpha, Beta sequence and DNN have increased percentage 5, 6, 3, 4, 5 but CASCADED have better performance compare of DNN increased percentage 4, 6, 9, 8, 7.

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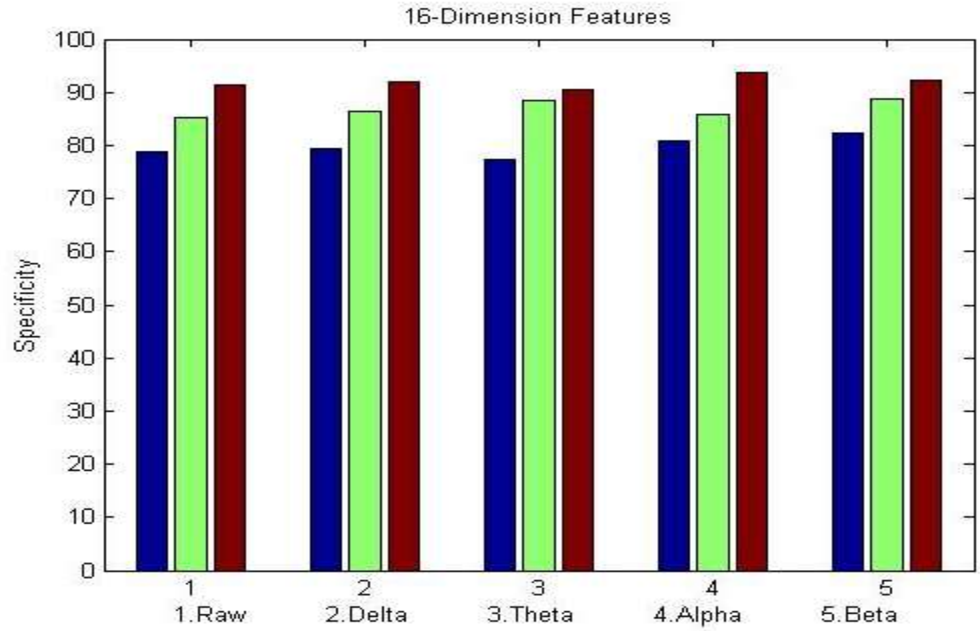

Figure 9: Performance of Specificity parameter using EBL, DNN and Cascaded Neural Network with $16DF$ and all signal bands. Blue color bar represents the ensemble learning machine technique, green color represents the deep neural network technique and red color represent the cascaded neural network technique. In the perspective of signal bands raw, delta, theta, alpha, beta have cascaded technique have better specificity performance comparison of remaining techniques. EBL have specificity 78.67, 79.49, 77.26, 80.74, 82.31 with Raw, Delta, Theta, Alpha, Beta sequence and DNN have increased percentage 7, 6, 10, 5, 6 but CASCADED have better performance compare of DNN increased percentage 6, 5, 2, 7, 4

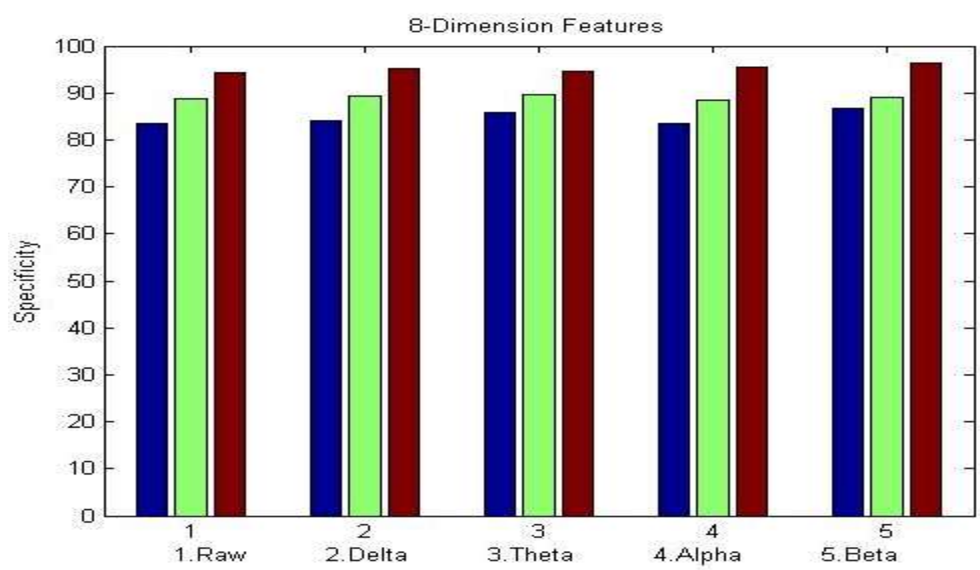

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Figure 10: Performance of Specificity parameter using EBL, DNN and Cascaded Neural Network with 8-DF and all signal bands. Blue color bar represents the ensemble learning machine technique, green color represents the deep neural network technique and red color represent the cascaded neural network technique. In the perspective of signal bands raw, delta, theta, alpha, beta have cascaded technique have better specificity performance comparison of remaining techniques. EBL have specificity 83.36, 84.11, 85.84, 83.37, 86.76 with Raw, Delta, Theta, Alpha, Beta sequence and DNN have increased percentage 5, 4, 5, 5, 3 but CASCADED have better performance compare of DNN increased percentage 6, 6, 6, 7, 7.

VI. Conclusion and Future Scope

The classification and prediction of motor imagery data (EEG) are always critical for the analysis in concern of accuracy. Due to the diversity of data, the selection of features and classification algorithms has a specific limitation. Beyond the limitation design cascaded algorithm for the process of classification of EEG data. The cascaded classifier merge two neural network models, such as self-organized map (SOM) and radial basis function (RBF). By the nature of the SOM model, it self-learning algorithms based on the process of winner and successor. Another is RBF, and it is a fast and single hidden layer network model for the prediction and classification. The proposed algorithm is very efficient in the manner of complexity and accuracy. The proposed algorithm tested on the reputed benchmark of the dataset, such as BCICIV. This dataset is freely available for study and research process. These datasets have different bands of data for different odder of disease. The proposed algorithms compare with two existing algorithms, such as EBL and DNN. The EBL methods are ensemble methods of a different classifier, and DNN methods are deep neural network methods. The efficiency of results indicates that the proposed approach is compare good than these two approaches.

REFERENCES

[1] Wafeek, Nourhan, Roaa I. Mubarak, and Mohamed E. Elbably. "A Novel EEG Classification Technique Based on Particle Swarm Optimization for Hand and Finger Movements." In International Conference on Advanced Intelligent Systems and Informatics, pp. 115-124. Springer, Cham, 2019.

[2] Ammar, Sabrina, and Mohamed Senouci. "Seizure detection with single-channel EEG using Extreme Learning Machine." In 2016 17th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA), pp. 776-779. IEEE, 2016.

[3] Kirar, Jyoti Singh, and R. K. Agrawal. "Relevant feature selection from a combination of spectral-temporal and spatial features for classification of motor imagery EEG." Journal of medical systems 42, no. 5 (2018): 78.

[4] Miao, Minmin, Hong Zeng, Aimin Wang, Changsen Zhao, and Feixiang Liu. "Discriminative spatial-frequency-temporal feature extraction and classification of motor

ISSN: 2005-4262 IJGDC
Copyright ⓒ2021 SERSC

imagery EEG: An sparse regression and Weighted Naïve Bayesian Classifier-based approach." Journal of neuroscience methods 278 (2017): 13-24.

[5] Mishuhina, Vasilisa, and Xudong Jiang. "Feature weighting and regularization of common spatial patterns in EEG-based motor imagery BCI." IEEE Signal Processing Letters 25, no. 6 (2018): 783-787.

[6] Kumar, J. Satheesh, and P. Bhuvaneswari. "Analysis of Electroencephalography (EEG) signals and its categorization–a study." Procedia engineering 38 (2012): 2525-2536.

[7] Taran, Sachin, Varun Bajaj, Dheeraj Sharma, Siuly Siuly, and A. Sengur. "Features based on analytic IMF for classifying motor imagery EEG signals in BCI applications." Measurement 116 (2018): 68-76.

[8] Pereira, Luis AM, João P. Papa, André LV Coelho, Clodoaldo AM Lima, Danillo R. Pereira, and Victor Hugo C. de Albuquerque. "Automatic identification of epileptic EEG signals through binary magnetic optimization algorithms." Neural Computing and Applications 31, no. 2 (2019): 1317-1329.

[9] Vrbancic, Grega, and Vili Podgorelec. "Automatic classification of motor impairment neural disorders from EEG signals using deep convolutional neural networks." Elektronika ir Elektrotechnika 24, no. 4 (2018): 3-7.

[10] Nakisa, Bahareh, Mohammad Naim Rastgoo, Dian Tjondronegoro, and Vinod Chandran. "Evolutionary computation algorithms for feature selection of EEG-based emotion recognition using mobile sensors." Expert Systems with Applications 93 (2018): 143-155.

[11] Zhang, Ranran, Xiaoyan Xiao, Zhi Liu, Wei Jiang, Jianwen Li, Yankun Cao, Jianmin Ren, Dongmei Jiang, and Lizhen Cui. "A new motor imagery EEG classification method FB-TRCSP+ RF based on CSP and random forest." IEEE Access 6 (2018): 44944-44950.

[12] Hamad, Asmaa, Essam H. Houssein, Aboul Ella Hassanien, and Aly A. Fahmy. "Feature extraction of epilepsy EEG using discrete wavelet transform." In 2016 12th international computer engineering conference (ICENCO), pp. 190-195. IEEE, 2016.

[13] Akkar, Hanan AR, and FB Ali Jasim. "Intelligent training algorithm for artificial neural network EEG classifications." IJ Intelligent Systems and Applications 5 (2018): 33-41.

[14] Lotte, Fabien, Laurent Bougrain, Andrzej Cichocki, Maureen Clerc, Marco Congedo, Alain Rakotomamonjy, and Florian Yger. "A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update." Journal of neural engineering 15, no. 3 (2018): 031005.

[15] Islam, Md Rabiul, Toshihisa Tanaka, and Md Khademul Islam Molla. "Multiband tangent space mapping and feature selection for classification of EEG during motor imagery." Journal of neural engineering 15, no. 4 (2018): 046021.

ISSN: 2005-4262 IJGDC
Copyright ⓒ2021 SERSC

[16] Kumar, Shiu, and Alok Sharma. "A new parameter tuning approach for enhanced motor imagery EEG signal classification." Medical & biological engineering & computing 56, no. 10 (2018): 1861-1874.

[17] Schiratti, J-B., Jean-Eudes Le Douget, Michel Le van Quyen, Slim Essid, and Alexandre Gramfort. "An ensemble learning approach to detect epileptic seizures from long intracranial EEG recordings." In 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 856-860. IEEE, 2018.

[18] Pillay, Kirubin, and Maarten De Vos. "A unifying Bayesian approach for preterm brain-age prediction that models EEG sleep transitions over age." arXiv preprint arXiv:1809.07102 (2018).

[19] Jin, Zhichao, Guoxu Zhou, Daqi Gao, and Yu Zhang. "EEG classification using sparse Bayesian extreme learning machine for brain–computer interface." Neural Computing and Applications (2018): 1-9.

[20] Rahman, Md Mosheyur, Mohammed Imamul Hassan Bhuiyan, and Anindya Bijoy Das. "Classification of focal and non-focal EEG signals in VMD-DWT domain using ensemble stacking." Biomedical Signal Processing and Control 50 (2019): 72-82.

[21] Dutta, Sumanto, Sumit Hazra, and Anup Nandy. "Human Cognitive State Classification Through Ambulatory EEG Signal Analysis." In International Conference on Artificial Intelligence and Soft Computing, pp. 169-181. Springer, Cham, 2019.

[22] Takakura, T. "Plant growth optimisation using a small computer." In Symposium on Greenhouse Design and Environment 46, pp. 147-156. 1973.

[23] Cai, Wei, Weiwei Yang, and Xiaoqian Chen. "A global optimization algorithm based on plant growth theory: plant growth optimization." In 2008 International conference on intelligent computation technology and automation (ICICTA), vol. 1, pp. 1194-1199. IEEE, 2008.

[24] Guney, Kerim, A. Durmus, and Suad Basbug. "A plant growth simulation algorithm for pattern nulling of linear antenna arrays by amplitude control." Progress In Electromagnetics Research 17 (2009): 69-84.

[25] Banerjee, Sandeep, Varun Alur, and Divya Shah. "Patient Nonspecific Epilepsy Detection Using EEG." In Soft Computing and Signal Processing, pp. 541-548. Springer, Singapore, 2019.

[26] Al Ghayab, Hadi Ratham, Yan Li, Siuly Siuly, and Shahab Abdulla. "Epileptic seizures detection in EEGs blending frequency domain with information gain technique." Soft Computing 23, no. 1 (2019): 227-239.

[27] Janghel, Rekh Ram, Satya Prakash Sahu, Gautam Tatiparti, and Mangesh Kose. "Noise Removal from Epileptic EEG signals using Adaptive Filters." In Machine Intelligence and Signal Analysis, pp. 37-47. Springer, Singapore, 2019.

[28] Krishnamurthi, Rajalakshmi, and Mukta Goyal. "Hybrid Neuro-fuzzy Method for Data Analysis of Brain Activity Using EEG Signals." In Soft Computing and Signal Processing, pp. 165-173. Springer, Singapore, 2019.

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