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Ensemble Classifier Framework for Epileptic Seizure Classification of EEG Signals

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ABSTRACT: A procedure of investigation of Electroencephalogram sign utilizing wavelet change and characterization utilizing AI strategies is created in this research work. EEG sign are non-stationary that makes the visual investigation tedious and may need quantitative examination to uncover shrouded qualities of the signals. Artificial Neural Networks alongside wavelets give capacities to synthesize and analyze the signals and information that shows standard conducts punctuated with unexpected changes. This research work focuses on segregation between two classes of EEG signals; one obtained from healthy persons and other from epileptic patients. This article proposes a technique for analyzing the brain signals, solid extraction of qualities utilizing diverse mother wavelets as Haar, Coiflet, Daubechies and Symlet. It encompasses arrangement of epilepsy issue utilizing neural systems. A thorough examination focuses to most appropriate mother wavelet to extricate the qualities that further go about as information to the machine learning algorithm. The experimental outcomes got in this exploration work demonstrate that the proposed NN-D ensemble classification strategy yielded greatest grouping precision of 99.4% when contrasted with different other ensembles. The high classification accuracy of the ensemble framework gives clear indication that statistical features obtained from DWT coefficients of the EEG signal yielded a more efficient and reliable solution for differentiation between the epileptic and non-epileptic classes and has a future prospect for classification of other non-stationary biomedical signals. Subsequently, it demonstrates the viability of the proposed strategy for classification of epileptic EEG signals.

Keywords: Wavelet transform; Electroencephalogram; Neural Network Ensemble; Skew; Energy.

I. INTRODUCTION

Artificial Neural Networks (ANN) is considered as raw electronic model that is established based on neural structure of brain. It learns while experiencing different cases of the same problem termed technically as training of ANN. It is considered as an information-processing paradigm which process the information derived by brain information system constituted by the biological nervous system. ANN constitutes interconnecting artificial neurons termed as input and output nodes that are programmed to mimic the properties of biological neurons to encounter some specific problems [1]. It is created or configured to solve artificial intelligence problems without creating real biological system model such as biomedical signal analysis, speech recognition, image analysis, adaptive control etc.

The World Health Organization estimates that approximately, almost 1 % population has the neurological disorders [2]. This figure leads to numerous research works to identify brain disorder and related problems and their treatments. Amongst the various brain disorders, epilepsy is the prime disorders and paramount to the figures. Epilepsy is considered as neurological disorder that cause electrical disturbance in the brain, leading to strange sensations, emotions, behaviour or sometimes loss of consciousness, muscle spasms etc [3].

Electroencephalogram (EEG) signals provide detailed information about the signals generated by electrical activity of human brain which are important for examining and diagnosing of the neurological disorders, such as Alzheimer, Epilepsy, Insomnia etc. The primeval methods of analyzing EEG signals are based on the linear computations, though linear mathematics is not appropriate for investigation of chaotic and complex seizures. The brain signals as EEG are characterized by non-stationary time behaviour that would not produce the finest result if processed with Fourier transforms [4]. These signals can be easily described in the time and frequency domain and can be acquired non- invasively, that makes this technique more appropriate to be used for this research work. A number of transformation methods such as Wavelet Packet transform (WPT), Wigner Valley (WV) decomposition, Wavelet Transform (WT) [5], etc, are available for the representation of a signal in time-frequency domain. Spectral analysis [6], Hilbert Huang transform [7], Discrete wavelet transform (DWT) [8,9], nonlinear dynamics analysis [10] are different methods reported in literature that have been applied for EEG feature extraction. In this research work, wavelet transform function has been used for analysis, diagnosis and processing of bio-signals as it represents salient capacities in multi-resolution representation. Numerous wavelet families exist for signal characterization and selection of suitable wavelet is an open research issue.

Epilepsy is caused due to brain cells' excessive electrical discharge. The signs of this medical problem are abnormal movements and seizures. Non-seizure EEG signals are differentiated from seizure EEG signals by rhythmic sinusoidal characteristic patterns [11]. Due to the non-linear and non-stationary behavior of EEG signal, it is preferable to use frequency – time domain methods as DWT analysis to characterize and to derive different attributes of EEG, for feature extraction in particular [12]. The visual detection by health professionals is not very accurate owing to non-apparent of the difference in EEG activity between epileptic and non-epileptic seizures. Thus, researchers and clinicians have strong inclination towards the development of automated detection techniques for more precise detection of abnormalities in EEG recordings. Lot of researchers has developed various techniques for automated analysis and detection of seizures using features extracted from wavelet techniques. A number of techniques are used to predict the type of disorder such as Support Vector Machine, Minimum Message Length, Naive Bayes classifier, Artificial Neural Network [13-15]. Different approaches for estimation have been proposed and research is being carried forward.

An extensive literature review of this field has been done and some of it is reported in this section. The authors in [16] used DWT to extract features from EEG signals which are given as input to ANN for classification. In [3] authors have utilized time-frequency methods. They have adopted NN techniques for epileptic seizures detection. Research work proposed by authors in [17] used a combination of Elman network and features extracted from time and frequency analysis for classification of epileptic signal. From the literature, it is observed that rare of prior methods are available related to EEG signal processing utilizing the neural network ensemble (NNE). The novelty of the proposed ensemble lies in its computational simplicity, processing capability to analyze signals in challenging practical applications. The rest of the paper is organized as follows: The methodology adopted, EEG dataset and signal processing techniques employed in this paper are covered in Section 2. Section 3 presents the experimental results obtained from the proposed algorithm and discussion thereof followed by conclusion.

II. MATERIALS AND METHODS

A. Database Selection

The University of Bonn provided the database of Electroencephalogram (EEG) signals used in this research work. This database consists of EEG data from three different events, healthy subjects (normal), seizure-free intervals (inter-ictal states) and seizure state (ictal)[18]. EEG signals were digitized at 173.61 Hz using 12-bit A/D converter, the band-pass filter settings 0.53–40 Hz (12 dB/Octave) were applied in the original signal. In this paper, three classes given by acronyms Z, F and S, each having 100 single channel EEG signals are selected. The various human activities used for measuring the brain activity were normal person with eyes open (Z), during ictal state (F) and during Seizure state (S).

B. Methodology

In this research work, we propose a novel method for classification of normal and epileptic brain signals employing hybrid algorithms termed as "ensemble". Various mother wavelets (in DWT) are used to extract feature vectors that characterize the EEG signals in time and frequency domain resulting in various frequency sub-bands.

Different models are proposed termed as NN-H, NN-D, NN-C and NN_S specifically for the task of epilepsy detection. The performance metrics as Sensitivity, Specificity, Accuracy and ROC curves are used for the evaluating the performance of presented algorithm. Fig 1 depicts the methodology adopted by the authors in this research work. The later sections describe the various techniques employed to achieve the research objectives.

C. Wavelets

EEG being a non–linear, non-stationary signal, wavelet transform is preferred over other transforms for signal analysis. This transform is divided into two major categories: the discrete wavelet transform used for compression and reconstruction of data, whereas continuous wavelet transform is similar to the Fourier transform and is normally used for feature detection and analyzing signals.

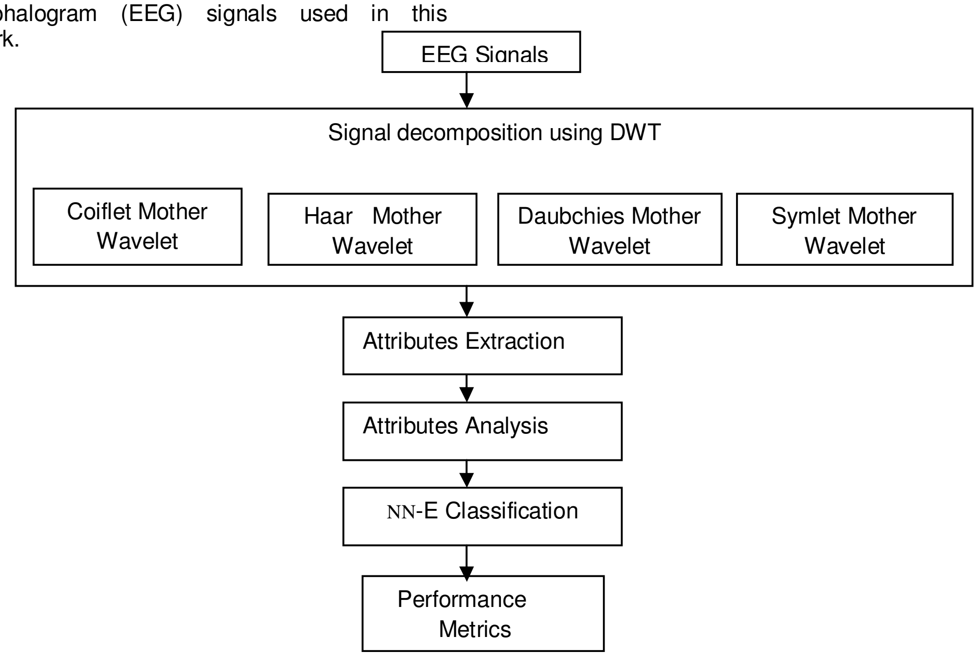


Fig 1: The proposed methodology for classification of EEG signals.

The frequencies are scaled versions of a subspace. This cause shifts in one of the generating function ψ in L2(R) i.e. the mother wavelet generates this subspace in all situations The frequency band [1/a, 2/a] of scale a is generated by the functions basically called child wavelets [19].

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi\left[\frac{t-b}{a}\right] \quad (1)$$

where a is the positive defining of the scale and b defining the shift is any real number.
The pair (a, b) defines a point in the right half-plane R+ × R.

$$x_a(t)=\int_R WT_\psi\{x\}(a,b).\psi_{a,b}(t)\,db \quad (2)$$

The coefficients are given as:

$$WT_\psi\{x\}(a,b)=(x,\psi_{a,b})=\int_R x(t).\psi_{a,b}(t)\,dt \quad (3)$$

By using all wavelets coefficients, it is not possible to analyse computationally, thus a discrete subset is sufficiently picked to reconstruct a signal of the upper half-plane from the corresponding wavelet coefficients, thus resulting in use of discrete wavelet transform[20]. Therefore, the child wavelets are:

$$\psi_{m,n}(t)=a^{-m/2}\psi\left(a^{-m}t-nb\right) \quad (4)$$

For finite energy a sufficient condition for the reconstruction of any signal x is given as :

$$x(t)=\sum_m\sum_n(x,\psi_{m,n}).\psi_{m,n}(t) \quad (5)$$

where

$$\{\psi_{m,n}:m,n\in Z\}$$

Coiflet Wavelet. These are type of discrete wavelets that contain some scaling functions with disappearing moments. Hence, the two functions - the wavelet & scaling function must be normalized by a factor 1/sqrt (2). Mathematically, Coiflet wavelet can be represented as [21]:

$$B_k=(-1)^k C_{N-1-K} \quad (6)$$

where N - wavelet index, k - coefficient index, B – wavelet coefficient and C – coefficient of scaling function.

Haar wavelet. Haar wavelet is a sequence of functions that form a wavelet family of rescaled "square-shaped" thus considered the simplest wavelet among all [21]. The mother wavelet function $\psi(t)$ for haar wavelet is given by

$$\psi(t)=\begin{cases}1 & 0\le t<1/2\\ -1 & 1/2\le t<1\\ 0 & otherwise\end{cases} \quad (7)$$

Daubechies wavelet. This wavelet is a family of orthogonal wavelets and is classified by a maximum no. of disappearing moments [22]. So if there are even number N of values for a signal f, then each value

a_m of $a_1 = (a_1,\ldots, a_{N/2})$

is equal to a scalar product of f with a 1-level scaling signall V^1m:

$$a_m = f \cdot V^1{}_m \quad (8)$$

Similarly, each of the value d_m of $d_1 = (d_1,\ldots, d_{N/2})$ is equal to a scalar product of f with a 1-level wavelet $W^1{}_m$:

$$d_m = f \cdot W^1{}_m \quad (9)$$

so,

$$\phi(t)=\begin{cases}1 & 0\le t<1\\ 0 & otherwise\end{cases} \quad (10)$$

III. ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial Neural Network is hierarchy of layers with neurons arranged alongside these layers. The basic unit of computation in the neuron is called a node or unit which is elementary information-processing unit. The neurons are connected to external sources through input and output layers. A weight (w) is associated with each input node and is assigned on the basis of its relative importance to other inputs and is the means of long-term memory. Artificial Neural Networks is based on learning algorithm based on learning by repeated adjustment of these weights [23]. ANN needs to be trained by the provided input data by two different methods: Supervised Training and Unsupervised Training. If the training is supervised, the steps involved in the algorithm comprises of comparison of the actual outputs with the desired outputs associated with the training patterns. After training, the network is tested by the remaining data using k cross fold validation technique. The underlying principle that the network follows is the information is unidirectional and hence moves only in forward direction.

All classification models in the present work were trained and tested with calculated attributes and then validated using k-fold cross validation. In this paper, we have used 10-fold cross-validation to train and test extracted features for all classifiers.

A. Performance metrics

The performance of any classifier is authenticated by measuring the cases that are truly classifies in the right case and quantifying by calculating Accuracy, Sensitivity, and Specificity. These parameters are characterized by the accompanying formulae:

$$\text{Accuracy} = \frac{P^T+N^T}{P^T+N^F+P^F+N^T}$$

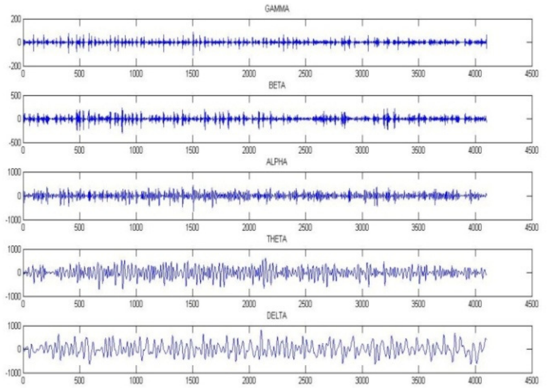
$$\text{Sensitivity} = \frac{p^T}{p^T+N^F}$$

$$\text{Specificity} = \frac{N^T}{N^T+P^F} \quad (11)$$

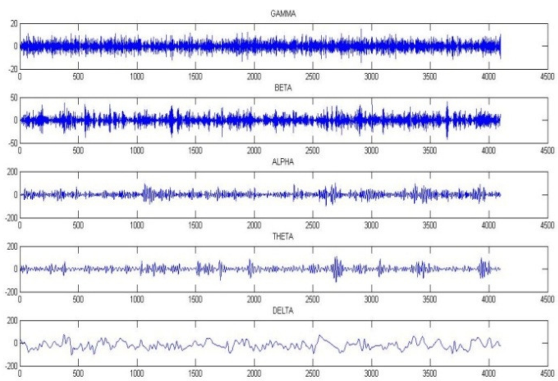
False Positive (P^F) is number of incorrectly classified cases; True Positive (P^T) is number of correctly classified cases. True Negative (N^T) is number of correctly classified normal patients and False Negative (N^F) is number of incorrectly classified healthy patients. Accuracy gives the measure of the percentage of correct classification of epileptic cases and non-epileptic patients [24].

IV. RESULTS AND DISCUSSION

In the research pertaining to EEG signals, an accurate frequency band and features in these bands is required. In order to extract specific frequency band, wavelet transforms was applied which generated spectral resolution fine enough to resolve the signals. In this work we have used different wavelets – Haar Wavelet, Symlet Wavelet, Coiflet Wavelet and Daubechies Wavelets to divide a single EEG signal into 5 different frequency sub-bands signals – delta, theta, alpha, beta, and gamma in frequency domain. All the coefficients for all the mother wavelets functions are calculated but some selected results using specific mother wavelet is reported as depicted in Fig. 2.



(i)



(ii)

Fig. 2. Extracted wavelet coefficients of (i) ictal state (ii) normal state.

Figure 2 (i) shows the categorization of EEG signal of an ictal patient. In this the delta signal has high number of peaks which shows high order of randomness and instability of mind. The beta and gamma signals have very high frequency and rise and drops in the signal values. Similarly, Fig. 2 (ii) shows the categorization of EEG signal of a healthy patient. In this the delta signal has least number of peaks which shows low order of randomness and stability of mind. The beta and gamma signals have very high frequency and less rise and drop in the signal values.

A. Attribute Selection and Extraction

As the standard database provides the data that has been sampled at 173.61 Hz, we chose the number of selected levels to be 5. The features are extracted out of the various sub band, mentioned below which also result in reduction of dimensionality of the signals. [25]. The various features used in this research work are calculated for each sub-band coefficients values: Mean, Average power, Standard deviation, Skewness, Kurtosis , Entropy, Energy and Maxima and minima of the each sub-band of wavelet coefficients [26-27].

B. Attribute Analysis

The available EEG datasets has the curse of dimensionality which makes it difficult to estimate the accuracy of classification from a limited number of samples. In this work, various attributes including statistical parameters, were calculated for the different categories of signals at each decomposition level. The attributes used are mean standard deviation, variance, skewness, kurtosis, energy, power that provide the difference between various patients. he graphs of the extracted features in comparison with all three states of mind (i.e. ictal, inter-ictal and healthy) for delta waves. The observations are- Skewness and Kurtosis value is greatest in Inter-Ictal patient and least in Seizure patient [28]. Energy value is greatest in Seizure patient and least in healthy individual. Entropy is positive in Seizure patient and negative in Healthy individual.

C. Ensemble Framework Design

The feature vectors extracted from the various sub bands are given as input to the Neural network classifier. The input layer constituted nodes equal to number of features taken as inputs and output layer had two nodes corresponding to the output classes. The classifier performance was obtained with different topology having different number of nodes in hidden layer and the topology with maximum efficiency and performance is reported.

IV. DISCUSSION

For all the NN- ensembles; NN-H neural network with Haar wavelets, NN-S is NN with Symlet coefficients, NN-C refers to NN with Coiflet coefficients and NN-DB with NN Daubechies mother wavelets were experimentally tested for classification accuracy. Results are tabulated after employing 10 fold cross validation for training, testing and validating performance accuracies.

In order to investigate the superiority of the ensemble classifier, further experiments were conducted. The statistical measures namely sensitivity (SEN) and specificity (SPEC) and overall Classification Accuracy (OCA) were calculated from Confusion matrix (CM) to assess the performance of the proposed networks. In Table 1 summary of all the ensembles designed are given which shows that Sensitivity of all the ensembles are high than Specificity. It can be seen from the table that amongst all, NN-D ensemble gives the highest classification accuracy of 99.4% with high sensitivity of 99.2% and high specificity of 99.6% in distinguishing two kinds of EEG signals, followed by NN_ Coiflet with an accuracy of 90.0% as shown in Fig 3. As 10- fold cross validation has been adopted, to conclude that NN-D represents best stability and generalization capability in discriminating epileptic EEG.

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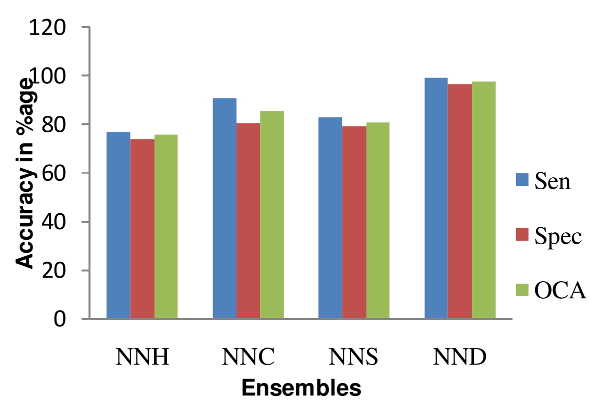

Fig. 3. Performance comparison of all the proposed ensembles in terms of Sensitivity, Specificity and overall classification accuracy.

As observed by the various experiments, it is concluded that NN with DB coefficients achieved by Daubechies mother wavelet give the better results. To validate the results further, ROC curve was plotted for the same and area under the curve was also calculated shown in Fig. 4.

As seen from Table 1 and 2, the NN-D with 9 nodes in the hidden layer gives the better performance, it is observed that ROC curves with same configuration are also the best with area under the curve being maximum with 0.993.

Table 1: Performance of various classifiers with varying nodes.

Accuracies (in %)							
Ensemble	**No o Hidden nodes**	**Training perf.**	**Test perf.**	**Validation perf.**	**Error function**	**Hidden activation**	**Output activation**
NNH	5	75.24	81.81	68.18	Entropy	Exponential	Softmax
	4	75.24	79.54	70.45	Entropy	Logistic	Identity
NNS	9	81.42	81.33	78.66	Entropy	Tanh	Tanh
	5	78.57	84.00	77.33	Entropy	Tanh	Softmax
NNC	7	89.42	88.00	89.66	Entropy	Exponential	Softmax
	11	85.71	85.33	84.66	Entropy	Tanh	Tanh
NND	8	98.85	100.00	98.00	Entropy	Logistic	Softmax
	9	99.57	100.00	99.33	Entropy	Logistic	Softmax

Table 2: Classification Results obtained by different Ensemble systems.

Ensemble		***CM***		***Sen. Spec.***	***OCA***
NNH		Normal	Ictal		
	Normal	185	65	74%	75.6%
	Ictal	57	193	77.3%	
NNC		Normal	Ictal		
	Normal	227	23	90.8%	90.1%
	Ictal	47	223	89.4%	
		Normal	Ictal		
NNS	Normal	207	43	82.8%	81.0%
	Ictal	52	198	79.2%	
NND		Normal	Ictal		
	Normal	248	2	99.2%	99.4%
	Ictal	1	249	99.6%	

Note: CM: Confusion Matrix for classification,
Sen.: Sensitivity Spec: Specificity classification expressed in percentage, OCA: Overall Classification Accuracy expressed in percentage.

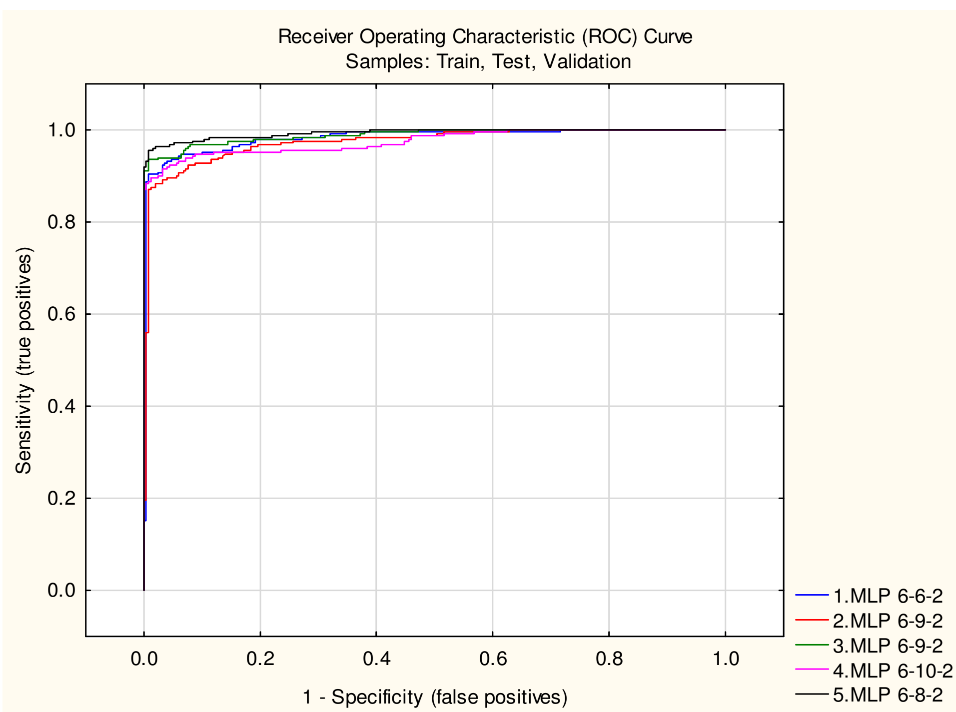

Fig. 4. ROC curves for different configurations of NN-DB ensemble.

Table 3: Comparison of the results obtained by proposed method.

Authors	Year	Method Employed	OA %
Subasi, Ercelebi [17]	2007	WT+ANN	92
Ubeyli [31]	2010	LS-SVM model-based method coefficients	99.5
Nicolaou *et al* [30]	2012	Permutation entropy using SVM	93.5
Fu, *et al.,* [8]	2014	Time-frequency image using SVM	96.2
Bhattacharyya [33]	2017	Empirical wavelet transform	99.4
Proposed	2019	NN-DB ensemble	99.4
Note: OA : Overall Accuracy in %			

The proposed approach of designing an ensemble classifier has two main advantages: one is to utilize the DWT as feature extractor, the other is to employ of NN resulting in ensemble of NN –WT classifier [29,32]. This algorithm model and framework will be a suitable candidate for extensive clinical validation in term of the stable structure and superior performance. The comparative performance on the basis of overall accuracy is tabulated in Table 3.

Our proposed framework, as demonstrated in the present study, yielded higher accuracy rates with Neural Network ensemble with DB as mother wavelet indicating superior discriminatory performances. In addition, with this proposed algorithm, we have achieved high classification accuracy than our previous study using the same EEG dataset.

V. CONCLUSION AND FUTURE SCOPE

The work performed results in a system of prognostication of the epileptic seizure from EEG signals with high accuracy and less computational complexity. Further, various ensembles give satisfactory results of classification of these signals using various attributes calculated from the wavelet coefficients. To draw reliable conclusions, different mother wavelets are considered in the experiments and NN-D ensemble model is finally constructed for EEG classification. The proposed framework is capable of differentiating among normal and epileptic patient with clinically significant classification accuracy of 99.4%. In this research paper, deep and elaborate experiments are performed resulting in following conclusion: The high classification accuracy of the ensemble framework gives clear indication that statistical features obtained from DWT coefficients of the EEG signal yielded a more efficient and reliable solution for differentiation between the epileptic and non-epileptic classes and has a future prospect for classification of other non-stationary biomedical signals using the proposed algorithm.

CONFLICT OF INTEREST

There is no conflict of interest by any author.

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