ISSN: 2229-6956 (ONLINE)
DOI: 10.21917/ijsc.2021.0326

ENSEMBLE FEATURE SELECTION (EFS) AND ENSEMBLE HYBRID CLASSIFIERS (EHCS) FOR DIAGNOSIS OF SEIZURE USING EEG SIGNALS

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Abstract

Epilepsy is the neural disorder that occurs in the individual mind which affects nearly 50 million people around the world. It is also said to be the universal disorder which affects all ages. The disturbance that occurs in the nervous system causes seizure. The classification of epileptiform activity in the EEG plays an essential role in the identification of epilepsy. To extract the relevant information and to improve the accuracy level from the given EEG signals, Fuzzy Based Cuckoo Search (FCS) and ant colony optimization (ACO) methods are planned to select the related and best information's. Finally utilizes the Ensemble Hybrid Classifiers (EHCs) which combine the procedure of Modified Convolutional Neural Network (MCNN), Improved Relevance Vector Machine (IRVM) and Logistic Regression (LR) classifiers for analysis of EEG signals. The planned effort is implemented to notice the irregularity in three different levels of EEG signals (normal, affected and unaffected).

Keywords:

Epilepsy, Seizure, Ant Colony Optimization, Convolution Neural Network

1. INTRODUCTION

Epilepsy is a nervous system disorder whose nerve activity in the brain is troubled, results in causing seizures. This disorder is also said to be a universal disorder disturbing all age groups [1]. Hereditary factor, infection in brain, stroke, tumour and high fever are the various reasons of epilepsy [2]. Epilepsy is noticed as the medical sign of an irregular and extreme expulsion of a set of neurons in the human brain [3]. Electroencephalography is an essential tool for the assessment and treatment of neurophysiologic disorders associated to epilepsy. The occurrence of seizures in the EEG is a significant factor in the identification of epilepsy. EEG spectrum holds few characteristics which consists of four main frequency bands namely delta (<4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13-30 Hz). Seizures are classified into focal (simple partial), generalized (complex partial) and tonic-clonic seizures, based on the loss of awareness or damaged and motor involvement [4].Cytomegalovirus infections during pregnancy also leads to epilepsy disorder by birth[23] About 125,000 people are affected by epilepsy every time, in that 30 percentage of people are below 18 years [5].

Above 50% of people with epilepsy have additional clinical issues (Autism Spectrum Disorder, depression). Recently, bodily condition (diabetes, arthritis) has also been related to epilepsy [6]. To select the best solution and to reduce the features, Ant colony optimization (ACO) and Fuzzy Based Cuckoo Search is mainly used to reduce the trade and to improve the performance.

The nonlinear method like Artificial Neural Network (ANN) and Support Vector Machine (SVM) are used for the classification of EEG Pattern. In the present effort classification of EEG signals is done with the kernel based learning known as relevance Vector Machine along with the Sparse Bayesian algorithm[7][8]. Logistic regression is also used for the exact identification of EEG pattern with together constitute an Ensemble Hybrid Classifier (EHC) which provides classification accuracy.

2. RELATED WORKS

EEG records can be used to compare the normal cases with abnormal cases suffering from a variety of disorders. The discharges in the EEG records can be assessed and noticed as the malfunction in the mind [9]. The cause of attack, mode of spreading and the brain connectivity decides the signs and symptoms of epileptic seizures [10]. Cuckoo search Algorithm used brood parasitism and Levy Flight is one of the characteristic used to produce new solution [11]. ACO technique was introduced in the early 1990's [12] [13]. Ant Colony Optimization algorithm [14] has been suggested to extract the immaterial or unimportant features, and to choose only the significant features. Experts have shown that the behavior of social insects can be described by a prototype in which the communication is only possible. The plan of an ant algorithm is to use few form of trail to coordinate the agents. The distribution of pheromone plays the main role to acquire a possible alternative track which helps to find the way, when complication or transform takes place [15].

A novel approach was recommended to identify the seizures using deep convolution network [16]. Logistic regression classifier (LRC) is one of the widely used multivariable analysis version used in biomedicine mainly to examine the binary result [17] [18]. The selection of the expositive variables to be incorporated in the logistic regression is found on the previous information of seizure and the analytical relationship between the variable and seizure action [19] [20].

3. METHODOLOGY

In the proposed system, new Ensemble Feature Selection (EFS) is introduced which combines the procedure of Fuzzy based Cuckoo Search (FCS) algorithm and Ant Colony Optimization (ACO) feature selection algorithm for feature reduction.

Ensemble Hybrid Classifiers (EHCs) is introduced which combines the procedure of Modified Convolutional Neural Network (MCNN), Improved Relevance Vector Machine (IRVM) and Logistic Regression (LR) classifiers for the analysis of EEG signals. The architecture of the proposed system is given in Fig.2.

3.1 FUZZY BASED CUCKOO SEARCH ALGORITHM

Cuckoo search optimization algorithm was by Yang and Deb [21]. CS algorithm uses the concept of brood parasitism. One of the most powerful features used by this optimization algorithm is Levy Flight. Levy Flight is used to create new result, modification is made to improve and to prove the excellence in the searching process. One of the concepts used along with the CS algorithm is fuzzy Logic. This method allows only two possible values 1(true) and 0 (false). The main function used in the fuzzy logic is triangular membership function.

3.2 ANT COLONY OPTIMIZATION ALGORITHM

To eradicate the irrelevant features or unneeded features and to select the finest features, one of the best feature selection optimization algorithms termed Ant colony optimization algorithm is used.

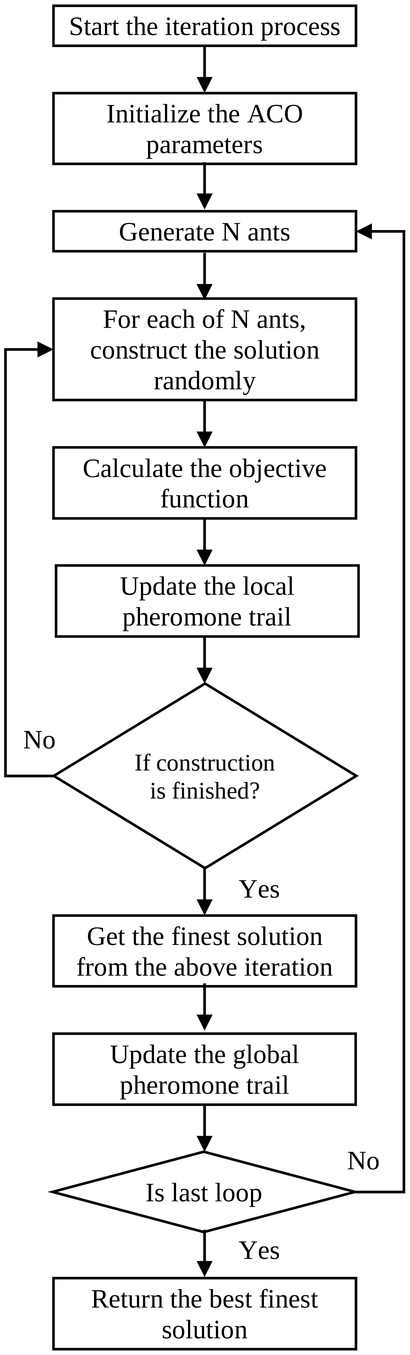

Fig.1. ACO Algorithm

This algorithm is stimulated by the foraging behavior of ant colony and mainly used to solve the complex optimization problems. Based upon the various characteristics and their habits, the ant colony has different types of ant algorithms like food resources, partition effort, ranking of reproduction and collective transportation. ACO optimization algorithm uses one of the classes known as meta-heuristic.

When ants moves from one place to another place in search of food, the ants deposit a chemical substance known as pheromone, this pheromone helps the other ants to track their members in a group and the substance deposited on the land forms a mark, which helps to spot the food that was previously identified by other ants, which increases the probability and also results in finding the optimal solution. It is one of the strong optimization algorithm to solve the complex finest trail problem. The ant will move from point a to point b with the probability

$$P_{a,b} = \frac{\left(T_{a,b}^{\alpha}\right)\left(n_{a,b}^{\beta}\right)}{\sum\left(T_{a,b}^{\alpha}\right)\left(n_{a,b}^{\beta}\right)} \quad (1)$$

where, $T_{a,b}^{\alpha}$ is the pheromone quantity from node a to b. α and β are the parameters given to control the influence of amount of pheromone and the heuristic correspondingly. $n_{a,b}$ refers to the heuristic content moving from node a to b.

Heuristic method is mainly used to resolve general class computational problems to acquire an efficient result and also to take a quick decision in the case of complex data.

Each individual ant alter the surroundings using two different method: Local trail updating and Global Trail updating

3.2.1 Local Trail Updating:

The ant moves from source to destination in search of food by depositing the pheromone, the amount of pheromone is updated each time when the ant moves from point to point on the boundaries by using the following equation.

$$\tau_{ab}(t) = (1-\rho).\tau_{ab}(t-1)+\rho.\tau_0 \quad (2)$$

where, ρ is the constant value of evaporation and τ_0 is the primary value assigned to the pheromone trails is computed using the formula.

$$\tau_0 = (n/L_n)\text{-}1 \quad (3)$$

where, n is the number of nodes and L_n is the total length covered between the total nodes, formed using the heuristics.

3.2.2 Global Trail Updating:

The path being used by all the ants is finally converged to the shortest path, modifies the boundaries in its path by using the following equation.

$$\tau_{ab}(t)=(1-\rho).\tau_{ab}(t-1)+(\rho/L^{+}) \quad (4)$$

where, L^{+} refers to the distance of the finest path produced by one of the ants. ACO algorithm is shown in Fig.1.

ACO Algorithm:

Step 1: Initialize the parameters (pheromone trail).

Step 2: Begin the iteration process

For each individual ant

Construct the solution using the pheromone trail.

Step 3: Check whether all the ants have generated the solution.

Step 4: Update the local and global pheromone trail.

Step 5: Converge all the solution into single finest solution.

Step 6: Stop the process.

4. ENSEMBLE HYBRID CLASSIFIER FOR SEIZURE CLASSIFICATION

The data is trained and tested using the relevance vector machine to transform the information in the required form and also to show the clarity in the seizure classification for the given EEG pattern.

5. MODIFIED CONVOLUTION NEURAL NETWORK

The three different types of layers namely input layer, hidden layer and output layer are very important in the CNN. The input operation is processed using the convolution layer and produces result which is interconnected again with the help of pooling layer. Each neuron is interconnected with other neuron with the help of fully connected layers. All these layers that perform different operations are said to be the hidden layers. The hidden layers will not be the same for all the process, it changes based on the input and output.

5.1 IMPROVED RELAVANCE VECTOR MACHINE

Relevance vector machine is one of the algorithms which use the set of mathematical functions known as kernel function. The main function of the kernel is to take the input of different form (low dimension) and transform into the required form (high dimension). These kernel function are of different types (Linear, Non-Linear, Gaussian kernel, Polynomial, radial basis function (RBF) and sigmoid kernel). In this present system the Gaussian kernel function is used. Gaussian Kernel converts the dot product in the unbounded proportional intervals into Gaussian function of the space between points in the data interval. When the space between the two points are closer than the position represents in the kernel space will be small, when the points are far apart then the position represents in the kernel space will be at a right angle or 90 degree. Relevance vector machine uses Sparse Bayesian learning structure of kernel technique is used, to acquire the sparse result and for classification of EEG signals, which reduces the cost and computational difficulties. It is an appropriate method for real time approach. RVM is same as SVM one of the extra features added which makes the relevance vector machine more informative in providing probabilistic classification or probabilistic predictions of neural disorders. Gaussian Kernal function is computed using the formula.

$$g\left(\vec{X}\right)=\sum_{n=1}^{N}\vec{W}_n^T f\left(\frac{\left\|\vec{X}-\vec{X}_n\right\|}{\sigma}\right) \tag{5}$$

$$g\left(\vec{X}\right)=\sum_{n=1}^{N}\vec{W}_n^T f\left(\left\|\vec{X}-\vec{X}_n\right\|\right) \tag{6}$$

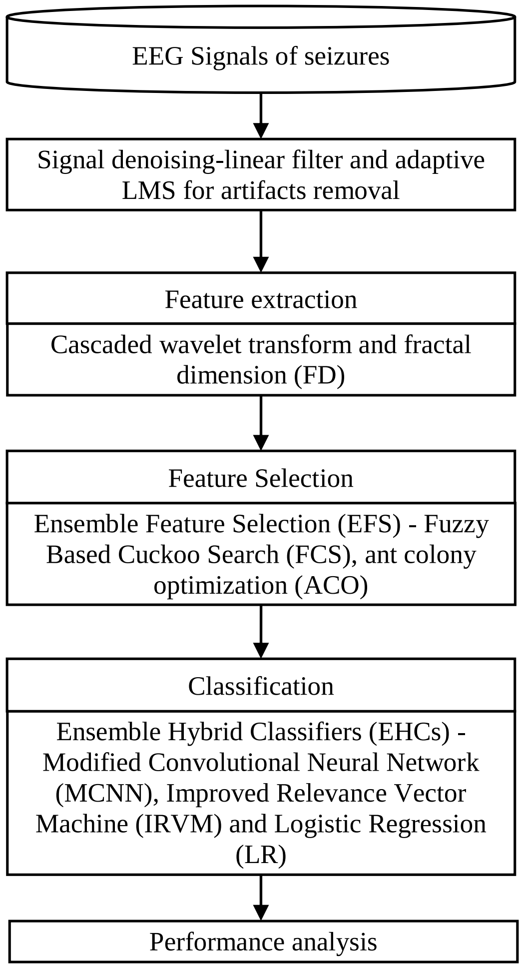

Fig.2. Architecture of proposed system

5.2 LOGISTIC REGRESSION

Logistic regression is an analytical process in which the result can be estimated on independent multivariable's [22]. The result is measured with the help of dichotomous variable (where only two results are possible).The dependent variable is also allowed with the binary result (1 (true) and 0 (false)).

6. EXPERIMENTAL RESULTS

Confusion matrix is used for estimating the performance of the classification model. It is represented by $n \times n$ matrix, n is number of target classes. Matrix helps to observe the relations between the actual result and predicted result.

Table.1. 2×2 confusion matrix with four values

Class	**Positive Actual value**	**Negative Actual value**
Positive Actual value	TP	FP
Negative Actual value	FN	TN

where, *TP* is True Positive, *FP* is False Positive, FN is False Negative and TN is True Negative.

In order to evaluate the result achieved from the application, performance analysis is measured in the terms of specificity (true negative rate) and sensitivity (true positive rate), Time Complexity and Accuracy, these measures are evaluated using confusion matrix.

6.1 SENSITIVITY

The sensitivity is also known as true positive rate (ability to classify the individual affected by seizures), which is calculated by using the formula

$$\text{Sensitivity} = TP/(TN+FN) \tag{7}$$

A performance comparison of sensitivity is shown in Fig.3. A comparison is done with the previous and present effort with the merits of sensitivity in which the present effort shows the accurate result and also has better classification performance for the given EEG pattern.

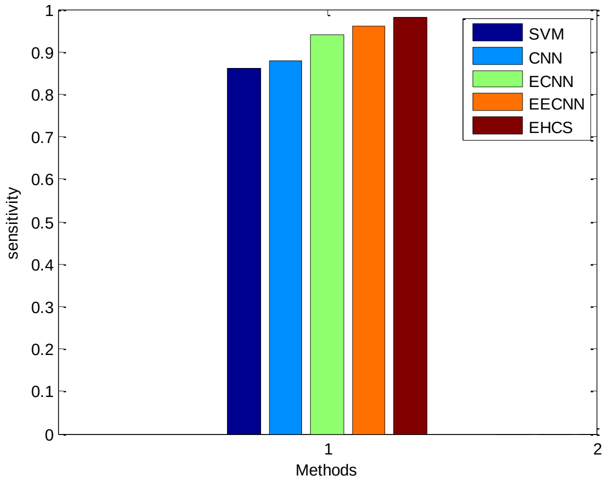

Fig.3. Performance Comparison of Sensitivity

6.2 SPECIFICITY

The Specificity is also known as true negative rate (ability to classify the individual not affected by seizure), which is calculated by using the formula

$$\text{Specificity} = TN/(TN+FP) \tag{8}$$

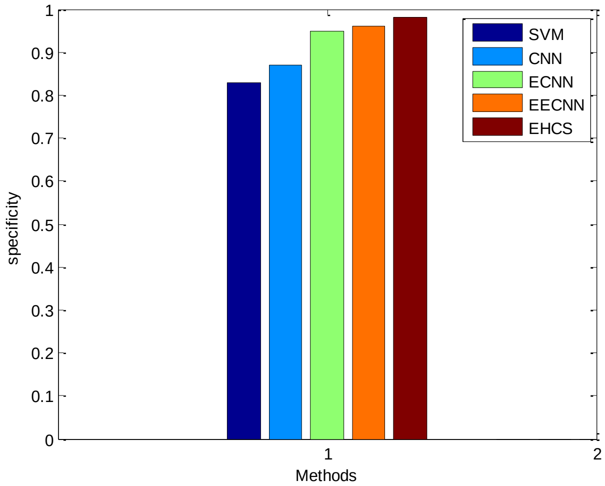

Fig.4. Performance Comparison of Specificity

A performance comparison of specificity is shown in Fig.4. A comparison is done with the performance of the current effort (ensemble hybrid classifiers) which shows the precise outcome and improvement in the classification accuracy for the given EEG signal dataset.

6.3 ACCURACY

Performance is evaluated in the terms of accuracy and calculated by using the formula

$$\text{Accuracy} = (TP+TN)/(TP+FP+FN+TN) \tag{9}$$

The existing work and the present work are compared with the merits of accuracy, which shows the greater classification accuracy with the less amount of implementation time. The performance comparison of accuracy is given in Fig.5.

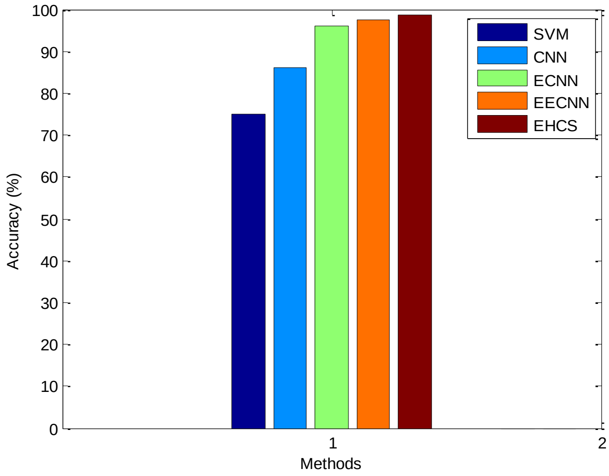

Fig.5. Performance Comparison of Accuracy

6.4 TIME COMPLEXITY

The present method shows the better performance with the less amount of execution time, when compared with the previous work. The performance comparison of time complexity is given in Fig.6.

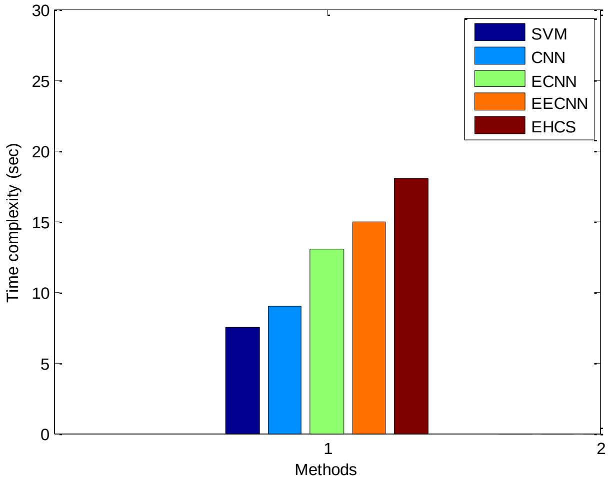

Fig.6. Performance Comparison of Time Complexity

7. CONCLUSION

Preprocessing is done to remove the immaterial information, to strengthen the signals and to avoid the loss of information's. Then the EEG pattern is processed using the feature extraction algorithm to extract only the relevant information, to select the best solution from the given raw dataset, the fuzzy based cuckoo search algorithm and ant colony optimization algorithm is used. To improve the performance of classification we concentrate on the Gaussian kernel function, which transform from one form to the required form. The sparse Bayesian learning model is implemented to prevent the signals from incompleteness for the typical IRVM. The logistic regression method is used to show the effectiveness of the present system in terms of accuracy and reduction of performance sensitivity, specificity and less computational time.

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