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Epileptic Detection from the Eeg Signal using the Anti colony Optimization Technique with Deep Neural Network

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Abstract: Extensively used technique to diagnose the epilepsy is EEG. The research objective is to check the variations of frequency found in the epileptic EEG signals.. The EEG dataset were acquired from online database of the Bonn University (BU). Then, butterworth type two filter was implemented to remove the unwanted artifacts from the acquired EEG signals. Further, Multivariate Variational Mode Decomposition (MVMD) methodology was applied to decompose the denoised EEG signals. The signal decomposition helps in finding the necessary information, which required to model the complex time series data. Then, the features were extracted from decomposed signals by using fifteen entropy, linear and statistical features. In addition, ant colony optimization technique was proposed for optimizing the extracted features. The optimized feature vectors were classified by Deep Neural Network (DNN) that includes two circumstances (seizure and healthy), and (Interictal, ictal, and normal). The accuracy attained using the ant colony with deep neural network is 98.12% using the BU EEG dataset, respectively related to the existing models.

Index values: Butterworth type two filter, deep neural network, anti colony optimization, epileptic seizure detection, and multivariate variational mode decomposition.

I. INTRODUCTION

In the field of medical sciences this is been reported that a sudden inclination is found among the neurological disorders .On an average there are about 5% rises among the epilepsy cases in India[1-2]. It is a disease which leads to the loss of consciousness, physical variation in the movements, strange emotions, muscle spasms and death [3]. So, it is the need of this hour to detect the epilepsy at early stage to reduce the death rate. Epilepsy is characterized by re-current seizures that results from the extreme discharges of the brain cells [4-6]. For epilepsy recognition, the EEG signals are widely utilized for investigating the brain activities [7]. EEG is a deep palpation technique that significantly estimate the neuronal and electrical activities in high temporal resolution [8-9].

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The other imaging techniques, which are used for inspecting the brain activities are Magnetic Resonance Imaging (MRI), Functional MRI (FMRI), computed tomography, positron emission tomography, etc.

To address these concerns and also to improve the epilepsy detection, several automated systems are developed in the past studies such as l_1 penalized regression [13], Least Squares Support Vector Machine (LSSVM) [14], neural mass mode [15], artificial neural network [16], SVM [17-18], kernel principal component analysis [19], long short term memory [20], etc.

In the conventional approaches, it is difficult to identify the suitable EEG representation such that the non-epileptic patterns are differentiable from epileptic patterns. To overcome this issue, a new optimization based model is proposed for enhancing the performance of epilepsy recognition. Initially, the EEG recordings were acquired from BU EEG databases. Then, butterworth type 2 filter was implemented to remove the artifacts (eye movements) from the acquired signals. Compared to other filtering techniques, Butterworth type 2 filter has fast processing speed and limited error. The denoised EEG signals were decomposed by employing MVMD in order to analyse the subtle changes in frequency. Then, entropy, linear and statistical features were combined to extract the feature vectors from the decomposed signals. Further, the extracted features were optimized using anticolony optimizer. ACO help to determine the optimal solution in less computational time. The performance of ACO may be improved by introducing approaches like modification of transition rule, parallel ACO [26]. It may be hybridized with other techniques for better results. The optimized feature vectors were classified by using DNN classifier that includes two cases (seizure and healthy), and (Interictal, ictal, and normal). Compared to other classifiers, DNN effectively allows a good time reduction technique. In the result and discussion section, the proposed model performance was evaluated by means of accuracy, Positive Predictive Value (PPV), specificity and sensitivity. A few research papers are surveyed in the section 2. The explanation about the proposed model is detailed in the section 3. In section 4, the experimental consequences are detailed with tabular and graphical representation. Section 5 indicates the conclusion of the present study.

II. LITERATURE SURVEY

B. Suguna Nanthini at al. [4] has used EEG signals for detecting the seizures using the supervised learning method. The performance analyses is based on by the confusion matrix .

The wavelet transform was used for analysing the signals in the spatial domain. The same problem is examined with an SVM classifier in the second analysis [10]. The classifier achieves 90% accuracy.

J.T Murphy *et al*, [5] used cross bispectrum features for recognizing epilepsy in EEG dataset. SVM was used for extracting the features. The EEG database was used for verifying the effectiveness of the developed system. From the experimental consequence, the developed system attained superior performance in epilepsy detection related to other models in light of accuracy, specificity and sensitivity. However, SVM classifier supports only binary classification, which was considered as a major concern in this study. M.K Ahirwal *et al*, [22] implemented Tunable Q wavelet Transform (TQWT) for epilepsy recognition on the basis of non-linear features. In this study, BU EEG database was undertaken for experimental investigation that includes three classes such as seizure, non-seizure and pre-seizure.It was confirmed that the developed model attained better performance in epilepsy recognition. In large dataset, the random forest leads to data imbalance that may results in poor classification performance.

H. Peng, *et al*, [23] developed an approach towards the sparse representation for epilepsy recognition. Initially, homotopy approach was utilized for attaining the sparse representation of EEG coefficients In this research, the developed approach performance was verified on two databases; BU EEG and Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) database. The developed approach required more manual intervention that was considered as a major concern.A new optimization based model is proposed for enhancing the performance of epilepsy recognition in this research article.

III. PROPOSED MODEL

The detailed explanation about the proposed model is given this section. The proposed model includes six phases; Signal collection: BU EEG databases, Preprocessing : Butterworth type 2 filter, Signal decomposition: MVMD, Feature extraction: combination of entropy, linear and statistical features, Feature optimization: Anti Colony optimizer, and Classification: DNN. The work flow of proposed model is indicated in figure 1.

3.1 Dataset description In this section, the undertaken database (BU EEG) is described . The BU EEG database consists of five EEG sub-sets such as F, N, O, S, and Z for both epileptic and healthy subjects [27-28].Each EEG segment consists of 4096 sampling points with the duration of 23.06 seconds For 5 healthy subjects, the sub-sets "O" and "Z" are recorded with eyes open and closed. The sample collected BU EEG signals are graphically indicated in figure 3.

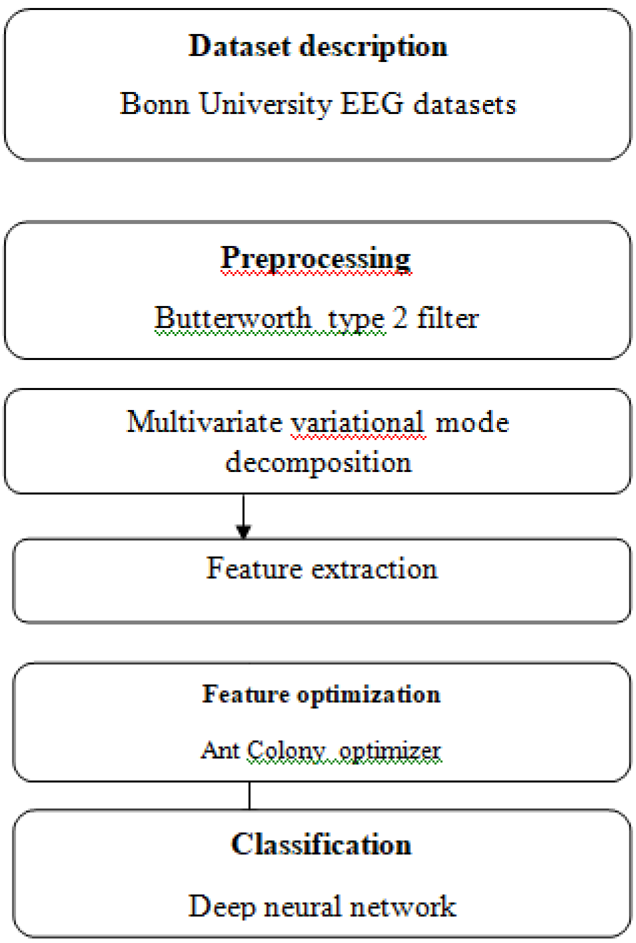

Figure 1. Flow chart of the proposed model

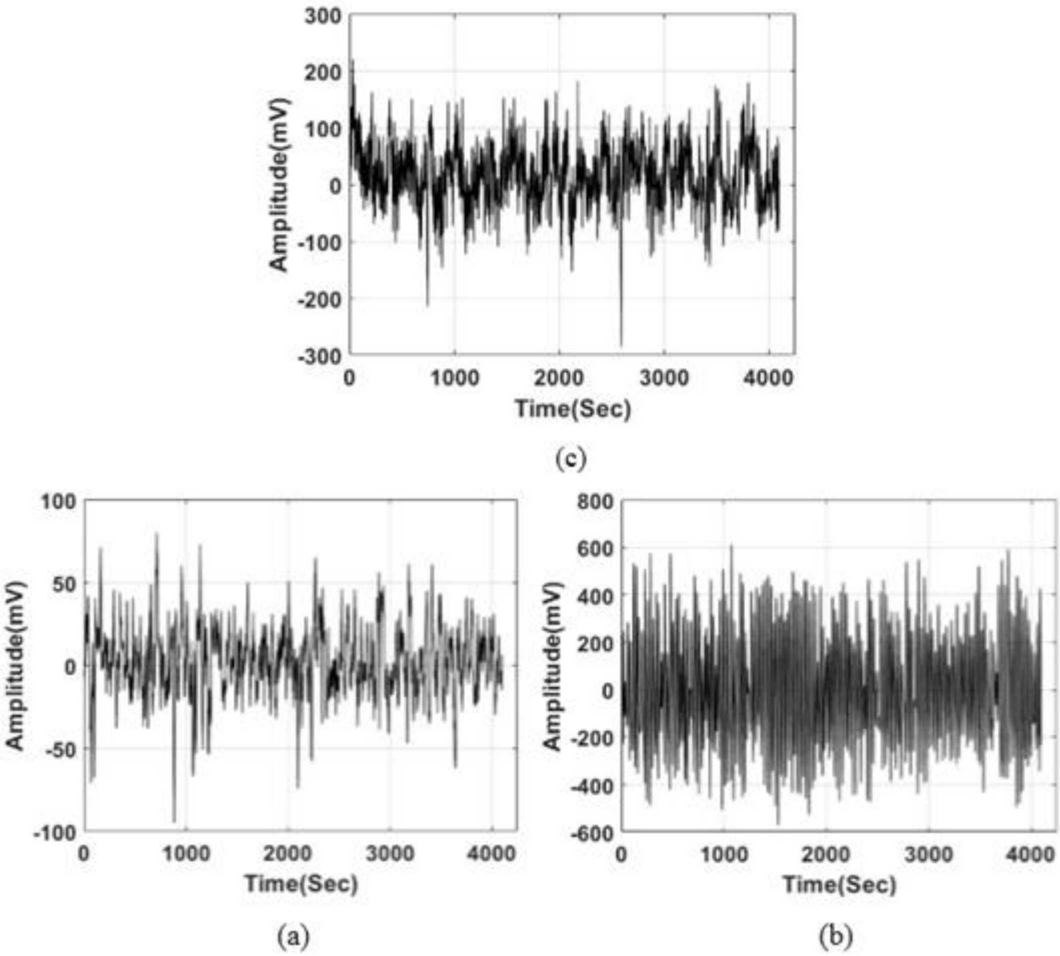

Figure 2. BU EEG database; a) Ictal signal, b) Interictal signal, and c) Normal signal

3.2 Pre Processing

After acquisition, butterworth type 2 filter was implemented for eliminating the unwanted noises (muscle and eye movements) from the acquired signals. The Butterworth type 2 filter has small rolloff , so it requires several components. In the passband, it has linear phase response with higher band it has stop band specifications.The butterworth filter gives flat maximally response .Related to other filtering methods, the undertaken filter has fast execution speed and limited absolute error. The butter worth type 2 filter formula is indicated in equation (1).

$$\left\{ Butter\ worth\ \ type\ 2\ filter\ H(jw) = \frac{1}{\sqrt{1+\varepsilon^2\left(\frac{w}{Wp}\right)}} \middle| 2 \right\}$$

(1)

Where 'n' indicates the filter order, 'ω' = $2\pi f$, ε is maximum pass band gain

Then, the MVMD technique is implemented to decompose the denoised signals, which is the extension of VMD. The objective of MVMD is used to extract the pre-determined ber of multivariate modulated oscillations $u_k(t)$ from the denoised signals $x(t)$ which includes n number of channels C, $x(t) = [x_1(t), .. x_C(t)]$. The mathematical representation of $x(t)$ is indicated in equation (2).

$$x(t) = \sum_{k=1}^{K} u_k(t)$$

(2)

Where, $u_k(t) = [u_1(t), .. u_C(t)]$. To extract $u_k(t)$, the vector analytic representation of $u_k(t)$ is changed as $u_+^k(t)$ [29]. The $u_k(t)$ bandwidth is calculated by considering l_2 normalization of the gradient function $u_+^k(t)$. The resultant cost function $f$of MVMD is utilized in the VMD optimization problem that is mathematically defined in equation (3).

$$f = \sum_k \left\| \partial_t [e^{-jwk^t} u_+^k(t)] \right\|_2^2 \quad (3)$$

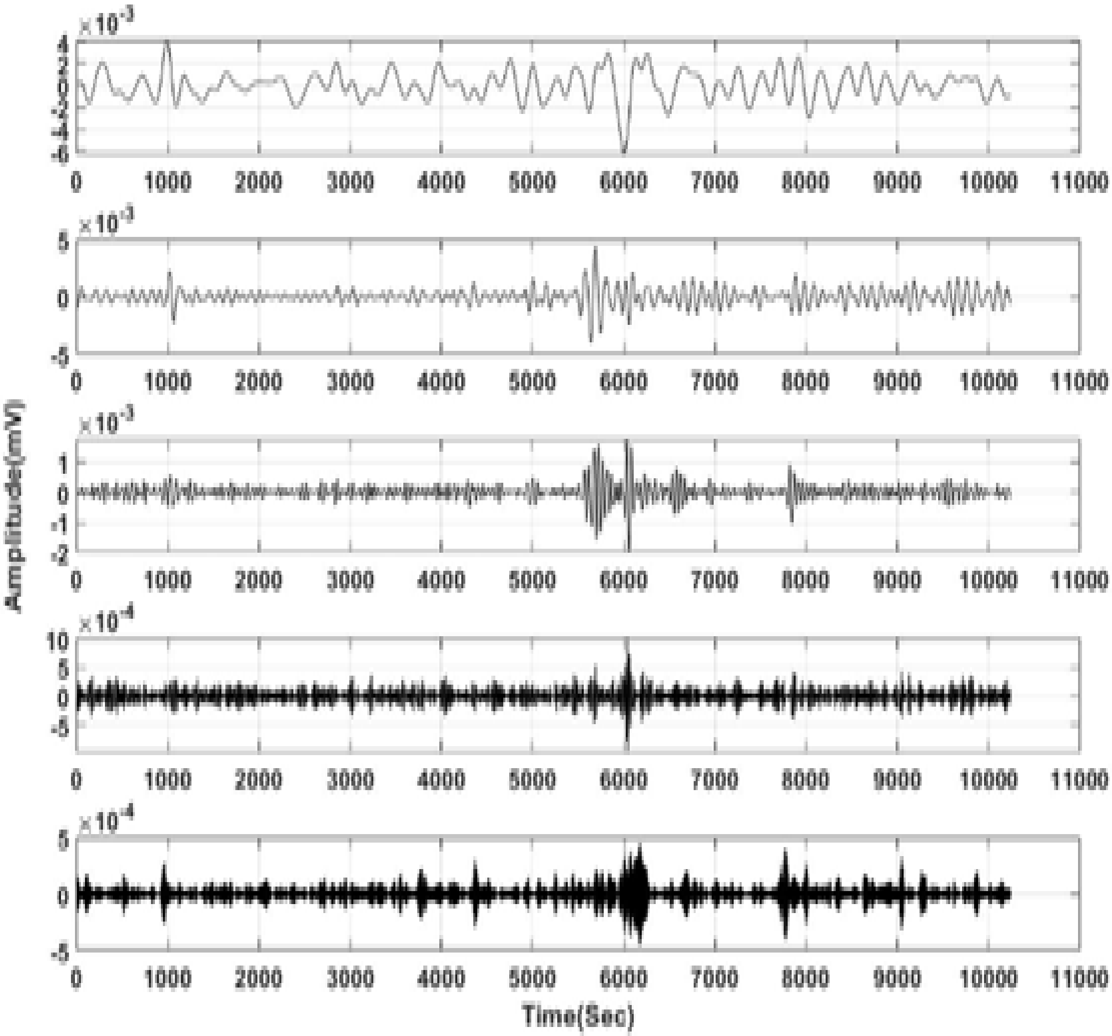

Figure 3. Sample decomposed EEG signal

3.3 Feature extraction and optimization

After decomposing the EEG signals, feature extraction is performed by using statistical and Linear features. The major benefit of combining more features results in effective occlusion and clutter. Then, the extracted feature vectors are given as the input to anti colony optimizer for optimizing the active features. The general characteristics of an ant are as follows,

- Ant colony optimization algorithm (ACO) is a probabilistic approach for the determination of various arithmetic problems.
- It helps to find the optimal paths best suited by ants for the sake of searching the food.
- Firstly these ants wander randomly for the search of food.
- When an ants finds the source of food, it walks back to the colony leaving "markers" (pheromones) that show the path has food.

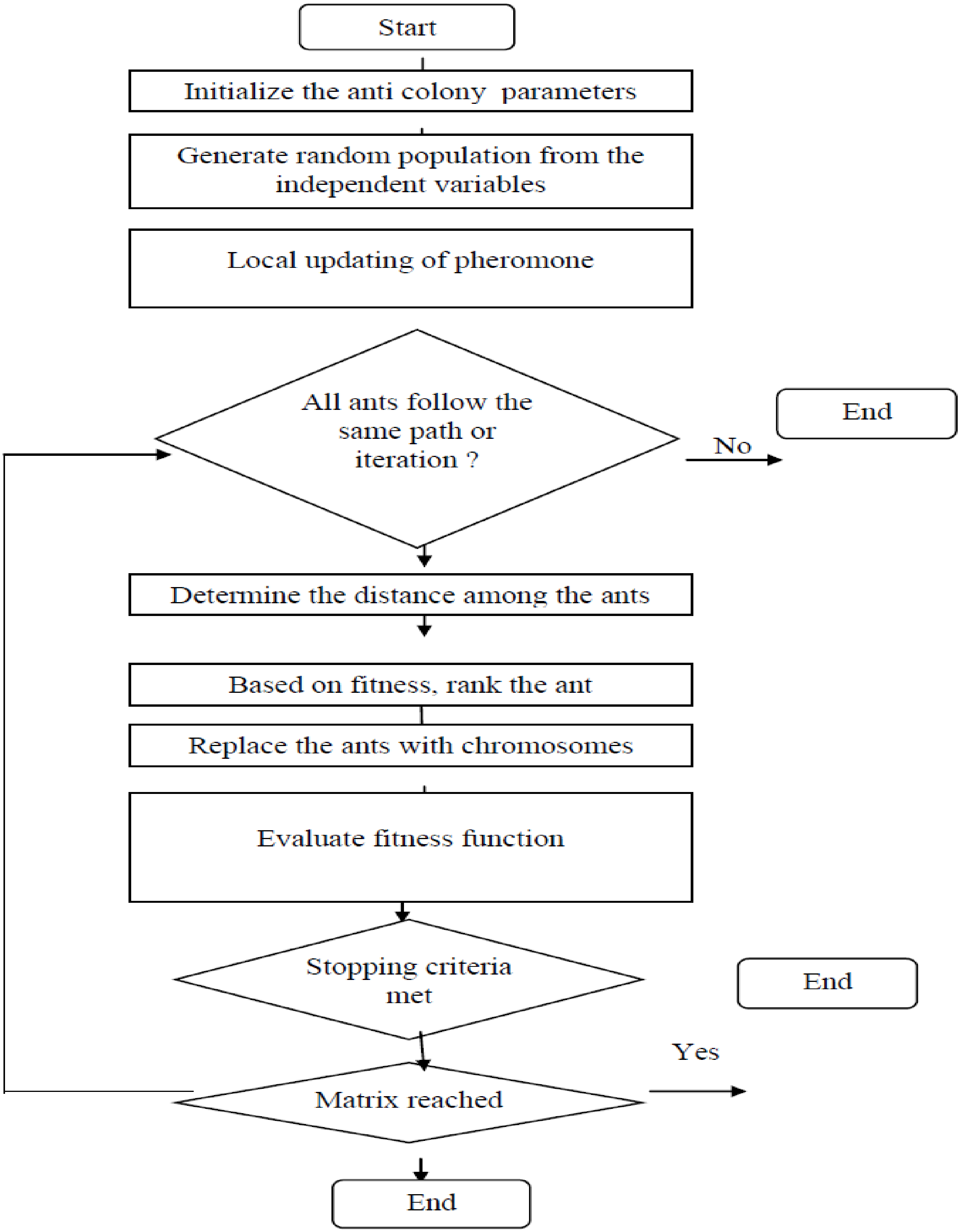

Figure 4. Anti Colony Optimization Flow Chart

3.4 Classification

The DNN is a feed forward network that contains multiple transformation layers and non-linearity with the output of every layer which feeds into the succeeding layers. The DNN model is mathematically presented in the equations (9) and (10).

$$Z^{(l)} = y^{(l-1)} W^{(l)} + b^{(l)} \quad (9)$$

$$y^{(l)} = g(Z^{(l)}) \quad (10)$$

Where, $y^{(l-1)}$ is stated as the input to layer l and output of prior layers $l-1$, $Z^{(l)}$ is indicated as the vector of pre-activations layers l, $W^{(l)} \in \mathbb{R}^{n_i \times n_o}$ is stated as the matrix of learnable biases, $l \in [1, \ldots L]$ is represented as the l^{th} layer, $y^{(L)}$ is indicated as the final layer output, $y^{(l)} \in \mathbb{R}^{n_0}$ is specified as the output layer, $g(.)$ is represented as the nonlinear activation layer, and $y^{(0)}$ is indicated as the input to the model. In this study, ReLU is utilized in the hidden layers for faster learning and computation efficiency related to other activation functions. The output layer uses a softmax non-linearity in order to deliver a probabilistic interpretation of the models output that is mathematically denoted in equation (11).

$$softmax(Z^{(L)}) = \frac{expZ_k}{\sum_{k=1}^{K} expZ_k} \quad (11)$$

Where, K is indicated as output classes, and the output layer comprises of K number of neurons. The DNN learning is formulated as an optimization issue for minimizing a cost function. In this study, cross entropy loss function is utilized to deal with classification problem, which is defined in equation (12).

$$C = -\sum_{k=1}^{K} \hat{y}_k \log (y_k^{(L)}) \quad (12)$$

Where, $y^{(L)}$ is denoted as the model output, and $\hat{y}_k \in \{0,1\}^k$ is indicated as the encoded label.

IV. RESULT AND DISCUSSION

In this study, MATLAB 2018a environment was used for executing all the experiments with i7 3.0 GHz processor, 3 TB memory, 8 GB RAM, 2 GB GPU, and windows 10 operating system. **Benchmark approaches:** For comparing the efficacy of the proposed model, several approaches are considered as the benchmark like sparse representation with DLWH [23], PDCA [24], and 2D reconstructed phase space with LSSVM [25]. **Undertaken databases:** In this work, the exhaustive simulations are carried out with some of the standard and widely used database like BU EEG database. The detailed explanation about the undertaken databases are indicated in table 1.

Table 1. Description of the dataset

Dataset	Subjects	Total signals	Electrodes	Classes
BU EEG	500	500	One	Ictal, interictal, and normal

In this scenario, the proposed epilepsy recognition model is quantified by using accuracy, specificity, sensitivity, and PPV with (k=10) fold cross validation. All the observations in the dataset are eventually utilized for testing and training that is considered as a major benefit of k fold cross-validation. The general formula for calculating classification accuracy, specificity, sensitivity, and PPV are defined in the equations (13-16).

$$Accuracy = \frac{TP+TN}{FN+TP+FP+TN} \times 100 \quad (13)$$

$$Specificity = \frac{TN}{FP+TN} \times 100 \quad (14)$$

$$Sensitivity = \frac{TP}{FN+TP} \times 100 \quad (15)$$

$$PPV = \frac{TP}{FP+TP} \times 100 \quad (16)$$

Where, TP is specified as true positive, FP is represented as false positive, TN is indicated as true negative and FN is stated as false negative.

The undertaken optimization techniques are simulated in the same environment and database for investigating the proposed model (Ant Colony-DNN) performance.

Table 2. Performance analysis of proposed model with dissimilar classifiers in BU EEG database

Classifier	Accuracy (%)	Specificity (%)	Sensitivity (%)	PPV (%)
NN	33.39	29	89	33.33
KNN	93.33	95	85.00	90
MSVM	93.84	95	90	89.89
DNN	**98.12**	**98.34**	**98.24**	**98.38**

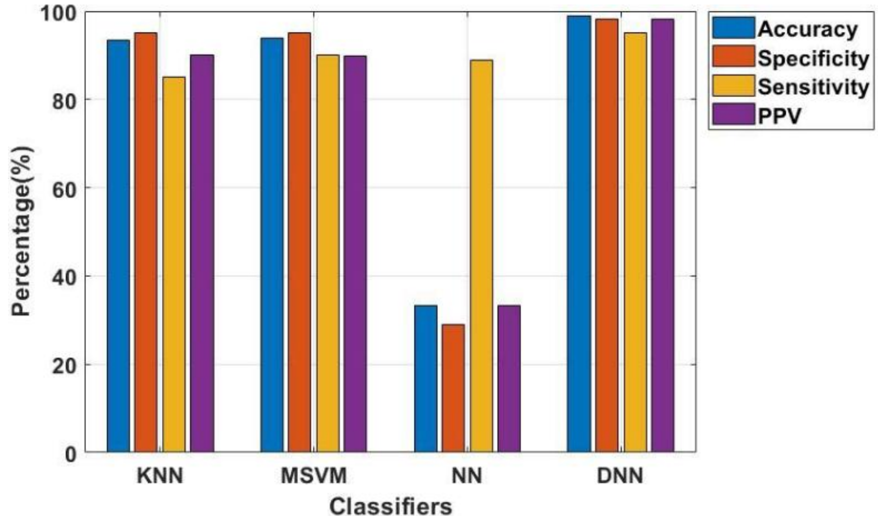

Figure 5. Graphical evaluation of proposed model with dissimilar classifiers in BU EEG database

Table 3. Performance analysis of proposed model with dissimilar optimizers in BU EEG database

Optimizer	Accuracy (%)	Specificity (%)	Sensitivity (%)	PPV (%)
PCA-DNN	80.29	79.21	78.68	68.51
PSO-DNN	87.64	85.18	87.81	75.68
BAT-DNN	88	87.26	86.45	78.12
Firefly-DNN	98.99	98.32	95.07	98.13
Anti Colony Optimization-DNN	**98'.12**	**98.01**	**98.0**	**97.32**

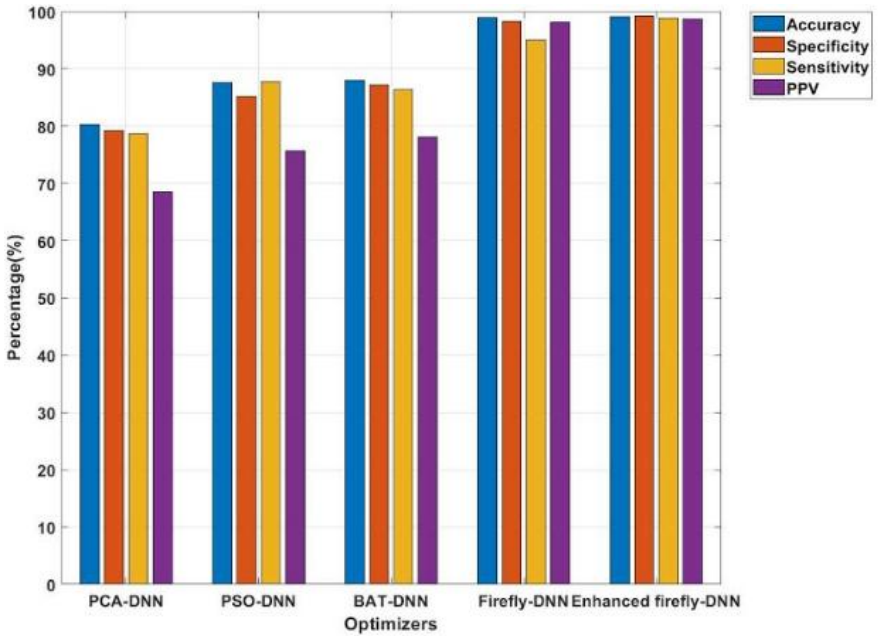

Figure 6. Graphical evaluation of proposed model with dissimilar optimizers in BU EEG database

V. CONCLUSION

In this research article, a new optimization based model is proposed for enhancing the performance of epilepsy recognition. The proposed model majorly includes three phases such as decomposition, optimization of extracted features, and classification. After signal collection, MVMD is utilized to decompose the EEG signals into time frequency bands. Then, anti colony optimization algorithm is applied to select the active feature vectors, which are classified by employing DNN classifier. In the experimental segment, the proposed model performance is evaluated in light of PPV, accuracy, specificity, and sensitivity. In BU dataset, the proposed model showed maximum of 1.4% improvement in accuracy compared to the existing research papers. From the futuristic approach, a hybrid decomposition method can be implemented to improve the epilepsy recognition performance.

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