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An Adaptive Optimized Schizophrenia Electroencephalogram Disease Prediction Framework

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Abstract

Electroencephalogram (EEG) signal analysis has become an interesting and required area in the medical industry to analyze brain function for different diseases. But, the EEG signal's noise features might degrade the signal prediction's exactness score. So, the presented article aims to develop a novel EEG signal analysis system named a novel Firefly-based Deep Belief Signal Specification (FbDBSS). In addition, the disease signal considered in this research work is Schizophrenia (SZ) signal. Initially, the SZ signal with a normal EEG signal is trained to the system, and preprocessing function is performed. Then the filtered signal is entered into the classification layer for the feature extraction and signal analysis function. Furthermore, the proposed design is executed in the python environment, and the robustness score has been measured in terms of accuracy, sensitivity, and error rate. The chief parameter of the proposed FbDBSS design is compared with other models and has gained the finest 3% of improved signal analysis accuracy and sensitivity score.

Keywords Electroencephalogram signal analysis · Schizophrenia signal · Abnormal signal classification · Signal frequency · Neural approach

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1 Introduction

The common neurological disorder is Schizophrenia (SZ), which has severe and chronic effects during adulthood. It affects 28million people approximately over worldwide [1]. Moreover, the SZ is classified under five different types, such as Paranoid, disorganized, catatonic, undifferentiated, and residual. Hence, SZ is a long-term brain disorder; SZ-affected patients experience disorganized speech, hallucinations, delusions, etc.; SZ prognosis needs long-term medication and economic burden [2]. For SZ identification, electromyograms (EMG) and electrocardiograms (ECG) have been utilized [3]. However, these models did not perform well due to a lack of methods and standardized tools. In addition, for SZ diagnosis, Electroencephalogram (EEG) signals offer essential information over the other methods [4]. EEG signals are economical, nonradioactive, and noninvasive [5]. Therefore, EEG signals have been commonly used to detect brain abnormalities. EEG is a device that allows electrical signals activity in the brain was recorded [6]. Moreover, EEG recordings comprise signals data collected from electrodes that vary based on non-stationary or periodic time [7]. EEG data are important, enabling brain activity analysis and study [8]. Many nonlinear and linear analysis techniques are utilized in EEG signal processing [9].

The EEG signal-based SZ classification is shown in Fig. 1. Researchers have recently presented many techniques for EEG artifact removal, which occurs during the EEG signals recording phase [10]. Early diagnosis of SZ helps to mitigate brain impairments, even though disease detection is difficult for a specialist [11]. Computer software analyzes and monitors the EEG signal data [12]. Hence, the data is complex to interpret by an expert; therefore, Computer-Aided-Diagnosis (CAD) systems are developed to assist experts in disorders evaluation [13]. Generally, CAD system dependent on feature extraction and signal processing is categorized into four: frequency, deep learning (DL), time, and time–frequency-based domain [14]. In time-domain-based processing, the nonlinear and linear features are extracted from EEG signals [15]. Consequently,

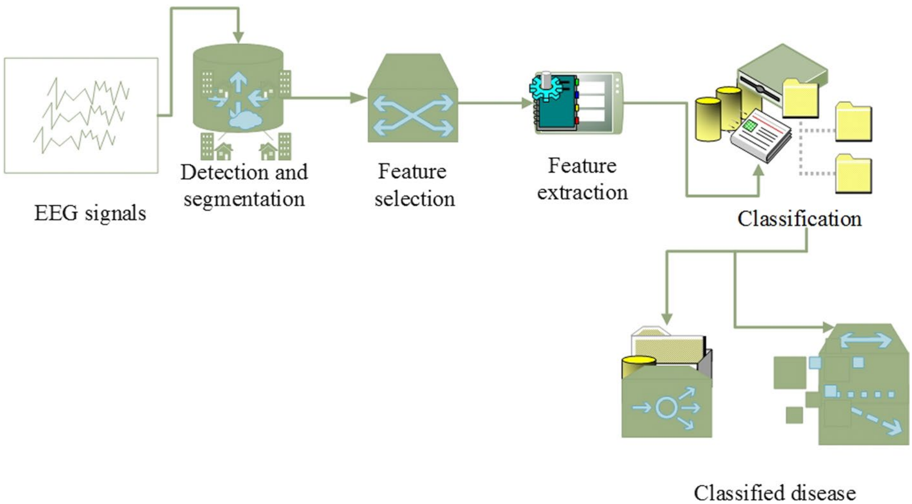

Fig. 1 EEG signal-based SZ classification

in frequency processing, required features are taken from the EEG signals spectrum, although time–frequency features express the EEG signal's intrinsic behavior [16].

Moreover, various machine learning (ML) and artificial intelligence (AI) methods have been utilized for classifying normal subjects and SZ patients [17]. In traditional ML, selecting the proper feature-extracting technique for diagnosing SZ is demanding, requiring great knowledge in the AI field and signal processing [18]. To resolve this issue, DL methods have been utilized in recent years to diagnose SZ by EEG signals [19]. Various studies were conducted to classify the disease type in earlier stages; however, the SZ-appropriate classification was not recognized [20]. In addition, several methods for EEG-based disease diagnosis developed recently, such as DepHNN [21], CAD-CNN [22], ADASYN [23], etc. Besides, the boosting models [31] and the optimization mechanisms [32] are utilized as the feature selection model for the EEG signal data. Using the boosting features selection model high feature extraction outcome has been gained. But, it has minimized the classification exactness score. In addition, the iterative feature reduction model [33] was executed to classify the abnormal signal and its severity range from the trained EEG signal data. Here, the process has been continued till a suitable optimal outcome has been gained. Hence, it has recorded high computational complexity.

On the other hand, the signal processing models like wavelet transform [34], Fourier transforms [35], and Gaussian model [36] were well utilized in the signal processing application for finding the best-featured signal. Compared to the boosting and optimization models, this signal-based approach has provided the finest feature extraction outcome with filtering parameters. However, this model required more features for extracting present features in the trained signal data. Also, it is not suitable for signal classification. Considering these issues, the Deep learning (DL) model has been considered in this present work to reduce computational complexity and for the finest feature selection and classification outcome. Moreover, the DL mechanism has hyperparameter variables sufficient for processing the multi objectives like feature extraction and classification. Considering this advancement in the DL model, which is chosen for this current research work? In this work, the preprocessing function is also incorporated in the deep belief model's hidden layer, which has afforded the finest filtering outcome. Then to gain the possible classification outcome, the fitness function of the firefly is updated in the classification layer of the Deep belief neural model.

The key step process of this research work is described as follows,

- To collect the schizophrenia EEG (SZ-EEG) signal and train to MATLAB system, which contains both abnormal and normal signals.
- Then, a novel Firefly-based Deep Belief Signal Specification (FbDBSS) model was designed with suitable parameters.
- Consequently, the training noise can be extracted in the preprocessing phase then the preprocessed data is utilized for the classification process.
- Firefly fitness has afforded the finest abnormal EEG signal specification exactness score.
- Finally, the key metrics have been measured to value the designed EEG model's effectiveness in classification time, accuracy, frequency response, and power consumption.

The present research chapter is designed as the second section has demonstrated the recent associated literature of EEG signal analysis systems. Consequently, the difficulty score in the EEG signal specification framework is described in the third section. Moreover, the 4th section has explained the proposed problem's solution. Also, the 5th section describes the gained outcome of the proposed scheme. Finally, the research discussion has been ended in the 6th section.

2 Related Work

Some of the recent literature related to Electroencephalogram (EEG) is described as follows:

The mental disorder can be identified using EEG signals to analyze the patient's mental state. For the screening of Depression, Sharma et al. [21] have proposed an intelligent EEG-based computer-aided (CAD) Hybrid Neural system named Depression deep networks. Moreover, a Convolutional Neural model is utilized for temporal windowing learning, and for performing sequence learning, a Long-Short-term scheme is used. The results indicated the hybrid deep networks model is less complex, accurate, and helpful in depression detection by EEG signals. However, depression severity cannot be diagnosed by this method.

Aslan and Akin [22] have presented a CAD technique for the automatic detection of schizophrenia (SZ) from the records of EEG. A continuous Wavelet-based Transform method is utilized to convert the signal into 2D. In addition, datasets are trained by the Visual Geometry model, and an advanced convolutional neural approach extracts the key features. The result indicated that the presented model has high classification accuracy and accurately detects diseases. Moreover, for complex models, the computation time is high.

Attention hyperactivity disorder and conduct disorder are convoluted brain disorders. For that, an automated framework was developed by Tor et al. [23] for diagnosing hyperactivity and disorder problems. The dataset is balanced using Adaptive-synthetic (ADASYN) sampling, and the discrete wavelet approach and empirical mode process can decompose the EEG signals. The result demonstrated that the presented method had attained 97.88% accuracy for classification. However, the processing time is high, and earlier diagnosis of hyperactivity and contact disorder does not apply to this model.

Khessiba et al. [24] have presented two kinds of networks, i.e., the 1D-UNet model that contains a deep one-dimensional-based convolutional approach and UNET, which combines 1D-UNet architecture and a long-short-term approach for predicting the state-of-vigilance of individuals based on the diagnosis of brain activity using EEG signals. The experimental result demonstrated that the presented networks have attained higher precision, improved the classification performance, and maintained prediction stability. Moreover, the EEG signal's multi-label classification isn't possible, and execution time is higher.

The complex disorder in elders is Dementia; the diagnosis of Dementia is a difficult task. Sharma et al. [25] have presented a multi-class-based Support-Vector-Machine (SVM) for classifying features of EEG during relaxing-state, motor-speed-test (MST), and resting-state events. The main purpose is to detect mild cognitive impairment (MCI) by dementia classification. The result indicated that the proposed method reduces the MCI diagnostic boundary condition using EEG features with 91.23% accuracy. However, the classification accuracy is less due to the increasing features.

Sharma et al. [37] have introduced the biomarker scheme for analyzing the EEG signal and to specify the disease severity. Hence, this biomarker scheme has recorded the finest prediction and classification outcome of SZ. However, the biomarkers methods need alteration based on each dataset's features. But, altering the biomarker model is difficult.

To earn the finest prediction and classification outcome, Bagherzadeh et al. [38] have introduced the hybrid DL model in the vision of convolution and recurrent neural paradigm. The reason for designing the hybrid DL is to tackle the issues of CNN in prediction by the recurrent neural features. Usually, CNN has reported limited prediction accuracy because of the limited features. Here, these issues were solved using the recurrent features. Hence, the finest prediction and feature selection outcome was gained. But it has recorded high resource usage and algorithm complexity.

A configuration pattern model was implemented for the EEG signal processing application by WeiKoh et al. [39]. Here, the disease signal and the severity range were calculated from the image data to make the EEG signal classification process automatic. Initially, the EEG signal was converted to images then the configuration pattern was applied for the feature selection and signal classification process. The outstanding classification exactness score was obtained. However, it was recorded more computational time.

To reduce the algorithm complexity and to reach the finest normal and SZ specification outcome, Khare et al. [40] have introduced the decision support system with the required disease type's classification condition. The limited resources and features were sufficient for executing this model and attaining the exact prediction outcome. However, a wrong prediction is reported if the images are too complex.

Several disease signal classification models have existed in the past with different and unique metrics. The main issues that the described model has reported are wrong prediction and high algorithm complexity scores because of using different mechanisms to meet the objectives. These issues were motivated by this research. This research work has implemented deep features with optimal parameters to classify the disease signal by analyzing the signal frequency range. The surveyed algorithms utilized each specific model for each process at each step, like filtering feature extraction, prediction, and classification. This way has led to cause high algorithm and computational complexity. So, the present work has defined all the processes in the optimized deep networks, which has afforded the finest preprocessing outcome, feature selection prediction, and classification outcome.

3 System Mode and Problem Description

Nowadays, the signaling system has been enriched by the advance of deep networks and optimization strategy. However, analyzing the complex signal is difficult because the signal gathered from network sites contains more noise. Considering this issue, several filtering techniques have been implemented to remove the EEG signal noise. But some approaches have taken more and high power consumption to eliminate the noise content from the EEG signal data. Still, satisfactory results are not found for the further classification process.

The main problem in the EEG signal classification system is a noisy signal. The classification process is more complex if the noise isn't removed during the filtering process. The problem in finding the disease EEG signal is illustrated in Fig. 2. These issues have motivated this present research to implement a better preprocessing and signal classification model using deep features.

4 Proposed FbDBSS for Classifying SZ EEG Signal

The present research aims to design a novel h model to classify the normal and abnormal EEG signals (SZ). Here, the preprocessing function has been framed in the initial layer of the FbDBSS approach; it gives the finest error removal results. Consequently, the

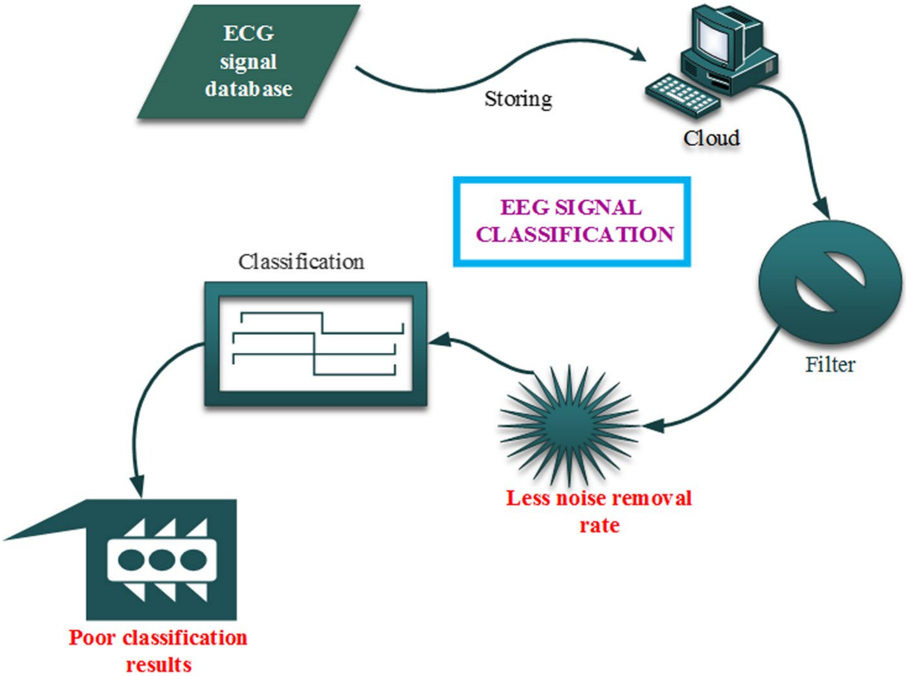

Fig. 2 EEG signal analysis system with the problem

noise-removed data is utilized for feature extraction and classification process. Here, the proper noise removed and data and firefly fitness have afforded the finest signal specification results. The proposed design is described in Fig. 3.

The proposed novel FbDBSS is tested with benchmark SZ EEG signal data that included 39 normal signals and SZ signals. Finally, the classification efficiency has been validated in chief metrics like exactness, sensitivity, *f*-score, and precision. Finally, a comparative analysis has been conducted to estimate the percentage of the disease signal classification rate. Moreover, the utilized symbols in the proposed approach are described in Table 1.

4.1 Design of FbDBSS Layer

The novel FbDBSS has been developed based on the deep belief model [29] and the firefly algorithm [30]. To analyze the robustness of the designed system, one of the EEG signals is taken, which is SZ-EEG. Furthermore, for classifying the SZ-EEG, a novel scheme has been introduced called FbDBSS, which involves two modules: deep neural features and optimization process.

$$f(es) = es\{1, 2, 3, 4, 5, ...n\} \tag{1}$$

The primary function of the EEG signal classification system is to train the specific required EEG signal for analysis. Moreover, the training process of the EEG signal has been executed by Eq. (1). Here, es is the EEG signal dataset and $f(es)$ is denoted by the training function.

Here, the collected EEG signal data is described es. The designed novel FbDBSS approach has several frames: training layer, hidden layer, classification layer, optimal

Fig. 3 proposed FbDBSS Architecture

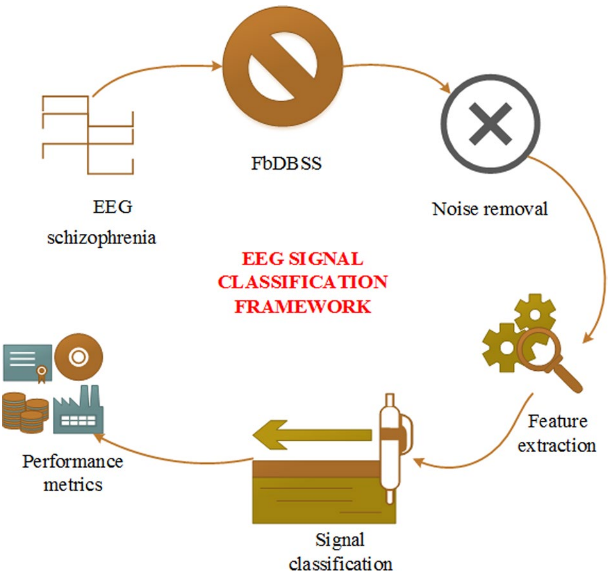

Table 1 Symbols description

Symbols specification	
es	EEG signal dataset
$f(es)$	Training function
n	n number of data
x	Error features
b	Error tracing
Ef	Error filtering
β	Disease features searching parameter
F_e	Feature extraction
d_f	Disease feature
n_f	Normal feature
P_e	Prediction variable
α	Disease classifying variable
α_y	Tested disease features
α_x	Saved disease features
C^*	Classification function
r	Random variable
$r(P_e)$	Random selection
S_n	True negative
S_f	False positive
S_p	True positive
S_{fn}	False negative

solution layer, and output layer. Moreover, these layers design is described in Fig. 4. In the data training layer, the SZ EEG signal benchmark data has been trained as the input. Consequently, the noise filtering process is performed in the hidden layer. Finally, the feature extraction and signal analysis functioned in the classification phase.

4.1.1 Preprocessing

Filtering the signal is more important to gain the finest classification results, so the error pruning function is incorporated with the deep neural networks. The process preprocessing has functioned in Eq. (2).

$$Ef(x) = \frac{1}{2}b(x)\|es - x(es)\| \tag{2}$$

Here, x is the error features, b the error tracing variable, and Ef is the error filtering parameter. The raw signal dataset contains highly noisy features that make it complex in abnormal signal classification. Hence, the preprocessing function has been performed in the hidden phase of the deep belief neural model.

4.1.2 Feature Extraction and Disease Feature Prediction

The collected raw signal contains some disease and normal features, so the entire present features in the signal were extracted before classifying the abnormal signal. In addition, the β parameter is taken from the firefly function, which is attraction analyzing parameter. Here, it is utilized to analyze the normal and disease features.

$$F_e = \beta\left(\frac{d_{f+n_f}}{es}\right) \tag{3}$$

Here, β is the search parameter; Search the present features and track the disease parameters. The feature extraction variable is described as F_e, the disease feature is represented as $d_{f,}$ and the normal feature is determined as n_f. Moreover, the process feature extraction is performed by Eq. (3).

$$P_e = \beta\left(\frac{d_f}{F_e}\right) \tag{4}$$

After predicting the present features from the trained data then, the disease signal was forecasted. Hence, the detection of the disease signal is analyzed using Eq. (4). Here P_e is the prediction variable.

4.2 Classification of SZ Disease

Once the disease signal features were predicted, the classification of SZ disease has been functioned using Eq. (5). Moreover, the parameter α taken from the firefly's fitness is the brightness firefly. In this proposed research, α the SZ disease classifying variable and C^* denoted as the classification function.

$$C^* = \alpha_y(P_e) + r(P_e) \tag{5}$$

Furthermore, the SZ disease features are stored in the fitness module of a firefly; that is α_y, here, the saved SZ disease features are determined as y. Moreover, r is the random variable $r(P_e)$ denoted by the random selection of the predicted disease signal features for the testing purpose. During the classification function, if the testing signal matches the saved α_x signal, it is classified as SZ disease.

Algorithm 1: FbDBSS

start

{

$int\, es;$

//initializing SZ EEG signal data

Preprocessing function ()

{

$int\, b, x;$

// initializing the preprocessing variable

$Ef \rightarrow es - noisy \quad features$

// error free data has been attained

}

Feature extraction ()

{

$int\, \beta, d_f, n_f;$

// feature extraction variables were initiated

$F_e \rightarrow d_f + n_f$

// all present features have been extracted

}

Disease signal prediction ()

{

$P_e \rightarrow d_f$

// here, the disease signal has been forecasted by eqn. (4)

}

Classification ()

{

$int\, C^*, y, \alpha, r;$

// initializing the classification variables

$C^* \rightarrow \alpha_y(P_e)$

// here, the SZ disease signal features were stored in the α_y *variable; during the testing function, the SZ disease signal was predicted by matching the saved SZ disease features with the test signal features*

}

}

Stop

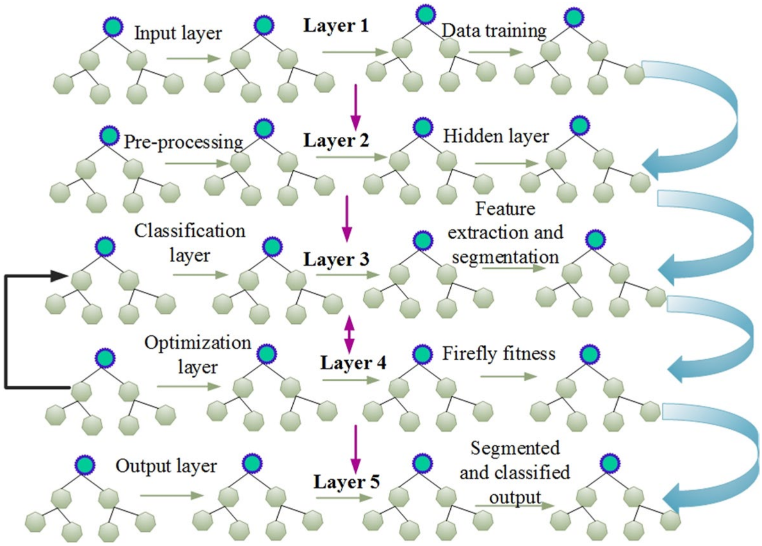

Fig. 4 Layers of the proposed FbDBSS

The function of the proposed novel FbDBSS has been described in algorithm 1 and Fig. 5. Here, the filtering process functioned with the deep neural layer that has yielded the finest error removal results. The epoch functions have been iterated again and again till the suitable range of the error-free signal is met.

5 Results and Discussion

The designed novel FbDBSS system is executed in the MATLAB environment and runs on the Windows 10 platform. The main objective of this research chapter is to specify the SZ signal from the trained raw dataset. The benchmark dataset contains several ranges of SZ disease signals and normal signals, including normal and SN features. Also, the normal and the SZ signal was determined in the form of labeling format that is 0's and 1's. Here, '0' determines the normal signal, and '1' determines the SZ signal. In addition, the training testing ratio for the considered data is 80:20, which means training is 80% and testing 20%. The dataset was present in the form of EEG signal JPEG; after training, it was converted into a digital signal, and the further process was executed. Hence, the execution parameter details are tabulated in Table 2. Initially, the noise features in the dataset are filtered in the preprocessing layer. Here, incorporating the preprocessing module in the deep networks has tended to earn the finest noise filtering rate.

Moreover, the working performance of the designed model is validated by the testing process of two different signals, normal and SZ; those outcomes and the process are described in the case study.

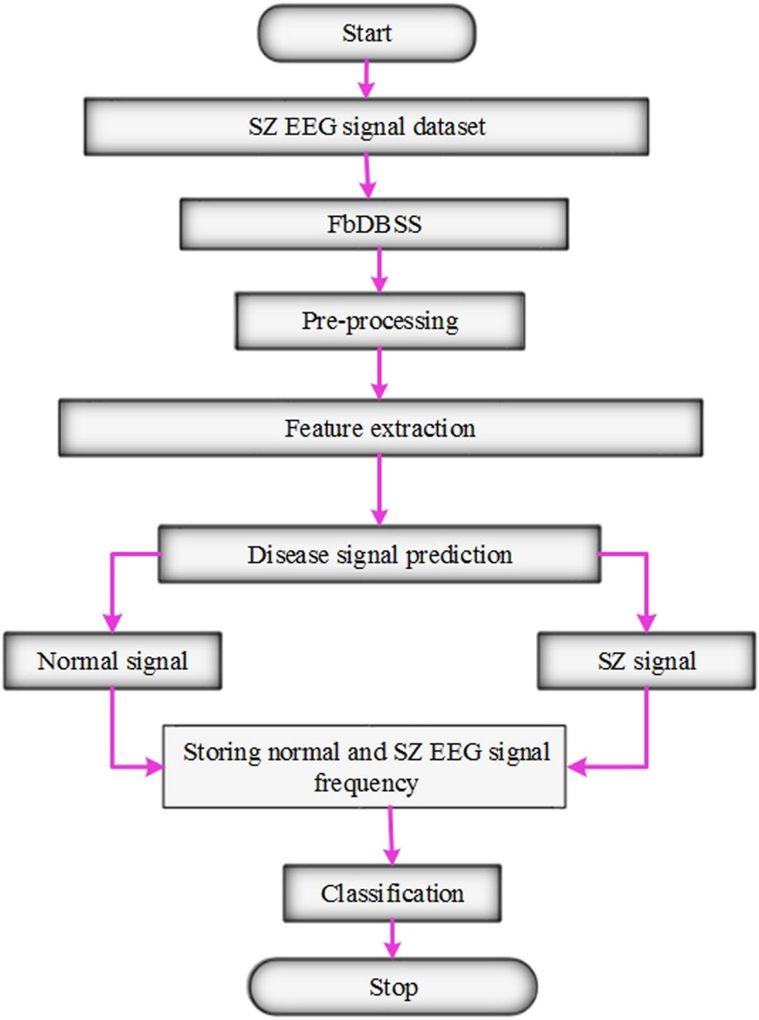

Fig. 5 The proposed FbDBSS workflow

Table 2 Parameter specification

Execution parameter details	
Programming language	MATLAB
version	R2020b
Operating system	Windows 10
RAM	12 Gb
Processor	Intel core
Dataset	EEG signal data
Dataset type	EEG signal image data
Training model	Deep belief neural network
Parameters tuning	Firefly optimization

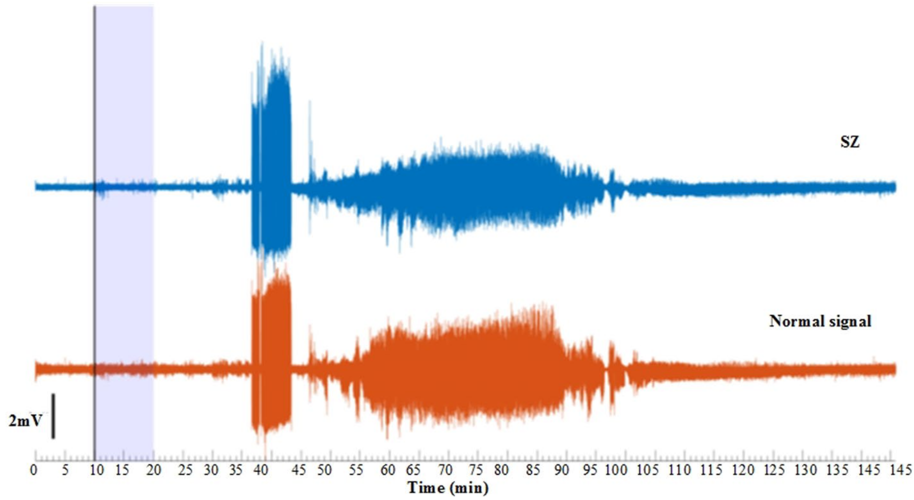

Fig. 6 EEG signal input Normal and SZ

5.1 Case Study

One of the SZ EEG signals is taken to validate the designed model for testing purposes. Here, the SZ signal has been classified by matching the normal signal frequency range with the abnormal signal frequency.

When training the dataset, the signal range of normal and disease signals has been gained; this is described in Fig. 6. Moreover, the filtering is processed in the hidden layer, and after that, feature extraction of the SZ and the normal signal is detailed in Fig. 7.

After analyzing the EEG signal features, the frequency variation of the imported signal has been validated and matched with one another.

Classification time and frequency: Classifying the SZ disease signal from the trained EEG signal is more complex. Because the signal is present in the form image. So, before initiating the signal specification function, converting the image form signal to the binary data is a more required task in all cases. Hence, if the signal is unclear, the time taken for the binary process is too large. Thus, the estimation of the overall time is the most crucial parameter in signal analysis cases. Hence, the time was calculated.

The frequency response statistics about SZ and norm EEG signal are illustrated in Fig. 8. Based on the signal variation; the SZ signal has been predicted in the classification phase. Moreover, the efficiency of the normal and abnormal signal classification is measured in terms of the actual class.

Power consumption: Measuring the computation cost of the executed techniques is crucial for the robustness analysis system. Moreover, the computation cost parameter is validated using dual key parameters: power usage and time consumption. Besides, signal processing chiefly depends on power and frequency modulation.

The required power to classify the normal and the SZ disease signal is described in Fig. 9 here; the minimum required power to identify the SZ EEG signal is 5 dB, and the power utilization for recognizing the normal signal is 3 dB.

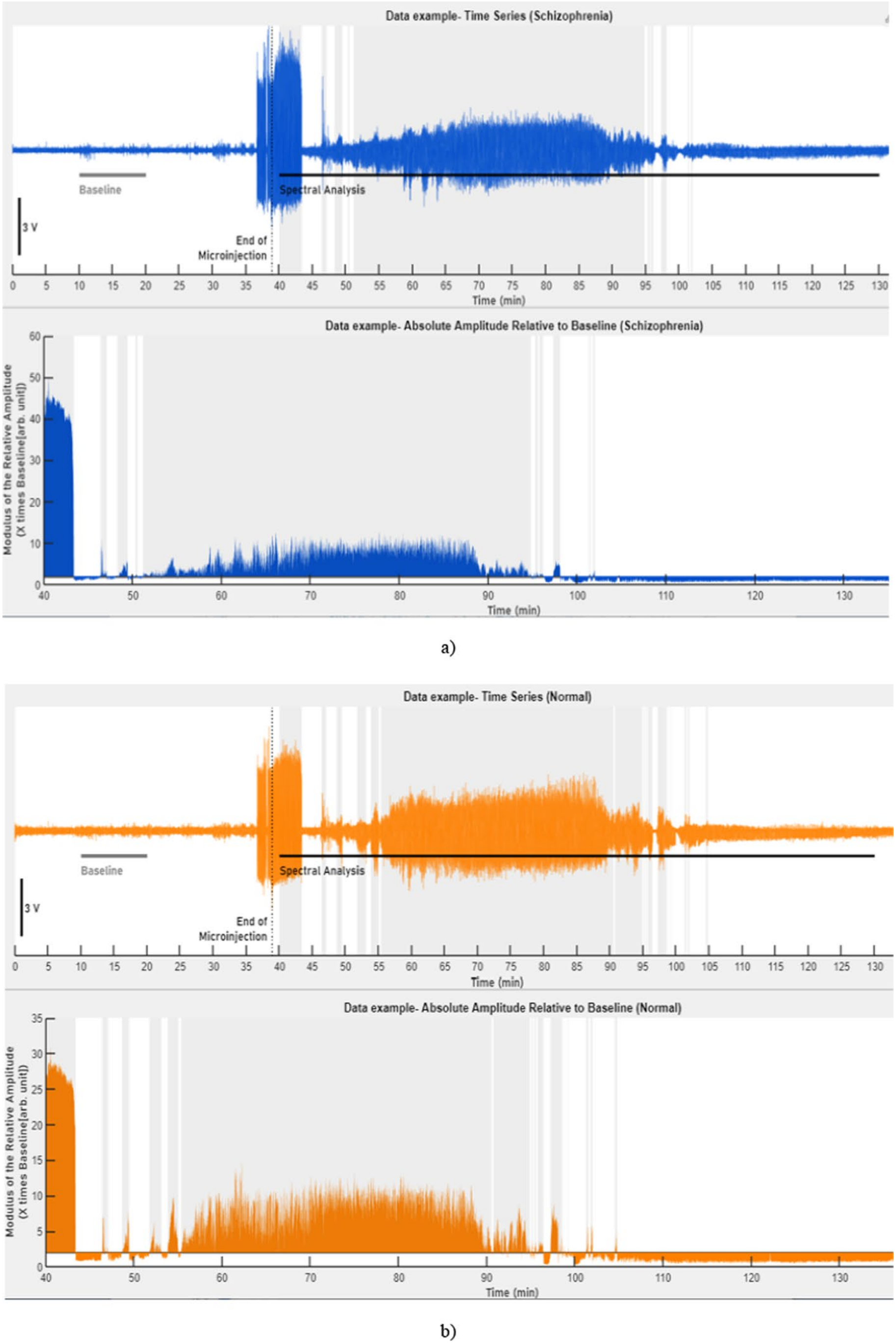

Fig. 7 Feature prediction of normal and SZ

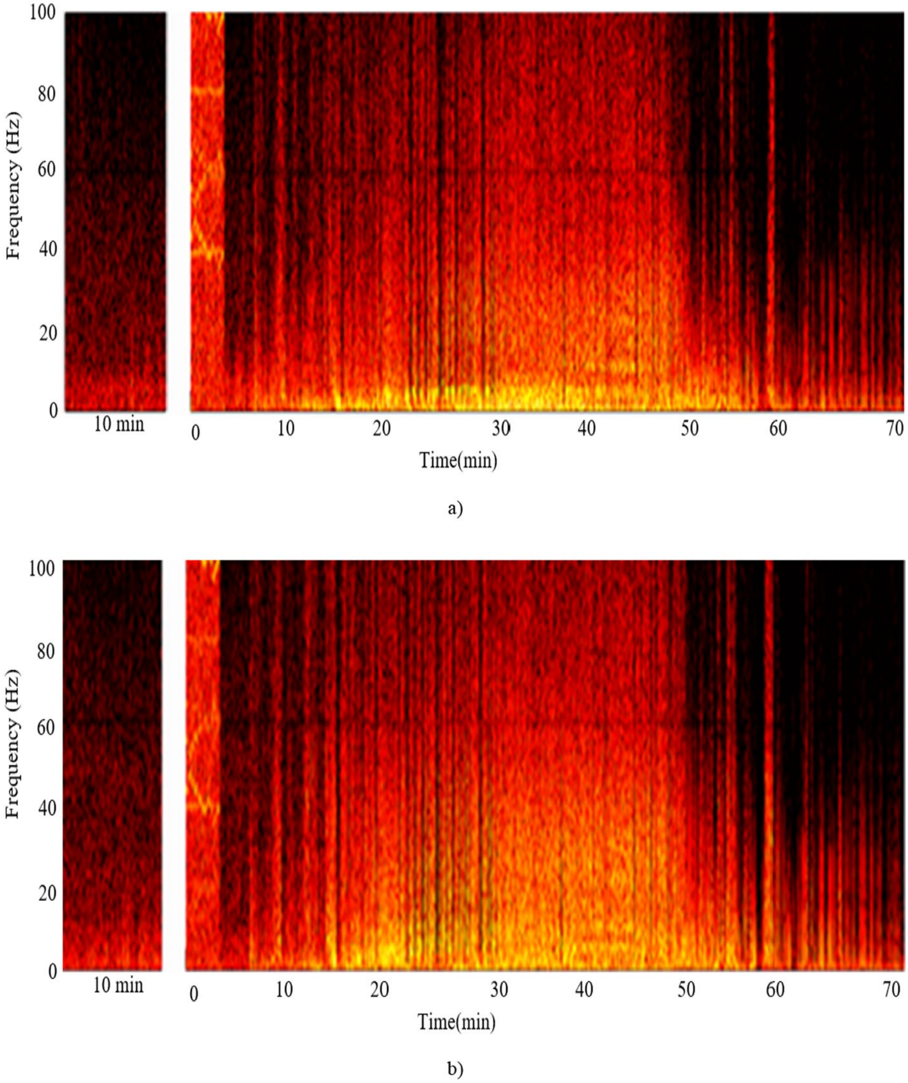

Fig. 8 Frequency response: **a** frequency response of SZ disease signal, **b** normal signal

5.2 Performance Analysis

To measure the classification improvement score, some of the recent techniques adopted are Empirical-Mode-Decomposition (EMD) [26], DeprVet [27], and Colatz pattern (CP) [28]. In addition, the proposed scheme has been tested with dual phases with and without optimization (WO).

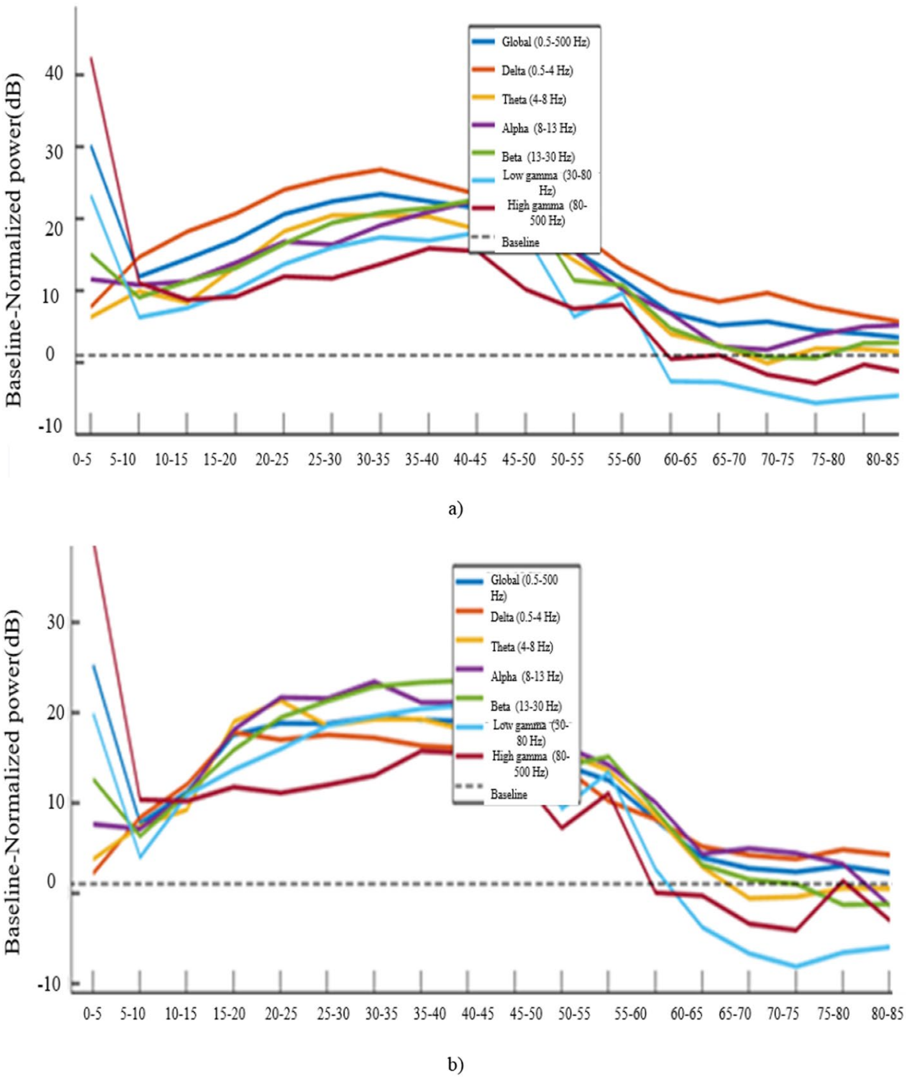

Fig. 9 power consumption: **a** SZ, **b** normal EEG signal

5.2.1 Accuracy and Precision

The parameter accuracy and precision have been validated to measure the abnormal EEG signal's prediction rate. Moreover, accuracy has been valued using Eq. (6) The exactness score of the abnormal signal classification has been observed by processing this equation.

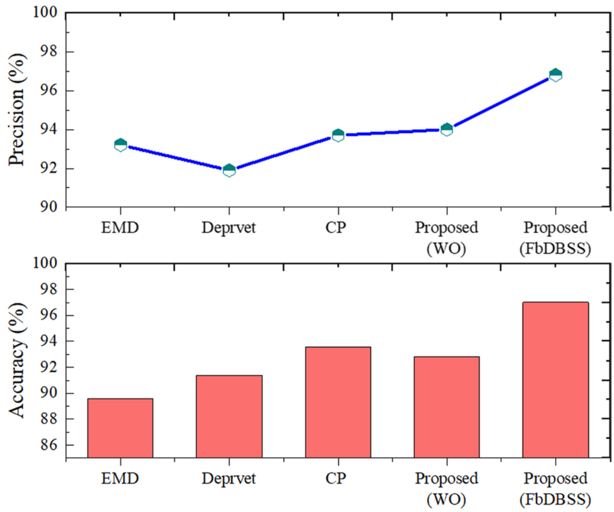

Fig. 10 Accuracy and precision validation

Here, S_p represents true positive, S_n denotes true negative, S_f determines false positive, and S_{fn} denotes false negative.

$$Accuracy = \frac{S_p + S_n}{S_p + S_f + S_{fn} + S_n} \tag{6}$$

The parameter precision has been observed to find the stability range for attaining high accuracy in signal classification systems. Hence, the precision was validated by taking the measure of the positive prediction. Moreover, the precision metrics have been measured by Eq. (7).

$$\text{Precision} = \frac{S_p}{S_p + S_f} \tag{7}$$

The model EMD has gained an EEG signal classification exactness score of 89.59% and a precision of 93.21%. The Deprvet has gained the EEG signal specification accuracy as 91.4% and 91.9% precision score. Moreover, the method CP has recorded the classification accuracy as 93.58% and precision as 93.7%. Besides, the proposed model has earned the highest abnormal signal classification rate of 97% and precision of 96.8%. Also, the proposed deep belief method is checked for the without optimization cases. For that, it has gained 92.8% accuracy and 94% precision. Hence, the statistics of accuracy and precision are described in Fig. 10.

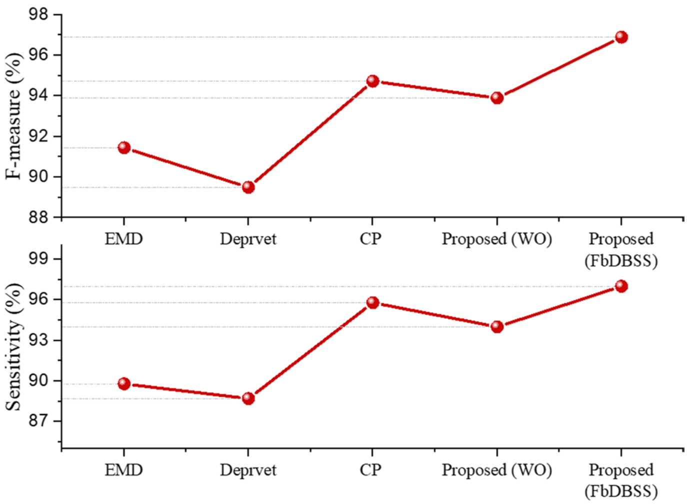

Fig. 11 Assessment of sensitivity and *F*-measure

Table 3 Comparison assessment

	Comparison statistics			
	Accuracy (%)	Precision (%)	*F*-score (%)	Sensitivity (%)
EMD	89.59	93.21	91.45	89.79
Deprvet	91.4	91.9	89.5	88.7
CP	93.58	93.70	94.73	95.79
Proposed (WO)	92.8	94	93.9	94
Proposed (FbDBSS)	97	96.8	96.9	97

Table 4 overall performances of FbDBSS

Overall performance	
Parameters	Validated outcomes
Accuracy	97
Precision	96.8
F-measure	96.9
Recall(sensitivity)	97
Execution time	19 s
Power consumption	5 dB

5.2.2 *F*-score and Sensitivity

To find the positive features from the entire observation in the actual class, the sensitivity score has been measured, which is also defined as recall. Hence, the sensitivity metrics were validated using Eq. (8).

$$sensitivity = \frac{S_p}{S_p + S_{fn}} \tag{8}$$

The *F*-measure metrics were validated to know the mean measure of the precision and sensitivity score. Moreover, the utilized formula to value the *f*-score rate is provided in Eq. (9).

$$F - measure = \frac{2 * (sensitivity \times precision)}{sensitivity + precision} \tag{9}$$

The EMD model obtained an EEG signal classification sensitivity score of 89.79% and a *F*-score of 91.45%. The Deprvet technique measured the EEG signal specification sensitivity score as 88.7% and 89.5% *F*-score. In addition, the CP method has earned the classification sensitivity as 95.79% and 94.73% *f*-score. Besides, the designed FbDBSS model has earned the highest sensitivity rate at 97% and *F*-score at 96.9%. Also, the performance of the proposed FbDBSS has been checked without optimization cases. In that, it has gained 94% sensitivity and 93.9% *F*-score.

The statistics of *F*-measure and sensitivity are described in Fig. 11, and the overall comparison is detailed in Table 3.

To check the performance and necessity of this model in the EEG signal processing system, compared existing models were tested in the same platform. Finally, the same parameters were validated and compared with the proposed approach. In addition, to justify the need for the optimal model in this present deep belief neural system, the performance parameters were validated in dual phases with and without optimization. Here, the better outcome is the score for an optimized deep network, i.e., for novel FbDBSS. It has proved the need for the optimization approach for the EEG disease signal classification system.

6 Discussion

All the validated parameters have relieved that the proposed novel FbDBSS model has earned outstanding results than the old methods. The overall performance of the proposed scheme is described in Table 4.

Hence, the designed paradigm is suitable for the EEG signal analysis to specify the abnormal and normal signals. Besides, the key reason for earning this better outcome is the involvement of the preprocessing process in the deep neural layer. The deep neural usually has the desired acceptable quantity of noise. So, processing the filtering in the neural approach has earned the finest outcome. The filtering layer function was activated repeatedly until the desired noise was attained.

7 Conclusion

The presented work has aimed to design a novel efficient EEG abnormal signal classification system to enrich the signal analysis process. A novel FbDBSS has been designed with the required signal analysis parameter for classifying the SZ disease signal. It is tested with the benchmark EEG signal dataset, and the robustness of the proposed model has been analyzed in dual phases with and without firefly fitness. Incorporating the firefly fitness in the deep networks has achieved the best abnormal signal classification results. Hence, the proposed novel FbDBSS has earned the highest abnormal signal classification score of 97%; compared to the previous model; it has increased the classification accuracy to 3%. Moreover, the earned sensitivity score in predicting the abnormal signal is 97%; compared to previous approaches, the presented model has maximized the sensitivity score by up to 3%. Furthermore, the proposed approach has maintained the stability range in predicting the abnormal signal, gaining the 97% for accuracy and sensitivity parameters. However, the present model's parameter is insufficient for analyzing the severity probability. In the future, designing the probability identification parameter along with this implemented approach will enrich the EEG signal processing system by providing exact information about the disease signal and severity.

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Data Availability Data sharing not applicable to this article as no datasets were generated or analysed during the current study

Declarations

Conflict of interest The authors declare that they have no potential conflict of interest.

Human Animal and Rights All applicable institutional and/or national guidelines for the care and use of animals were followed.

Informed Consent For this type of analysis, formal consent is not needed.

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