A Design of Bat based Optimized Deep Learning Model for EEG Signal Analysis

Varun Gupta (varungupta57678@gmail.com)
KIET Group of Institutions: Krishna Institute of Engineering & Technology https://orcid.org/0000-0002-8898-9348
Pankaj Kumar
CCS University: Chaudhary Charan Singh University
Neeraj Kumar
Electronics & Communication Department Dronacharya group of institutions

Research Article

Keywords: EEG Signal, Normal Patient, Depressed Patient Data, Time and Frequency Range, Band Power, Convolutional Layer, Depression Rate

Posted Date: November 16th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1290818/v1

A Design of Bat based Optimized Deep Learning Model for EEG Signal Analysis

***Varun Gupta·AbhasKanungo·Pankaj Kumar·Neeraj Kumar·ChandanChoubey**

Abstract Depression is one of the mental illnesses that negatively affect a person's thinking, action, and feeling. Thus the rate of depression is identified by analyzing Electroencephalogram (EEG) signals, but it has the problem of classifying depression rate because of noise. In this paper, a novel Bat-based UNET Signal Analysis (BUSA) framework is designed to organize the depression rate of patients with an EEG dataset. This technique involves preprocessing, feature selection, feature extraction, and classification. After the data training process preprocessing function was activated to remove the noise in the brain signal. Hereafter, the noiseless signal is used for the further process. Here, the fitness of the bat is upgraded in the UNET classification layer. Moreover, the brain signal's feature selection and depression rate were classified using the bat fitness that has helped to gain the desired output. Finally, performance metrics of the proposed BUSA technique are compared with other existing methods regarding the accuracy, AUC, precision, recall, and power. In that, the developed framework has attained better results to classify depression rates.

KeywordsEEG Signal•Normal Patient•Depressed Patient Data•Time and Frequency Range•Band Power•Convolutional Layer•Depression Rate

---

*Varun Gupta,
Associate Professor, Department of Electrical and Electronics Engineering,
KIET Group of Institutions,
Delhi-NCR, Ghaziabad, Uttar Pradesh - 201206, India.
E-mail: vargup2@gmail.com

AbhasKanungo,
Assistant Professor, Department of Electronics and Communication Engineering,
KIET Group of Institutions,
Delhi-NCR, Ghaziabad, Uttar Pradesh - 201206, India.
E-mail: abhas.kanungo@kiet.edu

Pankaj Kumar,
Assistant Professor, Department of Electronics & Communication Engineering,
SCRIET, CCS University Meerut Uttar Pradesh - 250003 India.
E-mail: nadarpankaj.miet@gmail.com

Neeraj Kumar,
Assistant Professor, Department of Electronics and Communication Engineering,
Dronacharya Group of Institutions, Greater Noida, India.
E-mail: iet_neeraj@yahoo.com

ChandanChoubey,
Associate Professor, Department of Electronics and Communication Engineering,
Dronacharya Group of Institutions, Greater Noida, India.
E-mail: er.choubey.chandan@gmail.com

1 Introduction

Generally, EEG is an electrical activity used to record the brain in the scalp (Satapathy and Loganathan 2021). It is used to measure the electrical signal of the brain with the Brain-Computer Interface (BCI) (Li and Huang 2021). Moreover, it will deliver the mental activity-related information, and the EEG signals are unique, non-stationary, and weak because they contain much noise (Nagabushanam et al. 2020). So, EEG signals are the most crucial task to process and analyze EEG signals (Rus et al. 2017). It includes four jobs for processing like feature selection, feature extraction, classification, and preprocessing(Sreedharan et al. 2018). The basic process of signal analysis in EEG is detailed in fig.1.

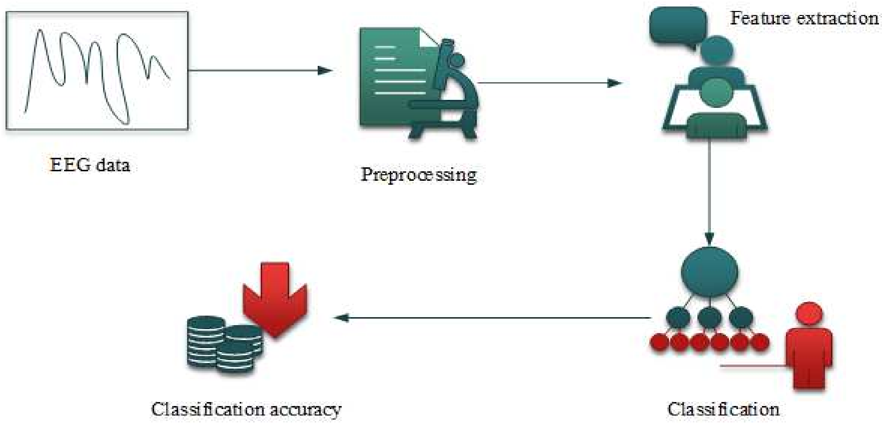

Fig. 1 Signal analysis of EEG

Furthermore, it deals with the classification and feature extraction of EEG signals and transfers the gained EEG signal to the feature vector with the help of the classifier (Zazzaro et al. 2019). For better analysis of EEG signal, the feature extraction to the certain EEG category is needed (Kim et al. 2018). Moreover, feature extraction extracts relevant and meaningful data or information for assisting good analysis (Barata et al. 2018; Scapicchio et al. 2021). Also starts with raw signal data of EEG and creates the values of the feature vector (Rudas and Laki 2019). However, signal processing of EEG contains Autoregressive (AR), Fourier transform; entropy and discrete wavelet transform (Gupta and Pachori 2020). This provides a wide range of EEG signals which is useful to the time-frequency transformation and contains various sub-bands to attain accurate information (Khare and Bajaj 2020). Moreover, the AR technique contains forecasted variable interests that are helpful to linear combinations of variable past values (Büyükşahin and Ertekin 2019). Additionally, the coefficient of AR technique is helpful to feature vector of BCI system but it is more difficult to gather the transient features of EEG signals because of noisy signal and error rate (Subasi et al. 2019; Gu et al. 2021).

Nonetheless, many techniques were developed for feature extraction of EEG signals, but it has the issue of information loss (Islam et al. 2021). The main issues of the EEG signal are noisy data, miss classification, and loss of information (Rajasekar and Pushpalatha 2020; Amin et al. 2019). There are a lot of techniques introduced to overcome these issues, such as the EMD-AR technique (Zhang et al. 2018), EEG-AR model (Ouyang et al. 2020), convolution neural system (Dose et al. 2018), and so on, but has the issues of noise in the signal, loss of information, improper classification (Algan and Ulusoy 2021). So, this paper has developed a novel AR and deep learning algorithm for modeling and analysis of EEG signals. It will solve the problem of information loss noise error.

The arrangement of this article is structured as follows. The related work based on EEG signal is detailed in section 2, and the system model and problem statement are elaborated in section 3. Also, the process of the planned methodology is described in section 4. Finally, achieved outcomes of the developed technique are mentioned in section 5, and the conclusion was detailed in section 6.

2 Related Works

A few recent literature surveys based on EEG signal is detailed below,

Zhang et al.(2018) have proposed an EEG-based Empirical Mode Decomposition (EMD) and Auto-Regressive (AR) technique for classifying the emotional data. Initially, the EMD technique is employed and decomposed to the EEG signal; it will calculate the features based on the function of intrinsic mode. Thus the developed technique attains 86.28% in emotion recognition, but noise present in the signal is high.

EEG is mostly used as a tool for assisting diagnosis in epilepsy. It has recorded the epilepsy diagnosis of the patient. Ouyang et al.(2020) were designed an EEG AR model to predict the error in the patient through epilepsy control. Thus the technique assists the diagnosis using epilepsy without the discharge of epileptiform. However, the classification rate of patient diagnosis is less because of the noisy signals.

Zhanget al.(2017) have developed an AR technique and wavelength packet rottenness to classify the signal based on the brain system. Moreover, the AR coefficient calculates the features depending on the assembling, and the sub-band has decomposed the EEG signals. Thus the calculated feature extraction is fed into the vector machine to classify EEG signal. But the process of classification takes more time to classify the signal.

Generally, EEG and Brain-Computer Interface (BCI) are used to increase the classification's performance. Dose et al.(2018) have proposed a convolution neural system for generalized learning features. It will reduce the dimension, and a fully connected layer is helpful for classification. Thus the developed technique attains better results in classification accuracy as 80.38%. But it has various dimensions, so some misclassification has occurred.

Zhang et al.(2019) have designed a convolutional recurrent attention technique for encoding the EEG signals high-level representation and generalized pattern with good performance. Moreover, the recurrent attention technique explores EEG signals of temporal dynamics; it has mainly focused on discriminative temporal periods. But it has the problem of error noise in the signal, so it is more difficult to attain better outcomes in EEG signal.

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

- The normal and abnormal EEG signal standard dataset was initially taken from a net source and trained in the system.

- Consequently, a novel Bat based UNET signal analysis model is designed in the MATLAB environment.
- Then the present noise in the EEG signal is removed in the preprocessing frame.
- Then the preprocessed signal enters into the classification layer of the optimized deep learning model.
- While testing process, the sensed patient EEG dataset is trained to the system; by matching the patient EEG dataset with normal EEG dataset, the Depression rate is predicted successfully in the MATLAB environment.
- Hereafter, the evaluated metrics are validated with other existing models in terms of accuracy, AUC, power, precision, and recall.

3 System Model and Problem Statement

Several neural-based algorithms were used to estimate the brain signal; EEG has been taken, then to analyze the health of the brain signal. Moreover,the sampling frequency regularized the EEG signal by converting the signal to 256Hz. Furthermore, feature extraction process was done to analyze the signal based on the activity of the electrical brain. Using Fourier and wavelet transform, the important features are set. But it has a problem in classifying EEG signals because of noise signals, less accuracy, and high execution time. The system model and problem definition are detailed in fig.2.

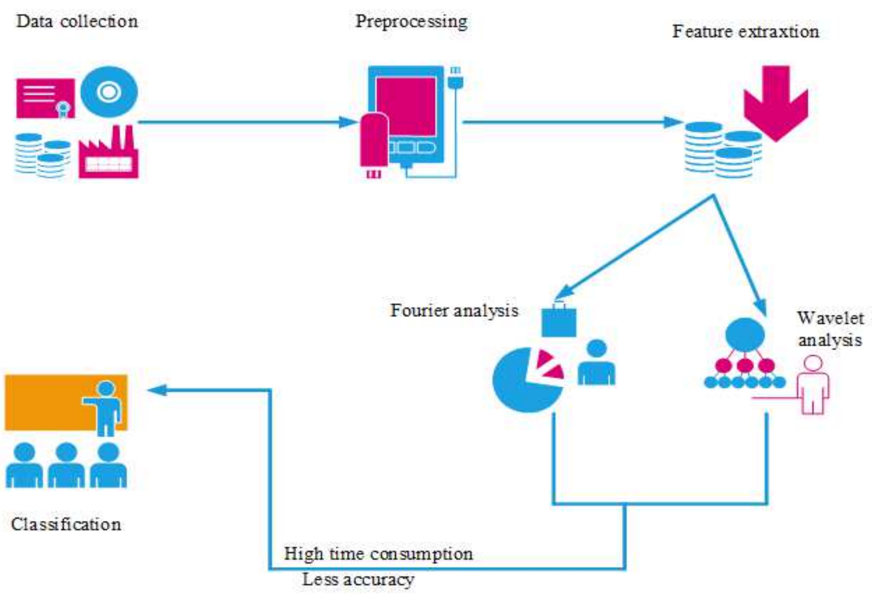

Fig. 2 System model and problem statement

The EEG signal system plays a vital role in analyzing the human depression rate. However, the key demerits of the EEG signal system are less accuracy in depression classification. The automated type is impossible in the EEG signaling framework if the depression ranges are not classified. In addition, if the data is too complex, then it reports very few depression classification measures. Also, the conventional model takes more time to complete the process.

4 Proposed BUSA Methodology for EEG Signal Classification

In the beginning phase, the EEG signals are taken from the standard datasets and trained in the system. Then a novel Bat based UNET signal analysis (BUSA) framework is designed in the MATLAB environment. In the initial phase, the errors are removed in the preprocessing layers. Hereafter, the error-free data enters into the classification layer. Thus the architecture of the proposed technique is shown in fig.3.

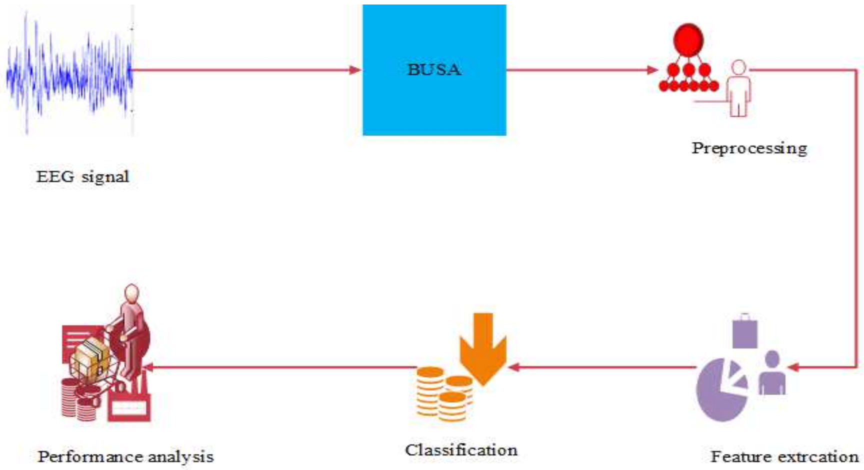

Fig. 3 Proposed BUSA framework

The fitness of the bat is utilized to specify the depression rate from the trained EEG signal. Finally, the presented model is validated concerning the accuracy, precision, AUC, recall, and power.

4.1 Pre-processing

Generally, the collected dataset of EEG signal presents a large level of noise that occurs due to various reasons. Thus the noise occurs based on the body of motion collecting EEG signals. The collected datasets are transferred to the convolutional layer for removing the error and noise present in the dataset using Eqn. (1),

$$\eta = \sqrt{\frac{1}{m}\sum_{a=1}^{m} k_i - \bar{k}} \tag{1}$$

Where, k_i is denoted as the rate of input EEG signal and $\bar{k}$ is considered as the mean value of the input dataset. Moreover, η is denoted as preprocessing and m is considered as noise present in the EEG signal. Thus the preprocessing helps to attain perfect classification of depression rate also it will change the raw signal into a normal neutral signal.

4.2 Feature Extraction

Then the preprocessed dataset is sent to the Maxpooling layer, which will extract the features of the EEG signal with the help of the Band-pass Butterworth filter. Thus, feature extraction happens based on common frequency bands such as theta, alpha, delta, and beta. Moreover, the frequency range of delta was 0.5-4 Hz, and the frequency range of theta was 4-8 Hz. Also, alpha has a frequency range of 8-13 Hz, and the frequency range of beta was 13-30 Hz. The feature extraction's main process is to extract the related features of depression rate based on time-frequency series.

Moreover, bat fitness is used in the developed technique for extracting the features of the input EEG signal based on the function of time or frequency and signal energy. It will convert the discrete-time signal into a discrete frequency sequence using eqn. (2).

$$K_x = \sum_{a=0}^{m=1} k_i h(t) e^{\frac{-j2\pi mp}{m}} \quad for \quad p = 0,1,......m-1 \tag{2}$$

Where m is denoted as the number of samples and $h(t)$ is designated as the signal. Moreover, p is called a time-domain signal. The signal dimension provides more information near the nature of the system, and the fractional extent is used to estimate the experimental data dimension. Moreover, the correlation dimension redirects the degree of the association among state-space points that measure the system's complexity. Thus the probability of points in the same set is obtained using Eqn. (3).

$$Q(t) = \frac{2}{D(D-1)} \sum \theta\left(f - |k(i) - k(j)|\right) \tag{3}$$

Let, $Q(t)$ is denoted as the correlation integral and θ is called as the probability of complexity in the system. Moreover, D is denoted as the dimension of the estimated slope value, $k(i)$ and $k(j)$ is denoted as the fractional dimension of the EEG signal.

4.3 Feature Selection

Generally, feature selection is the process of pattern recognition it will select the features based on the subset. Generally, feature selection enhances classification accuracy performance and deals with high-dimensional data. Thus the difference of the generated new features is compared with depressed patients and normal patients. While the vector length of each chromosome corresponds to one of the features, it will select the feature, and the feature selection happens based on the k value of samples. At the same time, the k value is less than 0.05 means that the features are selected. Moreover, feature selection is based on relative power, center frequency, correlation dimension, power spectral entropy, band power, and DFT. The process of the developed framework is detailed in fig.4.

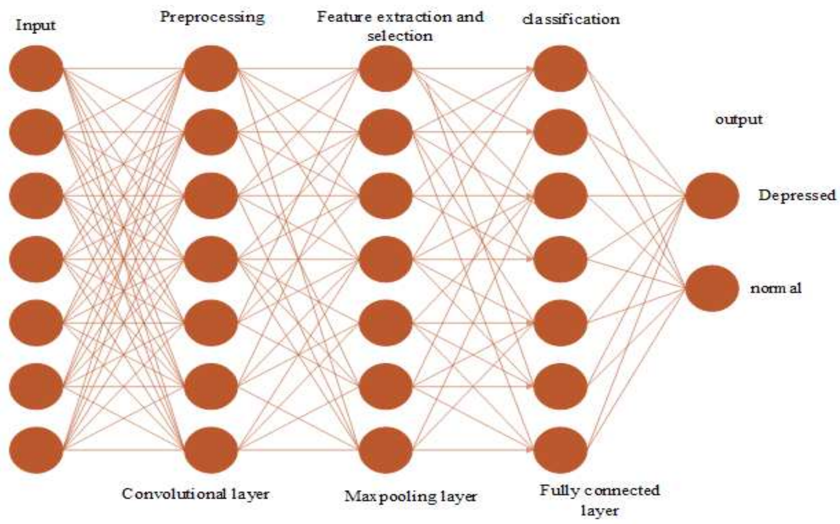

Fig. 4 Process of BUSA framework

4.4 Classification

Furthermore, selected features are sent to the fully connected layer and update the fitness function of a bat in this layer. Initially, it identified the rate of depression in the collected EEG signal by comparing normal EEG signals with the help of bat fitness. Next, calculate the distance between the selected and unknown samples using bat fitness obtained by eqn. (4),

$$Fr_a^t = \alpha Fr_a^t, b_a^{t+1} = b_a^0 - \exp(-\phi t) \tag{4}$$

Algorithm:1 Design BUSA framework for classifying depression rate in brain

Start

{

Initialize input

//Standard dataset of EEG signal

Design BUSA

// classify depression rate

{

Pre-processing *// convolution layer*

For all ($\eta \in m$)

// η - pre-processing

// m - noise present in the EEG signal

{

Remove noise

}

End for

Feature extraction *//Maxpooling layer*

- ***EEG band power***

$\delta \rightarrow$ *0.5-4 Hz*

$\theta \rightarrow$ *4-8 Hz*

$\alpha \rightarrow$ *8-13 Hz*

$\beta \rightarrow$ *13-30 Hz*

- ***Discrete Fourier Transform (DFT)***

//extract features based and time and frequency

- ***Correlation dimension***

$Q(t) \rightarrow k(i), k(j)$

// $k(i)$ and $k(j)$ - fractional dimension of EEG signal.

Feature Selection

// select the features based on the subset

If($k < 0.05$)

{

Selected features

}

End if

Classification *// Fully connected layer*

update fitness of bat

//enhance classification performance

If ($Fr_a^t < 7234$)

// Fr_a^t *- depression rate classifier.*

{

Normal patient

}

Else If ($Fr_a^t > 7234$)

{

Depressed patient

}

End if

output

}

End

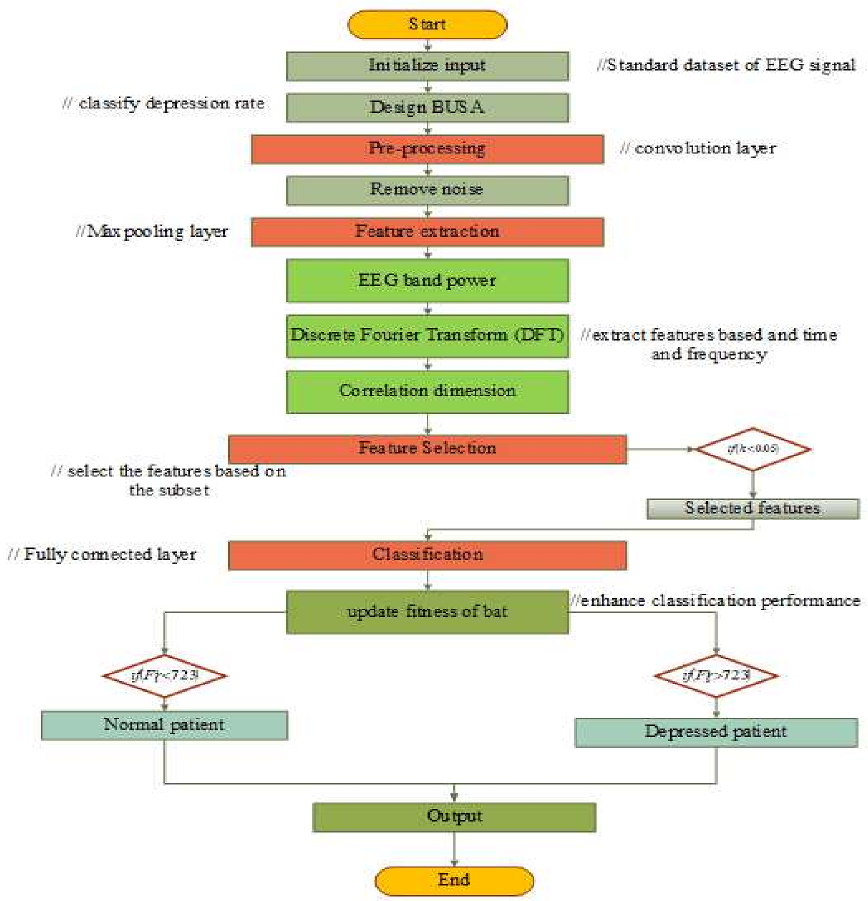

Fig. 5 Flowchart of proposed BUSA framework

Where, α and ϕ are denoted as constant, b_a^0 is denoted as depression rate of the normal patient, b_a^{t+1} is represented as depression rate of affected patient and Fr_a^t is called as depression rate classifier.

Based on some conditions, it will classify the normal patient and depressed patient, while the depression rate is $Fr_a^t > 1$ means depressed patient but $Fr_a^t = 1$ means normal patient. Thus the designed algorithm of the BUSA framework is detailed in algorithm.1 and the flowchart of the designed BUSA framework is shown in fig.5.

5 Results and Discussion

Initially, the proposed BUSA framework is implemented in the MATLAB tool, and the efficiency of the developed replica is measured with other existing techniques regarding the accuracy, recall, precision, AUC and power. Furthermore, the introduced method classifies the depression rate of EEG signals. Finally, a successive score of the presented model is compared with other models to verify the proficiency score of the designed model.

5.1 Case Study

Generally, EEG is one of the non-invasive techniques used to monitor brain activity with various classifications and detection of brain disorders. Moreover, depression is a prevalent disease it will cause disability. So classifying the depression rate using EEG signal is the most critical task. Thus the developed BUSA framework is implemented in this case study. Initially, collect the EEG signal dataset of various patients based on the channel location. Thus the channel location includes F7, Fz, F6, C6, C7, Cz, H6, H8, T2, T5, T3, O2, O1, FP1, O6, FP2, etc., and the channel location is detailed in fig.6.

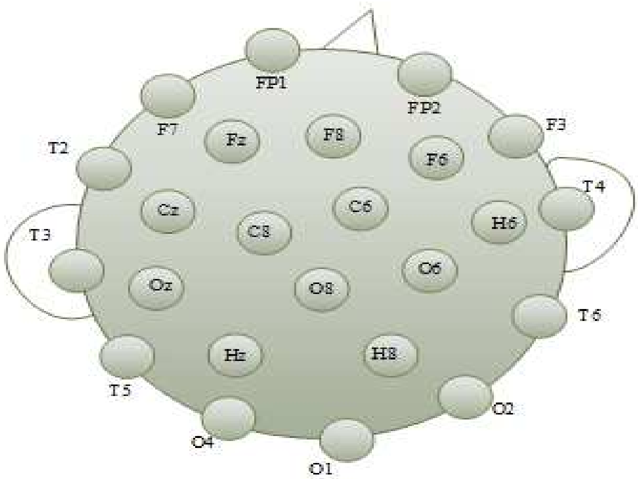

Fig. 6 Channel location

Then the collected EEG signal dataset is sent to the convolutional layer. The preprocessing contains a 1-42Hz Bandpass filter for removing the errors and noise present in the signal. Additionally, the preprocessed dataset is sent to the Maxpooling layer and the layer extracts the features based on the channel location. Moreover, feature extraction includes correlation dimension, DFT, and band power. Thus the band power contains beta, alpha, theta, delta, and gamma also, the range of the frequency is varies based on the channel location. The use of feature selection is choosing important information used for a classifier. Thus the features selection maximizes the relevant features to the classifier's target. At the next level, the fitness function of a bat in the fully connected layer is updated which identifies and classifies the depression rate of the patient to the normal patient. Moreover, it classifies the EEG signal based on normal and depressed patients. Thus the classified depression rate is detailed in the Table1.

Table 1 Classified results

No. of. dataset	No. of. samples	Sampling frequency	Depression rate	Classified results
4500	2500	40Hz	7170	Normal
			7340	Depressed
			7156	Normal
			7239	Depressed
			7423	Depressed
			7012	Normal

Thus the depression rate is classified based on the channel location of each electrode also the location of the channel varies while changes in the EEG signal. Thus the developed BUSA framework attains better results to classify depression rate.

5.2 Performance metrics

The planned BUSA model is implemented in LABVIEW or MATLAB tool, and the success rate of the designed scheme was analyzed using comparison assessment with regards to accuracy, AUC, power, recall, and precision. Thus the achieved performance is compared with other existing techniques such as Classification of Emotion by AutoRegressive (AR) and Empirical Decomposition (CEAED) model (Zhang and Zhang 2018), Analysis of EEG AR Modeling (AARM) (Ouyang et al. 2020), Classification of EEG signals using AR and Wavelet Packet Decomposition (AR-WPD) (Zhang et al. 2017), end-to-end deep learning method to MI-EEG signal classification (E2E-EEG) (Dose et al. 2018), Convolutional Recurrent Attention (CRA) technique (Zhang et al. 2019), Classification of Normal and Depressed EEG signals (CND) (Akbari et al. 2021) and Prediction of Major Depressive Disorder (PMDD) (Hasanzadeh et al. 2019).

5.2.1 Accuracy

The accuracy of the BUSA framework is identified based on the performance of classifying depression rates. Moreover, the accuracy of classifying depression rates can be expressed using eqn. (5),

$$Accuracy = \frac{IP + IN}{IP + AP + AN + IN} \tag{5}$$

Where, IP is denoted as a true classification of depression rate, IN is represented as a true negative classification of depression rate. Moreover, AP is expressed as a false positive classification of depression rate and AN is called a false-negative classification of depression rate. The comparison of accuracy with the exciting technique is detailed in fig.7.

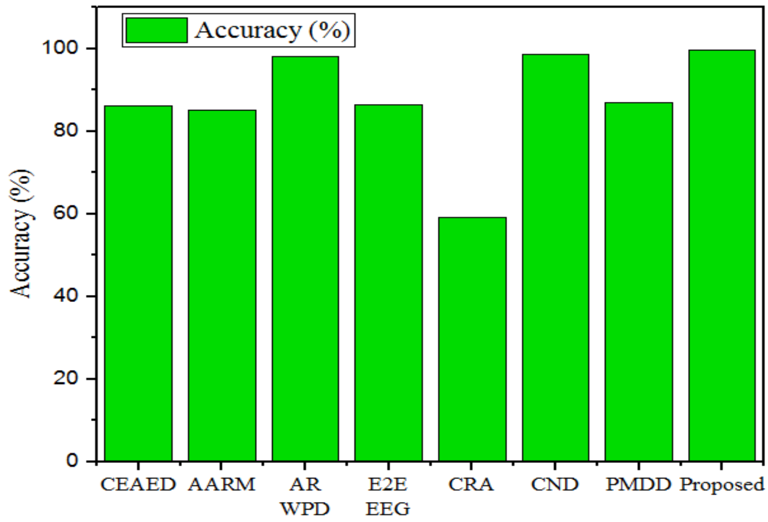

Fig. 7 Comparison of accuracy

The achieved accuracy rate of the proposed BUSA technique is compared with other existing replicas such as CEAED, CRA, CND, and so on. Thus the CEAED andAARM replicas attained 96.28% and 85.17% as accuracy, and the AR-WPD method gained 98.2% accuracy. Moreover, the E2E-EEG and PMDD methods attained 86.49% and 87% accuracy; also the CND technique achieved 98.76%. Additionally, the developed BUSA technique achieves 99.64% accuracy.

5.2.2 Power

Initially, power is calculated by the quantity of the activity in a certain frequency of the band signal. The coherence among various electrodes is reflected in the degree of connection in the brain region. Thus the power is calculated based on the frequency range and appropriate average frequency for obtaining power values.

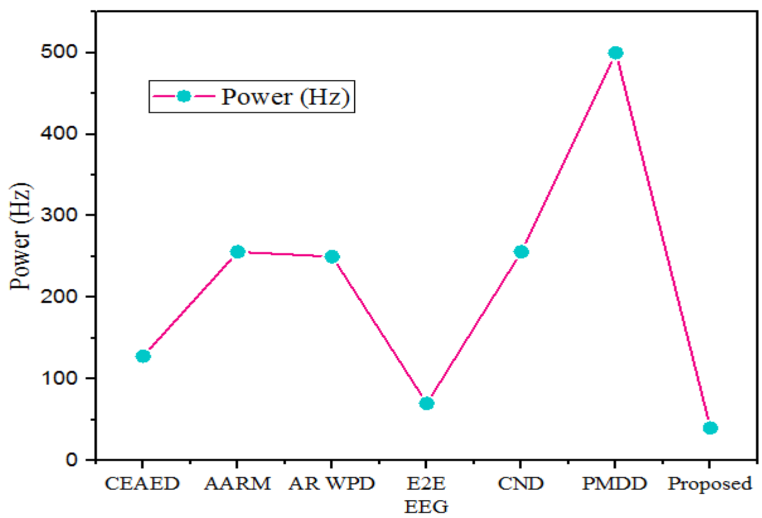

Fig. 8 Comparison of power

The CEAED and AARM techniques gained 128 and 256Hz in power alsoAR-WPD replica attained 250Hz in power. Moreover, E2E-EEG and CND techniques achieved 70Hz and 256Hz in power also PMDD replica attains 500Hz in power. Thus the developed BUSA techniques attain 40Hz in power. Because of the less power rate, errors noise generated by the EEG signal is reduced and the comparison of power is shown in fig.8.

5.2.3 Precision

The computation of precision (P) is operated for recognizing the success of the proposed BUSA technique while classifying the depression rate. In addition, the measurement of precision rate is obtained using eqn. (6) and comparison of precision has shown in fig.9.

$$P = \left(\frac{A_c}{A_c + Q_c} \right) \tag{6}$$

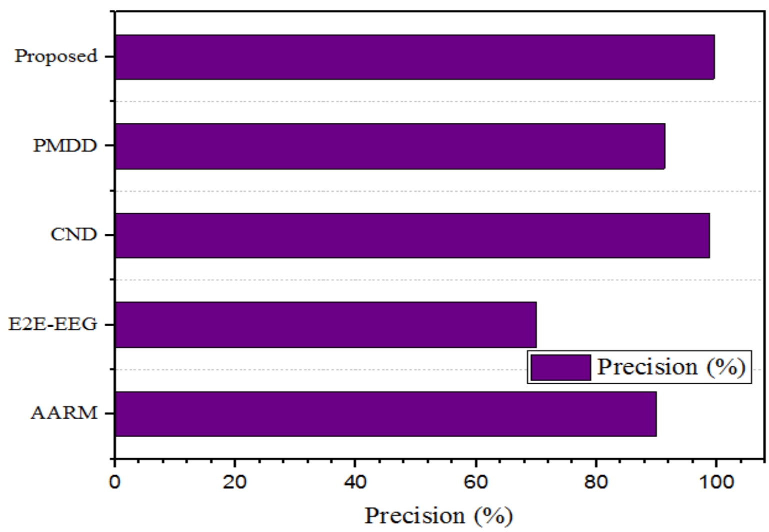

Fig. 9 Comparison of precision

Thus AARM replica attained 89.98% in precision, and the E2E-EEGmethod gained 69.97% precision. Moreover, the CND method attained 98.65% Precision, and the PMDD technique achieved 91.3%. Additionally, the developed BUSA technique achieves 99.45% in precision.

5.2.4 Recall

Measurement of recall (R) is measured to classify the depression rate of the developed BUSA technique. Additionally, recall is the term of true positive value to the addition of false-negative and true positive value. Moreover, the recall calculation of the BUSA method was obtained using eqn. (7),

$$\mathrm{Re}call = \frac{IP}{IP + AN} \tag{7}$$

The achieved recall rate of the proposed BUSA technique is compared with other existing replicas such as AARM, E2E-EEG, CND, and PMDD. Thus the AARM replica attained 81.81% recall, and the E2E-EEG method gained 67.35% recall. Moreover, the CNDmethod attained 98.47% recall, and the PMDD technique achieved 82.6%. Additionally, the developed BUSAtechnique achieves 99% in recall and the comparison of recall with the exciting technique is detailed in fig.10.

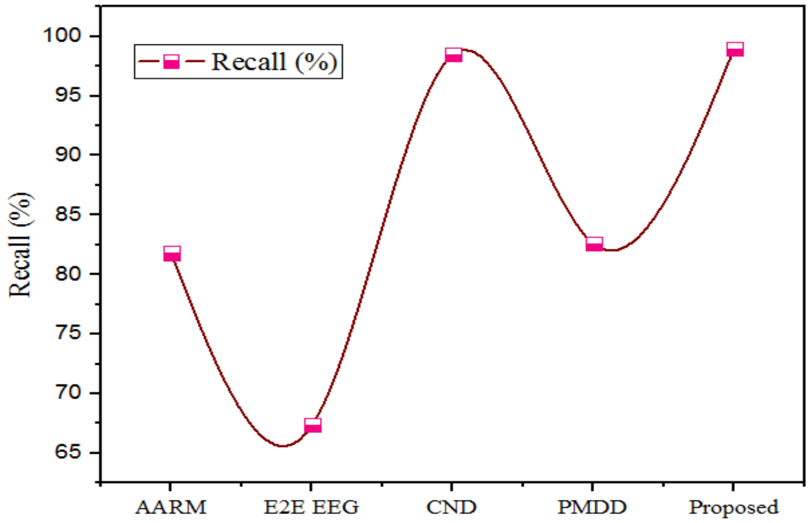

Fig. 10 Comparison of recall

5.2.5 *Area under Curve (AUC)*

It is the ratio of the measure of the capability to a classifier to separate among classes also helpful for the summary of the ROC curve. It will provide better performance in the classification of depression rates using EEG signals. Moreover, AUC measures the classified rate depending on the gained absolute values. The comparison of the AUC is shown in fig.11.

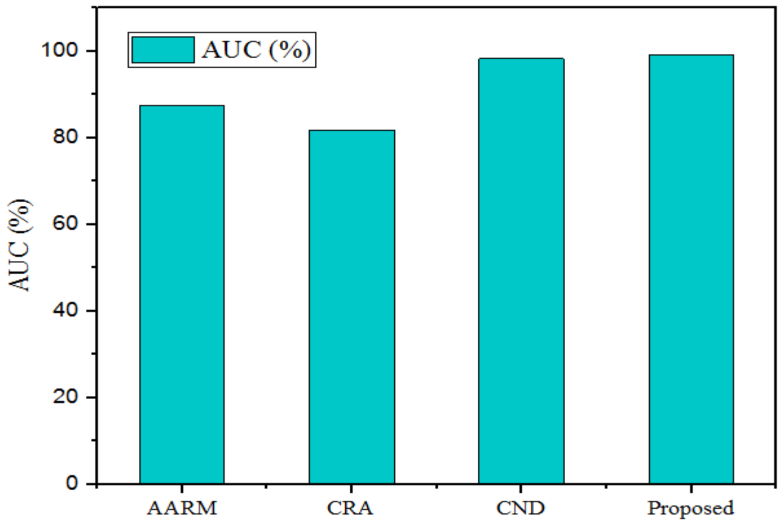

Fig. 11 Comparison of AUC

The gained performance of the developed BUSA framework is compared with other existing techniques such as CRA, CND and AARM. Moreover, the CND technique attained AUC is 98.3% and the AARM technique gained 87.54% in AUC. Furthermore, the CRA method attains 81.86% in AUC but the developed technique attains high performance in AUC as 99.2%.

5.3 Discussion

By reviewing all the metrics in the previous section, the proposed BUSA has gained the finest results. It has revealed the stability of the proposed system in analysing the brain EEG signals.In addition, the reason for attaining the best accuracy is the up-gradation of the bat fitness in the UNET layer.Usually, the fitness of the bat is echo sound to find the location. Here, that fitness function is taken into an account to track the signal features to analyze the depression rate that has yielded the finest outcome. The outstanding gained metrics of BUDA framework comparisons are tabulated in Table2.

Table 2 Overall performance

	Performance assessment			
Methods	Accuracy	precision	Recall	AUC
AARM	85.17	88	83	87.54
CRA	59.21	78	76	81.86
CND	98.76	92.1	91	98.3
Proposed (BUSA)	99.64	99.98	99.95	99.2

Hence, the validation results have described that the proposed BUSA approach has improved the EEG signal classification system. Also, it is capable of performing in all EEG signal classification applications. Moreover, the limitation in this proposed work is design complexity. So, in future designing, the fuzzy set with this proposed model will be attained improved results.

6 Conclusion

In the medical field, EEG signal system has attained the major contribution to analyzing the brain function of individuals. Hence, the depression rate of the brain signal was estimated using any neural approaches or optimization framework. The main drawback behind in the EEG signal system is a noisy signal. The noisy signal can reduce classification accuracy by affording the low depression rate estimation so, in this work, a novel BUSA technique is proposed to classify the depression rate of patients. Here, the classification parameter of the UNET was tuned by bat fitness to gain the finest results. By the mathematical modeling in the MATLAB, the proposed technique gained an accuracy of 99.64%, recall of 99.95%, AUC of 99.2%, and precision of 99.98%. Hence, the proposed BUSA model has improved the depression rate classification accuracy up to 20% compared to other techniques. Thus, the obustness of the proposed technique was proved.

Acknowledgement

None

Compliance with Ethical Standards

1. Disclosure of Potential Conflict of Interest:

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

2. Statement of Animal and Human Rights

   i. *Ethical Approval*

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

   ii. *Informed Consent*

   For this type of analysis formal consent is not needed.

References

Akbari H, Sadiq MT, Rehman AU (2021) Classification of normal and depressed EEG signals based on centeredcorrentropy of rhythms in empirical wavelet transform domain. Health InfSciSyst 9(1):1-15. https://doi.org/10.1007/s13755-021-00139-7

Algan G, Ulusoy I (2021) Image classification with deep learning in the presence of noisy labels: A survey. Knowl Based Syst 215:106771. https://doi.org/10.1016/j.knosys.2021.106771

Amin SU, Alsulaiman M, Muhammad G et al (2019) Deep Learning for EEG motor imagery classification based on multi-layer CNNs feature fusion. Future GenerComputSyst 101:542-554. https://doi.org/10.1016/j.future.2019.06.027

Barata C, Celebi ME, Marques JS (2018) A survey of feature extraction in dermoscopy image analysis of skin cancer. IEEE J Biomed Health Inform 23(3):1096-1109. DOI: 10.1109/JBHI.2018.2845939

Büyükşahin ÜÇ, Ertekin Ş (2019) Improving forecasting accuracy of time series data using a new ARIMA-ANN hybrid method and empirical mode decomposition. Neurocomputing 361:151-163. https://doi.org/10.1016/j.neucom.2019.05.099

Dose H, Møller JS, Iversen HK et al (2018) An end-to-end deep learning approach to MI-EEG signal classification for BCIs. Expert SystAppl 114:532-542. https://doi.org/10.1016/j.eswa.2018.08.031

Gu X, Cao Z, Jolfaei A et al (2021) EEG-based brain-computer interfaces (BCIs): A survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications. IEEE/ACM Trans ComputBiolBioinform 18(5):1645-1666. DOI: 10.1109/TCBB.2021.3052811

Gupta V, Pachori RB (2020) Classification of focal EEG signals using FBSE based flexible time-frequency coverage wavelet transform. Biomed Signal Process Control 62:102124.

https://doi.org/10.1016/j.bspc.2020.102124

Hasanzadeh F, Mohebbi M, Rostami R (2019) Prediction of rTMS treatment response in major depressive disorder using machine learning techniques and nonlinear features of EEG signal. J Affect Disord 256:132-142. https://doi.org/10.1016/j.jad.2019.05.070

Islam MR, Islam MM, Rahman MM et al (2021) EEG Channel Correlation Based Model for Emotion Recognition. ComputBiol Med 136:104757. https://doi.org/10.1016/j.compbiomed.2021.104757

Khare SK, Bajaj V (2020) Time-frequency representation and convolutional neural network-based emotion recognition. IEEE Trans Neural Netw Learn Syst 32(7):2901-2909. DOI: 10.1109/TNNLS.2020.3008938

Kim C, Sun J, Liu D, Wang Q, Paek S (2018) An effective feature extraction method by power spectral density of EEG signal for 2-class motor imagery-based BCI. Med BiolEngComput 56(9):1645-1658. https://doi.org/10.1007/s11517-017-1761-4

Li X, Huang H (2021) Multimodal magnetic resonance image and electroencephalogram constrained fusion algorithm using deep learning. Soft Comput. https://doi.org/10.1007/s00500-021-06574-8

Nagabushanam P, Thomas George S, Radha S (2020) EEG signal classification using LSTM and improved neural network algorithms. Soft Comput 24:9981–10003. https://doi.org/10.1007/s00500-019-04515-0

Ouyang CS, Yang RC, Chiang CT et al (2020) EEG autoregressive modeling analysis: A diagnostic tool for patients with epilepsy without epileptiform discharges. ClinNeurophysiol 131(8):1902-1908. https://doi.org/10.1016/j.clinph.2020.04.172

Rajasekar P, Pushpalatha M (2020) Huffman quantization approach for optimized EEG signal compression with transformation technique. Soft Comput 24(19):14545-14559. https://doi.org/10.1007/s00500-020-04804-z

Rudas Á, Laki S (2019) On activity identification pipelines for a low-accuracy EEG device. 2019 18th IEEE International Conference on Machine Learning and Applications (ICMLA), IEEE. DOI: 10.1109/ICMLA.2019.00238

Rus ID, Marc P, Dinsoreanu M et al (2017) Classification of EEG signals in an object recognition task. 2017 13th IEEE International Conference on Intelligent Computer Communication and Processing (ICCP), IEEE. DOI: 10.1109/ICCP.2017.8117036

Satapathy SK, Loganathan D (2021) Prognosis of automated sleep staging based on two-layer ensemble learning stacking model using single-channel EEG signal. Soft Comput 25:15445–15462. https://doi.org/10.1007/s00500-021-06218-x

Scapicchio C, Gabelloni M, Barucci A et al (2021) A deep look into radiomics. Radiol Med 126:1296–1311. https://doi.org/10.1007/s11547-021-01389-x

Sreedharan NPN, Ganesan B, Raveendran R et al (2018) Grey Wolf optimisation-based feature selection and classification for facial emotion recognition. IET Biom 7(5):490-499.

Subasi A, Jukic S, Kevric J (2019) Comparison of EMD, DWT and WPD for the localization of epileptogenic foci using Random Forest classifier. Measurement 146:846-855. https://doi.org/10.1016/j.measurement.2019.07.026

Zazzaro G, Cuomo S, Martone A et al (2019) Eeg signal analysis for epileptic seizures detection by applying data mining techniques. Internet of Things 14:100048. https://doi.org/10.1016/j.iot.2019.03.002

Zhang D, Yao L, Chen K et al (2019) A convolutional recurrent attention model for subject-independent eeg signal analysis. IEEE Signal Process Lett 26(5):715-719. DOI: 10.1109/LSP.2019.2906824

Zhang Y, Liu B, Ji X, Huang D (2017) Classification of EEG signals based on autoregressive model and wavelet packet decomposition. Neural Process Lett 45(2):365-378. https://doi.org/10.1007/s11063-016-9530-1

Zhang Y, Zhang S, Ji X (2018) EEG-based classification of emotions using empirical mode decomposition and autoregressive model. Multimed Tools Appl 77(20):26697-26710. https://doi.org/10.1007/s11042-018-5885-9