Improved seizure detection using optimized time sequence based deep learning framework

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ABSTRACT

Epilepsy disease originates due to the presence of disordered neurons, and epilepsy detection stands as a challenging task for neurologists. With recent advances, electroencephalography (EEG)-based analysis is increasingly supported by deep learning and metaheuristic optimization approaches in order to improve the test results. This experiment uses a convolutional neural network (CNN) model hybridized with bidirectional long short-term memory (BiLSTM). CNN leverages the work with improved feature extraction cum classification supports, and BiLSTM keeps the time sequence of data in both the forward and backward direction for improving signal mapping purposes. To reduce the computational overhead and improve execution accuracy, a hybrid optimization algorithm called secretary bird optimization algorithm (SBOA) is used to fine-tune the execution. Key classification parameters such as accuracy, sensitivity, and specificity reflect the model's strong predictive capability, with accuracy reaching up to 98.49%. The proposed method demonstrates the potential for high-performance EEG-based seizure detection, paving the way for future integration with edge computing devices to support remote clinical diagnostics and continuous monitoring in real-world healthcare applications.

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1. INTRODUCTION

As epilepsy is a life-distressing disease, the most advisable step is to detect the presence of seizure signals in order to provide clinical suggestions to save the lives of the neuro-disorder patients. Presently, a convolutional neural network (CNN) is considered as the advanced classification technique in the field of epilepsy detection, which consists of one input layer, one output layer, and more than one convolutional layer, where the input layer is connected with the first convolutional layer and the output layer is connected to the last convolutional layer [1]. This CNN comprises millions of neurons, and each neuron is mathematically expressed as: $y = f(xW + b)$, 'y' is the output parameter, 'x' is the input parameter, 'W' is the weight matrix, 'b' is the bias value, and 'f' is the activation function [2]. Also, metaheuristic algorithms are emerging as the most powerful and popularly used algorithms, which are integrated with machine learning algorithms [3]. There are different types of metaheuristic algorithms, such as nature-inspired, bio-inspired, swarm-inspired, and trajectory-based algorithms [4]. There are different types of neural disorders and Parkinson's disease is one among them characterized by showing slow movement, postural instability, rigidity reflecting the degenerative condition of the brain. Although the treatment of this disease is a time span factor, still then the perfect analysis of the disease will be considered as a core part of clinical procedures. Till yet, the electroencephalography (EEG) test and magnetic resonance imaging (MRI) of the scalp are useful to diagnose the symptoms of Parkinson's disease. It requires the correct seizure signal analysis, and preferably, the best analysis is performed with deep learning algorithms like sub-band analysis with gated recurrent unit (GRU) [5] and multiscale CNN [6]. Sometimes, there are also the possibilities of artifacts intermixed with the signals, due to which the correct seizure prediction and detection become tough, and the performance accuracy becomes lower. In this case, the deep learning models must be integrated with learnable capacity, and the model is called a learnable and explainable wavelet neural network [7], [8]. When the EEG signal is recorded, it appears irregular and non-smooth for which it becomes difficult to measure seizure frequency [9]. A lightweight convolution transformer (LCT) is proposed [10] for cross-patient seizure detection, which produces smoothness in seizure signals.

Depression is a special case of a seizure symptom that may happen due to personal problems, and deep depression affects the free thinking of a person. The useful tools employed for depression detection are an encoder for data compression, long short-term memory (LSTM) for expressing the temporal vibrations of the recorded signal, and an attention mechanism to introduce parallelism among the compressed information [11]. But if the signal is complex and noisy in nature, then the Riemannian spectral clustering [12] method is followed to identify the outliers [13]. There are some special cases where dataset privacy is maintained [14] along with seizure detection from the privacy point of view of patient information. Some typical neural networks are devised for specific diseases, like Alzheimer's disease detection [15] performed with Adazd-Net [16] and an automated deep neural network [17] model. Wang *et al.* [18] proposed a hybrid model using a support vector machine (SVM) and kernel sparse representation classification (KSRC); Wu *et al.* [19] proposed a spatial feature fused convolutional network (SCNet) for EEG pathology detection.

To overcome the processing complexity, metaheuristic optimization algorithms are integrated with neural networks. This paper uses the secretary bird optimization algorithm (SBOA) to fine-tune the model and to reduce the operational overhead [20]. Deep learning with sequential arrangement [21] integrating with LSTM [22] ensures data dependencies over time, and also real-time-based deep learning models [23], [24] ensure EEG detection in a crucial time frame [25]. Most of the work implements EEG detection by integrating deep learning and a bidirectional long short-term memory (BiLSTM) model to analyze spatial relationship among EEG signal by CNN, and then temporal analysis by using BiLSTM [26]–[28].

All the mentioned review articles enhance the accurate EEG detection by integrating optimization techniques, feature extraction methods, and statistical approaches to machine intelligence. Although notable improvements are already placed in seizure detection, several significant limitations still exist. Numerous techniques involve intricate preprocessing, which hampers their practical use in real-time systems. Some models are tested only on specific datasets, limiting their generalizability across different EEG signals.

To address the limitations of earlier seizure detection models, we propose an enhanced approach that combines a CNN and BiLSTM to perform the robust feature extraction, classification, and pertaining of time series data elements. Further, it uses an improved metaheuristic optimization technique, SBOA, to fine-tune the model and to reduce the processing complexity. This hybrid method fine-tunes the model parameters efficiently, reducing training loss and time. Our final result, achieved at 100 epochs, shows an accuracy of 98.49%, sensitivity of 96.05%, specificity of 97.03%, Matthews correlation coefficient (MCC) of 97.01%, and area under the curve (AUC) of 0.97.

The rest of our article is elaborated in sections 2 to 4. Section 2 is the core part of the experiment explains about the method used with the sub-sections of 2.1 that elaborates flow of work, 2.2 elaborates the features of experimental Bonn EEG dataset, 2.3 states the techniques of EEG data pre-processing, 2.4 states data augmentation, 2.5 states about the voting models, 2.6 presents the BiLSTM network, and 2.7 presents the optimized SBOA algorithm. Section 3 presents experimental results and discussions, and section 4 states the conclusion and future scope of the paper.

2. METHOD

2.1. Flow of work

This proposed model for EEG detection, depicted in Figure 1, is a framework to optimize the test accuracy and to reduce the processing complexity. At first, it applies the sequence of the pre-processing pipeline to improve data quality, followed by data augmentation for improving the model's generalization. Then it tries for deep learning models for classification.

2.2. Clinical datasets

The Bonn University dataset, which is collected from Physionet, is a publicly available EEG database center [21]. It is a multiclass EEG signal database. There are five classes present in the datasets, class A to class E, and each dataset contains 100 txt files with 4,096 samples in ASCII format. Classes A to D contain normal signal and class E contains seizure signals. There are 100 channels present in each data set. For collecting EEG signal, the electrodes are kept over the head of the patient and inside intracranial regions of the head for a time period of 23.6 seconds. Figure 2 depicts the sample images collected from EEG patients.

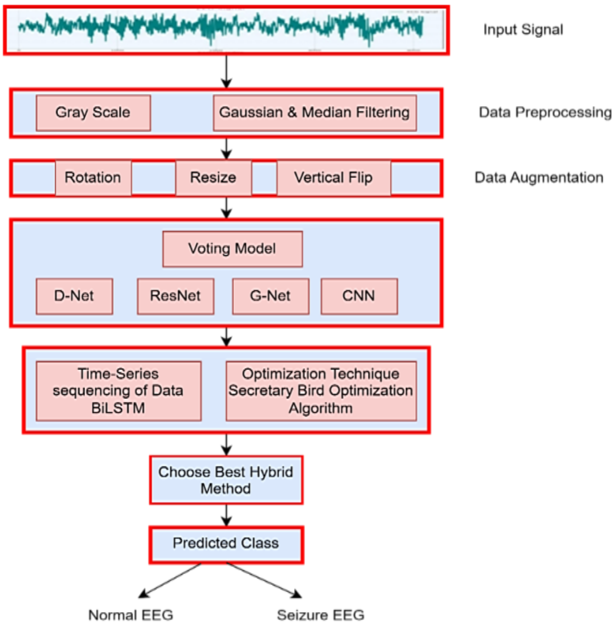

Figure 1. Proposed model describing the flow of the work

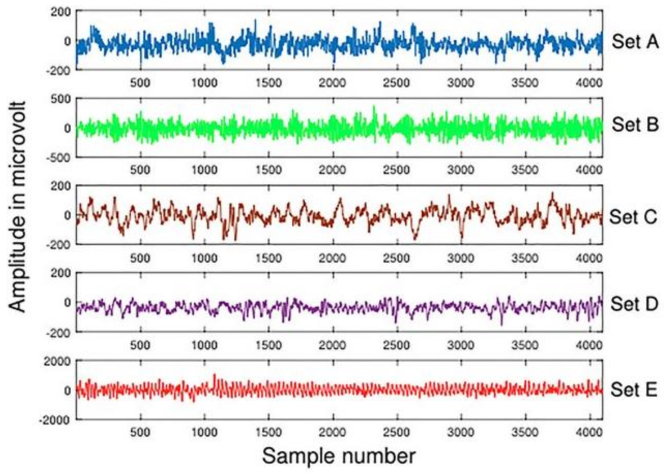

Figure 2. Bonn multiclass EEG signal images

2.3. Data pre-processing

Data pre-processing is a pipeline of conversion and filtration techniques that comes after data collection to boost the accuracy and consistency of the test result. Initially, the images were converted to grayscale, followed by noise reduction using Gaussian and median filtering. Contrast was then enhanced using contrast limited adoptive histogram equalization (CLAHE) to highlight important features. The images were resized to a standard dimension, and min-max normalization was applied to scale pixel values uniformly, ensuring readiness for accurate and efficient analysis. Figure 3 shows the pre-processed images.

2.4. Data augmentation

To enhance the variability of EEG image samples and ameliorate the model's generalization capability, a comprehensive data augmentation strategy was employed. This process helps to mitigate overfitting by introducing diverse visual patterns into the training dataset. The applied transformations included image rotation, horizontal and vertical flipping, resizing, color jittering, the addition of Gaussian noise, and intensity modifications. These augmentations simulate realistic alterations that could occur in EEG imaging conditions, thereby enabling the model to learn more robust and generalized representations. Examples of these augmented images are illustrated in Figure 4.

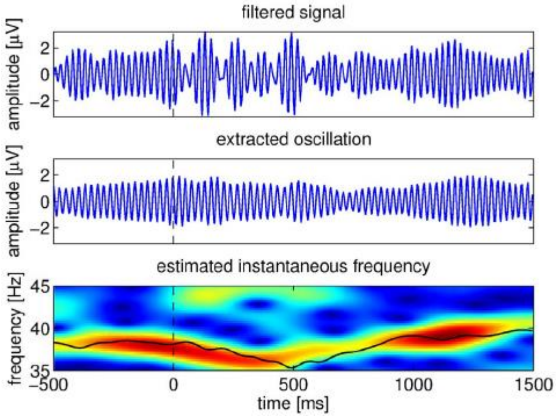

Figure 3. Pre-processed image of EEG signal

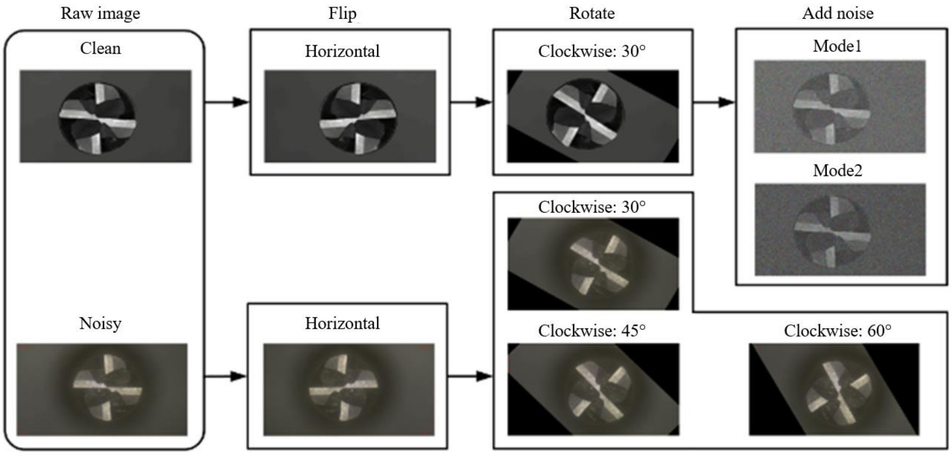

Figure 4. Data augmentation images

2.5. Voting model

After the data augmentation phase, the ensemble learning method is applied to the seizure signal to get the optimum result. Here, the ensemble learning technique uses D-Net, ResNet, G-Net, and CNN as the voting classifier, and the resulting output is the combined majority of each of the voting classifiers. The 1D-CNN used here is a sequential CNN built up with layers such as Conv1D, MaxPooling1D, flatten, dense, and dropout layers. The Conv1D layer uses 64 filters, kernel size is 3, activation function used is "rectified linear unit (ReLU)," and it processes EEG signals in sequential order. In the MaxPooling1D layer, CNN uses a window of pool size 2. The flattened layer re-arranges the extracted features and then flattens the channel dimension. The dense layer uses 256 neurons, and the activation function used here is ReLU. ReLU processes the signals and helps the CNN to learn nonlinear patterns. The dropout layer uses regularization technique for preventing overfitting in CNN. It has a dropout rate of 0.5. This CNN uses dense layers and dropout layer alternatively. The result is specified in Table 1. Figure 5 depicts the steps of selecting the ideal voting model and Table 1 stores the accuracy, loss and val-loss values of the chosen voting models.

Table 1. Voting classifier performance result

Layer	Output
Conv1D	(18, 64)
MaxPooling1D	(9, 64)
Conv1D	(7, 128)
MaxPooling1D	(3, 128)
Flatten	(384)
Dense	(256)
Dropout	(256)
Dense	(128)
Dropout	(128)
Dense	(1)

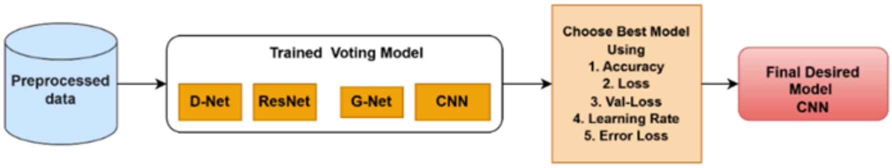

Figure 5. Steps of choosing best voting model as CNN

Successfully run the models listed in Table 2, and after completion, it is found that the result obtained in CNN model supersedes the results with D-Net, ResNet, and G-Net. The accurate rate of CNN is 89.08, loss value is 0.16, and val-loss value is 0.15. Then, test the other performance metrics to prove the superiority of CNN model among D-Net, ResNet, and G-Net models. The performance measures in terms of accuracy, sensitivity, specificity, and AUC scores are listed in Table 3.

Table 2. Accuracy, loss, and val-loss of voting models

	D-Net			ResNet			G-Net			CNN		
	Acy	Loss	V-loss	Acy	Loss	V-loss	Acy	Loss	V-loss	Acy	Loss	V-loss
Test1	75.02	0.25	0.33	79.02	0.17	0.32	80.01	0.27	0.34	89.01	0.26	0.36
Test2	75.04	0.24	0.21	79.02	0.16	0.32	80.02	0.28	0.24	89.03	0.21	0.32
Test3	75.06	0.22	0.25	79.04	0.23	0.31	80.05	0.25	0.33	89.04	0.18	0.25
Test4	75.06	0.18	0.23	79.05	0.28	0.31	80.06	0.21	0.29	89.06	0.19	0.29
Test5	75.82	0.17	0.21	79.06	0.22	0.29	80.07	0.19	0.28	89.08	0.16	0.15

Table 3. Performance metrics of preferred models

Models	Accuracy (%)	Sensitivity (%)	Specificity (%)	MCC	AUC
D-Net	75.82	78.62	76.09	78.03	0.77
ResNet	79.06	79.19	79.28	80.32	0.79
G-Net	80.07	80.09	81.03	80.04	0.80
CNN	89.08	89.01	90.01	89.09	0.89

2.6. Bidirectional long short-term memory

After the signals are extracted by voting models, it requires an appropriate ordering of representation is required. Here, the extracted EEG signals underwent through a time series sequential representation of data ordering, called as BiLSTM, which can successfully handle persistent dependencies in time sequencing data [26] as specified in Table 4, and Figure 6 depicts architecture of BiLSTM model. BiLSTM integrates the signal flow of two LSTMS, one in forward direction and other in reverse direction, with a single output layer.

Table 4. Dependencies in time sequencing data

Layer	Output
Input	(178, 1)
Dense	(178, 32)
Bidirection	(256)
Dropout	(256)
Batch_normalization	(256)
Dense	(64)
Dropout	(64)
Batch_normalization	(64)
Dense	(2)

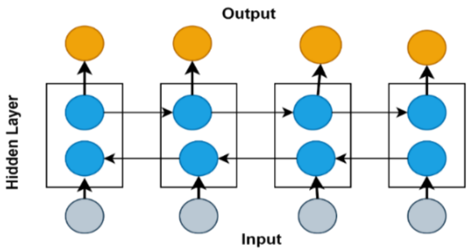

Figure 6. BiLSTM architecture

2.7. Optimized SBOA algorithm

Secretary bird is an African striking bird which looks similar to the eagle bird, having wings of grey-brown feathers, chest is white in color, and belie part is deep black in color. The most peculiar characteristic of secretary bird is its hunting style and evading style while it travels through grasslands. These two natures are mathematically formulated in the form of exploration and exploitation. While it prays the snakes in the grasslands, its haunting style is defined as exploration phase in the global search space, and while it escapes from the rodents, it is called as exploitation in the local search space. Both of the exploration and exploitation are the major contributions of the secretary bird's characteristics to solving the optimization problems in the search space. Our proposed model uses this optimized algorithm to reduce the testing complexity and to improve the accuracy rate, as shown in Algorithm 1.

Algoritm 1. CNN-BiLSTM-SBOA model
Input: the raw EEG signal
Output: extracted seizure EEG signal and normal EEG signal
List N // The number of features
$for\ i = 1 : N$
{
    Extract the features with PCA
    Store the time series sequence of data using BiLSTM
    Classify the features with CNN
    Optimize the performance using SBOA
}
Find the result

2.7.1. Mathematical modelling

The mathematical modelling of the SBOA is presented as follows:

i) Initial phase: the random initialization of the position of secretary bird is in (1).

$$X_{i,j} = lb_j + r \times (ub_j - lb_j), i = 1,2,\dots,N, j = 1,2,\dots,Dim \tag{1}$$

Where X_i is the position of the i^{th} Secretary bird $ub_j$and lb_j are the upper and lower bounds, and r is a random number between 0 and 1.

ii) Haunting strategy of secretary bird (exploration phase): this phase is divided into three stages: searching the prey, ingesting the prey, and attacking the prey. The total haunting time is equally divided into time intervals as in (2).

$$t < \frac{1}{3}T, \frac{1}{3}T < t < \frac{2}{3}T \text{ and } \frac{2}{3}T < t < T. \tag{2}$$

Where t is the current iteration, and T is the total number if iteration.

iii) Updating secretary bird's position

$$t < \frac{1}{3}T, x_{i,j}^{newP1} = x_{i,j} + (x_{random\_1} - x_{random\_2}) \times R_1 \tag{3}$$

$$X_i = \begin{cases} x_{i,j}^{newP1}, if F_i^{newP1} < F_i \\ X_{i,}, else \end{cases}$$

Consuming the prey is mathematically expressed as (4)-(10).

$$RB = randm(1, Dim) \tag{4}$$

$$\text{While } \frac{1}{3}T < t < \frac{2}{3}T,\ x_{i,j}^{newP1} = x_{best} + exp\left(\left({}^{t}/_{T}\right)\wedge 4\right) \times (RB - 0.5) \times \left(x_{best} - x_{i,j}\right) \tag{5}$$

$$X_i = \begin{cases} x_{i,j}^{newP1}, if F_i^{newP1} < F_i \\ X_{i,}, else \end{cases} \tag{6}$$

$$\text{While } t > \frac{2}{3}T, x_{i,j}^{newP1} = x_{best} + \left(\left(1 - \frac{t}{T}\right) \wedge \left(2 \times \frac{t}{T}\right)\right) \times x_{i,j} \times RL \tag{7}$$

$$X_i = \begin{cases} x_{i,j}^{newP1}, if F_i^{newP1} < F_i \\ X_{i,}, else \end{cases} \tag{8}$$

$$RL = 0.5 \times Levy(Dim) \tag{9}$$

$$Levy(D) = s \times \frac{u \times \sigma}{|v|^{\frac{1}{n}}} \tag{10}$$

Where S is a fixed constant. Then σ is defined as (11).

$$\sigma = \left[\frac{\Gamma(1+\eta) \times sin\left(\frac{\pi\eta}{2}\right)}{\Gamma\left(\frac{1+\eta}{2}\right) \times \eta \times 2\left(\frac{\eta-1}{2}\right)}\right]^{\frac{1}{n}} \tag{11}$$

iv) Escape strategy (exploitation phase): the escape strategy introduces a perturbation factor $\left(1 - \frac{t}{T}\right)^2$. The mathematical formulation of the escape strategy is (12)-(13).

$$x_{i,j}^{newP2} = \begin{cases} C_1 : x_{best} + (2 \times RB - 1) \times \left(1 - \frac{t}{T}\right)^2 \times x_{i,j,} if r < r_i \\ C_2 : x_{i,j,} + R_2 \times \left(x_{random} - K \times x_{i,j,}\right), else \end{cases} \tag{12}$$

$$X_i = \begin{cases} x_i^{new,P2}, if F_i^{newP2} < F_i \\ X_{i,}, else \end{cases} \tag{13}$$

3. EXPERIMENTAL RESULTS AND DISCUSSION

The implementation and training of the proposed CNN-BiLSTM-SBOA model were carried out on a high-performance computing system to ensure efficient execution and accurate convergence. The system was equipped with an Intel Core i7 11th generation processor, 32 GB of RAM, and an NVIDIA GeForce RTX 3080 GPU with 10 GB of dedicated memory for accelerated computation. The model was developed using Python 3.9 in a TensorFlow and Keras environment, executed on Ubuntu 20.04 LTS. All experiments were run with compute unified device architecture (CUDA) and CUDA deep neural network (cuDNN) support to leverage GPU-based parallel processing and reduce training time.

To train the proposed model effectively, we initially collected a total of 4,096 EEG images. To enhance the dataset's diversity and improve model generalization, we applied six augmentation techniques, resulting in an expanded dataset of 28,672 images. This enriched dataset was then divided into training, testing, and validation sets using a 70:15:15 ratio. This ensures that the model is trained on a large portion of the data while also being evaluated and validated on separate subsets to prevent overfitting. Table 5 illustrates the dataset distribution across each category, and Table 6 shows the performance values of the voting models with different test durations.

Table 5. Splitting with ratio

Set	Percentage (%)	Number of images
Training	70	20,070
Testing	15	4,301
Validation	15	4,301
Total	100	28,672

Table 6. Accuracy, loss, and val-loss of voting models

	D-Net			ResNet			G-Net			CNN		
	Acc	Loss	Val-loss	Acc	Loss	Val-loss	Acc	Loss	Val-loss	Acc	Loss	Val-loss
Test1	75.02	0.25	0.33	79.02	0.17	0.32	80.01	0.27	0.34	89.01	0.26	0.36
Test2	75.04	0.24	0.21	79.02	0.16	0.32	80.02	0.28	0.24	89.03	0.21	0.32
Test3	75.06	0.22	0.25	79.04	0.23	0.31	80.05	0.25	0.33	89.04	0.18	0.25
Test4	75.06	0.18	0.23	79.05	0.28	0.31	80.06	0.21	0.29	89.06	0.19	0.29
Test5	75.82	0.17	0.21	79.06	0.22	0.29	80.07	0.19	0.28	89.08	0.16	0.15

Successfully run the models listed in Table 6, and after completion, it is found that the result obtained in CNN model supersedes the results with D-Net, ResNet, and G-Net. The accurate rate of CNN is 89.08, loss value is 0.16, and val-loss value is 0.15. Then test the other performance metrics to prove the superiority of CNN model among D-Net, ResNet, and G-Net models. The performance measures in terms of accuracy, sensitivity, specificity, and AUC scores are listed in Table 7.

Table 7. Performance measure metrics of chosen models

Models	Accuracy (%)	Sensitivity (%)	Specificity (%)	MCC	AUC score
D-Net	75.82	78.62	76.09	78.03	0.77
ResNet	79.06	79.19	79.28	80.32	0.79
G-Net	80.07	80.09	81.03	80.04	0.80
CNN	89.08	89.01	90.01	89.09	0.89

After analyzing the outcomes of performance metrics of Tables 6 and 7, we found that the CNN model is the best choice of voting model for EEG signal detection with the Bonn EEG dataset. Although the results of Tables 6 and 7 are sufficient to prove that CNN can be preferred in EEG detection, and the results of CNN are also matching with the results of the existing models, it lacks a sequential time series representation of signals. To overcome this, we integrate CNN with BiLSTM, and the hybrid CNN-BiLSTM easily process the long sequence of time series data. The accuracy rate of CNN stagnated with 89.08%, which needs to improve. For improving performance measures of hybrid CNN-BiLSTM model, we combine it with the optimization algorithm, SBOA, and the outcomes of proposed CNN-BiLSTM-SBOA is listed in Table 8.

Table 8. Proposed CNN-BiLSTM-SBOA

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	MCC	AUC score
CNN-BiLSTM-SBOA (Bonn dataset and A-E class)	98.49	96.05	97.03	97.01	0.97

To evaluate the generalization ability of the CNN-BiLSTM-SBOA model, k-fold cross-validation was employed. The dataset was divided into k subsets, and the model was trained k times, each time using a different subset as the validation set. The result is produced in Table 9. This method helps to ensure robust performance and prevents overfitting. For validating the testing outcomes of our proposed model, we compare the performance measures of accuracy, sensitivity, specificity, and Kullback-Leibler (KL) divergence loss function values of our model with the existing models, and the result findings are presented in Table 10.

Table 9. 9-fold validation over our proposed model

Fold	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	Time taken (sec)
2	97.23	95.13	96.61	0.96	150
3	97.72	95.51	96.72	0.966	180
5	97.91	95.72	96.86	0.966	210
7	98.12	95.91	96.89	0.968	240
9	98.49	96.05	97.03	0.97	270

Table 10. Performance comparison with existing models

Models	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC score	KL divergence loss
Multiscale convolutional [6]	92.5	93.1	91.9	92.4	0.39
A learnable and explainable wavelet [7]	89.3	88.4	88.7	0.88	0.48
Deep learning-based attention mechanism [8]	98.38	-	-	-	0.33
Channel-weighted spatial–temporal [9]	97.23	-	-	-	0.32
Proposed CNN-BiLSTM-SBOA (A-E class)	98.49	96.05	97.03	0.97	0.29

Here KL divergence loss function is used to compare two data distributions in the case of assessing dataset and model drift. Mathematically, it is expressed as (14).

$$D\ KL(P||Q) = \sum_x P(X) \times \log\left(\frac{P(X)}{Q(X)}\right) \tag{14}$$

Where X is the possible event in the probability search space, $P(X)$ and $Q(X)$ are the probabilities of X in the distribution of P and Q, and the ratio $P(X)/Q(X)$ represents the likelihood of event X according to P compared to Q. The ROC-AUC plot and loss-epoch plot of the proposed model are depicted in Figures 7 and 8.

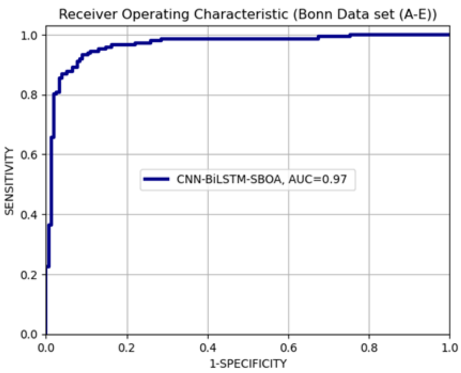

Figure 7. ROC-AUC plot of CNN-BiLSTM-SBOA model for Bonn EEG (A-E) dataset

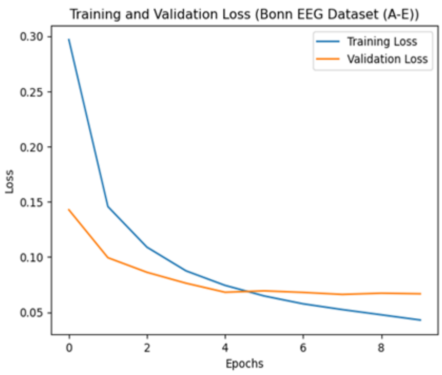

Figure 8. Model loss of CNN-BiLSTM-SBOA for Bonn (A-E) dataset

4. CONCLUSION

This study improves the EEG detection by integrating deep learning with an optimization technique. The applied 1D sequential CNN proves its superiority over other voting models with the testing accuracy of 89.08%, sensitivity of 89.01%, specificity of 90.01%, MCC of 89.09%, and AUC score of 0.89. The time sequence ordering of EEG signals is integrated with a BiLSTM network to enhance the sequential data processing by addressing the vanishing gradient problem. Further to improve the test accuracy, to reduce the over-fitting problem, and to increase the learning rate, the hybrid CNN-BiLSTM model is combined with the chosen SBOA optimization technique, yielding an accuracy of 98.49%, sensitivity of 96.05%, specificity of 97.03%, MCC value of 97.01%, ROC-AUC value of 0.97, and KL divergence loss value of 0.29. These performance measures of the proposed CNN-BiLSTM-SBOA prove its efficiency in epilepsy detection. The future work will focus on improved anomaly detection by separating noise and artifacts from the EEG signals and integrating edge devices for advanced clinical diagnosis.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in the Bonn dataset at https://www.ukbonn.de/epileptologie/arbeitsgruppen/ag-lehnertz-neurophysik/downloads/.

REFERENCES

[1] J. Xu, K. Yan, Z. Deng, J. X. Liu, J. Wang, and S. Yan, "EEG-based epileptic seizure detection using deep learning techniques: a survey," *Neurocomputing*, vol. 610, 2024, doi: 10.1016/j.neucom.2024.128644.

[2] V. P. Balam, "Systematic review of single-channel EEG-based drowsiness detection methods," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 11, pp. 15210–15228, 2024, doi: 10.1109/TITS.2024.344224.

[3] P. Mallik, A. K. Nayak, S. K. Mohapatra, and K. P. Swain, "SH-OSP: a hybrid algorithm using spotted hyena optimizer enabled with optimal stochastic process for epileptic seizure detection," *SN Computer Science*, vol. 5, no. 8, 2024, doi: 10.1007/s42979-024-03488-8.

[4] I. Ahmad *et al.*, "An efficient feature selection and explainable classification method for EEG-based epileptic seizure detection," *Journal of Information Security and Applications*, vol. 80, 2024, doi: 10.1016/j.jisa.2023.103654.

[5] N. Khalid and M. S. Ehsan, "Critical analysis of Parkinson's disease detection using EEG sub-bands and gated recurrent unit," *Engineering Science and Technology, an International Journal*, vol. 59, 2024, doi: 10.1016/j.jestch.2024.101855.

[6] L. Qiu, J. Li, I. Zhong, W. Feng, C. Zhou, and J. Pan, "A novel EEG-based Parkinson's disease detection model using multiscale convolutional prototype networks," *IEEE Transactions on Instrumentation and Measurement*, vol. 73, pp. 1–14, 2024, doi: 10.1109/TIM.2024.3351248.

[7] Y. Yu, Y. Li, Y. Zhou, Y. Wang, and J. Wang, "A learnable and explainable wavelet neural network for EEG artifacts detection and classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 32, pp. 3358–3368, 2024, doi: 10.1109/TNSRE.2024.3452315.

[8] C. Divvala and M. Mishra, "Deep learning-based attention mechanism for automatic drowsiness detection using EEG signal," *IEEE Sensors Letters*, vol. 8, 2024, doi: 10.1109/LSENS.2024.3363735.

[9] X. Li, J. Tang, X. Li, and Y. Yang, "CWSTR-Net: a channel-weighted spatial–temporal residual network based on nonsmooth nonnegative matrix factorization for fatigue detection using EEG signals," *Biomedical Signal Processing and Control*, vol. 97, 2024, doi: 10.1016/j.bspc.2024.106685.

[10] S. Rukhsar and A. K. Tiwari, "Lightweight convolution transformer for cross-patient seizure detection in multi-channel EEG signals," *Computer Methods and Programs in Biomedicine*, vol. 242, 2023, doi: 10.1016/j.cmpb.2023.107856.

[11] N. F. Ali, N. Albastaki, A. N. I. Belkacem, M. E. Adel, and M. Atef, "A low-complexity combined encoder-LSTM-attention networks for EEG-based depression detection," *IEEE Access*, vol. 12, pp. 129390–129403, 2024, doi: 10.1109/ACCESS.2024.3436895.

[12] M. S. Yamamoto *et al.*, "Modelling complex EEG data distribution on the Riemannian manifold toward outlier detection and multimodal classification," *IEEE Transactions on Biomedical Engineering*, vol. 71, no. 2, pp. 377–387, 2024, doi: 10.1109/TBME.2023.3295769.

[13] T. Islam, M. Basak, R. Islam, and A. D. Roy, "Investigating population-specific epilepsy detection from noisy EEG signals using deep-learning models," *Heliyon*, vol. 9, no. 12, 2023, doi: 10.1016/j.heliyon.2023.e22208.

[14] C. Zhao, R. Peng, and D. Wu, "Source-free domain adaptation (SFDA) for privacy-preserving seizure subtype classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 2315–2325, 2023, doi: 10.1109/TNSRE.2023.3274563.

[15] H. S. Ohal and S. Mantri, "Exploring EEG-based biomarkers for improved early Alzheimer's disease detection: a feature-based approach utilizing machine learning," *Measurement: Sensors*, vol. 36, 2024, doi: 10.1016/j.measen.2024.101403.

[16] S. K. Khare and U. R. Acharya, "Adazd-Net: automated adaptive and explainable Alzheimer's disease detection system using EEG signals," *Knowledge-Based Systems*, vol. 278, 2023, doi: 10.1016/j.knosys.2023.110858.

[17] M. M. Islam, M. R. Islam, and M. S. Islam, "An efficient human computer interaction through hand gesture using deep convolutional neural network," *SN Computer Science*, vol. 1, 2020, doi: 10.1007/s42979-020-00223-x.

[18] Q. Wang *et al.*, "A hybrid SVM and kernel function-based sparse representation classification for automated epilepsy detection in EEG signals," *Neurocomputing*, vol. 562, 2023, doi: 10.1016/j.neucom.2023.126874.

[19] T. Wu, Y. Fan, Y. Zhong, X. Cheng, X. Kong, and I. Chen, "SCNet: a spatial feature fused convolutional network for multi-channel EEG pathology detection," *Biomedical Signal Processing and Control*, vol. 86, 2023, doi: 10.1016/j.bspc.2023.105059.

[20] Y. Fu, D. Liu, J. Chen, and I. He, "Secretary bird optimization algorithm: a new metaheuristic for solving global optimization problems," *Artificial Intelligence Review*, vol. 57, 2024, doi: 10.1007/s10462-024-10729-y.

[21] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: dependence on recording region and brain state," *Physical Review E*, vol. 64, no. 6, 2001, doi: 10.1103/PhysRevE.64.061907.

[22] A. T. Mohan and D. V Gaitonde, "A deep learning based approach to reduced order modelling for turbulent flow control using LSTM neural networks," 2018, *arXiv:1804.09269*.

[23] M. Shen, P. Wen, B. Song, and Y. Li, "An EEG based real-time epilepsy seizure detection approach using discrete wavelet transform and machine learning methods," *Biomedical Signal Processing and Control*, vol. 77, 2022, doi: 10.1016/j.bspc.2022.103820.

[24] L. S. Vidyaratne and K. M. Iftekharuddin, "Real-time epileptic seizure detection using EEG," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, pp. 2146–2156, 2017, doi: 10.1109/TNSRE.2017.2697920.

[25] M. Alhussein, G. Muhammad, and M. S. Hossain, "EEG pathology detection based on deep learning," *IEEE Access*, vol. 7, pp. 27781–27788, 2019, doi: 10.1109/ACCESS.2019.2901672.

[26] A. Britto *et al.*, "A multi-dimensional hybrid CNN-BiLSTM framework for epileptic seizure detection using electroencephalogram signal scrutiny," *Systems and Soft Computing*, vol. 5, 2023, doi: 10.1016/j.sasc.2023.200062.

[27] N. A. Samee, N. F. Mahmoud, E. A. Aldhahri, A. Rafiq, M. S. A. Muthanna, and I. Ahmad, "RNN and BiLSTM fusion for accurate automatic epileptic seizure diagnosis using EEG signals," *Life*, vol. 12, no. 1946, 2022, doi: 10.3390/life12121946.
[28] U. G. Redwan, T. Zaman, and H. B. Mizan, "Spatio-temporal CNN-BiLSTM dynamic approach to emotion recognition based on EEG signal," *Computers in Biology and Medicine*, vol. 192, 2025, doi: 10.1016/j.compbiomed.2025.110277.

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