



Innovative ML-driven Recognition of EEG Patterns in Cognitive Training

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Abstract: Electroencephalogram (EEG) patterns depict electrical activity in the brain. They reveal insights into neurological functions, aiding in diagnosing conditions like epilepsy, sleep disorders, and brain injuries. The purpose of this research is to establish an innovative machine learning (ML)-driven recognition of EEG patterns in cognitive training. In this study, we propose an innovative Dynamic Artificial Rabbit Search-driven Advanced Bidirectional Long Short-Term Memory (DAR-ABLSTM) for robust classification of EEG patterns in cognitive training tasks. EEG was employed to investigate the impact of various forms of cognitive training on brain activity. We obtained EEG recordings from 50 healthy individuals during cognitive training and after a five-week programme. A signal processing procedure is employed to preprocess the obtained raw signal data. Our proposed model employs a novel approach stimulated by the foraging behavior of rabbits to enhance the classification of EEG patterns. We also conducted a t-test using SPSS analytical software to evaluate the pre- and post-cognitive training measures. The proposed recognition model is implemented in Python software. In the findings assessment phase, we effectively assess the performance of our proposed DAR-ABLSTM in classifying EEG patterns across multiple evaluation metrics, such as sensitivity (94.53%), accuracy (97.01%), F1-score (95.72%) and specificity (96.62%). Our experimental results demonstrate the capability and reliability of the proposed recognition in dynamic scenarios. The results of the analysis showed that both the negative and positive moods had significantly changed. The study suggests varying responses to different cognitive training methods.

Keywords: Electroencephalogram (EEG) patterns, Cognitive Training, Recognition Model, Dynamic Artificial Rabbit Search-driven Advanced Bidirectional Long Short-Term Memory (DAR-ABLSTM), SPSS.

1. Introduction

Analyzing the electrical signals of the brain to improve cognitive abilities is referred to as EEG pattern recognition in cognitive training [1]. EEG is an inexpensive approach that uses sensors applied to the scalp to record electrical impulses produced by brain activity [2]. These impulses are recorded as waveforms, which display diverse mental states and features. EEG detection of styles is utilised in cognitive conditioning to tune and have a look at those waveforms to understand the effects of different thinking procedures and conditioning programmes on brain characteristics [3].

EEG is frequently used in conjunction with retraining processes at some stage of intellectual retraining. Biofeedback aims to train people on how to actively manipulate their cerebral activity [4]. During mental tasks or meditation periods, users receive instantaneous feedback on their EEG characteristics. Through the use of this input, humans can enhance their cognitive and mental well-being by learning how to reduce undesirable brain activities [5]. The benefits of EEG detection of patterns in mental stimulation are evident in several domains, including healing therapy, athletics, and education. EEG-based mental stimulation has been shown to aid students in educational contexts

with attention, memory, and the ability to solve problems [6]. EEG training is used by athletes to improve mental toughness and concentration. In a medical environment, EEG training is used to assist patients in better managing their neurological activity to cure disorders including depressive disorders, anxiety, and epilepsy [7]. A potential multidisciplinary strategy that combines computer technology, behavioural science, and neurology to improve mental health and memory skills is EEG recognition of patterns for intellectual training [8]. Those technologies have the potential to improve educational results, sports performance, and treatment for a range of neurological and psychological problems by offering insights into brain activity and enabling customised training programmes [9]. Recent developments in portable EEG technology are facilitating easier and more affordable cognitive stimulation. Permanent tracking of brain function outside of conventional neuroscience labs is made possible by this portable EEG equipment [10]. Users of portable EEG headsets can participate in cognitive stimulation while continuing with their regular lives, as they are more convenient to use and less intrusive. This enhanced accessibility encourages EEG-based cognitive training to be used more frequently and consistently, which facilitates long-term research and practical applications. Sophisticated techniques for signal processing and machine learning algorithms are employed to identify EEG patterns [11]. EEG patterns

in cognition are susceptible to noise, which could obscure genuine mind activity. Additionally, the spatial resolution of EEG is relatively low, making it tough to pinpoint unique brain areas involved. Furthermore, character variability in EEG signals can complicate the generalization of outcomes throughout distinct subjects [12]. The purpose of this paper is to propose an innovative Dynamic Artificial Rabbit Search-driven Advanced Bidirectional Long Short-Term Memory (DAR-ABLSTM) for robust classification of EEG patterns in cognitive training tasks. In the remaining part of this paper, part 2 represents the related work, part 3 provides the methodology, and part 4 describes the results and discussion. Part 5 discusses the conclusion of the paper.

2. Related work

This section, Table 1, shows all the most recent advances in EEG-based emotion recognition, cognitive assessment, and other neural applications. It presents a comprehensive overview of machine learning and deep learning techniques, analytical frameworks, and clinical applications used to enhance understanding in these domains. The table organises key goals, methods, and results, allowing you to easily compare the new ideas and discoveries emerging from modern research.

Table 1. Comparative Literature Review Analysis of Proposed Study

Study	Objective	Methodology	Key Findings
[Roshdy <i>et al.</i> , 2024] [13]	Integration of multiple ML models and CNNs for multi-input EEG-based emotion analysis	Combined DeepFace CNN with an EEG-based CNN model	Enabled effective processing of multi-modal emotion and brain data for deeper emotional understanding
[Gong <i>et al.</i> , 2024] [14]	Development of the CiABL model for emotion recognition	Completeness-induced Adaptive Broad Learning integrating paradigm-relevant and independent info	Improved cross-subject generalization and accurate estimation of global features
[Aslan <i>et al.</i> , 2024] [15]	EEG-based brain region analysis for emotional evaluation	Used three EEG datasets focusing on brain region segmentation	The frontal region and the left hemisphere produced superior emotion detection accuracy
[Jha <i>et al.</i> , 2024] [16]	EEG-based emotion detection using CNNs	Multi-column CNN with leaky ReLU and DEAP dataset	Captured spatial features effectively, improving emotion recognition performance
[Chen <i>et al.</i> , 2024] [17]	Detection of Unfavourable Driving States (UDS) using EEG	Trained CNNs with 30-transmission EEG data	Reduced driving risk via functional brain connectivity and transfer learning
[Li <i>et al.</i> , 2023] [18]	Multi-category emotion detection using EEG	Proposed MESNPs model with spatial network structure patterns	Enhanced classification accuracy, capturing topological graph patterns
[Jiménez-Guarneros <i>et al.</i> , 2020] [19]	EEG decoding within Sparse Bayes Learning (SBL)	Used a low-rank weighted matrix in the end-to-end EEG decoder	Achieved neurophysiologically significant spatio-temporal structures outperforming other models

[Ding <i>et al.</i> , 2022] [20]	Emotion classification through EEG using CNN	T-Sception model with multi-scale, asymmetric convolution	Outperformed previous CNN models on classification and F1 metrics
[Xu <i>et al.</i> , 2020] [21]	EEG-based motor imagery classification	Deep multi-view feature learning for brainwave analysis	Significantly improved accuracy in motion-related task classification
[Chakravarthi <i>et al.</i> , 2022] [22]	PTSD-based emotional assessment via EEG	CNN-LSTM leveraging ResNet-152	Produced higher accuracy in emotion assessment than prior models
[Singh <i>et al.</i> , 2021]	Anxiety assessment in athletes via EEG	Used a portable NeuroSky EEG band recording	A revealed correlation between EEG band variations and anxiety levels
[Kanna <i>et al.</i> , 2024] [23]	Stroke prediction and detection	Analyzed risk factors using patient EEG	Enabled early detection and reduced stroke severity impact
[Kanna <i>et al.</i> , 2024] [24]	Anxiety and stress detection from audio signals	Deep neural network trained on Kaggle emotional audio data	Accurately classified emotional states, including nervousness and sadness
[Mohapatra <i>et al.</i> , 2022] [25]	Cognitive load measurement in operators	EEG-based power density metrics during training	Provided a reliable measure of mental workload changes during learning
[Iqbal <i>et al.</i> , 2021] [26]	Neural rehabilitation under VR environments	fMRI combined with VR-assisted EEG analysis	Predicted therapy success via neuron activity mapping
[Ansado <i>et al.</i> , 2021] [27]	Cognitive memory rehabilitation using VR	Real-time EEG with a virtual environment for MCI patients	Improved scenario memory skills through adaptive VR situations
[Tan <i>et al.</i> , 2021] [28]	Effect of working memory training on social anxiety (SA)	EEG-based pre- and post-treatment analysis	Significant WM and attention bias improvements after training
[Zhao <i>et al.</i> , 2020] [29]	Review of neurofeedback-based cognitive enhancement	Systematic review (2014–2020) on biofeedback studies	Identified diverse outcomes enhancing cognitive functions
[Da Silva and De Souza, 2021] [30]	Neurofeedback-based ADHD improvement in children	30 QEEG-guided NF sessions in clinical trial	Improved attention and cognitive functions in the ADHD group
[Teo <i>et al.</i> , 2021] [31]	EEG-based BCI for ADHD–ASD therapy	8-week BCI-based intervention	Demonstrated cognitive improvement post neurofeedback
[Qu <i>et al.</i> , 2020] [32]	EEG analysis of writing and typing	Muse headset with 4 electrodes in cognitive tasks	Showed distinct EEG patterns for writing vs. typing efforts
[Molina <i>et al.</i> , 2020] [33]	EEG-based study of schizophrenia cognitive decline	Gamma oscillation analysis during FCT therapy	Identified neuro markers predicting therapy response
[Jeon and Cai, 2022] [34]	EEG study of VR-based construction hazard perception	VR simulation of workplace hazards	Correlated EEG patterns with risk perception responses
[Cruz-Garza <i>et al.</i> , 2022] [35]	Cognitive effects of educational room design	EEG and cognitive testing under 4 classroom layouts	Spatial configuration affected EEG and learning performance
[Trambaiolli <i>et al.</i> , 2021] [36]	Neurocognitive evaluation using structural MRI	Review of 10 out of 1912 MRI-related studies	Compared methodologies and therapeutic effectiveness
[Gómez <i>et al.</i> , 2021] [37]	EEG-derived cognitive load across scenarios	Multi-context EEG generalizability study	Validated consistency of cognitive burden measures
[Zhou <i>et al.</i> , 2022] [38]	Cross-task cognitive strain analysis in HRI	EEG-based deep model for human–robot tasks	Highlighted the limits of EEG data generalization across tasks
[Israsena <i>et al.</i> , 2021] [39]	EEG-based neurofeedback for elderly memory	Single-channel, inexpensive EEG headset	Improved memory retention and accessibility in older adults
[Merlet <i>et al.</i> , 2024]	EEG under mindfulness	EEG connectivity and	Found distinct EEG changes in

[40]	practice	rhythm analysis	mindful vs. non-mindful individuals
[Russo <i>et al.</i> , 2024] [41]	EEG-based acrophobia detection	Real-time EEG framework for fear-of-heights measurement	Provided an accurate phobia quantification system
[Romero-Borquez <i>et al.</i> , 2024] [42]	EEG study on gaming and cognition	Compared brainwave patterns across game genres in VR	Linked EEG changes to focus and cognitive engagement
[Asha <i>et al.</i> , 2024] [43]	EEG microstate analysis for memory functions	Studied encoding and retrieval activity	Supported diagnostic and treatment guidance through microstate mapping
[Zhang <i>et al.</i> , 2024] [44]	EEG-based neural computing for sleep issues	Proposed DCNet with self-supervised contrastive learning	Learned representations enabling efficient sleep disorder diagnosis
[Chattopadhyay, 2024] [45]	EEG correlation with cognitive learning (CL) and ADHD	RECSAE model integrating EEG attention features	Supported cognitive tracking and ADHD-related instruction
	EEG study of VR puzzle-based stimulation	Used spectral entropy and MSC to assess activity	Found higher cognitive stimulation with Tetris gameplay

3. Methodology

In this section, we provide a comprehensive explanation for data collection, preprocessing (z-score normalization), feature extraction (wavelet transform), classification, cognitive test, and statistical analysis.

3.1 Data collection

EEG recordings are acquired from fifty healthy participants both during and following a five-week cognitive training program. To pre-process the acquired raw signal data, a signal processing approach is used.

3.2 Preprocessing

To normalize the EEG signal's magnitude and remove an offset impact in the input data, apply the Z-score normalization formula. z denotes the normalization value, the mean of the EEG signal is denoted by μ , x denotes the original value and σ is the standard deviation value of the EEG signal. Presented as in Equation (1).

$$\frac{z=(x-\mu)}{\sigma} \quad (1)$$

By constraining the range of values in the raw data, this approach enhances the gradient flow in the neural network while it is being trained. As a result, the training procedure is expedited and the convergence rate is raised [46]. To set the starting point of an EEG signal to zero, the mean of the electrical signal must be removed from the total signal. As a result, the baseline will be moved to zero, which makes it easier to detect signal changes and contrast various EEG measurements.

3.3 Feature extraction

We use the wavelet transform (WT) for feature extraction. This technique helps identify neurological problems by detecting localized patterns in EEG data, such as shocks and acute waveforms. When studying non-stationary data like EEG, the wavelet transform performs better than conventional Fourier approaches. The definition of the WT of a signal $f(x)$ is,

$$W_r f(x) = f(x) * \psi_r(x) = -\frac{1}{r} \int_{-\infty}^{+\infty} f(t) \psi\left(\frac{x-t}{r}\right) dt \quad (2)$$

r is the scale factor. A basic waveform dilating $\psi_r(x)$ based on the rating ratio r is $\psi_r(x) = \frac{1}{r} \psi\left(\frac{x}{r}\right)$. The WT has the moniker "dyadic WT" if $r = 2^j$ ($j \in Z, Z$ is the integral set). The dynamic WT of an electronic communication is calculated using the following equations.

$$R_{2^j} f(m) = \sum_{k \in Z} h_k R_{2^{j-1}} f(m - 2^{j-1}k) \quad (3)$$

$$W_{2^j} f(m) = \sum_{k \in Z} g_k R_{2^{j-1}} f(m - 2^{j-1}k) \quad (4)$$

Here, the smoothing operator R_{2^j} is used. While $W_{2^j} f(m) = d_j$, d_j is a high-frequency coefficient that represents the detail of original signals $R_{2^j} f(m) = a_j$, a_j is a low-frequency component that approximates the original signals. The WT is thought to be more appropriate for examining irregular signals, while the discrete wavelet transformation offers a variable time-frequency decomposition of the signal. The signal structure, utilising the multiresolution formulation, can be properly described by a minimal set of equations in the wavelet domain.

When analyzing signals using the WT, the choice of the proper wavelet and the number of decomposition levels are crucial. The main frequency elements of the signal determine the total amount of breakdown levels. The levels are chosen so that the

portions of the signal that exhibit significant associations with the necessary frequencies for signal classification are preserved in the wavelet coefficients. Four breakdown levels were selected as the number. Typically, tests are conducted using many wavelet types, and the one that provides the greatest efficiency is chosen for the given application.

3.4 Classification

We proposed the Dynamic Artificial Rabbit Search-driven Advanced Bidirectional Long Short-Term Memory (DAR-ABLSTM) as a classification method.

3.4.1 Dynamic Artificial Rabbit Search (DAR)

The rabbit is forced to eat the grasses close to other people's nests as part of the diversionary foraging technique, which can deter predators from finding its nest. Additionally, by employing the randomized hiding technique, a rabbit may arbitrarily decide to hide in any of its own shelters, potentially lowering the likelihood that its adversaries will be able to capture.

Using the instructions of the given method, each iteration modifies the place of residence for each bunny, which is subsequently evaluated by the fitness function. The methods become increasingly sophisticated as the process goes on. Each beginning occupied spot is assigned, by Equation (5), to a random location inside the searching space:

$$Y_i = lb + [ub - lb] \times rand(1, dim) \quad i = 1, 2, \dots, n \quad (5)$$

3.4.1.1 Distract from the gathering

Based on the DAR's detour foraging behaviour, each seeking individual decides to change its location with respect to some additional searching organisms randomly selected from the cluster and join the disruption. The following is the suggested scientific interpretation of the rabbit's diversion searching:

$$R_i(pt + 1) = Y_j(pt) + X \times (Y_i(ipt) - Z_j(ipt)) + round((0.05 + v)0.5 \times) \times SND \quad (6)$$

$$X = c \times L \quad (7)$$

$$c(m) = \begin{cases} 1 & \text{if } m = e(l) \\ 0 & \text{else} \end{cases} \quad \text{and } m = 1, \dots, dim \quad (8)$$

$$e = randperm(d), n_1 \sim N(0,1) \quad (9)$$

$$L = \sin(2\pi u_3) \times (f - f^{((pt-1)/S_{max})^2}) \quad (10)$$

3.4.1.2 Asymmetric Sealing

A rabbit will frequently dig several tunnels close to its nest to ensure that it has a place to hide in case it needs to flee from danger. In this respect, the equation is given.

$$b_{i,j}(pt) = L_j(pt) + G.H.L_j(pt), j = 1, \dots, m \text{ and } i = 1, \dots, dim \quad (11)$$

$$G = \frac{S_{max} + 1 - ir}{S_{max}} \cdot u_4 \quad (12)$$

Rabbits require a safe place for concealment in order to survive. They become deterred from selecting any old hole among the ones that they have to hide in to remain hidden as a result. The mathematical expression for the random hiding approach is as follows:

$$q_i(pt + 1) = L_i(pt) + L \times (v_5 \times b_{i,j}(s) - L_j(pt)) \quad (13)$$

Whenever both diversion eating and randomised hiding proves successful, the rabbit's location changes as follows:

$$Z_i(pt + 1) = \begin{cases} Z_i(pt) & f(Z_i(pt) \leq f(Q_i(pt + 1))) \\ Q_i(pt + 1) & f(Z_i(pt) \leq f(Q_i(pt + 1))) \end{cases} \quad (14)$$

3.4.1.3 Decrease in Power

When simulating the transition from the diversion foraging-related detection stage to the exploiting phase represented by variable hiding, an energy component is considered. The subsequent variables define the power component in the formula above:

$$B(pt) = 4 \left(1 - \frac{pt}{S_{max}}\right) \ln \frac{1}{q} \quad (15)$$

3.4.2 Advanced Bidirectional LSTM

Additionally, any NN can utilise sequencing data in both forward and backward directions, as per the ABI-LSTM approach. The forward layers y_s hidden result sequencing determines the number of samples for the time from index 1 to $s - 1$. The final result was encapsulated from y_{s-1} with a time index $s - 1$ till the completion requirement was satisfied. The input gate determines whether the current input P_s changed nation, the gate that forgets G_s verifies whether it was repaired, and the result gate P_s determines whether it is sent to the next cell. At this point, z_s is thought to be a possible substitute for the memory cell. Equations (16) to (21) are used to calculate the current LSTM cell, where y_s denotes the state that is hidden, y_{s-1} earlier hiding nation, J_s^* the prior result state, and y_s the final output as defined in Equation (22).

$$V_s = \Psi(M_V P + B_V J_s + Y_V y_{s-1} + X_V) \quad (16)$$

$$G_s = \Psi(M_G P + B_G J_s + Y_G y_{s-1} + X_G) \quad (17)$$

$$P_s = \Psi(M_P P + B_P J_s + Y_P y_{s-1} + X_P) \quad (18)$$

$$z_s = \Psi(M_Z P + B_Z J_s + Y_Z y_{s-1} + X_Z) \quad (19)$$

$$y_s = G_s * y_s + V_s * z_s \quad (20)$$

$$J_s = P_s * \text{tang}(y_s) \quad (21)$$

$$J_s^* = \Psi(Z_1[\vec{J}_s, \vec{J}_s] + \vec{A}_z) \tag{22}$$

In general, the sigmoid activation feature is used with ABI-LSTM. The Sigmoid/Logistic activating function which yields numbers between 0 and 1, accepts any real integer as an input. A mathematical function with a distinctive t-shaped curve, also known as a stochastic curve, is called a sigmoid function for short. Numerous sigmoid functions, such as logistic and hyperbolic tangent operations, have been used to stimulate neurons that are artificial.

Equation (23) illustrates the appropriate activated function using ABI-LSTM logic. Mish is a novel self-regularized unconventional activated function that has been verified experimentally against the best designs and activation functions on a number of well-known standards. It plays a crucial role in the neural network's development processes and effectiveness.

$$e(c) = c.tang(t(c)) \tag{23}$$

$$\text{Where, } t(c) = \ln(1 + f^c) \tag{24}$$

In general, a loss functional based on dense categories cross entropy is chosen. It generates a

category index for the category that matches the most probable. Equation (25) provides the enhanced losses function according to ABI-LSTM.

$$NRL = f_{mae}/IMAPE \tag{25}$$

$$f_{mae} = \frac{1}{K} * \sum_{p=1}^L |O(p) - Q(p)| \tag{26}$$

Where $O(p)$ represents the true value, $Q(p)$ the expected value, and L represents the sum of the true and forecasted values. Usually, Equation (27) is used to define MAPE.

$$MAPE = \frac{1}{\bar{n}} \sum_{p=1}^K \frac{O(p)-Q(p)}{O(p)} \tag{27}$$

The suggested method bases the computation of IMAPE on Equation (28).

$$IMAPE = \frac{1}{\bar{n}} \sum_{p=1}^K \frac{\log_cosh}{O(p)} \tag{28}$$

$$\text{Where, } \log_cosh = \sum_{p=1}^K \log(cosg(O(p) - Q(p))) \tag{29}$$

In addition, the overall output of the ABI-LSTM is shown as J_s^* indicating the classification result. In Figure 1, framework of the ABI-LSTM model is shown.

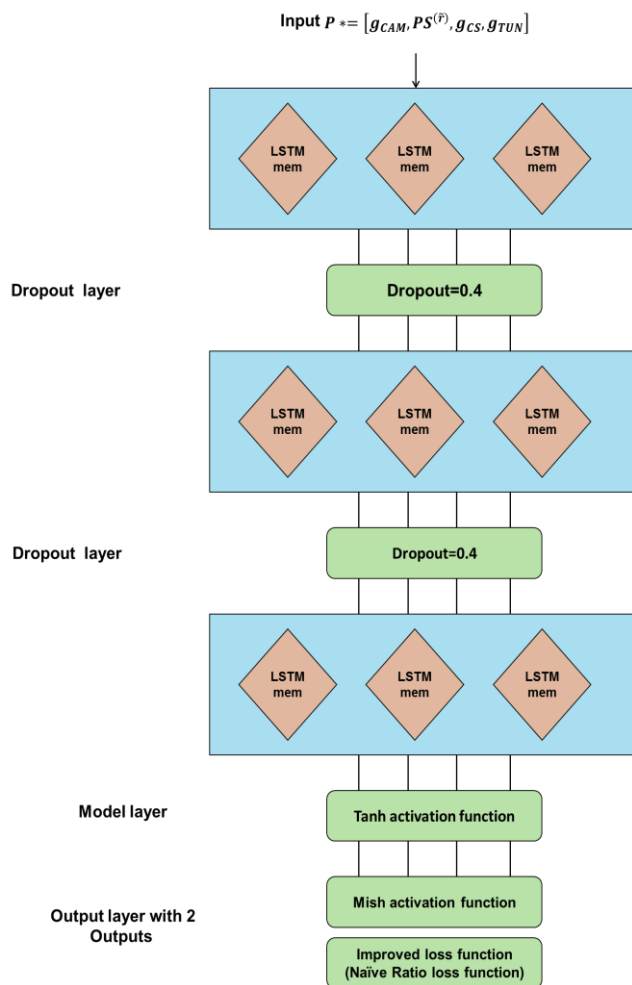


Figure 1. Framework of ABILSTM

3.4.3 DAR-ABLSTM

The advantages of both methods are used in a hybrid strategy that uses Advanced Bidirectional LSTM (ABLSTM) and Artificial Rabbit Search (ARS) for EEG patterns in cognitive training. ARS is used to optimize the identification of important EEG variables [47], increasing the effectiveness of the extraction of features. It is modeled after the interpersonal and inquisitive actions of rabbits. The time-dependent relationships in the EEG data are then modeled and classified using the advanced BLSTM, which processes patterns in both backward and forward orientations for improvement. The objective of this DAR-ABLSTM is to enhance the resilience and accuracy of identifying patterns in cognitive instruction. Algorithm 1 represents the DAR-ABLSTM algorithm.

Algorithm 1. DAR-ABLSTM algorithm

Step 1: Initialize rabbit population P with random solutions

Step 2: Evaluate fitness of each rabbit in P

Step 3: Define ABLSTM architecture (input_size, hidden_size, output_size, etc.)

Step 4: Initialize ABLSTM model

Step 5: for each generation do for each rabbit i in population P do Update position of rabbit i using dynamic artificial rabbit search algorithm Evaluate fitness of updated rabbit I If fitness(new_position) > fitness (current_position) then

current_position = new_position

Select top rabbits based on fitness

Step 6: end for

Step 7: Preprocess EEG signals (filtering, artifact removal, normalization, etc.)

Step 8: Split data into training and testing sets

Step 9: Transform data into sequences suitable for LSTM input

Step 10: for each epoch do

for each batch in training data do

Forward pass through ABLSTM

Compute loss (e.g., cross-entropy loss)

Backward pass to compute gradients

Update model weights using optimizer

end for

Step 11: end for

Step 12: Predict on testing set using trained ABLSTM

Step 13: Compute evaluation metrics (accuracy, sensitivity, specificity, etc.)

Step 14: Print evaluation metrics

Step 15: Visualize performance (optional)

3.4.4 Cognitive Evaluations

Two kinds of cognitive evaluations were assessed. There are memory tests and Positive and Negative Affect Scheduling (PANAS).

3.4.4.1 Memory test

Automatic Working Memory Analysis (AWMA), an electronic instrument for evaluating functioning and short-term memory, was used to administer a memory test. Featuring a user-friendly interface, AWMA is intended to give teachers and researchers a useful and practical means of screening their students for serious working memory issues. There were two different kinds of verbal short-term memory tests. Word recall comes first, followed by digit recall in second place. Applicants in the digits remember test must listen to an assortment of integers and then correctly recall each one in the correct order. The only difference between word recall and digit recall is that phrases are heard and recalled, whereas numbers are ignored.

Verbal memory work tests were divided into two categories: listening recollection as well as listening recollection procedures. In hearing recall, the subjects must confirm if an assortment of spoken phrases is true or untrue and must also remember the last word in each sentence in order. The speed at which replies were produced during the hearing recall assignment is an indicator of the listener recall process. In the spatially recall test, participants are shown a succession of shapes and must mentally control the objects to recall the order in which they should be placed. The speed at which responses to the spatial memory test are made is measured during the processing stage.

3.4.4.2 PANAS

The PANAS is a 16-thing self-reported measure that evaluates both positive and negative effects. Subjects' self-reported data are used to measure their emotions and thoughts (good or negative) as time pass as part of a psychological study. Eight positive and negative sentiments were identified from a set of sixteen things. Positive emotions include excitement, curiosity, strength, alertness, inspiration, determination, attentiveness, and activity. Negative emotions include anxiety, fear, nervousness, embarrassment, irritability, anger, upset, and guilt. Following completion, the individuals are instructed to assign a 5-point rating to each emotion they experienced throughout that allotted period.

3.4.5 Statistical analysis

A matched samples t-test was a cognitive memory test that used SPSS software to examine positive and negative subjective factors as well as spatial recall, digit recall process, listening recall, digit recall, and listening recall process.

4. Result Analysis

In this section, we evaluate the t-test for the memory test and PANAS. First, we used 5 subjects both pre and post to evaluate the five memory recall tests such as listening, digital, process of listening, spatial, and process of spatial. Then we utilize eight positive and negative emotions to measure PANAS. Finally, we compare our proposed method (DAR-ABLSTM) with existing method, spectral features based CNN (CNN-SF), temporal CNN (CNN-T), spectral CNN (CNN-S) and LSTM).

Figure. 2 and Figure. 3 represents the performance of five recall tests for six subjects. According to this performance, no significant changes happened pre- and post-testing in both recall tests. Table 2 represents the mean and standard deviation (SD) values.

4.2 Outcome of PANAS

Figure. 4 displays the outcomes of eight positive emotions. In the figure, attentiveness and curiosity have slightly increased post compared to pre-testing.

4.1 Memory Recall Test

Table 2. Values of the memory test

Name of recall	Pre (Mean ±SD)	Post (Mean ±SD)
Digit	95.01±12.46	94.99±12.64
Listening	99.24±19.29	99.90±17.39
Process of Listening	80.01±3.48	82.79±3.54
Spatial	100.24±17.67	99.54±17.06
Process of spatial	99.14±17.29	99.87±17.31

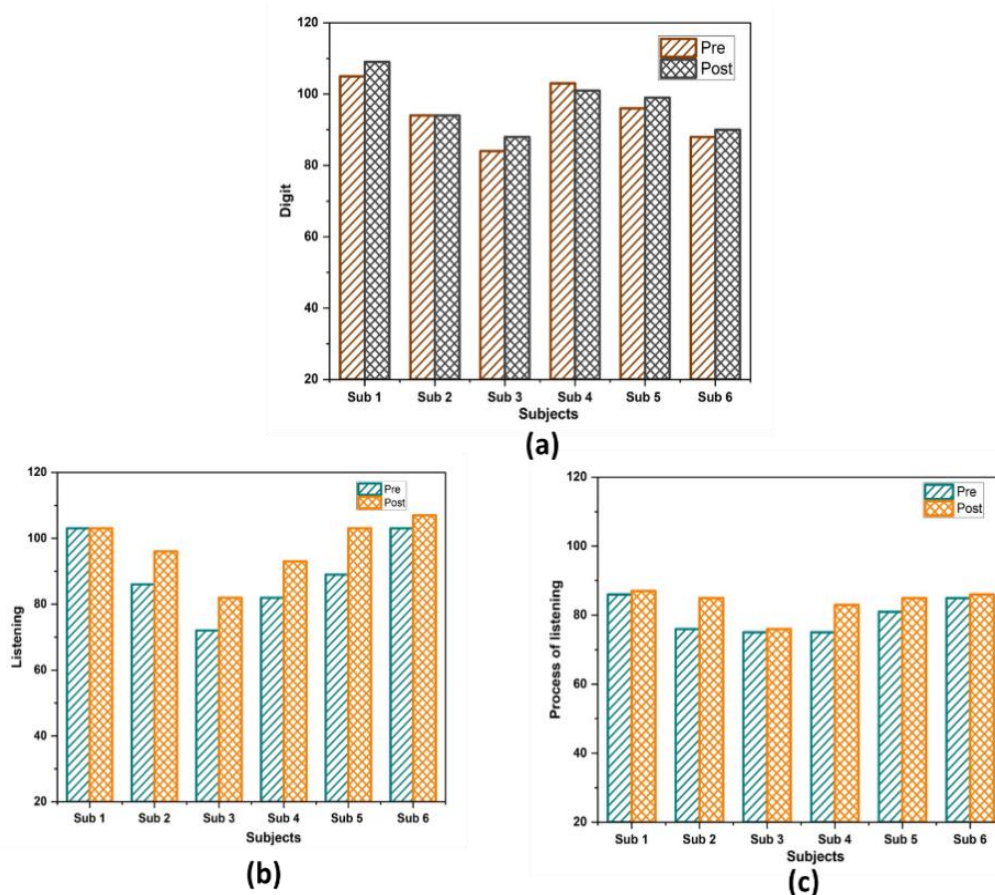


Figure 2. Performance of memory test (a) Digit (b) listening (c) Process of Listening

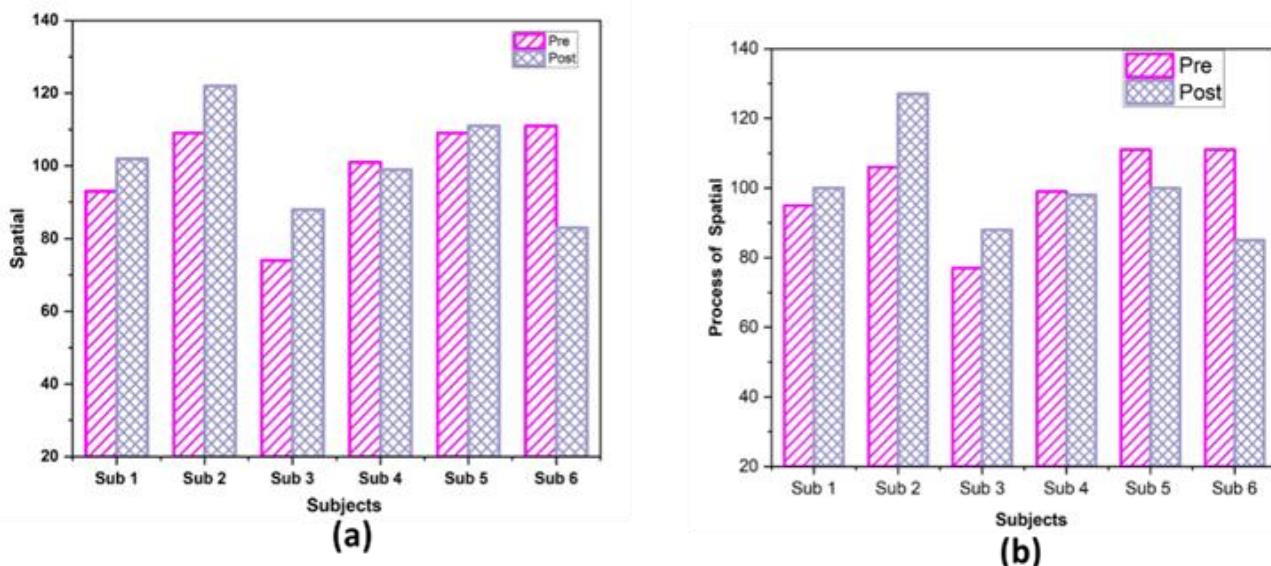


Figure 3. Performance of memory test (a) Spatial (b) Process of spatial

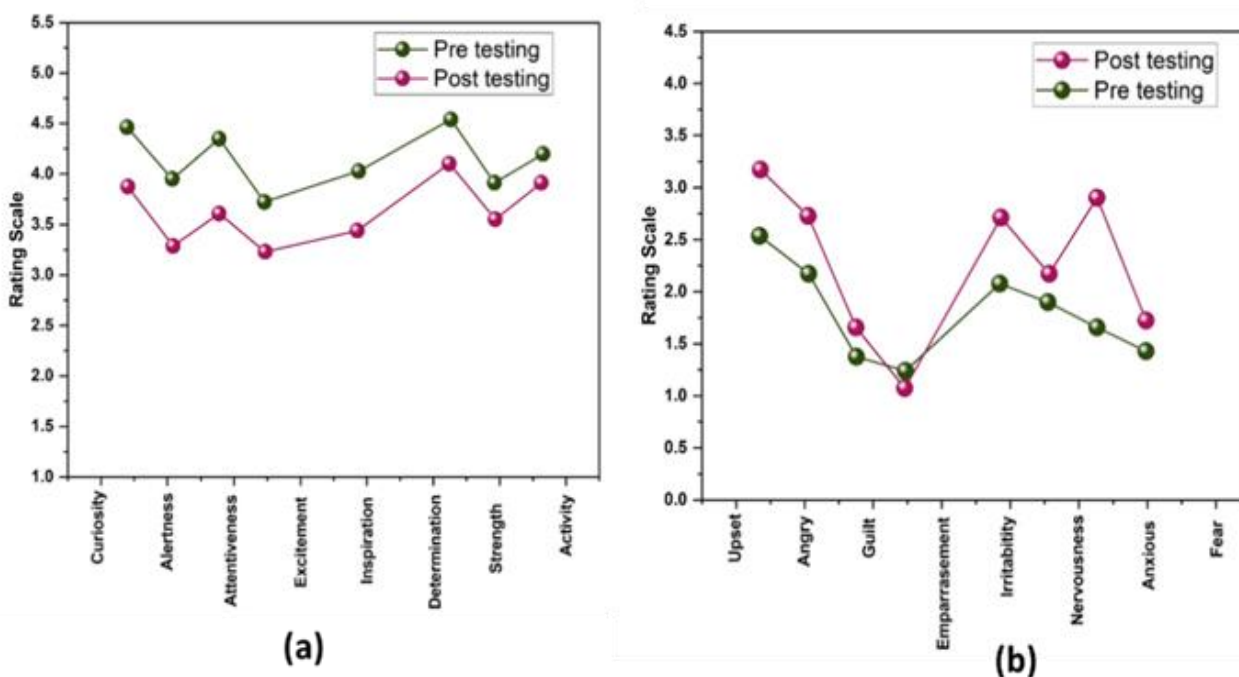


Figure 4. Outcomes of PANAS test (a) Positive emotion (b) Negative emotion

Table 3. Values of accuracy and F1-score

Methods	Accuracy (%)	F1-score (%)
CNN-SF	94.08	93.62
CNN-T	71.09	68.71
CNN-S	92.38	91.84
LSTM	76.78	76.08
DAR-ABLSTM [Proposed]	97.01	95.72

On the contrary, determination, excitement, strength, alertness, inspiration, and activity have no changes in both tests.

compare the performance of methods based on parameters such as sensitivity (%), accuracy (%), F1-score (%), and specificity (%).

The proposed recognition model is implemented in Python software. We evaluate and

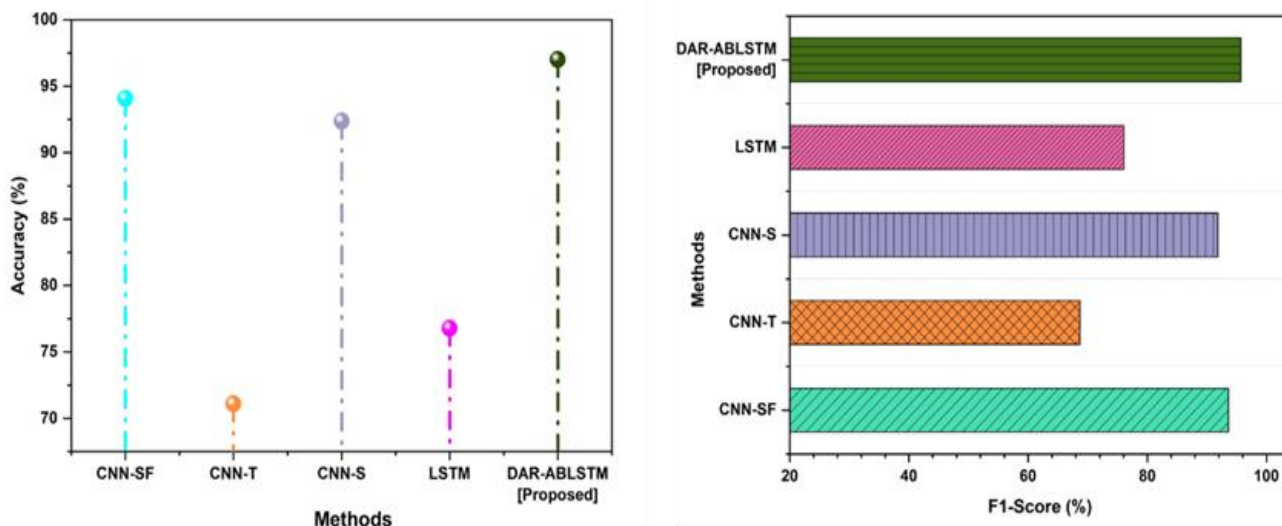


Figure 5. Performance of accuracy and F1-score

Table 4. Values of sensitivity and specificity

Methods	Sensitivity (%)	Specificity (%)
CNN-SF	92.7	95.31
CNN-T	70.71	71.35
CNN-S	91.98	92.6
LSTM	80.72	73.18
DAR-ABLSTM [Proposed]	94.53	96.62

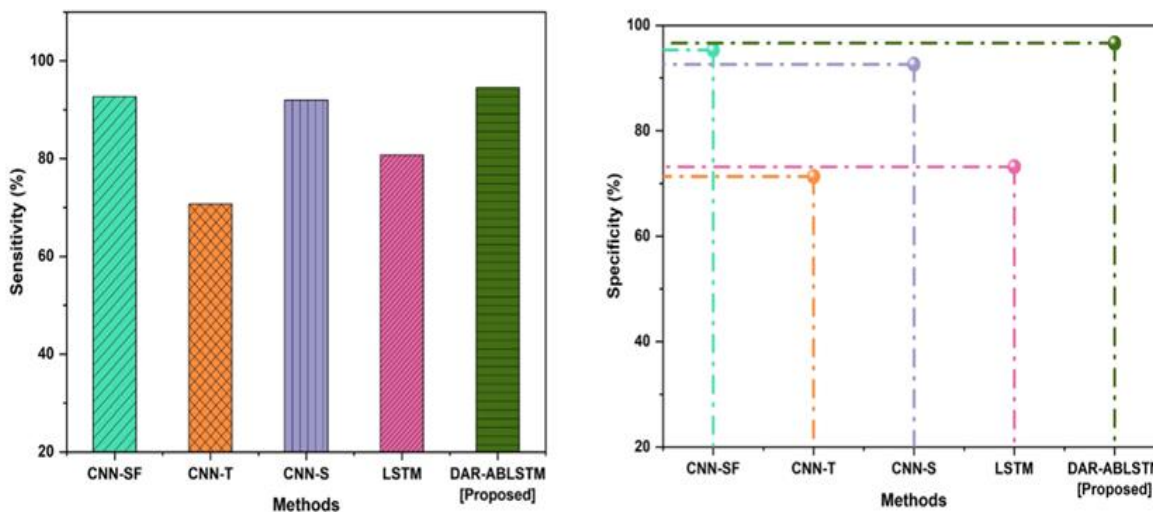


Figure 6. Evaluation of sensitivity and specificity

Accuracy measures the model's capacity to effectively identify and distinguish between extraordinary cognitive states or training results as indicated by the EEG signals. The F1-score is the integrated mean of recall and precision, ensuring that both false positives and false negatives are accounted for. Fig. 5 and Table 3 represent the performance of accuracy and F1-score. The existing method (CNN-SF,

CNN-T, CNN-S and LSTM) attained accuracy (94.08%, 71.09%, 92.38% and 76.78%), F1-score (93.62%, 68.71%, 91.84% and 76.08%) and our proposed method DAR-ABLSTM attained accuracy (97.01%) and F1-score (95.72%). When compared to existing methods, our proposed method outperformed.

Sensitivity measures how effectively the version detects applicable EEG patterns that correspond to successful cognitive results. Specificity evaluates how effectively the method avoids false positives by efficiently identifying times when there is no relevant EEG sample associated with cognitive training. Fig. 6 and Table 4 display the evaluation of sensitivity and specificity. The existing method (CNN-SF, CNN-T, CNN-S and LSTM) scored sensitivity (92.7%, 70.71%, 91.98% and 80.72%) and specificity (95.31%, 71.35%, 92.6% and 73.18%). When compared to the existing method, our proposed method DAR-ABLSTM scored sensitivity (94.53%) and specificity (96.62%). Regarding these outcomes, our proposed method has superior performance to the existing method.

5. Discussion

The DAR-ABLSTM model combines the Artificial Rabbit Search algorithm's ability to optimise metaheuristics with Bidirectional LSTM's ability to model temporal sequences. This enables the dynamic selection of features and the learning of more insights from complex EEG data [48]. This hybridisation gives it a clear edge over traditional deep learning methods because it optimises hyperparameters on the fly, which leads to better performance metrics: 97.01% accuracy, 94.53% sensitivity, 96.62% specificity, and a 95.72% F1-score. Even though these results are encouraging, there are some problems that need to be fixed. The dataset was restricted to healthy individuals, indicating the necessity for extensive validation across clinical populations, including patients with cognitive impairments or stress-related disorders. Adding multimodal datasets, like physiological or behavioural signals [49], could also make classification more reliable and applicable to more situations. In short, the proposed DAR-ABLSTM model holds considerable promise for enhancing automatic EEG pattern recognition and cognitive training evaluation. Its high accuracy and ability to learn on its own are important steps toward intelligent neuroinformatics systems that can monitor and train cognitive skills in real time.

6. Conclusion

Brain electrical activity is represented by patterns on an electroencephalogram (EEG). They provide light on how the nervous system works, which helps in the diagnosis of diseases like seizures, insomnia, and brain traumas. This work aims to develop a novel approach for cognitive training that uses machine learning (ML) to recognise EEG patterns. In this paper, we introduce a dynamic artificial rabbit search-driven advanced bidirectional long short-term memory (DAR-ABLSTM) for strong EEG pattern categorisation in cognitive training activities. EEG

recordings from 50 healthy participants were acquired both during and following a five-week programme of cognitive training. The collected raw signal data is pre-processed using a signal-processing method. As a result, we evaluate two cognitive tests: a memory test, which consists of five recall tests using six subjects, and a PASAS test, which assesses eight positive and negative moods. After that, we evaluated the effectiveness of the suggested approach and contrasted it with the existing method based on metrics such as F1-score (95.72%), sensitivity (94.53%), accuracy (97.01%), and specificity (96.62%). When compared to the existing method, our proposed method outperformed.

6.1. Limitation and future scope

The 50-person sample size may limit the applicability of the results to larger and more diverse groups. By enabling quick modifications based on the identification of EEG patterns, this integration may boost adaptive learning and pave the way for more successful cognitive enhancement and rehabilitation techniques. Furthermore, extending the model's usefulness and resilience could involve examining how well it works in various demographics and cognitive contexts.

References

- [1] C. Li, N. Bian, Z. Zhao, H. Wang, B.W. Schuller, Multi-view domain-adaptive representation learning for EEG-based emotion recognition, *Information Fusion*, 104, (2024) 102156. <https://doi.org/10.1016/j.inffus.2023.102156>
- [2] H. Darwish, A.A. Malah, K.A. Jallad, N. Ghneim, (2024) ArEEG_Chars: Dataset for envisioned speech recognition using EEG for Arabic characters, arXiv preprint arXiv: 2402.15733. <https://doi.org/10.48550/arXiv.2402.15733>
- [3] B. Chen, C.P. Chen, T. Zhang, GDDN: Graph domain disentanglement network for generalizable EEG emotion recognition, *IEEE Transactions on Affective Computing*, 15(3), (2024) 1739 – 1753. <https://doi.org/10.1109/TAFFC.2024.3371540>
- [4] F.K. Bardak, M.N. Seyman, F. Temurtaş, Adaptive neuro-fuzzy based hybrid classification model for emotion recognition from EEG signals, *Neural Computing and Applications*, 36(16), (2024) 9189-9202. <https://doi.org/10.1007/s00521-024-09573-6>
- [5] M.S. Al-Quraishi, W.H. Tan, I. Elamvazuthi, C.P. Ooi, N.M. Saad, M.I. Al-Hiyali, H.A. Karim, S.S.A. Ali, Cortical signals analysis to recognize intralimb mobility using modified RNN and various EEG quantities, *Heliyon*, 10(9), (2024) e30406. <https://doi.org/10.1016/j.heliyon.2024.e30406>

- [6] D. Li, L. Xie, Z. Wang, H. Yang, Brain emotion perception inspired EEG emotion recognition with deep reinforcement learning, *IEEE Transactions on Neural Networks and Learning Systems*, 35(9), (2023) 12979 - 12992. <https://doi.org/10.1109/TNNLS.2023.3265730>
- [7] S. Asadzadeh, T.Y. Rezaii, S. Beheshti, S. Meshgini, Accurate emotion recognition utilizing extracted EEG sources as graph neural network nodes, *Cognitive Computation*, 15(1) (2023) 176-189. <https://doi.org/10.1007/s12559-022-10077-5>
- [8] D. Duan, W. Zhong, F. Hu, L. Ye, Q. Zhang, (2023) Exploring gender differences in emotion recognition with electroencephalography. In: 2023 15th International Conference on Advanced Computational Intelligence (ICACI), IEEE, and Seoul, Korea. <https://doi.org/10.1109/ICACI58115.2023.10146194>
- [9] M. Buzzelli, S. Bianco, P. Napolitano, Unified framework for identity and imagined action recognition from EEG patterns, *IEEE Transactions on Human-Machine Systems*, 53(3), (2023) 529 - 537. <https://doi.org/10.1109/THMS.2023.3267898>
- [10] S. Liu, Z. Wang, Y. An, J. Zhao, Y. Zhao, Y.D. Zhang, EEG emotion recognition based on the attention mechanism and pre-trained convolution capsule network. *Knowledge-Based Systems*, 265, (2023) 110372. <https://doi.org/10.1016/j.knosys.2023.110372>
- [11] R. Hassan, S. Hasan, M.J. Hasan, M.R. Jamader, D. Eisenberg, T. Pias, (2020) Human attention recognition with machine learning from brain-EEG signals, in: 2020 IEEE 2nd Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (ECBIOS), IEEE, Tainan. <https://doi.org/10.1109/ECBIOS50299.2020.9203672>
- [12] Y.Gao, X. Fu, T. Ouyang, Y. Wang, EEG-GCN: spatio-temporal and self-adaptive graph convolutional networks for single and multi-view EEG-based emotion recognition. *IEEE Signal Processing Letters*, 29, (2022) 1574-1578. <https://doi.org/10.1109/LSP.2022.3179946>
- [13] A. Roshdy, A. Karar, S.A. Kork, T. Beyrouthy, A. Nait-ali, Advancements in EEG emotion recognition: leveraging multi-modal database integration. *Applied Sciences*, 14(6), (2024) 2487. <https://doi.org/10.3390/app14062487>
- [14] X. Gong, C.P. Chen, B. Hu, T. Zhang, CiABL: completeness-induced adaptative broad learning for cross-subject emotion recognition with EEG and eye movement signals, *IEEE Transactions on Affective Computing*, 15(4), (2024) 1970 - 1984. <https://doi.org/10.1109/TAFFC.2024.3392791>
- [15] M. Aslan, M. Baykara, T.B. Alakuş, Analysis of brain areas in emotion recognition from EEG signals with deep learning methods. *Multimedia Tools and Applications*, 83(11), (2024) 32423-32452. <https://doi.org/10.1007/s11042-023-16696-w>
- [16] S.K. Jha, S. Suvvari, M. Kumar, Emotion recognition from electroencephalogram (EEG) signals using a multiple column convolutional neural network model. *SN Computer Science*, 5(2), (2024) 213. <https://doi.org/10.1007/s42979-023-02543-0>
- [17] J. Chen, H. Wang, E. He, A transfer learning-based CNN deep learning model for unfavorable driving state recognition, *Cognitive Computation*, 16(1), (2024) 121-130. <https://doi.org/10.1007/s12559-023-10196-7>
- [18] C. Li, P. Li, Y. Zhang, N. Li, Y. Si, F. Li, Z. Cao, H. Chen, B. Chen, D. Yao, P. Xu, Effective emotion recognition by learning discriminative graph topologies in EEG brain networks, *IEEE Transactions on Neural Networks and Learning Systems*, 35(8), (2023) 10258-10272. <https://doi.org/10.1109/TNNLS.2023.3238519>
- [19] M. Jiménez-Guarneros, P. Gómez-Gil, Custom domain adaptation: a new method for cross subject, EEG-based cognitive load recognition. *IEEE Signal Processing Letters*, 27, (2020) 750-754. <https://doi.org/10.1109/LSP.2020.2989663>
- [20] Y. Ding, N. Robinson, S. Zhang, Q. Zeng, C. Guan, Tsception: capturing temporal dynamics and spatial asymmetry from EEG for emotion recognition. *IEEE Transactions on Affective Computing*, 14(3), (2022) 2238 - 2250. <https://doi.org/10.1109/TAFFC.2022.3169001>
- [21] J. Xu, H. Zheng, J. Wang, D. Li, X. Fang, Recognition of EEG signal motor imagery intention based on deep multi-view feature learning, *Sensors*, 20(12), (2020) 3496. <https://doi.org/10.3390/s20123496>
- [22] B. Chakravarthi, S.C. Ng, M.R. Ezilarasan, M.F. Leung, EEG-based emotion recognition using hybrid CNN and LSTM classification. *Frontiers in Computational Neuroscience*, 16, (2022) 1019776. <https://doi.org/10.3389/fncom.2022.1019776>
- [23] K. Singh, S. Singh, J. Malhotra, Spectral features based convolutional neural network for accurate and prompt identification of schizophrenic patients. *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine*, 235(2), (2021) 167-184. <https://doi.org/10.1177/0954411920966937>
- [24] R.K. Kanna, S.V. Athawale, M.Y. Naniwadekar, C.S. Choudhari, N.R. Talhar, S. Dhengre, Anxiety controlling application using EEG neurofeedback system, *EAI Endorsed Transactions on Pervasive Health and*

- Technology, 10, (2024).
<https://doi.org/10.4108/eetpht.10.5432>
- [25] M.U. Iqbal, M.A. Shahab, M. Choudhary, B. Srinivasan, R. Srinivasan, Electroencephalography (EEG) based cognitive measures for evaluating the effectiveness of operator training. *Process Safety and Environmental Protection*, 150, (2021) 51-67.
<https://doi.org/10.1016/j.psep.2021.03.050>
- [26] J. Ansado, C. Chasen, S. Bouchard, G. Northoff, How brain imaging provides predictive biomarkers for therapeutic success in the context of virtual reality cognitive training, *Neuroscience & Biobehavioral Reviews*, 120, (2021) 583-594.
<https://doi.org/10.1016/j.neubiorev.2020.05.018>
- [27] W. Tan, Y. Xu, P. Liu, C. Liu, Y. Li, Y. Du, C. Chen, Y. Wang, Y. Zhang, A method of VR-EEG scene cognitive rehabilitation training, *Health Information Science and Systems*, 9(1), (2021) 4. <https://doi.org/10.1007/s13755-020-00132-6>
- [28] X. Zhao, C. Dang, J.H. Maes, Effects of working memory training on EEG, cognitive performance, and self-report indices potentially relevant for social anxiety. *Biological Psychology*, 150, (2020) 107840.
<https://doi.org/10.1016/j.biopsycho.2019.107840>
- [29] J.C. Da Silva, M.L. De Souza, Neurofeedback training for cognitive performance improvement in healthy subjects: a systematic review. *Psychology & Neuroscience*, 14(3), (2021) 262.
<https://psycnet.apa.org/doi/10.1037/pne0000261>
- [30] S. Rajabi, A. Pakize, N. Moradi, Effect of combined neurofeedback and game-based cognitive training on the treatment of ADHD: a randomized controlled study. *Applied Neuropsychology: Child*, 9(3), (2020) 193-205.
<https://doi.org/10.1080/21622965.2018.1556101>
- [31] S.H.J. Teo, X.W.W. Poh, T.S. Lee, C. Guan, Y.B. Cheung, D.S.S. Fung, H.H. Zhang, Z.Y. Chin, C.C. Wang, M. Sung, T.J. Goh, Brain-computer interface based attention and social cognition training programme for children with ASD and co-occurring ADHD: a feasibility trial. *Research in Autism Spectrum Disorders*, 89, (2021) 101882.
<https://doi.org/10.1016/j.rasd.2021.101882>
- [32] X. Qu, Q. Mei, P. Liu, T. Hickey, (2020) Using EEG to distinguish between writing and typing for the same cognitive task, in: *Brain Function Assessment in Learning: Second International Conference*, Springer, Heraklion, Greece, 66-74.
https://doi.org/10.1007/978-3-030-60735-7_7
- [33] J.L. Molina, M.L. Thomas, Y.B. Joshi, W.C. Hochberger, D. Koshiyama, J.A. Nungaray, L. Cardoso, J. Sprock, D.L. Braff, N.R. Swerdlow, G.A. Light, Gamma oscillations predict pro-cognitive and clinical response to auditory-based cognitive training in schizophrenia. *Translational Psychiatry*, 10(1), (2020) 405.
<https://doi.org/10.1038/s41398-020-01089-6>
- [34] J. Jeon, H. Cai, Multi-class classification of construction hazards via cognitive states assessment using wearable EEG. *Advanced Engineering Informatics*, 53, (2022) 101646.
<https://doi.org/10.1016/j.aei.2022.101646>
- [35] J.G. Cruz-Garza, M. Darfler, J.D. Rounds, E. Gao, S. Kalantari, EEG-based investigation of the impact of room size and window placement on cognitive performance, *Journal of Building Engineering*, 53, (2022) 104540.
<https://doi.org/10.1016/j.jobe.2022.104540>
- [36] L.R. Trambaiolli, R. Cassani, D.M. Mehler, T.H. Falk, Neurofeedback and the aging brain: a systematic review of training protocols for dementia and mild cognitive impairment. *Frontiers in Aging Neuroscience*, 13, (2021) 682683.
<https://doi.org/10.3389/fnagi.2021.682683>
- [37] L.C. Gómez, R. Hervás, I. Gonzalez, V. Villarreal, Studying the generalisability of cognitive load measured with EEG. *Biomedical Signal Processing and Control*, 70, (2021) 103032.
<https://doi.org/10.1016/j.bspc.2021.103032>
- [38] Y. Zhou, Z. Xu, Y. Niu, P. Wang, X. Wen, X. Wu, D. Zhang, Cross-task cognitive workload recognition based on EEG and domain adaptation, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 30, (2022) 50-60.
<https://doi.org/10.1109/TNSRE.2022.3140456>
- [39] P. Israsena, S. Jirayucharoensak, S. Hemrungron, S. Pan-Ngum, Brain exercising games with consumer-grade single-channel electroencephalogram neurofeedback: pre-post intervention study. *JMIR Serious Games*, 9(2), (2021) e26872. <https://doi.org/10.2196/26872>
- [40] I. Merlet, M. Guillery, L. Weyl, M. Hammal, M. Mallia, S. Mallia, A. Biraben, C. Ricordeau, D. Drapier, A. Nica, EEG changes induced by meditative practices: state and trait effects in healthy subjects and in patients with epilepsy. *Revue Neurologique*, 108(4), (2024) 326-347.
<https://doi.org/10.1016/j.neurol.2024.02.387>
- [41] S. Russo, I.E. Tibermacine, A. Tibermacine, D. Chebana, A. Nahili, J. Starczewski, C. Napoli, Analyzing EEG patterns in young adults exposed to different acrophobia levels: a VR study, *Frontiers in Human Neuroscience*, 18, (2024) 1348154.
<https://doi.org/10.3389/fnhum.2024.1348154>
- [42] J. Gomez Romero-Borquez, C. Del-Valle-Soto, J.A. Del-Puerto-Flores, R.A. Briseño, J. Varela-Aldás, Neurogaming in virtual reality: a review of video game genres and cognitive impact, *Electronics*, 13(9), (2024) 1683.
<https://doi.org/10.3390/electronics13091683>

- [43] S.A. Asha, C. Sudalaimani, P. Devanand, G. Alexander, A.M. Lathikakumari, S.V. Thomas, R.N. Menon, Analysis of EEG microstates as biomarkers in neuropsychological processes – review, *Computers in Biology and Medicine*, 173, (2024) 108266. <https://doi.org/10.1016/j.compbimed.2024.108266>
- [44] Y. Zhang, L. Sun, D. Gupta, X. Ning, P. Tiwari, DCNet: a self-supervised EEG classification framework for improving cognitive computing-enabled smart healthcare. *IEEE Journal of Biomedical and Health Informatics*, 28(8), (2024) 4494-4502. <https://doi.org/10.1109/JBHI.2024.3357168>
- [45] S. Chattopadhyay, RECSAE: An interactive model of relevance cognitive load, spatial memory, ADHD and EEG for special educators and mental health professionals. *Diagnostics and Therapeutics*, 3(1), (2024) 1-8. <https://doi.org/10.55976/dt.3202412081-8>
- [46] J. Gomez Romero-Borquez, C. Del-Valle-Soto, J.A. Del-Puerto-Flores, F.R. Castillo-Soria, F.M. Maciel-Barboza, Implications for serious game design: quantification of cognitive stimulation in virtual reality puzzle games through MSC and SpEn EEG analysis. *Electronics*, 13(11), (2024) 2017. <https://doi.org/10.3390/electronics13112017>
- [47] M. Pušica, A. Kartali, L. Bojović, I. Gligorijević, J. Jovanović, M.C. Leva, B. Mijović, Mental workload classification and tasks detection in multitasking: deep learning insights from EEG study. *Brain Sciences*, 14(2), (2024) 149. <https://doi.org/10.3390/brainsci14020149>
- [48] J. Sun, Y. Sun, A. Shen, Y. Li, X. Gao, B. Lu, An ensemble learning model for continuous cognition assessment based on resting-state EEG, *npj Aging*, 10(1), (2024) 1. <https://doi.org/10.1038/s41514-023-00129-x>
- [49] T. Qin, W. Fias, N. Van de Weghe, H. Huang, Recognition of map activities using eye tracking and EEG data. *International Journal of Geographical Information Science*, 38(3), (2024) 550-576. <https://doi.org/10.1080/13658816.2024.2309188>

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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Authors Contribution Statement

R. Kishore Kanna: Conceptualization, Methodology, Investigation, Writing - Original Draft, Writing - Review & Editing. Pravin R. Kshirsagar: Validation. Bhuvan Unhelkar: Supervision. Biswajit Brahma: Resources. Soujanya Duvvi: Formal analysis. Jhum Swain: Writing - Review & Editing. All the authors read and approved the final version of the manuscript.

Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.