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Novel Attention-Tuned CNN for Emotion and Stress Recognition Using EEG in Cognitive Therapy Sessions

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Abstract: Emotional and stress responses are essential for interpreting cognition and mental health in therapy. Traditional models insufficiently seize the complicated temporal-spatial correlations in EEG data, resulting in imprecise assessments of patients' emotional states. This research presents a Novel Attention-Tuned deep learning (DL) model for recognizing emotions and stress by real-time EEG signals gathered during Cognitive Therapy Sessions, intending to improve recognition accuracy and the interpretability of neural activity connected to psychological states. 2000 EEG data were collected, which undergoes preprocessing employing adaptive median filtering to eliminate noise and artifacts. Discrete Wavelet Transform (DWT) using features is extracted to both temporal and spectral characteristics of the brain's activity patterns. The See-See Partidge Chicks-driven Attention-Tuned Convolutional Neural Network (SSPC-Att-CNN) model is used to recognize human emotions and stress levels by examining EEG data. This architecture integrates convolutional layers for spatial feature learning with an attention mechanism that adaptively concentrates on the most informative EEG regions corresponding to emotional arousal and stress variations. A SSPC Optimization (SSPCO) algorithm is employed for feature selection, enhancing computational efficacy and robustness. Experimental evaluation was conducted on python 3.10 for standard EEG datasets which demonstrates that the proposed AT-CNN significantly outperforms conventional DL models in recognizing emotional valence in accuracy of 82.10 %, arousal in the accuracy of 97.89%, and stress intensity levels. The system provides real-time cognitive monitoring, giving therapist's objective insights into emotional regulation and stress patterns. This improves Artificial Intelligence (AI)-assisted psychological assessment tools and promotes a data-driven understanding of emotions in therapy.

Keywords: EEG, Attention-Tuned CNN, Emotion Recognition, Stress Detection, Cognitive Therapy, Feature Selection, Brain Dynamics.

1. Introduction

The human neurological system is a system that controls emotions based on external and internal stimuli. These are not simple psychophysiological systems of emotions, the emotional states are relevant to clinical psychology and neuroscience since it influences the mental health, cognitive, attention, and therapeutic involvement [1, 2]. Stress being both body and mind reaction is one of the greatest emotional responses that are caused by stress or hazardous circumstances. Short-term stress can also raise attention, but in the long run or with improper management, stress predisposes an individual to depression, insomnia, heart disease, and cognitive impairment [3]. The diagnosis of stress early is important to patients who have cognitive or psychological therapy with an aim of ensuring that they respond to it on time and achieve successful treatment outcomes.

Electroencephalogram (EEG) signal has been applied in emotional computing because of the development of non-invasive sensor technologies. EEG can identify neural activity in the prefrontal cortex and amygdala, stress and anxiety, and emotional control [4, 5]. EEG is also useful in monitoring the emotional condition of patients during cognitive therapy sessions since at real time the emotional condition of people varies as those respond to therapeutic stimuli, mental activities or cognitive restructuring activities. Through continuous monitoring of mood and stress, therapists can determine how patients respond, the underlying suffering and tailor treatment involvements.

Emotion classification based on EEG data interpretation has been significantly enhanced by AI, machine learning (ML), and deep learning (DL) methods. The fact that EEG data is highly non-linear; is noisy and subject-dependent makes it difficult to apply traditional machine learning methods despite their promising results [6, 7]. The performances of DL approaches have been shown to be better since they extract domain-invariant and hierarchical factors in raw EEG data automatically. The latest DL methods have achieved high-accuracy emotion recognition outcomes, and this implies a lot of potential in the wearable and therapeutic context [8, 9]. The efficacy of EEG-based emotion identification is hampered by problems such as inter-subject variability, low signal-to-noise ratios, and difficulties in simulating subtle emotional shifts. Studies reveal that recognition accuracy differs greatly among datasets and methods [10]. Additionally, difficulties with capturing subtle emotional alterations and weak generalization persist, particularly in therapeutic contexts [11, 12].

To improve the precision and precision of identifying human emotions and stress levels in connection to psychological states, the research uses SSPC-Att-CNN for EEG analysis. The following are the main highlights of this broad research project:

- Real-time EEG data is recorded throughout cognitive therapy sessions. To eliminate noise and artifacts, the data is further preprocessed using adaptive median filtering.
- The SSPC-Att-CNN model uses EEG data to assess human emotions and stress levels to enhance the interpretability and recognition accuracy of brain activity linked with psychological states.

There are five sections to the research: An overview and key issues are presented in Section 1; previous EEG studies on stress and emotion are examined in Section 2, with any gaps noted; Section 3 describes a recommended methodological approach. Section 4 uses comparative experiments to assess the efficacy of the framework; Section 5 offers findings, contributions, limitations, and suggestions for additional research.

2. Related Works

Table 1 provides a comprehensive overview of prior research by outlining its primary objectives, methodological approaches, significant findings, and associated limitations.

2.1 Research gap

Existing research in emotion and stress recognition struggles with the accuracy of biomarkers and machine learning models due to inconsistent disease dataset testing [13,14]. As opposed to minimum processing time and usage of resources, proper pre-training of facial expressions is also important [15, 16]. The SSPC-Att-CNN model is an improvement of EEG data analysis; it employs an Attention Mechanism (AM) and adaptive median filtering to address stress-related regions. The SSPCO algorithm enhances the process of feature selection and computational efficiency because it learns spatial information using convolutional layers.

3. Methodology

EEG data is registered and preprocessed on adaptive median filtering during the cognitive therapy as shown in figure 1. DFWT is used to extract the frequency bands and features of the data with the aim of identifying patterns of brain activity that are associated with stress and emotions. This data is analyzed with the SSPC-Att-CNN algorithm to identify the level of stress and human emotions with high accuracy.

3.1 Data Collection

EEG Emotion and Stress Recognition Dataset: **https://www.kaggle.com/datasets/freshersstaff/eeg-emotion-and-stress-recognition-dataset/data.**
Stress, arousal and emotional valence indicators collected in the process of cognitive treatment render important EEG data. Such data can be utilized in the study of human-state modeling, stress monitoring, and emotion detection because it includes details about the participants and the context of the sessions in which they took place (25 % of it was used in training, and the rest 75 % was reserved to test).

3.2 Data Preprocessing

Smoothing the signal, adaptive median filtering helps in the preparation of EEGs by eliminating a high frequency noise, impulse artifacts and unexpected spikes. This improves the quality and reliability of signals used to extract features and classify emotions and stress, particularly in times when the patient is in motion or having a temporary stress response.

Table 1. Comparative evaluation of EEG-Based Emotion and Stress Recognition Approaches

Reference	Objective	Method	Result	Limitation
[13]	Manage negative emotions using an EEG-based mobile app	"Motus Up" EEG smartphone app	F1-score: 82.3%; Accuracy: 82.29%; Precision: 84.5%; Recall: 80.3%	No biomarkers; complex emotion-recognition algorithms
[14]	Detect stress during mental arithmetic	CNN + BLSTM; DWT for noise removal and decomposition	Accuracy: 99.20%	Tested only on limited datasets
[15]	Multimodal emotion recognition	Attention-based CNN for facial + CNN for EEG features	Accuracy: 96–97% (DEAP, MAHNOB-HCI)	Requires better pre-trained facial models
[16]	Stress identification from EEG	Symmetric deep convolutional adversarial network (SDCAN)	Accuracy: 87.62% (4 stages), 81.45% (5 stages)	Mostly frequency-domain features
[17]	Improve human-computer interaction (HCI) via emotion recogniion	EEG-based system with preprocessing, a hybrid DL model	Accuracy: 98%	Relies on EEG only
[18]	Identify stress states from the EEG	StressNet: 2D-CNN + (LSTM); EEG decomposed into alpha, beta, theta bands	Accuracy: 97.8% on DEEP and SEED	Dataset limitation; complexity of the hybrid model
[19]	Assess mood changes pre–post art therapy	LSTM-based EEG emotion classifier using 2s frames, 10s sequences	Accuracy: 93.24%	Only two emotional groups; only healthy participants
[20]	Emotion recognition via EEG	ECLGCN (graph convolutional neural networks (GCNN) + LSTM)	Outperforms state-of-the-art on DEAP	Multi-classifier performance limitation
[21]	Stress recognition using EEG	K-Nearest Oracles Union (KNORA)-U dynamic ensemble selection (DES) with DWT	Accuracy: 99.14%	Needs more EEG data
[22]	Categorize human emotions from the EEG	DWT features + peripheral signals; DEAP dataset	N/A	Limited electrode coverage
[23]	Improve emotion recognition	Multi-source domain transfer discriminative dictionary learning modeling (MDTDDL)	Satisfactory classification	High computational cost
[24]	Detect psychological stress using EEG	FFT-based spectral features + SVM and Naive Bayes	Accuracy: 98.21%	Single gender, single modality, frontal-lobe data only
[25]	Identify emotion-eliciting EEG segments	EEG segment extraction, subject-specific vs. subject-independent classification	Subject-specific: 80.87%; Subject-independent: 67%	Performance drop in subject-independent mode
[26]	Stress induction via mental math	Phase Locking Value (PLV), temporal/spectral features, functional connectivity; SVM classifier	Accuracy: 93.2%	Epoch duration limitation (1–10 s)
[27]	Emotion classification (3 states)	DWT (db6) + time & frequency features	Accuracy: 71.52%	Moderate accuracy
[28]	Predict active mood from EEG	SVM-based ML models	F1-score: 84.73%	Limited to EEG signals only

[29]	Emotion recognition from EEG	Bi-LSTM + Binary Gray Wolf Optimizer (BGWO) for feature selection	Accuracy: Valence 99.45%, Arousal 96.87%, Liking 99.68%	High data acquisition cost
[30]	DBN-CRF hybrid architecture for high-precision emotion detection via EEG.	Deep belief networks with glia chains (DBN-GCs)	Superior classification	Requires multi-channel, high-quality EEG data.
[31]	For EEG emotion identification, compare DL models	DNN, CNN, LSTM, CNN-LSTM	Accuracy: CNN 94.17%, CNN-LSTM 90.12% (DEAP)	Needs more EEG data

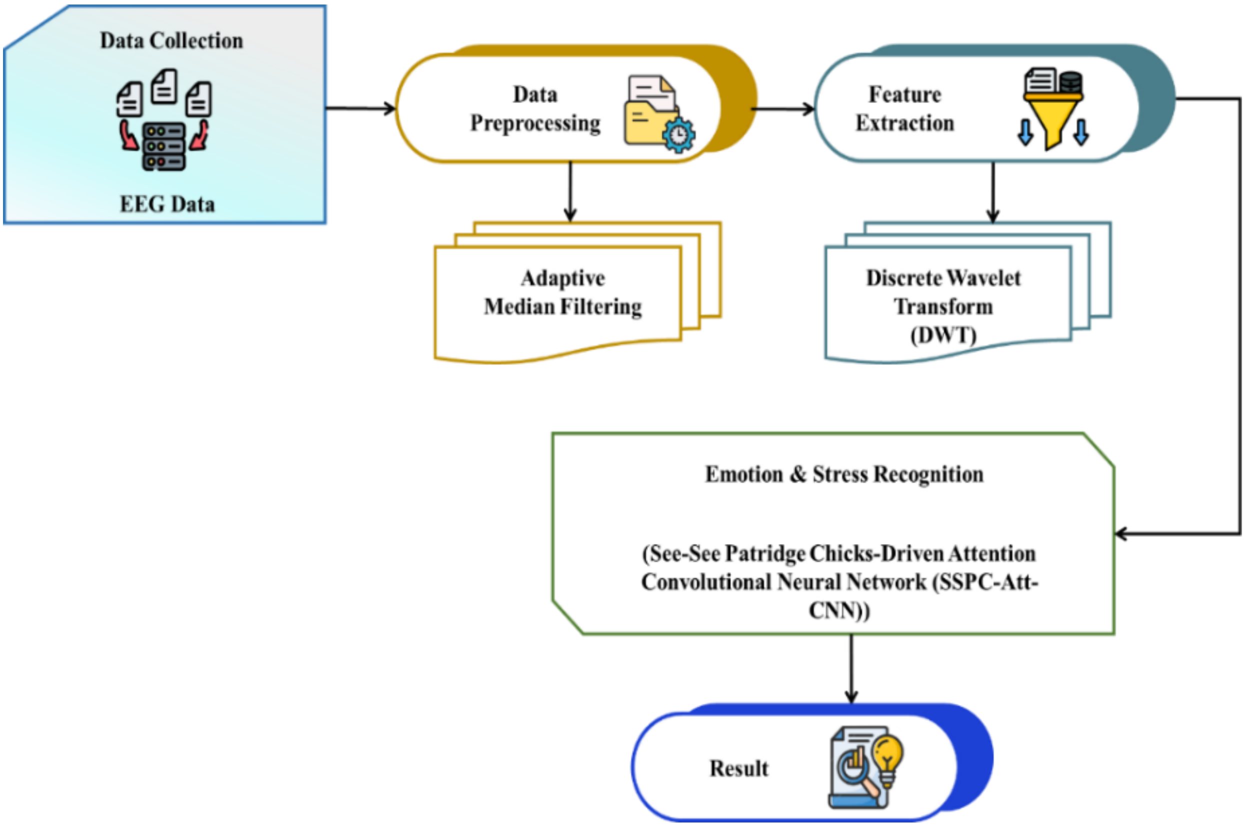


Figure 1. Overall framework for emotion and stress recognition by utilizing EEG data.

3.2.1 Adaptive Median Filtering

During EEG preprocessing, adaptive median filtering efficiently lowers noise without altering important brain signals. The $(j,i)^{th}$ pixel is only changed if it is found to be noisy, and the original value is maintained when the filter is in switching mode. The window size is limited to 7x7 to minimize noise while maintaining EEG waveform features like stress and emotion. The approach for adaptive switching filtering using these parameters is described in the document:

1. Begin with the (3x3) filtering window form $w_{(j,i)}^{(0)}$ and matching (3x3) window from the binary flag image $e_{(j,i)}^{(s)}$.

2. Count the number of pixels in the current filtering window that are recognized as noise-free based on the corresponding binary flag window.

3. The filtering window's size is increased iteratively by adding one pixel to each of its four corners if the number of uncorrupted pixels in the window does not surpass half of the total number of pixels $(denoted\ by\ T_{in} = \frac{1}{2[3\times3]})$.

4. Median filtering in EEG data utilizes only noise-free pixels within the filtering window, excluding the current noisy pixel, resulting in reduced distortion and enhanced filtering outcomes.

3.3 Feature Extraction using DWT

The DWT analyzes non-stationary EEG signals related to stress and emotions in cognitive therapy by decomposing these signals into time-frequency subbands, enhancing emotion and stress detection models via the identification of subtle changes in arousal and cognitive strain. This produces approximation (A1) and detail (D1) coefficients by first-level decomposition using low-pass and high-pass filters:

$$e(s) = \sum_{l=-\infty}^{l=+\infty} D_{m,l} \oslash (2^{-m}s - l) + \sum_{l=-\infty}^{l=+\infty} \sum_{l=-\infty}^{l=+\infty} 2^{\frac{-i}{2}} c_{i,l} \psi(2^{-i}s - l) \quad (1)$$

Where, e represents the original input EEG data, s is the continuous or discrete time/space index of the signal, i is the decomposition level for detail components, approximation and detail coefficients are indicated by $c_{i,l}$ and $D_{m,l}$, respectively, the level is denoted by m, and the scale function is represented by ∅, l is the translation index that moves the wavelet or scaling along the signal, $2^{\frac{-i}{2}}$ is the normalization factor maintaining equal energy across wavelet scales, ψ is the wavelet function used for generating detail components. The procedure is repeated after the initial approximation is dissected. After the process is complete, there are m+1 decomposed signals.

The study applied the Daubechies 4 (db4) mother wavelet function at level 4 for optimizing signal feature detection which is plotted in figure 2. The filtered signal was broken down using the discrete wavelet transform into detail coefficients (C1: 30–60 Hz) and approximation coefficients (B1: 0.1–30 Hz), which were then separated into four levels (B4: 0.1–4 Hz and C4: 4–8 Hz). Results indicated that utilizing all coefficients led to the highest accuracy in classifying emotions and stress in cognitive therapy.

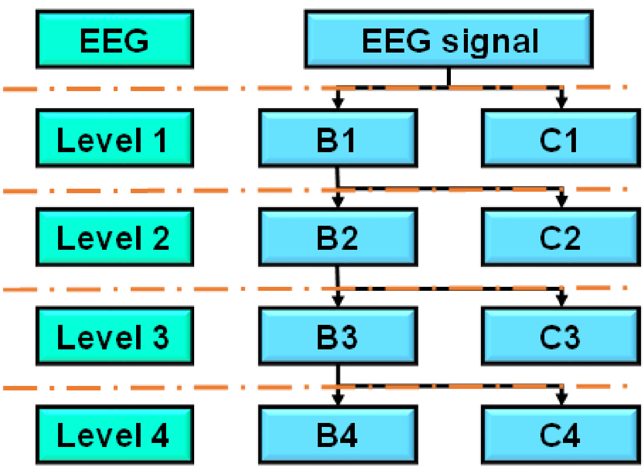


Figure 2. EEG signal breakdown using 4-level DWT.

A discrete signal is denoted by $T(m)$, where $m = 1, 2, \ldots, M$, and M indicates the number of signal samples. The following methods were used to create the feature vectors. The variance of the signal is expressed in equation (2), where U_t is the variance of the EEG samples.

$$U_t = \frac{1}{M} \sum_{m=1}^{M} (T(m) - \mu_t)^2 \quad (2)$$

The signal samples mean is specified by μ_t. σ_t , the standard deviation of the signal is presented in equation (3):

$$\sigma_t = \sqrt{\frac{1}{M} \sum_{m=1}^{M} (T(m) - \mu_t)^2} \quad (3)$$

The signal samples mean is denoted as μ_t. In equation (4), the kurt, kurtosis of the signal is represented:

$$kurt = F\left[\left(\frac{T(m) - \mu_t}{\sigma_t}\right)^4\right] \quad (4)$$

Where $F[\,]$ indicates the anticipated value, the mean is denoted by μ_t, and the mean and standard deviation of signal samples is denoted by σ_t. Equation (5) provides the EEG signal's non-normalized spectral entropy (Ent). Specifically, in equation (6), the log energy-based power (LBP) of the signal is presented:

$$Ent = \sum_{m=1}^{M} |T(m)|^2 \log |T(m)|^2 \quad (5)$$

$$LBP = \log\left(\frac{1}{M} \sum_{m=1}^{M} |T(m)|^2\right) \quad (6)$$

3.4 SSPC-Att-CNN Model is used for Recognizing Human Emotion and Stress Levels

To evaluate human emotions and stress, the SSPC-Att-CNN model, a DL framework, employs convolutional layers for spatial feature extraction and an AM to focus on important EEG regions. By prioritizing pertinent EEG channels and time segments, it improves feature extraction through convolution and pooling layers. Additionally, it enhances resilience, accuracy, and efficiency by optimized feature selection using the SSPCO technique, which is helpful for sparse EEG data.

3.4.1 AM for Highlighting the Most Relevant EEG Features

By continuously modifying EEG signal weights and concentrating on important EEG segments during cognitive treatment, AMs improve emotional data processing and overcome the limitations of traditional models that might overlook small emotional cues. This approach results in a vector that summarizes concealed states, calculated from the encoded EEG representations as shown in equation (7):

$$O(z_s | z_{<s}, d) = h(g_s, z_{s-1}, d) \quad (7)$$

z_s is current predicted output at step s, $z_{<s}$ is series of all previously predicted outputs, d denotes context vector summarizing relevant EEG information from all encoder states, $h(.)$ indicates the non-linear function of the decoder, the decoder output from the prior time step is z_{s-1}, and the present decoder hidden state corresponding to step s is g_s. The alignment score allows the AM to evaluate the relevance of encoder and decoder states for calculating this context vector, as shown in equation (8):

$$f_{li} = u_b^S \tan g\,(X_b g_{l-1} + V_b g_i) \quad (8)$$

f_{li} is the alignment score measuring relevance between decoder state g_{l-1} and encoder state g_i, u_b^S is the weight vector that transforms the hidden alignment activation to the scalar score, $\tan g\,(.)$ is the activation function introducing non linearity. X_b is the learnable weight matrix applied to the previous decoder hidden state g_{l-1}. V_b denotes the weight matrix mapping the encoder hidden state g_i to the alignment space. As shown in equation (9), the alignment scores are then normalized into attention weights using the softmax function:

$$b_{li} = \frac{\exp(f_{li})}{\sum_{\delta=1}^{S} \exp(f_{l\delta})} \quad (9)$$

b_{li} is the attention weight representing the importance of encoder state g_i for decoder step l. $\exp(.)$ is the exponential function used to convert energy scores to positive values. $\sum_{\delta=1}^{S} \exp(f_{l\delta})$ denotes the normalization term assuring all attention weights sum to 1. The context vector is calculated as the weighted sum of encoder annotations in accordance with equation (10):

$$d_l = \sum_{i=1}^{S} b_{li} g_i \quad (10)$$

Where

$u_b \in Q^m, X_b \in Q^{m\times m}, and\ V_b \in Q^{m\times 2m}$ are weight matrices. The context vector summarizing relevant EEG information from decoder step l is indicated by d_l. Prioritizing emotionally significant EEG patterns, the alignment model considers the previous decoder state and each encoder hidden state g_i, focusing on alpha, theta, or gamma rhythm changes associated with stress or emotional variations. It employs temporal-spectral EEG features for detecting stress or emotional responses during therapy, as illustrated in Figure 3, thereby enhancing interpretability and resilience in challenging cognitive treatment environments. Where W indicates the input EEG feature sequence, z_l is the current decoder prediction/output. z_{l-1} is previously predicted output. $\sum b_{li} g_i$ is the weighted sum used to generate context vector.

3.4.2 CNN for Extracting Deep Spatial and Frequency-Related Patterns from EEG Signals

CNNs enable automatic mood and stress level detection by transforming unstructured EEG data into actionable feature representations for use in cognitive therapy, mental health monitoring, and human-computer interfaces.

3.4.2.1 Convolutional Layer

Convolutional layers apply convolution to the provided EEG data. Let e_1 be the filter with a kernel size of $m \times n$ applied to the input$D(w_{v,u})$. Each CNN neuron has $m \times n$ input connections in i, j . Equation (11) computes the layer's final output:

$$D(w_{v,u}) = \sum_{j=-\frac{v}{2}}^{\frac{m}{2}} \sum_{i=-\frac{n}{2}}^{\frac{n}{2}} e_1(j,i) w_{v-j,u-i} \quad (11)$$

A more rich and varied representation of the input can be computed by applying multiple filters $e_1$with $l, K \in \mathbb{M}$. the filters e_1 are developed by distributing the weights of neighboring neurons.

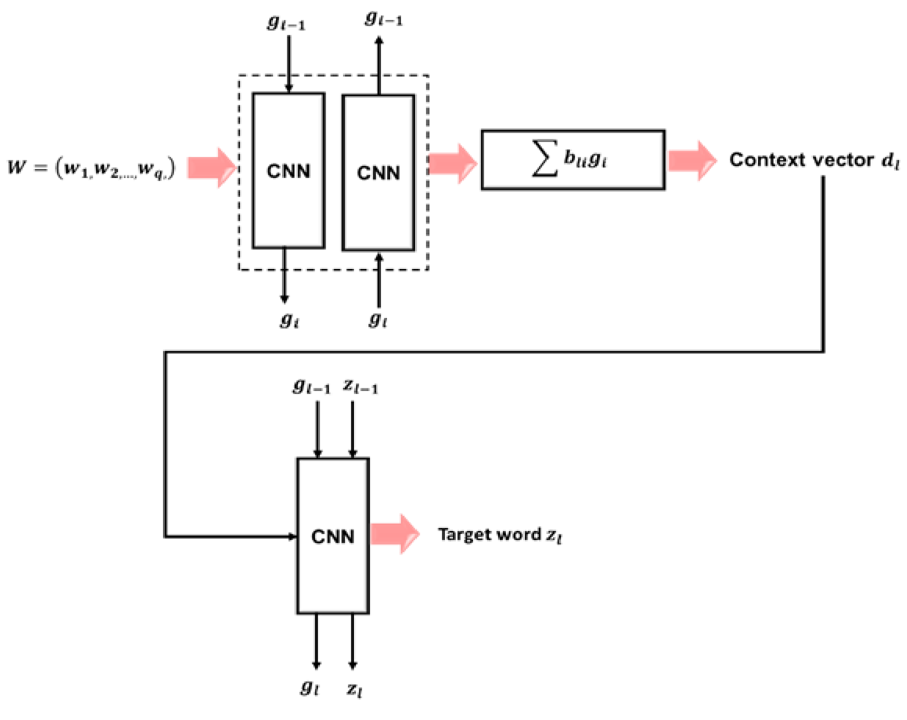


Figure 3. Encoder–decoder framework with an AM

3.4.2.2 Max Pooling

By using the maximum function across the input w_j, max pooling lowers the in Input EEG data. In the format of equation (12), the output computes if n is the filter's size:

$$N(w_j) = \max\{w_j + l, j + k \,\Big|\, |l| \le \frac{n}{2}, |k| \le \frac{n}{2}\ l, k\ \in\ \mathbb{M}\} \quad (12)$$

The result of max pooling at index j is represented by $N(w_j)$. The input EEG value in the pooling neighborhood centered at j is denoted by $w_j + l, j + k$. And the local spatial offsets inside the pooling window are denoted by l and k. n is the size of the pooling window. Max {.} is the maximum operation over the pooling region. M is the set of valid integer indices for pooling offsets. In relation to the filter size, this layer exhibits translational invariance.

3.4.2.3 Rectified Linear Unit (ReLU)

The equation (13) is utilized by a ReLU which is a cell in a neural network, to calculate its output given w:

$$Q(w) = \max(0, w) \quad (13)$$

$Q(w)$ denotes the ReLU-activated output value. The input EEG feature value before activation is denoted as w. $\max(0, w)$ produces non-negative output. By enhancing sparse features and avoiding exponential computations, using these cells improves the efficiency of information transmission.

3.4.2.4 Fully Connected Layer

Every neuron in the Multilayer Perceptron is connected to every other neuron in the layer before it, making it a completely interconnected layer. Let X be the number of neurons in the fully connected layer which is clearly picturized in figure 4, and let E(w) represent the input EEG data of size l. A Matrix $X_{1\times l}$ is the outcome.

$$E(w) = \sigma(X * w) \quad (14)$$

σ specifies the so-called activation function. σ defines the identity function in the network. The EEG feature vector of size l is specified by w. X indicates the weight matrix of dimension 1xl.

3.4.2.5 Output Layer

The EEG input data's output layer aligns the number of classes with its dimensionality by using a single hot vector for class representation. The resultant class for the output vector w is provided by equation (15):

$$D(w) = \{j \,|\, \exists j \forall i \ne j: w_i \le w_j\} \quad (15)$$

3.4.2.6 Softmax Layer

The mistake is transmitted back via a Softmax layer. If M is the input vector's dimension, Softmax computes a mapping such that equation (16):

$$T(w): \mathbb{Q}^M \to [0,1]^M \quad (16)$$

$[0,1]^M$ is the probability vector space. $T(w)$ is the softmax transformation of the vector w. Equation (17) is used to determine the output for each component 1 ≤ i ≤ M:

$$T(w)_i = \frac{f^{wi}}{\sum_{j=1}^{M} f^{wj}} \quad (17)$$

$\sum_{j=1}^{M} f^{wj}$ is the normalization assuring all probabilities =1. $T(w)_i$ is the probability assigned to class i. f^{wi} is the exponential term.

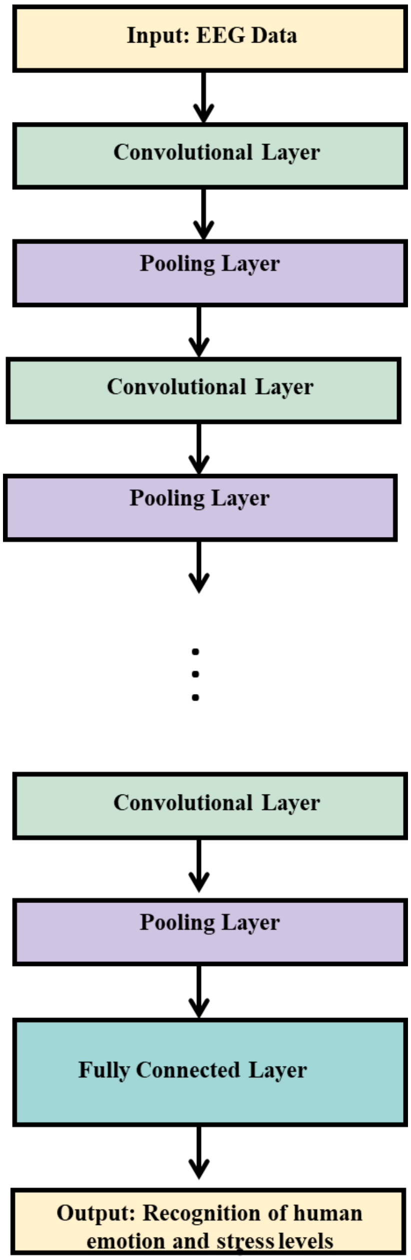


Figure 4. Conceptual model of CNN.

3.4.3 SSPCO for Selecting and Refining the Most Relevant EEG Features

The SSPCO method, inspired by chicks aligning behind their mother, models optimization problems where chicks represent particles seeking ideal solutions. By fine-tuning their movement equations to favor higher values, particles converge on optimal feature subsets improve the detection and interpretability of EEG signals associated with emotions and stress, as shown in Figure 5(a). Based on Figure 5(b), the given document states that a particle s movement to a new position $W_s + 1$ and W_e depends on both its priority variable and its prior velocity U_s. Particles assess their positions relative to higher-priority particles during each algorithm iteration, influencing their movement.

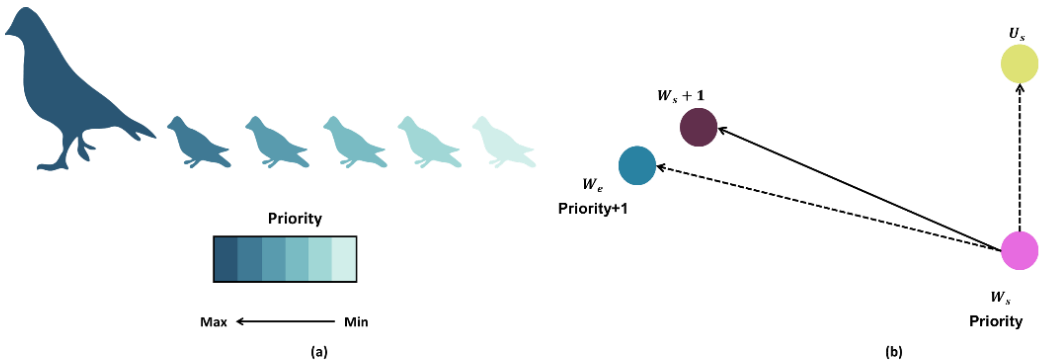


Figure 5. The graphical representation of (a): Chicks' motion in SSPCO algorithm, (b): Particles' motion in SSPCO algorithm

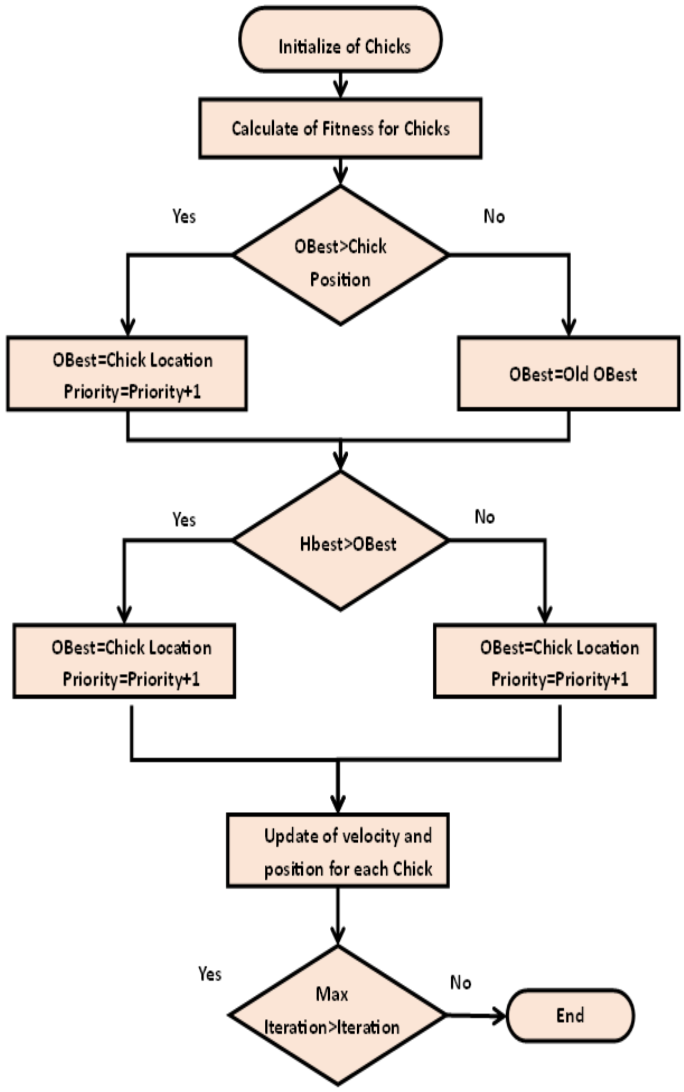


Figure 6. Flowchart of SSPCO algorithm

Those closer to ideal solutions are prioritized, ultimately aiming to identify the "motherbird," the particle achieving the best cost and closest to the ideal solution from the outset. Equation (18) defines the priority variable for particle j:

$$j_{priority} \quad (18)$$

In evaluations, a unit is incremented to a particle's priority variable when it surpasses its best local optimal or personal experience, according to equation (19):

$$if\ W_j.cost > pb_j^s \rightarrow pb_j^s = o_j^s\ and\ j_{priority} = j_{priority} + 1 \quad (19)$$

The cost of each particle in the benchmark is specified as $W_j.cost$, pb_j^s is each particle's best individual experience, and o_j^s is each particle's location. Equation (20) indicates that the evaluation process increases the particle's priority variable by one unit if the local optimum exceeds the global optimum, and decreases it if not:

$$if\ \ pb_j^s > gb^s \rightarrow gb^s\ = pb_j^s\ and\ j_{priority} = j_{priority} + 1 \quad (20)$$

The global optimum is gb^s. Equation (21) illustrates the particle swarm method, paralleling the emotional equation of each particle.

$$o_j^{s+1} = o_j^s + u_j^{s+1} \quad (21)$$

u_j^{s+1} is each particle's or chick's velocity. The chickens were arranged in an array based on a priority variable. Equation (22) is used to calculate the particle velocity:

$$u_j^{s+1} = x * u_j^s + d * rand\ \ * [o(chick_{(j+1)_{priority}}) - o_j^s] \quad (22)$$

In particle dynamics, a particle's velocity (`u_j^s) is affected by previous velocities via a coefficient (x). Furthermore, a random number is generated by $rand()$ to simulate movement variability, and a coefficient (d) indicates the influence of the particle's position, u_j^{s+1} is the new velocity for the next iteration. Additionally, the equation takes into account$o(chick_{(j+1)_{priority}})$, which denotes the present location o_j^s of a particle with a higher priority that affects the velocity of the current particle. Figure 6 shows a flowchart that demonstrates this method. Algorithm 1 displays the SSPC-Att-CNN for EEG-based Stress & Emotion Recognition:

Algorithm 1. SSPC-Att-CNN for EEG-based Emotion & Stress Recognition

Input: EEG signals X
Output: Predicted Emotion/Stress label Y

1. Initialize Attention Mechanism (AM)

- Set weights u_b,X_b,V_b

- Initialize context vector D = 0

2. Initialize CNN

- Define convolutional layers,pooling,fully connected,softmax

- Initialize CNN weights W_CNN

3. Initialize SSPCO Optimization

- Initialize particles representing feature subsets

- Assign priority to each particle

- Define mother particle as the best solution

4. Preprocess EEG data X

- Apply filtering,normalization,segmentation

5. for each EEG segment s in X:

a.Apply Attention Mechanism

- Compute attention scores and context vector:

$$\sum_{i=1}^{S} b_{li} g_i \qquad [Context\ vector;\ Eq. 10]$$

b.Apply CNN

- Convolution operation for spatial feature extraction:

$$D(w_{v,u}) = \sum_{j=-\frac{v}{2}}^{\frac{m}{2}} \sum_{i=-\frac{n}{2}}^{\frac{n}{2}} e_1(j,i) w_{v-j,u-i} \quad [Eq. 11]$$

c.Combine features: H_s = concatenate(d_l,CNN_features)

6. Apply SSPCO for Feature Selection

For each particle p in the population:

i.Evaluate fitness based on classification accuracy using H_s

ii.Update priority and position if improved:

$$u_j^{s+1} = x * u_j^s + d * rand\ * [o(chick_{(j+1)_{priority}}) - o_j^s]\ [Eq. 22]$$

$H\_p\ =\ H\_p\ +\ u\_p$

7. Classification

- If features are satisfactory (fitness > threshold):

Feed into Fully Connected + Softmax layer

Predict label Y_s

Else:

Re-optimize features with SSPCO

8. Output final prediction

- Aggregate predictions for all segments s → final label Y

The SSPC-Att-CNN model assesses human emotions and stress via EEG signals, integrating an Attention module with CNN and SSPCO techniques. The Attention component focuses on important brain rhythms, while CNN layers process raw EEG data using convolution, pooling, and ReLU activations. The SSPCO technique improves resilience and classification accuracy in cognitive treatment through a simulation of partridge chick movements.

4. Experimental Setup

The SSPC-Att-CNN model, developed in Python 3.10, was trained and evaluated using the EEG Emotion and Stress Recognition Dataset. It underwent performance comparison with BGWO-Bi-LSTM, DBN-CRF, and CNN-LSTM models, adhering to standardized training methods and hyperparameter settings, while ensuring consistency through identical hardware and software.

4.1 Correlation Structure and Feature Distribution Analysis of EEG-Based Emotion–Stress Dataset

Minimal multicollinearity and diverse feature contributions, indicating independence among EEG measurements like mean and standard deviation are revealed in figure 7(a). Prior to training the SSPC-Att-CNN model, Figure 7(b) emphasizes the importance of individual and session variability and pairwise feature interactions for assessing feature significance, identifying outliers, and understanding data behavior.

4.2 Hierarchical Clustering and Distribution Analysis of Stress Levels across Subjects and Sessions

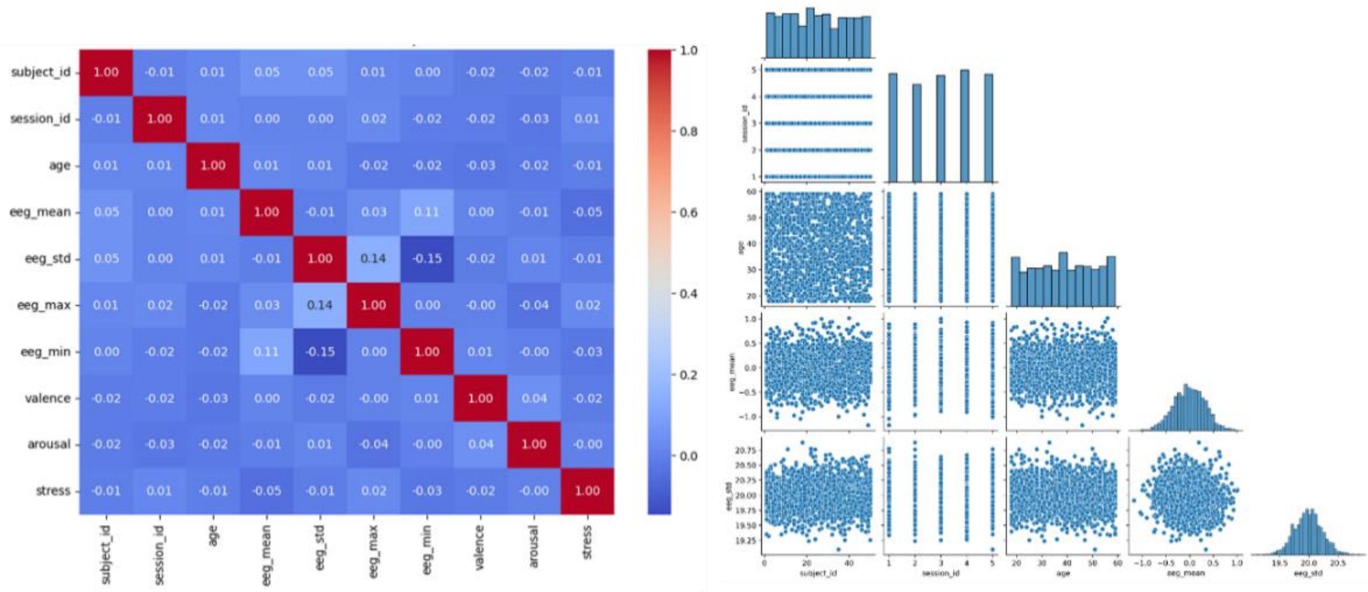
The EEG research shows that utilizing hierarchical clustering, as shown in figure 8(a), ML algorithms, especially SSPC-Att-CNN, can classify stress levels (Low, Medium, and High). The substantial inter-subject heterogeneity among 50 people in figure 8(b) shows that a robust Attention-Tuned CNN is needed to generalize patterns for precise stress detection in therapeutic contexts.

4.3 Stress Signal Analysis Using Rolling Statistics and Time Series Visualization

Time series charts of subject dispersion and stress data stability are used to illustrate effective stress detection. Starting stress values, rolling mean, and standard deviation are shown in Figure 9(a) to aid in model convergence during the SSPC-Att- A thorough stress recognition model is made possible by the random subject ID assignments shown in Figure 9(b) to guarantee objective training data.

4.4 Parallel Coordinates Analysis of Subject Data

Feature influence when the EEG dataset is analyzed for subject_id, session_id, and age across emotion/stress classes (0, 1, 2) is illustrated in figure 10.



(a) (b)

Figure 7. The graphical illustration of **(a):** Correlation and **(b):** Distribution Analysis of Extracted EEG Features and Psychological Labels

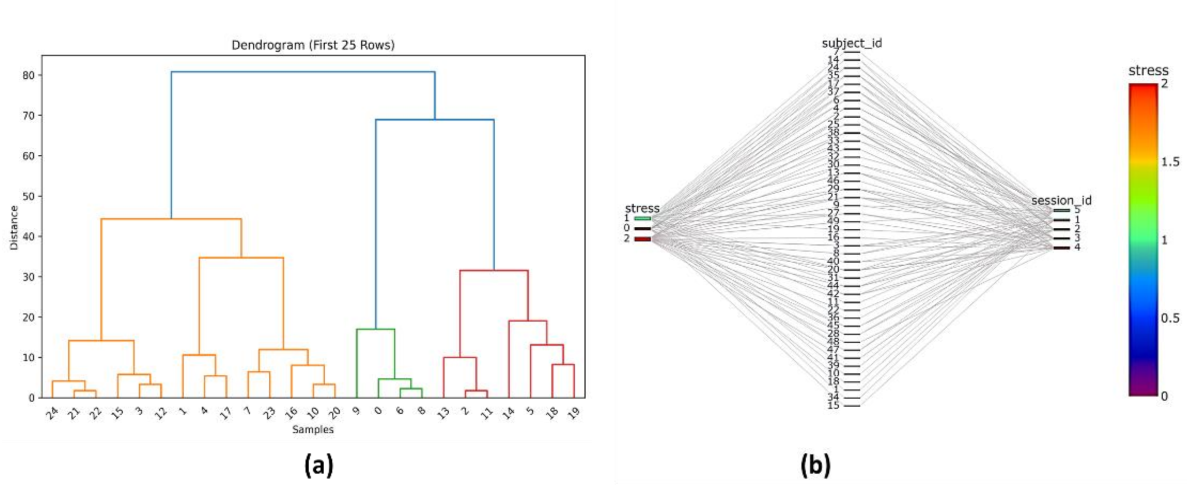


Figure 8. The depiction of **(a):** Hierarchical Clustering Dendrogram of EEG Samples, **(b):** Parallel Coordinates Plot of Stress Levels across Subjects and Sessions

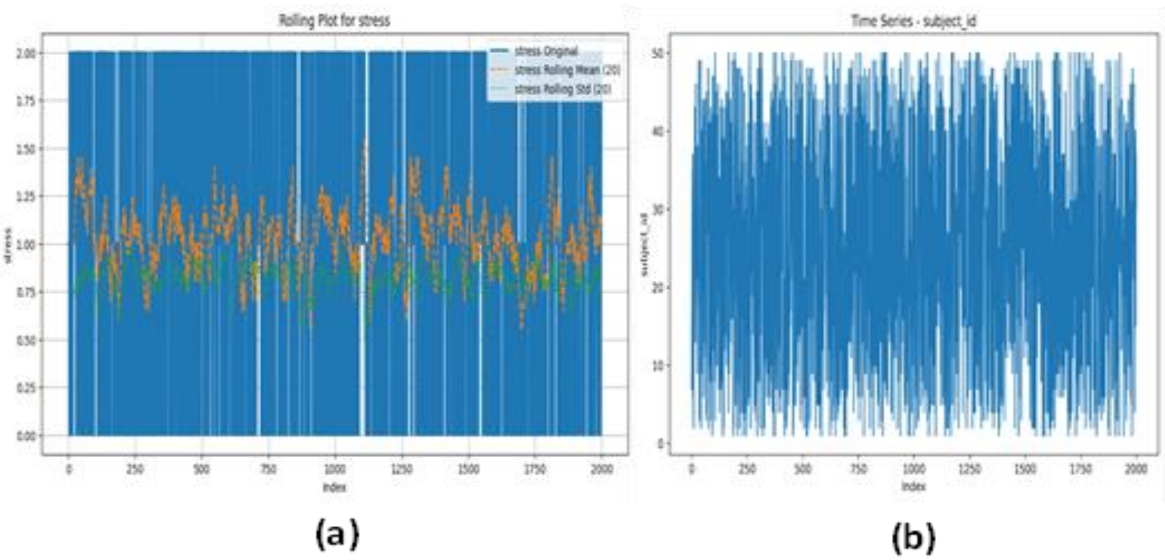


Figure 9. The graphical representation of (a): Rolling Statistics of Stress Levels over Time and (b): Time Series Plot of Stress Levels for Subject_ID

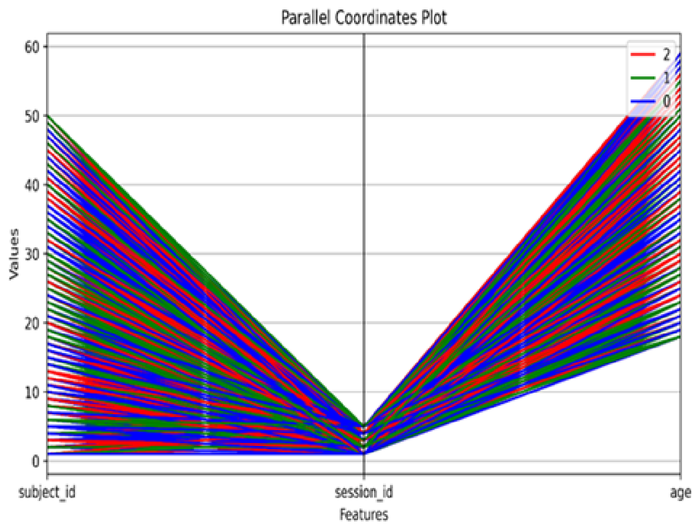


Figure 10. Distribution of Stress/Emotion Classes Across Demographic and Session Features

The SSPC-Att-CNN model uses demographic information and a large amount of EEG data that has been augmented using SSPCO and processed employing DWT to improve emotion/stress recognition in cognitive therapy.

4.5 Feature Distribution and Contribution Analysis

The Andrews Curves in figure 11(a) demonstrate the separability of Low, Medium, and High stress classes from multi-dimensional EEG data, making the "High" stress group easier to classify. Figure 11(b) highlights important contributions from attributes. Utilizing these EEG features, the SSPC-Att-CNN seeks to reliably distinguish stress levels in real-time for therapeutic monitoring.

4.6 Subject-Specific Data Distribution Analysis

This image displays a number of graphs showing the data distribution: The sampling frequency of subject IDs is displayed in Figure 12(a); the stress levels during several sessions are displayed in Bubble Plot (b) and Hexbin Plot (c). The correlation between subject ID, session ID, age, and stress levels is shown in a 3D scatter plot (d). The goal is to utilize the SSPC-Att-CNN for analyzing multi-subject EEG data to identify stress-related brain patterns to assist in treatment monitoring.

4.7 Training and testing validation for accuracy and loss

The SSPC-Att-CNN model enhances over the course of training, as demonstrated by increasing accuracy and decreasing loss in both training and testing shown in figure 13(a,b), indicating effective generalization for cognitive and therapeutic evaluation, minimal overfitting, and efficient learning of emotional and stress-related EEG patterns.

4.8 Metrics Explanation

A variety of metrics, including accuracy, precision, recall, f1-score, and dropout probability, are used to assess the model's effectiveness. The results are compared with those of other current techniques:

4.8.1 Accuracy

The SSPCO-Att-CNN's performance in identifying stress and emotional states from EEG data is primarily evaluated by accuracy, as indicated in equation (23). Its reliability in cognitive therapy monitoring hinges on the percentage of correctly classified samples post attention-based feature refinement and SSPCO-driven feature selection.

$$\text{Accuracy} = \frac{TP+TN}{FP+FN+TP+TN} \tag{23}$$

Where

TP = correctly classified emotional/stress states

TN = correctly identified non-target states

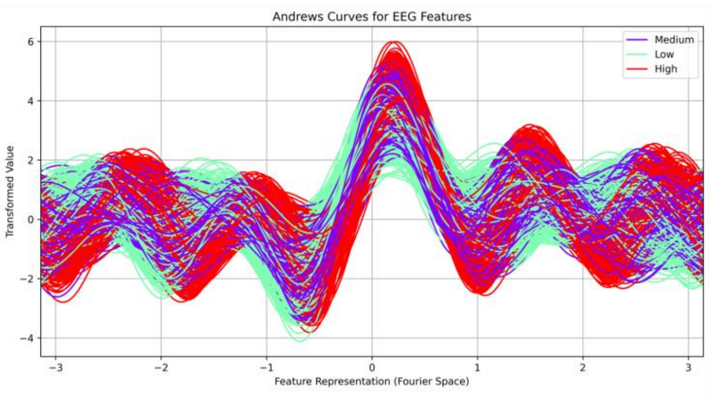
FP= Misclassified emotional/stress states

FN= Missed emotional/stress states

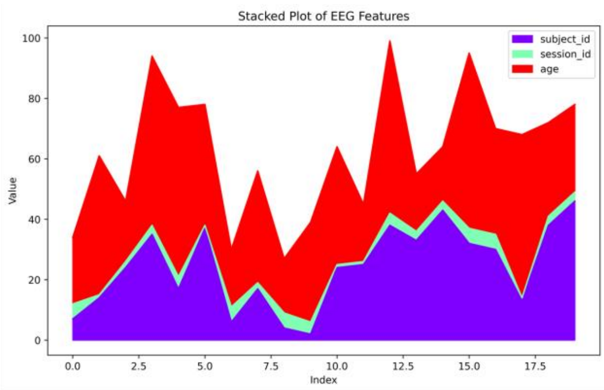
4.8.2 Precision

Precision of positive predictions is estimated by an equation (24) that evaluates the SSPCO-Att-CNN as a valid classifier of stress or emotional conditions in a positive category. The model identifies significant EEG areas selected by AM and SSPCO utility of features to reduce false alarms.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{24}$$



(a)



(b)

Figure 11. The graphical illustration of **(a):** Andrews curves of EEG features by Stress Level, **(b):** Stacked Area Plot of Subject Information over Index.

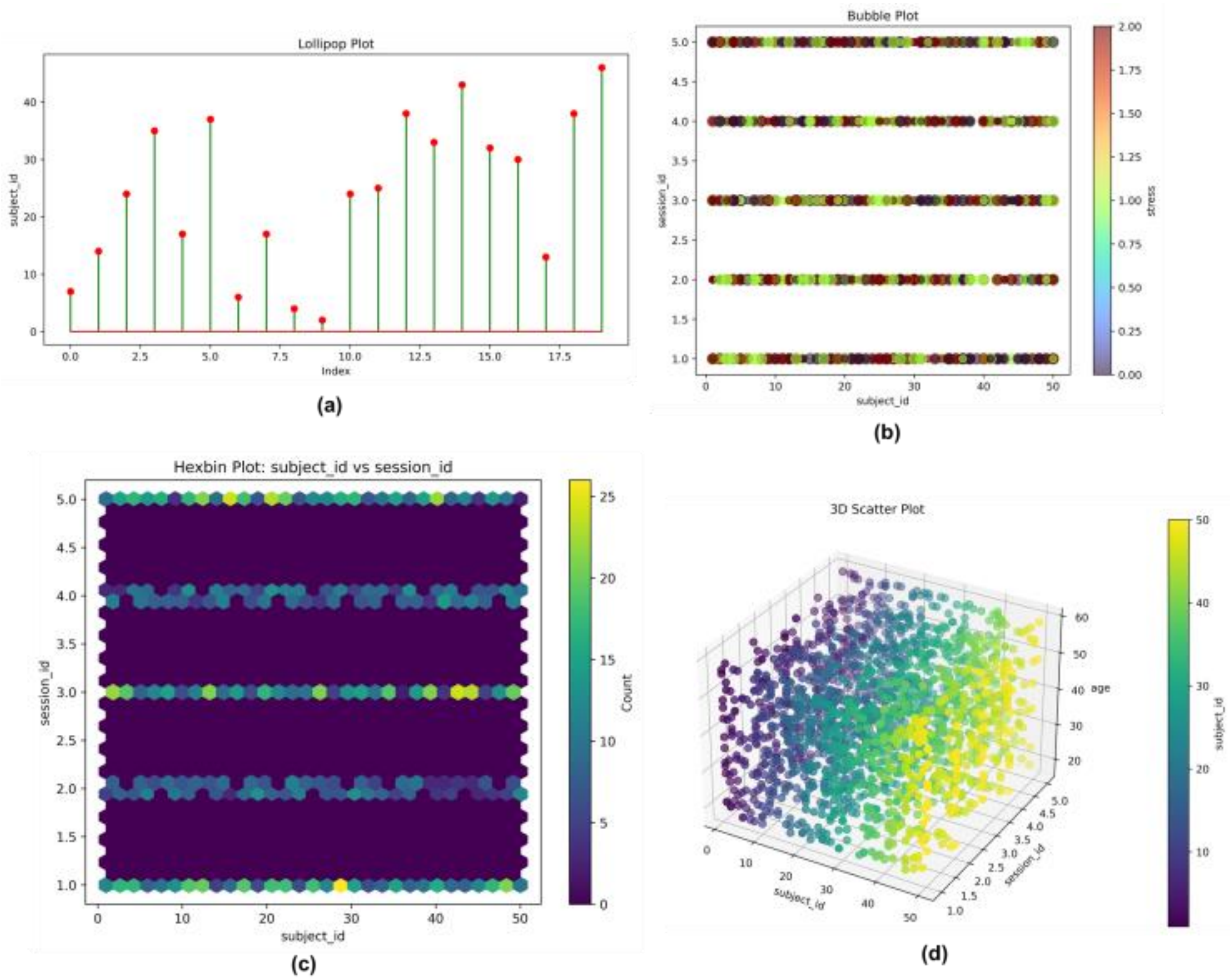


Figure 12. The representation of **(a):** Lollipop plot, **(b):** Bubble Plot, **(c):** Hexbin Plot, **(d):** 3D scatter plot.

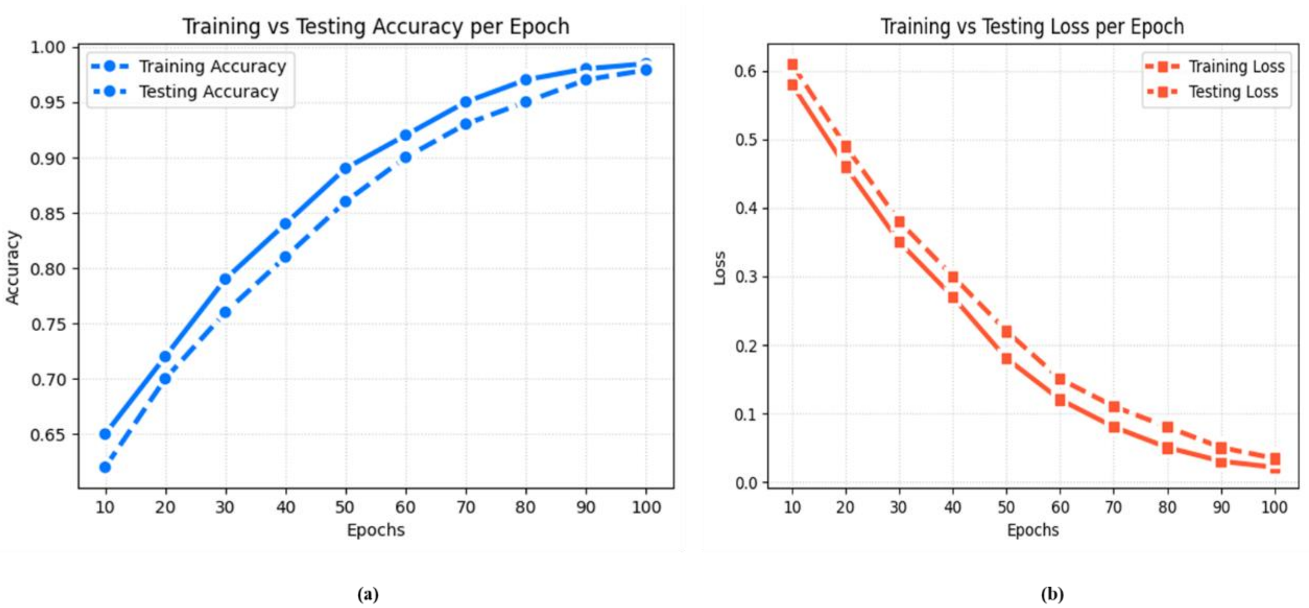


Figure 13. The representation of Training vs. Testing of **(a)** Accuracy, **(b)** Loss.

4.8.3 Recall

The recall is calculated as TP / FN and equation (25) is used to measure the ability of the SSPCO-Att-CNN to detect stress and emotional states based on the EEG data. It shows how the model can be used to capture major physiological patterns in the process of cognitive therapy without omitting important details.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (25)$$

4.8.4 F1-score

The F1-score is an evaluation of the SSPCO-Att-CNN in question in terms of its capacity to detect stress and other emotional states based on EEG signals as illustrated in equation (26). It is a trustworthy indication of the ability of the model to minimize the number of false predictions during the monitoring of cognitive treatment and accurately identifies real psychological states.

$$\text{F1-score} = \frac{2*\text{precision}*\text{recall}}{\text{precision+recall}} \quad (26)$$

4.8.5 Dropout probability

By randomly eliminating certain neurons during training, the SSPCO-Att-CNN uses dropout probability to improve model resilience and reduce overfitting in EEG emotional and stress pattern learning.

4.9 Performance Comparison between Existing and Proposed Methods for Arousal in EEG data

SSPC-Att-CNN model achieves superior performance in identifying emotional and stress states during cognitive therapy, with 97.89% accuracy, 98.10% precision, 97.53% F1-score, and 96.34% recall as shown in table 2.. It outperforms BGWO-Bi-LSTM across all metrics, while DBN-CRF shows significantly lower accuracy and F1-score which is clearly plotted in figure 14.

4.10 Performance Comparison between Existing and Proposed for Valence in EEG data

With an accuracy of 82.10% and an F1-score of 80.23%, the SSPC-Att-CNN model outperforms the DBN-CRF model, which has a 77.20% accuracy and a 70.89% F1-score in identifying emotional states from EEG data as shown in table 3. The SSPC-Att-CNN model shows superior valence recognition reliability, as indicated in table 4 and figure 15.

Table 2. Comparison of Performance Metrics between the Suggested and Existing Approaches.

Methods	Arousal			
	Accuracy (%)	Precision (%)	F1-Score (%)	Recall (%)
BGWO-Bi-LSTM [29]	96.87	97.32	96.22	95.14
DBN-CRF [30]	76.13	-	70.16	-
SSPC-Att-CNN [proposed]	97.89	98.10	97.53	96.34

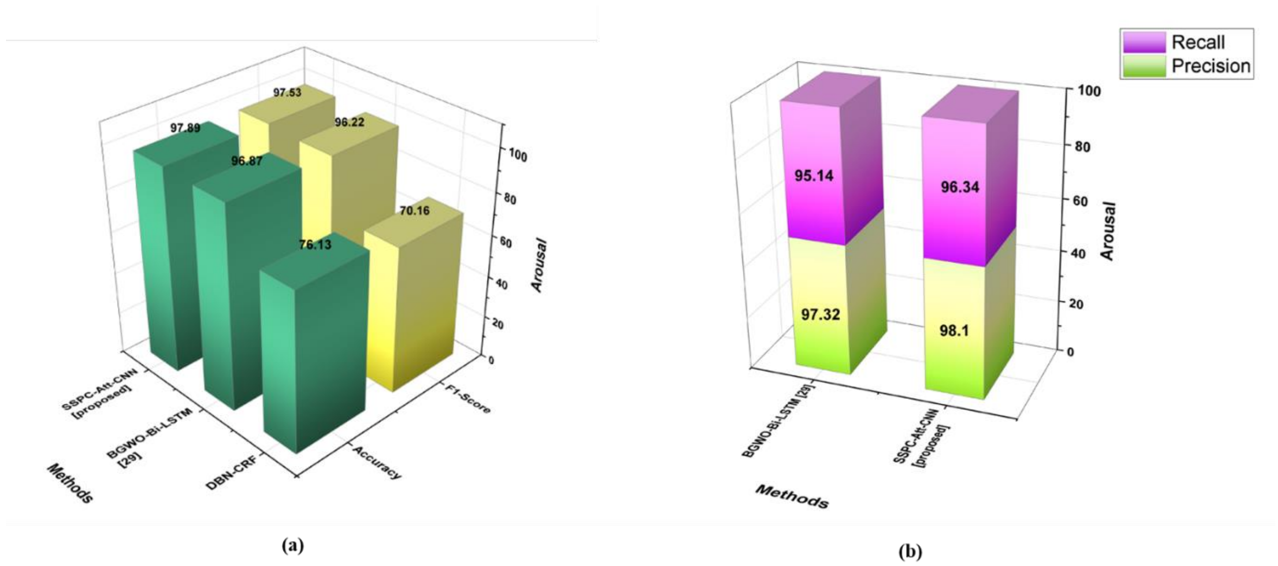


Figure 14. Graphical representation of **(a):** Accuracy and F1-score, **(b):** Recall and precision in arousal

Table 3. Comparison of accuracy and F1-score for valence.

Methods	Valence	
	Accuracy (%)	F1-score (%)
DBN-CRF [30]	77.20	70.89
SSPC-Att-CNN [proposed]	82.10	80.23

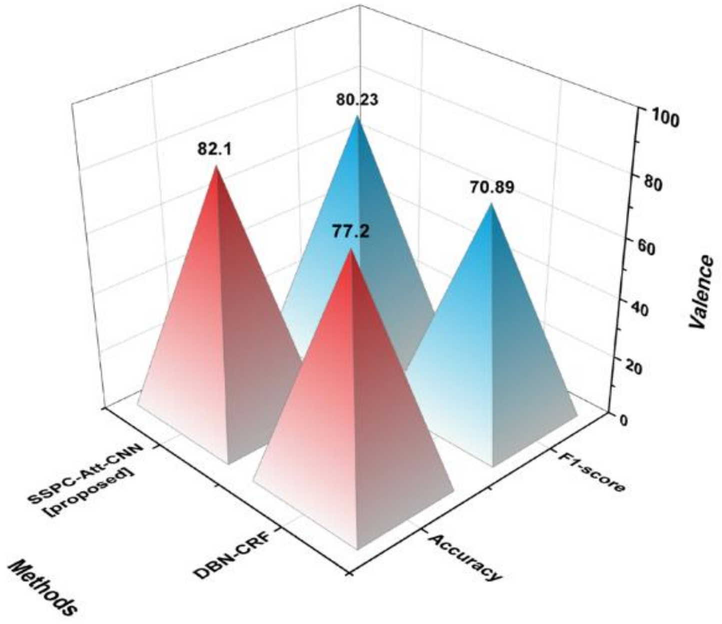


Figure 15. Graphical representation of Accuracy and F1-score for valence.

Table 4. Contrast of dropout probability across existing and proposed methods.

Dropout probability	LSTM [31]	CNN-LSTM [31]	SSPC-Att-CNN [proposed]
20	0.58	0.62	0.80
50	0.71	0.89	0.90
90	0.51	0.48	0.70

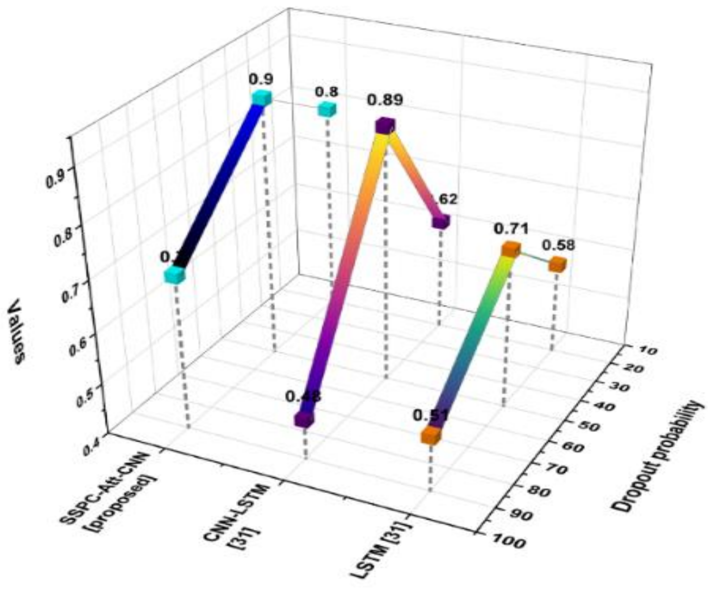


Figure 16. Graphical representation of Dropout probability.

4.11 Performance Comparison between Existing and Proposed Methods for Dropout Probability in EEG data

Results show that dropout rates significantly influence EEG-based emotion and stress detection models in cognitive therapy. The SSPC-Att-CNN model surpassed LSTM and CNN-LSTM models at different dropout levels, achieving peak performance at 50% dropout (0.90) and satisfactory results at 20% and 90% (0.80 and 0.70) as shown in figure 16. This highlights the model's resilience to over- and under-regularization and emphasizes the importance of AM and SSPCO in enhancing dependability for real-time stress and mood monitoring.

Earlier research show that although multi-frequency EEG data may be efficiently analyzed using BGWO-Bi-LSTM [29] and DBN-CRF [30] models, the difficulties associated with EEG technology restrict data collecting. CNN-LSTM hybrid models [31] outperform conventional machine learning methods in emotional classification. By employing AMs to extract important features, the SSPC-Att-CNN model improves recognition accuracy with limited EEG data, thereby addressing these limitations. This development makes real-time emotional and stress monitoring in cognitive therapy applications more practical and dependable.

5. Discussion

The SSPC-Att-CNN framework was key to the development of this study. Unlike other studies in the area, this framework accomplished an unprecedented separation of emotional valence and state arousals of 82.10 and 97.89% respectively. This advancement was made possible thanks to an architecture with a biologically motivated, multilayer friedman of optimizers and attention mechanisms that captured in full detail the neural signatures of the participants of the therapists during of the stress relief therapies. This, however, has to do with the state of the scaffolds architecture design in neuroscience [32]. It is widely acknowledged that with respect to state arousal, there are specific and very robust physiological signatures. This is not the case with valence, which is in stark contrast due to the very complex neural circuitry that governs it. The results of these models provided evidence that certain properties of the arousal response were present [33]. This resulted in the development of models tailored to the spectra of the autonomic responsiveness that had an active response and robust response features. More specifically, the proposed neural template that crowned the cortical valence appraisal network was hypothesized to be the product of the system’s complexity. The attention mechanisms from the study are capable of detecting the GP SSD and guiding the user’s attention towards the spatially relevant electrodes.

The purpose of this framework is to organize and create a database of EEGs such that the clinically relevant signals are extracted and stored that pertain to the cognitive and emotional activity in the signals of delta, theta, alpha, beta, and gamma bands. Moreover, given the emotional adaptivity of the architecture in real time, together with the architecture's cross-frequency bands representation of different mental states, it is considerable that the architecture is employing DWT to extract relevant features [34]. The system's multi-resolution approaches also provided an answer to one of the key challenges that earlier systems faced that only used time-domain or frequency-domain techniques, which advanced the systems significantly. Receiving real-time feedback while treating a client truly captures a change in approach, allowing therapists to witness, unobtrusively, the real-time emotional responses of clients. The current methods therapists use to 'see' clients' emotional states are self-reports, which are especially flawed due to social desirability, self-awareness deficits, and inarticulation of self-emotion. What patients do not verbalize in terms of emotional responses and stress allows clinicians to make real-time clinical refinements. The capability of the system to log sessions and analyze emotional self-regulation over time also benefits the system design and analysis of future case studies. Clinicians no longer need to rely on points of the time after the fact, gap interval measures and a host of other methodologies designed to determine if changes, due to the application of the therapy, are present. This will especially benefit patients who experience emotional and affective dysregulation, anxiety disorders, PTSD, and depression. The appreciation which ought to be credited to feature selection in the SSPC Optimization approach merits mention. There is hardly any feature selection work to date in the literature that deals with the unprecedented dimensionality and intra-channel correlation of multi-channel EEG data. Using nature inspired optimization [35], SSPCO aims to explore the feature space of the imbalanced class dataset and hence identify the relevant and most informative features. This is beneficial in enhancing the class separability while simultaneously alleviating the computational burden and overfitting.

The adaptive median filtering technique was employed in the initial elements of the pipeline and was used to eliminate the effects of the patients\’ movement, and of the electrical noise in the clinical environment before the commencement of the section artifact subtraction. What sets this method apart is how deep of a focus it allows the model to achieve when matching specific types of brain activity to different emotions and allows it to progressively hone the model’s description of the neural activity to a given behavioral state. These attributes improve the model interpretability and transparency [36].

The emotions data is sparse across multiple demographics, clinical subgroups and geopolitics, which relates to the EEG data that has been compiled in 2000 with a large breadth of emotions. Psycho-emotional responses can be examined from several angles, such as demographic, modeling, cultural, and psychiatric interrelations. The complexity and interrelations of these factors can determine one's psycho-emotional response [37]. The more disparate this factor is among different models, the more difficult is the scope of the data, specifically to the subpopulation the model is predicted to significantly under-fit and whose attributes correspond to the highest levels of predictive power. It is important to note the value of this factors in the model validation process. In addition, the model did not take into account the possible longitudinal inertia in the model predictions across emotions. The emotional state differentiation tracking system within the system still needs improvements (already tracking differentiation being state differentiation tracking changes is not the same in changes state). More interdisciplinary and cross sector mental health collaboration to shift to the more targeted psychiatry is inspired. In the mental health care disciplines, the collaboration should strengthen synergistic imperatives to merge AI mental health diagnostics and efficiency, personalization, precision, and outcome improvements of therapy [38]. The effectiveness of AI in mental health care is determined by the efficiency of the targeted algorithms. The absence of such systems and the value associated should not result in the unethical separation of mental health care from integrating such more advanced systems.

The first thing that should be attended to is the oversight concerning the emotional factors registered and paired with the EEG during the training of mental health professionals. Since allied clinical professionals will be retaining complete decision-making control, the systems are meant to function as auxilliary systems to the discretion of the clinicians. However, systems will algorithmically and inappropriately undercut the complexity of the decisions, constituting a need for the clinician to execute clinical decision-making. Since this is a clinical intervention, the necessary debriefing to obtain informed consent in regard to the contravening the privacy risks of the recording of therapeutic sessions ought to be improved [39]. Finally, concerning the ongoing recording of several EEG channels, the various available EEG devices ought to be taken into consideration concerning the contextual parameters that are characterized with simplicity, affordability, and user friendliness. Some specific contextual ethics regarding the emotional surveillance technology in real time of clinical participants are already in place and ought to be taken into consideration [40].

6. Conclusion

Research was able to increase the interpretability and recognition accuracy of brain activity linked to psychological emotions. The initial step in the research is collecting EEG data from the Emotion and Stress Recognition dataset. Further, it is preprocessed using adaptive median filtering to eliminate noise and artifacts. Features are extracted to seize temporal, spectral characteristics of the brain's activity patterns employing DWT. In this research, an SSPC-Att-CNN model is used on EEG data to recognize human emotions and stress levels. Performance evaluation results clearly showed that the framework outperformed others. The proposed model achieved 97.89% accuracy, 98.10% precision, 97.53% F1-score, and 96.34% recall for arousal in EEG data. Additionally, the suggested model's accuracy of 82.10%, F1-score of 80.23%, and dropout of 50% (0.90), which significantly above existing requirements, indicated the usefulness of the framework for identifying emotions and stress levels using EEG data in cognitive therapy sessions.

6.1 Limitations and Future Scope

The SSPC-ATT-CNN model detects stress and emotions from EEG signals, but challenges like noise, electrode variations, and processing demands limit its real-time application. Future research should focus on developing lightweight, real-time, multimodal, and customized versions of cognitive therapies to increase their robustness.

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Author Contribution Statement

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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