Inertia factor and crossover strategy based particle swarm optimization for feature selection in emotion classification

Shilpa Somakalahalli Byreddy[1], Shashikumar Dandinashivara Revanna[2]
[1]Department of Computer Science and Engineering, Cambridge Institute of Technology, Affiliated to Visvesveraya Technological University, Belagavi, India
[2]Department of Computer Science and Engineering, Sai Vidya Institute of Technology, Affiliated to Visvesveraya Technological University, Belagavi, India

Article Info

Article history:

Received Oct 29, 2024
Revised Apr 2, 2025
Accepted Jul 2, 2025

Keywords:

Electroencephalography
Emotion recognition
Gated recurrent unit
Inertia factor and crossover
Strategy and particle swarm
Optimization

ABSTRACT

Emotion recognition using electroencephalography (EEG) is a better choice because it can't be easily mimicked like facial expressions or speech signals. The emotion of EEG signals is not the same and vary from human to human, as everyone has different emotional responses to similar stimuli. Existing research has achieved lesser classification accuracy as it relies on whole feature subsets that include irrelevant features for classifying emotions. This research proposes the inertia factor and crossover strategy (IFCS)-based particle swarm optimization (PSO) algorithm to select relevant features for classification, which removes irrelevant features and enhances classification performance. Then, the self-attention with gated recurrent unit (SA-GRU) method is developed to classify the valence and arousal emotion classes, which focuses much on the significant parts of emotions and reaches high classification accuracy. The proposed IFCS-PSO and SA with GRU method achieved an accuracy of 98.79% for the valence class and 98.03% for the arousal class of the DEAP dataset, outperforming traditional approaches such as convolutional neural networks (CNN).

Corresponding Author:

Shilpa Somakalahalli Byreddy
Department of Computer Science and Engineering, Cambridge Institute of Technology
Affiliated to Visvesveraya Technological University
Bengaluru, India
Email: shilpasb442@gmail.com

1. INTRODUCTION

Emotions play a crucial role in the evolution of neurophysiological processes and the development of awareness [1]. Human emotions are considered a complex psychological state, which is majorly integrated with the reasoning, perception, and intelligence phases of human beings [2]. With the progression of interfaces in the brain-computer, the analysis of human emotions has minimized the burden on physically and mentally impaired people when communicating with others [3]-[5]. Emotion is represented as the activity of internal neurons that derive responses and behaviours based on various external stimuli [6]. Electroencephalogram (EEG) signals are majorly utilized, between various biological signals, for detecting emotions by placing electrodes on the scalp [7]. Psychiatric and neuroscientific research on emotion analysis suggests that humans are capable of a limited group of significant emotions [8]. The two-dimensional circumplex valence-arousal (V-A) method is majorly utilized for quantifying emotion states [9]. From a psychological perspective, the V-A framework is integrated with stimuli to understand and categorize emotional responses. Valence refers to the effective quality that represents positive or negative emotions, ranging from disturbance to happiness [10], while arousal refers to the emotion intensity. By various research, classical machine learning (ML)-based emotion recognition techniques extract handcrafted features from EEG signals based on time, frequency, or time-frequency domains and next exploit features in various supervised classifiers [11], [12]. Deep learning (DL), a type of ML approach that automatically learns the feature hierarchy and classifiers at the end of trends [13]. The features extracted through DL approaches are adopted into inherent structural patterns of information, hence, much discrimination and robustness than handcrafted features [14]. Like ML approaches, DL does not need feature descriptors.

Wang *et al.* [15] presented a DL model for multimodal emotion recognition based on the integration of EEG signals and facial expressions for better classification. Initially, a pre-trained convolutional neural network (CNN) was utilized to extract facial features from facial expressions. An attention mechanism was then implemented to extract complex features from facial frames. CNNs were then employed to extract spatial features from the actual EEG signals that utilized local and global convolution kernels for feature learning. However, the presented method did not resize the signals, which affected the performance of the model. Pandey and Seeja [16] implemented a subject independent emotion recognition approach from EEG signals using variational mode decomposition (VMD) for feature extraction and deep neural network (DNN) as a classifier.

In the implemented method, VMD was used to attain intrinsic mode functions (IMF) from the EEG data. For each IMF, two features, such as peak value of power spectral density and initial variance of signals were measured, and these features were fed to the DNN for classification. The method used the whole set of features for classification, which minimized performance due to irrelevant and inappropriate features. Samavat *et al.* [17] suggested a hybrid CNN and bidirectional long short-term memory (Bi—LSTM) for emotion recognition. The CNN extracted time-invariant features from the original EEG data, while the Bi-LSTM allowed long-range lateral interactions among the features. An adaptive regularization technique was applied to each parallel layer of the CNN for considering the spatial data of EEG electrodes. The suggested method executed all processes in parallel, which improved computational efficiency. However, the method faced the issue of gradient vanishing during training, which minimized classification performance.

Hussain *et al.* [18] developed a lightweight pyramidal one-dimensional CNN with a few learnable parameters. Using this method, a two-phase ensemble classifier was developed. Every channel was scanned in the initial layer to generate predictions, which were fused by majority voting. The next phase fused the predictions of whole signal channels using majority voting to predict the emotional state. The developed method employed a pyramidal structure of CNN with less complexity and did not need a large amount of data to learn.

However, CNN was not much suitable for sequence data, which reduced classification performance. Joshi and Ghongade [19] introduced the modified differential entropy (MD-DE) feature extractor for detecting the non-linearity and non-Gaussian EEG signals. The BiLSTM and multi-layer perceptron (MLP) were utilized for classifying the emotional states of subjects. The Bi-LSTM network learned long-term time series EEG and spatial data from various brain regions. However, the method has limited classification performance due to less focus on significant phases of emotions. The essential contributions of this research are as:

- The inertia factor and crossover strategy (IFCS)-based particle swarm optimization (PSO) for feature selection is developed, which eliminates irrelevant features and feeds the relevant features for classification.
- The self attention–gated recurrent unit (SA-GRU)-based classification approach is developed, which classifies different emotion classes with high classification accuracy.
- The SA mechanism is used in the GRU layer, which focuses on significant phases of emotions in the signals and mitigates gradient vanishing issues to enhance classification performance.

The research paper is organized as follows: section 2 describes the proposed approach. Section 3 presents the results and discussion. The conclusion of this research is provided in section 4.

2. PROPOSED METHOD

The effective optimization-based feature selection algorithm and the DL-based classification are developed to classify emotions. The DEAP, MAHNOB-HCI, and SEED datasets are used, which contain EEG signals of emotions, these are pre-processed using resizing and label encoding. Then, statistical features are extracted to differentiate emotion classes, and the irrelevant features are eliminated using the developed IFCS-PSO algorithm. At last, the various classes of emotions are categorized using SA-GRU. Figure 1 illustrates the process of emotion classification using EEG signals.

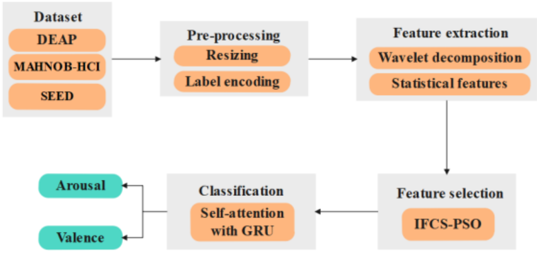

Figure 1. Process of emotion classification using EEG signals

2.1. Dataset

The dataset used for this research is DEAP, a multimodal dataset generally used to study human emotional states [20]. In this dataset, 32 subjects are examined, and 40 videos, each 63 seconds, are chosen as trigger stimuli. Additionally, the central nervous system, peripheral physiological system, and facial expressions of the initial 22 subjects are recorded. Figure 2 represents sample images from the dataset. The MAHNOB-HCI dataset [21] includes 25 subjects, 20 trail of every subject, 38 available channels, and a 30 second length for rating emotion. The SEED dataset [22] includes 15 subjects recorded in the brain-like computing and machine intelligence (BCMI) laboratory, with classes of positive, negative, and neutral emotions. Each video clip is about 4 minutes, and each subject watches 5 clips per emotion.

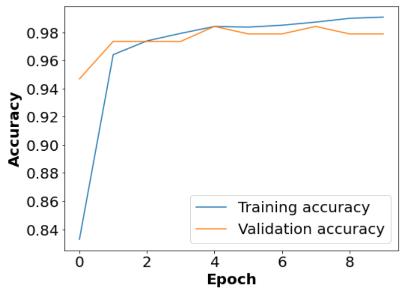

Figure 2. Accuracy vs epoch on valence class

2.2. Pre-processing

The signals in the dataset are pre-processed using resize and label encoding methods. The pre-processing phase is explained: resizing–the signals in the dataset are reshaped into a 2D matrix before being fed into the feature extraction phase. Where the rows represent the channels, and the columns represent the time-series data for each channel. This process structures the data uniformly for feature extraction and improves performance. Label encoding–the emotions in the dataset are encoded using categorical labels such as valence and arousal. High valance represents positive emotion, while low Valance represents negative emotion. The categorical labels are transferred to numerical values utilizing label encoding. This process allows the method to process emotional states effectively.

2.3. Feature extraction

- Wavelet decomposition-EEG signals are non-stationary, meaning their statistical properties change over time. Wavelet decomposition is an efficient technique for analyzing these signals, as it gives both frequency and time data. Every EEG signal is decomposed to various frequency bands utilizing wavelet transform. This resulted from the wavelet coefficients representing the signals in different frequency bands. These sub-band signals capture the inherent oscillations in the brain integrated into various cognitive and emotional states.
- Statistical features–after wavelet decomposition, statistical features are extracted from the coefficients of wavelet for each frequency band. These features include mean, variance, skewness, kurtosis, and energy. These features effectively analyze the characteristics of the signals, allowing the method to differentiate among various emotional states. A total of 128 features were extracted and given as input to the feature selection phase for selecting relevant features.

2.4. Feature selection

The extracted features are provided as input to the feature selection phase, which selects the relevant features for classification. In this research, the inertia factor and crossover strategy–particle swarm optimization (IFCS-PSO)-based feature selection method is used, which eliminates inappropriate features and provides the relevant features for emotion classification. The inertia factor (ω) controls the balance between exploration and exploitation in PSO. A high inertia factor supports exploration, while a low inertia factor leads to exploitation. The inertia is minimized over iterations to transition from exploration to convergence. The crossover strategy in PSO, inspired by the genetic algorithm (GA), where solutions exchange data to improve diversity. By employing the crossover process, good feature subsets are produced, and local optima are avoided. The crossover process allows particles to exchange features, supporting the algorithm in retaining useful traits from various solutions. The IFCS-PSO is a swarm of particles that flies in the search area to seek the optimum solution [23]. Each particle i in a D-dimensional area includes velocity and position, and its respective mathematical formulas are given in (1) and (2).

$$V_i = [V_{i1}, V_{i2}, \dots, V_{iD}],\ \ i = 1,2,\dots,N \tag{1}$$

$$X_i = [X_{i1}, X_{i2}, \dots, X_{iD}],\ \ i = 1,2,\dots,N \tag{2}$$

In (1)-(2), the V_i and X_i represent the velocity and position vectors of the particles, D represents the number of dimensions, and N represents the size of the swarm. In the initial phase of the IFCS-PSO optimization process, the position and velocity of each particle are randomly generated within a range. In the iterative process of IFCS-PSO, each particle i is guided by $gbest$ (global best particle), which is the best particle identified so far, and its $Pbest$ (personal best position) to update its position and velocity. Here, the inertia factor (IF) of adaptive adjustment is used to improve the convergence rate and searchability of traditional PSO. In traditional PSO, the inertia weight is fixed, a large inertia weight is used for global search, while a small inertia weight is used for local search. This reduces both the the searchability and convergence rate of PSO. So, it is essential to adjust the inertia factor for self-adaption, and to modify and increase the particle size during the global search to enhance the optimization process. The mathematical formula for inertia weight with an adjustment strategy is given in (3).

$$\omega_n^t = \begin{cases} \omega_{min} + (\omega_{max} - \omega_{min}) \frac{f(x_h^t) - f_{min}^t}{f_{avg}^t - f_{min}^t}, f(x_h^t) \le f_{avg}^t \\ \omega_{max}, f(x_h^t) > f_{avg}^t \end{cases} \tag{3}$$

In (3), ω_{max} and ω_{min} represent the current maximum and minimum IFs, respectively. $f(.)$ represents the fitness function, while f_{avg}^t represents the average fitness of all particles and f_{min}^t represents the minimum fitness of all particles. After adjusting the IF for PSO, the mathematical formula for updating the position is given in (4) and (5).

$$V_{id}(t+1) = \omega_n^t V_{id}(t) + c_1 r_1 \big(Pbest_{id}(t) - X_{id}(t)\big) + c_2 r_2 \big(gbest_d(t) - X_{id}(t)\big) \tag{4}$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \tag{5}$$

In these equations, ω_n^t represents the inertia factor with the adjustment strategy. c_1 and c_2 represent the coefficients of cognitive and social acceleration, and r_1 and r_2 are random variables. After the particles update their position and velocities, their personal best position is updated, and the mathematical formula is given in (6). In the (6), the personal best position of a particle is updated only if the fitness of the generated particle X_i is better than its current fitness $Pbest_i$. The mathematical formula for updating gbest is given in (7).

$$Pbest_i(t+1) = \begin{cases} X_i(t+1) & if\ f\big(X_i(t+1)\big) < f\big(Pbest_i(t)\big) \\ Pbest_i(t) & orelse \end{cases} \tag{6}$$

$$gbest(t+1) = \begin{cases} Pbest_i(t+1), & if\ f\big(Pbest_i(t+1)\big) < f\big(gbest(t)\big) \\ gbest(t), & orelse \end{cases} \tag{7}$$

The process of IFCS-PSO is repeated until the stopping criteria are met. The stopping criteria are a population size of 30 and a maximum of 100 iterations. Then, the crossover strategy is employed to ensure population diversity in traditional PSO.

2.4.1. Crossover strategy

In the crossover strategy of IFCS-PSO, m particles are sorted based on their fitness, and half of the particles with the highest fitness are directly carried into the following generation. The remaining half of the particles are crossed, and two are randomly selected as parents. The real number crossing technique is utilized to get two individuals, and this phase is repeated till $\frac{m}{2}$ individuals are generated. Before and after the crossover, all particles are sorted based on their fitness, and half of the particles with the highest fitness are selected for the next generation. Additionally, particles that did not participate in the crossover process are included to increase the population further. This strategy enhances population diversity by preserving the best individuals and the ability of global optimum is increased. The selected relevant features of 101 are given as input to the classification phase to classify the different classes of emotions.

2.5. Classification using self-attention with GRU

In this research, the self-attention with GRU method is used to classify the different classes of emotions. The GRU is a variant of long short-term memory (LSTM), which has a simpler architecture than LSTM and effectively captures long-term series in sequential data like EEG signals [24], [25]. The parameters used in the GRU model include a learning rate of 0.0001, the adam optimizer, a binary-cross entropy loss function, a batch size of 32, and 10 epochs. The GRU majorly has two phases, such as the update and the reset gate. Let the input data at time t be represented as x_t. The update gate determines which state data from the past rejected. When past state data h_{t-1} and x_t are fed into the present state h_t, the higher the value of the update gate, the more state data is provided from the past. The mathematical formula for calculating the value of the update gate is given in (8).

$$z_t = \sigma(W_z + U_z h_{t-1} + b_z) \quad (8)$$

In (8), σ represents the sigmoid function, b_z represents bias of the update gate, W_z represent weights of the update gate. The reset gate determines the extent to which past state data contributes to the present state. A smaller reset gate value indicates minimal influence from past state data on the current state. The mathematical formula for the reset gate is given in (9).

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (9)$$

In (9), r_t represents the result of the reset gate at time t, b_r represents the bias of the reset gate, and U_r and W_r represent the weights of the reset gate. The output gate h_t of GRU is affected by $z_t, h_t, and\ h_{t-1}$. The mathematical formula for calculating the output gate is given in (10) and (11). In the below equations, the $*$ represents multiplication operation. After that, the self–attention mechanism is used to focus more effectively on emotions in the signals and mitigate the gradient vanishing issue.

$$\hat{h}_t = tanh(W * [r_t * h_{t-1}], x_t) \quad (10)$$

$$h_t = z_t * h_{t-1} + (1 - z_t) * \hat{h}_t \quad (11)$$

2.5.1. Self-attention layer

The attention mechanism is employed by GRU to learn the significant and insignificant phases of features. A weight is applied to each input based on the interaction among input terms. Consider the input sequence $X = [x_1, x_2, \dots, x_N]$ and the output sequence as $H = [h_1, h_2, \dots, h_N]$. Initially, three weight matrices are multiplied with the input matrix X. The X is transformed into three different matrices: $Q, K, and\ V$. The normalized values are multiplied by the weights of matrices V, and the mathematical formulas for the different matrices are given in (12) to (14).

$$Q = W_Q X \quad (12)$$

$$K = W_k X \quad (13)$$

$$V = W_V X \quad (14)$$

The similarity among K and V is then measured. The formula for the Q matrix includes query vectors, represented as $Q = [q_1, q_2, \dots, q_N]$. The k matrix includes key vectors, represented as $K = [k_1, k_2, \dots, k_N]$. The v matrix includes value vectors, represented as $V = [v_1, v_2, \dots, v_N]$. The similarity is measured by q-vectors with multiple k-vectors, and these similarity scores are then normalized by softmax function. At last, the weigh coefficients α are derived. The mathematical formulas are given from (15) to (17). At last, the dot product for the attention score is scaled, and the mathematical formula is given in (18).

$$h_N = att((K,V), q_n) \tag{15}$$

$$h_N = \sum_{s=1}^{N} \alpha_{ns} v_s \tag{16}$$

$$h_N = \sum_{s=1}^{N} softmax(score(k_s, q_n)) * v_s \tag{17}$$

$$H = V * softmax\left(\frac{K^T Q}{\sqrt{D_k}}\right) \tag{18}$$

3. EXPERIMENTAL RESULTS

The proposed technique is simulated in a python 3.10.12 environment with the configurations of Windows 10 (64 bit) OS, Intel core i5 processor, and 8GB RAM. The metrics used for evaluating the proposed technique are accuracy, recall, precision, and F1-score for two different classes: valence and arousal. Additionally, the accuracy graphs, loss graphs, confusion matrix, and Receiver Operation Curve (ROC) are evaluated for both classes of valence and arousal.

In Table 1, the performance of IFCS-PSO algorithm is evaluated with different metrics for the two classes of arousal and valence. The existing algorithms considered for evaluating the performance of PSO are the Memetic Optimization Algorithm (MOA), Bat Optimization Algorithm (BOA), and Spider Monkey Optimization (SMO). The proposed IFCS-PSO algorithm achieved 98.79% accuracy, 98.21% precision, 99.10% recall, and 98.65% F1-score for the valence class. The proposed IFCS-PSO algorithm achieved 98.03% accuracy, 98.07% precision, 98.17% recall, and 98.13% F1-score for the arousal class.

Table 1. Performance of IFCS-PSO based feature selection algorithm

Algorithms	Classes	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
MOA	Valence	93.71	93.65	93.8	93.72
	Arousal	94.36	94.42	94.49	94.45
BOA	Valence	85.02	84.88	85.13	85.00
	Arousal	85.28	85.15	85.54	85.34
SMO	Valence	75.93	75.8	75.99	75.89
	Arousal	76.21	76.1	76.29	76.2
IFCS-PSO	Valence	98.79	98.21	99.10	98.65
	Arousal	98.03	98.07	98.17	98.13

In Table 2, the performance of the SA with GRU algorithm is evaluated with different metrics for the two classes of arousal and valence. The existing classifiers considered for evaluating the performance of SA with GRU are CNN–LSTM, and recurrent neural network (RNN). The proposed Attention with GRU classifier achieved 98.79% accuracy, 98.21% precision, 99.10% recall, and 98.65% F1-score for the valence class. The proposed SA with GRU achieved 98.03% accuracy, 98.07% precision, 98.17% recall, and 98.13% F1-score for the arousal class.

Table 2. Performance of Attention with GRU based classifier

Classifiers	Classes	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN-LSTM	Valence	91.78	91.34	91.91	91.62
	Arousal	92.45	92.67	92.53	92.6
LSTM	Valence	83.85	83.67	83.92	83.79
	Arousal	84.32	84.5	84.27	84.38
RNN	Valence	89.44	89.46	89.45	89.45
	Arousal	90.87	90.72	91.13	90.92
SA with GRU	Valence	98.79	98.21	99.10	98.65
	Arousal	98.03	98.07	98.17	98.13

In Table 3, the performance of the IFCS-PSO algorithm is evaluated with different inertia factor and crossover startegies for the two classes of arousal and valence. The algorithms like IFCS-MOA, IFCS-BOA, and IFCS-SMO are considered to evaluate the performance of the IFCS-PSO algorithm. The proposed IFCS-PSO algorithm achieved 98.03% accuracy, 98.07% precision, 98.17% recall, and 98.13% F1-score for the arousal class.

Table 3. Performance of different inertia factor and crossover startegy

Algorithms	Classes	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
IFCS-MOA	Valence	91.72	91.48	91.93	91.65
	Arousal	92.28	92.67	92.85	92.61
IFCS-BOA	Valence	87.41	86.72	88.19	87.58
	Arousal	86.94	87.26	87.82	87.49
IFCS-SMO	Valence	78.15	77.64	78.92	78.47
	Arousal	74.36	74.18	74.71	74.53
IFCS-PSO	Valence	98.79	98.21	99.10	98.65
	Arousal	98.03	98.07	98.17	98.13

In Table 4, the performance of different emotions is evaluated with metrics such as precision, recall, and F1-score. The different emotions, such as sad, angry, relaxed, and happy, are considered to evaluate the performance. The averge precision obtained is 98.41%, the recall is 98.43%, and the F1-score is 98.42% across the different emotions.

Table 4. Different emotion evalutaion

Different emotions	Precision (%)	Recall (%)	F1-score (%)
Sad	98.26	99.08	98.67
Angry	98.97	98.57	98.77
Relaxed	98.47	98.17	98.32
Happy	97.96	97.88	97.92
Average	98.41	98.43	98.42

Figures 2 and 3 represent the accuracy vs. epoch graphs for the valence and arousal classes. In Figure 2, the validation accuracy starts higher than the training accuracy, representing that the classifier is well generalizable and performs well on the validation set. Figures 4 and 5 represent the confusion matrix for the valence and arousal classes. These figures show that the classifier performs well, with high recall and precision for both classes. The accuracy is approximately 98.5%. The method is efficient in classifying Class 1 instances with high recall. Figure 6 below represents the confusion matrix for different emotions.

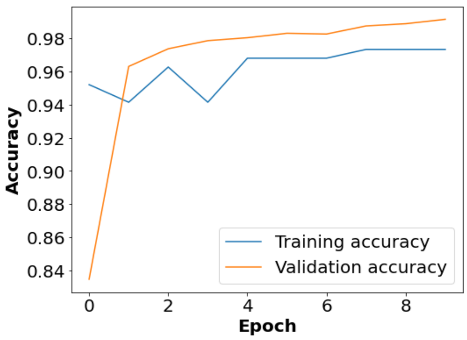

Figure 3. Accuracy vs epoch on arousal class

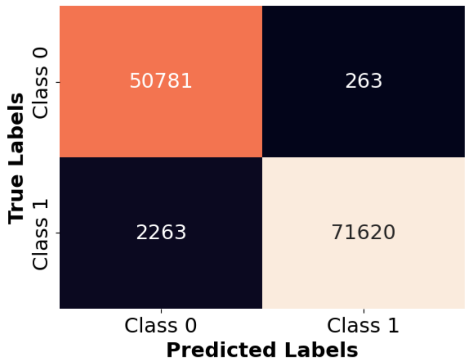

Figure 4. Confusion matrix for valence class

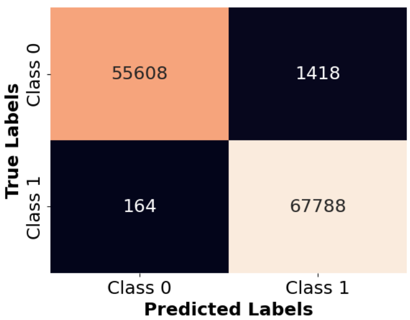

Figure 5. Confusion matrix for arousal class

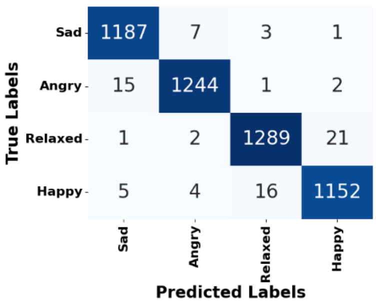

Figure 6. Confusion matrix for different emotions

3.1. Comparative analysis

The performance of the IFCS-PSO and attention with GRU method is compared with existing research like CNN [16], VMD and DNN [17], 1D-CNN [18], and MD-DE BiLSTM [20] on the DEAP, MAHNOB-HCI, and SEED datasets with Valance and Arousal classes. The proposed IFCS-PSO and SA with GRU method achieved 98.79% accuracy on the valence class and 98.03% accuracy on the Arousal class. The relevant features are selected using the IFCS-PSO algorithm for classification. The performance of traditional PSO is improved by using the inertia factor and crossover strategy, which improves the searchability, convergence rate, and population diversity of PSO for selecting the relevant features. Classification is then performed using SA with GRU to classify the two classes with high classification accuracy when compared to existing research. Table 5 presents the comparative analysis of the IFCS-PSO with the GRU method. The following table compares the proposed method with the DEAP, SEED, and MAHNOB-HCI datasets on the valence and arousal emotional classes.

Table 5. Comparative Analysis of IFCS-PSO and Attention with GRU method

Methods	Dataset	Classes	Accuracy(%)
CNN [16]	DEAP	Valence	96.63
		Arousal	97.15
	MAHNOB-HCI	Valence	96.69
		Arousal	96.26
VMD and DNN [17]	DEAP	Valence	62.50
		Arousal	61.25
1D-CNN [18]	DEAP	Valence	98.43
		Arousal	97.65
	SEED		81.54
MD-DE BiLSTM [20]	DEAP	Valence	73.5
		Arousal	75
	SEED		76.29
Proposed IFCS-PSO and SA with GRU method	DEAP	Valence	98.79
		Arousal	98.03
	MAHNOB-HCI	Valence	97.24
		Arousal	96.85

3.2. Discussion

The results of the proposed IFCS-PSO and SA with GRU method are described with the experimental setup and evaluated against existing methods. Compared to some existing research like CNN [16], VMD and DNN [17], and 1D-CNN [18] on the DEAP, MAHNOB-HCI, and SEED datasets with Valance and Arousal classes. The accuracy, loss, confusion matrix, and ROC curve are analyzed to show the performance of the classifier. The existing CNN [16] method does not resize the signals, which affects the performance of the model. The VMD and DNN [17] methods use the entire set of features for classification, which minimizes classification performance. The 1D-CNN [18] method suffers from the gradient vanishing problem during training, which also minimizes the classification performance. However, in this research, relevant features are selected using the IFCS-PSO algorithm for classification. The performance of traditional PSO is improved by using the inertia factor and crossover strategy, which improves the searchability, convergence rate, and population diversity of PSO for selecting relevant features. Then, classification is performed using SA with GRU, which classifies the two classes with high classification accuracy when compared to existing research.

4. CONCLUSION

The efficient emotion classification approach is developed to classify different classes of emotions in EEG signals. Here, the DEAP, SEED, and MAHNOB-HCI datasets containing EEG signals are used, and it is pre-processed using resizing. The resizing process adjusts the EEG signals to a uniform range, and the signals are labelled using labelled encoding. Then, meaningful features are extracted using wavelet decomposition, which extracts statistical features to differentiate between the different emotion classes. The IFCS-PSO-based feature selection algorithm is developed, which eliminates irrelevant features and provides the most significant features for classification. The various classes of emotions are classified using the SA with GRU method, which improves classification performance and provides high classification accuracy. In the future, a pre-trained model can be used for feature extraction to extract deep features to further enhance classification performance.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Shilpa Somakalahalli Byreddy	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	✓
Dandinashivara Revanna Shashikumar		✓				✓		✓	✓	✓	✓	✓		

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

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in DEAP, MAHNOB-HCI, and SEED at https://www.kaggle.com/datasets/samnikolas/eeg-dataset, https://www.kaggle.com/datasets/samnikolas/eeg-dataset, and https://bcmi.sjtu.edu.cn/home/seed/ reference numbers [20]-[22].

REFERENCES

[1] S. T. Aung *et al.*, "Entropy-based emotion recognition from multichannel EEG signals using artificial neural network," *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, p. 6000989, Oct. 2022, doi: 10.1155/2022/6000989.

[2] S. Bagherzadeh, K. Maghooli, A. Shalbaf, and A. Maghsoudi, "Recognition of emotional states using frequency effective connectivity maps through transfer learning approach from electroencephalogram signals," *Biomedical Signal Processing and Control*, vol. 75, p. 103544, May. 2022, doi: 10.1016/j.bspc.2022.103544.

[3] O. Saha, M. S. Mahmud, S. A. Fattah, and M. Saquib, "Automatic emotion recognition from multi-band EEG data based on a deep learning scheme with effective channel attention," *IEEE Access*, vol. 11, pp. 2342-2350, Nov. 2022, doi: 10.1109/ACCESS.2022.3224725.

[4] T. Dhara, P. K. Singh, and M. Mahmud, "A fuzzy ensemble-based deep learning model for EEG-based emotion recognition," *Cognitive Computation*, vol. 16, no. 3, pp. 1364-1378, Aug. 2023, doi: 10.1007/s12559-023-10171-2.

[5] X. Lin, J. Chen, W. Ma, W. Tang, and Y. Wang, "EEG emotion recognition using improved graph neural network with channel selection," *Computer Methods and Programs in Biomedicine*, vol. 231, p. 107380, Apr. 2023, doi: 10.1016/j.cmpb.2023.107380.

[6] M. Ramzan, and S. Dawn, "Fused CNN-LSTM deep learning emotion recognition model using electroencephalography signals," *The International journal of neuroscience*, vol. 133, no. 6, pp. 587-597, Aug. 2021, doi: 10.1080/00207454.2021.1941947.

[7] X. Wang, Y. Ma, J. Cammon, F. Fang, Y. Gao and Y. Zhang, "Self-supervised EEG emotion recognition models based on CNN," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 1952-1962, 2023, doi: 10.1109/TNSRE.2023.3263570.

[8] G. Xu, W. Guo, and Y. Wang, "Subject-independent EEG emotion recognition with hybrid spatio-temporal GRU-Conv architecture," *Medical & Biological Engineering & Computing*, vol. 61, no. 1, pp. 61-73, Nov. 2022, doi:10.1007/s11517-022-02686-x.

[9] Y. Wei, Y. Liu, C. Li, J. Cheng, R. Song, and X. Chen, "TC-Net: A transformer capsule network for EEG-based emotion recognition," *Computers in Biology and Medicine*, vol. 152, p. 106463, 2023, doi: 10.1016/j.compbiomed.2022.106463.

[10] Y. Zheng, J. Ding, F. Liu, and D. Wang, "Adaptive neural decision tree for EEG based emotion recognition," *Information Sciences*, vol. 643, p. 119160, Sep. 2023, doi: https://doi.org/10.1016/j.ins.2023.119160.

[11] S. Liu, Y. Zhao, Y. An, J. Zhao, S. H. Wang, and J. Yan, "GLFANet: A global to local feature aggregation network for EEG emotion recognition," *Biomedical Signal Processing and Control*, vol. 85, p. 104799, Aug. 2023, doi: 10.1016/j.bspc.2023.104799.

[12] S. Liu, Z. Wang, Y. An, J. Zhao, Y. Zhao, and Y. D. Zhang, "EEG emotion recognition based on the attention mechanism and pre-trained convolution capsule network," *Knowledge-Based Systems*, vol. 265, 2023, doi: 10.1016/j.knosys.2023.110372.

[13] C. Li *et al.*, "Effective emotion recognition by learning discriminative graph topologies in EEG brain networks," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 8, pp. 10258-10272, Aug. 2024, doi: 10.1109/TNNLS.2023.3238519.

[14] O. A. Conejo, D. L. Almanza-Ojeda, J. L. C. Hernandez, and M. A. I. Manzano, "Emotion recognition in EEG signals using the continuous wavelet transform and CNNs," *Neural Computing and Applications*, vol. 35, no. 2, pp. 1409-1422, Sep. 2022, doi: 10.1007/s00521-022-07843-9.

[15] S. Wang, J. Qu, Y. Zhang, and Y. Zhang, "Multimodal emotion recognition from EEG signals and facial expressions," *IEEE Access*, vol. 11, pp. 33061-33068, Mar. 2023, doi: 10.1109/ACCESS.2023.3263670.
[16] P. Pandey, and K. R. Seeja, "Subject independent emotion recognition from EEG using VMD and deep learning," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 5, pp. 1730-1738, May. 2022, doi: 10.1016/j.jksuci.2019.11.003.
[17] A. Samavat, E. Khalili, B. Ayati and M. Ayati, "Deep learning model with adaptive regularization for EEG-based emotion recognition using temporal and frequency features," in *IEEE Access*, vol. 10, pp. 24520-24527, 2022, doi: 10.1109/ACCESS.2022.3155647.
[18] M. Hussain, E. U. H. Qazi, H. A. AboAlSamh, and I. Ullah, "Emotion recognition system based on two-level ensemble of deep-convolutional neural network models," *IEEE Access*, vol. 11, pp. 16875-16895, Feb. 2023, doi: 10.1109/ACCESS.2023.3245830.
[19] V. M. Joshi, and R. B. Ghongade, "IDEA: Intellect database for emotion analysis using EEG signal," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 7, pp. 4433-4447, 2022, doi: 10.1016/j.jksuci.2020.10.007.
[20] DEAP dataset, 2021, "EEG Dataset," [Online]. Available: https://www.kaggle.com/datasets/samnikolas/eeg-dataset (Accessed on August 2025)
[21] "MAHNOB-HCI dataset," 2021, [Online]. Available: https://github.com/paperswithcode/paperswithcode-data?tab=readme-ov-file (Accessed on August 2025)
[22] "SEED Dataset," 2019, [Online]. Available: https://bcmi.sjtu.edu.cn/home/seed/ (Accessed on August 2025)
[23] T. M. Shami, S. Mirjalili, Y. A. Eryani, K. Daoudi, S. Izadi, and L. Abualigah, "Velocity pausing particle swarm optimization: A novel variant for global optimization," *Neural Computing and Applications*, vol. 35, no. 12, pp. 9193-9223, Jan. 2023, doi: 10.1007/s00521-022-08179-0.
[24] Y. Zhou, X. He, J.P. Montillet, S. Wang, S. Hu, X. Sun, J. Huang, and X. Ma, "An improved ICEEMDAN-MPA-GRU model for GNSS height time series prediction with weighted quality evaluation index," GPS Solutions, vol. 29, no. 3, p.113, 2025, doi: https:10.1007/s10291-025-01867-z
[25] E. H. Houssein, A. Hammad, N. A. Samee, M. A. Alohali, and A. A. Ali, "TFCNN-BiGRU with self-attention mechanism for automatic human emotion recognition using multi-channel EEG data," *Cluster Computing*, vol. 27, no. 10, pp.14365-14385, Jul. 2024, doi: 10.1007/s10586-024-04590-5

BIOGRAPHIES OF AUTHORS

Shilpa Somakalahalli Byreddy Assistant Professor in the Department of CSE, Cambridge Institute of Technology, Bangalore. She received a BE and M.Tech. degree from Visvesvaraya Technological University (VTU). She is Currently pursuing her PhD in VTU. Her research interests include Machine Learning, Big Data analytics and Depression recognition and analysis. She has around 8 years of teaching experience. In order to enhance her knowledge, she has enrolled and taken up the Nptel Exams. She can be contacted at email: shilpasb442@gmail.com.

Dandinashivara Revanna Shashikumar received BE degree from Mysore University and ME degree from Bangalore University, Bangalore and Ph.D. in Information and Communication Technology of Fakir Mohan University, Balasore, Orissa. He is currently working as Professor and HoD, Dept. of Computer Science and Engineering, Sai Vidya Institute of Technology, Visvesvaraya Technological University (VTU). His research interests include Microprocessors, Pattern Recognition, and Biometrics, Computer Networks, Data mining and Data Warehouse He has published 20 research publications in referred National and International Journals. He is the reviewer for some of the international journals. He can be contacted at email: shashikumardr99@gmail.com.