IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 21 February 2025, accepted 13 March 2025, date of publication 28 March 2025, date of current version 12 May 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3555526

RESEARCH ARTICLE

EEG-Based Emotion Detection Using Roberts Similarity and PSO Feature Selection

MUSTAFA HUSSEIN MOHAMMED[1], **MUSTAFA NOAMAN KADHIM**[2], **DHIAH AL-SHAMMARY**[2], **AND AYMAN IBAIDA**[3]

[1]Computer Techniques Engineering Department, Al-Mustaqbal University, Babylon 51001, Iraq
[2]College of Computer Science and Information Technology, University of Al-Qadisiyah, Al Dewaniyah 58002, Iraq
[3]Intelligent Technology Innovation Laboratory, Victoria University, Melbourne, VIC 3011, Australia

Corresponding author: Ayman Ibaida (ayman.ibaida@vu.edu.au)

This work was supported by Al-Mustaqbal University, Babylon, Iraq, and Victoria University, Australia.

ABSTRACT In this paper, a novel classifier based on Robert's similarity measure is introduced for emotion detection using electroencephalogram (EEG) signals. Traditional machine learning classifiers machine learning such as k-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), Logistic Regression (LR), and Random Forest (RF), often struggle to accurately capture both linear and nonlinear patterns in EEG signals and face limitations in handling high-dimensional datasets. The proposed classifier addresses these challenges by segmenting EEG signals into block sizes categorized as small (1 to 10 samples), medium (20 to 100 samples), and large (200 to 1,000 samples), demonstrating particularly strong performance with medium and large block sizes to capture essential features. Integration of Particle Swarm Optimization (PSO) for feature selection, with Robert's similarity as the fitness function, effectively refines the feature set, boosting classification accuracy and computational efficiency. Evaluation on an EEG brainwave dataset demonstrated that the method achieved an accuracy of 98.75% with feature selection, compared to 94.04% without it in emotional state detection. The results demonstrate that the proposed classifier is a valuable tool for diverse fields, including healthcare by detecting patient stress, education by assessing student engagement, customer service by monitoring satisfaction, and smart environments by enabling adaptive responses. Furthermore, the classifier has potential for broader industrial applications, such as improving workplace productivity by monitoring employee stress and enhancing safety in autonomous vehicle systems, making it a versatile solution for emotionally-aware systems across multiple domains.

INDEX TERMS Roberts similarity, electroencephalography (EEG) signal, emotion recognition, particle swarm optimization (PSO), machine learning classifiers.

I. INTRODUCTION

Emotion is a psycho-physiological experience derived from both conscious and unconscious perceptions of situations or traits, and is closely related to mood and personality [1]. Emotions, unsurprisingly, play a major role in daily social interactions. This is evident in areas such as clinical settings and human-computer interaction, where emotion recognition significantly enhances communication and user experience.

The associate editor coordinating the review of this manuscript and approving it for publication was Asadullah Shaikh.

Recently, emotion recognition has garnered increasing attention in various applications, including e-learning, virtual reality, recommendation systems, marketing, gaming, and healthcare [2]. These fields leverage emotion recognition technologies to create more interactive and personalized user experiences.

There are two major divisions of emotion recognition systems based on physiological and non-physiological signals [3]. Physiological signals involve internal bodily responses such as heart rate and electrical activity in the brain, whereas non-physiological signals involve outward expressions like facial cues, tone of voice, and bodily expressions.

Among physiological signals, electroencephalography (EEG) is the most useful because it cannot be manipulated. Due to the availability of increasingly non-invasive apparatus which is not very expensive to access, most of the current research has resulted in interest in EEG-based emotion recognition instead of technically expensive Magnetoencephalography (MEG) and Magnetic Resonance Imaging (MRI) techniques [4]. Its non-invasive nature, speed, and cost-efficiency have solidified EEG place as a preferred tool for examining the brain responses to emotional stimuli [5].

In recent years, artificial intelligence, particularly machine learning, has become widely applied across various fields, including emotion recognition and disease detection The traditional approaches to emotion recognition have been highly dependent on physiological signals, and the associated machine learning techniques include Decision Tree (DT) [6], Support Vector Machines (SVM) [7], Logistic Regression (LR) [8], K-Nearest Neighbors (KNN) [9], and Random Forest (RF) [10].

In relation, most of the traditional algorithms are poorly capable of accurately handling the high-dimensional and non-linear characteristics embedded in physiological signals (EEG), thus resulting in a low accuracy rate [11], [12].

In response to these challenges, our proposed approach incorporates the Roberts similarity measure to more effectively capture both linear and nonlinear patterns in EEG signals for emotion state detection. This measure enhances the identification of intricate and minute characteristics in physiological data to provide more correct and reliable detection of emotions. The main contributions of the study are as follows:

- Novel classifier based on Robert's similarity measure is introduced to capture both linear and nonlinear patterns in EEG signals. By segmenting EEG data into small (1)–10 samples), medium (20–100 samples), and large (200–1,000 samples) scales, it addresses the limitations of traditional classifiers. This approach enhances detection of emotional states in complex, high-dimensional data.
- Integration of Particle Swarm Optimization (PSO) for feature selection, with Robert's similarity as the fitness function, allows for the selection of relevant features and the removal of irrelevant and redundant ones, improving accuracy and reducing computational complexity.
- The proposed classifier achieves an accuracy of 98.75% with feature selection and 94.04% without feature selection in emotional state detection, demonstrating its potential for practical implementation in medical and other organizational contexts to detect emotional states, as shown in Fig. 1.

Evidently, several industrial organizations are working potentially to have real case scenario for EEG emotions detection. For example, Imec and Holst Centre has produced a new potential headset that can read and detect EEG emotions that can be used widely in the future by therapeutic, learning and gaming applications. Figure 2. Shows a real picture of the EEG headset emotion reader [13].

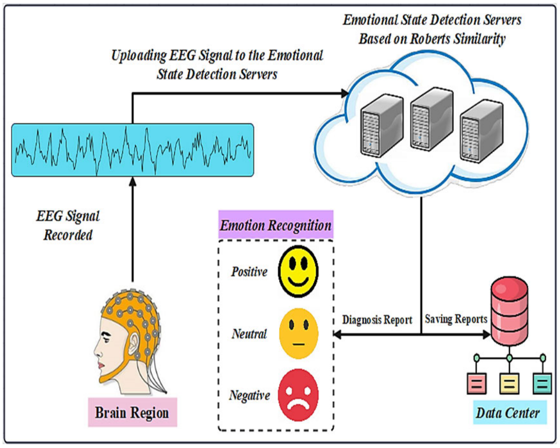

FIGURE 1. Emotional state detection based on EEG signals with the proposed classifier.

FIGURE 2. EEG emotion reading prototype produced by Imec and Holst Centre.

II. RELATED WORK

The recent works proposed on EEG-based emotion recognition have emphasized improving the classification performance and optimization of features using various classifiers in machine learning and deep learning. For instance, Chowdary et al. [14] proposed EEG-based emotion recognition using three models: Gated Recurrent Units (GRU), Long Short-Term Memory (LSTM), and Recurrent Neural Network (RNN). Feature selections of the proposed models were done utilizing statistical features. The models were evaluated on an EEG Brainwave dataset, yielding accuracies of 95%, 97%, and 96% for RNN, LSTM, and GRU, respectively. Even though the accuracy in the case of LSTM is higher, runtime and memory performance in the case of GRU are good. García-Hernández et al. [15] have utilized a genetic algorithm to reduce high-dimensional EEG data, selecting 49 optimal features from 2548. Their Artificial Neural Network (ANN) model achieved up to 95.87% accuracy, outperforming traditional methods. The reduced feature set makes real-time emotion detection feasible, with potential applications in portable devices and human-computer interaction systems.

Cardoso-Moreno et al. [16] have proposed a simple four-layer 1D Convolutional Neural Network (CNN) for emotion classification using EEG signals. The model achieved competitive accuracies of 98.36% and 95.31% on the EEG Brainwave Dataset. Although it performs slightly lower than complex ensemble models, its small size (5,000 parameters) and simplicity make it ideal for real-time applications in Brain-Computer Interface (BCI) systems. Rankhambe et al. [17] have proposed an optimized wavelet transform integrated with the flower pollination algorithm for artifact removal from EEG signals while preserving signal energy. This method, combined with a deep CNN, achieved a high accuracy of 99% in classifying four levels of anxiety. It works effectively to analyze the impacts of binaural beats on various types of brainwaves: delta, theta, alpha, beta, and gamma, demonstrating superior performance over traditional techniques such as KNN, SVM, and LDA.

The work of Rahman et al. [18] classified three basic emotions using machine learning models trained by EEG data. They used the chi-square as a feature selection method and sparsePCA for feature extraction. With sparsePCA, LGBM achieved the peak accuracy at 99.25%, while SVM excelled in detecting negative emotions. Alibrahim and Kurdi [19] have developed a hybrid machine learning model combining GRU and Attention Mechanisms to enhance emotion recognition using EEG data. Their Gated-Attention Neural Network (GANN) has achieved a 94% classification accuracy on the EEG Brainwave Dataset, surpassing previous methods. However, they have noted that further testing is needed to confirm its generalization on diverse datasets.

Nag et al. [20] have identified emotion detection by seven kinds of machine learning models from EEG signals. They have chosen an appropriate feature selection technique, the Iterative Dichotomiser 3 (ID3) algorithm. Among the classifiers, the best performing one is XGBoost, which gives a maximum accuracy of 99%, whereas the poorest performance is given by GNB, which has achieved an accuracy of 72%. Rini et al. [21] have presented a comparison in performance between CNN and Deep Neural Network (DNN) on EEG emotion classification after tuning their hyperparameters and using different splits, including 80:20, 70:30, and 60:40. Compared to DNN-98.18%, CNN achieved the best performance of 98.36%. Among the splits, the 80:20 split yielded the best performance. It shows that CNN is good for extracting the feature in space, while DNN may catch temporal patterns.

Bardak et al. [22] propose a hybrid algorithm that combines power spectral density for feature extraction with Adaptive Neuro-Fuzzy Inference System classifiers for EEG-based emotion recognition. The model recorded an accuracy of 95.97% for the Feeling Emotions dataset and 73.49% for the DEAP dataset, respectively. This showed its efficacy in classifying different emotional states. Reddy et al. [23] proposed a heuristic-aided transformer-based model for EEG emotion recognition. It therefore proposes a 5-level DWT for signal decomposition, feature extraction using LR, and optimal feature selection using Adaptive Bald Eagle Search Optimization (ABESO). The classifier used is that of the Optimized Block Recurrent Transformer (OBRT) classifier, tuned with ABESO, giving an accuracy of 96% with a precision of 94%. Table 1 provides a summary of recent studies on EEG-based emotion recognition, highlighting the various models, feature selection techniques, and classification accuracies achieved in each study.

TABLE 1. Summary of recent studies on EEG-based emotion recognition.

Ref.	Year	Feature selection technique	Classifier	Accuracy
[14]	2022	Statistical features	LSTM	97
[15]	2023	Genetic algorithms (GA)	ANN	95.87
[16]	2023	N/A	1D CNN	98.36
[17]	2023	Flower Pollination Algorithm	Deep CNN	99
[18]	2023	Chi-square	LGBM	99.25
[19]	2024	Attention mechanism	GANN	94.21
[20]	2024	ID3	LIME	99
[21]	2024	N/A	CNN	98.36
[22]	2024	Power spectral density	ANFIS	95.97
[23]	2024	ABESO	OBRT	96

III. METHODOLOGY

An overview of the proposed methodology is presented in Fig. 3 and consists of three main stages.

- The first stage preprocesses EEG signals using Min-max normalization in order to standardize all signals to consistency can be achieved and successive stages can be improved.
- Feature selection is the second stage, where the most relevant features are selected by PSO. The selected features are evaluated using the Roberts similarity score, with the goal of improving the classification accuracies while simultaneously reducing irrelevant features.
- Lastly, the dataset is split into 70% for training and 30% for testing. After that, the classifier categorizes the emotions into three classes: positive, neutral, and negative, then calculates the different evaluation metrics, showing the performance of the trained model. It includes accuracy, F1-score, precision, recall, and confusion matrix. This again goes back to feature selection in case of unsatisfactory results to improve the features for increasing accuracy. This is an iterative process for continuous optimization and adaptability of the model to do emotion detection with EEG signals effectively.

A. DATASET DESCRIPTION

This research utilizes the ''EEG Brainwave Dataset: Feeling Emotions'' obtained from Kaggle, as the primary dataset [23]. The dataset comprises EEG recordings from two subjects, one male and one female, collected using a Muse EEG head-

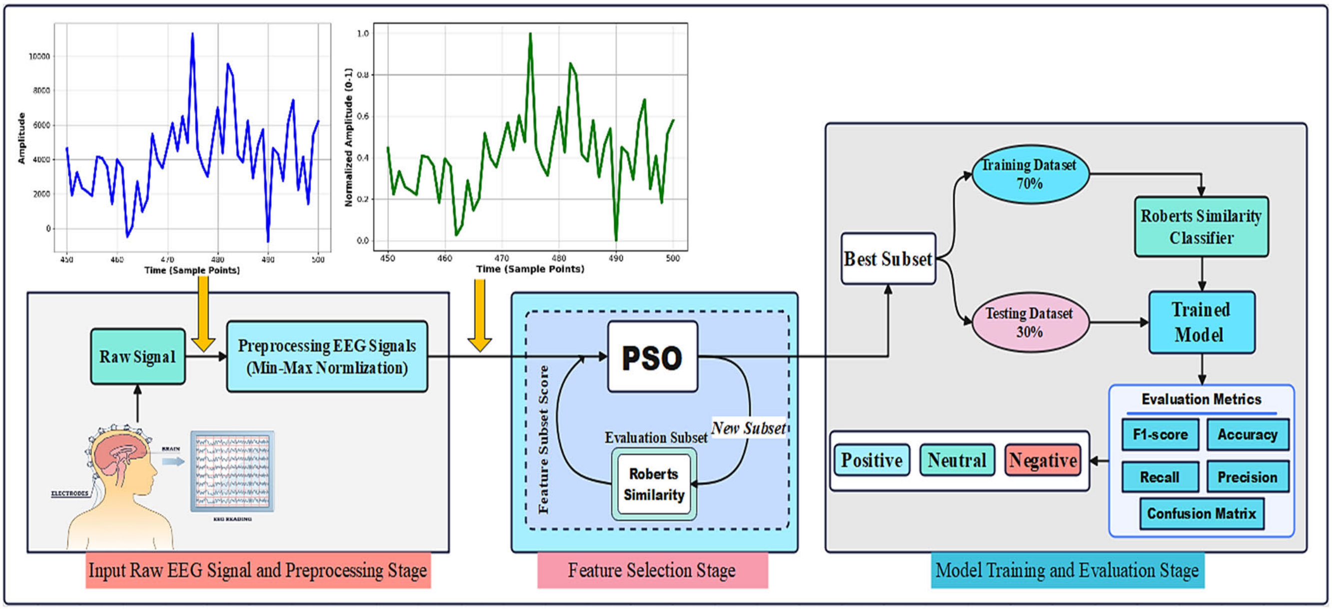

FIGURE 3. Workflow of the proposed methodology.

set. These recordings were captured while the participants were exposed to various emotional stimuli categorized into three classes: positive, negative, and neutral emotional states. Each emotional state was observed for a duration of three minutes, providing a total of 2132 samples, distributed as 708 for positive emotions, 708 for negative emotions, and 716 for neutral states.

Although the dataset is limited in subject diversity, its consistent structure and categorization across different emotional states offer a valuable opportunity to evaluate emotion recognition techniques. This dataset accessibility and standardization also allow for comparative studies with other models in emotion recognition research. Furthermore, the dataset is clean and does not contain any missing or null values, ensuring the quality and reliability of the data for analysis. Moreover, the dataset maintains an equal distribution of samples across emotional classes, preventing any class imbalance issues during model testing and training. Figure 3 illustrates the distribution of these emotional classes.

The dataset captures a diverse range of emotions by categorizing them into specific positive (happiness, surprise), negative (sadness, anger, fear), and neutral (baseline brain activity) states. EEG signals were recorded using four key electrode locations (TP9, AF7, AF8, TP10), strategically chosen for their ability to detect brainwave activity related to emotions. Emotional stimuli, including carefully selected movie clips, were used to evoke real-world emotional responses, while neutral state recordings provided a baseline for comparison. The raw EEG signals were resampled to 150Hz to ensure high temporal resolution, capturing a total of 324,000 data points across the emotional stimuli. This detailed structure makes the dataset valuable for emotion recognition studies. The dataset includes a total of 2,549 features extracted from the EEG signals, representing

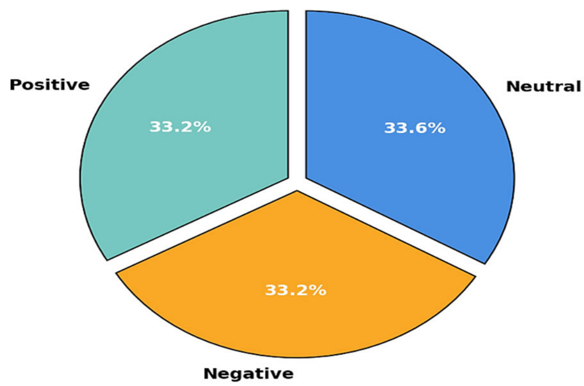

FIGURE 4. Class distribution of emotional states in the EEG brainwave dataset.

a comprehensive analysis of brainwave characteristics. The feature extraction process for the dataset was performed by the authors using a sliding window technique, analyzing the signal in overlapping segments. The window moved in increments of 1 second, starting at time $t = 0$ and $t = 0.5$, which allowed for the extraction of both time-domain and frequency-domain features, essential for capturing the dynamic changes in brain activity in response to emotional stimuli, providing a rich set of features for emotion recognition tasks. The information on the dataset is summarized in Table 2. Figure 4 visualizes the raw EEG signals for each emotional class, illustrating the differences in amplitude patterns across positive, negative, and neutral states.

B. PREPROCESSING DATASET

Preprocessing is a crucial step in preparing data for machine learning classifiers, as it helps to standardize the input, improve the model's performance, and ensure that all features

TABLE 2. Details of EEG brainwave dataset.

Attribute	Details
Dataset Name	EEG Brainwave Dataset: Feeling Emotions
Participants	2 individuals (1 male, 1 female)
Electrode Locations	TP9, AF7, AF8, TP10
Emotional Classes	Positive, Neutral, Negative
Recording Duration	3 minutes per emotional state
Class Distribution	Positive: 708 samples (happiness, joy) Negative: 708 samples (sadness, anger, fear) Neutral: 716 samples (baseline, no stimuli)
Total Samples	2132
Number of Features	2549 extracted EEG features
Sampling Rate	Resampled to 150 Hz

contribute equally to the learning process [25]. Inconsistent scaling or variations in data can hinder the model's ability to learn effectively, potentially leading to suboptimal performance and reduced accuracy. In this work, the main preprocessing technique is represented by the Min-Max normalization of the EEG signal range between 0 and 1. Min-Max normalization is defined by the following Eq. (1).

$$S_{norm} = \frac{S - S_{min}}{S_{max} - S_{min}} \tag{1}$$

In this equation, S is the original value, represents the original value, while S_{min} and S_{max} are the minimum and maximum values in the dataset, respectively. The normalized value is denoted by S_{norm}. Normalization is a crucial preprocessing step that ensures all features are placed within the same range, enhancing the classifier's performance by accelerating convergence and reducing computational demands. However, a key challenge lies in selecting the appropriate range for transformation, as this choice can significantly impact the model's outcomes. Min-Max normalization addresses this by scaling the original amplitude values of the signal to a defined range, ensuring uniformity across features. This highlights the importance of meticulous preprocessing to optimize the classifier's performance and achieve accurate results.

C. FEATURE SELECTION BASED ON PSO FOR EMOTION RECOGNITION

Feature selection is a critical step in building efficient and effective emotion recognition models, as it directly influences both the accuracy and computational efficiency of the system. The primary objective of feature selection is to identify the most relevant subset of features from the overall feature set, which not only improves model performance but also reduces overfitting and computational costs [26].

In this paper, PSO is employed for feature selection. PSO is a population-based optimization algorithm inspired by the social behavior of birds flocking or fish schooling. The algorithm models potential solutions as "particles" in a search space, which collectively explore and converge on optimal or near-optimal solutions over successive iterations. Each particle adjusts its position based on its own experience (personal best) and the swarm's collective experience (global best), making PSO particularly suitable for solving high-dimensional problems such as emotion recognition, where the feature space is complex and large.

In PSO, each particle represents a potential solution encoded as a vector in a D-dimensional search space. The position of the i-th particle is represented as a vector $L_i = [L_1, L_2, L_3, L_4, \ldots\ldots, L_D]$, where each dimension corresponds to a specific feature. The movement of each particle is governed by its velocity vector $C_i = [C_1, C_2, C_3, C_4, \ldots\ldots, C_D]$, which determines the direction and magnitude of the particle's movement. Two essential components influence this movement: the personal best "pbest", which is the best solution the particle has found so far, and the global best "gbest", which is the best solution found by the entire swarm [27]. The velocity and position of each particle are updated iteratively based on the following equations:

$$C_i(t+1) = wC_i(t) + M1R1(pbest - L_i(t)) + M2R2(gbest - L_i(t)) \tag{2}$$

$$L_i(t+1) = L_i(t) + C_i(t) \tag{3}$$

where, t represents the current iteration step, while w represents the inertia weight, which balances exploration (searching new areas) and exploitation (refining known good solutions). The value of w is typically set between 0.1 and 1. The constants M_1 and M_2 control the particle's attraction to its personal best and the global best positions, respectively, while the random factors R_1 and R_2 (values between 0 and 1) introduce randomness into the movement, helping the swarm to avoid getting trapped in local optima. Over successive iterations, particles adjust their velocities and positions based on these factors, enabling the swarm to converge towards the optimal or near-optimal solution for the given problem (selection of effective features in high-dimensional datasets).

The application of PSO in this study focuses on feature selection for EEG-based emotion recognition. The key steps are as follows:

- **Feature space representation:** The search space consists of all possible subsets of available features, represented as binary vectors. Each particle's position encodes whether a feature is selected (1) or not (0). For instance, a particle position vector $L_i = [0, 1, 1, 0, 0, \ldots.., 1]$ indicates the selected features. This representation allows PSO to explore various feature combinations systematically.
- **Selecting effective features by PSO:** For EEG-based emotion recognition, features are derived from specific frequency sub-bands (Alpha, Beta, Gamma, Theta, Delta) associated with different emotional states: Positive (happiness, joy), Neutral (baseline states), and Negative (sadness, anger). Alpha, Beta, Gamma, Theta, and Delta all have distinct roles in emotion recogni-

tion [28]. PSO emphasizes features from sub-bands like Theta, Alpha, and Gamma, which are more relevant for emotion classification. Less relevant bands, such as Delta, are typically excluded, leading to improved classification accuracy and reduced feature redundancy.

- **Feature encoding:** Binary encoding simplifies the selection process, where a "1" signifies inclusion, and a "0" signifies exclusion of a feature. For example, $L_i = [0, 1, 1, 0, 0, 1]$ represents a subset of features. This encoding method enables efficient evaluation and optimization of feature subsets during the PSO process.
- **Feature subset evaluation:** A novel fitness function based on the Roberts similarity measure is used in the PSO framework to evaluate feature subsets. It quantifies the subset's effectiveness in improving classification accuracy while minimizing redundancy by emphasizing the correlation between selected features and target classes. This integration enables PSO algorithm to converge on optimal feature subsets, enhancing emotion recognition performance. Figure 6 illustrates the integration of Roberts similarity into the PSO process.

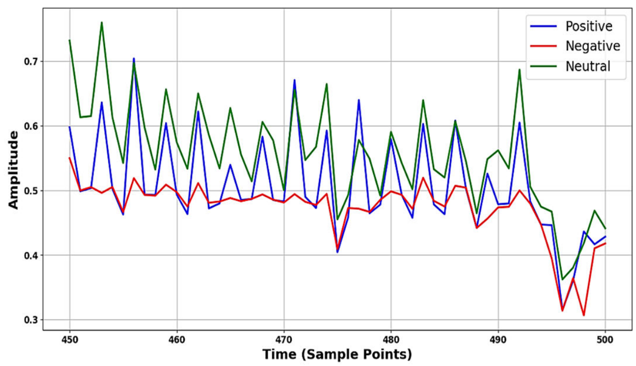

FIGURE 5. Comparison of EEG signal patterns across positive, negative, and neutral emotional states.

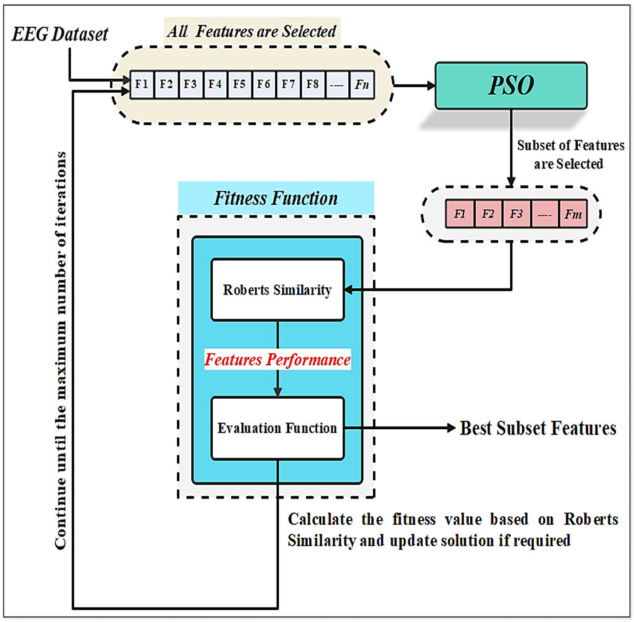

FIGURE 6. Roberts-PSO.

D. ROBERTS SIMILARITY

This paper introduces a novel classifier based on the Roberts similarity measure for emotion recognition using EEG signals.

The choice of Roberts similarity over other traditional similarity measures is due to its unique ability to compute the matching between two objects using a mathematical approach that involves the ratio of the minimum value of the first object to the maximum of the second object, multiplied by the sum of both vectors. This proportionality offers a distinctive method of measuring similarity, which has not been previously explored or applied to emotion recognition from EEG data.

Unlike other similarity measures, Roberts similarity provides a nuanced view of the overlap between feature vectors by scaling the minimum value against the maximum and incorporating both vectors in the calculation. This allows for a more precise comparison of signal patterns, particularly in high-dimensional EEG data. As a result, it is especially effective in distinguishing fine-grained patterns associated with different emotional states. The similarity value ranges from 0 to 1, with a score of 1 indicating a high degree of similarity and a score closer to 0 reflecting dissimilarity [29].

To enhance its applicability to real-world conditions and different datasets, the proposed classifier integrates a segmentation process as a key solution. The EEG signals are divided into smaller units, referred to as blocks, for more granular analysis. This segmentation strategy enables the classifier to capture localized patterns within the signals, improving its adaptability across varying technical conditions and dataset characteristics. By breaking down the EEG signal into small pieces, the classifier ensures highly accurate matching, thereby increasing robustness and generalizability. The proposed classifier is described as follows:

- **Signal segmentation:** Divide each EEG signal $\boldsymbol{Y}$ (from either the training or testing data and contains a total of $\boldsymbol{S}$ features) into non-overlapping blocks of size $\boldsymbol{q}$. This segmentation helps in breaking down the signal into smaller segments, allowing for a more detailed comparison. Mathematically, the segmentation is defined by the following Eq. (4).

$$\textbf{\textit{Blocks of EEG Signal}}\,(\boldsymbol{Y}, \boldsymbol{q}) = \left\{ y\,[i : i+q] \mid i = 0, b, 2q, \ldots.., \left(\left\lceil \frac{s}{q} \right\rceil - 1 \right) \times q \right\} \quad (4)$$

- **Roberts similarity calculation:** The Roberts similarity between corresponding blocks from the testing and training signals is calculated to assess their degree of overlap. Specifically, for each pair of blocks, denoted as $\boldsymbol{b_A}$ from the testing signal $\boldsymbol{A}$ and $\boldsymbol{b_B}$ from the training signal $\boldsymbol{B}$, the similarity score is computed using the Eq. (5).

$$\boldsymbol{Roberts\ Similarity}(\boldsymbol{b_A},\boldsymbol{b_B}) = \frac{\sum_{i=1}^{r}(a_i, b_i)\frac{min(a_i,b_i)}{max(a_i,b_i)}}{\sum_{i=1}^{r}(a_i, b_i)} \tag{5}$$

In this equation, $\boldsymbol{a_i}$ and $\boldsymbol{b_i}$ represent the $\boldsymbol{i}$-th feature values in the respective blocks $\boldsymbol{b_A}$ and $\boldsymbol{b_B}$, and r is the total number of features within each block.

- **Block labeling:** Once the similarity scores are calculated for each block in the testing signal relative to the corresponding blocks in all training signals, the label of the most similar training block is assigned to the test block. For a given test signal $\boldsymbol{A}$, this process results in a set of predicted labels for each block, denoted as $Label(\boldsymbol{b_1}), Label(\boldsymbol{b_2}), \ldots\ldots, Label(\boldsymbol{b_Z})$, where $\boldsymbol{Z}$ is the total number of blocks in the test signal. To determine the final classification for the entire EEG signal, a majority voting strategy is applied to the block labels. The final label is then calculated using Eq. (6).

$$\boldsymbol{Label_{signal}}(\boldsymbol{A}) = Majority(Label(b_1), Label(b_2), \ldots\ldots, Label(b_z)) \tag{6}$$

This majority rule ensures that the overall classification decision is based on the most dominant emotional pattern identified across the signal's segments. By relying on the majority of block labels, the classifier can effectively reduce the impact of any noisy or misclassified blocks, leading to a more reliable and consistent final classification result. As illustrated in Figure 7, the proposed method involves dividing EEG signals into blocks, computing Robert's similarity for each block, and using majority voting to determine the final emotion class for the entire EEG signal. This systematic approach effectively captures and classifies emotional patterns with high precision.

E. PERFORMANCE METRIC

Evaluating the performance of the emotion classification models requires using several key metrics: confusion matrix, precision, accuracy, recall, and F1-score. Each of these metrics offers unique insights into the model's ability to distinguish between positive, negative, and neutral emotions. Below is an explanation of each metric in the context of emotion classification, along with its corresponding mathematical formula.

- The confusion matrix visually presents the classification results by comparing the true labels to the predicted labels for each emotion class. As shown in Fig. 8, for a three-class emotion problem, it is structured as follows:
- Accuracy is a general indicator of the model's overall performance and calculates the proportion of correct predictions across all emotion classes. It measures how well the model distinguishes between positive, negative, and neutral emotions overall. The formula for accuracy is represented by Eq. (7).

$$\boldsymbol{Accuracy} = \frac{\text{True Neutrals} + \text{True Negatives} + \text{True Positives}}{\text{Total Number of Predictions}} \tag{7}$$

- Precision measures the proportion of correct predictions for a specific emotion class out of all predictions made for that class. For instance, precision for positive emotions indicates how often the model is correct when it predicts a positive emotion. High precision means fewer false positives for that emotion. The formula for precision is represented by Eq. (8).

$$\boldsymbol{Recall} = \frac{\text{True Positives}}{\text{False Negatives} + \text{True Positives}} \tag{8}$$

- Recall evaluates the model's ability to detect all true positive instances of an emotion. It reflects how well the model captures positive emotions and is crucial when it is important not to miss any positive cases, such as when a particular emotional state needs to be identified with high sensitivity, as shows in Eq. (9).

$$\boldsymbol{Precision} = \frac{\text{True Positives}}{\text{False Positives} + \text{True Positives}} \tag{9}$$

- The F1-score merges precision and recall into a unified metric, offering a balanced assessment. It is particularly useful when there is an uneven distribution of emotions, ensuring that the model performs well across both precision and recall, without favoring one over the other, as shows in Eq. (10).

$$\boldsymbol{F1 - score} = 2 \times \frac{Recall \times Precision}{Precision + Recall} \tag{10}$$

TABLE 3. System configuration and development environment specifications.

Components	Details
Software Language	Python
IDE	VSC
Operating system	Windows 10 Pro
Graphics Card	8 GB
Processor	Core i7 Gen6
Memory	16 GB

IV. EXPERIMENTS AND EVALUATION

The conducted experiments took place on a system running Windows 10 Pro, with the specifics of the hardware setup summarized in Table 3. The primary programming language used was Python, and the development and execution of the code were done through Visual Studio Code (VSC), an Integrated Development Environment (IDE).

The upcoming sections focus on evaluating the performance of widely used classifiers such as KNN, SVM, DT, LR, and RF, along with a newly introduced classifier that

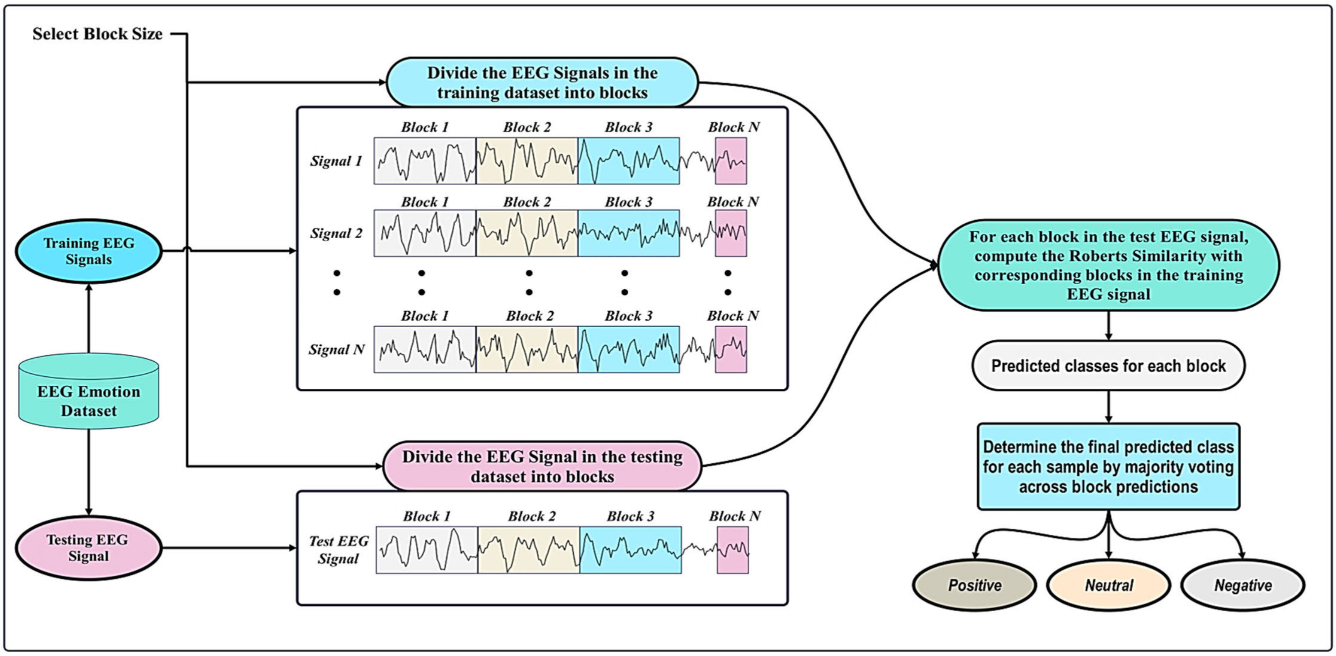

FIGURE 7. Workflow of the proposed classifier based on the Roberts similarity.

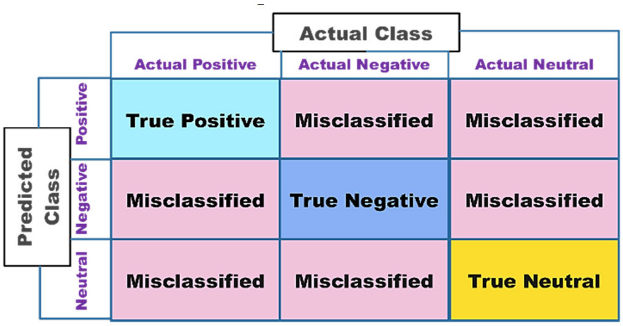

FIGURE 8. Confusion matrix for a three-class emotion.

TABLE 4. Performance of standard classifiers and proposed classifier without feature selection (PSO).

Classifier	Recall	Precision	F1-Score	Accuracy
KNN	88.28	88.57	88.24	88.28
SVM	91.39	91.66	91.32	91.41
LR	90.32	90.66	90.20	90.31
DT	89.04	89.36	89.10	89.06
RF	93.91	94.07	93.89	93.91
Proposed classifier (Robert's similarity)	94.05	94.23	94.14	94.04

leverages Robert's similarity. The evaluation is based on five key metrics: confusion matrix, recall, precision, F1 score, and accuracy. We conducted the analysis under two scenarios: initially without applying PSO for feature selection and where PSO was employed to select optimal or relevant features from a high dimension dataset.

A. CLASSIFIERS PERFORMANCE WITHOUT PSO FEATURE SELECTION

This section evaluates the performance of various classifiers, including the proposed Roberts similarity-based classifier, DT, SVM, LR, KNN, and RF, in classifying EEG signals for emotion recognition. The classifiers were tested without applying PSO for feature selection, and their performance was measured through accuracy, recall, precision, and F1-score, supported by confusion matrix analysis for the positive, negative, and neutral classes. The performance of classifiers was summarized in Table 4. KNN achieved an accuracy of 88.28% but experienced noticeable misclassifications. DT performed slightly better, reaching 89.06% accuracy, while LR showed more consistency with an accuracy of 90.31%. SVM outperformed these classifiers, reaching an accuracy of 91.41%. RF provided a substantial improvement, achieving 93.91% accuracy. However, the proposed classifier based on Robert's similarity reached the highest accuracy at 94.04%, demonstrating its superior ability to classify EEG signals without feature selection.

The confusion matrix results provided further insights into classifier performance across the positive, negative, and neutral emotional states, as illustrated in Fig 9. KNN correctly classified 173 positive cases, 206 negative cases, and 186 neutral cases, but misclassified 39 positive cases, 7 negative cases, and 29 neutral cases, resulting in a total of 75 errors. KNN struggled to distinguish positive emotions from other classes. RF exhibited stronger performance, correctly classified 189 positive cases, 209 negative cases, and 203 neutral cases, but still misclassified 24 instances for the positive class, 3 for the negative class, and 12 for the neutral class, resulting in a total of 39 errors. RF demonstrated robustness across all categories and minimized errors compared to other classifiers.

SVM accurately predicted 176 positive cases, 211 negative cases, and 198 neutral cases but encountered 36 errors for the positive class, 2 for the negative class, and 17 for the neutral class, totaling 55 errors. LR correctly classified 170 positive cases, 209 negative cases, and 199 neutral cases, but recorded 43 errors for the positive class, 3 for the negative class, and 16 for the neutral class, resulting in 62 total errors. LR exhibited the highest error rate for positive emotions, indicating challenges in distinguishing them from other categories. DT correctly classified 186 positive cases, 181 negative cases, and 203 neutral cases, but misclassified 26 positive cases, 32 negative cases, and 12 neutral cases, which resulted in 70 errors overall. The large number of errors in the negative class suggested that DT had difficulty distinguishing negative emotions from other categories.

In response to these challenges, our proposed approach incorporates the Roberts similarity measure to more effectively capture both linear and nonlinear patterns in EEG signals for emotion state detection. By dividing EEG signals into blocks for granular analysis, the proposed classifier captures both global and localized patterns those other standard classifiers often fail to identify. This measure enhances the identification of intricate and minute characteristics in physiological data, enabling more accurate and reliable emotion detection. Without using any feature selection techniques, the proposed classifier outperformed all standard classifiers, correctly classifying 202 positive cases, 211 negative cases, and 187 neutral cases. It registered just 11 positive, 1 negative, and 26 neutral misclassifications, leading to a total of 38 errors. The superior performance of the proposed approach, particularly in recognizing positive emotions, highlights its effectiveness in capturing subtle differences in EEG patterns associated with emotions while handling both linear and nonlinear features directly from raw data.

B. CLASSIFIERS PERFORMANCE WITH PSO FEATURE SELECTION

In this section, PSO feature selection was applied to select an optimal subset from the EEG emotion dataset. PSO reduced computational load and processing time, while also enhancing accuracy by selecting the most relevant features.

Table 5 shows the improvements achieved by PSO, highlighting the accuracy, precision, recall, and F1-scores of each classifier with the feature selection process applied.

The results in Table 5 highlight a marked improvement in classifier performance with the use of PSO for feature selection. KNN achieved a markedly higher accuracy of 96.56%, reflecting the impact of PSO in refining feature selection. SVM reached an accuracy of 93.28%, maintaining strong precision with the optimized feature set. LR improved to 95.31% accuracy, displaying greater consistency with PSO. DT reached 97.03% accuracy, indicating a substantial enhancement over results without feature selection. RF demonstrated the highest accuracy among standard classifiers, reaching 98.12% and confirming the benefits of reduced feature dimensionality. The proposed classifier using Robert's similarity outperformed all others, achieving an accuracy of 98.75%, indicating the effectiveness of PSO in optimizing feature selection for superior classification.

TABLE 5. Performance of standard classifiers and proposed classifier with feature selection (PSO).

Classifier	Recall	Precision	F1-Score	Accuracy
KNN	96.56	95.59	96.57	96.56
SVM	93.28	93.70	93.49	93.28
LR	95.31	95.39	95.35	95.31
DT	97.02	97.04	97.03	97.03
RF	98.12	98.14	98.13	98.12
Proposed classifier (Robert's similarity)	98.75	98.76	98.75	98.75

The confusion matrix results in Fig. 10 provide additional insights into how each classifier's performance improved with PSO, compared to the results without PSO. KNN, with PSO, correctly classified 200 positive cases, 208 negative cases, and 210 neutral cases, resulting in a total of 22 errors (13 positive, 4 negatives, 5 neutral). Without PSO, KNN had 75 errors, indicating that PSO reduced misclassifications.

The most notable improvement was observed in the positive class, where errors decreased from 39 to 13, showcasing better precision in identifying positive emotions. SVM, after PSO, accurately identified 181 positive cases, 211 negative cases, and 205 neutral cases, resulting in 43 errors (32 positive, 1 negative, 10 neutral). Previously, SVM had 55 errors without PSO, reflecting a moderate reduction. The greatest improvement was seen in the neutral class, where errors decreased from 17 to 10, indicating enhanced differentiation with the optimized feature set.

LR showed substantial improvements with PSO, correctly classifying 193 positive cases, 206 negative cases, and 211 neutral cases, reducing errors to 30 (20 positive, 6 negatives, 4 neutral). This marks a significant reduction from the 62 errors recorded without PSO, amounting to a 28-error decrease. Improvements were particularly notable in the positive class, where misclassifications dropped from 43 to 20, and in the neutral class, where errors reduced from 16 to 4. DT, with PSO, correctly classified 206 positive cases, 203 negative cases, and 212 neutral cases, resulting in 19 errors (7 positive, 9 negatives, 3 neutral). Compared to its previous 70 errors without PSO, DT performance significantly improved, particularly in the negative class, where errors dropped from 32 to 9.

This reduction highlights DT enhanced accuracy with feature selection, especially for distinguishing negative emotions. RF demonstrated significant improvement with PSO, reducing errors to just 12 (9 positive, 3 negatives, 0 neutral) compared to the 39 errors recorded without PSO. The most notable enhancement was observed in the neutral class, where misclassifications dropped from 12 to zero, highlighting RF

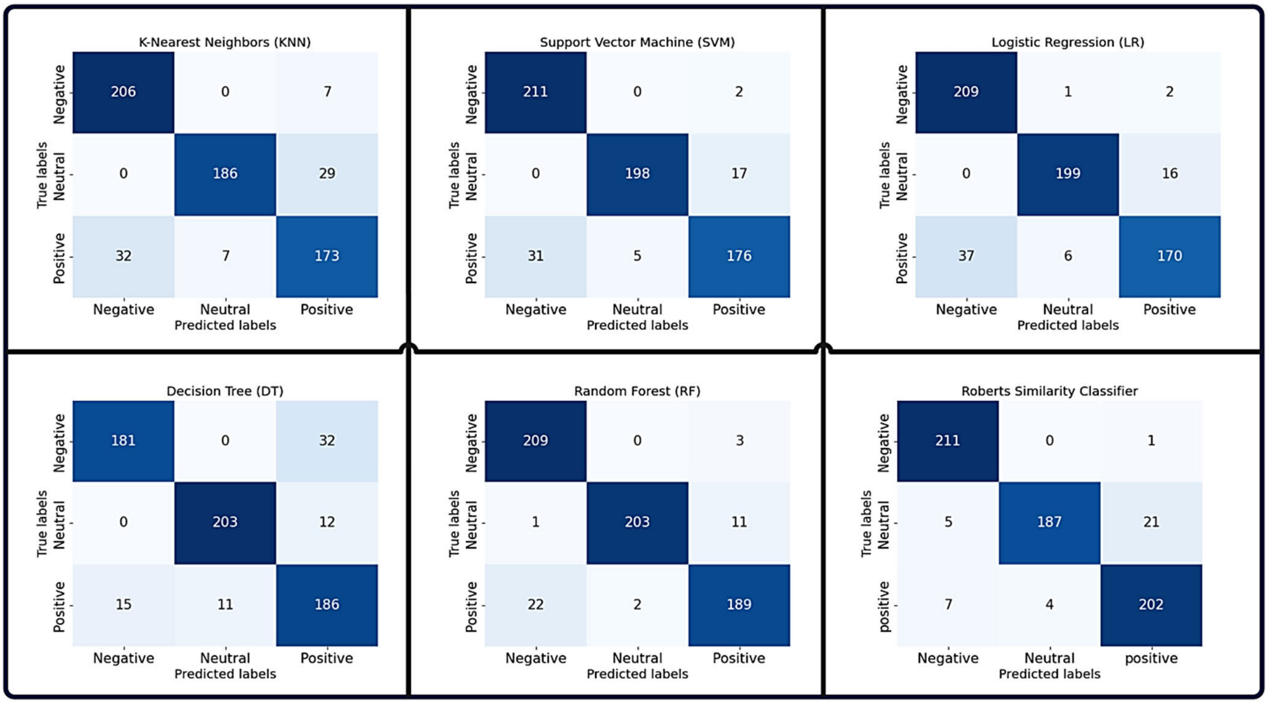

FIGURE 9. **Confusion matrix of the standard machine learning classifier and proposed classifier without using PSO feature selection.**

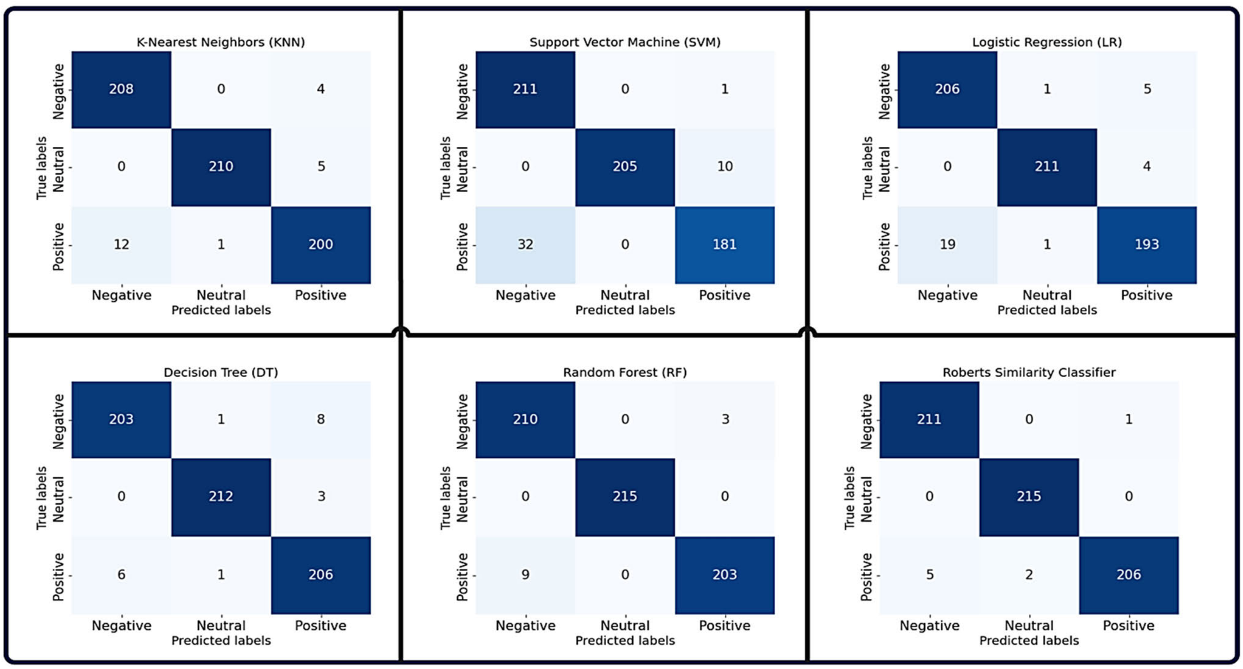

FIGURE 10. **Confusion matrix of the standard machine learning classifier and proposed classifier with PSO feature selection.**

enhanced robustness and precision in identifying neutral emotions with the optimized feature subset.

The proposed classifier based on Robert's similarity demonstrated exceptional capability in capturing both linear and nonlinear relationships between features, particularly after feature selection with PSO. By leveraging PSO, the classifier emphasized features from critical EEG sub-bands such as Theta, Alpha, and Gamma, which are known to be more relevant for emotion classification. This targeted feature selection enhanced the classifier's ability to identify intricate patterns within the EEG signals that correlate with emotional states. With PSO refining the feature set, the proposed classifier achieved a total of just 8 errors (7 positive and 1 negative), compared to 38 errors without feature selection. Errors in the positive class decreased from 11 to 7, while errors in the neutral class dropped from 26 to 0, reflecting

TABLE 6. Proposed classifier performance without PSO feature selection based on EEG signal segment sizes (small, medium, large.)

Small segment with varying block size	2	3	4	5	6	7	8	9	10
Accuracy (%)	88.43	89.34	91.21	90.49	91.89	92.22	93.77	89.89	90.56
Medium segment with varying block size	20	30	40	50	60	70	80	**90**	100
Accuracy (%)	93.88	92.56	88.34	87.44	89.89	90.11	93.91	**94.04**	92.78
Large segment with varying block size	200	300	400	500	600	700	800	900	1000
Accuracy (%)	88.01	89.92	92.39	92.87	93.03	93.69	91.19	90.98	93.31

TABLE 7. Proposed classifier performance with PSO feature selection based on EEG signal segment sizes (small, medium, large).

Small segment with varying block size	2	3	4	5	6	7	8	9	10
Accuracy (%)	96.94	97.20	97.88	97.78	97.82	97.43	97.09	97.76	98.50
Medium segment with varying block size	20	30	40	50	60	70	80	**90**	100
Accuracy (%)	95.21	98.37	95.09	98.09	97.66	97.91	97.51	**98.75**	97.28
Large segment with varying block size	200	300	400	500	600	700	800	900	1000
Accuracy (%)	97.63	98.12	98.21	97.61	98.38	97.45	97.90	98.61	98.30

significant improvements in precision and robustness. These results highlight the classifier's ability to effectively utilize features from the most relevant sub-bands, enabling it to accurately differentiate emotional states by capturing subtle and complex EEG signal variations. This demonstrates the proposed classifier's superior performance in recognizing emotional patterns in EEG data.

C. ANALYSIS PERFORMANCE OF THE PROPOSED CLASSIFIER WITH VARIOUS BLOCK SIZE

This section evaluates the accuracy of the proposed classifier with Robert's similarity across different block sizes and scales, both with and without PSO.

Three block size scales were used: small (1 to 10 samples), medium (20 to 100 samples), and large (200 to 1,000 samples). Results were analyzed across two scenarios, with and without PSO, revealing the effects of feature selection on classification accuracy. The evaluation was conducted in two scenarios: one without PSO, where the classifier utilized the entire feature set, and another with PSO, where feature selection emphasized the most relevant features with varying block and segment size.

In Table 6, which presents accuracy without PSO feature selection, the small-scale block sizes from 1 to 10 samples per block showed a pattern of increasing accuracy as block size grew. Accuracy started at 88.43% with a block size of 2, reaching a peak of 93.77% at a block size of 8. However, a slight decrease in accuracy occurred at block sizes 9 and 10, indicating an optimal small block size near 8. Moving to the medium scale, accuracy fluctuated more prominently. Beginning at 93.88% for a block size of 20, accuracy then declined at intermediate sizes, falling to 88.34% at 40 and 87.44% at 50, before achieving a peak of 94.04% at a block size of 90.

This indicates that larger medium block sizes can enhance accuracy. For large-scale blocks ranging from 200 to 1,000 samples per block, accuracy remained stable, starting at 88.01% for a block size of 200 and peaking at 93.69% for a block size of 700. Although medium block sizes maintained consistent accuracy, the lack of feature selection in this scenario likely limited the classifier's ability to capture nuanced patterns, as evidenced by the minimal improvement in accuracy across scales. This indicates that without PSO, the classifier's capacity to generalize patterns in EEG data is restricted.

Table 7, showing accuracy with PSO feature selection, demonstrated consistent improvements across all scales. For the small scale, accuracy rose steadily with PSO, beginning at 96.94% for a block size of 2 and reaching 98.50% at 10 samples per block. Unlike the non-PSO scenario, there was no drop in accuracy at larger block sizes, indicating greater stability across the small scale. In the medium scale, accuracy with PSO remained high and consistent, starting at 95.21% for a block size of 20 and peaking at 98.75% at a block size of 90. Most block sizes in this range achieved above 95% accuracy, emphasizing PSO effectiveness in minimizing accuracy fluctuations within medium blocks. For the large-scale blocks, PSO produced notable accuracy improvements, keeping accuracy consistently above 97% across all block sizes. Accuracy began at 97.63% for a block size of 200 and peaked at 98.61% at 900. This consistent high performance with PSO suggests that feature selection optimizes the classifier's focus on the most relevant patterns, making it particularly efficient at distinguishing emotional states across varying sample sizes.

The proposed classifier effectively segmented EEG signals into various block sizes, allowing for a more granular analysis of the inherent similarities crucial for recognizing distinct emotional states. By structuring the signals into specific blocks, the classifier, utilizing the Roberts similarity measure, successfully captured both linear and nonlinear patterns within the EEG data.

When PSO was applied for feature selection, the classifier's performance further improved across all block sizes, significantly reducing accuracy fluctuations, particularly at medium and larger block scales. PSO emphasized the most relevant features, such as those from critical sub-bands like Theta, Alpha, and Gamma, ensuring consistently high accuracy across small, medium, and large block sizes. This integration of signal segmentation, PSO feature selection, and the Roberts similarity measure proved exceptionally advantageous for larger block sizes, where the proposed classifier achieved its highest accuracy, highlighting its robustness and precision in emotion recognition. Figure 11 illustrates the

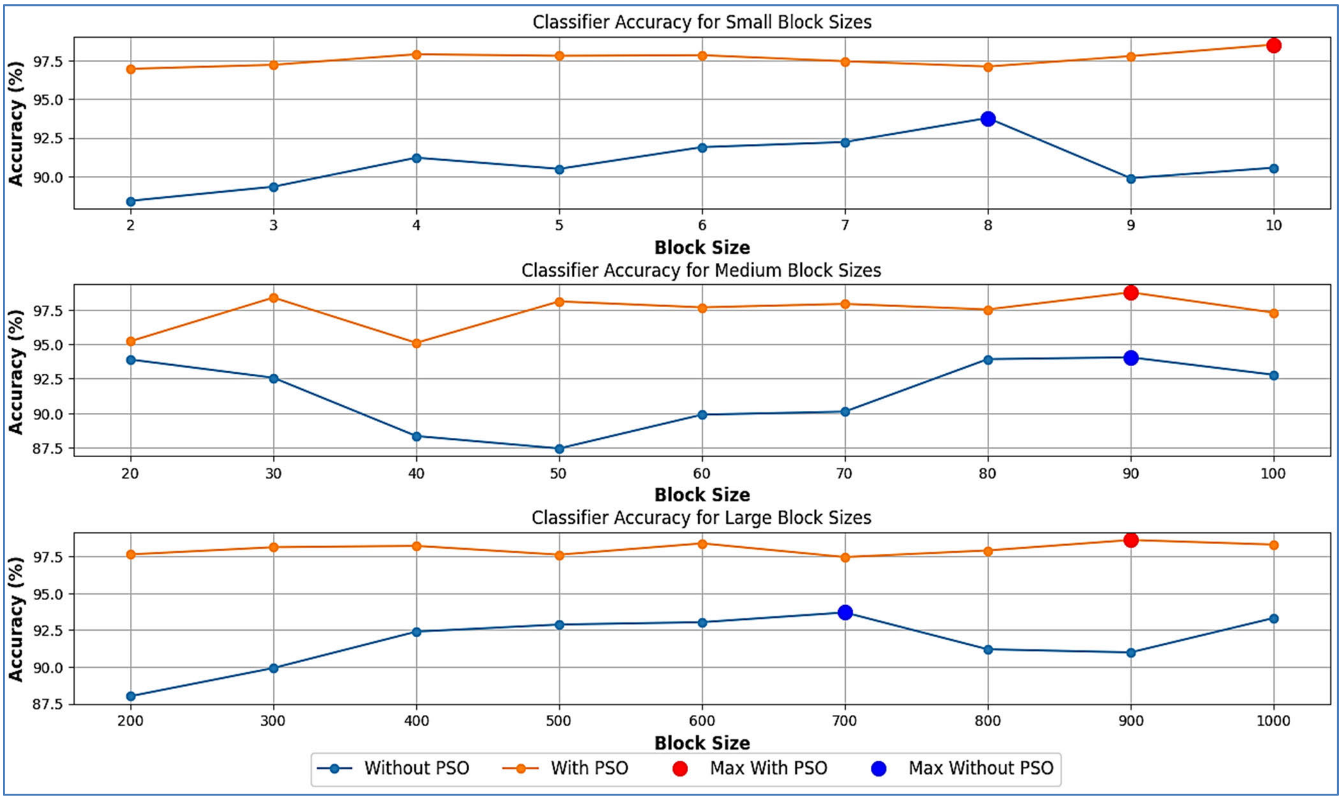

FIGURE 11. Accuracy of the proposed classifier across different scales and block sizes with/without PSO.

accuracy achieved by the proposed Roberts similarity classifier across various scales and block sizes, comparing results with and without PSO.

D. COMPARING WITH RECENT STUDIES

Recent studies in EEG signal classification for emotion detection have explored various optimization and classification methods.

Techniques such as GA with ANN, ABESO with OBRT, and Principal Component Analysis (PCA) with LSTM have achieved accuracies ranging from 95.87% to 97%. Additionally, the Aquila Fireworks Optimization Algorithm (AFOA) with a Block Recurrent Transformer Network achieved 96.65%, while Opposition-based Food Foraging-Pelican Optimizer (O-FFPO) with Radian Basis-Recurrent Neural Networks (RB-RNN) recorded 93%. More recently, PCA combined with Recurrent Neural Networks (RNN) achieved 96%, and PCA with SVM reached 98.42%. Moreover, CatBoost with Least Absolute Shrinkage and Selection Operator (LASSO) regression recorded 95.40%.

While these approaches represent significant progress in EEG-based emotion detection, the proposed method in this study surpasses prior methods. By employing PSO for feature selection and leveraging the novel Roberts similarity classifier, the proposed achieved an outstanding accuracy of 98.75%, surpassing previous models. This is the highest reported accuracy among the compared models, as summarized in Table 8. Compared to existing models, the proposed method offers three key advantages. First, it achieves the highest reported accuracy of 98.75%, surpassing prior methods that ranged from 93% to 98.42%, demonstrating superior robustness in EEG-based emotion detection. Second, the model optimizes feature selection using PSO, reducing computational complexity by eliminating redundant features and selecting only the most relevant ones. Third, the Roberts

TABLE 8. Comparison between the approach in this study and related works.

Study and year	Feature selection	Classifier	Accuracy
García-Hernández et al. (2023) [15]	GA	ANN	95.87
Reddy et al. (2024) [23]	ABESO	OBRT	96
M. Priyadarshani et al. [30] (2024)	PCA	LSTM	97
Reddy et al. [31] (2024)	AFOA	Block Recurrent Transformer Network and Hybrid Variational Autoencoder	96.65
Sageengrana et al. [32] (2024)	O-FFPO	RB-RNN	93
Reddy et al. [33] (2024)	PCA	RNN	96
Pichandi et al. [34] (2024)	PCA	SVM	98.42
Prakash and Poulose. [35] (2025)	LASSO	CatBoost	95.40
Proposed	**PSO**	**Robert similarity**	**98.75**

similarity measure enhances pattern recognition and generalization by effectively distinguishing subtle variations in EEG signals, making it more reliable for fine-grained emotion classification. To further improve real-world applicability, the classifier integrates a segmentation process that divides EEG signals into smaller blocks for localized pattern analysis. This segmentation strategy enhances adaptability across different datasets and technical conditions, ensuring highly accurate matching, increased robustness, and greater generalizability.

E. LIMITATIONS OF THE STUDY

Despite the promising results of the proposed approach, there are a few limitations to consider:

- **Sensitivity to noise:** The classifier's accuracy may be affected by noise and missing values in the dataset. Since EEG signals are prone to artifacts, disruptions in segmentation and block sizes could impact reliability. Future work could explore advanced denoising techniques to mitigate this issue.
- **Scalability concerns:** The current dataset, consisting of three classes, achieved high accuracy with the chosen segmentation block size of 90. However, when applied to datasets with additional classes or different signal characteristics, the optimal block size may vary. Other classes in the dataset may require different block sizes to maintain high accuracy. Future studies should explore how the segmentation strategy can be adapted to handle varying block sizes for different classes, ensuring scalability and robustness across diverse datasets.
- **Preprocessing constraints:** This study utilizes Min-Max normalization as the sole preprocessing technique. Alternative methods, such as z-score normalization, max-absolute scaling, or other scaling techniques, were not investigated. Exploring these methods could reveal additional ways to optimize classifier performance.
- **Feature selection optimization:** The study employs a wrapper-based feature selection method using PSO. While effective, hybrid methods that combine filter and wrapper techniques could be explored to identify a more optimal subset of features, potentially enhancing the performance and efficiency of the proposed classifier.

V. CONCLUSION

This study introduced a novel classifier for EEG-based emotion detection, using the Robert's similarity measure to capture both linear and nonlinear patterns within EEG signals. The classifier segments EEG data into different block sizes, specifically small (1 to 10 samples per block), medium (20 to 100 samples per block), and large (200 to 1,000 samples per block) scales, applying PSO for feature selection to refine the feature set. This structured approach enhances the classifier's ability to identify essential patterns for precise classification across varying scales. The proposed method achieved a high classification accuracy of 98.75%, surpassing recent models such as ANN, LSTM, and RB RNN, along with traditional machine learning classifiers such as KNN, SVM, DT, LR, and RF, which typically achieve accuracies between 93% and 98.12%. These results underscore the effectiveness of the proposed classifier in EEG emotion detection, establishing a new benchmark compared to prior approaches. However, has some limitations. While smaller block sizes increase the precision of feature capture, they require more processing time than larger blocks, which may affect scalability in time-sensitive applications. Future research could explore advanced hybrid feature selection techniques that combine filter methods with optimization algorithms such as the Salp Swarm Algorithm (SSA), Harris Hawk Optimization (HHO), and Bat Algorithm (BA) to further enhance classification accuracy and computational efficiency. These improvements could allow the proposed classifier to operate more effectively across diverse EEG datasets, ultimately advancing the field of EEG-based emotion classification.

REFERENCES

[1] U. Retkoceri, "Remembering emotions," *Biol. Philosophy*, vol. 37, no. 1, p. 5, Feb. 2022, doi: 10.1007/s10539-022-09834-5.

[2] M. Maithri, U. Raghavendra, A. Gudigar, J. Samanth, P. D. Barua, M. Murugappan, Y. Chakole, and U. R. Acharya, "Automated emotion recognition: Current trends and future perspectives," *Comput. Methods Programs Biomed.*, vol. 215, Mar. 2022, Art. no. 106646, doi: 10.1016/j.cmpb.2022.106646.

[3] R. Yuvaraj, A. Baranwal, A. A. Prince, M. Murugappan, and J. S. Mohammed, "Emotion recognition from spatio-temporal representation of EEG signals via 3D-CNN with ensemble learning techniques," *Brain Sci.*, vol. 13, no. 4, p. 685, Apr. 2023.

[4] X. Wang, Y. Ren, Z. Luo, W. He, J. Hong, and Y. Huang, "Deep learning-based EEG emotion recognition: Current trends and future perspectives," *Frontiers Psychol.*, vol. 14, Feb. 2023, Art. no. 1126994.

[5] S. M. Alarcão and M. J. Fonseca, "Emotions recognition using EEG signals: A survey," *IEEE Trans. Affect. Comput.*, vol. 10, no. 3, pp. 374–393, Jul. 2019, doi: 10.1109/TAFFC.2017.2714671.

[6] R. Alhalaseh and S. Alasasfeh, "Machine-learning-based emotion recognition system using EEG signals," *Computers*, vol. 9, no. 4, p. 95, Nov. 2020, doi: 10.3390/computers9040095.

[7] L. Pan, Z. Yin, S. She, and A. Song, "Emotional state recognition from peripheral physiological signals using fused nonlinear features and team-collaboration identification strategy," *Entropy*, vol. 22, no. 5, p. 511, Apr. 2020, doi: 10.3390/e22050511.

[8] I. Ul Hassan, R. H. Ali, Z. U. Abideen, A. Z. Ijaz, and T. A. Khan, "Towards effective emotion detection: A comprehensive machine learning approach on EEG signals," *BioMedInformatics*, vol. 3, no. 4, pp. 1083–1100, Nov. 2023.

[9] A. Rajalakshmi and S. S. Sridhar, "Classification of yoga, meditation, combined yoga–meditation EEG signals using L-SVM, KNN, and MLP classifiers," *Soft Comput.*, vol. 28, no. 5, pp. 4607–4619, Mar. 2024.

[10] L. Trujillo, D. E. Hernandez, A. Rodriguez, O. Monroy, and O. Villanueva, "Effects of feature reduction on emotion recognition using EEG signals and machine learning," *Exp. Syst.*, vol. 41, no. 8, p. 13577, Aug. 2024.

[11] G. Feng, H. Wang, M. Wang, X. Zheng, and R. Zhang, "A research on emotion recognition of the elderly based on transformer and physiological signals," *Electronics*, vol. 13, no. 15, p. 3019, Jul. 2024.

[12] M. Sadiq, M. N. Kadhim, D. Al-Shammary, and M. Milanova, "Novel EEG feature selection based on Hellinger distance for epileptic seizure detection," *Smart Health*, vol. 35, Mar. 2025, Art. no. 100536, doi: 10.1016/j.smhl.2024.100536.

[13] B. Brouwers. (Jun. 3, 2018). *Holst Centre Introduces EEG Headset for Emotion Detection*. [Online]. Available: https://innovationorigins.com/en/holst-centre-introduces-eeg-headset-emotion-detection/

[14] M. K. Chowdary, J. Anitha, and D. J. Hemanth, "Emotion recognition from EEG signals using recurrent neural networks," *Electronics*, vol. 11, no. 15, p. 2387, Jul. 2022, doi: 10.3390/electronics11152387.
[15] R. A. García-Hernández, J. M. Celaya-Padilla, H. Luna-García, A. García-Hernández, C. E. Galván-Tejada, J. I. Galván-Tejada, H. Gamboa-Rosales, D. Rondon, and K. O. Villalba-Condori, "Emotional state detection using electroencephalogram signals: A genetic algorithm approach," *Appl. Sci.*, vol. 13, no. 11, p. 6394, May 2023.
[16] M. A. Cardoso-Moreno, C. Macias, T. Alcantara, M. Soto, H. Calvo, and C. Yañez-Marquez, "Convolving emotions: A compact CNN for EEG-based emotion recognition," presented at the IEEE Symp. Ser. Comput. Intell. (SSCI), Oct. 2023.
[17] D. Rankhambe, B. S. Ainapure, B. Appasani, and A. V. Jha, "A flower pollination algorithm-optimized wavelet transform and deep CNN for analyzing binaural beats and anxiety," *AI*, vol. 5, no. 1, pp. 115–135, Dec. 2023.
[18] A. A. Rahman, M. R. Kabir, R. H. Ratul, F. A. Shamns, M. M. Nishat, and F. Faisal, "An efficient analysis of EEG signals to perform emotion analysis," in *Proc. 4th Int. Conf. Artif. Intell., Robot. Control (AIRC)*, Cairo, Egypt, May 2023, pp. 1–7, doi: 10.1109/airc57904.2023.10303179.
[19] R. Alibrahim and H. Kurdi, "GANN: EEG-based emotion classification using context-aware gated attention neural network," *Proc. Comput. Sci.*, vol. 241, pp. 234–241, Jan. 2024, doi: 10.1016/j.procs.2024.08.032.
[20] A. Nag, H. Mondal, S. R. Raihan Kabir, M. R. Islam, M. E. Ahmed, and S. M. Hasan Jamil, "Emotion decoding: An extensive examination of electroencephalogram signals using explainable machine learning," in *Proc. 6th Int. Conf. Electr. Eng. Inf. Commun. Technol. (ICEEICT)*, Dhaka, Bangladesh, May 2024, pp. 604–609, doi: 10.1109/iceeict62016.2024.10534518.
[21] D. P. Rini and W. Kurnia Sari, "Optimizing hyperparameters of CNN and DNN for emotion classification based on EEG signals," *Int. J. Inf. Commun. Technol. (IJoICT)*, vol. 10, no. 1, pp. 1–12, Jun. 2024, doi: 10.21108/ijoict.v10i1.857.
[22] F. K. Bardak, M. N. Seyman, and F. Temurtaş, "Adaptive neuro-fuzzy based hybrid classification model for emotion recognition from EEG signals," *Neural Comput. Appl.*, vol. 36, no. 16, pp. 9189–9202, Jun. 2024.
[23] C. Narsimha Reddy, S. Mahesh, and K. Manjunathachari, "Hybrid feature integration model and adaptive transformer approach for emotion recognition with EEG signals," *Comput. Methods Biomechanics Biomed. Eng.*, vol. 27, no. 12, pp. 1610–1632, Sep. 2024.
[24] J. J. Bird, L. J. Manso, E. P. Ribeiro, A. Ekárt, and D. R. Faria, "A study on mental state classification using EEG-based brain-machine interface," in *Proc. Int. Conf. Intell. Syst. (IS)*, Sep. 2018, pp. 795–800, doi: 10.1109/IS.2018.8710576.
[25] M. Noaman Kadhim, D. Al-Shammary, and F. Sufi, "A novel voice classification based on gower distance for Parkinson disease detection," *Int. J. Med. Informat.*, vol. 191, Nov. 2024, Art. no. 105583.
[26] M. Sadiq, M. N. Kadhim, D. Al-Shammary, and A. M. Milanova, "Novel EEG classification based on Hellinger distance for seizure epilepsy detection," *IEEE Access*, vol. 12, pp. 127357–127367, 2024.
[27] D. Al-Shammary, M. Noaman Kadhim, A. M. Mahdi, A. Ibaida, and K. Ahmed, "Efficient ECG classification based on chi-square distance for arrhythmia detection," *J. Electron. Sci. Technol.*, vol. 22, no. 2, Jun. 2024, Art. no. 100249.
[28] J. J. Bird, A. Ekart, C. D. Buckingham, and D. R. Faria, "Mental emotional sentiment classification with an EEG-based brain-machine interface," in *Proc. Int. Conf. Digit. Image Signal Process. (DISP)*. U.K.: Springer, 2019, pp. 1–7.
[29] M. Mosbah and B. Boucheham, "Matching measures in the context of CBIR: A comparative study in terms of effectiveness and efficiency," in *Recent Advances in Information Systems and Technologies*, Á. Rocha, A. M. Correia, H. Adeli, L. P. Reis, and S. Costanzo., Cham, Switzerland: Springer, 2017, pp. 245–258.
[30] M. Priyadarshani, P. Kumar, K. S. Babulal, D. S. Rajput, and H. Patel, "Human brain waves study using EEG and deep learning for emotion recognition," *IEEE Access*, vol. 12, pp. 101842–101850, 2024.
[31] C. H. N. Reddy, S. Mahesh, and K. Manjunathachari, "Intelligent optimal feature selection-based hybrid variational autoencoder and block recurrent transformer network for accurate emotion recognition model using EEG signals," *Signal, Image Video Process.*, vol. 18, no. 2, pp. 1027–1039, Mar. 2024.
[32] S. Sageengrana, S. Selvakumar, and S. Srinivasan, "Optimized RB-RNN: Development of hybrid deep learning for analyzing student's behaviours in online-learning using brain waves and chatbots," *Exp. Syst. Appl.*, vol. 248, Aug. 2024, Art. no. 123267.
[33] G. R. K. Reddy, A. D. Bhavani, and V. K. Odugu, "Optimized recurrent neural network based brain emotion recognition technique," *Multimedia Tools Appl.*, vol. 84, no. 8, pp. 4655–4674, Mar. 2024.
[34] S. Pichandi, G. Balasubramanian, and V. Chakrapani, "Hybrid deep models for parallel feature extraction and enhanced emotion state classification," *Sci. Rep.*, vol. 14, no. 1, p. 24957, Oct. 2024.
[35] A. Prakash and A. Poulose, "Electroencephalogram-based emotion recognition: A comparative analysis of supervised machine learning algorithms," *Data Sci. Manage.*, 2025. [Online]. Available: https://doi.org/10.1016/j.dsm.2024.12.004

MUSTAFA HUSSEIN MOHAMMED received the M.Sc. degree in computer engineering. He is currently a Researcher with Al-Mustaqbal University. His research interests include artificial intelligence (AI), wireless sensor networks, and predictions of dynamic target tracking algorithms for error tolerance.

MUSTAFA NOAMAN KADHIM received the B.Sc. degree in computer techniques engineering from the Al-Imam Al-Kadhim College for Islamic Sciences, Al-Qadisiyah, Al Diwaniyah, Iraq, in 2021, and the M.Sc. degree in computer techniques engineering from the Electrical Engineering Technical College, Middle Technical University. He is currently a Researcher with the University of Al-Qadisiyah, Al Diwaniyah. His research interests include computer vision, machine learning, deep learning, and the IoT.

DHIAH AL-SHAMMARY received the Ph.D. degree in computer science from RMIT University, in 2014. He was with several universities in both Iraq and Australia. He was with some silicon valey-based companies, such as Optcts and AgilePQ. He has published with his Australian-USA team a potential patent for designing new post-quantum data encryption with high performance. He has several publications at highly reputed venues. His special interests include data security and privacy, clustering techniques, classifications methods, optimization, and networking.

AYMAN IBAIDA received the Ph.D. degree in computer science and IT from RMIT University, Australia, in 2014. He was a Lecturer with the Computer College, Dubai, from 2006 to 2008. He was a Technical Lead with AgilePQ Australia Ltd., and a Co-Founder of EyeCura Pty Ltd. He is currently a Lecturer with Victoria University. His research interests include AI and machine learning in biomedical applications, diagnoses, and patient health records security; and cyber security in healthcare systems.