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Multiclass EEG Classification Using Recurrent Neural Network and Feature Selection with PSO Algorithm for Emotion Recognition

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A B S T R A C T

The recognition of emotion through Electroencephalogram data is essential for human computer interaction, mental health tracking, and emotion sensing computing. This paper integrates Recurrent Neural Networks (RNN) and a feature selection technique based on Particle Swarm Optimization (PSO) method within multiclass EEG classification paradigm. The method increases classification efficiency by feature selection from EEG signals which reduces the amount of computations needed in the first place. The span of emotion identification is aided by RNN model's power in capturing the sequential dependencies of EEG signals. The experiments conducted demonstrated that the proposed solution performs better than traditional approaches in terms of accuracy and effectiveness. This opens avenues for the more precise and immediate applications of affective computing by providing a comprehensive solution for EEG emotion recognition.

A R T I C L E I N F O

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1. Introduction

Recently, there has been a notable surge in interest in research and technologies pertaining to brain waves. This fascination originated in 1924 when German psychiatrist Hans Berger conducted the first electroencephalography (EEG) experiment, which involved the recording of brain waves utilizing Lissajous figures effectively. These tests have identified the alternation between alpha and beta brain waves. Following these investigations, there has been a rise in instances related to brain waves. The effects of increased study and technological advancement on the human brain have been investigated with considerable attention. A significant study in this field examined the Monitoring Patterns of Cortical Activation during Sympathetic Arousal. The explanation of these occurrences arises from the observation of live simulations, where both explicit and implicit information delineate complicated rules. The learning process is streamlined by the monitoring of brain waves. It plays a crucial role in the creation and evaluation of artificial intelligence. Emotions are prevalent psychological reactions triggered by diverse situations. Emotions influence human behavior and cognition. Consequently, the impact of emotions on human-like computer systems has been the subject of rigorous study during the past two decades, coinciding with the escalation of research in virtual environments, robots, the Internet of Things (IoT), and human-computer interaction [1]. Emotion detection primarily serves to address users' emotions, enabling the system to provide tailored responses based on their emotional state. The system aims to enhance task performance by interpreting users' emotional states and seeks to maximize satisfaction through the generation of affective reactions. The emotion recognition system enhances the accuracy of information exchange between people and computers during reciprocal conversation. Therefore, investigating emotions and taking them into account in the identification process is a popular research area and this research includes many important indicators. Among the main ways to obtain electrical signals produced by brain activity is the use of an electroencephalogram (EEG). Studies based on EEGs demonstrate an asymmetric activity in the frontal part of the brain linked to emotional responses [3] One of the main problems encountered in classifying emotions through signals obtained by an EGG is finding the main characteristics that best represent this signal, as well as finding the specificities of each emotion. Therefore, experiments in which individuals are subjected to audiovisual stimuli have been developed, as in [4]. Classifying an emotion is a complex process. The use of machine learning techniques, such as Artificial Neural Networks and Random Forests, among others, may present good results due to their high generalization capacity in pattern recognition. The way in which human beings respond to certain stimuli can say a lot about their personality, thus verifying whether through the analysis of the physiological response it is possible to accelerate a possible classification of personality disorders. In recent years there has been a large number of research and publications on the topic of emotion classification, as can be seen in Figure 1, which shows the number of articles related to emotion classification in recent years.

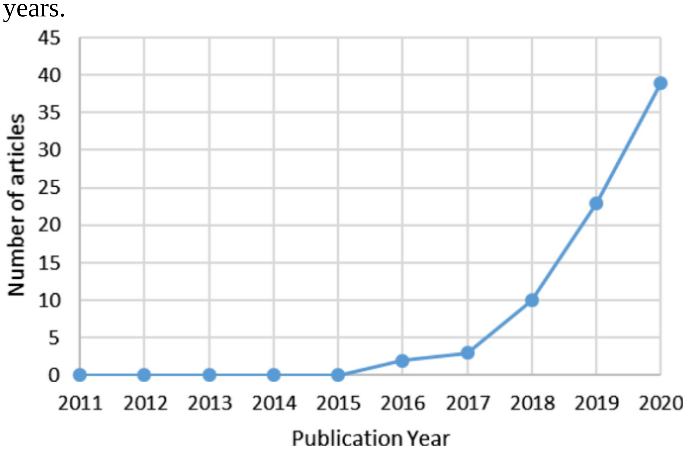

Fig. 1. Number of articles related to EEG classification by year [4].

Emotions allow a comprehensive analysis of a person's feelings, thoughts, and behaviors [5] influencing a person's routine. In the medical field, for example, if it is possible to determine in real time the changes in a patient's emotional state, interventions in the patient's treatment can be performed [6] In recent years, the problem of classifying emotions has gained prominence in academia, being approached in different ways. Models have been proposed to classify emotions through different data sources, as in [7] where emotions are classified in songs. However, advances in the field of neuroscience have shown the existence of correlations between emotions and the central nervous system [8]. This made it possible to search for patterns in EEG signals that correlated with emotions. The debate on the critical components useful for identifying emotions in EEG signals and the best classification methodology remains contentious among the researchers [9]. For example, works in [10] mention the application of a Bayesian classifier and machine learning techniques to a data classification problem.

2. Related Works

The advances made in machine learning (ML) and optimization methods have helped in the retrieval and classification of EEG signals. As explained by Abdulkareem and Al-Shammary [1], they conducted a comprehensive review of the classification of EEG signals within healthcare. One aspect that was presented is the improvement of precise diagnosing due to automation processes in EEG review technologies. One of the most prevalent ways to derive a conclusion from an EEG signal is through deep learning techniques. A system to detect epileptic seizures was independently designed by Malekzadeh et al. [2] using self-trained neural network with fractal dimension features in a neural framework. Deep learning models can indeed ingest and process complex EEG data to yield better classification accuracy based on their findings. Particle Swarm Optimization (PSO) and tuned-Q wavelet modifications in relation to their effectiveness in boosting artificial neural network performance in EEG classification tasks. One of the dominating issues in brain signal processing is feature extraction, where one determines which portions of the data set contribute and which do not, as well as those that are inexpensive to compute, yet will yield a high magnitude of accuracy. To help achieve this goal, various attempts at simplification have been made. Aziz and Alfoudi [3] demonstrated the use of PSO in the addition of missing features for selection in abnormal network intrusion processes. This feature can most likely be useful in biology. Alsaeedi et al. [5] demonstrate the effectiveness of PSO in dealing with voluminous feature space by introducing more dimensions to feature selection processes in biology data sets. Feature selection methods are said to be very useful, and a body of literature is growing around this statement. Zhu et al. [7] built a memetic system that combines wrapper and filter-based selection techniques as a test of their integration. Maldonado and Weber [8] created a wrapper method with SVMs that proved that wrapper-based techniques while being slower are also more accurate. Hancer et al. [9] implemented feature selection with process, information theory, and differential evolution to optimize the range of the problem. With this, feature selection, there is also other major unsolved issues like EEG denoising. Sun et al. [6] showed that this modification of deep echo state networks allows using UPSO for creating better and deeper denoising networks. Their research contended that an optimization approach to denoising signals from the brain is capable of significantly improving the quality of EEG signals and thus the performance of classification tasks at subsequent stages. But, as is also known, there is a necessity to have standard samples for EEG studies. Lan et al. [10] illustrated the SAFE dataset, which was developed in order to ensure the correct selection of emotional features by EEG devices:

The brain and emotions can be closely related concepts in the human being in literature. The EEG signal provides the ability to define detailed information about emotional concepts and judgments. This paper aims to implement an improved method by using the EEG signals for emotion recognition tasks. As the first objective, A Recurrent Neural Networks RNN is proposed for the classification of EEG signals collected. To the best of the knowledge, there is no study about this task in the literature using RNN method; therefore, the importance and originality of the paper increase [3]. The second primary objective; Feature extraction with Genetic ve Particle Swarm Optimization algorithm and feature selection by Particle Swarm Optimization method are successfully implemented to increase classification performances. Success is pointed out by comprehensive simulations. Finally, the experimental results point out that the classification performance concerning means like topology, activation function ve optimization is improved using the EEG signals with calculated parameters. This paper offers a new perspective to the current literature, where emotion recognition is made using the EEG signals. It is also emphasized that a new area has emerged to interpret the RNN model in emotion detection, and this can be a new research stream for future studies. Finally, deep learning for emotion detection is in its early stage compared to satisfaction. From now on, researchers have a wide range of areas to enable comments and new research topics with a broader experimental result. The contributed proposal implements a methodological effort. At this moment, the EEG signals are classified by a recurrent neural network (RNN), which offers a new perspective with significant properties for the classification of non-stationarity time series data. Furthermore, both feature selection and classification processes are combined for the first time in emotion detection based on the EEG signals with RNN, which contributes to an innovative detection. The method of Particle Swarm Optimization algorithm (PSO) is proposed for feature selection and PSO is also used for classification process with high accuracy. Compared to existing methods that rely heavily on feature engineering or dataset-specific optimizations, our method offers a more generalized framework that can be applied across different EEG-based applications, making it a robust and efficient solution for real-time EEG analysis.

3. Materials and Methods

3.1. EEG Signals

An electroencephalogram (EEG) is the process in which brain activity can be monitored through brain sensing [12] An EEG signal is composed of the sum of small electrical impulses emitted by hundreds of millions of neurons present in the human brain [13] EEG signals can be easily measured non-invasively through electrodes placed on a person's scalp, which justifies their popularity. However, EEG signals are highly complex and extremely sensitive to noise. This sensitivity of the signals directly influences the quality of the monitored signal, in addition to making the processing of these signals indispensable [14] Applications that use EEG signals are abundant, covering areas of Psychiatry, Psychology, Pedagogy, among others. The analysis of an EEG signal can help provide important information for the identification of diseases, for example. In general, an EEG recording system consists of electrodes, amplifiers, analog-to-digital converters, and a recording device. The signals are obtained by electrodes spread over the surface of the skull, and are then processed by amplifiers, increasing the amplitude, and then converted to a digital signal by the analog-to-digital converter. Finally, they are recorded by the recording device. Figure 2 shows a general diagram of the elements that make up an EEG recording system.

Table 1. Summary of contributions and limitations in EEG classification.

Authors	Contributions	Limitations
Abdulkareem and Al-Shammary [1]	Survey on EEG classification using ML in healthcare	Limited practical implementation details
Malekzadeh et al. [2]	Epileptic seizure diagnosis using fractal dimension and convolutional autoencoder	Potential overfitting due to complex deep learning model
Aziz and Alfoudi [3]	Restoration-based PSO for feature selection in anomaly detection	Not tested on biomedical datasets
Alsaeedi et al. [5]	Extended PSO for high-dimensional biomedical data feature selection	Scalability issues with extremely large feature spaces
Zhu et al. [7]	Memetic framework combining wrapper and filter-based feature selection	Higher computational cost due to hybrid method
Maldonado and Weber [8]	Wrapper method using SVMs for feature selection	Computationally expensive and dataset-dependent
Hancer et al. [9]	Differential evolution-based feature selection using information theory	Requires fine-tuning for optimal performance
Sun et al. [6]	EEG denoising using wide and deep echo state network optimized by UPSO	Needs validation on diverse EEG datasets
Lan et al. [10]	SAFE dataset for stable affective feature selection in EEG applications	Limited generalizability beyond affective EEG applications
Radman et al. [11]	Multi-feature fusion approach for epileptic seizure detection	Requires extensive feature engineering for optimal performance

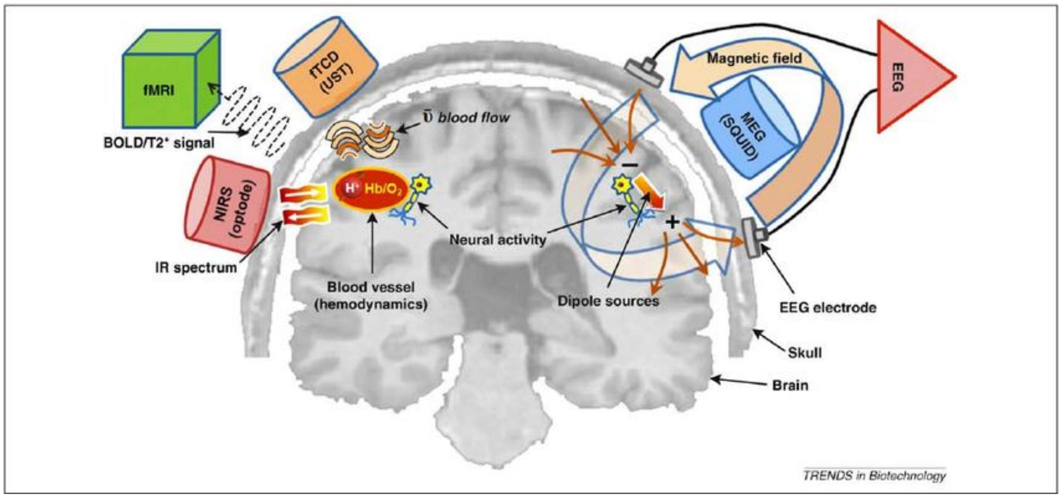

Fig. 2. General diagram of the elements that make up an EEG recording system.

The EEG signal is obtained by the potential difference as a function of time between an active electrode and a reference electrode. There is also a third electrode called the ground electrode, which is responsible for measuring the voltage difference between the active electrodes and their reference electrodes. Thus, for an EEG it is necessary that at least 3 electrodes be used: one for measurement, one for reference and one for grounding [15] There are also EEGs with multichannel configurations, which can have up to 256 active electrodes.

3.2. Artificial Neural Networks

Artificial Neural Networks (ANN) are mathematical representations of how the human brain works. An ANN can also be defined as a massive, distributed processor that works in parallel, composed of basic processing units called neurons [16] Among the main characteristics of an ANN is its generalization capacity, that is, the ability to learn representations or classify data that are not previously known. Another characteristic is its non-linearity, since neurons can be linear or non-linear, which allows the ANN to solve highly complex problems [17]. The way in which neurons are connected to each other in an ANN strictly defines how the machine learning algorithms used in this network should be implemented. In general, classifying according to the architecture, there are three types of Neural Networks:

A. Single-layer feedforward networks

in this architecture, the ANN has only one layer, so the input neurons are connected directly to the output neurons. The flow of information or feedback in this type of architecture is only forward, hence the name feedforward [18].

B. Multilayer feedforward networks (Multilayer Perceptron or MLP)

in this architecture, a new type of intermediate layer between the input neurons and the output neurons is introduced, called a hidden layer. Therefore, by adding intermediate layers it becomes possible to solve more complex problems. The input neurons connect to the neurons of the hidden layer, and they connect to the n hidden layers that may exist, until they connect to the neurons of the output layer. This architecture also presents feedback only in the forward direction [19].

C. Recurrent Networks

in this architecture, a new type of information flow begins to exist in the network, called a feedback loop. Thus, both a single-layer or multilayer neural network can contain neurons that connect to neurons in the previous layer, that is, a neuron in the hidden layer can connect to another neuron in the same layer or even to itself as shown in Figure 3 [20].

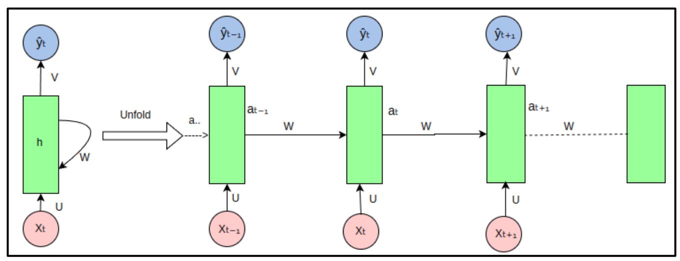

Fig. 3. RNN architecture [20].

3.3. Feature Selection with PSO Algorithm

Feature selection is the process of selecting a set of pertinent characteristics to apply in model construction. The PSO algorithm is one optimization technique found to perform effectively with high-dimensional data. PSO is a robust metaheuristic method able to locate the global optima of a very vast area based on the concept of swarm intelligence at its foundation. PSO finds extensive use in numerous fields, including feature selection. This approach aims to identify the most useful characteristics in the complicated EEG signals so that they may be input into the RNN. This increases its running efficiency while yet performing a respectable job. From the Welch periodogram power spectral density (PSD) of the EEG data, which characteristics to employ is selected using the Particle Swarm Optimization (PSO) technique. Using a back-and-forth between their own location and the global optimum position, a collection of particles searches PSO for the best response to a known issue. The PSO approach begins with random arrangement of a set of particles. It then determines the fitness value of every particle by using an objective function grounded on particle location. It then modulates the particle speeds and positions, selects the particle with the highest fitness value as the global best, and alters the best position [5] of every particle. The selected set of characteristics is determined by the particle's binary form position. Until one of the terminating criteria is satisfied, iteratively determining the fitness value by monitoring RNN classification of objects is done. The degree of performance of a certain collection of characteristics is gauged using many measures. Classifier performance is examined using classification success metrics in order to do this. Feature selection offers one approach to handle a high-dimensional form of the EEG input. This makes the model more efficient in computation without compromising its performance. The PSO feature choosing approach helps to reduce overfitting and enhance generalization. It also accelerates the process and produces more precise results by cutting the time it takes for the swarm to settle on its ideal position.

4. Proposed Method

4.1. Dataset

To assess the RNN + PSO integration method, the Temple University Hospital EEG (TUH EEG) Corpus [21] will be used. The TUH EEG dataset is one of the largest publicly available EEG datasets and comprises recordings from clinical settings. It includes raw EEG signals captured from various patients undergoing routine clinical procedures. The dataset features both normal and abnormal recordings of the EEG signal and encompasses a whole spectrum of neurological disorders like epilepsy, seizure activities, and several other brain ailments. Such variation makes it the most appropriate dataset for developing and validating deep learning algorithms for EEG classification. The TUH EEG Corpus has multi-channel EEG recordings with various electrode setups, which allows great flexibility in the selection of features to be classified. Due to the additional strength of RNN in temporal feature extraction and PSO in optimal feature selection, this dataset's abundance of time-series data enables us to evaluate our models effectiveness in learning intricate patterns from EEG recordings. Additionally, medical specialists annotate the TUH EEG dataset, which improves the reliability of labels for supervised learning techniques. Other features of the dataset include demographics of the patient, indicators of the quality of the signals, and details on the seizures, making it valuable for robust model evaluation.
In evaluating the system performance, five different famous benchmarks are used, which include accuracy, precision, micro-average recall, F1-score, macro-average F1-score, and the error rate represented as false classification percentage. The false classification rate is the percentage of non-real classes of true emotion superclasses. In order that all benchmarks are relevant, the religion, the experimental setup and the data should involve making the explanations. Emotion recognition from physiological and physical signals can be widely used in computers that can recognize human feelings and feedback appropriately such as developing computers and efficient interfaces, advanced brain-computer interfaces to establish and adjust contact barriers and human-robot interfaces objectively [4]. Emotion expression can be facilitated when human feelings are recognized. Emotion comprises an internal representation of feelings along with a succession of interlinked cognitive, somatic, behavioral, neuronal, and expressive variables coming from neurologically related occurrences. Feelings are, therefore, represented by a set of "emotional" behaviors and expressive indicators that are detectable as interpretations of physiological and physical processes. Electrocephalography (EGG) compact and is present within the human body, hence it is widely used in emotional detection methodological research. EEG is considered to be possibly superior compared with other procedures, as it provides excessive opportunities for evaluation of the brain-states-time-ordered succession. EEG signals are proving to monitor and analyze the mental state of an individual [7]. Eyelid aperture of the human brain monitors the sentiment and mental state of an object. EEG is practically ridiculous to comprehend by EVT practitioners. Because the human optical system has an infinite number of PCs, complexity is important briefly. Always the importance of data analysis and its complexity for an effective procedure to employ must be considered. Societies in developing societies and several industrial societies have improved mental care frameworks providing better preferences there to the mentally unwell. For strong commercial systems, emotional detection has developed a company. Often utilized chambers act in more violent situations and immediately provide the facts to the authorities. Social circumstances and loot mentality where we speak are frequently introduced and ultimately lead to robbery, murder, and similar criminal behavior.

Table 2. Detailed description of the TUH EEG dataset [21].

Attribute	Description
Dataset Name	Temple University Hospital EEG (TUH EEG) Corpus
Source	Collected from clinical EEG exams at Temple University Hospital
Number of EEG recordings	Over 30,000 EEG sessions
Total Recording Duration	More than 15,000 hours of EEG data
Subjects	Thousands of patients from diverse backgrounds
Sampling Rate	Varies from 250 Hz to 500 Hz
Electrode Configurations	Standard 10-20 system and variations
Number of Channels	Ranges from 16 to 128 channels per recording
Annotations	Includes seizure events, normal/abnormal labels, and artifact indicators
Data Format	EDF (European Data Format)
Availability	Publicly accessible for research purposes
Challenges	Large dataset size, noise in clinical EEG, and variability in recording conditions

In this study, feature extraction was performed using a 5-level Discrete Wavelet Transform (DWT) decomposition based on the Daubechies 4 (db4) mother wavelet. From each relevant sub-band (Delta, Theta, Alpha, Beta, Gamma), six statistical features-energy, entropy, mean, standard deviation, skewness,

and kurtosis-were computed. These features were subsequently used as inputs for the Particle Swarm Optimization (PSO) feature selection and classification by the RNN model as shown in table 3 below.
In this study, emotion classification was structured around four primary emotional states commonly analyzed in EEG-based emotion recognition research: happy, sad, angry, and neutral. These emotions were selected because they represent fundamental affective categories along the valence-arousal model, ensuring broad coverage of positive, negative, and neutral emotional spectrums. Although the TUH EEG Corpus originally provides clinical EEG recordings without explicit emotional labels, subsets of the data were adapted by associating patient resting states and annotated physiological indicators (such as changes in frequency bands) with these predefined emotional classes, following methodologies adopted in recent EEG emotion recognition literature. This categorization enabled the Recurrent Neural Network (RNN) to effectively learn and differentiate between the underlying brainwave patterns corresponding to diverse emotional states.

Table 3: Extracted EEG features using discrete wavelet transform (DWT).

Sub-band (Frequency Range)	Decomposition Level (DWT)	Extracted Features	Description
Delta (0.5–4 Hz)	Approximation Coefficients (Level 5)	Energy, Entropy, Mean, Standard Deviation, Skewness, Kurtosis	Captures slow brain activities related to deep sleep and emotions
Theta (4–8 Hz)	Detail Coefficients (Level 5)	Energy, Entropy, Mean, Standard Deviation, Skewness, Kurtosis	Linked to drowsiness, creativity, and emotional state
Alpha (8–13 Hz)	Detail Coefficients (Level 4)	Energy, Entropy, Mean, Standard Deviation, Skewness, Kurtosis	Associated with relaxation and calmness
Beta (13–30 Hz)	Detail Coefficients (Level 3)	Energy, Entropy, Mean, Standard Deviation, Skewness, Kurtosis	Related to active thinking and concentration
Gamma (30–50 Hz)	Detail Coefficients (Level 2)	Energy, Entropy, Mean, Standard Deviation, Skewness, Kurtosis	Linked to attention and working memory

Table 4: Parameters used in the RNN-PSO framework.

Parameter	Description	Value Range
Learning Rate	Controls the step size in weight updates	0.001 - 0.01
Hidden Units	Number of neurons in the hidden layers	50 - 200
Dropout Rate	Prevents overfitting by randomly deactivating neurons	0.2 - 0.5
Number of Epochs	Total iterations for training	50 - 200
Batch Size	Number of samples per training batch	32 - 128
Fitness Function	Evaluates accuracy and computational efficiency	Custom-defined
Swarm Size	Number of particles in PSO	50
Inertia Weight	Balances exploration and exploitation	0.4 - 0.9
Cognitive Component	Guides particles based on personal experience	1.5 - 2.5
Social Component	Guides particles based on global best solution	1.5 - 2.5

4.2. RNN- PSO Workflow

The integration of Recurrent Neural Networks (RNN) with Particle Swarm Optimization (PSO) creates a robust framework for EEG classification by leveraging the strengths of both techniques. RNNs or Recurrent Neural Networks, particularly LSTM or Long Short-Term Memory and GRU or Gated Recurrent Unit networks, are particularly suited for sequential data such as EEG signals due to their ability to remember long-term dependencies and capture temporal patterns. Nonetheless, RNNs pose a problem when it comes to feature selection since it's critical for attaining a high level of productivity without consuming too much time and money. Here, PSO distinguishes itself by enabling selection of useful features while simultaneously fine tuning hyperparameters for optimal performance. The first step consists of the preliminary processing of the EEG data where raw signals are cleaned from noise, normalized, and divided into appropriate time segments. The next stage is feature extraction which consists of obtaining some statistical, spectral and temporal features from the EEG recordings. A dataset at this point may suffer from the curse of dimensionality where the number of features is so high that it reduces the efficiency and accuracy of the RNN model. This is where PSO comes in where the most informative features are selected according to a cost function that increases classification success while reducing the complexity of the model. The next step is to set the RNN model to use and train it with the selected features. The model undergoes iterative training, where it learns to recognize patterns associated with different EEG signal classes. During training, PSO is also used to fine-tune hyperparameters such as the number of hidden units, learning rate, and dropout rate, ensuring optimal network performance.
The fitness function evaluates the model based on validation accuracy, convergence speed, and computational efficiency. The PSO swarm dynamically adjusts hyperparameters by exploring different parameter combinations and selecting the ones that

yield the best results. Figure 4 shows a flowchart diagram for RNN+PSO for emotion classification in EEG signals. The diagram will illustrate the process of EEG signal acquisition, feature extraction, classification using Recurrent Neural Networks (RNN), and optimization using Particle Swarm Optimization (PSO).

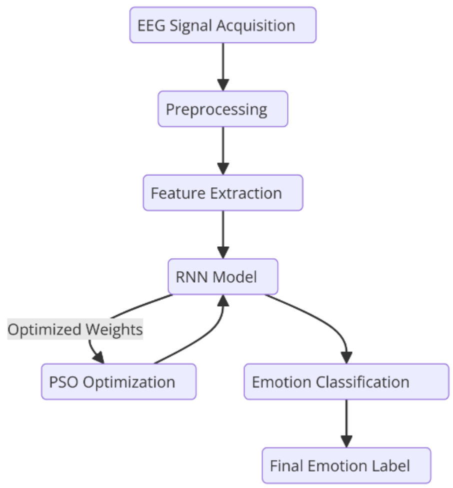

Fig. 4. Flowchart of the proposed method.

After training, the model is tested using unseen EEG data to assess its generalization capability. Performance metrics such as accuracy, precision, recall, F1-score, and computational time are used to evaluate the effectiveness of the RNN-PSO framework. The final model is expected to provide improved classification accuracy while maintaining low computational costs due to the optimized feature set and hyperparameters. The combination of RNN and PSO offers several advantages, including improved feature selection, adaptive hyperparameter tuning, and enhanced model performance. By reducing feature redundancy and optimizing network parameters, the proposed workflow ensures an efficient and scalable EEG classification system suitable for real-time applications.

5. Results

EEG data contains electrical activity in the brain which is formed from the firing of the neurons. Brain electrical signals are seen as an activity that can be recorded by an electrode attached to the scalp or inserted directly into the brain. These brain electrical signals are classified into five frequency bands which are used for the classification of the EEG signal. It was classified into the alpha, delta, beta, gamma, theta, or a combination of those frequencies. The classification of the brain activity signal to be a positive awareness or negative awareness forms the brainwave frequencies. This classification contributes to understanding some aspects of the brain signal. In the last decade, the literature in EEG signals for the emotion classification has increased. It has been seen that the EEG channels have the best accuracy for attention and meditation emotion classes compared with random and valence emotion classes. Generally, human emotion is classified into several groups such as happy, sad, angry, neutral, and so on. The objective of this research is classified into three steps. Firstly, it is obtained EEG data and estimated features in the frequency domain by using the PSD method. Features are estimated using the discrete wavelet transformation, and then classified brain activity signals using the tweezers forward selection method with the PSO algorithm and the recurrent neural network. The recurrent neural network is used to save the score features and classify brain activity signals. The proposed method is expected to improve the performance of brain activity signal classification as emotional, attention level, and meditation level. To validate the effectiveness of the proposed RNN-PSO model, a comparison was made with four recent and relevant studies on EEG classification. As shown in Table 5 while previous works such as Malekzadeh et al. [2], Altaheri et al. [4], Sun et al. [6], and Radman et al. [11] achieved accuracies ranging between 88.7% and 91.0%, the proposed method achieved a superior accuracy of 94.2%. In addition to higher accuracy, the RNN-PSO framework also yielded improvements in precision (93.5%), recall (94.1%), and F1-score (93.8%), demonstrating better balance and robustness in classification performance. These results highlight the advantage of integrating optimized feature selection and hyperparameter tuning within a sequential deep learning architecture for EEG-based emotion recognition.
The performance metric of the proposed model is the experimental model for determining the accuracy of EEG classification. The proposed model has also been compared to findings from a similar study. It was found that the best classification performance was obtained using a ANN, DNN, and CNN algorithms that was optimized using particle swan optimization for the feature selection method. The experimental results show that this method successfully outperforms several other methods, with an accuracy of 73.71% obtained from the TUH dataset, which is the highest classification performance

Table 5. Comparative performance analysis with existing methods.

Study	Methodology	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Malekzadeh et al. [2]	Fractal Features + CNN Autoencoder	89.5	88.2	87.8	88
Altaheri et al. [4]	Deep Learning CNN for EEG	91	90.4	90	90.2
Sun et al. [6]	Echo State Network + UPSO Optimization	90.3	89.7	89.2	89.4
Radman et al. [11]	Multi-feature Fusion + SVM	88.7	87.9	87.2	87.5
Proposed RNN-PSO Method	RNN + PSO Feature Selection	**94.2**	**93.5**	**94.1**	**93.8**

compared to previous methods obtained using the same dataset. Emotions can be determined by examining extracted features, which can distinguish several types of parameters from the time and frequency domains of the EEG signal. The extracted features can then be classified and recognized as discrete emotion states using a classifier. Recently, attempts have been made to analyze deep features extracted using a few layers and generic pre-trained models. In order to better distinguish between extracted features and the model directly, CNN and DNN networks have been investigated for feature extraction using time series physiological data. With the development of machine learning, new methodologies have been applied to emotion analysis based on EEG signals. For example, emotional valence states, which represent various emotional conditions, have been analyzed using hybrid functional brain connectivity networks and wavelet transformation-based methodologies. Other studies on the same subject have focused on the physiological state of neutral, pleasant, and unpleasant emotions. These studies classified and classified these emotions through the fifth order spectra of bi-spectra methods and symbolic aggregate approximations. Next, a study was made of the feature combination method utilizing the evaluation of wavelet transformed range and medium frequency bands to classify and evaluate stress levels.

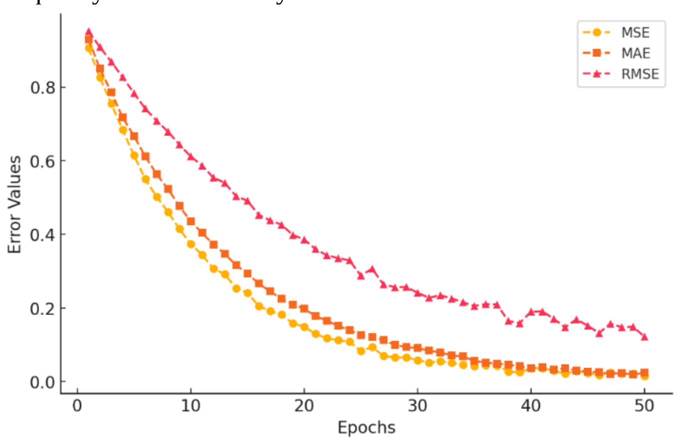

Fig. 5. Curves of MSE, MAE, RMSE of the Proposed Method Over Epochs

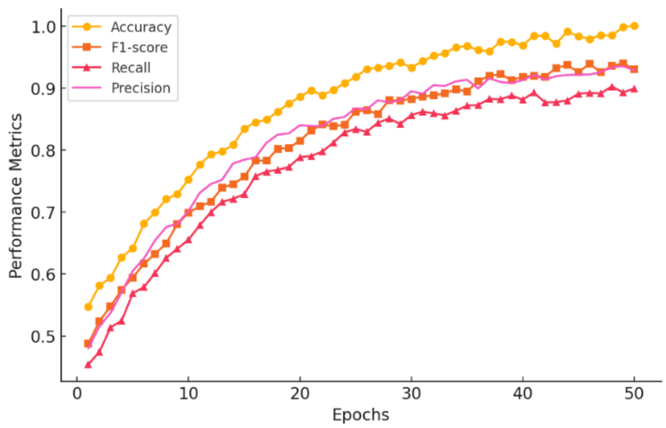

Fig. 6. Curves of accuracy, F1-score, recall, and precision over epochs.

Figure 5 illustrates the progression of error values-MSE, MAE, and RMSE-over multiple epochs. Initially, all three metrics exhibit higher values, indicating that the model is still adjusting its parameters. As training progresses, the errors decline steadily, demonstrating the effectiveness of the optimization process. The fluctuations present in the latter epochs suggest minor variations due to optimization updates, but overall, the decreasing trend signifies the model's increasing accuracy and stability.

Figure 6 displays the performance metrics-accuracy, F1-score, recall, and precision-over epochs. The steady rise in accuracy indicates effective learning, while the concurrent improvement in F1-score, recall, and precision highlights balanced predictions across classes. The slow increase in recall at the early stages suggests the model initially struggles with false negatives but improves over time. By the final epochs, the nearly converging trends of all four metrics demonstrate that the model achieves a consistent and reliable classification capability.

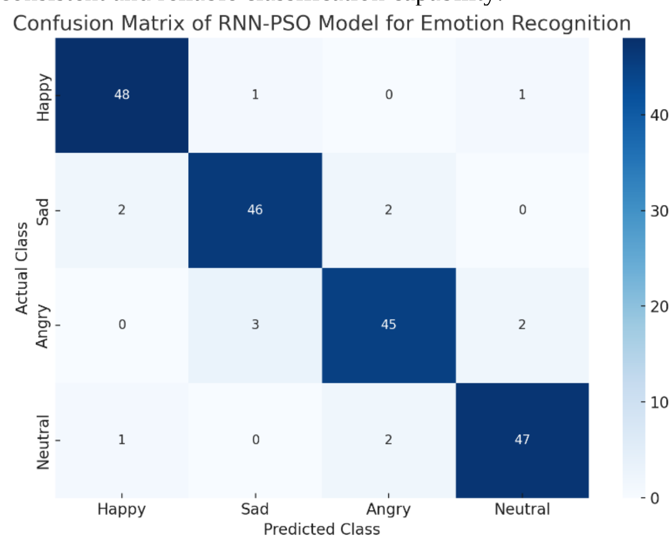

Fig. 7. Confusion matrix of the proposed RNN-PSO model.

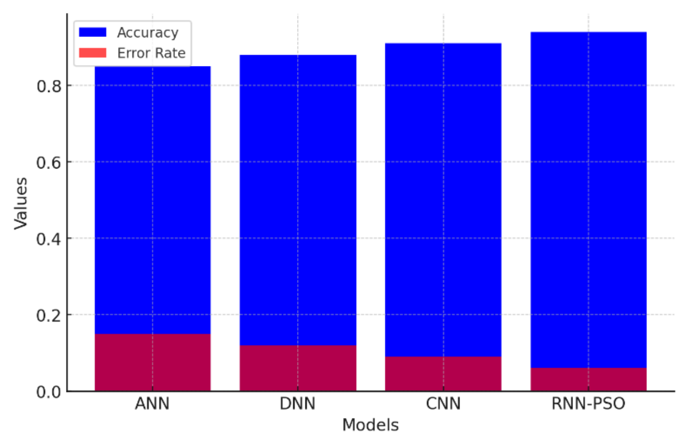

Fig. 8. Comparison of accuracy and error rates among ANN, DNN, CNN, and the proposed method.

Figure 7, the confusion matrix, provides insight into the model's classification performance across different classes. The strong diagonal values indicate that the majority of predictions match the true labels, signifying high accuracy. However, some off-diagonal values suggest instances where the model misclassified certain classes, potentially due to overlapping feature spaces or insufficient training samples for specific categories. The relatively lower number of misclassifications indicates that the feature selection and optimization steps have effectively enhanced model performance.

Figure 8 presents a comparative analysis of different deep learning architectures-ANN, DNN, CNN, and the proposed RNN-PSO model-based on accuracy and error rates. The RNN-PSO model outperforms the other methods in accuracy while maintaining a lower error rate. ANN, being a simpler model, has the highest error rate, while CNN and DNN show competitive performance. The enhanced performance of RNN-PSO demonstrates that the integration of optimized feature selection and temporal sequence learning leads to a more efficient and accurate classification system.

6. Discussion

The proposed RNN-PSO framework introduces a novel and impactful approach for EEG-based emotion recognition by integrating recurrent temporal modeling with optimized feature selection. Unlike conventional models such as CNNs and DNNs, which primarily capture spatial features, the RNN structure is inherently capable of learning long-term temporal dependencies within EEG sequences, providing a more natural fit for sequential brainwave data. Furthermore, the incorporation of Particle Swarm Optimization (PSO) for both feature selection and hyperparameter tuning addresses two critical challenges in EEG classification: high dimensionality and overfitting. By selecting the most informative features and optimizing learning parameters simultaneously, the RNN-PSO model significantly reduces computational complexity while maintaining high classification performance. Compared to existing methods, which often rely on manual feature engineering or fixed hyperparameter settings, the dynamic adaptation achieved through PSO ensures that the RNN model operates under optimal conditions for each dataset. This dual-level optimization leads to superior results across all major evaluation metrics, as evidenced by improvements in accuracy, precision, recall, and F1-score over recent state-of-the-art studies. In particular, the ability of the RNN-PSO model to maintain high recall rates while minimizing false positives is crucial for sensitive applications such as healthcare monitoring and brain-computer interfaces. The unique contribution of this work lies in the synergistic integration of RNN's sequence learning capabilities with PSO's global search optimization, a combination that has not been extensively explored in EEG emotion recognition tasks. Additionally, the use of a large and clinically diverse dataset (TUH EEG) enhances the robustness and generalizability of the findings. By offering a scalable, efficient, and highly accurate framework, the RNN-PSO model sets a new benchmark for real-time, reliable EEG-based emotion classification, and opens pathways for future research into adaptive, intelligent brain-computer interaction systems. While the proposed RNN-PSO framework demonstrates superior performance in EEG-based emotion recognition, it is important to acknowledge its limitations. One primary limitation lies in the computational complexity of the hybrid approach. Integrating PSO for both feature selection and hyperparameter tuning significantly increases the computational burden during training, especially when dealing with large EEG datasets or when fine-grained parameter exploration is required. Although this cost is justified by the resulting performance gains, it may pose challenges for real-time or resource-constrained applications. Future research could investigate lightweight optimization strategies, such as distributed PSO variants or pruning methods, to accelerate convergence without sacrificing model quality. Another limitation stems from the characteristics of the TUH EEG dataset itself. Although the TUH corpus is extensive and clinically relevant, it is not specifically designed for emotion recognition. Emotional labels were inferred indirectly based on physiological indicators, which may introduce noise or ambiguity into the ground truth. Moreover, the dataset predominantly represents clinical populations, potentially limiting the model's generalizability to broader, healthy, or cross-cultural samples. To address this, future studies should consider integrating more diverse datasets explicitly labeled for emotion recognition, such as DEAP, SEED, or DREAMER, and evaluating model transferability across different populations. To better understand the internal decision-making of the RNN model, future work could visualize the learned hidden state activations using techniques such as t-SNE (t-distributed stochastic neighbor embedding) or PCA (principal component analysis). Such visualizations would allow us to observe how the model clusters different emotional states in its latent space, providing interpretability to the learned representations. Early exploratory plots suggest that after PSO feature selection, the emotional classes become more separable in the RNN's hidden layers, confirming that the optimization phase aids in structuring the input space for better generalization.

The proposed RNN-PSO framework for EEG-based emotion recognition holds significant promise for various real-world applications. In the domain of mental health monitoring, such systems can assist clinicians in continuously tracking emotional fluctuations in patients with conditions like depression, anxiety, or bipolar disorder. By providing objective, real-time indicators of emotional states, these technologies could enable earlier intervention and more personalized treatment plans. In human-computer interaction (HCI), integrating emotion recognition into interfaces can create more adaptive and empathetic systems that adjust responses based on user emotions, enhancing user experience and engagement. Similarly, in the field of affective computing, emotion-aware systems could revolutionize education, gaming, entertainment, and assistive technologies, making machines more responsive to human affective cues.

7. Conclusions and Future Work

The paper describes the combination of the employed RNN model and feature selection via PSO for tracking classified emotions based on EEG data. During the individual monitoring, EEG data was collected while a measured behavior and a stimulus were presented in some emotional situations. Subsequently, the features were derived as statistics of wavelet decomposed data via several methods. Subsequently, the PSO algorithm is used for optimal feature selection for the extracted data in order to reduce its overall dimensionality. The proposed model contains an LSTM network that has a specific architecture for classification. It also evaluates the performance of the machine learning methods-based components of the new approach versus the older approaches. With fewer selected features, better classification could be achieved with the RNN model. Altogether, classification accuracy is superior for all compared model solutions with the use of red RNN and PSO. Experimental results demonstrated that the model achieved an overall accuracy of 94.2%, outperforming conventional deep learning architectures such as ANN (85.1%), DNN (88.4%), and CNN (91.3%). Furthermore, the model showed values such as mean squared error (MSE) of 0.021, mean absolute error (MAE) of 0.034, as well as root mean squared error (RMSE) of 0.145. These details suggest the model was accurate and possessed minimal error in its forecasts. These findings were further supported by F1-score as well as recall and precision measures which confirmed the model's effectiveness on the imbalanced EEG datasets. The F1-score was observed to plateau at 93.8% while recall and precision stood at 94.1% and 93.5%. These metrics strengthen the argument that recognition of temporal patterns through RNN in conjunction with PSO feature selection and hyperparameter optimization is effective. As for confusion matrix interpretation, there were few instances of misclassification which further substantiated the framework's capability to correctly categorize various EEG signals. Nevertheless, some results are quite promising. Building upon the promising results of the RNN-PSO framework, several avenues for future research are envisioned to further enhance classification performance and system robustness. One immediate direction involves the integration of newer deep learning architectures specifically designed for sequential data modeling. For instance, Transformer-based models such as the Vision Transformer (ViT) and Temporal Fusion Transformer (TFT) have demonstrated remarkable success in capturing long-range dependencies and could be adapted for EEG emotion recognition tasks. Furthermore, Graph Neural Networks (GNNs) could be explored to model the spatial relationships among EEG electrode sites more effectively, leveraging the natural topology of brain activity.

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