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EEG based Emotion analysis using Reinforced Spatio-Temporal Attentive Graph Neural and ContextNet techniques

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Abstract:
EEG-based emotion classification is considered to separate and observe the mental state or emotions. Emotion classification using EEG is used for medical, security and other purposes. Several deep learning and machine learning strategies are employed to classify the EEG emotion signals. They do not provide sufficient accuracy and have higher complexity and high error rate. In this manuscript, a novel Reinforced Spatio-Temporal Attentive Graph Neural Networks (RSTAGNN) and ContextNet for emotion classification with EEG signals is proposed (RSTAGNN-ContextNet-GWOA-EEG-EA). Here, the input EEG signals are taken from two benchmark datasets,namely DEAP and K-EmoCon datasets. Then, the input EEG signals are pre-processed,and the features are extracted utilizing ContextNet with Global Principal Component Analysis (GPCA). After that, the EEG signal emotions are classified using Reinforced Spatio-Temporal Attentive Graph Neural Networks method. RSTAGNN weight parameters are optimized under the Glowworm Swarm Optimization Algorithm (GWOA). The proposed model classifies the EEG signal emotions with high accuracy. The efficacy of the proposed method using the DEAP dataset attains higher accuracy by 24.05%, 12.64% related to existing systems, like Multi-domain feature fusion for emotion classification (DWT-SVM-EEG-EA-DEAP), EEG emotion finding utilizing fusion mode of graph CNN with LSTM (GCNN-LSTM-EEG-EA-DEAP) respectively. The efficiency of the proposed method using the K-EmoCon dataset attains higher accuracy 32.64%, 15.65% related to existing systems, like Toward Robust Wearable Emotion Realization along Contrastive Representation Learning (CAT-EEG-EA-K-EmoCon) and Human Emotion Recognition using Physiological Signals (CAT-EEG-EA-K-EmoCon) respectively.

Keywords: *emotion recognition, electroencephalogram (EEG), reinforced spatio-temporal attentive graph neural networks (RSTAGNN), glowworm swarm optimization algorithm (GWOA)*

1. Introduction

Emotions have a significant role in human decision-making, interaction, and cognitive processes [1]. As technology and knowledge of emotions advance, there are more prospects for autonomous emotion identification systems [2].

There have been successful scientific advances in emotion identification utilizing text, audio, facial expressions, or gestures as stimuli [3]. However, one of the new and intriguing routes this research is taking is the use of EEG-based technology for automatic emotion identification, which is becoming less invasive and more economical, leading to widespread usage in healthcare applications [4]. The emotions of a person can be identified using physiological signals or non-physiological signals like video and audio. Between these, the physiologic signals such as EEG (Electroencephalogram), ECG (Electrocardiogram), SC (Skin Conductance), and Electromyogram (EMG) accurately define the emotion of humans related to the other counterparts, but it does not provide enough results of classification of emotions [5]. This reason lies in the fact that EEG signals are measured directly at the surface of the brain, representing the actual human condition. EEG-based emotion analysis is useful for patients suffering from stroke, seizure diagnosis, autism, attention deficit, and mental retardation [6]. Several deep learning and machine learning methods are used to categorize the EEG emotion signals from the input dataset, but those methods do not provide sufficient accuracy, and the complexity and error rate were high [10–14]. The goal of this paper is to overcome these issues.

The main contributions of this manuscript are summarized below:

- A novel RSTAGNN and ContextNet for emotion classification with EEG signals is proposed (RSTAGNN-ContextNet-GWOA-EEG-EA).
- The input EEG signals are taken from two benchmark datasets such as DEAP [14] and K-EmoCon dataset [15].
- The input EEG signals are pre-processed, and feature extraction is done using ContextNet with Global Principal Component Analysis (GPCA) [7].
- After that, the EEG signal emotions are classified using the Reinforced Spatio-Temporal Attentive Graph Neural Networks (RSTAGNN) [8] method.
- RSTAGNN weight parameters are optimized using GWOA [9]. Finally, the model classifies the EEG signal emotions with high accuracy.
- The proposed technique is executed in the MATLAB. The metrics, like accuracy, precision, recall, and f-score, are evaluated.

- Then, the efficiency of RSTAGNN-ContextNet-GWOA-EEG-EA method using DEAP dataset is evaluated with existing DWT-SVM-EEG-EA-DEAP [10], GCNN-LSTM-EEG-EA-DEAP [11] and the performance of K-EmoCon dataset is compared with existing systems, like CAT-EEG-EA-K-EmoCon [12] and CAT-EEG-EA-K-EmoCon [13] respectively.

The remaining manuscript is specified as follows: section 2 divulges related works, the proposed methodology is illustrated in Section 3, the results and discussion are exemplified in Section 4, and the conclusion of the manuscript is given in Section 5.

2. Literature Survey

Among various research works on EEG based Emotion analysis using DEAP and K-EmoCon dataset, a few recent investigations are assessed here,

Khateeb et al. [10] presented multiple domain feature fusion for emotion characterization utilizing the DEAP dataset (DWT-SVM-EEG-EA-DEAP). The imageries were pre-processed to transfer data as well as reduce data dimensionality. After that, multi-domain features were extracted to identify stable features to classify the EEG emotion signals. Then, these signals were classified using support vector machine classifier. But, the complexity was high.

Yin et al. [11] presented multiple domain feature fusion for emotion categorization under DEAP dataset (GCNN-LSTM-EEG-EA-DEAP). Initially, the input data was calibrated using 3s baseline data that were split into 6s segments using a time window; after that, the differential entropy was extracted from every segment for constructing the feature cube. Then, these feature cubes were fused with graph convolutional neural networks including long- or short-term memories neural networks for classifying EEG signal emotional data.

Dissanayake et al. [12] presented Toward Robust Wearable Emotion Identification including Contrastive Representation Learning (SigRep-EEG-EA- K-EmoCon). The input EEG emotion signals were taken from the K-EmoCon dataset. Then, these signals were pre-processed to lower the signal resampling. After that, the statistical features were extracted. Those extracted features were used in the self-supervised technique to classify the EEG emotion signal with high accuracy. But the complexity was greater.

Yang et al. [13] presented Mobile Emotion Identification utilizing Multi Physiological Signals with Convolution-augmented Transformer (CAT-EEG-EA-K-EmoCon). The input EEG emotion signals were taken from the K-EmoCon dataset. Particularly, it uses arousal and valence dimensions, learning connections, and reliance across several modal physiological data to identify the users' emotions.. This method provides better accuracy but the error rate was high.

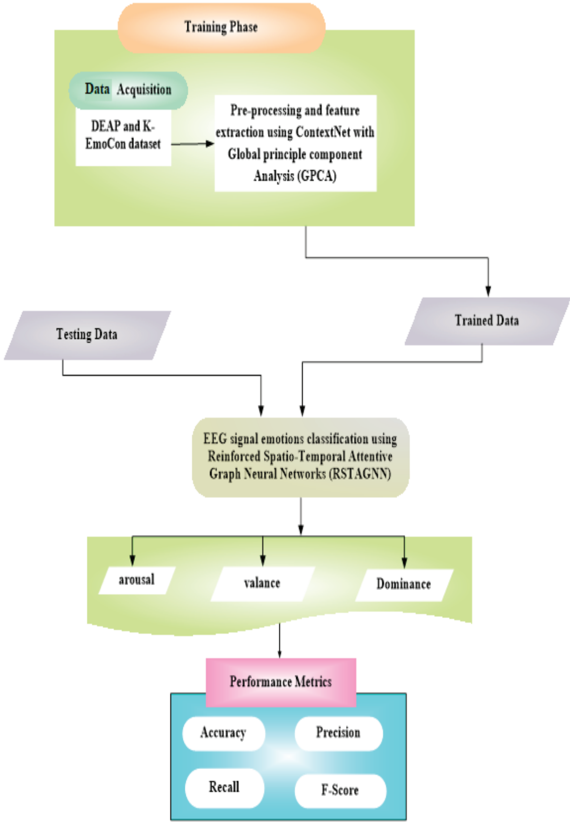

Figure 1. Proposed system

3. Proposed Methodology

In this section, a novel RSTAGNN and ContextNet for emotion classification using EEG signals is explained. Figure 1 depicts the block diagram of the proposed system.

3.1. Data Acquisition

The input datasets are taken from the DEAP and K-EmoCon datasets. The DEAP dataset is made up of physiological recordings from 32 people who viewed 40 one-minute-long music videos. K-EmoCon is a multiple modal dataset that involves a detailed explanation of ongoing emotions experienced through naturalistic conversations. The dataset has multiple modal measurements taken with commercial devices during 16 sessions of partner discussions of about 10 minutes duration on a social topic, including video recordings, EEG, and peripheral physiological cues. These two data sets are then pre-processed, and features are extracted with ContextNet with GPCA.

3.2. Pre-processing and Feature Extraction Using ContextNet with Global Principle Component Analysis (GPCA)

In this, pre-processing is done for two datasets, such as the DEAP dataset and the K-EmoCon. The data sets are captured with several devices along dissimilar sampling rates. To merge the signal frequency, first split the continual signals into four-second window sizes through a one-second overlap. The data transformation and data reduction process is used.

Here, the pre-processing is done for reducing the individual differences of the dataset for varying age, gender, and personality. The pre-processing is done using the convolution layer of the multi-task learning ContextNet by data transformation and data reduction.

Here, the data transformations are used to reduce the EEG data values from both datasets during the training process; otherwise, this may affect the performance of the classification. Then, the data transformation of the input dataset using the convolution layer of the multitask learning ContextNet and its equation is given in Equation (1)–(2)

$$EEG_{signal}(Preprocessing)(h)[a_i^T; W^T] = h_z(y_i^T; W_z^T) \quad (1)$$

where

$$y_i^T = h_f(a_i^T; W_f^T) \quad (2)$$

where h_f is represented as the context aware function with data transformation parameters are W_z^T, h_z, h_f, the specified task with context representation of data is represented as the W_f^T, y_i^T, and the particular task with context for transforming the data is given with task T, h is the number of input EEG emotional signals from the dataset with i^{th} context. Then, the data reduction process takes place after transforming the data using equation (2) and the data reduction equation is given in (3).

$$y_i = h_f(a_i; W_f) \quad (3)$$

Brain Wave data also contains some duplicate entries and are removed. The final 2-dimensional vector is the pre-processed input for Convolution layer. Then, the final pre-processed equation is given in Equation (4).

$$a_T(L) = a_T * h_\varphi = \sum_{L=0}^{L-1} (\varphi_{L,1}(F_O^{-1}X)^L + \varphi_{L,2}((F_I^{-1}X^T)^L))a_T \quad (4)$$

Equation (4) is known as the final pre-processed equation, and the data dimensions are reduced to improve the classification process. Then, the pre-processing signals are given to GPCA and the ReLu layer for extracting statistical features, domain features, and the frequency features from input EEG signal datasets. GPCA creates a low-dimensional data representation that captures as much of the data's diversity as possible. GPCA is applied with the number of features set as 32. So, the two dataset shapes after preprocessing are 32 participants x 40 trails x 32 channels x 32 data. Here, the data is normalized for eliminating the dimension, and the normalized global data is given to the feature extraction process using GPCA, and is given in Equation (5),

$$sa_{features(ji)} = \frac{a_{features(ji)} - \bar{A}_i}{\sigma_i} \quad (5)$$

where $sa_{features(ji)}$ is represented as the normalized data from the pre-processed used to extract the features, and $\bar{A}_i$ is represented as the global data of the GPCA.

It employs 100 initial convolution filters and a three-row, one-column convolutional kernel. Between each convolutional layer, dropout is used. Max Pooling Layer is the following layer. Over 3x3 blocks, this pooling is a typical 2-dimensional max pooling. To obtain CNN accuracy, the maximum pooled output is flattened and applied with soft plus activation. Using GPCA with the ContextNet method, statistical features such as mean and variance are extracted, and time domain features, such as Hjorth parameters and entropy features, are extracted as EEG signals. Here, Hjorth parameters are activity A_f, mobility M_f, complexity C_f, where f is represented as the features and its formulas are given in equations (6)–(8)

$$A_f = Variance(z_i) \quad (6)$$

$$M_f = \sqrt{\frac{Variance(z_i')}{Variance(z_i)}} \quad (7)$$

$$C_f = \frac{M_f'}{M_f} \quad (8)$$

Where z_i implicates input EEG signal, $Variance(z_i')$ implicates variance of initial derivative of input signal, $Variance(z_i)$ is represented as signal variance, and M_f' is represented as mobility of initial derivative of input EEG signal (z_i').

After that, the entropy feature is extracted by splitting EEG signals into 10 equal parts with no overlapping, and its equation is given in (9)

$$Entropy_f = \sum_{i=1}^{m_1} h(z_i) \log_b h(z_i) \quad (9)$$

where m_1 is represented as the $1/10^{th}$ of the total EEG signals (m), h refers count of features.

Frequency domain features of the EEG signal features are extracted using the non-stationary and nonlinear and its sub bands are represented as the alpha sub bands (8–15 Hz), beta (16–32 Hz), and gamma sub bands (>32 Hz), then the power rates are estimated using these sub-bands is given in Equation (10),

$$frequency_f = \frac{1}{m} \sum_{i=1}^{m_1} h(z_i)^2 \quad (10)$$

where z_i is represented as frequency domain, power rates are designed to alpha, beta, and gamma subbands. These extracting features are given to the RSTAGNN to categorize EEG signal emotions based on arousal, valance, and dominance.

3.3. EEG Signal Emotions Classification Using Reinforced Spatio-Temporal Attentive Graph Neural Networks (RSTAGNN)

RSTAGNN is used to classify EEG signal emotions, such as arousal, valance, and dominance. It consists of three parts: diffusion convolution on directed graph, spatial-temporal encoder, and multi-step prediction decoder. In this, the feature-extracted EEG signals are given to the input of diffusion convolution on directed graph. It is an L-order directed graph convolution network, and its equation is given in Equation (11)

$$a_T(L) = a_T * h_\varphi = \sum_{L=0}^{L-1} (\varphi_{L,1}(F_O^{-1}X)^L + \varphi_{L,2}((F_I^{-1}X^T)^L))a_T \tag{11}$$

where h_φ is represented as the convolution filter with feature extracted EEG signals, $*$ refers to diffusion convolution, L refers count of diffusion steps, $\varphi_{L,1}$ and $\varphi_{L,2} \in \mathfrak{J}^L$ represents trainable parameters of the two graph directions, $F_O = diagonal(X)$ is represented as the out-degree diagonal matrix, $F_I = diagonal(X^T)$ is represented as in-degree diagonal matrix and its complexity is given in Equation (12).

$$O(L) = O(L|\xi|) \ll O(M^2) \tag{12}$$

where ξ is represented as the weight parameter for representing complexity.

The spatial attention weights of the EEG signals are represented using the Spatio-temporal Traffic Encoder, and their equation is provided in Equation (13)

$$\beta_T^j = \frac{\exp(\beta_T^j)}{\sum_{i=1}^{M} \exp(\beta_T^j)} \tag{13}$$

where T refers to the time step with i^{th} and j^{th} EEG signals, M refers to number of samples, β refers to the weight parameter for representing accurateness of the EEG signal emotion classification. Then the EEG emotion signals are classified using the Multi-step Prediction Decoder, and its equation is given in (17) with the attention weights w'_T, T for every hidden state, namely soft functions are normalized to [0, 1], and its equation is given in (14)

$$\chi'_T, T = Soft\ \max(w'_T, T) = \frac{\exp(w'_T, T)}{\sum_{T=1}^{t} \exp(w'_T, T)} \tag{14}$$

where χ is represented as the weight parameter for representing the error rate of the EEG signal emotion classification.

To enhance the classification accuracy of RSTAGNN, GWOA is used for optimizing the proposed model. Here the weight parameters are ξ, β, χ, where ξ is represented as the complexity, β is represented as the accuracy, χ is represented as the error rate, these parameters are optimized using GWOA by minimizing ξ, χ and maximizing β.

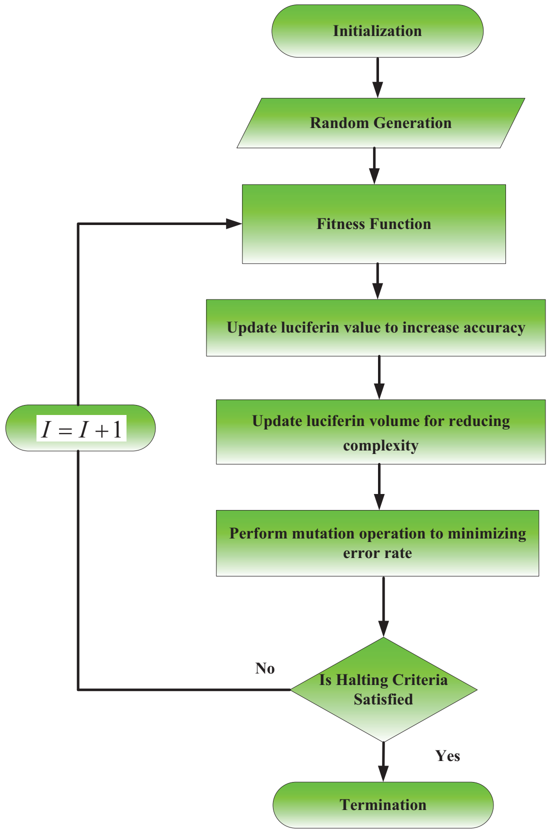

Figure 2. Flowchart for GWOA to optimize RSTAGNN

3.4. Stepwise Process of GWOA for Optimizing RSTAGNN

GWOA optimizes the parameters of RSTAGNN. These parameters are optimized for assuring accurate classification of the EEG emotion signals. GWO is defined as swarm cognizance. Figure 2 portrays the flow chart for the GWOA for optimizing RSTAGNN. The stepwise processing of GWOA is delineated below,

Step 1: Initialization

Initially, all glowworms have approximately equal levels of luciferin depending on the lesser and upper bounds of glowworms production power and control parameters. The initial population of glowworm is represented as I.

Step 2: Random Generation

Afterward the initialization procedure, the input parameters are created randomly. The maximal fitness values are designated with respect to the exact classification of the EEG emotion signals.

Step 3: Fitness Function

It is examined to attain the objective function, which is an exact classification of the EEG emotion signals with optimum value. RSTAGNN weight parameters are selected as ξ, β, χ, where ξ is represented as the complexity, β is represented as the accuracy, χ is represented as the error rate, and these parameters are optimized using GWOA by minimizing ξ, χ and maximizing β. The fitness function is articulated in Equation (15),

$$Fitness\ function = Maximize(\beta), minimize(\xi, \chi) \tag{15}$$

Step 4: Update luciferin value to increase accuracy β.

In GWOA, every glowworm updates its location through a pre-determined amount of trials. The glowworm's position update is exhibited in Equation (16),

$$\gamma_i^g = d * Tansig\left(1 - \frac{g}{g_{\max}}\right)\beta_i \tag{16}$$

here d refers random count of normal distribution at $[0, 3]$, $Tansig$ refers tangent sigmoid operations, g refers to the current iteration count, $g_{\max}$ refers to the maximal number of iterations, and β_i is represented as the optimizing parameter for increasing accuracy.

Step 6: Update luciferin volume for reducing complexity ξ.

Here, luciferin volume is used to reduce the complexity of the system while classifying the EEG emotion signals. Exploration of glowworm for ideal solutions is determined using Equation (17),

$$\beta = \frac{1}{1 + NI_j^i} \tag{17}$$

Let β imply a randomly chosen location, j for glowworm, i for reducing computational complexity to classify EEG emotional signal, and NI_j^i represents the new source.

Step 7: Perform mutation operation to minimize error rate χ.

The mutation process acts under probability values on the basis of fitness values presented by glowworm. For this purpose, a fitness base selection strategy is employed. This is articulated in Equation (18),

$$N(M) = \left\{\chi\left(\frac{S}{2} * \left(1 - \frac{g}{g_{\max}}\right)\right) + 1\right\} \tag{18}$$

where, the training data of RSTAGNN for classifying EEG emotion signals with high accuracy denotes $N(M)$, g implies current iteration count, $g_{\max}$ denotes ideal location, S refers maximal count of iterations, χ refers round for minimizing error rate.

Step 8: Termination.

The optimum weight-parameters ξ, β, χ are chosen at RSTAGNN under GWOA iterative repeat step 3 until fulfilling the halting criterion $I = I + 1$. At the end, RSTAGNN classifies EEG emotion accurately by diminishing the error and complexity utilizing GWOA.

In this manuscript, a novel RSTAGNN and Context Net for emotion classification using EEG signals is effectively executed. The RSTAGNN-ContextNet-GWOA-EEG-EA method is executed in MATLAB environment. The output of the proposed method using DEAP dataset attains higher precision by 32.99%, 46.64% estimated to the existing systems, like DWT-SVM-EEG-EA-DEAP and GCNN-LSTM-EEG-EA-DEAPand the performance of the proposed system using K-EmoCon dataset attains higher precision 15.75%, 31.86% related to existing systems, like SigRep-EEG-EA-K-EmoCon and CAT-EEG-EA-K-EmoCon respectively.

4. Results and Discussion

In this section, a novel RSTAGNN and ContextNet for emotion classification with EEG signals is discussed. The experiments are conducted using MATLAB on the GPU workstation with an Intel Xeon CPU @ 3.20GHz and 32.0GB RAM. The performance metrics, like precision, Accuracy, f-score, recall are examined to authenticate the effectiveness of the proposed system. The performance of the proposed system using DEAP dataset is analyzed to the existing systems, like DWT-SVM-EEG-EA-DEAP [10], GCNN-LSTM-EEG-EA-DEAP [11] respectively, and the performance of K-EmoCon dataset is compared with existing system like CAT-EEG-EA-K-EmoCon [12] and CAT-EEG-EA-K-EmoCon [13] respectively.

4.1. Dataset Description

Experiments are conducted using DEAP and K-EmoCon datasets. Of the total dataset, 80% was used for training and 20% for testing.

4.2. Performance Metrics

The evaluation parameters, such as the accuracy, precision, recall, f-score for detecting emotion from input EEG signals, are analyzed, and the performance equation is given in (19).

$$\begin{aligned} Accuracy &= \frac{TT + TN}{TT + NT + NN + TN} \\ Precesion &= \frac{TT}{TT + TN} \\ Recall &= \frac{TT}{TT + NT} \\ F - Score &= 2 \times \frac{recall \times precision}{recall + precision} \end{aligned} \tag{19}$$

here (T_P) indicates True Positive, (T_N) refers True Negative, (F_P) represents False Positive, (F_N) indicates False Negative.

4.3. Comparison of Performance Analysis with various methods used for EEG Emotion Analysis

The below section portrays comparison tables of the proposed method compared with the existing method.

Table 1 shows the performance analysis of the EEG emotion using the DEAP database. The accuracy analysis of the proposed method shows 34.94%, 28.94% higher Valence accuracy, 23.95%, 28.94%, higher Arousal accuracy, and 28.94%, 27.84%, higher Dominance accuracy. The precision analysis of the proposed method shows 34.94%, 28.94%, higher Valence precision, 23.95%, 28.94%, higher Arousal precision, and 28.94%, 27.84%, higher Dominance precision. The recall analysis of the proposed method shows 34.94%, 28.94% higher Valence recall, 23.95%, 28.94%, higher Arousal recall, and 28.94%, 27.84%, higher Dominance recall.

Table 1. Performance metrics of EEG emotion Analysis using the DEAP dataset

Performance metrics	Labels	Methods		
		DWT-SVM-EEG-EA-DEAP	GCNN-LSTM-EEG-EA-DEAP	Proposed Context NET-CNN-RSTAGNN-EEG-EA-DEAP
Accuracy	Valence	62.75	64.75	95.30
	Arousal	67.42	63.84	87.50
	Dominance	61.64	64.86	89.06
Precision	Valence	64.86	69.08	76.65
	Arousal	71.08	53.75	83.87
	Dominance	43.86	69.05	74.97
Recall	Valence	69.84	54.86	76.86
	Arousal	52.86	64.74	77.86
	Dominance	53.75	69.07	75.86
F-Score	Valence	66.75	64.85	77.65
	Arousal	58.64	66.85	87.86
	Dominance	66.65	55.85	74.75

Table 2. Performance metrics of EEG emotion Analysis using K-EmoCon dataset

Performance metrics	Labels	Methods		
		SigRep-EEG-EA-K-EmoCon	CAT-EEG-EA-K-EmoCon	Proposed Context NET-CNN-RSTAGNN-EEG-EA-DEAP
Accuracy	Valence	69.67	48.85	88.564
	Arousal	47.06	68.86	78.95
Precision	Valence	55.96	63.65	78.56
	Arousal	85.96	68.76	64.64
Recall	Valence	68.78	45.86	77.85
	Arousal	67.86	53.86	63.86
F-Score	Valence	69.86	50.76	75.64
	Arousal	63.87	56.97	76.95

The F-score analysis of the proposed method shows 34.94%, 28.94%, higher Valence F-score, 23.95%, 28.94%, higher Arousal F-score, 28.94%, 27.84%, higher Dominance F-score related to the existing system like DWT-SVM-EEG-EA-DEAP and GCNN-LSTM-EEG-EA-DEAP respectively.

Table 2 shows the performance analysis of the performance metrics of EEG emotion nalysis utilizing K-EmoCon data set. The accuracy analysis of the proposed method attains 32.75%, 35.75% higher Valence accuracy and 25.75%, 26.86% higher Arousal accuracy. The precision analysis of the proposed method shows 32.86%, 26.86% higher Valence precision, 31.86%, 26.86% higher Arousal precision. The recall analysis shows 32.86%, 44.75% higher Valence recall, 25.75%, 25.87% higher Arousal recall. The F-score analysis shows 25.86%, 31.75% higher Valence F-score, 25.86%, 33.86%, higher Arousal F-score related to the existing system like Sig Rep-EEG-EA-K-EmoCon and CAT-EEG-EA-K-EmoCon respectively.

4.4. Justification

Emotions are crucial for decision-making, planning, reasoning, and other aspects of human mentality. For e-healthcare systems, it is increasingly important to recognize these emotions. The use of biosensors like the Electroencephalogram (EEG) to identify patients' mental states who may require particular care provides crucial feedback for ambient assisted living (AAL). This study explored the purpose of deep learning classification for EEG-basedemotion analysis and evaluated its performance on DEAP and K-EmoCon datasets. The rate of emotion recognition confirms that there is sufficient information in the EEG data to distinguish between various emotional states. Notably, the suggested findings support the feasibility of using fewer electrodes to train classifiers for real-time HCI applications. The accuracy between other kinds of features is somewhat different, then the outcomes show that statistical features are appropriate for emotion recognition. Performance is likely to improve when training incorporates more data or better-quality, higher-resolution videos are verified. Compared to a single model using the same input video size, a bigger one, the Reinforced Spatio-Temporal Attentive Graph Neural Networks performed better overall and saved a significant amount of time regarding training and inference. It enable EEG signal emotions classification using video recordings, EEG, and peripheral physiological cues, also scientifically interesting along clinically impactful. Simulation outcomes show that the RSTAGNN-ContextNet-GWOA-EEG-EA provide higher accuracy of 38.58%, and 43.87%, higher F-score of 23.64%, 31.91%, higher precision of 32.67%, and 45.39%, higher recall of 34.09% and 45.51% for DEAP dataset compared with existing methods, like

DWT-SVM-EEG-EA-DEAP and GCNN-LSTM-EEG-EA-DEAP respectively. For the K-EmoCon dataset, the proposed RSTAGNN-ContextNet-GWOA-EEG-EA method provides higher accuracy of 58.31% and 56.34% higher F-Measure of 45.56% and 23.31% higher precision of 25.69%, 54.39%, higher recall of 45.17% and 21.33% compared with existing methods like CAT-EEG-EA-K-EmoCon and CAT-EEG-EA-K-EmoCon respectively.

5. Conclusion

In this manuscript, RSTAGNN and ContextNet for emotion classification using EEG signals is effectively executed. The RSTAGNN-ContextNet-GWOA-EEG-EA method is activated in MATLAB environment. The efficacy of the proposed method using DEAP dataset attains higher precision 32.99%, 46.64% compared with the existing systems, like DWT-SVM-EEG-EA-DEAP and GCNN-LSTM-EEG-EA-DEAP [11] respectively. The performance of the proposed method using K-EmoCon dataset attains higher precision 24.17% and 12.39% compared with the existing systems, like CAT-EEG-EA-K-EmoCon and CAT-EEG-EA-K-EmoCon respectively.

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