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Article

Enhanced Bird Swarm Algorithm with Deep Learning based Electroencephalography Signal Analysis for Emotion Recognition

Mohammed H. Al-Farouni[1]

[1] Department of Computer Technical Engineering, College of Technical Engineering, The Islamic university, Najaf, Iraq

*Corresponding author: (email: mohammed97@iunajaf.edu.iq)

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Abstract: Bioelectric signals comprise a massive count of data, and researchers in various domains containing cognitive neuroscience, psychiatry, and so on. Emotion is a vital part of regular human communication. The emotional conditions and dynamics of brain are connected by electroencephalography (EEG) signal which is utilized by Brain-Computer Interface (BCI), for providing optimum human-machine interaction. EEG-based emotion detection was extremely utilized in military, human-computer interactions, medicinal analysis, and other domains. Identifying emotions utilizing biological brain signals need accurate and effectual signal processing and extracting features approaches. But, one of the essential problems facing the emotion detection method, utilizing EEG signal is the detection accuracy. In this aspect, this study develops an Enhanced Bird Swarm Algorithm with Deep Learning based Electroencephalography Signal Analysis for Emotion Recognition (EBSADL-ESEG) technique. The ultimate aim of the EBSADL-ESEG technique lies in the recognition of emotions using the EEG signals accurately. To perform this, the EBSADL-ESEG technique initially extracts the statistical features from the EEG signals. In addition, the EBSA technique is employed for optimal feature selection process. Moreover, the gated recurrent unit (GRU) with root mean square propagation (RMSProp) optimizer is utilized for classifying distinct emotions (arousal, valence, and liking). The experimental analysis of the EBSADL-ESEG model is tested on DEAP dataset and the outcomes are investigated under diverse measures. The comprehensive comparison study revealed better outcomes of the EBSADL-ESEG model over other DL models.

Keywords: Bioelectric signals; EEG signals; Emotion recognition; Brain computer interface; Deep learning.

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1. Introduction

Emotion is a physiological state of the different thoughts, behaviors, and feelings of integrated

humans along with physiological and psychological reactions produced by many external stimulations [1]. Emotion occupies a crucial part of day-to-day work and life. It is essential to correctly identify emotion in various domains [2]. In recent times, the study of emotion detection was used in emotional calculation, psychology, computer vision (CV), medical treatment, artificial intelligence, and so on [3]. For instance, emotion detection is useful in the diagnosis of schizophrenia, depression, etc. It assists physicians to understand true emotions of the patient [4]. Moreover, emotion detection by computer might bring satisfactory user-human-computer interaction experience. Electroencephalography (EEG) was a cost effective and reliable technology employed for measuring activity of the brain [5]. Emotion recension using EEG signals includes many stages being implemented in sequence to fulfill the requirement of brain-computer interface (BCI). Conventionally, such stages comprise eliminating artefacts from EEG signals, mining spectral or temporal features from the frequency domain or EEG signal's time, correspondingly, and lastly, developing a multi-class classification algorithm [6]. Feature quality considerably increased performance of the emotion classifier algorithm. Thus, EEG-based emotion detection becomes a hot topic. EEG had a major contribution in the study of emotion detection and demonstrated the activity of brain regions was closely connected with certain types of emotion states [7].

EEG-based emotion detection method is developed mainly from two aspects: classical deep learning (DL) and machine learning (ML) [8]. In emotion detection method based on classical machine learning (ML), feature was manually extracted to input to Support Vector Machine (SVM), Naive Bayes (NB), and other techniques to recognize and classify [9]. The emotion detection method related to DL learn deep feature automatically and recognize emotion via Recurrent Neural Network (RNN) and (Long Short-Term Memory (LSTM), thereby efficiently simplifying the procedure of feature extraction. DL realizes end-to-end mapping that is useful to resolve nonlinear problems. Given the effects of emotion detection by Deep Belief Networks (DBN), Convolution Neural Networks (CNN), , and RNN [10].

This study develops an Enhanced Bird Swarm Algorithm with Deep Learning based Electroencephalography Signal Analysis for Emotion Recognition (EBSADL-ESEG) technique. The ultimate aim of the EBSADL-ESEG technique lies in the recognition of emotions using the EEG signals accurately. To perform this, the EBSADL-ESEG technique initially extracts the statistical features from the EEG signals. In addition, the EBSA technique is employed for optimal feature selection process. Moreover, the gated recurrent unit (GRU) with root mean square propagation (RMSProp) optimizer is utilized for classifying distinct emotions (arousal, valence, and liking). The experimental analysis of the EBSADL-ESEG model is tested on DEAP dataset and the outcomes are investigated under diverse measures.

2. Related Works

Ashokkumar et al. [11] present a dynamic pattern learning algorithm relevant to entropy to enable EEG signal for subject-independent emotion detection have stronger classification and generalization through Ensemble learning and RNN. Firstly, dynamic entropy measurement is employed to derive successive entropy values over time from EEG signals in quantitative EEG calculation. Topic and Russo [12] introduce an innovative method for emotion detection that relies on the creation of feature mapsrelated to holographic (HOLO-FM) and topographic (TOPO-FM) representations of EEG signal features. DL is exploited as a extractor of feature on feature map and later feature extracted is combined for the classification method to identify dissimilar types of emotion. Choi et al. [13] introduced a multi-modal fusion network that incorporates EEG and video modality networks. To compute attention weight of the corresponding EEG and facial video features, a multimodal attention network using bi-linear pooling related to low-rank decomposition, is developed. Lastly, the continuous domain valence value is calculated by means of attention weights and modality network outputs.

In [14], proposed a technique called multi-source domain transfer discriminative dictionary learning modeling (MDTDDL). The technique incorporates dictionary learning and transfers learning in learning models involving the concept of manifold smoothness, subspace learning, large margin, and margin-related discriminant embedding. The domain-specific conversion matrix proposes EEG signals from different fields into transfer subspace. Subasi et al. [15] introduce a new automatic emotion detection architecture that employs EEG signals. The presented technique is lightweight, and it comprises four important stages that involve: a classification stage, a reprocessing stage, a feature extraction stage, and feature dimension reduction stage.

Liu et al. [16] developed a multi-level features guided capsule network (MLF-CapsNet) for multichannel EEG-oriented emotion detection to conquer such problems. The presented technique was an end-to-end architecture that could concurrently extracted features from the raw EEG signal and define emotional state. In contrast to CapsNet, it integrates multilevel feature maps learned by distinct layers during the formation of the primary capsules such that the ability of feature representations will be improved. Cui et al. [17] introduce end-to-end Regional-Asymmetric CNN (RACNN) for emotion detection that comprises temporal, regional, and asymmetric feature extractor. Particularly, a continuous 1D convolution layer was applied in temporal extractors for learning time-frequency representation. Next, regional extractor of feature comprises 2D convolutional layers for capturing regional data amongst physically adjacent channels. In the meantime, the author proposes an Asymmetric Differential Layer (ADL) in asymmetric feature extractors by considering the asymmetry properties of emotional response that could take the discriminatory data between the right and left hemispheres of the brain.

3. The Proposed Model

In this study, we have developed a new EBSADL-ESEG approach for emotion recognition process. The presented EBSADL-ESEG technique analyses the EEG signals to classify three different types of emotions namely arousal, valence, and liking. In the presented EBSADL-ESEG technique, three processes are involved namely statistical feature extraction, feature selection using EBSA, GRU classification, and RMSProp optimizer. Figure 1 represents the block diagram of EBSADL-ESEG system.

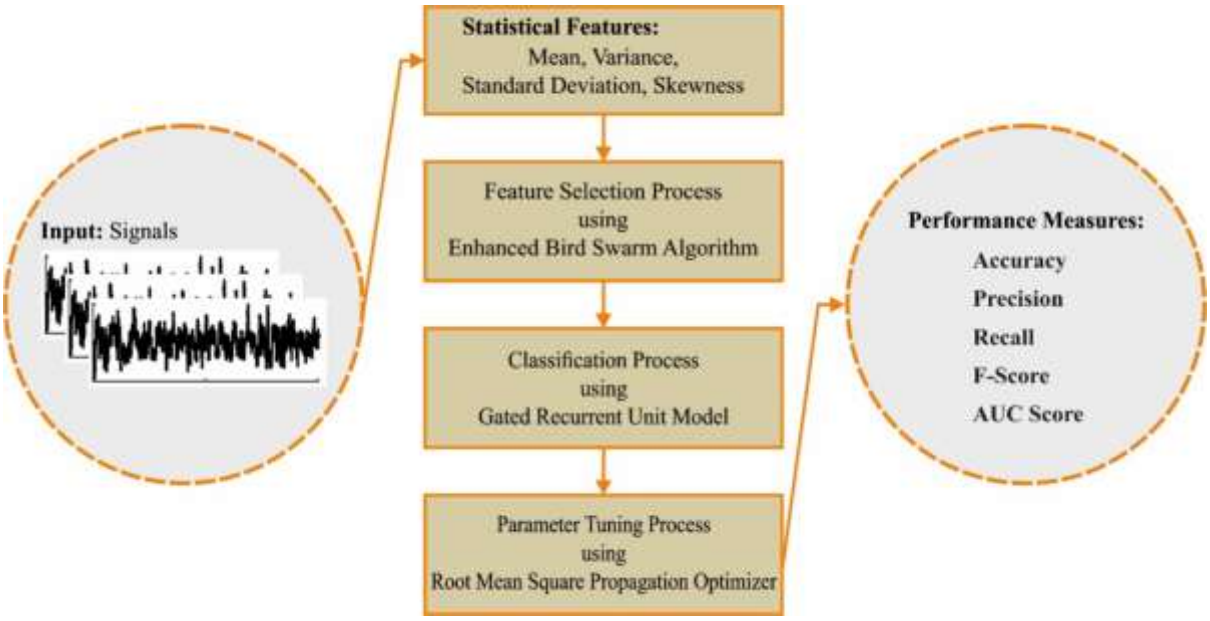


Figure 1: Block diagram of EBSADL-ESEG system

3.1. Statistical Features

The EEG signal is a non-stable signal in the time field. Therefore, a time-domain feature like statistical information is examined, for explaining the signal property suitably [18]. The group of statistical features can be calculated in the EEG signals like variance, mean, and standard deviation, deviation which calculates percentage of signal asymmetries around their mean, and kurtosis that calculates the count of signal tails. The subsequent formulas clarify the statistical extracting features under this case:

Mean:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

Variance:

$$V = \frac{1}{n+1}\Sigma_{i=1}^{n}|x_i - \mu|^2 \tag{2}$$

Standard Deviation:

$$\sigma = \sqrt{V} = \sqrt{\frac{1}{n+1}\sum_{i=1}^{n}|\, x_i - \mu|^2} \tag{3}$$

Skewness:

$$S = \frac{\frac{1}{n}\Sigma_{i=1}^{n}(x_i - \mu)^3}{\left(\sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(x_i - \mu)^2}\right)^3} \tag{4}$$

Kurtosis:

$$K = \frac{\frac{1}{n}\sum_{i=1}^{n}(\, x_i - \mu)^4}{(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\, x_i - \mu)^2})^2} \tag{5}$$

3.2. Feature Selection using EBSA

At this stage, the EBSA technique is applied for selecting the features effectively. BSA projected by Meng et al. [19], is a new intelligent bionic system that depends on multi-search and multi-group systems; it reproduces the bird's vigilance, foraging, and flight performances, and employs this SI to resolve the optimizing problem. The bird's swarm approach is a fundamental of 5 rules:

Rule1: every bird is switching betwixt foraging and vigilant performances, and integrated bird forage and retain vigilance is inspired as a random decision.

Rule2: when foraging, each bird upgrade and record its previous great skill and swarm preceding optimal ability with food patches. The skill is also employed to search the food. Instant share of social information is over the group.

Rule3: if it can be kept vigilance, every bird tries to move nearby the swarm center. It can be activated if managed by disturbance because of swarm competitions. The bird with more stocks is extremely feasible to center swarms than bird with lease stock.

Rule4: bird flies to other places regularly. When flying to other places, the bird often switches

betwixt shrub and production. The bird with maximal stocks was producer, and bird with minimal is scrounger. Other birds hainghigher and lesser reserves are randomly selected for scroungers and producers.

Rule5: producer actively searches for food. The scroungers randomly follow producers seeking food.

According to Rule1, it could be defined that time interval of every bird flight efficiency FQ, probability of foraging performances $P(P \in (0,1$ and uniform arbitrary number $\delta \in (0,1)$.

Once the count of iterations is lower than FQ and $\delta \leq P$, bird is foraging performance. Rule2 was expressed mathematical method as:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + (p_{i,j}^{t} - x_{i,j}^{t}) \times C \times rand(0,1) + (g_{j}^{t} - x_{i,j}^{t}) \times S \times rand\ (0,1), (6)$$

whereas C and S are 2 positive numbers; the preceding is termed as cognitive accelerated coefficient, and the last is termed as social accelerated coefficient [20]. At present, $p_{i,j}$ defines the i^{th} bird better earlier location and g_j implies the best preceding swarm location.

If the count of iterations is lower than FQ and $\delta > P$, bird was vigilance performance. Rule3 has expressed mathematical process as:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + A_1(mean_{j}^{t} - x_{i,j}^{t}) \times rand(0,1) + A_2(p_{k,j}^{t} - x_{i,j}^{t}) \times rand\ (-1,1), (7)$$

$$A_1 = a_1 \times \exp\left(-\frac{pFit_i}{sumFit + \varepsilon} \times N\right), \quad (8)$$

$$A_2 = a_2 \times \exp\left(\left(\frac{pFit_i - pFit_k}{|pFit_k - pFit_i| + \varepsilon}\right) \times \frac{N \times pFit_k}{sumFit + \varepsilon}\right) \quad (9)$$

whereas a_1 and a_2 refers to the 2 positive constants in 0 and 2, $sumFit$ denotes the sum of swarms' better fitness value, and $pFit_i$signifies the optimal fitness value of i^{th} bird. At this time, $\varepsilon$is employed to avoid zero-division error as minimal constant in computer. $mean_j$ demonstrates that the j^{th} element of complete swarm's average location. Once the count of iterations is corresponding FQ, the bird was flight performance which is divided as performance of scrounger and producer with fitness. Rule3 and Rule4 were expressed mathematical method as:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + randn\ (0,1) \times x_{i,j}^{t}, \quad (10)$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \left(x_{k,j}^{t} - x_{i,j}^{t}\right) \times FL \times rand\ (0,1), \quad (11)$$

whereas FL ($FL \in [0,2]$) depicts that scrounger is follow producer to seek food.

Chebyshev chaotic map is an extensive and further uniform distribution range [21], and it could be distributed in the interval of -1 and 1. Once $k \geq 2$ (k is the order), no matter that adjacent the primary value is selected, iterated series is uncorrelated and chaotic, and ergodic in this range.

$$x_{n+1} = \cos(karccosx_n) x_n \in [-1,1] \quad (12)$$

The EBSA utilizes the formula for generating uniformly distributing points for initializing the place of bird swarms, enhancing the global searching capability of primary population, and enhancing the solution precision of the technique. The fitness function (FF) assumes classifier accuracy and FSs count. It will maximize the classifier accuracy and diminishes the set size of FSs. So, subsequent FF was employed to evaluate individual solutions, as demonstrated in Eq. (13).

$$Fitness = \alpha * ErrorRate + (1 - \alpha) * \frac{\#SF}{\#All_F} \quad (13)$$

whereas ErrorRate stands for the classifier error rate utilizing FSs. ErrorRate refers to the

computed percentage of incorrect classification (by GRU methods) to count of classifiers made, formulated as a value betwixt zero and one. (ErrorRate defines complement of classifier accuracy), $\#SF$ demonstrates count of FSs and $\#All_F$ stands for the entire count of elements in a novel database. α is leveraged to control the importance of subset length and classifier quality. During this experiment, α is fixed to 0.9.

3.3. Emotion Recognition using Optimal GRU Model

Lastly, the RMSProp optimizer with GRU model is exploited for emotion classification process. To simplify the trained method of LSTM method, GRU network has been presented based on LSTM [22]. In GRU is easy if related to infrastructure of LSTM, and effects are equivalent to LSTM. Afterward chosen the GRU network to learn the time dependency from the signal. Figure 2 depicts the architecture of GRU. There are 2 gates: the reset and update gates (which integration is forgotten as well as input gates):

$$r_t = \sigma_{\log}(W^r x_t + U^r h_{t-1} + b^r) \quad (14)$$

$$z_t = \sigma_{\log}(W^z x_t + U^z h_{t-1} + b^z) \quad (15)$$

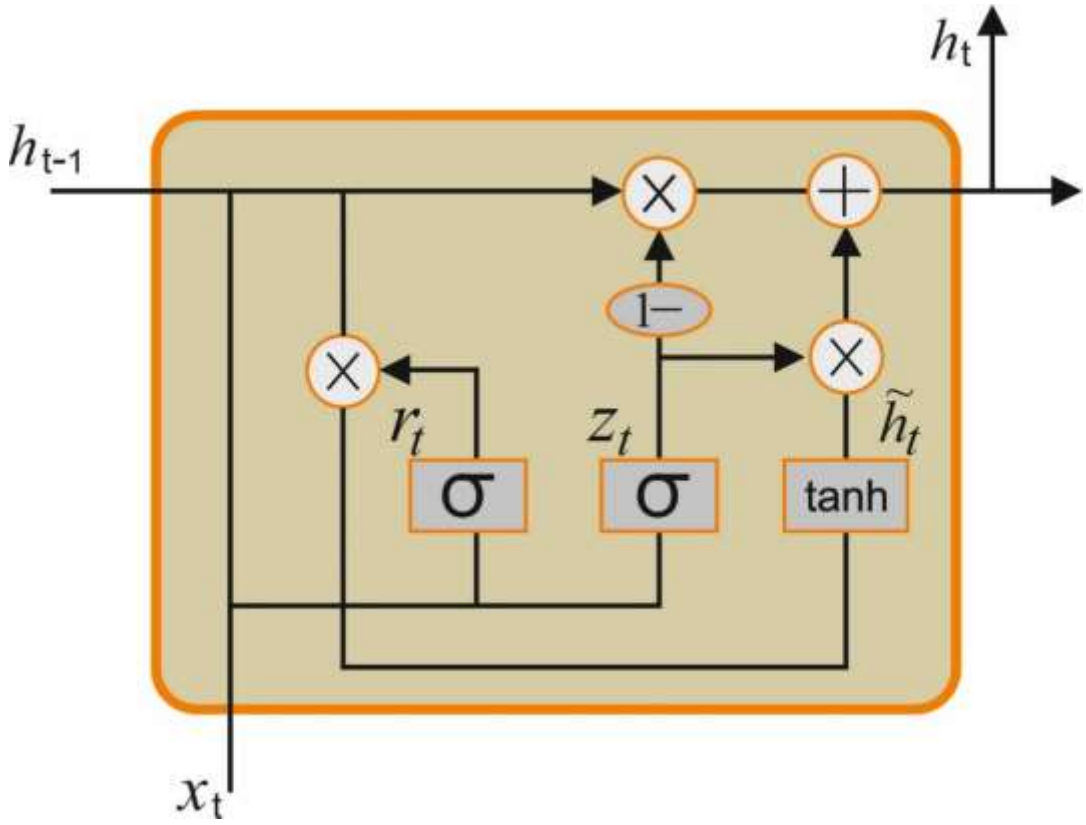


Figure 2: Structure of GRU

The update gate has been employed to control the range whereas the state data in the earlier moment was conveyed to the present state, and reset gate manages that several data in the earlier state were formulated in the current candidate set

$$\tilde{h}_t = \tanh(W^h x_t + U^h(r_t \circ h_{t-1}) + b^h) \quad (16)$$

$$h_t = z_t \circ h_{t-1} + (1 - z) \circ \tilde{h}_t \quad (17)$$

In which r_t refers to the reset gate, z_t implies the update gate, x_t defines the input vector, h_t demonstrates the hidden state at time t, h_{t-1} implies the hidden state in the previous unit, W and U

illustrate the weighted matrices, b signifies the deviation parameter. $\sigma_{\log}$ symbolizes the logistic sigmoid function.

In order to enhance the trained efficacy of GRU technique, the RMSProp optimization was executed. As RMSprop is the augmentation procedure of Adagrad, the upgrade process of RMSprop was analogous to Adagrad [23]. For RMSprop, it can evaluate an exponential decay average of squared gradients.

$$G_t = \beta G_{t-1} + (1-\beta) g_t \odot g_t$$
$$= (1-\beta) \sum_{\tau=1}^{t} \beta^{t-\tau} g_\tau \odot g_\tau \quad (18)$$

β stands for the rate of decay which is commonly mentioned that set as 0.9. Similarly, the upgrade variable values in RMSprop are related to Adagrad:

$$\triangle \theta_t = -\frac{\alpha}{\sqrt{G_t + \varepsilon}} \odot g_\tau. \quad (19)$$

Also, the generalization model of Adagrad was employed. g'_t is defined as:

$$g'_t = \frac{1}{\sqrt{G_t + \varepsilon}} \odot g_\tau, \quad (20)$$

and the upgrade value of RMSprop was defined as:

$$\Delta\theta_t = -\alpha g'_t. \quad (21)$$

Therefore, the RMSprop is an optimized method-based gradient. Based on the case, the rate of learning optimized manner was employed to enhance the trained efficacy.

4. Results and Discussion

This section examines the performance of the EBSADL-ESEG model on the EEG related emotion recognition process on DEAP dataset [24]. The dataset holds 3820 samples with three major classes and each class holds two subclasses as defined in Table 1.

Table 1 Dataset details

DEAP Dataset				
Subclass	Instance in each class			
	Valence	Arousal	Liking	Total No. of Instance (sub class)
High	566	536	424	1526
Low	714	744	856	2314
Total Number of Instances (class)	1280	1280	1280	3840

Figure 3 exhibits the confusion matrices of the EBSADL-ESEG method on valence class of emotion recognition. On entire dataset, the EBSADL-ESEG model has recognized 504 samples into high and 711 samples into low class. In addition, on 70% of TR database, the EBSADL-ESEG

approach has recognized 359 samples into high and 492 samples into low class.

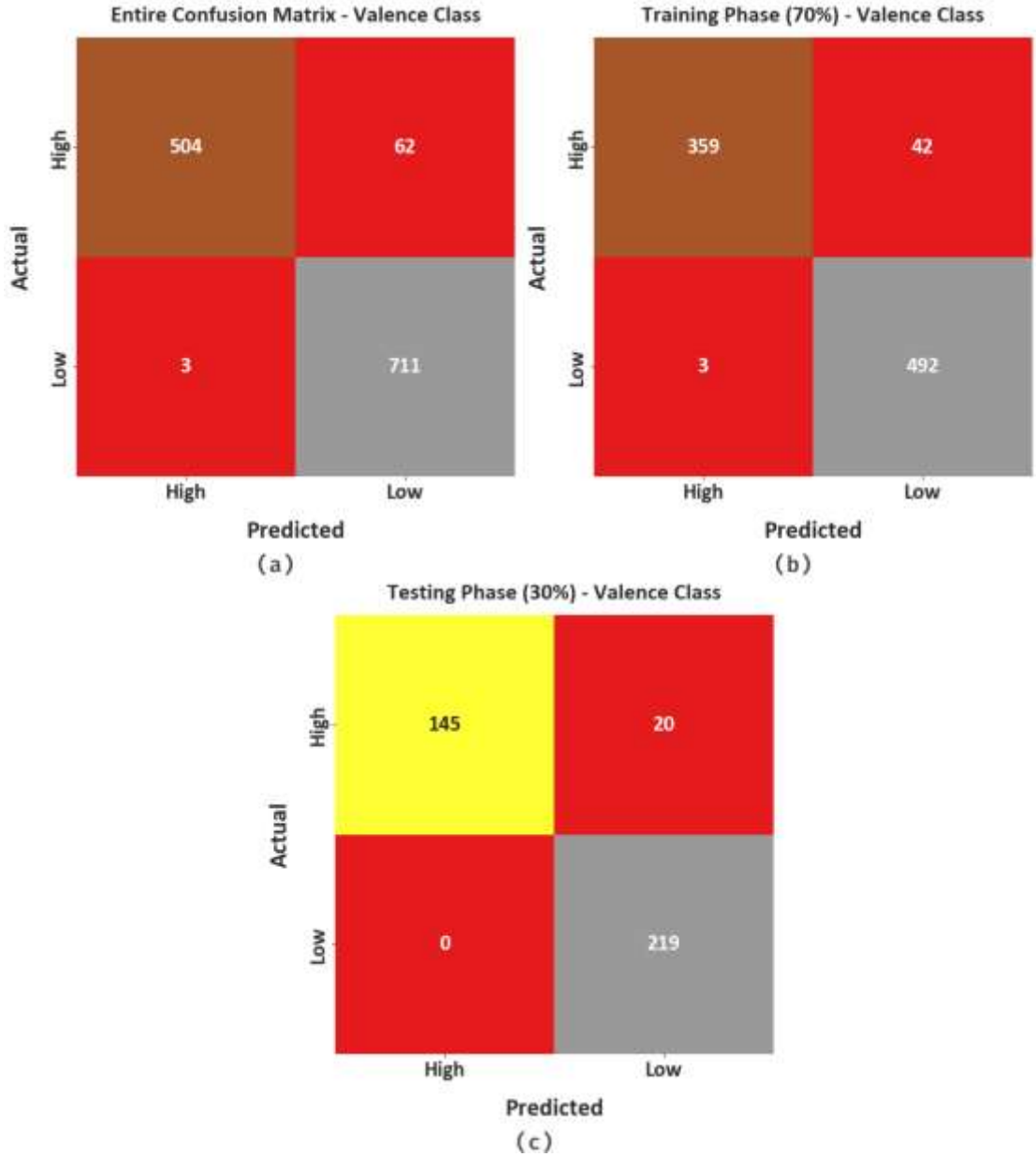


Figure 3: Confusion matrices of EBSADL-ESEG system under valence class (a) Entire database, (b) 70% of TR database, and (c) 30% of TS database

Table 2 represents the emotion recognition outcomes of the EBSADL-ESEG model on valence class. The results denoted that the EBSADL-ESEG model has properly identified both the low and high classes. On entire dataset, it is observed that the EBSADL-ESEG model has offered average $accu_{bal}$ of 94.31%, $prec_n$ of 95.69%, $reca_l$ of 94.31%, F_{score} of 94.79%, and AUC_{score} of 94.31%.

Table 2: Emotion recognition outcome of EBSADL-ESEG approach under valence class

Valence Class					
Subclass	Accuracybal	Precision	Recall	F-Score	AUC Score
Entire Class					
High	89.05	99.41	89.05	93.94	94.31
Low	99.58	91.98	99.58	95.63	94.31
Average	94.31	95.69	94.31	94.79	94.31
Training Phase (70%)					
High	89.53	99.17	89.53	94.10	94.46
Low	99.39	92.13	99.39	95.63	94.46
Average	94.46	95.65	94.46	94.86	94.46
Testing Phase (30%)					
High	87.88	100.00	87.88	93.55	93.94
Low	100.00	91.63	100.00	95.63	93.94
Average	93.94	95.82	93.94	94.59	93.94

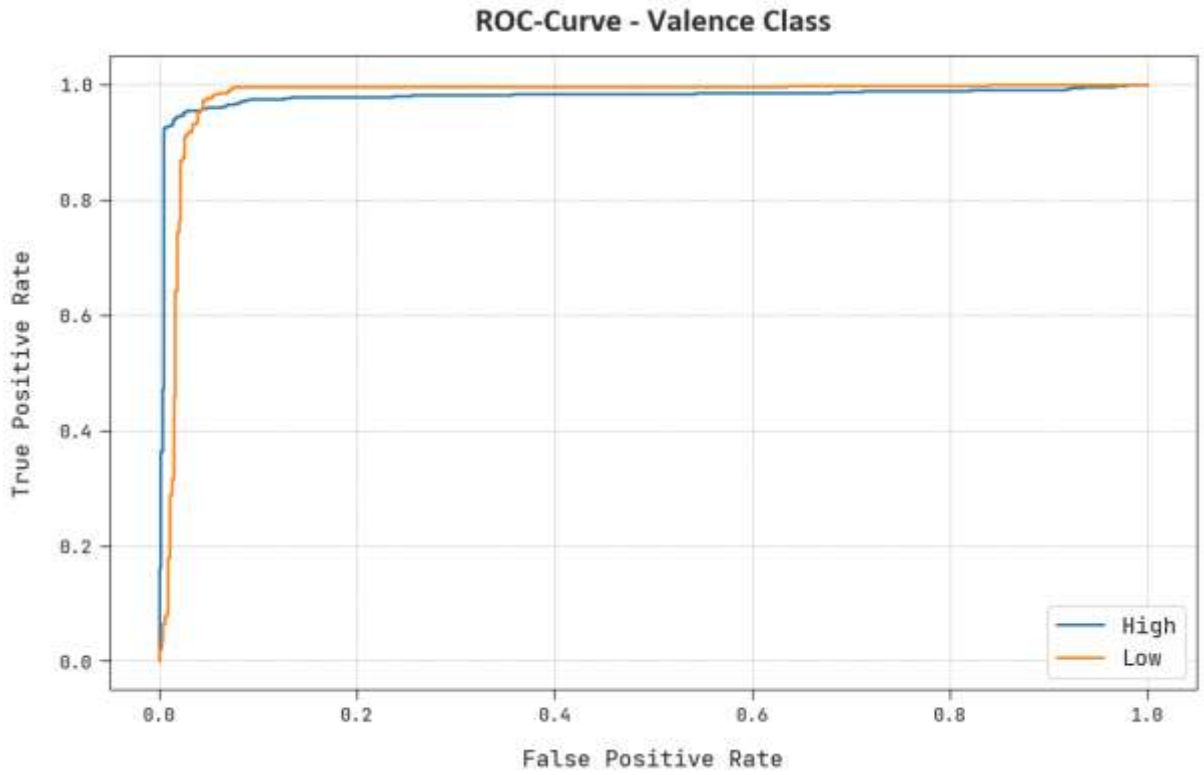


Figure 4: ROC analysis of EBSADL-ESEG approach under valence class

A detailed ROC investigation of the EBSADL-ESEG system in valence class is represented in Figure 4. The outcome stated the EBSADL-ESEG system has revealed its capability in classifying various classes.

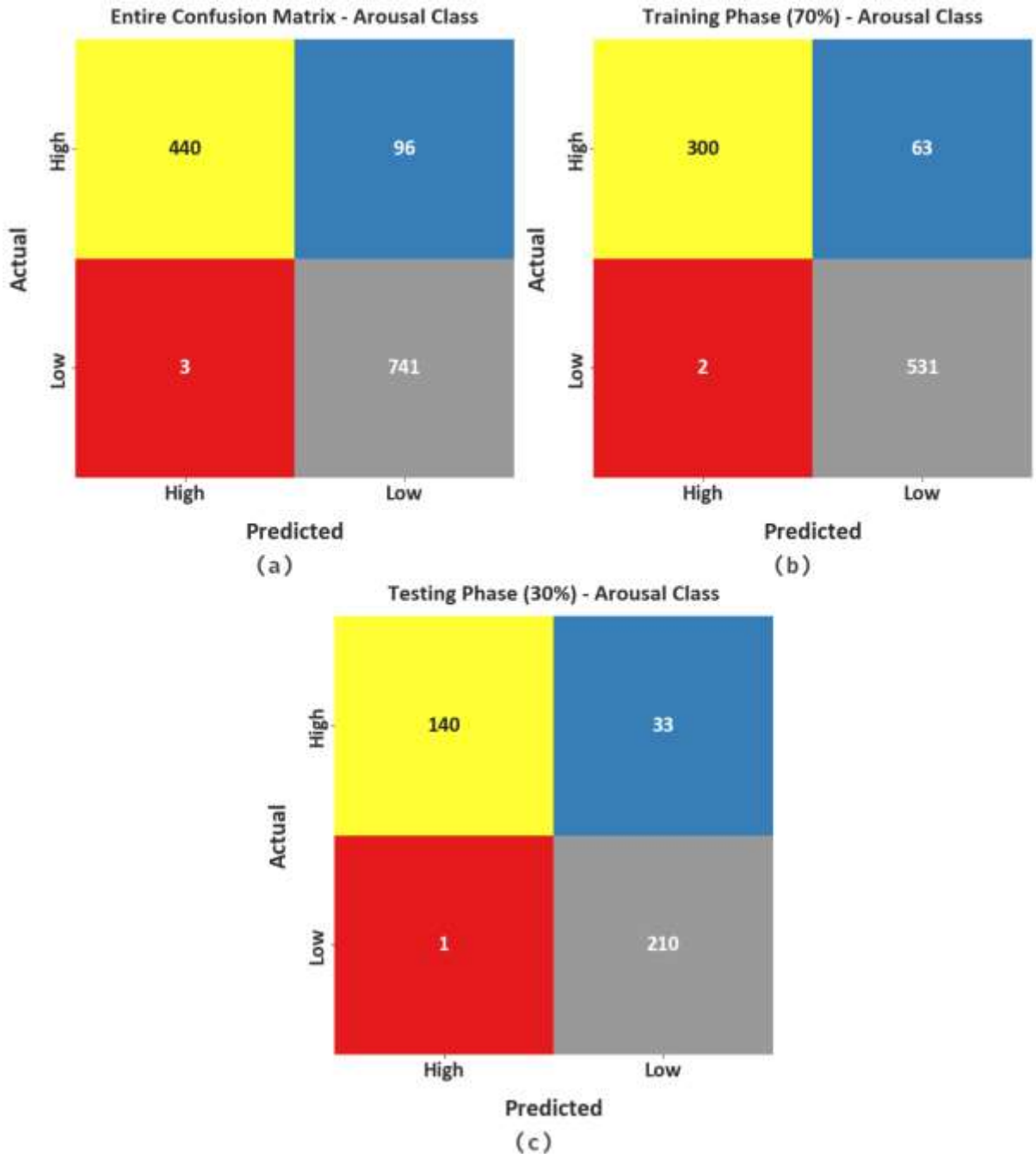


Figure 5: Confusion matrices of EBSADL-ESEG system under Arousal class (a) Entire database, (b) 70% of TR database, and (c) 30% of TS database

Figure 5 illustrates the confusion matrices of the EBSADL-ESEG approach on Arousal class of emotion recognition. On entire dataset, the EBSADL-ESEG system has recognized 440 samples into high and 741 samples into low class. Followed by, 70% of TR database, the EBSADL-ESEG methodology has recognized 300 samples into high and 531 samples into low class.

Table 3 exemplifies an emotion recognition outcome of the EBSADL-ESEG algorithm on Arousal class. The outcomes referred that the EBSADL-ESEG methodology has properly identified both the low and high classes. On entire dataset, it can be clear that the EBSADL-ESEG algorithm has obtainable average $accu_{bal}$ of 90.84%, $prec_n$ of 93.93%, $reca_l$ of 90.84%, F_{score} of 91.81%,

and AUC_{score} of 90.84%.

Table 3 Emotion recognition outcome of EBSADL-ESEG approach under Arousal class

Arousal Class					
Subclass	Accuracybal	Precision	Recall	F-Score	AUC Score
Entire Class					
High	82.09	99.32	82.09	89.89	90.84
Low	99.60	88.53	99.60	93.74	90.84
Average	90.84	93.93	90.84	91.81	90.84
Training Phase (70%)					
High	82.64	99.34	82.64	90.23	91.13
Low	99.62	89.39	99.62	94.23	91.13
Average	91.13	94.37	91.13	92.23	91.13
Testing Phase (30%)					
High	80.92	99.29	80.92	89.17	90.23
Low	99.53	86.42	99.53	92.51	90.23
Average	90.23	92.86	90.23	90.84	90.23

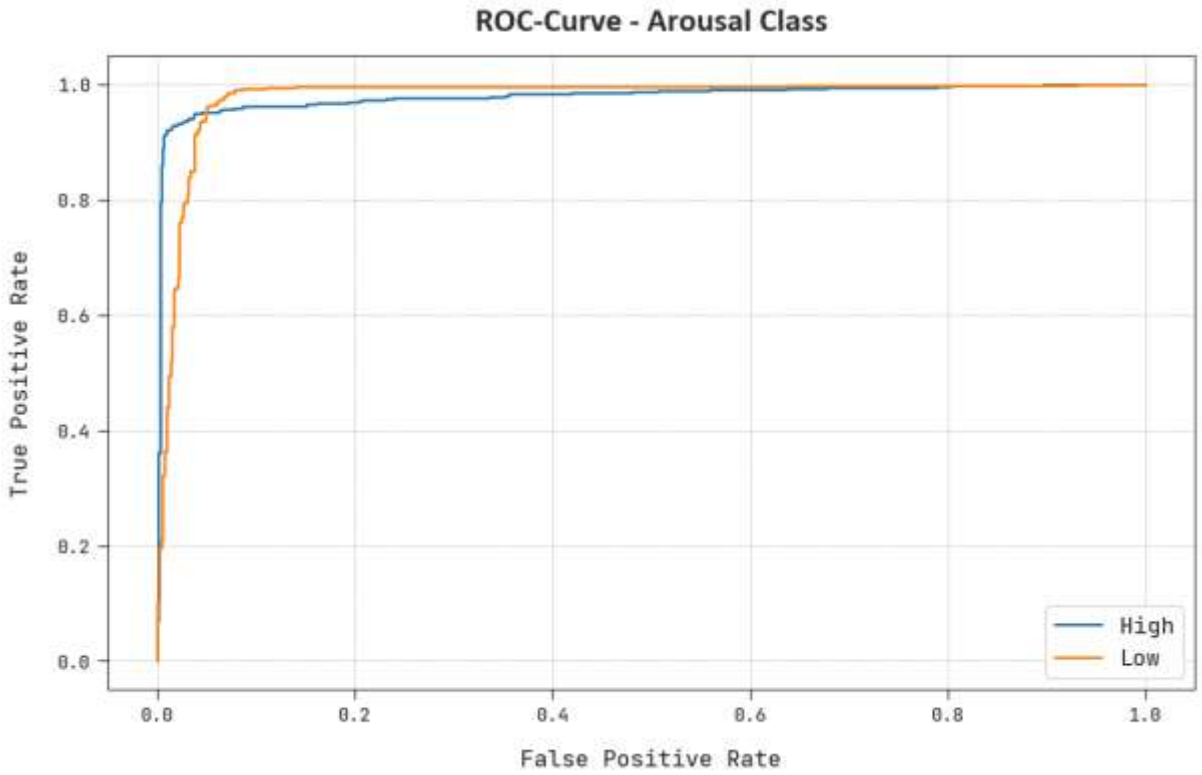


Figure 6: ROC analysis of EBSADL-ESEG approach under Arousal class

A comprehensive ROC study of the EBSADL-ESEG algorithm under Arousal class is described in Figure 6. The results denoted the EBSADL-ESEG methodology has displayed its capability in cataloging several classes.

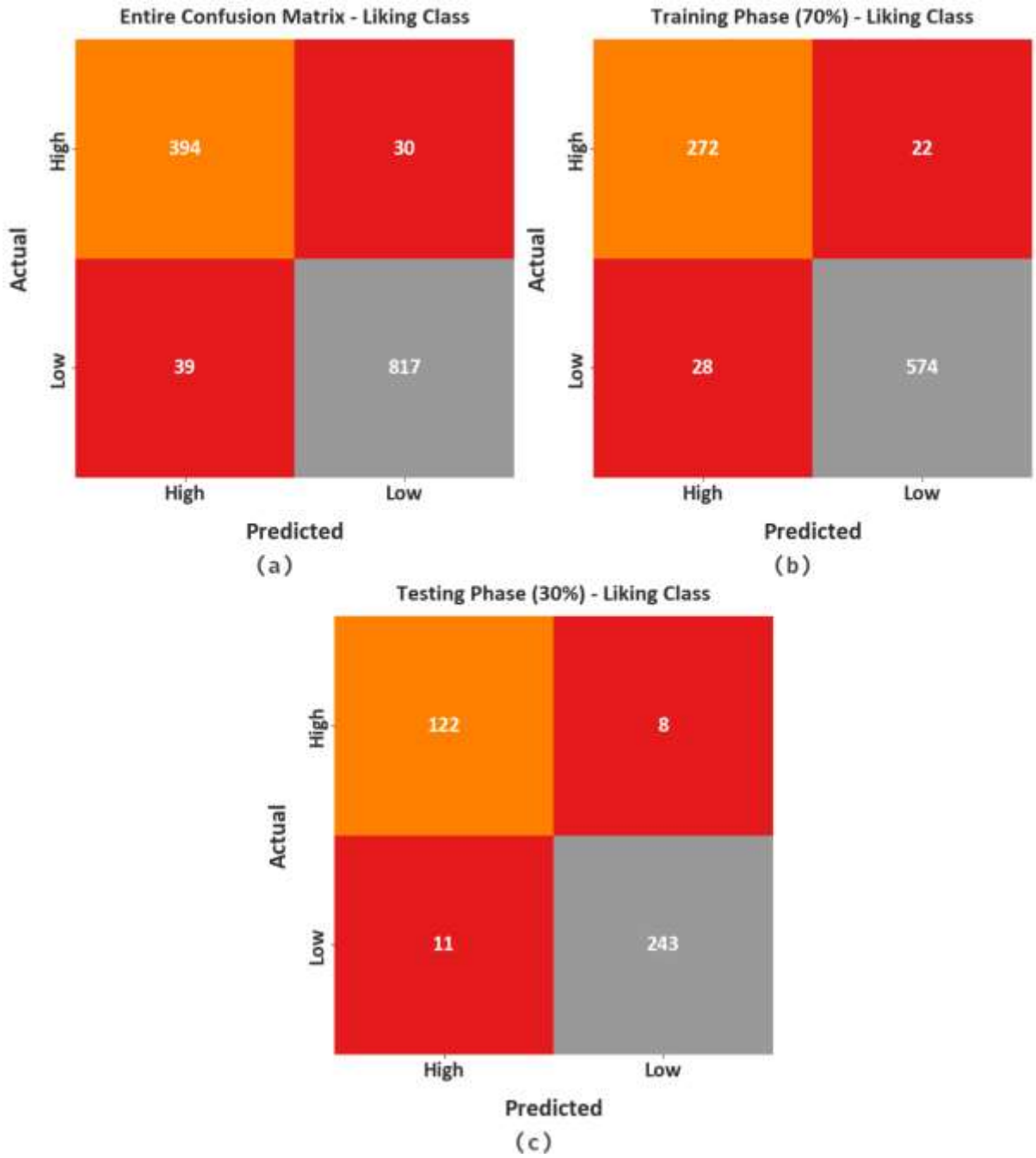


Figure 7: Confusion matrices of EBSADL-ESEG system under Liking class (a) Entire database, (b) 70% of TR database, and (c) 30% of TS database

Figure 7 depicts the confusion matrices of the EBSADL-ESEG approach under Liking class of emotion recognition. On entire dataset, the EBSADL-ESEG system has recognized 394 samples into high and 817 samples into low class. Moreover, on 70% of TR database, the EBSADL-ESEG algorithm has recognized 272 samples into high and 574 samples into low class.

Table 4 demonstrates an emotion recognition outcome of the EBSADL-ESEG algorithm on Liking class. The outcomes pointed out that the EBSADL-ESEG approach has properly identified both the low and high classes. On entire dataset, it can be experimental that the EBSADL-ESEG system has accessible average $accu_{bal}$ of 94.18%, $prec_n$ of 93.73%, $reca_l$ of 94.18%, F_{score} of

93.95%, and AUC_{score} of 94.18%.

Table 4 Emotion recognition outcome of EBSADL-ESEG approach under Liking class

Liking Class					
Subclass	Accuracybal	Precision	Recall	F-Score	AUC Score
Entire Class					
High	92.92	90.99	92.92	91.95	94.18
Low	95.44	96.46	95.44	95.95	94.18
Average	94.18	93.73	94.18	93.95	94.18
Training Phase (70%)					
High	92.52	90.67	92.52	91.58	93.93
Low	95.35	96.31	95.35	95.83	93.93
Average	93.93	93.49	93.93	93.70	93.93
Testing Phase (30%)					
High	93.85	91.73	93.85	92.78	94.76
Low	95.67	96.81	95.67	96.24	94.76
Average	94.76	94.27	94.76	94.51	94.76

A detailed ROC examination of the EBSADL-ESEG approach under Liking class is demonstrated in Figure 8. The outcomes exposed the EBSADL-ESEG algorithm has outperformed its capability in categorizing various classes.

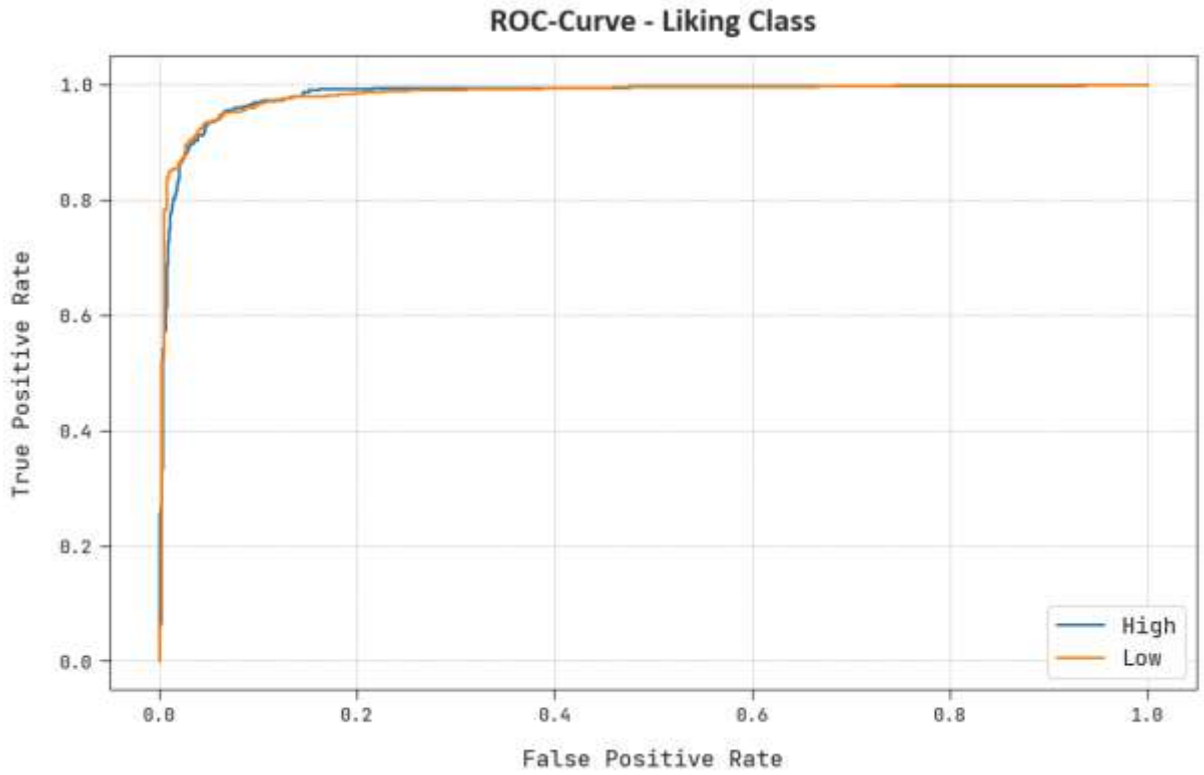


Figure 8: ROC analysis of EBSADL-ESEG approach under Liking class

Table 5 and Figure 9 illustrate the overall emotion recognition results of the EBSADL-ESEG model. The results implied the enhanced outcomes of the EBSADL-ESEG model under all classes. It is noticed that the EBSADL-ESEG model has reached average $accu_y$ of 93.45%, $prec_n$ of 94.76%, $reca_l$ of 93.45%, F_{score} of 93.87%, and AUC_{score} of 93.45%.

Table 5 Overall emotion recognition outcome of EBSADL-ESEG approach

Classes	Accuracy	Precision	Recall	F-Score	AUC Score
Valence	94.46	95.65	94.46	94.86	94.46
Arousal	91.13	94.37	91.13	92.23	91.13
Liking	94.76	94.27	94.76	94.51	94.76
Average	93.45	94.76	93.45	93.87	93.45

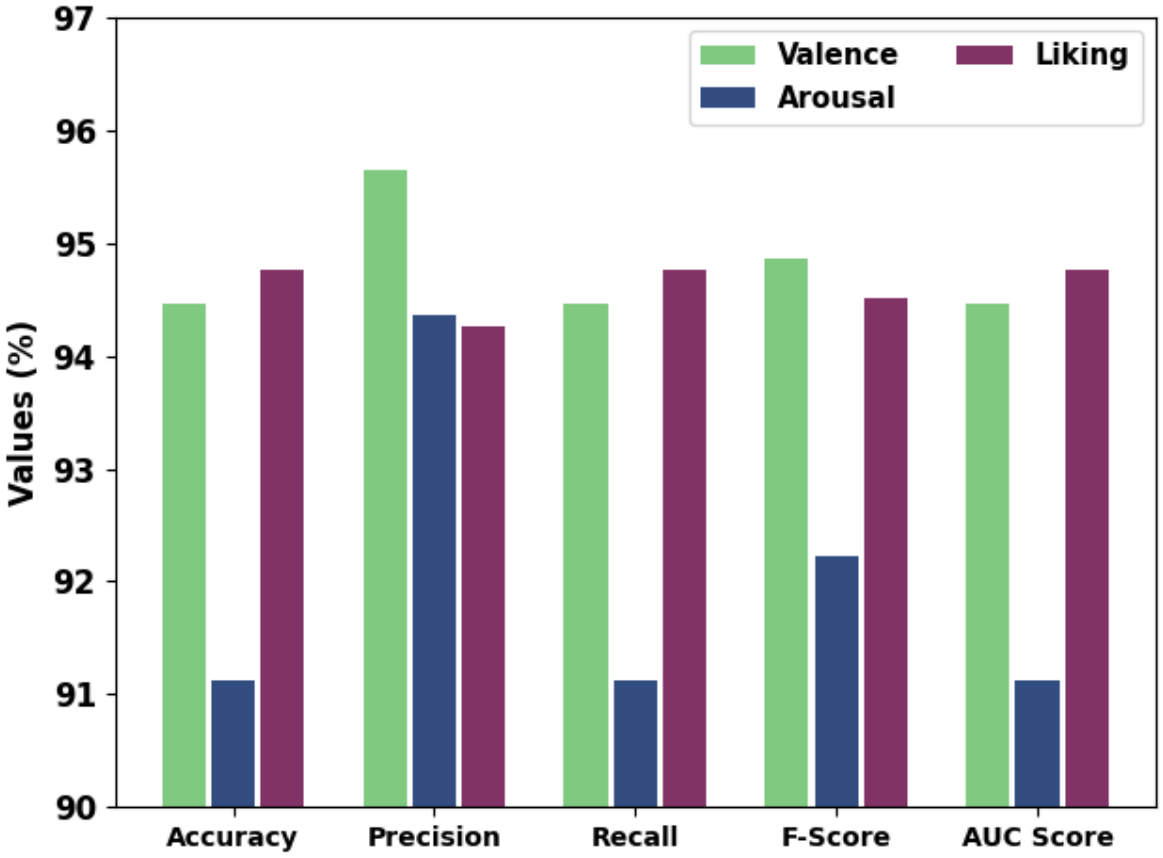


Figure 9: Overall emotion recognition outcome of EBSADL-ESEG approach

Finally, a detailed comparativeinspection of the EBSADL-ESEG method with recent models is given in Figure 10 and Table 6 [18]. The experimental values demonstrated that the SVM, RF, MLP, and ANN models have resulted to lower $accu_y$ of 79.22%, 76.38%, 70.24%, and 74.11% respectively. Next, the LSTM-RNN model has reached slightly increased $accu_y$ of 86.14%.

Table 6: Accuracy analysis of EBSADL-ESEG approach with existing algorithms

Methods	Accuracy
EBSADL-ESEG	93.45
SVM Model	79.22
CNN Model	90.48
LSTM-RNN	86.14
Random forest	76.38
MLP Model	70.24
ANN Model	74.11

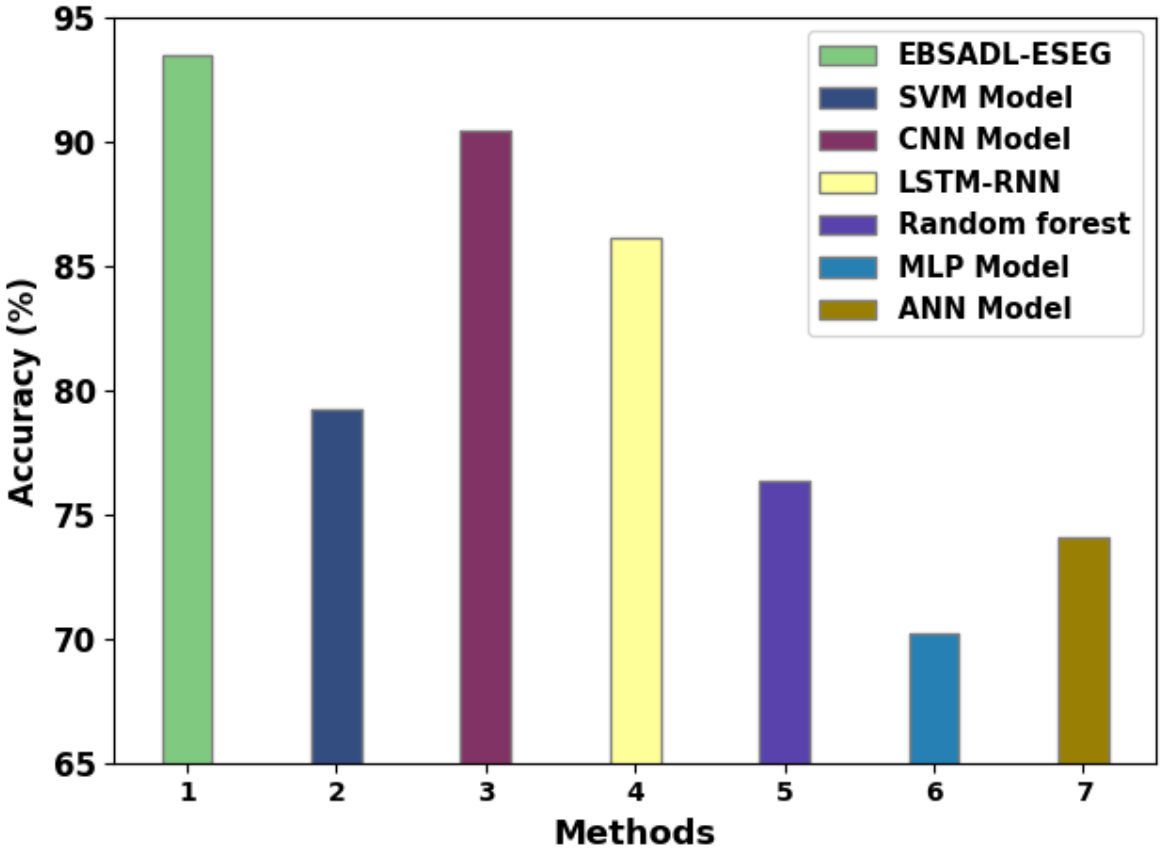


Figure 10: $Accu_y$ analysis of EBSADL-ESEG approach with existing algorithms

Although the CNN model has gained reasonable $accu_y$ of 79.22%, the EBSADL-ESEG model has shown maximum $accu_y$ of 93.45%. These results assured the enhancements of the EBSADL-ESEG model over other models.

5. Conclusion

In this study, we have developed a new EBSADL-ESEG technique for emotion recognition process. The presented EBSADL-ESEG technique analyses EEG signals to classify three different types of emotions namely arousal, valence, and liking. Primarily, the EBSADL-ESEG technique derived the statistical features from the EEG signals. Besides, the EBSA approach is employed for optimal feature selection process. Finally, the RMSProp optimizer with GRU model is leveraged for emotion classification. The experimental analysis of the EBSADL-ESEG model was tested on DEAP dataset and the outcomes were investigated under diverse measures. The comprehensive comparison study stated better outcomes of the EBSADL-ESEG model over other DL models. In future, the effiencyof the EBSADL-ESEG method will be enhanced using hybrid metaheuristics based hyperparameter optimization process.

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