



Automated EEG based Emotion Detection using Bonobo Optimizer with Deep Learning on Human Computer Interaction

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Abstract

Recently, Emotion detection utilizing EEG signals develops popularity in domain of Human-Computer Interaction (HCI). EEG (electroencephalography) is a non-invasive approach, which processes electrical action from the brain through electrodes located in the scalp. An emotion recognition approach could not only be significant for healthy people among them disabled persons for detecting emotional changes and is utilized for different applications. It is significant to realize that emotion recognition in EEG indications is a difficult task owing to difficult and subjective nature of emotions. In recent times, Machine learning (ML) algorithms like Random Forests or Support Vector Machines (SVM) and Deep Learning (DL) systems namely Recurrent Neural Network (RNN) or Convolutional Neural Network (CNN) are trained on EEG feature extracted and connected emotional labels for classifying the user emotional state. This study presents an Automated EEG-based Emotion Detection using Bonobo Optimizer with Deep Learning (AEEGED-BODL) technique on HCI applications. The goal of the study is to analyze the EEG signals for the classification of several kinds of emotions in HCI applications. To achieve this, the AEEGED-BODL technique uses Higuchi fractal dimension (HFD) approach for extracting features in the EEG signals. Besides, the AEEGED-BODL technique makes use of the quasi-recurrent neural network (QRNN) approach for the detection and classification of distinct kinds of emotions. Furthermore, the BO system was demoralized for optimum hyperparameter selection of QRNN model, which helps in attaining an improved detection rate. The simulation validation of AEEGED-BODL algorithm was simulated on EEG signal database. The comprehensive result stated best outcome of the AEEGED-BODL algorithm over other recent approaches

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1. Introduction

The Brain-Computer Interface (BCI) has subdomain of Human-Computer Interaction (HCI). The BCI allows the connection between electronic devices (e.g. computer, mobile phones) and the human brain [1]. The BCI has provided support to impaired people. The BCI model builds the interaction of users with the device, which utilizes EEG signals and so on. The several processing stages in the BCI center focus on understanding the intentions of the brain signals and converting them into activities [2]. From a subject's brain, the BCI system acquires signals, extraction of information from the obtained signals, and uses this information to specify the intentions of the subject that may have produced those signals. EEG signals are also applied in non-medical conditions namely supervision, games, and entertainment education [3]. Emotions have performed a crucial role in human cognizance, specifically in perception, human interaction, human intelligence, and reasonable decision-making. Researching and understanding human feelings are essential to existence [4]. Categorization of automatic emotion utilizing Machine Learning (ML) and Artificial Intelligence (AI) newly glowed curiosity, as it might be used in variety of HCI applications. To be efficacious, an artificial sensitive intelligence method should have comprehensive understanding of human sentimental perception and link among emotions and sentimental expression [5]. HCI and collaboration might be established in types of domains, comprising, gaming, therapy, medicine, etc. With the aim of achieving higher levels of user satisfaction, regularly researchers are working to enhance efficiency and the flexibility of HCI [6]. Consequently, HCI methods should be proficient in obtaining a total perception of different human sensations and emotive expressions. Human thoughts and feelings would be communicated in verbal and non-verbal [7]. Hence, HCI techniques should be capable to interpret, identify and estimate the human non-verbal expressions.

Human emotion identification or detection is a main technological complication affecting computation, which majorly resolves the issues of computer systems accurately understanding, processing, and detecting the sensitive data communicated by human beings [8]. As emotion acts a key role in the domain of HCI and AI, it has newly obtained wide-ranging consideration in the domains of engineering research. Lately, numerous development of EEG-based BCI emotion identification methods are used. Moreover, quick developments in ML and DL have allowed computers or machines for understanding, recognize, and analyse feelings [9]. This research examines the emotional identification techniques that depend on multi-channelled EEG signal-based BCIs and offers a summary of what achieved in this domain. It also offers outline of databases and techniques applied to prompted expressive conditions [10]. As reported by the traditional emotional detection pathway, reviews numerous EEGs, namely Feature Selection/Reduction (FS/FR), Feature Extraction (FE), Artificial Neural Networks (ANNs), ML technique and DL technique.

This study presents an Automated EEG-based Emotion Detection utilizing Bonobo Optimizer with Deep Learning (AEEGED-BODL) technique on HCI applications. The goal of the study is to inspect the EEG signals for the classification of numerous kinds of emotions in HCI applications. To achieve this, the AEEGED-BODL technique uses Higuchi fractal dimension (HFD) approach for extracting features in the EEG signals. Besides, the AEEGED-BODL technique makes use of the quasi-recurrent neural network (QRNN) approach for the detection and classification of distinct kinds of emotions. Furthermore, the BO system was employed for optimal hyperparameter selection of QRNN model that helps in attaining improved recognition rate. The simulation validation of AEEGED-BODL technique simulated on EEG signal dataset.

2. Related Works

Wu et al. [11] presented emotion detection method was dependent upon the hierarchical LSTM-NN for Video-EEG signal communication. An input is facial-video and EEG signals in subjects if it can be observing emotion-stimulated video. The outcomes equivalent to emotion detection results. Facial-video features and equivalent EEG feature extraction depends on FCN at every time point. Algarni et al. [12] present a DL-based method for emotion detection by EEG signs that contains features extraction, data selection, classification, and feature selection (FS) phases. The Binary GWO has executed the FS task. At the classification phase, the stacked BiLSTM approach has been employed for recognizing human emotions.

Zhang [13] examined an expression-EEG interaction multi-modal emotion detection approach utilizing a deep automatic encoder. Primarily, the DT was carried out as an objective FS approach. Afterwards, bimodal deep automatic encoder implemented to fuse facial expression and EEG indications. The third layer of BDAE feature extraction is to train supervised learning. Eventually, the LIBSVM approach has been employed for completing classifier tasks. Hwang et al. [14] introduce a novel emotion detection approach employing a CNN but avoiding the loss of local data. The presented technique comprises 2 phases. An initial phase creates topology-preserving variance entropy features but keeps distance from center electrode to other electrodes. Next phase studies presented CNN for estimating 3-class emotional states (negative, neutral, positive).

Choi et al. [15] introduce a multi-modal fusion network that combines video and EEG modality networks. Eventually, continuous domain valence values can be calculated by employing 2 modality network outputs and attention weight. Gao et al. [16] present a novel DL structure called a channel-fused dense convolution system, for EEG-based emotion detection. Primary, the authors utilize a 1D convolutional layer for receiving weighted integration of contextual features besides temporal dimensional in EEG signals. Afterwards, simulated by recent object classification approaches, the authors utilize 1D dense infrastructures for capturing electrode correlations along the spatial size. Iyer et al. [17] suggest a new approach for human emotion detection utilizing EEG signals. The authors are assumed that 3 emotions like positive, neutral, and negative. These EEG indications can be divided into 5 frequency bands based on EEG rhythms as well as difference entropy was calculated on distinct frequency band modules. The CNN and LSTM-based hybrid approach was established to correct emotion recognition. In [18], a model that depends on Deep CNNs (DCNNs) was proposed that is categorize 3 emotions such as neutral, positive, and negative in EEG signals dependent upon musical stimuli with maximum reliability. Therefore, a widespread dataset of EEG signals is gathered but volunteers are listening to positive and negative music for stimulating the emotional state. This structure of the presented method comprises a group of 6 convolutional layers and 2 FC layers.

3. The Proposed Model

In this paper, we projected unique AEEGED-BODL technique for identification and categorization of different sentiments in HCI applications. The drive of research is to inspect the EEG signals for the classification of several kinds of emotions in HCI applications. To achieve this, the AEEGED-BODL technique follows three major phases of operations namely HFD feature extraction, QRNN-based emotion recognition, and BO-based hyperparameter tuning. Fig. 1 depicts workflow of AEEGED-BODL methodology.

A. HFD Feature Extraction

In this research, HFD employed to derive feature from input EEG signals. FD was extremely utilized and is a role vital play in several fields [19]. Related research demonstrated that the FD can differentiate various emotional states of the brain. Thus, the FD is employed for expressing the difficulty of equivalent EEG signals.

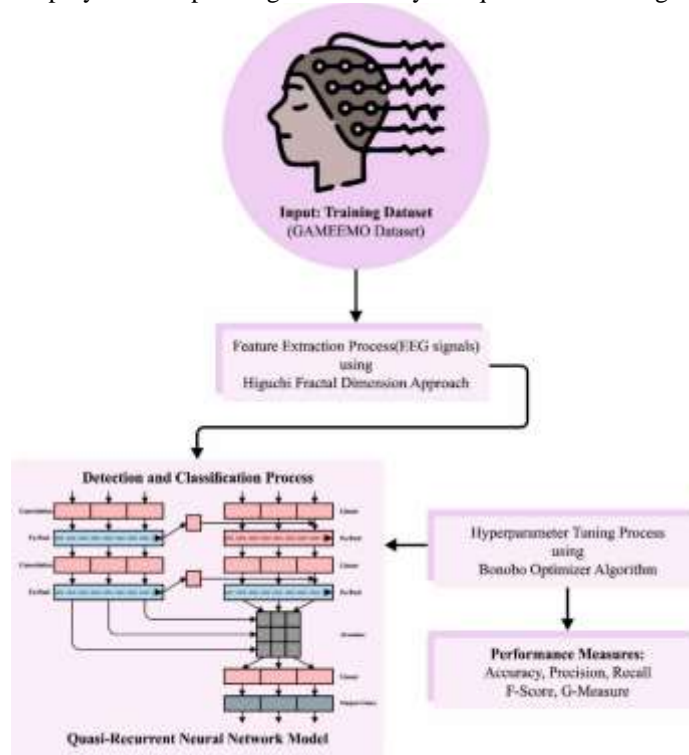


Figure 1: Workflow of AEEGED-BODL approach

The details of the HFD are expressed as follows. To provide a time sequences $\{x(i), i = 1, 2, n\}$, a reconstructed order is shown as:

$$x_k^m: x(m), x(m+k), \dots, x\left(m + \left\lfloor \frac{N-m}{k} \right\rfloor \times k\right), \quad (1)$$

whereas m refers to the primary time and k represents interval time. k sets of $L_m(k)$ are developed as:

$$L_m(k) = \frac{n-1}{\left\lfloor \frac{n-m}{k} \right\rfloor k^2} \sum_{i=1}^{\left\lfloor \frac{n-m}{k} \right\rfloor} |x(m+ik) - x(m+(i-1)k)|, \quad (2)$$

$\langle L(k) \rangle$ whereas $\langle L(k) \rangle$ signifies the average value of $L_m(k)$ and one connection occurs as follows.

$$\langle L(k) \rangle \propto k^{-FD_x}. \quad (3)$$

Afterwards, FD_x is attained by logarithmic interpolation among distinct k (ranging from 1 to k_{max}) and its connected $L_m(k)$.

$$FD_x = \frac{\langle L(k) \rangle}{-\ln k} \quad (4)$$

B. Emotion Recognition using QRNN Model

For recognition and classification of emotions, QRNN model is utilized. A QRNN model was used for capturing the representing features in the input dataset with deep network architecture [20]. QRNN incorporates the benefits of CNN and LSTM as a kind of RNN. Not unlike LSTM, QRNN enables the processing of time sequence datasets with long-term temporal dependency. QRNN could deal with the task by parallel calculation to speed up the training model. Similar to CNN.

Various features extracted in the multi-sensor signals can be collected to set up training datasets $\{R_t, L_t\}_{t=1}^{T-1}$, whereas $R_t \in \mathbb{R}^{n'}$ shows the dataset of n' hidden extraction features at t time, T shows length of an input signal. L_t represents the respective class label at t time. The QRNN layer contains two subcomponents, vi., pooling convolutional and components. The convolution component captures the representation of the input dataset, where different filters on the processed input dataset can implement parallel processing. The pooling element was performed for reducing the representation size of a feature. The working procedure in QRNN has four different steps.

Firstly, the masked convolution operator converts input series $I \in R^{(T-1) \times n'}$ for producing a series $Z \in R^{(T-1) \times m}$ of m -dimension candidate vector Z_t by the bank of m filters with width of k from convolution module. Furthermore, convolution was adopted

Quasi-Recurrent Pooling for producing a series of tensors F and 0 for input of gating architecture from pooling module. The tanh non-linearity was applied for processing the candidate tensor, the additional convolution uses a component-wise sigmoid. Each procedure in the convolution module was formulated as follows:

$$\begin{cases} Z = \varphi(W_Z * I) \\ F = \sigma(W_f * I) \\ 0 = \sigma(W_o * I) \end{cases} \quad (5)$$

In Eq. (5), $W_Z, W_f, W_o \in \mathbb{R}^{k \times n' \times m}$ denotes the convolution filter bank, and $*$ represents the masked convolutional operator. φ and σ indicate tanh and element-wise sigmoid, correspondingly.

Next, attained candidate tensor, F , and 0 are split for producing a sequence of z_t, f_t and $o_t (t = 1, 2, \dots, n)$, and this state was transmitted to the pooling module.

During pooling module of QRNN, this states z_t, f_t and o_t are consecutively provided as the semi-circular function quasi-recurrent pooling that can be handled by the output and forget gates that might mix states across time steps, as follows:

$$C_t = f_t \odot C_{t-1} + (1 - f_t) \odot z_t \quad (6)$$

$$h_t = o_t \odot C_t \quad (7)$$

In which, \odot implies the element-wise multiplication. The forget gate f_t control the prior state data C_{t-1} for entering the present computation procedure, and keeping the weighted balance among the existing candidate z_t and recurrent data C_{t-1} . The output gate o_t manages existing state data C_t to outcome of QRNN.

Lastly, as quasi-recurrent pooling was always conducted from the loop, a massive amount of pooled outcomes $h_t (t = 1, 2, \dots, n)$ is produced. This hidden state was concatenated with the procedure of the outcome of QRNN.

The FC dense layer has been used as a resultant layer from the QRNN model, whereas the outcome of QRNN layer h_t was provided and finally, the multisensory signals are combined into the predictive class \hat{L}_t , as follows:

$$\hat{L}_t = W_o h_t \quad (8)$$

In Eq. (8), W_o represents the weighted vector of the dense layer and \hat{L}_t denotes the predicted RUL.

C. Hyperparameter Tuning using BO Algorithm

In this work, BO algorithm utilized for hyperparameter selection of QRNN technique. BO is a novel intelligent heuristic optimizer system stimulated by the interesting aspects of the reproductive and social strategies of bonobos, frequently called pygmy chimpanzees [21]. In the case of the fission type, it can be separated into various groups with different sizes and compositions and move through the territory. In the case of fusion type, it again combines with members of a group to implement certain actions. Bonobos have four dissimilar approaches to reproduction namely restrictive mating, consortship mating, promiscuous mating, and extra-group mating to retain perfect social harmony. The search method with a self-adjusting parameter was introduced so that it could effectively handle various states while resolving the problem. In addition, fusion is a new technique in meta-heuristic approaches that select the mating partner. This natural technique was modelled mathematically in BO for resolving optimizer problems. Fig. 2 depicts the flowchart of the BO algorithm.

At first, BO involves two conditions: positive and negative situations. The negative state represents the lack of the above mentioned conditions for comfortable and well living. At the same time, the positive state was suitable for comfortable living circumstances. In all the iterations, BO begins with the initialization of the parameter. BO parameter comprises user-defined and non user-defined parameters. The user-defined parameter is the size of populations (N), and iteration count (it). BO works with 2 sizes of populations like random population initialization and constant population size. Whereas, non user-defined parameters of BO, including extra-group mating probability (P_{xgm}), phase probability (P_p), negative phase count of all bonobos, and positive phase count (PPC) are evaluated for identifying the alpha bonobo (α_{Bo}) that is the better solution amongst directional probability (P_d), each bonobo in (npc), and temporary sub-group size factor ($tsgs$ actor).

Then, objective values of population are at their existing state. While the ending condition is not accomplished, other bonobos are chosen by fission-fusion social approach of bonobos, which participate during mating. Based on situation type, the mating strategy implemented is that distinct. Initially, the P_d value is fixed as 0.5 to give equivalent significance to both varieties of mating approaches in a specific situation. But based on the current situation its value was updated and phase count number. In the case of the negative situation, P_p values are between 0 and 0.5. For positive situations, The P_p value is between 1 and 0.5. If a random integer (r) ranges within in $[0,1]$, is equivalent to or lesser than p_p , the newest bonobo is produced by promiscuous or restrictive mating using the following expression:

$$Bo_new_j = Bo_j^i + r_1 \times scab \times (\alpha_{Bo}^j - Bo_j^i) + (1 - r_1) \times scsb \times g \times (Bo_j^i - Bo_j^p) \quad (9)$$

Where Bo_new_j and $0i$ denote the j^{th} variable of the spring and alpha bonobos, correspondingly, j changed from 1 to d , where d shows the overall amount of parameters for the optimization problems. Bo_j^i and $B\theta_j$ denote the j^{th} dimension of the i^{th} and p^{th} bonobos, correspondingly. r_1 indicates the random value produced within $[0,1]$. $scsb$ and $scab$ are sharing coefficients for selected p^{th} bonobo and α_{Bo} , correspondingly. g only proceeds 2 values 1 or -1 . If r is higher than or equivalent to p_p , the newest bonobo can be produced by the extra-group or consortship mating method.

If another random number (r_2) ranges from zero to one and is both equivalent to and lesser than P_{xgm} , a novel bonobo was produced by the extra-group mating process.

$$\tau_1 = e^{\left(r_4^2 + r_4 - \frac{2}{r_4}\right)} \quad (10)$$

$$\tau_2 = e^{\left(-r_4^2 + 2r_4 - \frac{2}{r_4}\right)} \quad (11)$$

$$Bo_new_j = Bo_j^i + \tau_1 (Var_max_j - Bo_j^i) \text{ if } (\alpha_{Bo}^j \geq Bo_j^i \text{ and } r_3 \leq p_d) \quad (12)$$

$$Bo_new_j = Bo_j^i - \tau_2 (Bo_j^i - Var_min_j) \text{ if } (\alpha_{Bo}^j \geq Bo_j^i \text{ and } r_3 > p_d) \quad (13)$$

$$Bo_new_j = Bo_j^i - \tau_1 (Bo_j^i - Var_min_j) \text{ if } (\alpha_{Bo}^j < Bo_j^i \text{ and } r_3 \leq p_d) \quad (14)$$

$$Bo_new_j = Bo_j^i + \tau_2 (Var_max_j - Bo_j^i) \text{ if } (\alpha_{Bo}^j < Bo_j^i \text{ and } r_3 > p_d) \quad (15)$$

$$Bo_new_j = \begin{cases} Bo_j^i + g \times e^{-r_5} (Bo_j^i - Bo_j^p) & \text{if } (r_2 > P_{xgm} \text{ and } g = 1 \text{ or } r_6 \leq p_d) \\ Bo_j^p & \text{if } (r_2 > P_{xgm}) \end{cases} \quad (16)$$

Where τ_1 and τ_2 denote the two intermediate values measured for defining the Bo_new_j value. r_3 , r_4 , r_5 and r_6 indicate the random integer between 0 and 1 and is not equivalent to 0. Var_min_j and Var_max_j show value of lower and upper bounds equivalent to the j^{th} dimension

When the fitness value of Bo_new is greater than Bo^i or a random number ranging from zero to one is equivalent to or lesser than P_{xgm} , then Bo_new is accepted. Furthermore, Bo^i is exchanged for the newest one in the bonobo population. But when the Bo_new fitness value is better than α_{Bo} , then Bo_new is recognized as α_{Bo} . Lastly, when α_{Bo} of the existing iteration takes the best fitness value than the prior iteration, and then the parameter of BO was changed. Fitness choice is an essential feature of BO system. An encoding solution employed to progress better candidate performances. Presently, accuracy value is main condition utilized in a strategy of FF.

$$Fitness = \max(P) \quad (17)$$

$$P = \frac{TP}{TP + FP} \quad (18)$$

In which, TP and FP stands for true and false positive values.

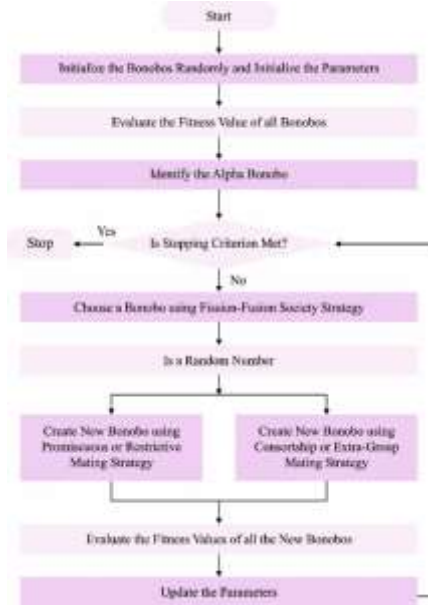


Figure 2: Flowchart of BO

4. Results and Discussion

The simulation outcome of AEEGED-BODL algorithm verified on GAMEEMO database [22]. Table 1 exemplifies the comprehensive explanation of database.

Table 1: Details of database

Classes	No. of instances
Boring	500
Calm	500
Horror	500
Funny	500
Total Samples	2000

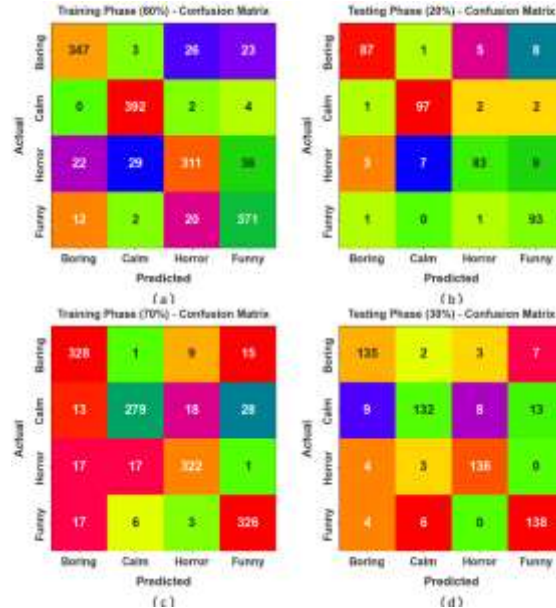


Figure 3: Confusion matrices of (a-b) 80:20 of TRAS/ TESS and (c-d) 70:30 of TRAS/ TESS
 The confusion matrices of AEEGED-BODL algorithm on EEG-based emotion recognition process demonstrated in Fig. 3. The result inferred that AEEGED-BODL approach recognized four distinct types of emotions accurately. In Table 2 and Fig. 4, emotion classifier consequence of AEEGED-BODL system clearly depicted at 80:20 of TRAS/TESS. The consequences represented that AEEGED-BODL approach recognizes four distinct class labels.

Table 2: Emotion classifier outcome of AEEGED-BODL algorithm on 80:20 of TRAS/TESS

Classes	$Accu_y$		$Prec_n$	$Reca_t$	F_{Score}	$G_{Measure}$
Training Phase (80%)						
Boring	94.63		91.08	86.97	88.97	89.00
Calm	97.50		92.02	98.49	95.15	95.20
Horror	91.56		86.63	78.14	82.17	82.28
Funny	93.94		85.48	91.60	88.44	88.49
Average	94.41		88.80	88.80	88.68	88.74
Testing Phase (20%)						
Boring	95.25		94.57	86.14	90.16	90.25
Calm	96.75		92.38	95.10	93.72	93.73
Horror	93.25		91.21	81.37	86.01	86.15
Funny	94.75		83.04	97.89	89.86	90.16
Average	95.00		90.30	90.13	89.94	90.07

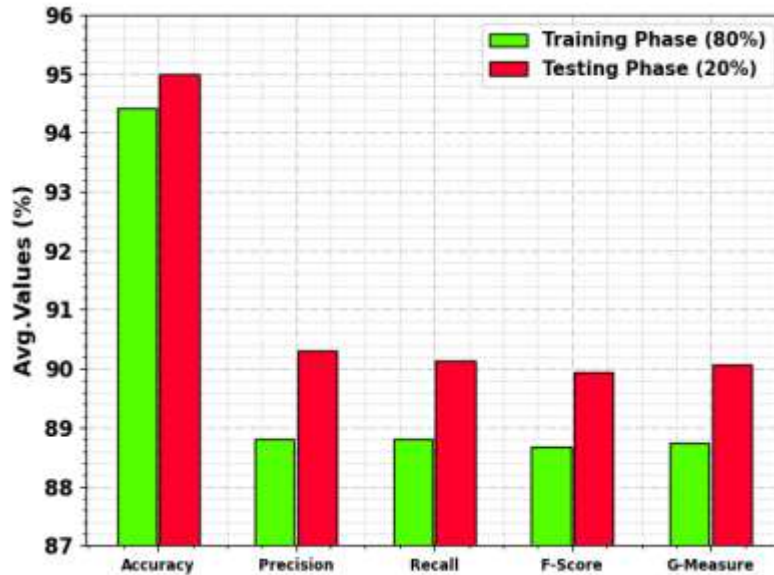


Figure 4: Average outcome of AEGED-BODL system on 80:20 of TRAS/TESS

On 80% of TRAS, AEGED-BODL model increases average $accu_y$, $prec_n$, $reca_l$, F_{score} , and $G_{measure}$ of 94.41%, 88.80%, 88.80%, 88.68%, and 88.74% respectively. Meanwhile, on 20% of TESS, AEGED-BODL model obtains average $accu_y$, $prec_n$, $reca_l$, F_{score} , and $G_{measure}$ of 95%, 90.30%, 90.13%, 89.94%, and 90.07% correspondingly.

Training and Validation Accuracy - (80:20)

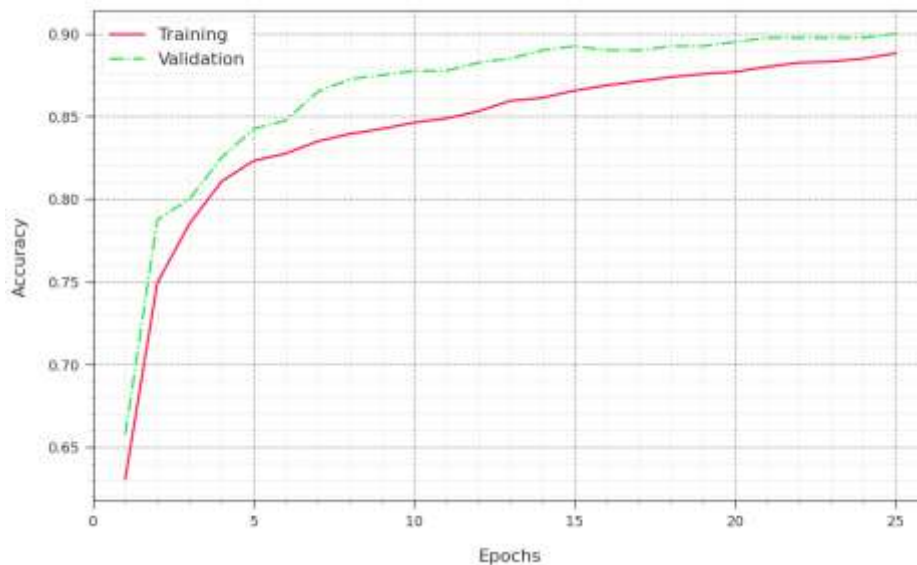


Figure 5: $Accu_y$ curve of AEGED-BODL algorithm on 80:20 of TRAS/TESS

Fig. 5 displays TRA_{accu_y} and VL_{accu_y} of AEGED-BODL method on 80:20 of TRAS/TESS. VL_{accu_y} determined by evaluation of AEGED-BODL technology on TRA dataset whereas the VL_{accu_y} intended by calculating outcome on a distinct TES database. The outcomes exhibit that TRA_{accu_y} and VL_{accu_y} rise with an increase in epochs. Consequently, the solution of AEGED-BODL methodology acquires improvement on TRA and TES dataset with a growth in count of epochs.

In Fig. 6, TRA_{loss} and VR_{loss} results of AEGED-BODL approach at 80:20 of TRAS/TESS are exposed. The TRA_{loss} determines error among predictive result and new values on TRA data. The VR_{loss} exemplifies the measure of the solution of the AEGED-BODL technique on individual validation data. The outcomes referred that TRA_{loss} and VR_{loss} tend to reduction with increasing epochs. It portrayed the enhanced performance of AEGED-BODL system and its capability to form correct classification. The decreased value of TRA_{loss} and VR_{loss} reveals better performance of the AEGED-BODL approach on taking patterns and relationships.

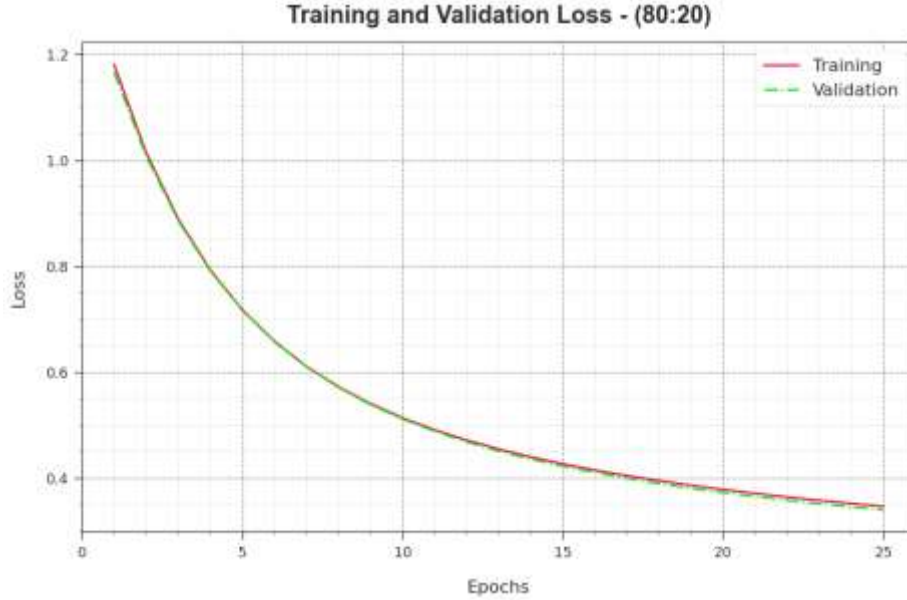


Figure 6: Loss curve of AEEGED-BODL algorithm on 80:20 of TRAS/TESS

In Table 3 and Fig. 7, emotion classification outcome of AEEGED-BODL algorithm clearly portrayed at 70:30 of TRAS/TESS. The simulation values represented that AEEGED-BODL methodology knows 4 several classes. On 70% of TRAS, AEEGED-BODL model obtains average $accu_y$, $prec_n$, $reca_l$, F_{score} , and $G_{measure}$ of 94.82%, 89.78%, 89.57%, 89.57%, and 89.62% correspondingly. In meantime, on 30% of TESS, AEEGED-BODL algorithm reaches average $accu_y$, $prec_n$, $reca_l$, F_{score} , and $G_{measure}$ of 95.08%, 90.25%, 90.42%, 90.21%, and 90.27% correspondingly.

Table 3: Emotion classifier outcome of AEEGED-BODL methodology under 70:30 of TRAS/TESS

ClassES	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	$G_{Measure}$
Training Phase (70%)					
Boring	94.86	87.47	92.92	90.11	90.15
Calm	94.07	92.08	82.54	87.05	87.18
Horror	95.36	91.48	90.20	90.83	90.83
Funny	95.00	88.11	92.61	90.30	90.33
Average	94.82	89.78	89.57	89.57	89.62
Testing Phase (30%)					
Boring	95.17	88.82	91.84	90.30	90.31
Calm	93.17	92.31	81.48	86.56	86.73
Horror	97.00	92.52	95.10	93.79	93.80
Funny	95.00	87.34	93.24	90.20	90.24
Average	95.08	90.25	90.42	90.21	90.27

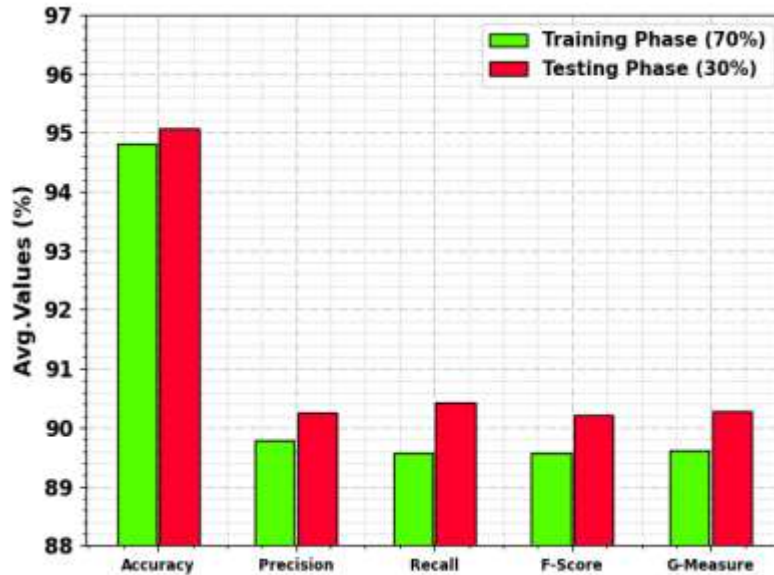


Figure 7: Average outcome of AEEGED-BODL algorithm on 70:30 of TRAS/TESS

Fig. 8 demonstrating TRA_accu_y and VL_accu_y of AEEGED-BODL methodology at 70:30 of TRAS/TESS. VL_accu_y determined by estimation of AEEGED-BODL model on TRA database but VL_accu_y calculated by estimating value on a distinct TES database. The outcomes exhibit that TRA_accu_y and VL_accu_y increase with a gain in epochs. Therefore, the performance of AEEGED-BODL technology is improved on TRA and TES database with a growth in count of epochs.



Figure 8: $Accu_y$ curve of AEEGED-BODL algorithm at 70:30 of TRAS/TESS

In Fig. 9, TRA_loss and VR_loss outcomes of AEEGED-BODL algorithm on 70:30 of TRAS/TESS are depicted. TR_loss demonstrates error among predictive result and new values on TRA data. The VR_loss represents measure of outcome of AEEGED-BODL algorithm on individual validation data. The outcomes inferred that TRA_loss and VR_loss tend to be lesser with rising epochs. It described higher solution of AEEGED-BODL methodology and its ability to create an exact classification. The lesser value of TRA_loss and VR_loss establishes greater outcome of AEEGED-BODL algorithm on taking patterns and relationships.

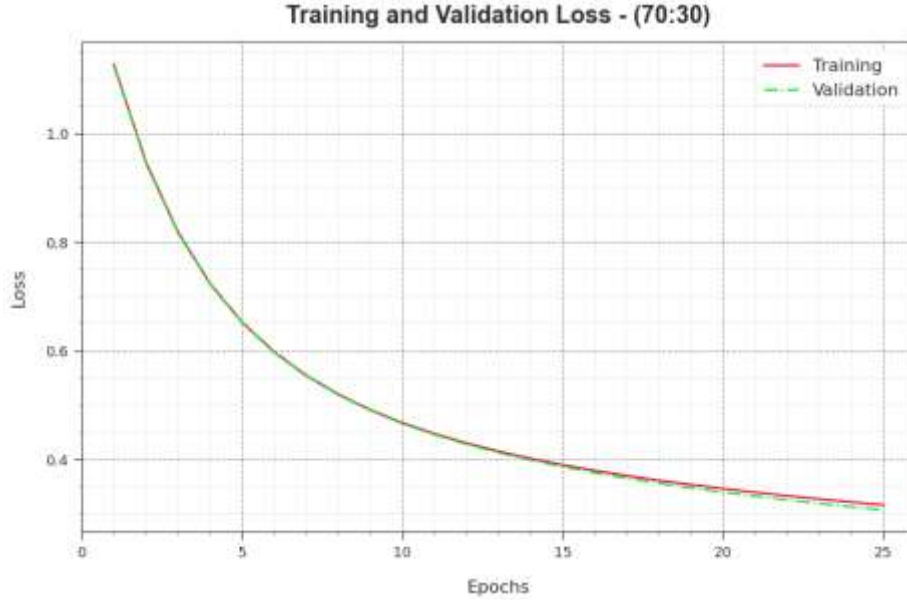


Figure 9: Loss curve of AEEGED-BODL system on 70:30 of TRAS/TESS

The comparative outcome of AEEGED-BODL technique with other DL models is in Table 4 and Fig. 10 [23-25]. The simulation values specify that EfficientNetB7 model exhibits poor results whereas the InceptionResNetV2, MobileNet, DenseNet201, and NASNetMobile models have reached considerably closer performance. However, the AEEGED-BODL technique has exhibited effectual outcomes with a maximum $accu_y$ of 95.08%, $prec_n$ of 90.25%, $reca_l$ of 90.42%, and F_{score} of 90.21%.

Table 4: Comparative outcome of AEEGED-BODL algorithm with other DL methodologies

Methods	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{score}$
AEEGED-BODL	95.08	90.25	90.42	90.21
InceptionResNetV2	91.45	82.70	82.89	84.05
MobileNet	90.55	81.90	79.56	80.03
DenseNet201	90.55	81.55	81.20	84.63
NASNetMobile	89.27	79.53	83.84	82.51
EfficientNetB7	80.18	82.00	80.00	80.00

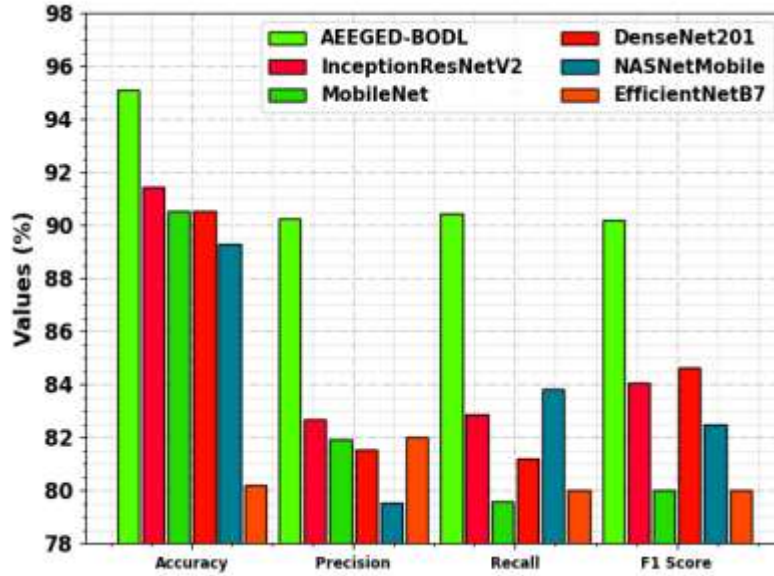


Figure 10: Comparative analysis of AEEGED-BODL algorithm with other DL methods

The data execution time (ET) analysis of AEEGED-BODL model with other DL approaches arises in Table 5 and Fig. 11. The simulation values specified that AEEGED-BODL approach gains the least ET of 8.10m. At the same time, the Inception ResNetv2, MobileNet, DenseNet201, NASNetMobile, and EfficientNetB7 models obtain increasing ET values of 15.35m, 13.59m, 14.18m, 14.54m, and 19.06m correspondingly. These outcomes demonstrated the improvised solutions of the AEEGED-BODL system.

Table 5: ET outcome of AEEGED-BODL system with other DL methodologies

Methods	Data Execution Time (m)
AEEGED-BODL	08.10
InceptionResNetV2	15.35
MobileNet	13.59
DenseNet201	14.18
NASNetMobile	14.54
EfficientNetB7	19.06

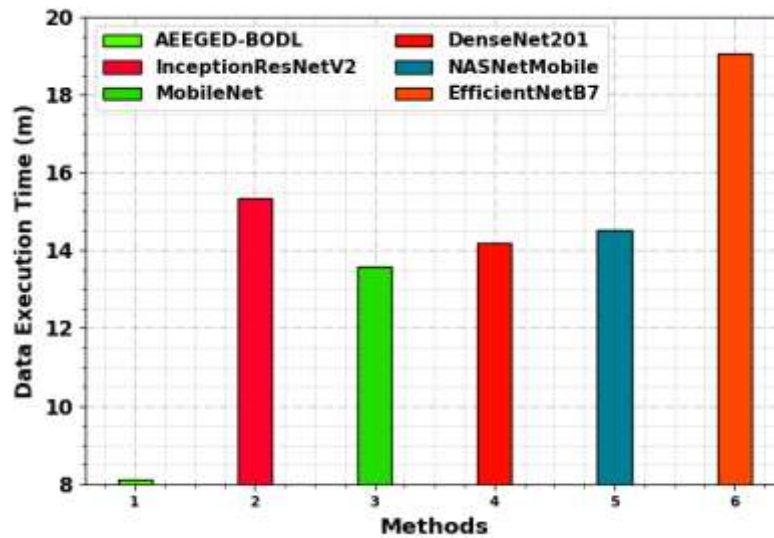


Figure 11: ET analysis of AEEGED-BODL algorithm with other DL methods

5. Conclusion

In this research, we projected a unique AEEGED-BODL model for recognition and classification of different emotions in HCI applications. The drive of the study is to analyze the EEG signals for the classification of numerous kinds of emotions in HCI applications. To achieve this, the AEEGED-BODL technique follows three major phases of operations namely HFD feature extraction, QRNN-based emotion detection, and BO-based hyperparameter tuning. In this work, BO system can be exploited for optimal hyperparameter selection of the QRNN system helps in attaining amended detection rate. The simulation result of the AEEGED-BODL approach can be examined on EEG signal dataset. The comprehensive results stated best efficiency of AEEGED-BODL system over other recent systems. In future, the performance of the AEEGED-BODL methodology has been tested on real-time EEG database.

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