Deep Neural Network for Electroencephalogram based Emotion Recognition

Shruti Garg\textsuperscript{1*}, Soumyajit Behera\textsuperscript{2}, Rahul K Patro\textsuperscript{2} and Ashwani Garg\textsuperscript{3}

\textsuperscript{1}Department of Computer Science and Engineering, Birla Institute of Technology, Ranchi-JH 835215, India
\textsuperscript{2}Department of Mathematics, Birla Institute of Technology, Ranchi-JH 835215, India
\textsuperscript{3}Faculty of Health, Biomedical Science and Medical Science, Griffith University, Queensland-4122, Australia
*Corresponding Author: Shruti Garg. Email: gshruti@bitmesra.ac.in

Abstract. Emotion recognition using electroencephalogram (EEG) signals is an aspect of affective computing. The EEG refers to recording brain responses via electrical signals by showing external stimuli to the participants. This paper proposes the prediction of valence, arousal, dominance and liking for EEG signals using a deep neural network (DNN). The EEG data is obtained from the AMIGOS dataset, a publicly available dataset for mood and personality research. Two features, normalized and power and normalized wavelet energy, are extracted using Fourier and wavelet transform, respectively. A DNN with three different activation functions (exponential linear unit, rectified linear unit [ReLU] and leaky ReLU) has been applied for single and combined features. The result of combined features with leaky ReLU is found to be the best, with a classification accuracy of 85.47, 81.87, 84.04 and 86.63 for valence, arousal, dominance and liking, respectively.

Keywords: Deep neural network, Emotion Recognition, EEG.

1. Introduction
Neural Networks (NNs) [1] are used in many research studies. Pattern recognition [2], image processing [3] and computer vision [4] are important applications of NNs. The electroencephalogram (EEG) is a tool used to record electrical activity in the human brain by providing external stimuli [5], as shown in figure 1.

![Figure 1. Procedure of EEG recording](image)

These EEG signals are used in the medical field for diagnosing mental diseases and abnormalities, as well as in research for identifying moods and personalities [7]. Moods cannot be identified by the different modalities of data because they do not produce a significant change in data [8]. There are several emotions generated in the human brain at any one stage of a mood. Thus, emotions are the basic unit to identify moods from images, texts, voices and physiological signals [9]. The EEG signal is a kind of physiological signal and is the preferred tool to identify emotions because it is a direct response of the human body, whereas voice and facial signals are acted/elicited responses [10]. Thus, an EEG-based emotion recognition (ER) model using a deep neural network (DNN) is presented in this paper.

Designing an EEG-based ER system involves the following steps:
• Data collection
• Pre-processing
• Feature extraction
• Classification

Data collection has been done in [10–17], in which [10–14] are publicly available EEG datasets, and [11, 14] provides pre-processed dataset for research. The DEAP [11] dataset is the most popular among researchers. In contrast, very few studies have been conducted using the AMIGOS [14] dataset because it is new and has a more complicated structure than DEAP. Moreover, it provides low accuracy compared to DEAP because of its imbalanced instances of data. AMIGOS provides a variable-length row according to the length of the video shown to different users, which makes the application of classification models more complicated [18]. This paper uses the AMIGOS dataset for emotion classification.

There are several literature studies on ER-based machine learning (ML), deep learning (DL) and other artificial intelligence systems [19]. These techniques are applied at the feature extraction and classification stages. The important features extracted from EEG signals for ER are entropy, energy and power from Fourier, wavelet and short-time Fourier transforms [20]. This paper studies ER and only discusses classification. A variety of ML methods, such as decision tree, support vector machine (SVM), k-nearest neighbour, naïve Bayes and random forest (RF), are used to identify emotions. Furthermore, DL methods, such as long-short term memory and convolution neural network, are used for ER [21]. A summary of ML and DL methods applied on four important datasets (DEAP [11], DREAMER [12], SEED [13] and AMIGOS [14]) is presented in Table 1.

Table 1. Summary of studies conducted on ER

| Ref., year | Dataset | Feature Extraction | Algorithm Category | Method | Accuracy |
|------------|---------|-------------------|--------------------|--------|----------|
| [22], 2017 | DEAP    | Wavelet Entropy, Energy | ML | KNN, SVM | 86.75% |
| [23], 2020 | Power, Entropy, Fractal Dimension, Statistical features, Wavelet Energy | ML | KNN, SVM | 78.96% |
| [24], 2020 | Multi-level feature Capsule Network (End to End network) | DL | Multi-level feature Capsule Network | 98.32% |
| [25], 2021 | Differential Entropy | DL | Graph Convolution Network+LSTM | 90.60% |
| [12], 2017 | DREAMER | Power Spectral Density | ML | SVM | 62.49% |
| [26], 2018 | Power Spectral Density | DL | Dynamic Graph CNN | 86.23% |
| [27], 2020 | Region asymmetric convolution neural network (RACNN) (End to End network) | DL | RACNN | 95.00% |
| [28], 2021 | Tomographic and Holographic 3D feature map constructed by DL | DL | CNN | 90.43% |
Table 1 shows that DL methods give better accuracy than ML methods. The highest accuracy was achieved on the DEAP dataset, and the lowest accuracy was achieved on the AMIGOS dataset, revealing that the AMIGOS dataset requires an efficient method.

Thus, a DNN for ER in the AMIGOS dataset using EEG signals has been proposed in this paper.

The rest of this paper comprises four more sections. Section 2 provides details of the emotion model used in the research. Section 3 details the methodology and the experiment. Section 4 comprises the results and discussions. Finally, section 5 provides a conclusion.

2. Emotion Model

There are two ways to recognise emotions in the field of affective computing. The first is in terms of discrete emotions, such as sadness, happiness, fear, anger and disgust [36]. The second is in terms of emotions models. Emotion models consist of emotion in terms of valence, arousal and dominance (VAD) [37]. All VAD are assessed between 1–9, where valence represents positivity of emotions, arousal represents excitement, and dominance represents domination towards content shown. Fig. 2 shows the change in VAD according to how much the subject likes the audio-visual content presented.

![Graph showing change in VAD](image-url)
Figure 2. Changes in Valence, Arousal and Dominance according to liking (a) Valance vs liking (b) Arousal vs liking (c) Dominance vs liking

It is evident from Fig. 2 that emotions are influenced by the liking of content. Thus, liking is also predicted along with VAD in this work.

3. Methodology

Emotion recognition has significant research importance in affective computing. It resembles human recognition if done by NNs, as NNs are known as simulations of the human brain [38]. Neural networks are utilised for recognising emotions in the AMIGOS dataset in the VAD model along with liking. The following are the ER steps:

1. Extraction of EEG data from the AMIGOS dataset and preparation of the CSV file.
2. Balancing the VAD emotions
3. Extraction of bands from the EEG data
4. Feature extraction and fusion
5. Application of DNN
6. Model evaluation

Fig. 3 depicts the block diagram of this paper’s work.

3.1 Dataset Description

AMIGOS is a multi-model dataset for personality and mood. This dataset consists of 40 subjects. All 40 people were shown 20 movies. Of the 20 movies, 16 were short videos (51 to 150 seconds long), and four were long videos (14:06 to 23:35 minutes long). Participants’ EEG, ECG, GSR and video signals were recorded while watching the movies. Each participant was assessed in terms of VAD, familiarity and liking, using both self-assessment and annotation by an external expert.

There are 17 columns present in the dataset. The first 14 represent the data recorded by 14 EEG electrodes, the next two gives the ECG signal recording, and the last one is the GSR signal data. The signals were pre-processed at a sampling frequency of 128 Hz. The five dimensions of emotions were measured on a scale of 1–9, where 1 is the lowest, and 9 is the highest.

Pre-processing:
For EEG:
1. The data has been downsampled to 128 Hz.
2. The reference has been averaged to a common reference.
3. The 4.0–45.0 Hz bandpass frequency filter has been pertained.
Here, VAD and liking are taken for classification as high and low classes, and their encoding is shown in Table 2.

### Table 2. Encoding of VAD and liking

| Emotion | Low | High |
|---------|-----|------|
| Valence | ≤ 4.5 | ≥ 4.5 |
| Arousal | ≤ 4.5 | ≥ 4.5 |
| Dominance | ≤ 4.5 | ≥ 4.5 |
| Liking | ≤ 4.5 | ≥ 4.5 |

#### 3.2 Feature Extraction:

Discrete Fourier transform and discrete wavelet transform have been used here for feature extraction. The feature taken from the Fourier transform is the normalized band power (NBP), and the normalized wavelet energy (NWE) was taken from the wavelet transform.

##### 3.2.1 Normalized Band Power

To calculate the NBP, the Fourier transform $X_k$ was first calculated using Equation 1.

$$X_k = \sum_{n=0}^{N-1} x_n e^{-2\pi nk/N}$$

where, $N$ is length of vector $x$ and $0 \leq k \leq N - 1$.

Then, the signal in the frequency domain was further decomposed into five frequency bands (4–8 Hz, 8–13 Hz, 13–16 Hz, 16–30 Hz and 30–45 Hz) to extract features. Beta bands were decomposed...
into two (Beta1 and Beta2) to equalise the dimensions with wavelet transform. The band power and NBP were calculated for each band from Equations 2 and 3.

\[ P_B = \sum_k |X_k|^2 \]  

(2)

Where \( P_B \) represents power of band B. \( k \) is length of each band.

\[ \hat{P}_B = \frac{P_B}{\sum_B P_B} \]  

(3)

Where \( \hat{P}_B \) is called normalized band power.

3.2.2 Normalized Wavelet Energy (NWE)

Wavelet energy is calculated here using multilevel Daubechies-4 wavelet transform. The multilevel wavelet transform decomposes the signal into different frequency bands and is obtained by successive low-pass filter \( h[n] \) and high-pass filter \( g[n] \) of the time domain signal \( x[n] \) as shown in Fig. 4.

Since the EEG signal provided in the dataset ranges from 4 Hz to 45 Hz, a five-level decomposition is sufficient for the band information, as shown in Figure 4.

**Figure 4.** Wavelet Decomposition of different bands

Finally, the features provided to the classifiers are NBP obtained from Fourier transform, NWE obtained from wavelet transform and \{NBP, NWE\}.

3.3 Neural Network

The NNs [38] are particularly designed to simulate the functioning of the human brain and consist of three basic units:

- Neuron
- Activation function
- Number of layers

The neuron is connected at different layers, as shown in Fig. 5.
The NN classifier uses layered architecture, a collection of multiple layers called input layer, hidden layer and output layer. Each layer consists of multiple neurons. The calculation done at each neuron is shown in Fig. 6.

The output of every neuron is the input for the next neuron. The same process is repeated for every neuron at each layer. Once the output of all output neurons is calculated, it will be compared with the actual output, and the weight change will be calculated by Equation (4).

\[
\text{Updated weight} = \text{old weight} + \text{learning rate} \times (\text{expected output} - \text{predicted output}) \times \text{input} \quad (4)
\]
4. Results and Discussions

The experiments conducted in this paper were done in Python 3.7 on a computer with an Intel i5 processor, 8 GB of RAM and an Nvidia graphics card. A DNN with three different activation functions (ELU, ReLU and leaky ReLU) was applied to determine VAD and liking in EEG signals. The architecture of the DNN used here is shown in Table 3.

Table 3. Architecture of DNN

| Layer      | Size   |
|------------|--------|
| Input      | 70x128 |
| Hidden 1   | 128x256|
| Hidden 2   | 256x512|
| Output     | 512x4  |

The batch size taken here is 32, and the binary cross-entropy loss function is used to calculate the loss.

The feature extraction is done by the NBP and NEW, along with the combined feature vector {NBP, NWE}. The accuracies obtained by different activation functions are shown in Table 4, with the highest accuracy in bold.

Table 4. Accuracies obtained by experiments

| S. No. | Feature Extraction | Activation function | Valence(%) | Arousal(%) | Dominance(%) | Liking(%) |
|--------|--------------------|---------------------|------------|------------|--------------|-----------|
| 1.     | NBP                | ELU                 | 65.00      | 55.60      | 60.32        | 79.95     |
|        |                    | ReLU                | 74.40      | 62.01      | 66.48        | 81.86     |
|        |                    | Leaky ReLU          | 75.50      | 68.37      | 66.76        | 81.88     |
| 2.     | NWE                | ELU                 | 81.80      | 75.65      | 78.97        | 83.95     |
|        |                    | ReLU                | 83.66      | 78.93      | 80.94        | 84.66     |
|        |                    | Leaky ReLU          | 83.89      | 78.97      | 80.96        | 84.73     |
| 3.     | NBP, NWE           | ELU                 | 84.41      | 78.76      | 81.09        | 85.45     |
|        |                    | ReLU                | 85.28      | 81.53      | 83.44        | 86.56     |
|        |                    | Leaky ReLU          | 85.47      | 81.87      | 84.04        | 86.63     |

Table 4 shows that the leaky ReLU with combined features gives the highest accuracy for all emotions. The validation vs training loss is shown in Figure 8 for the leaky ReLU activation function.

![Figure 8](image-url)
The outcome of the DNN is also compared with state-of-the-art methods by the applied stacking classifier. The ML methods ensembled in the stacking classifier are RF, Gaussian naïve Bayes, SVM and logistic regression, as shown in Table 5.

**Table 5. Comparison of present work with existing method**

| Ref, Year | Emotions | Modality | Features | Classifier |
|-----------|----------|----------|----------|------------|
| [14], 2018(Original paper) | A 57.7 | V 56.4 | D - | L - | EEG All band, PSD, spectral power asymmetry between 7 pairs of electrodes in the five bands | SVM |
| [33], 2018 | 71.54 | 66.67 | 72.36 | - | EEG Conditional Entropy (CF) feature, CNN based feature using EEG topography | Extreme learning machine (ELM) |
| [42], 2018 | 68.00 | 84.00 | - | - | EEG+ECG +GSR Time, frequency and Entropy domain features | GaussianNB, XGBoost |
| [43], 2019 | 83.02 | 79.13 | - | - | EEG PSD, Conditional Entropy, PSD image based Deep learning features | LSTM |
| [44], 2020 | 83.3 | 79.4 | - | - | EEG+ECG +GSR Spectrogram Representation | Bidirectional LSTM |
| [45], 2020 | 75.00 | 87.50 | - | - | EEG Spectrogram Representation | Deep Convolution Neural Network |
| [46], 2021 | 87.39 | 90.54 | - | - | EEG Features extracted from topographic and holographic feature map | CNN+SVM |
| Our Method | 80.77 | 69.89 | 71.75 | 78.40 | EEG NBD + NWE | Stacking Classifier |
| | 85.47 | 81.87 | 84.04 | 86.63 | EEG NBD + NWE | DNN |

Table 5 shows that the research problem of identifying emotions in the AMIGOS dataset was initially posed in 2018 by Correa et al. The accuracy achieved in their initial analysis was 57.7%. Then, different solutions using ML and DL were proposed in [33, 42–46] and have achieved accuracies up to 90.54%. However, only valence and arousal were predicted in [42–46], whereas VAD was predicted in [33]. Liking and VAD were predicted in the current work. Since VAD is highly dependent on liking, as shown in Fig. 2, the feature extraction is done in the time and frequency domain in [14]. On the other hand, 3D features were extracted in [44–46]. The combined features {NBP, NWE} were used to predict...
VAD and liking, which helped to achieve higher accuracy in the present work. Another observation made in this paper is that the leaky ReLU activation function of a DNN with combined features gives better accuracy than state-of-the-art methods.

The research on ER obtained from EEG signals using DL is not popular due to the limited availability of large datasets [47]. Although the dataset used in this present work is large, it consists of variable length instances, which restrict the ease of applicability of models [43]. The collection of EEG signal is a clinical process in which many individuals are not comfortable; thus, DL is applied in various research for speech and facial ER [48]. Thus, research on ER using DNNs from EEG signals is highly recommended. Two datasets [17, 49] for EEG-based ER have been proposed recently and could be explored in the future.

5. Conclusions

An EEG-based ER system was proposed in this paper. AMIGOS, a mood and personality dataset, was used for ER. The features extracted for classification are NBP and NWE. The combined features were used in the DL classifier to identify VAD and liking. It was observed that DNNs provide better accuracy than ML methods. The proposed system could be used to recommend songs/movies to viewers according to their liking.

The present work can be extended to identify emotions in other physiological signals, such as GSR, ECG and electrodermal activity. Furthermore, a multimodal system could be proposed for ER.

Reference:
[1] Oh JW, Lee IW, Kim JT and Lee GW 1999 Application of Neural Networks for Proportioning of ACI Materials Journal Jan 96(1).
[2] Bishop CM 1995 Neural networks for pattern recognition Oxford university press Nov 23.
[3] Egmont-Petersen M, de Ridder D and Handels H.2002 Image processing with neural networks—a review Pattern recognition Oct 1;35(10):2279-301.
[4] Zhou YT and Chellappa R 2012 Artificial neural networks for computer vision Springer Science & Business Media Dec 6.
[5] Barlow JS 1993 The electroencephalogram: its patterns and origins MIT press.
[6] Siuly S, Li Y and Zhang Y 2016 Electroencephalogram (EEG) and its background In EEG Signal Analysis and Classification pp. 3-21 Springer, Cham.
[7] Alarcão SM and Fonseca MJ 2017 Emotions recognition using EEG signals: A survey IEEE Transactions on Affective Computing 10(3):374-93.
[8] Schnall S 2010 Affect, mood and emotions Social and emotional aspect of learning pp. 59-64.
[9] Castellano G, Kessous L and Caridakis G 2008 Emotion recognition through multiple modalities: face, body gesture, speech In Affect and emotion in human-computer interaction pp. 92-103 Springer, Berlin, Heidelberg.
[10] Soroush MZ, Maghooli K, Setarehdan SK and Nasraboradi AM 2017 A review on EEG signals-based emotion recognition International Clinical Neuroscience Journal 4(4):118.
[11] Koelstra S, Muhl C, Soleymani M, Lee JS, Yazdani A, Ebrahimi T, Pun T, Nijholt A and Patras I 2011 Deap: A database for emotion analysis; using physiological signals IEEE transactions on affective computing 3(1):18-31.
[12] Katsigiannis S and Ramzan N 2017 DREAMER: A database for emotion recognition through EEG and ECG signals from wireless low-cost off-the-shelf devices IEEE journal of biomedical and health informatics 22(1):98-107.
[13] Zheng WL and Lu BL 2015 Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks IEEE Transactions on Autonomous Mental Development 7(3):162-75.
[14] Correa JA, Abadi MK, Sebe N and Patras I 2018 Amigos: A dataset for affect, personality and mood research on individuals and groups IEEE Transactions on Affective Computing.
[15] Khare SK and Bajaj V 2020 Time-frequency representation and convolutional neural network-based emotion recognition IEEE transactions on neural networks and learning systems.
[16] Gao Q, Wang CH, Wang Z, Song XL, Dong EZ and Song Y 2020 EEG based emotion recognition using fusion feature extraction method Multimedia Tools and Applications 79(37):27057-74.
[17] Joshi VM and Ghongade RB 2020 IDEA: Intellect database for emotion analysis using EEG signal Journal of King Saud University-Computer and Information Sciences.
[18] Siddharth S, Jung TP and Sejnowski TJ 2019 Utilizing deep learning towards multi-modal bio-sensing and vision-based affective computing IEEE Transactions on Affective Computing.

[19] Gu X, Cao Z, Jolfaei A, Xu P, Wu D, Jung TP and Lin CT 2021 EEG-based brain-computer interfaces (bcis): A survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications IEEE/ACM transactions on computational biology and bioinformatics.

[20] Supratak A, Wu C, Dong H, Sun K and Guo Y 2016 Survey on feature extraction and applications of biosignals In Machine learning for health informatics pp. 161-182 Springer, Cham.

[21] Zhang J, Yin Z, Chen P and Nicole B 2020 Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review Information Fusion. 59:103-26.

[22] Mohammadi Z, Frounchi J and Amir M 2018 Wavelet-based emotion recognition system using EEG signal Neural Computing and Applications. 28(8):1985-90.

[23] Nawaz R, Cheah KH, Nisar H and Yap VV 2020 Comparison of different feature extraction methods for EEG-based emotion recognition Biocybernetics and Biomedical Engineering 40(3):910-26.

[24] Liu Y, Ding Y, Li C, Cheng J, Song R, Wan F and Chen X 2020 Multi-channel EEG-based emotion recognition via a multi-level features guided capsule network Computers in Biology and Medicine 123:103927.

[25] Yin Y, Zheng X, Hu B, Zhang Y and Cui X 2021 EEG emotion recognition using fusion model of graph convolutional networks and LSTM Applied Soft Computing 100:106954.

[26] Song T, Zheng W, Song P and Cui Y 2018 EEG emotion recognition using dynamical graph convolutional networks IEEE Transactions on Affective Computing 11(3):532-41.

[27] Cui H, Liu A, Zhang X, Chen X, Wang K and Chen X 2020 EEG-based emotion recognition using an end-to-end regional-asymmetric convolutional neural network Knowledge-Based Systems 205:106243.

[28] Topic A and Russo M 2021 Emotion recognition based on EEG feature maps through deep learning network International Journal of Engineering Science and Technology.

[29] Qiu C, Qiao R, Xu X and Cheng Y 2019 Interpretable emotion recognition using EEG signals IEEE Access. 7:94160-70.

[30] Zhong P, Wang D and Miao C 2020 EEG-based emotion recognition using regularized graph neural networks IEEE Transactions on Affective Computing.

[31] Sharma R, Pachori RB and Sircar P 2020 Automated emotion recognition based on higher order statistics and deep learning algorithm. Biomedical Signal Processing and Control 58:101867.

[32] Wang F, Wu S, Zhang W, Xu Z, Zhang Y, Wu C and Coleman S 2020 Emotion recognition with convolutional neural network and EEG-based EFDMs Neuropsychologia 146:107506.

[33] Siddharth, Jung TP and Sejnowski TJ 2018 Multi-modal approach for affective computing In 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) pp. 291-294 IEEE.

[34] Siddharth S, Jung TP and Sejnowski TJ 2019 Utilizing deep learning towards multi-modal bio-sensing and vision-based affective computing IEEE Transactions on Affective Computing.

[35] Li C, Bao Z, Li L and Zhao Z 2020 Exploring temporal representations by leveraging attention-based bidirectional LSTM-RNNs for multi-modal emotion recognition Information Processing & Management 57(3):102185.

[36] Lench HC, Flores SA and Bench SW 2011 Discrete emotions predict changes in cognition, judgment, experience, behavior, and physiology: a meta-analysis of experimental emotion elicitations Psychological bulletin 137(5):834.

[37] Barrett LF 1998 Discrete emotions or dimensions? The role of valence focus and arousal focus Cognition & Emotion 12(4):579-99.

[38] Abdi H 1994 A neural network primer. Journal of Biological Systems 2(03):247-81.

[39] Clevert DA, Unterthiner T and Hochreiter S 2015 Fast and accurate deep network learning by exponential linear units (elus) arXiv preprint arXiv:1511.07289.

[40] Arora R, Basu A, Mianjy P and Mukherjee A 2016 Understanding deep neural networks with rectified linear units arXiv preprint arXiv:1611.01491.

[41] Kolbusz J, Rozyczki P and Wilamowski BM 2017 The study of architecture MLP with linear neurons in order to eliminate the “vanishing gradient” problem In International Conference on Artificial Intelligence and Soft Computing pp. 97-106 Springer, Cham.

[42] Tung K, Liu PK, Chuang YC, Wang SH and Wu AY 2018 Entropy-assisted multi-modal emotion recognition framework based on physiological signals In 2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES) pp. 22-26 IEEE.

[43] Siddharth S, Jung TP and Sejnowski TJ 2019 Utilizing deep learning towards multi-modal bio-sensing and vision-based affective computing IEEE Transactions on Affective Computing.
[44] Li C, Bao Z, Li L and Zhao Z 2020 Exploring temporal representations by leveraging attention-based bidirectional LSTM-RNNs for multi-modal emotion recognition Information Processing & Management. 57(3):102185.
[45] Singh G, Verma K, Sharma N, Kumar A and Mantri A 2020 Emotion Recognition using Deep Convolutional Neural Network on Temporal Representations of Physiological Signals In 2020 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT) pp. 1-6 IEEE.
[46] Topic A and Russo M 2021 Emotion recognition based on EEG feature maps through deep learning network International Journal of Engineering Science and Technology.
[47] Santamaria-Granados L, Munoz-Organero M, Ramirez-Gonzalez G, Abdulhay E and Arunkumar NJ 2018 Using deep convolutional neural network for emotion detection on a physiological signals dataset (AMIGOS) IEEE Access 7:57-67.
[48] Hossain MS and Muhammad G 2019 Emotion recognition using deep learning approach from audio–visual emotional big data Information Fusion 49:69-78.
[49] Arnau-González P, Katsigiannis S, Arevalillo-Herráez M and Ramzan N 2021 BED: A new dataset for EEG-based biometrics IEEE Internet of Things Journal.