



A Deep Learning Technique For Depressive Disorder Detection Using EEG Signal

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Abstract— Electroencephalogram (EEG) signal-based emotion recognition has attracted wide interests in recent years and has been broadly adopted in medical, affective computing, and other relevant fields. Depression has become a leading mental disorder worldwide. Evidence has shown that subjects with depression exhibit different spatial responses in neurophysiologic signals from the healthy controls when they are exposed to positive and negative. Depression is a common reason for an increase in suicide cases worldwide. EEG plays an important role in E-healthcare systems, especially in the mental healthcare area, where constant and unobtrusive monitoring is desirable. EEG signals can reflect activities of the human brain and represent different emotional states. Mental stress has become a social issue and could become a cause of functional disability during routine work. This paper proposed an adaptive approach based on deep learning for detecting depression using EEG. The algorithm first extracts features from EEG signals and classifies emotions using machine and deep learning techniques, in which different parts of a trial are used to train the proposed model and assess its impact on emotion recognition results.

Keywords— EEG, Emotion, Stress, Deep Learning, Machine Learning, E-healthcare.

I. INTRODUCTION

Depression, clinically known as Major Depressive Disorder (MDD), is one of the most common and debilitating mental health conditions worldwide. It is characterized by persistent feelings of sadness, hopelessness, loss of interest in daily activities, cognitive impairments, disturbances in sleep and appetite, and in severe cases, suicidal ideation[1]. According to the World Health Organization (WHO), depression affects over 280 million people globally, cutting across age, gender, and socioeconomic status. The growing prevalence of depressive disorders has raised significant public health concerns, as untreated depression can lead to chronic disability, reduced quality of life, and higher mortality rates. Despite the availability of pharmacological and psychotherapeutic interventions, the accurate, objective, and early detection of depression remains a critical challenge in clinical psychiatry[2].

Traditional diagnostic approaches for depression rely heavily on self-reported questionnaires, structured interviews, and clinician observations, such as the Hamilton Depression Rating Scale (HDRS) or the Beck Depression Inventory (BDI). While these tools are widely used, they are inherently subjective and prone to variability due to differences in patient reporting, cultural influences, and clinician judgment. Consequently, there is an urgent need for objective biomarkers that can support reliable and early detection of depressive disorders[3]. In recent years, neurophysiological signals have emerged as promising tools for exploring brain activity patterns associated with mental health conditions. Among them, Electroencephalography (EEG) has gained significant attention due to its non-invasive nature, high temporal resolution, affordability, and portability[4].

EEG measures the brain's electrical activity through electrodes placed on the scalp, capturing neural oscillations across different frequency bands such as delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (>30 Hz)[5]. Research has demonstrated that depressive disorders are often associated with abnormalities in these EEG rhythms, particularly in the frontal and temporal lobes, which

are regions strongly linked to emotional processing, decision-making, and cognitive control. For instance, depressed patients often exhibit reduced alpha activity, increased theta power, and asymmetric activity between the left and right frontal regions. These distinctive EEG biomarkers make EEG a valuable modality for developing objective diagnostic systems for depression detection[6].

With the rapid advancement of Machine Learning (ML) and Artificial Intelligence (AI) techniques, EEG signals can be analyzed more effectively to uncover hidden patterns indicative of depression[7]. Traditional statistical methods often fail to capture the complex, non-linear dynamics of brain activity, but machine learning approaches such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Random Forest (RF), and Logistic Regression have been applied successfully to classify depressive and non-depressive subjects based on EEG features. More recently, Deep Learning (DL) techniques, especially Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have demonstrated superior performance by automatically extracting high-level features from raw EEG data, thereby reducing the dependency on manual feature engineering[8].

In addition to classification tasks, EEG-based depression detection research has also explored feature extraction and selection methods such as wavelet transform, power spectral density (PSD), entropy measures, and functional connectivity analysis. These methods provide deeper insights into the temporal and spatial characteristics of brain activity in depressed individuals[9]. Furthermore, the integration of EEG with other modalities, such as functional Magnetic Resonance Imaging (fMRI), speech, and physiological signals, has opened new pathways for developing multimodal depression detection systems that are more accurate and robust[10].

The application of EEG for depression detection offers several benefits. First, it provides an objective biomarker-based approach that can complement clinical assessments. Second, EEG devices are relatively low-cost and widely available, making them suitable for large-scale screening in hospitals, clinics, and even home-based monitoring systems. Third, EEG-based systems can enable early detection, allowing timely therapeutic interventions before the disorder progresses to a severe stage[11].

However, there are also notable challenges. EEG signals are often contaminated by artifacts such as eye blinks, muscle activity, and environmental noise, which can affect classification accuracy. Additionally, depression is a heterogeneous disorder, and EEG patterns may vary significantly across individuals depending on age, gender, comorbidities, and medication use. Another challenge lies in the standardization of protocols, as differences in electrode placement, recording duration, and preprocessing methods can lead to inconsistent results across studies[12].

Despite these challenges, ongoing research in this field continues to advance rapidly. The fusion of EEG signal processing, artificial intelligence, and neuropsychiatry holds immense potential for building reliable, automated, and scalable tools for depression detection. Such systems can play a pivotal role not only in clinical diagnostics but also in remote mental health monitoring, personalized treatment planning, and preventive healthcare strategies[13].

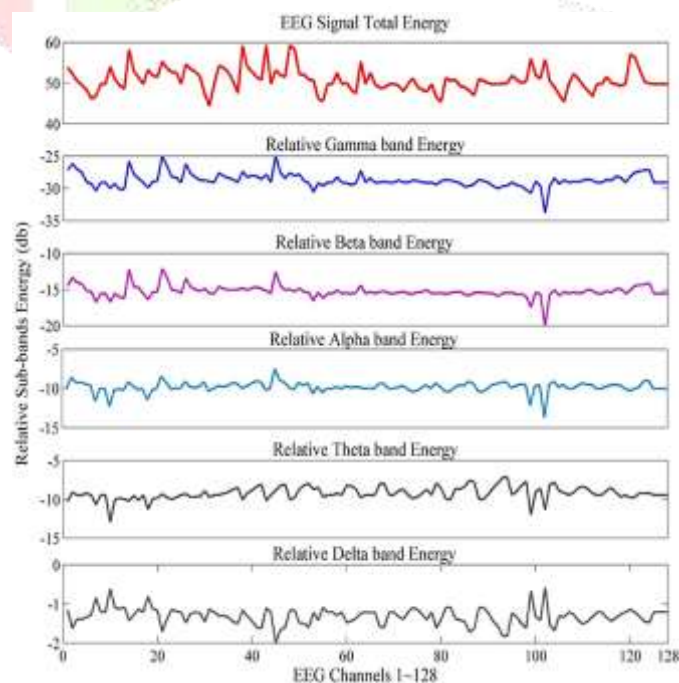


Figure 1: EEG Signal [1]

Stress is your body's reaction to a challenge or demand. In short bursts, stress can be positive, such as when it helps you avoid danger or meet a deadline[14]. EEG nonlinear dynamics features and frontal asymmetry of theta, alpha, and beta bands have been selected as biological indicators for chronic stress, showing relative greater right anterior EEG data activity in stressful individuals[15].

Facial expression recognition (FER) is currently one of the most active research topics due to its wide range of applications in the human-computer interaction field. An important part of the recent success of automatic FER was achieved thanks to the emergence of deep learning approaches[16]. However, training deep networks for FER is still a very challenging task, since most of the available FER data sets are relatively small. Although transfer learning can partially alleviate the issue, the performance of deep models is still below of its full potential as deep features may contain redundant information from the pre-trained domain[17].

Emotions often facilitate interactions among human beings, but the big variation of human emotional states make a negative effect on the reliable emotion recognition [18]. Multimodal emotion recognition is an emerging interdisciplinary field of research in the area of affective computing and sentiment analysis. It aims at exploiting the information carried by signals of different nature to make emotion recognition systems more accurate. This is achieved by employing a powerful multimodal fusion method[19]. The main motivation of this work is to make a optimize model of prediction of the depression using EEG signal.

II. METHODOLOGY

The suggested model of depressive disorder detection using EEG Signal is as below flow chart.

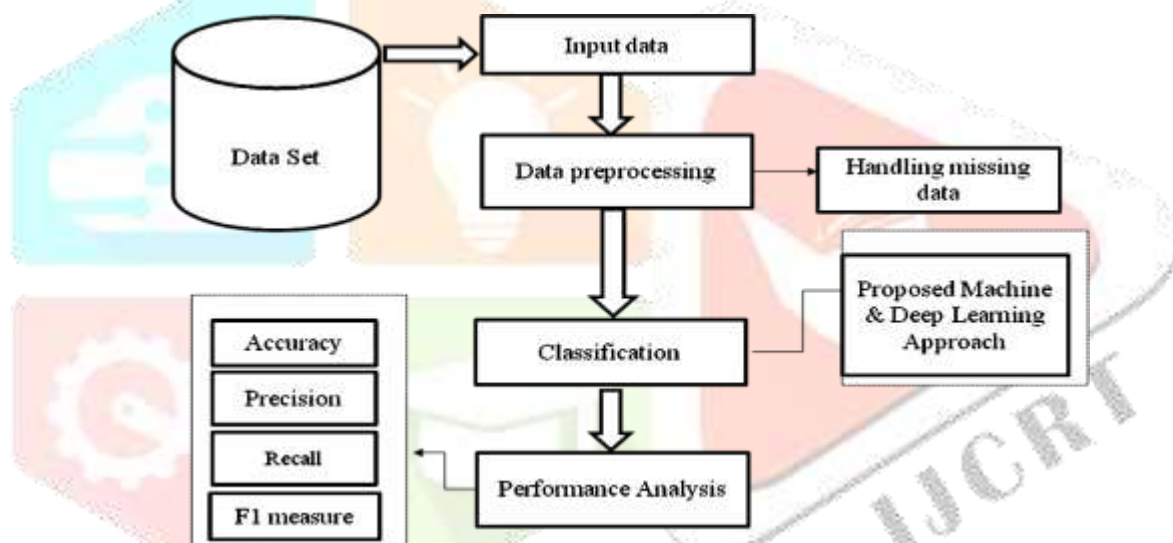


Figure 2: Flow Chart

Firstly, download the EEG dataset from kaggle website, which is a large dataset provider and machine learning repository Provider Company for research.

The EEG dataset have 2133 rows and CTA columns. The features of the dataset shows like # mean_0_a mean_1_a, mean_2_a, mean_3_a, mean_4_a, mean_d_0_a mean_d_1_a, mean_d_2_a mean_d_3_a etc.

The sample dataset of selected dataset is taken form `fft_0_b':fft_749_b`.

- Now apply the preprocessing of the data, here handing the missing data, removal null values.
- Now extract the data features and evaluate in dependent and independent variable.
- Now apply the classification method based on the machine learning (KNN) and deep learning (LSTM) approach.

KNN:- KNN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories. It classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.

RNN- LSTM:- Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning.

It can process not only single data points (such as EEG signal or EEG images), but also entire sequences of data.

The Long Short-Term Memory (LSTM) cell can process data sequentially and keep its hidden state through time.

A recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed or undirected graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior.

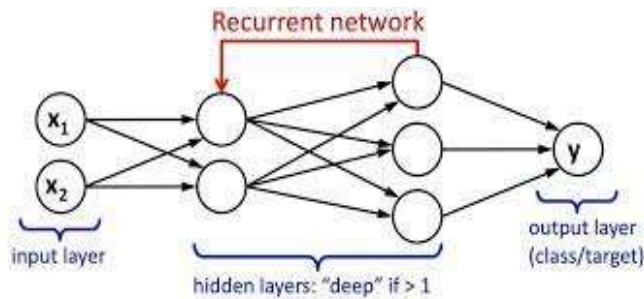


Figure 3: Basic RNN Architecture

Recurrent Layer

The Independently recurrent neural network addresses the gradient vanishing and exploding problems in the traditional fully connected RNN. Each neuron in one layer only receives its own past state as context information (instead of full connectivity to all other neurons in this layer) and thus neurons are independent of each other's history. The gradient back propagation can be regulated to avoid gradient vanishing and exploding in order to keep long or short-term memory. The cross-neuron information is explored in the next layers. IndRNN can be robustly trained with the non-saturated nonlinear functions such as ReLU. Using skip connections, deep networks can be trained.

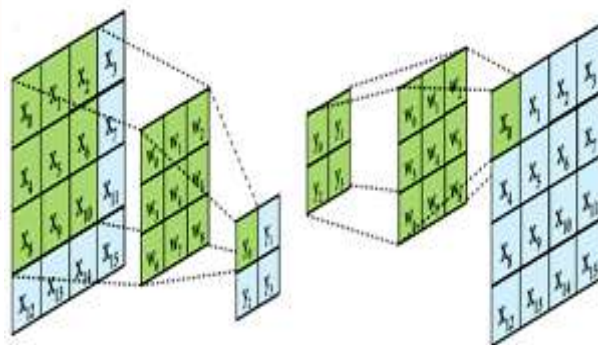


Figure 4: (a) Recurrent operation (b) Equivalent transposed recurrent operation

Mathematically the Recurrent operation can be expressed as-

$$g(x,y)=w*f(x,y)$$

Where

$g(x,y)$ = Image after filtering,

w = Filter kernel,

$f(x,y)$ = Input image

Initially the computer vision experts were designing the filters which were applied to the images for the analysis of various features of the image. Now days during the training process the weights i.e the values in the filter are updated automatically, this is the innovation of using the recurrent layer in the neural network. During the training process the network learns which features it needs to be extracted from the image.

- Now generate confusion matrix and show all predicted class like true positive, false positive, true negative and false negative.
- Now calculate the performance parameters by using the standard formulas in terms of the precision, recall, F_measure, accuracy and error rate.
- Precision is a measure of the accuracy, provided that a class label has been predicted. It is defined by:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

- Recall is the true positive rate:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

- F1 Score is needed to a balance between Precision and Recall

$$\text{F1_Score} = \frac{2x (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Classification Error = 100- Accuracy

III. SIMULATION AND RESULTS

The simulation is performed using python spyder software.

Index	# mean_0_a	mean_1_a	mean_2_a	mean_3_a	mean
0	4.62	30.3	-356	15.6	26.3
1	28.8	33.1	32	25.8	22.8
2	8.9	29.4	-416	16.7	23.7
3	14.9	31.6	-143	19.8	24.3
4	28.3	31.3	45.2	27.3	24.5
5	31	30.9	29.6	28.5	24
6	10.8	21	44.7	4.87	28.1
7	17.8	27.8	-102	16.9	26.9
8	11.5	29.7	34.9	10.2	26.9
9	8.91	29.2	-314	6.51	30.9
10	5.21	28.4	18.5	3.66	22.6
11	13.3	30.4	-149	11.8	28.3
12	30.1	32.7	29.4	28.3	24.3
13	19.3	31.7	-4.56	23.8	32.9

Figure 5: dataset

Figure 5 is showing the dataset of this research. The dataset is taken from the Kaggle website.

	0	1	2
0	0	1	0
1	1	0	0
2	1	0	0
3	0	1	0
4	0	1	0
5	0	0	1
6	1	0	0
7	0	1	0
8	1	0	0
9	0	1	0
10	0	0	1
11	1	0	0
12	1	0	0

Figure 6: Train dataset

Figure 6 is showing the training dataset which is used to train the model.

	0	1	2
0	0	0	1
1	0	0	1
2	0	0	1
3	1	0	0
4	0	0	1
5	0	0	1
6	1	0	0
7	0	0	1
8	1	0	0
9	0	0	1
10	1	0	0
11	1	0	0
12	1	0	0

Figure 7: Test dataset

Figure 7 is showing the test dataset which is used to test the proposed model.

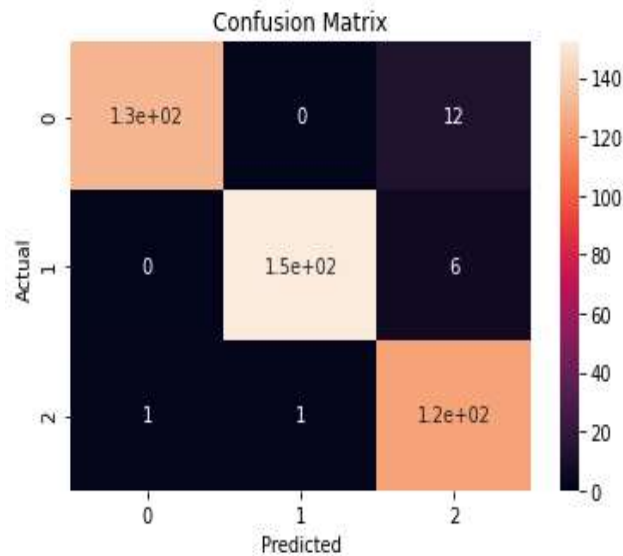


Figure 8: Confusion matrix

Figure 8 is showing the confusion matrix of the proposed model.

Table 1: Simulation Results of LSTM

Sr. No.	Parameters	Proposed Approach
1	Accuracy	96.48 %
2	Classification error	3.52 %
3	Precision	97%
4	Recall	97%
5	F-measure	97%

Table 2: Result Comparison

Sr. No.	Parameters	Previous Work [1]	Proposed Work
1	Accuracy	94.64%	96.48%
2	Classification Error	4.36 %	3.52%
3	Precision	94%	97%
4	Recall	96.55%	97%
5	F-measure	95%	97%

IV. CONCLUSION

This research proposed the efficient deep learning technique to identify the prediction from given dataset. The python spyder 3.7 software is used to simulate the work. Previous work classifier approach is achieved 94% accuracy while deep learning LSTM classifier approach is achieved 96% accuracy. Therefore the simulation results shows that the proposed approach gives significant better results than existing work. In future the other set can be taken and apply more classification and the regression methods and predict various other parameters.

REFERENCES

1. V. Paresh Kowli and H. P. Padole, "Detection of Major Depressive Disorder Using EEG Multifeature Fusion," in *IEEE Sensors Journal*, vol. 25, no. 1, pp. 1068-1075, 1 Jan.1, 2025, doi: 10.1109/JSEN.2024.3493960.
2. A. Habib, S. N. Vaniya, A. Khandoker and C. Karmakar, "MDDBranchNet: A Deep Learning Model for Detecting Major Depressive Disorder Using ECG Signal," in *IEEE Journal of Biomedical and Health Informatics*, vol. 28, no. 7, pp. 3798-3809, July 2024, doi: 10.1109/JBHI.2024.3390847.
3. S. Ahmed, F. Khan, and M. Hussain, "Wavelet Entropy-Based Feature Extraction for EEG Depression Detection," *IEEE Sensors Journal*, vol. 22, no. 18, pp. 18015–18023, 2022
4. A. Seal, R. Bajpai, J. Agnihotri, A. Yazidi, E. Herrera-Viedma and O. Krejcar, "DeprNet: A Deep Convolution Neural Network Framework for Detecting Depression Using EEG," in *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1-13, 2021, Art no. 2505413, doi: 10.1109/TIM.2021.3053999.
5. S. Sun, H. Chen, X. Shao, L. Liu, X. Li and B. Hu, "EEG Based Depression Recognition by Combining Functional Brain Network and Traditional Biomarkers," 2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2020, pp. 2074-2081, doi: 10.1109/BIBM49941.2020.9313270.
6. W. Zheng, J. Zhu and B. Lu, "Identifying Stable Patterns over Time for Emotion Recognition from EEG," in *IEEE Transactions on Affective Computing*, vol. 10, no. 3, pp. 417-429, 1 July-Sept. 2019, doi: 10.1109/TAFFC.2017.2712143.
7. W. Fang, K. Wang, N. Fahier, Y. Ho and Y. Huang, "Development and Validation of an EEG-Based Real-Time Emotion Recognition System Using Edge AI Computing Platform With Convolutional Neural Network System-on-Chip Design," in *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 9, no. 4, pp. 645-657, Dec. 2019, doi: 10.1109/JETCAS.2019.2951232.
8. P. J. Bota, C. Wang, A. L. N. Fred and H. Plácido Da Silva, "A Review, Current Challenges, and Future Possibilities on Emotion Recognition Using Machine Learning and Physiological Signals," in *IEEE Access*, vol. 7, pp. 140990-141020, 2019, doi: 10.1109/ACCESS.2019.2944001.
9. S. Wang, H. Chi, Z. Yuan and J. Geng, "Emotion Recognition Using Cloud Model," in *Chinese Journal of Electronics*, vol. 28, no. 3, pp. 470-474, 5 2019, doi: 10.1049/cje.2018.09.020.
10. R. A. Khalil, E. Jones, M. I. Babar, T. Jan, M. H. Zafar and T. Alhussain, "Speech Emotion Recognition Using Deep Learning Techniques: A Review," in *IEEE Access*, vol. 7, pp. 117327-117345, 2019, doi: 10.1109/ACCESS.2019.2936124.
11. S. Nemati, R. Rohani, M. E. Basiri, M. Abdar, N. Y. Yen and V. Makarenkov, "A Hybrid Latent Space Data Fusion Method for Multimodal Emotion Recognition," in *IEEE Access*, vol. 7, pp. 172948-172964, 2019, doi: 10.1109/ACCESS.2019.2955637.
12. H. Zhang, A. Jolfaei and M. Alazab, "A Face Emotion Recognition Method Using Convolutional Neural Network and Image Edge Computing," in *IEEE Access*, vol. 7, pp. 159081-159089, 2019, doi: 10.1109/ACCESS.2019.2949741.
13. P. M. Ferreira, F. Marques, J. S. Cardoso and A. Rebelo, "Physiological Inspired Deep Neural Networks for Emotion Recognition," in *IEEE Access*, vol. 6, pp. 53930-53943, 2018, doi: 10.1109/ACCESS.2018.2870063.
14. Y. Yang, Q. M. J. Wu, W. Zheng and B. Lu, "EEG-Based Emotion Recognition Using Hierarchical Network With Subnetwork Nodes," in *IEEE Transactions on Cognitive and Developmental Systems*, vol. 10, no. 2, pp. 408-419, June 2018, doi: 10.1109/TCDS.2017.2685338.
15. S. Zhang, S. Zhang, T. Huang, W. Gao and Q. Tian, "Learning Affective Features With a Hybrid Deep Model for Audio–Visual Emotion Recognition," in *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 28, no. 10, pp. 3030-3043, Oct. 2018, doi: 10.1109/TCSVT.2017.2719043.
16. G. Zhao, Y. Ge, B. Shen, X. Wei and H. Wang, "Emotion Analysis for Personality Inference from EEG Signals," in *IEEE Transactions on Affective Computing*, vol. 9, no. 3, pp. 362-371, 1 July-Sept. 2018, doi: 10.1109/TAFFC.2017.2786207.

17. H. Kim, Y. Kim, S. J. Kim and I. Lee, "Building Emotional Machines: Recognizing Image Emotions Through Deep Neural Networks," in IEEE Transactions on Multimedia, vol. 20, no. 11, pp. 2980-2992, Nov. 2018, doi: 10.1109/TMM.2018.2827782.
18. B. Xu, Y. Fu, Y. Jiang, B. Li and L. Sigal, "Heterogeneous Knowledge Transfer in Video Emotion Recognition, Attribution and Summarization," in IEEE Transactions on Affective Computing, vol. 9, no. 2, pp. 255-270, 1 April-June 2018, doi: 10.1109/TAFFC.2016.2622690.
19. Z. Liu et al., "A facial expression emotion recognition based human-robot interaction system," in IEEE/CAA Journal of Automatica Sinica, vol. 4, no. 4, pp. 668-676, 2017, doi: 10.1109/JAS.2017.7510622.
20. P. Tzirakis, G. Trigeorgis, M. A. Nicolaou, B. W. Schuller and S. Zafeiriou, "End-to-End Multimodal Emotion Recognition Using Deep Neural Networks," in IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 8, pp. 1301-1309, Dec. 2017, doi: 10.1109/JSTSP.2017.2764438.

