Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

EEG Emotion Recognition using Mutual Information Channel Selection

Ramprasad Kumawat[1], Dr. Manish Jain[2]

[1](Research Scholar)
Department of Electrical and Electronics Engineering
(Mandsaur University, Mandsaur, India, rpkumawat77@gmail.com
[2](Associate Professor)
Department of Electrical and Electronics Engineering
(Mandsaur University), Mandsaur, India, manish.jain@meu.edu.in

Abstract:- Numerous studies have shown that the temporal information of traditional long-short-term memory (LSTM) networks is especially useful for enhancing emotion recognition using electroencephalography (EEG). The interaction between different modalities and deep LSTM networks for high-level temporal-feature learning, however, requires further investigation. EEG data is frequently acquired from many channels across the brain, making good channel selection techniques critical in determining the optimum channels for a specific application. Channel selection helps reduce setup time and computing complexity while analysing EEG data, and filtering out noisy channels can increase system performance. Therefore, by examining the EEG signals as a collection of data points, we suggest mutual information based channel selection and an LSTM network for emotion recognition that can identify patterns in the data that correspond to different emotional states. The proposed network was evaluated using SEED IV, a publicly available dataset for EEG-based emotion recognition. According to the experiment results, the proposed LSTM network yielded a promising result with a 90.14% classification accuracy using just 10 electrodes.

Keywords— EEG (Electroencephalography), BCI (Brain Computer Interface), LSTM, mutual information, SEED-IV

I. INTRODUCTION

This Effective reasoning, planning, and the completion of some activities depend on the ability to recognize and understand emotions. In human-computer interaction systems for more effective and intimate interactions, automatic emotion identification is crucial. Various deep learning designs have been proposed to improve the accuracy of multimodal emotion recognition using electroencephalographic (EEG) signals among other biomedical signals, including auto-encoders, convolutional neural networks (CNNS), and recurrent neural networks (RNNs) [1,2,3]. These architectures were motivated by the huge achievement of deep neural networks in multiple recognition tasks.

RNNs, unlike other feed-forward networks, have received significant attention in the area of multidimensional emotion recognition utilizing EEG and other physiological signals because they can retrieve complicated temporal information from segments of varying durations. Several researches have shown that taking into account temporal information enhances RNN's effectiveness as a temporal feature extractor module [4, 5]. However, further research needs to be done on the temporal correlation information across various modalities and high-level temporal feature learning employing deeper RNNs.

To monitor voltage changes caused by emotions, scalp electrode insertion is done using a 10-20 system. Each electrode's acquired EEG signal is regarded as one channel. A better model for recognising emotions can be created by having a thorough grasp of how the brain reacts to diverse emotions. Studies on affective computing have shown a connection among EEG and emotions. However now that less costly wearable technology and dry electrodes have been developed [6]–[9], we may use EEG-based systems for practical purposes including detecting driver weariness and curing chronic diseases [10].

The EEG signal is noisy and has small amplitude. Due to low SNR, the data is corrupted with noise. These signals exhibit temporal asymmetry and non-stationary [11]. So, it takes a lot of time to analyse these signals. In the emotion identification system, feature extraction from pre-processed signals and classification are the two crucial phases. Typically, feature extraction is performed on a pre-processed EEG signal across a predetermined time window, and classification is carried out using supervised machine learning. These conventional feature extraction, selection, and classification techniques depend on feature selection and need for specialised domain knowledge. For feature selection, this has a cost that quadratically doubles with features; principal component analysis and Fisher projection are typically utilised [12].

This paper proposes a deep learning-based technique for improving the performance of an EEG-based emotion recognition system. We investigated if employing a subset of EEG channels in the frontal brain region improves classification ability. Based on this, we found the most effective EEG channel combination for emotion detection.

The present study makes the following contributions:

(1) We have used mutual information technique for channel selection to find optimum channels which gives better accuracy.

(2) To improve classification accuracy, we suggested a CNN-LSTM network that selects relevant features from provided characteristics.

II. RELATED WORK

Before By leveraging multiplicative gating operations and rapid pathways across time, the LSTM [13], a gated variation of RNN, prevents gradient explosion or vanishing difficulties. Our multimodal residual LSTM network effectively learns the temporal correlation across the modes by distributing the weights among the modes. The robustness of the speech data against content quality degradations and non-auditory distractions was greatly increased by this design, which was initially proposed for speaker recognition in videos [14]. The network has a tendency to collect temporal correlations across the modalities since all the modalities cooperate and compete with one another when learning the common weights. Additionally, by distributing the weights across the time steps in the LSTM, learning is resilient to the various emotional reflection velocities of the various modalities and may learn the correlation that uses the various temporal step biases.

By employing residual learning and layer normalisation, four residual LSTM layers are built for complicated, high-level learning of temporal information. While there are various methods for developing DNNs using spatial shortcut paths [15, 16, 17], it has been established that individual networks produce effective training and interpretation without the requirement for additional parameters. In order to efficiently train the deep RNN on long sequences, the residual LSTM network comprises both the temporary and spatial shortcuts offered by the LSTM and the residual network, respectively.

Many methods, including facial expressions, speech, EEG, pupillary diameter (PD), and electrooculography (EOG), have been used to recognise emotions [18, 19]. Moreover, multi-modal techniques have been widely used for emotion recognition while the aforementioned studies primarily concentrate on a single EEG modality [18, 19, 20, and 21]. EEG and eye movement features from the SEED dataset are combined using a fuzzy integral fusion approach by Lu et al. [21]. Lin et al. train a deep CNN by converting EEG into pictures and extracting the hand-crafted features from other peripheral physiological signals [18]. According to Liuet, All training of a multimodal autoencoder network, the mean accuracy on the SEED dataset was 91.0% [19].

Here is how the paper is set up. Our suggested LSTM model and feature extraction are discussed in Section 3. The experiment is thoroughly explained in section 4. Results are compared and discussed in Section 5. Section 6 serves as the conclusion.

III. METHODOLOGY

This section describes the feature extraction from EEG signal using power spectral density (PSD). Then we talk about channel selection and finally we discuss LSTM network.

3.1 Feature Extraction

One of the most important goals of EEG emotion detection research is to identify more precise emotional traits. Depending on the methods used for extraction, EEG characteristics can be categorised as either temporal or spatiotemporal. Throughout our research, we found power spectral density (PSD).

To determine the power spectrum of each band for a particular time sequence, the Welch approach [22], [23] is utilized. Assume the series is yd(n), where d=1, 2, 3,..., n (signal intervals), and B is the interval length. The Welch method defines the power spectral density as follows

$$\hat{P}d(f)=\frac{1}{BV}\left|\sum_{n=0}^{B-1} yd(n)w(n)e^{-j2\pi f}\right|^{2} \tag{1}$$

where V stands for normalization factor for power in window function and f is frequency band.

$$V=\frac{1}{B}\sum_{n=0}^{B-1}|w(n)|^{2} \tag{2}$$

where w(n) is windowed data. This PSD is based on periodograms obtained by converting the signal from the time to the frequency domain.

$$PWelch(f)=\frac{1}{l}\sum_{n=0}^{l-1}\hat{P}\mathrm{d}(\mathrm{f}) \tag{3}$$

3.2 Channel Selection:

In order to collect brain impulses, the electrodes are fastened to the scalp. The range of electrodes for different EEG headsets is 1 to 256. The frontal, parietal, temporal, and occipital lobes are identified by the letters F, P, T, and O in the worldwide 10-20 system, which also shows where the electrodes should be placed on the human skull. The letter Z (zero) is used to denote the position of the electrode on the midline between the two hemispheres of the brain, whereas the letter A symbolizes the position of the front electrode and the letter C does not represent a lobe but rather the middle area of the head. Odd numbers 1, 3, 5, and 7 are used to identify the electrodes in the left hemisphere. Even numbers 2, 4, 6, and 8 electrodes are located in the right hemisphere. It is reasonable to use as few electrodes as possible to solve these problems, and that is one of the main tasks of the EEG channel selection process. Consider the number of electrodes, the level of comfort of wearing the EEG measurement device, the time required to mount the device on the subject's head, the complexity and processing time of all recorded signals.

Mutual information (MI) refers to how much information an attribute under an assumption of independence offers regarding class membership. It measures the connection or correlation between the variables in the row and column. While mutual information gives information on both X and Y, it may be estimated using the formula (1), where p(x,y) is the joint probability distribution function of X and Y and p(x) and p(y) is the marginal probability distribution functions of X and Y. A greater mutual information value indicates that the relevant property can better predict class membership [24].

The mutual information may also be calculated using equation (2), where H(Y) is the marginal entropy, H(X|Y) and H(Y|X) are the conditional entropies, and H(X, Y) is $A_V^i=[a_{B1}^i a_{B2}^i.....a_{Bn}^i]$ the combined entropy of X and Y. The feature vector is formed by concatenating the features from each band. Here, it represents the feature vector of the i-th trial, denotes the features acquired from the j-th band of the i-th trial, and n signifies the total number of bands. The feature matrix $A_M[A_V^1;A_V^2;....A_V^n]$ is created by combining the feature vectors from each trial in the train data.

I(X,Y)=∑_(y∈Y)∑_(x∈X)⟦p(x,y)log((p(x,y))/(p(x)p(y)))⟧) (4)

$$I(X,Y) = H(Y) - H(Y \mid X) \quad (5)$$

$$= H(X,Y) - H(X \mid Y) - H(Y \mid X) \quad (6)$$

The mutual information is computed using (6) and the feature matrix, yielding MI = [J1, J2…JL], where JL represents the mutual information value of the ith feature.

3.3 LSTM Network:

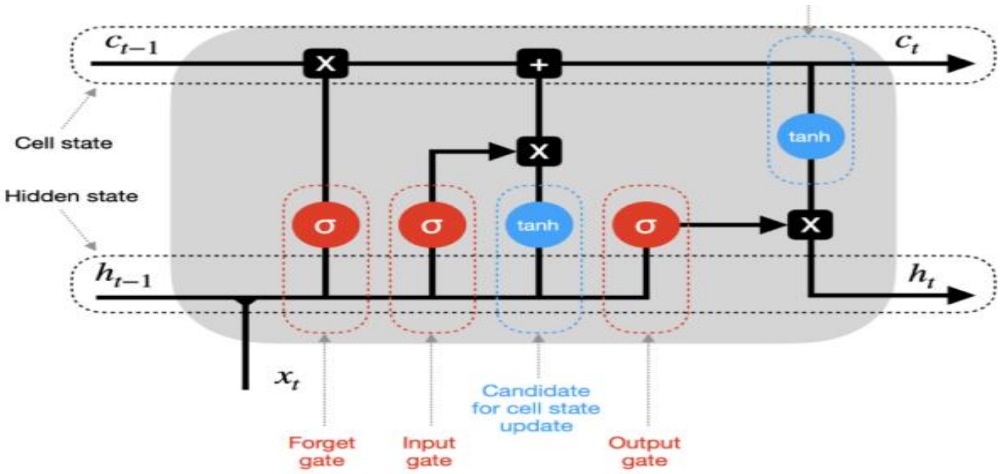

Figure 1: LSTM Recurrent Unit

The artificial recurrent neural network (RNN) architecture utilised in the field of deep learning is called long short-term memory (LSTM) [25]. The "memory cells" of LSTM, in contrast to normal RNNs, have a long-term memory. The input gate, forget gate, and output gate are three more gates that regulate the information flow into and out of the memory cells [26].

Conventional neural networks operate in a "feed forward" fashion, which means they process information by taking in input at one time step and producing an output at the following time step. LSTMs, on the other hand, have the ability to process data in a "recurrent" manner, which allows them to use input from a single time step to affect output from subsequent time steps. Because of this recurrent processing, LSTMs may learn from data sequences. The forget gate, the input gate, the output gate, and the cell state are the four essential parts of an LSTM network. How much data from the previous time step is kept in the current time step is determined by the forget gate. How much fresh data from the most recent time step is contributed to the cell state is determined by the input gate. The output gate regulates how much data from the current time step's cell state is used to generate an output. Last but not least, the cell state is a vector that symbolises the "memory" of the LSTM network; it in-cludes data from both the prior and present time steps [26].

Networks with long short-term memory are made to mimic complicated, sequential data. The vanishing gradient problem constrains typical RNNs; however LSTMs may learn long-term relationships via a technique called gated recurrent units (GRUs). GRUs have "forget" gates that let them to selectively erase data from past time steps, and "update" gates that let them decide how much data from the current time step should be carried over to the following time step. As a result, LSTMs are ideally suited for applications where it is crucial to recall and comprehend data from lengthy sequences. Moreover, LSTMs may be taught using a number of techniques, including as reinforcement learning, backpropagation, and time [25].

IV. EXPERIMENTAL SETUP

In this section, we describe the SEED IV dataset. This dataset is used to estimate the performance of our model. To justify our model, results are compared with other methods used earlier.

4.1 SEED IV dataset

15 people (7 men and 8 women) took part in the studies for the SEED-IV datasets. Each subject's 62-channel EEG data were captured throughout the experiment as they watched movie clips with various emotion classifications. Each subject was shown clips for three different sessions The SEED-IV dataset has 1,080 samples (72 samples x 15 people). There are four main types of emotions—happy, sad, fearful, and neutral—for each subject, with a total of 18 possible classes for each one. Hence there is a balance in the quantity of samples per subject or class.

A 1,000 Hz sample rate was used to simultaneously capture the signals. For the SEED-IV dataset, bandpass frequency filters with cut-off frequencies of 1-75 Hz were used to remove the irrelevant artefacts. The signals were downsampled using a sampling frequency of 200 Hz to speed up the processing. Moreover, in order to remove noise and other artefacts that had no relation to the EEG characteristics, the dataset supplier used the linear dynamic system technique [27].

4.2 Feature extraction and channel selection

PSD features are extracted against five frequency bands δ, θ, α, β, and γ bands with one second sliding window. These features are smoothened using linear discriminant system method to remove arte-facts and noise from EEG signal. There are 8145 samples for SEEDIV dataset and each sample has 62×5 i.e. 310 PSD features.

Mutual information technique is applied for channel selection after feature extraction. It is observed that F3, FC5, T7, C3, CP5, P7, P3, O1, AF3 and Fz are the best channels.So we have selected those channels and used features from them for classification.

4.3 Proposed LSTM model

We have used three LSTM layers with leaky ReLU, two batch normalization layers, two dropout layers and lastly a softmax layer for classificaion. Dropout layer is used to remove overfitting.

The system's loss is calculated using categorical cross-entropy. It's provided by:

$$Loss = -\sum_{i=1}^{n} x_i \log \overset{o}{x}_i \quad (7)$$

where Xi^ is the ith scalar model output, and Xi is the corresponding goal value of the ith class. Optimisation is used to modify the model's hyperparameters, reducing neural network loss. The Adam optimiser is used to update weights and biases.

V. RESULT AND DISCUSSION

Many studies have been conducted recently to examine the fascinating field of emotion identification. Despite these variations, the current methodologies provide useful concepts and outcomes. We used the data from nine participants for training, the data from three individuals for validation, and the data from three subjects for testing. Finally, we have contrasted our findings with those of other cutting-edge techniques. The suggested LSTM model is implemented using the Keras framework. Hardware requirements for the model's implementation include an Intel i5 CPU, 8GB of Memory, a Tesla K40 GPU, and a Windows 2010 operating system. We have chosen 40 epoch. We have used subject-independent emotion detection methodologies to assess the stability and usefulness of our model. The selection of 10 channels has reduced the size of dataset. Hence less number of channels are required to be trained giving less complexity.

Figure 2 and 3 shows the training and validation accuracy and loss graph for our proposed model.

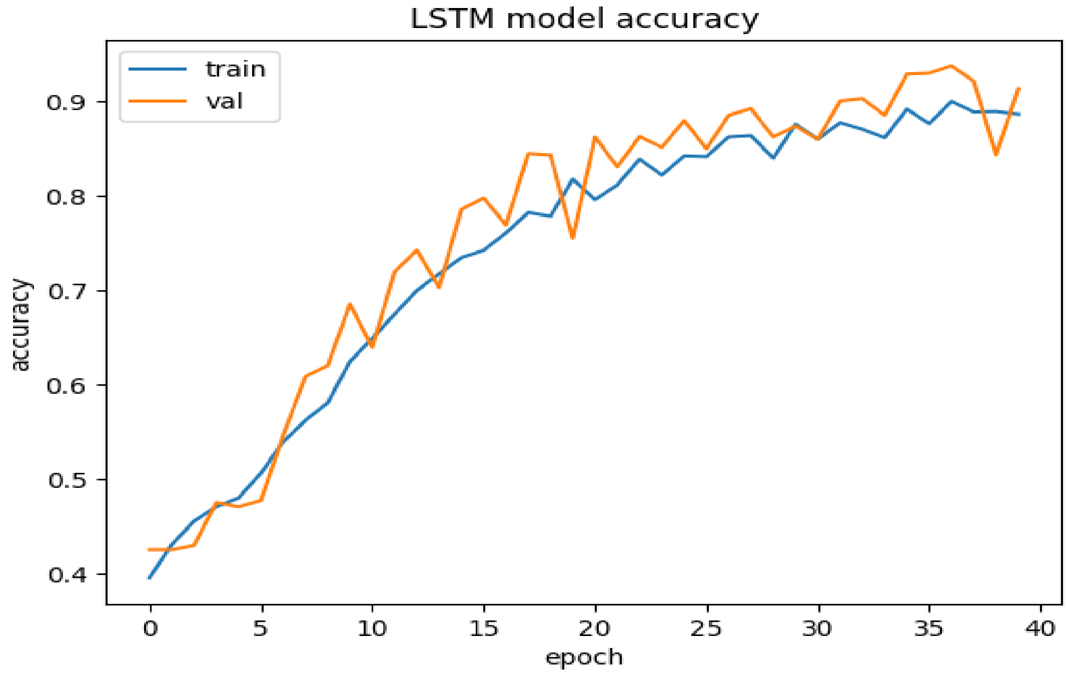

Figure 2: Training and validation accuracy for proposed model.

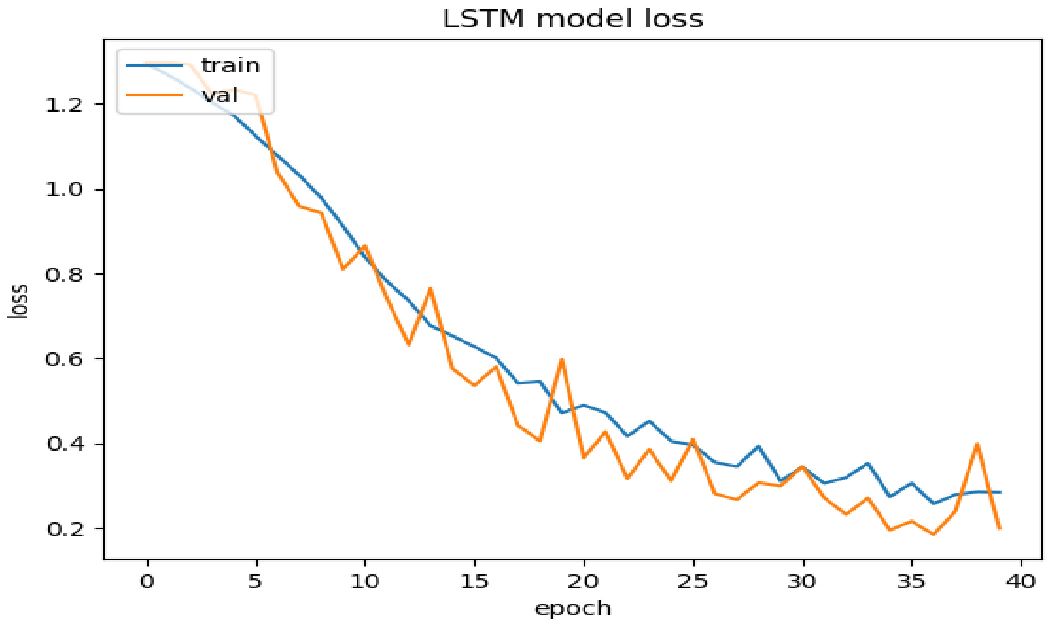

Figure 3: Training and validation loss for proposed model

The training and loss curves of a neural network are graphical representations that give information about the learning process and model performance during training. The above graph shows that our model is learning effectively.

5.1 Classification Report

TABLE I: EEG EMOTION RECOGNITION CLASSIFICATION PERFORMANCE FOR SEED IV DATASET WITH 10 CHANNELS

	Precision	Recall	F-1 Score	Support
0	0.97	0.85	0.91	700
1	0.61	0.95	0.74	287

2	0.97	0.91	0.94	1009
3	0.95	0.92	0.94	448

Table I provides a summary of the findings. The results shows that sad emotion detection with 10 channels is bit confusing but other emotions can be detected very well.

From figure 4, we conclude that the average emotion recognition accuracies of proposed LSTM in recognizing the four emotions are 97% (neutral), (61%) sad, 97% (fear) and 95% (happy). The above results show that sad and fear emotions are easier to recognize than neutral and happy.

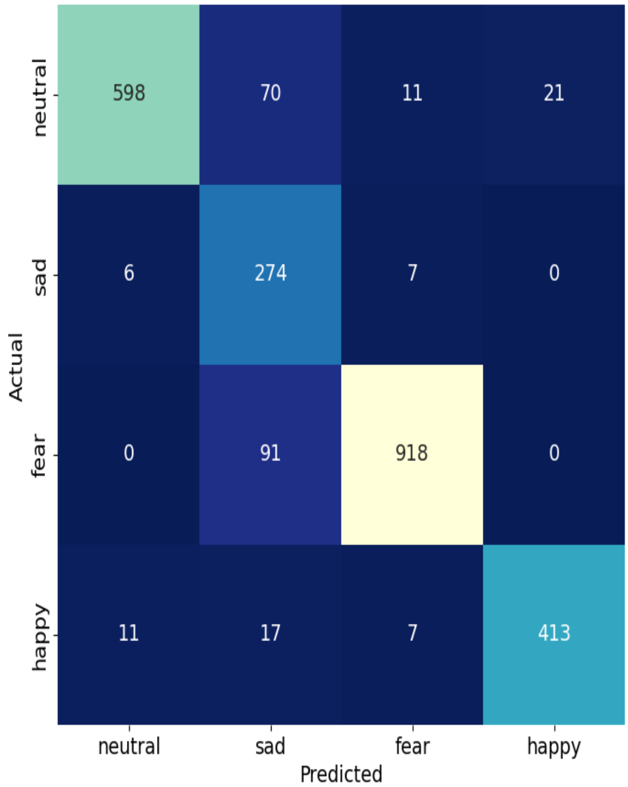

Figure 4: Confusion matrices of four emotions of subject independent data for proposed LSTM method on SEED IV database

5.2 Comparison with Other Methods

We have compared our model against twelve other approaches, including SVM [28], RF [29], CCA [30], GSCCA [31], DBN [32], GRSLR [33], GCNN [34], DGCNN [35], and CNN-LSTM [36] in order to verify that our LSTM is superior to them all. In order to have a clear comparison with our technique, we used the data from past research to compare all the aforementioned methodologies.

TABLE II: COMPARISON OF EEG EMOTION RECOGNITION CLASSIFICATION PERFORMANCE FOR SEED IV DATASET

Method	**Description**	**Accuracy/STD. (%)**
SVM [28]	Support vector machine	56.61/20.05
RF [29]	Random forest	50.97/16.22
CCA [30]	Canonical correlation analysis	54.47/18.48
GSCCA [31]	Group sparse canonical correlation analysis	69.08/16.66
DBN [32]	Deep belief network	66.77/7.38
GRSLR [33]	Graph regularized sparse linear regression	69.32/15.42
GCNN [34]	Graph convolution neural network	68.34/15.42
DGCNN [35]	Dynamic graph convolution neural network	69.88/16.29

CNN-LSTM [36]	Convolution neural network- LSTM	93.06/4.6
Proposed with 10 channels	LSTM	90.14/4.7

Our suggested LSTM model outperforms all other approaches on the SEED IV dataset, according to the data in Table II. The findings of the suggested technique outperform Emotion-Meter by 13.9% and BiHDM by 10.14%. Unlabeled testing data were used by the DANN and BiDANN algorithms to enhance performance. Several baseline approaches in our study have learned their models using simply labelled training data. We have also used labelled training data in our experiment to fairly compare different approaches. For testing, we have achieved an accuracy of 90.14% for 10 channels.

VI. CONCLUSION

Our work presents a classification model for subject independent emotion detection using the proposed LSTM network. It is observed that Power Spectral Density found on different frequency bands is more useful as it is a spectral feature. This article focused on subject-independent channel selection for BCI applications based on emotion. In order to do this, we investigated a channel reduction technique that restricts classification accuracy to a realistic range. By focusing on channels that consistently transfer task-related information across people, MI-based channel selection can improve generalization and boost the model's ability to generalize to new data set. The immense experiments on the SEED IV dataset have shown that propped LSTM network improves accuracy more than earlier methods even with 10 channels. The low value of standard deviation shows that model gives stable EEG emotion recognition.

Despite the positive experimental results obtained in this study, more research is needed to extract more discriminative EEG features for cross-subject emotion classification and select, construct, and optimize deep learning models for EEG-based emotion recognition with higher accuracy, robustness, and generalization. In addition, more studies should be done to incorporate emotions based brain neurogenic analysis into the analysis of experimental results. We will cover all of these topics in-depth in our future study project.

As LSTM networks can handle sequential data, they are excellent for tasks requiring emotion recognition. In conventional recurrent neural networks, the gradient can progressively shrink, making it challenging to train the network efficiently. LSTM networks can be trained more successfully since they have a gating mechanism to get around this issue.

REFERENCES

[1] Wenqian Lin, Chao Li, and Shouqian Sun. 2017. , "Deep Convolutional Neural Network for Emotion Recognition Using EEG and Peripheral Physiological Signal. In Image and Graphics,"Yao Zhao, Xiangwei Kong, and David Taubman (Eds.). Springer International Publishing, Cham, 385–394. https://doi.org/10. 1007/978-3-319-71589-6 33

[2] WeiLiu, Wei-LongZheng,andBao-LiangLu.2016. , "Emotion Recognition Using Multimodal Deep Learning," In Proceedings of the 23rd International Conference on Neural Information Processing - Volume 9948. Springer-Verlag, Berlin, Heidelberg, 521–529. https://doi.org/10.1007/978-3-319-46672-9 58

[3] M. Soleymani, S. Asghari-Esfeden, M.Pantic,and Y.Fu., "Continuous emotion detection using EEG signals and facial expressions,".In 2014 IEEE International Conference on Multimedia and Expo (ICME).1–6. https://doi.org/10.1109/ICME. 2014.6890301

[4] HaoTang,WeiLiu,Wei-Long Zheng,and Bao-LiangLu.," Multimodal Emotion Recognition Using Deep Neural Networks ,".In Neural Information Processing, Derong Liu,ShengliXie,YuanqingLi,DongbinZhao,andEl-SayedM.El-Alfy , 2017 (Eds.).SpringerInternationalPublishing,Cham,811–819. https://doi.org/10.1007/ 978-3-319-70093-9_86

[5] R. W. Picard, Affective Computing, MIT Press, US, (2000).

[6] R. Picard, E. Vyzas and J. Healey, "Towards Machine emotional intelligence: Analysis of affective Physiological state," IEEE transaction on Pattern Analysis and Machine Intelligence, no.10, pp. 1175-1191, (2001).

[7] C. Reshma, R. Rajshree, “A survey on Speech Emotion Recognition,” IEEE conference on Innovations in communication, Computing and Instrumentation, (2019).
[8] B.C. Ko, “A brief review of Facial Emotion recognition based on visual information,” Sensors, vol.18, no.2, pp. 401-420, (2018).
[9] Schmidt and L. J. Trainor, “Frontal brain electrical activity (EEG) distinguishes valance and intensity of musical emotions,” Cognition and Emotions, vol. 15, no. 4, pp. 487-500, (2001).
[10] C. Grozea, C. D. Voinescu and S. Fzli, “Bristle-sensors-low-cost flexible passive dry EEG electrodes for neuro feedback and BCI applications, “Journal of Neural Engineering, vol.8, no. 2, pp. 025008, (2011).
[11] Y. M. Chi, Y. T. Wang, C. Maier, T. P. Jung and G. Cauwenberghs, “Dry and noncontact EEG sensors for mobile brain computer interfaces,” IEEE transaction on Neural systems and Rehabilitation Engineering, vol. 20, no. 2, pp. 228-235, (2012).
[12] Sepp Hochreiter and Jürgen Schmidhuber,” Long Short-Term Memory.” Neural Comput.9,8(Nov.1997),1735–1780. https://doi.org/10.1162/neco.1997.9. 8.1735
[13] S. Katsigiannis and N. Ramzan. 2018.,” 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(Jan2018), 98–107. https://doi.org/10.1109/JBHI.2017.2688239
[14] B.H.Kimand S.Jo.,” Deep Physiological Affect Network for the Recognition of Human Emotions,” IEEE Transactions on Affective Computing (2018), 1–1. https://doi.org/10.1109/TAFFC.2018.2790939
[15] Nandini Bhandari, Manish Jain, “EEG Emotion Recognition using Convolution Neural Network”, in the 4th International Conference on Machine Intelligence and Signal
[16] Processing (MISP2022) organized by Department of Computer Science and Engineering, National Institute of Technology Raipur, India, March 12 - 14, 2022
[17] Julian Georg Zilly, Rupesh Kumar Srivastava, Jan Koutník,and Jürgen Schmidhuber,” Recurrent Highway Networks,” In Proceedings of the 34th International Conference on Machine Learning (Proceedings of Machine Learning Research),Doina PrecupandYeeWhye Teh(Eds.), Vol.70.PMLR,InternationalConventionCentre, Sydney,Australia,4189–4198. http://proceedings.mlr.press/v70/zilly17a.html, .2017
[18] Jiaxin Ma , Hao Tang , Wei-Long Zheng , Bao-Liang Lu,"Emotion Recognition using Multimodal Residual LSTM Network," MM '19: Proceedings of the 27th ACM International Conference on Multimedia October 2019 Pages 176–183 https://doi.org/10.1145/3343031.3350871
[19] L. F. Wang, J. Liu, B. Yang and C. S. Yang, “PDMS-based low cost flexible dry electrodes for long-term EEG measurement,” IEEE Sensors Journal, vol. 12, no. 9, pp. 2898-2904, (2012).
[20] Carlos Busso, Zhigang Deng, Serdar Yildirim, Murtaza Bulut, Chul Min Lee, Abe Kazemzadeh, Sungbok Lee, Ulrich Neumann, and Shrikanth Narayanan. 2004. Analysis of Emotion Recognition Using FacialExpressions, Speech and Multimodal Information. In Proceedings of the 6th International Conference on Multimodal Interfaces (ICMI ’04). ACM, New York, NY, USA, 205–211. https: /doi.org/10.1145/1027933.1027968
[21] YifeiLu, Wei-LongZheng, BinbinLi, and Bao-LiangLu.2015. Combining Eye Movements and EEG to Enhance Emotion Recognition. In Proceedings of the 24th International Conference on Artificial Intelligence (IJCAI’15). AAAI Press, 1170–1176. http://dl.acm.org/citation.cfm?id=2832249.2832411
[22] HaoTang, WeiLiu, Wei-LongZheng, and Bao-LiangLu.2017. Multimodal Emotion Recognition Using Deep Neural Networks. In Neural Information Processing, Derong Liu, ShengliXie,YuanqingLi,DongbinZhao,andEl-SayedM.El-Alfy (Eds.).Springer International Publishing,Cham,811–819. https://doi.org/10.1007/ 978-3-319-70093-9 86
[23] Shiu Kumar, Alok Sharma ,Tatsuhiko Tsunoda ,"An improved discriminative filter bank selection approach for motor imagery EEG signal classification using mutual information”, From 16th

International Conference on Bioinformatics (InCoB 2017) Shenzhen, China. September 20–22, 2017

[24] J. W. Gibbs, Elementary principles in statistical mechanics: developed with especial reference to the rational foundation of thermodynamics. Cambridge University Press, U. K. (2010).

[25] Y. Li, L. Wang, T. Song, W. Zheng, Y. Zong, "A novel Bi-hemispheric discrepancy model for EEG emotion recognition," IEEE transaction on Cognitive and Development systems, vol. 13, no. 2, pp. 354-367, (2021).

[26] SalmaAlhagry,AlyAly,and RedaEl-Khoribi.," Emotion Recognition based on EEG using LSTM Recurrent Neural Network," International Journal of Advanced Computer Science and Applications 8,10(2017). https://doi.org/10.14569/IJACSA. 2017.081046

[27] N. Jaitly and G. Hinton, "Learning a better representation of speech sound waves using restricted Boltzmann machines," IEEE International conference on Acoustics, Speech and signal processing (ICASSP), pp. 5884-5887, (2011).

[28] A. Suykens and J. Vandewalle, "Least squares support vector machine classifiers," Neural Processing Letters, vol. 9, no. 3, pp. 293-300, (1999).

[29] L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5-32, (2001).

[30] B. Thompson, "Canonical correlation analysis," Encyclopedia of Statistics in Behavioral Science, (2005).

[31] W. Zheng, "Multichannel EEG-based emotion recognition via group sparse canonical correlation analysis," IEEE transaction on Cognitive and development systems, vol. 9, no. 3, pp. 281-290, (2017).

[32] X. Zhou, M. Lin and J. Sun, "Shufflenet: An extremely efficient convolutional neural network for mobile devices," IEEE conference on Computer vision and pattern recognition (CVPR), (2018).

[33] Y. Li, W. Zheng, Z. Cui, Y. Zong and S. Ge, "EEG emotion recognition based on graph regularized sparse linear regression," Neural Processing Letters, pp. 1-17, (2018).

[34] M. Defferrard, X. Bresson and P. Vandergheynst, "Convolutional neural networks on graphs with fast localized spectral filtering," Conference on Neural information processing systems (NIPS), pp. 3844-3852, (2016).

[35] T. Song, W. Zheng, P. Song and Z. Cui' "EEG emotion recognition using dynamical graph convolutional neural networks," IEEE transactions on Affective Computing, vol. 11, no. 3, pp. 532-541, (2020).

[36] Nandini K. Bhandari, and Manish Jain, "Object Sovereign EEG Emotion Recognition," International Conference on Wireless Technologies, Networks and Science 2022, Al Balqa Applied University, Jordon, 5-6 October,2022. AIP conference proceedings