Comparison of EEG- Based Deep Neural Network Classifiers for Emotion Recognition using Selected Electrodes

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***Abstract*— In this study, SVM and DNN models were employed to classify participants' emotional states using the publicly available SEED dataset, achieving impressive accuracy rates of 79.8% for DNN and 79.4% for SVM, surpassing the accuracies of previous models. Furthermore, our electrode reduction study, which optimized electrode placement by focusing on emotionally relevant brain regions, yielded high accuracy. The use of EL further enhanced model accuracy to 81.3%. These classification results suggest that future research with more extensive datasets could lead to even more robust models. Consequently, this work has the potential to provide guidance for personalized recommendations in areas such as music, movies, books, and other choices tailored to individuals' emotional states.**

Keywords — EEG; emotion recognition; machine learning; deep learning; electrode reduction; ensemble learning.

I. INTRODUCTION

In recent years, studies have focused on emotion recognition with an emphasis on the frequency bands of brain signals obtained through Electroencephalography (EEG) and the identification of crucial EEG electrodes for emotion recognition. Zheng and Lu [1] noted in their research that an approach involving the separation of important frequency bands was pursued to select the most suitable band for emotional analysis. As a result of this investigation, the gamma band was identified as congruent with emotional steady-state visual evoked potentials for EEG-based emotion classification. Additionally, efforts have been directed toward utilizing only a few electrodes for emotion recognition purposes and determining optimal electrode placement positions [2, 3].

In Li and Feng study, they employed the Random Forest (RF) algorithm to assess the significance of EEG electrodes. They chose the wavelet transform (WT) method for feature extraction. Through the WT approach, they obtained features which were subsequently subjected to a classification process using Convolutional Neural Network (CNN) [4].

Kul et al. have demonstrated the significance of electrode placements in EEG-based emotion recognition studies. Upon examining the positions of channels, they have evidenced that the combined utilization of F3, F4, F7, and F8 channels yields more successful outcomes in comparison to other combinations. In accordance with preceding studies, they have achieved more accurate results through the utilization of Support Vector Machines (SVM) [5].

In their conducted study, Ozcan and Cizmeci have demonstrated that even when obtained from the same individual, EEG signals can be subject to degradation. Therefore, they have revealed that in the analysis of incoming EEG signals, CNN-based approaches prove to be more effective and yield successful results compared to prediction studies conducted using the Welch power spectral density method. This observation underscores the superiority of CNN based methods in handling EEG signals [6].

Li et al. have employed a fusion of spatial, frequency, and temporal features of EEG signals to define human emotions. These combined features have been mapped onto a two-dimensional image, thus generating a multidimensional feature map from EEG data. In this study, a hybrid deep neural network (DNN) was constructed by combining Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Recurrent Neural Networks (RNN) architectures. As a result, they achieved an average accuracy rate of 75.21%, underscoring the effectiveness of their approach in emotion recognition through EEG signals [7].

In this current study, drawing upon the research by Zheng and Lu [1], emotion analysis has been conducted through the extraction of features from EEG signals.

II. MATERIALS AND METHODS

The block diagram of the completed study is displayed in Fig 1.

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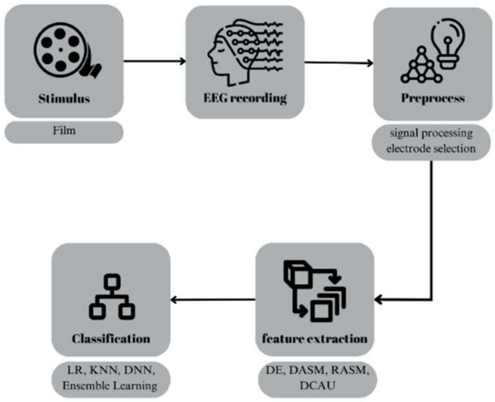

Fig 1. Block diagram of the study.

A. Dataset

In this study, the open-source SEED dataset, which is a commonly used resource for emotion analysis investigations, was employed. The SEED dataset comprises EEG recordings obtained using a 62-channel electrode configuration positioned according to the international 10-20 system. The recordings were conducted utilizing the anESI NeuroScan apparatus at a sampling rate of 1000Hz [1].

The SEED dataset contains EEG data from 15 participants [8]. These data were captured while participants were exposed to various emotional stimuli. The stimuli consisted of carefully selected film clips belonging to three distinct emotional categories: positive, negative, and neutral, aiming to evoke corresponding emotional responses [1].

B. Preprocessing

Zheng and Lu [1] employed a band-pass frequency filter to clean artefacts present in the EEG data. This filter was applied to signals within the frequency range of 0.3-50Hz, effectively removing noise and other unwanted signals. The filtered signal was then decomposed and sampled down to a sampling frequency of 200 Hz for each film clip's recorded EEG signals. To prevent signal overlap, all experiments were divided into segments of the same length, yielding approximately 3300 segments for each experiment.

C. Feature Extraction

Activities in different regions of the brain are observed in distinct frequency ranges, thus emphasizing the significance of decomposing EEG signals into frequency bands [9].

Feature extraction methods were employed to enhance the informational value of the data. In literature, it is observed that features such as Differential Entropy (DE), Differential Asymmetry (DCAU), Rational Asymmetry (RASM), DASM, and RASM have been utilized [1], [9]. These features have been employed in data analysis and exhibit various potentials for providing informative insights.

3) Electrode Selection

The electrode reduction method is employed to identify critical brain regions associated with emotion recognition. Previous studies have demonstrated that reducing the electrode array not only decreases computational complexity but can also filter out irrelevant noise [12].

In this study, initially, multi-channel EEG signals were used, extending up to 62 channels, and were utilized for model training. The DNN model was trained with the assumption that changing weights carry more information since it assigns higher weights to important features. The weight distribution analysis of the DNN model was used to identify critical channels and frequency bands. In this context, four different electrode configurations were selected and their performances were compared to the performance of the 62-electrode full setup. Electrode locations are shown in Fig 2.

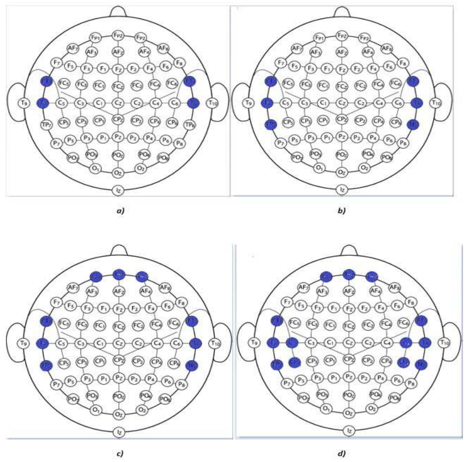

Fig 2. (a) 4-channel: FT7, FT8, T7, and T8; (b) 6-channel: FT7, FT8, T7, T8, TP7, TP8; (c) 9-channel: FP1, FPZ, FP2, FT7, FT8, T7, T8, TP7, TP8; (d) 12-channel: FT7, FT8, T7, T8, CP5, CP6, TP7, TP8, CP5, CP6, P7, P8.

III. RESULTS

After feature extraction, training was performed using LR, KNN, SVM, and DNN models. The parameters of the employed models are provided below.

LR: L2-regularized: 5

KNN: K=5

SVM: Linear Kernel was utilized (C parameter: 5.2)

DNN: Two hidden layers were used, with the first layer having a dimension of 300 and the second layer having a dimension of 200. The activation function used was the 'relu' function. The learning rate was set to 0.003.

In their study, Zheng and Lu [1] initially defined the output layers as sigmoid, however, experimental results indicated that for multi-class problems, the 'SoftMax' activation function yields better outcomes [11]. The error matrices of the trained models are depicted in Fig 3.

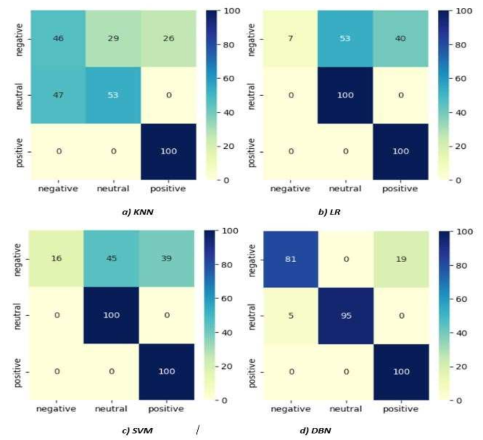

Fig 3. The error matrices of the models: a) Linear Regression, b) K-Nearest Neighbors, c) Support Vector Machine, d) Artificial Neural Network

As evident in Figure 3, our SVM and DNN models exhibit superior results compared to the other models. Considering these outcomes, separate trainings were conducted for the two models to delineate the distinctions between brain waves and features. Table I presents the training results for the SVM and DNN models based on four feature algorithms, and trainings were performed on the alpha, beta, theta, delta, and gamma signals of each extracted feature. Following the conducted trainings, the DE feature is observed to yield better results compared to the other features. Additionally, the significance of the Beta and gamma bands for emotion classification becomes apparent when compared to other bands.

Table II provides classification results based on electrode quantities. These results highlight a difference of 7.7 between the 4-channel and 62-channel trainings. Upon analyzing Table 1, the significance of the beta and gamma bands is clearly evident. However, this distinction becomes more challenging to discern in the case of the 4-channel experiment. As the number of electrodes increases, the accuracy rate is observed to rise, as evident from Table II. In the case of 12-channel training, only a marginal difference is observed in comparison with the 62channel training. Despite this slight variance in accuracy rate, disparities in speed and overall preprocessing steps emerge due to the difference in duration.

The Ensemble learning (EL) method was employed with the objective of enhancing accuracy. This method aims to strengthen predictions by amalgamating predictions from multiple models. In general, employing models with different architectures yields superior results in EL. In Table III, accuracy values of LR, KNN, SVM, and DNN models are displayed, along with the combined prediction outputs of these four models using the EL method. During the training process, when the EL method was applied utilizing 62 channels and the DE feature, training these four models collectively yielded higher accuracy compared to individually trained models. These four models were designed in accordance with the parameter configurations outlined in the results section.

TABLE I. ACCURACY VALUES OF MODELS ACCORDING TO FEATURE TYPES

Classification	*Feature*	*Delta*	*Theta*	*Alpha*	*Beta*	*Gamma*	*Total*
SVM	DE	52.9	57.9	63.0	72.8	70.5	79.2
	DASM	45.1	41.3	35.2	40.3	38.7	50.7
	RASM	45.1	42.2	36.8	43.3	39.1	50.7
	DCAU	45.1	43.8	49.5	52.4	54.6	60.7
DNN	DE	60.7	65.5	68.5	73.3	72..4	79.8
	DASM	55.8	61.4	48.0	49.8	50.9	66.2
	RASM	55.9	59.5	49.5	54.6	51.5	63.7
	DCAU	60.1	53.5	62.9	63.6	64.8	74.3

TABLE II. ACCURACY VALUES OF THE DNN MODEL BASED ON DIFFERENT ELECTRODE QUANTITIES AND FEATURE DEPENDENCIES

Electrode Number	*Feature*	*Delta*	*Theta*	*Alpha*	*Beta*	*Gamma*	*Total*
4	DE	38.3	41.1	46.7	48.4	49.7	72.1
	DASM	41.4	42.9	49.1	53.4	52.8	63.2
	RASM	41.7	40.1	45.51	44.01	46.87	61.4
6	DE	54.64	59.28	62.28	69.47	71.33	74.3
	DASM	42.41	46.82	51.34	58.94	60.09	61.8
	RASM	39.28	42.17	43.95	52.72	49.24	69.4
9	DE	52.41	58.47	64.74	72.4	76.8	77.6
	DASM	49.14	48.74	51.77	63.48	65.74	58.2
	RASM	43.4	45.8	58.1	64.4	65.8	69.3
12	DE	54.8	53.87	56.21	78.4	79.02	79.5
	DASM	53.89	52.64	55.92	72.87	71.25	60.1
	RASM	40.5	41.2	46.7	45.7	45.4	70.3

TABLE III. ENSEMBLE LEARNING MODELS

Classification	*Accuracy*	*Precision*	*Recall*	*F1*
LR	68.8	68.7	68.3	68.0
KNN	77.4	76.9	77.1	76.8
SVM	79.3	79.1	78.9	78.9
DNN	79.8	76.6	76.6	76.5
EL	81.3	80.4	80.7	79.6

IV. DISCUSSION

The conducted study assessed the performance of various models for emotion classification using EEG signals. According to the obtained results, SVM and DNN models outperformed the other models. Other studies related to emotion classification using the SEED dataset are presented in Table IV.

To further enhance the feature extraction process, Zheng and Lu [1] applied the Deep Belief Network (DBN) model to process the extracted features more comprehensively. As seen in Table IV, DBN exhibits higher performance. This result can be interpreted as an indicator of the insufficiency of the extracted features in carrying meaningful information [13, 14].

When these findings are combined with the EL model presented in Table III, the accuracy level achieved is determined to be 81.3%. These findings suggest that accuracy can be improved by employing more complex models.

TABLE IV. CLASSIFICATION PERFORMANCE FOR EMOTION RECOGNITION IN TASK-DEPENDENT EEG

Classification	*Accuracy*
Random forest [12]	78.46
Canonical correlation analysis [12]	77.63
Deep Belief Networks [1]	86.08
Our Study	81.3

Through the utilization of electrode reduction technique, significant brain regions associated with the emotion recognition process have been identified. The optimal electrode layout was determined through the analysis of weight distributions. The conducted analysis revealed an increase in accuracy rate with an increase in the number of critical channels identified. Notably, the configuration with 12 electrode channels exhibited comparable performance to that of the 62channel configuration. This observation underscores the potential of electrode reduction in reducing computational costs and filtering out irrelevant noise.

V. CONCLUSIONS

In conclusion, this study has supported the development of effective methods for emotion classification using EEG signals. Machine learning models such as SVM and DNN have demonstrated superior performance compared to other models. Furthermore, the electrode reduction technique has been employed to identify crucial brain regions associated with emotion recognition, leading to the achievement of high accuracy rates through optimal electrode placement.

Based on the obtained emotion classification results, systems offering recommendations such as music suggestions, movie recommendations, and other personalized systems aligned with users' emotional states could be developed. In the future, conducting experimental studies with larger datasets and employing various deep learning models could further propel progress in this domain.

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