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RESEARCH ARTICLE

Emotion Recognition from Electroencephalogram Signals based on Deep Neural Networks

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Abstract

Emotion recognition using deep learning methods through electroencephalogram (EEG) analysis has marked significant progress. Nevertheless, the complexities and time-intensive nature of EEG analysis present challenges. This study proposes an efficient EEG analysis method that foregoes feature extraction and sliding windows, instead employing one-dimensional Neural Networks for emotion classification. The analysis utilizes EEG signals from the Database for Emotion Analysis using Physiological Signals (DEAP) and focuses on thirteen EEG electrode positions closely associated with emotion changes. Three distinct Neural Models are explored for emotion classification: two Convolutional Neural Networks (CNN) and a combined approach using Convolutional Neural Networks and Long Short-Term Memory (CNN-LSTM). Additionally, two emotion labels are considered: four emotional ranges encompassing low arousal and low valence (LALV), low arousal and high valence (LAHV), high arousal and high valence (HAHV), and high arousal and low valence (HALV); and high valence (HV) and low valence (LV). Results demonstrate CNN_1 achieving an average accuracy of 97.7% for classifying four emotional ranges, CNN_2 with 97.1%, and CNN-LSTM reaching an impressive 99.5%. Notably, in classifying HV and LV labels, our methods attained remarkable accuracies of 100%, 98.8%, and 99.7% for CNN_1, CNN_2, and CNN-LSTM, respectively. The performance of our models surpasses that of previously reported studies, showcasing their potential as highly effective classifiers for emotion recognition using EEG signals.

Key Words: *Emotion recognition; EEG signals; Convolutional Neural Network (CNN); Long Short-Term Memory (LSTM)*

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1. Introduction

Emotion is a fundamental aspect of human behavior, fostering interpersonal communication and influencing rational decision-making [1-3]. Recognizing emotions offers valuable insights into individuals' interests, tastes, personality traits, and overall physical and mental well-being [4]. For instance, accurate emotion recognition can significantly enhance the quality of nursing and treatment for patients with expressive disorders, allowing nurses and doctors to better understand their feelings during care [5]. Moreover, emotion recognition holds vital implications for improving the reliability of human-machine interaction and enhancing social cognition in machines and robots [6,7]. Consequently, research in emotion recognition is imperative [8]. Despite its significance, existing studies on emotion recognition face challenges such as low accuracy and variability across individuals [9].

Previous studies have proposed several models to accurately classify and represent emotions [8]. One prominent model likens emotions to colors, where each emotion can encompass primary emotions. One researcher linked eight primary emotions to evolutionarily valuable properties, resulting in the categorization of anger, sadness, fear, curiosity, disgust, surprise, joy, and acceptance into eight main categories [10]. Another well-known model, introduced by Ekman, identifies six universal basic emotions: anger, fear, sadness, happiness, disgust, and surprise [11]. Additionally, a multi-dimensional model, proposed by Russell, characterizes emotions based on two dimensions: arousal and valence [12]. Arousal reflects the intensity of an emotion, ranging from arousal to relaxation, while valence categorizes emotions as positive or negative. Among the various emotion classifier models, the Russell model, featuring a vertical arousal axis and horizontal valence axis (as depicted in Figure 1), has been widely adopted as the standard model [12].

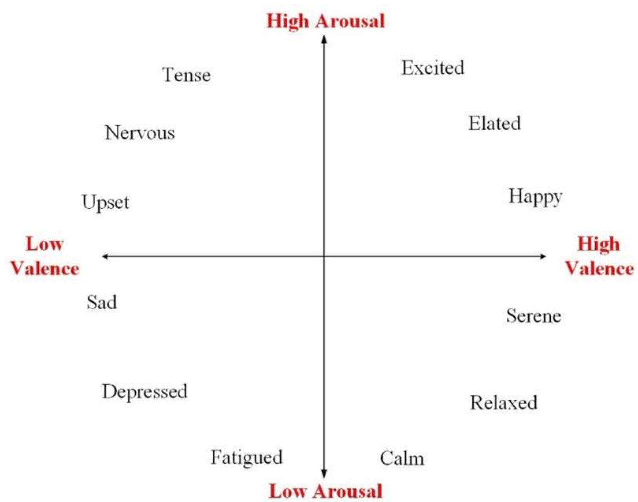

Figure 1: *Russell's two-dimensional emotion model.*

According to Figure 1, this study focuses on analyzing emotions based on two key components, Arousal and Valence. Specifically, the aim of this article is to identify and quantify negative and positive emotions, as well as assess their intensity.

Recently, various input modalities have provided abundant information about individuals and their emotional states. Commonly employed modalities include audiovisual interactions, encompassing facial expressions, eye gaze tracking, body movement detection, and speech and auditory analysis [13]. Moreover, previous studies have explored emotion recognition using physiological signals, such as electroencephalogram (EEG) signals and peripheral measures like electrocardiogram (ECG), respiration, skin resistance, and blood pressure [14-17]. Among these input modalities, EEG exhibits great potential compared to facial expression- and speech-based approaches, due to its non-invasive nature, tolerance to movement [13], and the inability for individuals to consciously disguise or control internal neural changes [18]. This article will delve into the capabilities of EEG for emotion recognition research, offering valuable insights into emotions and their complexities.

In contrast to previous studies where EEG signal segments required extensive feature extraction as a prerequisite for classification, our research aims to streamline EEG data classification by eliminating feature extraction and reducing preprocessing steps. We propose a novel method for classifying EEG signals, yielding remarkably high accuracy without the need for feature extraction techniques.

Additionally, we explore two distinct strategies for defining class labels. The first strategy incorporates four class labels: high valence and high arousal (HVHA), high valence and low arousal (HVLA), low valence and low arousal (LVLA), and low valence and high arousal (LVHA). The second strategy simplifies the classification process by considering only two labels: high valence (HV) and low valence (LV). Our experimental results demonstrate the effectiveness of our proposed method in achieving superior accuracy, making it a promising approach for EEG signal classification without the burden of feature extraction.

2. Related Work

Recently, emotion recognition based on EEG signals has seen significant advancements through the implementation of both end-to-end deep learning and step-by-step machine learning approaches [11]. A variety of machine learning algorithms have been employed in previous studies for EEG-based emotion recognition, including K-Nearest Neighbor (KNN) [19], Support Vector Machines (SVM) [20], Bayesian Networks (BNT) [21], and Decision Trees (DT) [21]. It is important to note that the accuracy of emotion recognition using these algorithms is influenced by factors such as the extracted features, the trained classifier, and the target dataset [22]. For EEG signal segment classification with conventional machine learning methods, feature extraction from EEG signal segments is a fundamental prerequisite step [23]. Table 1 provides an overview of some previous studies utilizing conventional machine learning methods for emotion recognition from EEG signals [24-28].

The utilization of deep learning methods in emotion recognition offers the advantage of automatically extracting high-level features from the data [29], eliminating the dependence on specific feature extraction techniques. Extensive research has demonstrated the superiority of deep neural networks (DNNs) over conventional machine learning methods for EEG-based emotion recognition in numerous cases [30]. Moreover, DNNs have exhibited exceptional performance in diverse applications such as computer vision [31], natural language processing [32], and biomedical signal processing [33], further attesting to their effectiveness. Table 2 presents an overview of several deep learning methods that have been proposed and employed for EEG-based emotion recognition in prior studies, encompassing DNN [34], convolutional neural networks (CNN) [35], long short-term memory (LSTM) [36], and a hybrid model combining CNN and LSTM (CNN-LSTM) [37]. These advanced techniques hold promise in enhancing the accuracy and efficiency of emotion recognition from EEG signals.

Table 1: *List of the previous studies based on conventional machine learning methods.*

Ref	Classes	Feature Extraction	Classification	Accuracy
[24]	Valence, Arousal, Dominance, Liking	PCA	SVM	70.52%
[25]	Valence, Arousal	PSD	SVM	79.54%
[26]	Valence, Arousal	STFT-PSD-DE-DCT	KNN	55.4%and 60.4%
[26]	Valence, Arousal	STFT-PSD-DE-DCT	SVM	59.1% and 63.1
[27]	Valence, Arousal, Dominance	-	SVM, K-NN, Naïve Bayes, hierarchical clustering	78.06%
[28]	Valence Arousal	EMD	LIBSVM	74.88% and 82.63%

Table 2: *The summary of the previous studies using DNNs for emotion recognition from EEG signals.*

Ref	Classes	Feature Extraction	Classification	Accuracy
[25]	Valence, Arousal	PSD	CNN	81.14% and 77.69%
[26]	Valence, Arousal	STFT-PSD-DE-DCT	CNN	77.27% and 73.51%
[37]	Valence Arousal	-	LSTM	90.1% and 87.9%
[37]	Valence Arousal	-	CNN-LSTM	91.8% and 91.6%
[38]	HVHA, HVLA, LVLA, LVHA	EMD	LSTM	88.42%
[39]	Valence, Arousal	-	RACNN	95%
[40]	Valence, Arousal	-	2DCNN-BiGRU	88.69% and 87.89%
[41]	Valence, Arousal	-	SNNs	82.75% and 84.22%
[42]	Valence, Arousal and Dominance	-	EmotionCapsNet (CNN based)	80.34%, 83.04% and 82.50%

3. Materials and Methods

The proposed method for emotion recognition from EEG signals is depicted in Figure 2. The process involves dataset selection and EEG signal preprocessing. The signals are then segmented into 60-second intervals and assigned class labels accordingly. Next, a stacked ensemble classifier is designed, comprising four deep neural networks in the first layer and conventional machine learning methods in the second layer.

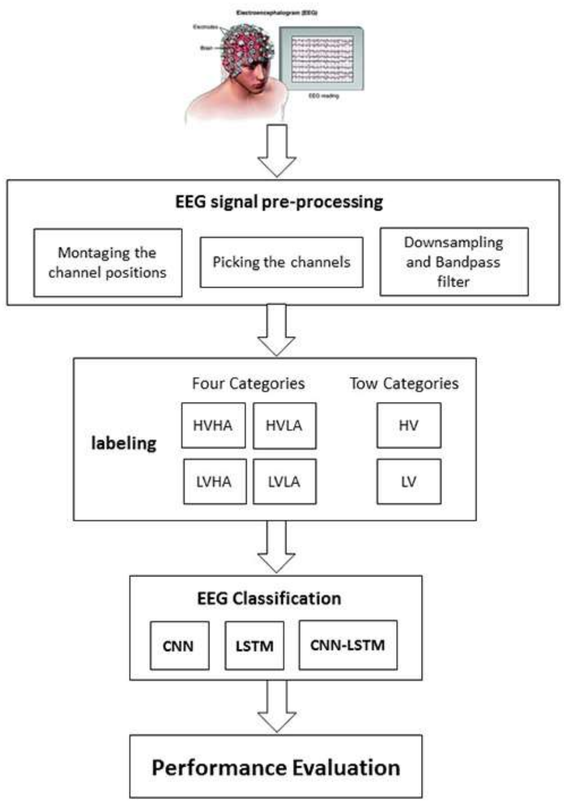

Figure 3: *The main steps of the proposed method in this study for emotion recognition from EEG signals.*

3.1. Dataset

In this study, we utilized "The Database for Emotion Analysis using Physiological Signals (DEAP)" [15], which is a publicly available EEG database. The DEAP dataset contains EEG and peripheral physiological signals of 32 participants who viewed 40 segments of 1-minute video clips representing various emotions. The participants comprised 16 females and 16 males, aged between 19 and 37, and the experiments were conducted in laboratories at Twente and Geneva universities. To account for slight differences between the two university setups, we relocated the electrodes for participants 23-32 to include all EEG signals in our analysis rather than excluding this group from the study.

3.2. Preprocessing

The preprocessing step consists of three sub-steps, as depicted in Figure 3. Initially, the raw EEG data is loaded into Google Colab, followed by montaging sensor location, selecting appropriate channels, and downsampling to 128Hz. Additionally, a bandpass filter between 3 and 47 Hz is applied to prepare the raw EEG for segmentation. Figure 3 illustrates that after the preprocessing step, the raw data, originally comprising 32 EEG channels, is converted into an EEG dataset with 13 channels, effectively removing EOG artifacts and noise. This transformation simplifies data handling and significantly reduces memory and RAM requirements during subsequent analysis.

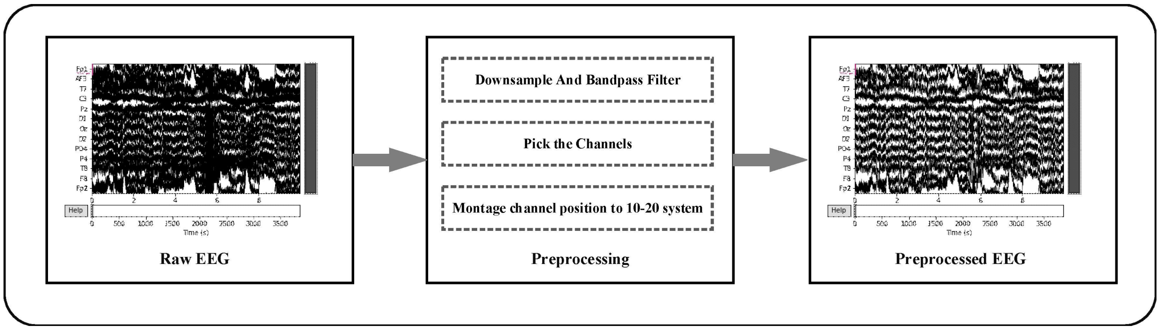

Figure 4: *The main steps for preprocessing EEG signals in this study.*

3.2.1. Montaging the channel positions

Within the DEAP database, there are two distinct groups of participants, each having their EEG signals recorded at separate universities. Consequently, the placement of certain EEG sensors varies between these groups. This discrepancy in sensor positioning necessitates adapting them to conform to a standard 10-20 system, significantly enhancing their visualization and usability during analysis and experimentation.

3.2.2. Picking the most informative channels

Based on the findings from previous studies [1,43-45], we have determined that the optimal approach for improving emotion recognition from EEG signals is by selectively removing non-informative EEG channels. In this study, we carefully identify and include only the most informative channels, which have shown the highest correlation with emotion changes, as reported by Laiyuan Tong [1]. These thirteen channels are based on the renowned 10-20 system, comprising "FP1," "T7," "PO4," "Pz," "FP2," "Oz," "F8," "T8," "P4," "O1," "FC5," "C3," and "CP2". The precise locations of these channels can be observed in Figure 5. Through our experimental endeavors, we ascertain that this strategic selection of channels yields the best performance for emotion recognition, resulting in superior outcomes as compared to alternative configurations. These refined results affirm the significance of channel selection as a crucial step in optimizing emotion recognition accuracy from EEG signals.

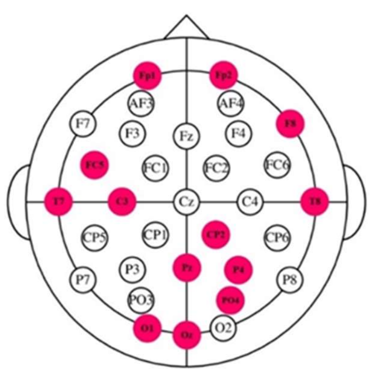

Figure 6: *Location of 13 EEG channels used in this study.*

3.2.3. Downsampling and bandpass filter

In this study, all physiological signals were initially recorded at a high sampling rate of 512 Hz [15]. However, to expedite data processing without compromising essential information, a downsampling technique was applied, reducing the sampling rate to 128 Hz. Furthermore, to enhance the signal quality and minimize the influence of unwanted noise, a bandpass filter with a frequency range of 3-47 Hz was meticulously selected and employed. This filtering process effectively isolates the relevant frequency components, ensuring that the subsequent analysis and interpretation are based on a clean and accurate representation of the physiological data.

3.3. EEG signal segmentation

Each participant's EEG data spans approximately 60 minutes, beginning with a baseline recording lasting around two minutes. Subsequently, 40 trials are conducted, wherein each trial consists of four steps:

1. An initial 2-second display of the experiment number.
2. A 5-second baseline recording to establish a stable reference state.
3. Presentation of a one-minute music video.
4. Self-assessment by participants of their levels of arousal, valence, liking, and dominance.

To maintain participant engagement and mitigate fatigue, a short break is provided after twenty trials. As a result, certain segments within each experiment lack specific information and can be excluded from the study. To address this, we meticulously mark the starting and ending moments of each music video for every participant.

Subsequently, these marked segments are cropped and transformed into a series of numerical values using the MNE library [46]. This transformation facilitates the generation of diagrams and simplifies model training, streamlining the subsequent analysis and interpretation of the EEG data. By leveraging the capabilities of the MNE library, we ensure efficient visualization and seamless integration of the EEG data for further analysis and experimentation.

3.4. Labeling method

First of all, we established four distinct emotional categories representing different combinations of valence and arousal: "High Valence-High Arousal" (HVHA), "High Valence-Low Arousal" (HVLA), "Low Valence-Low Arousal" (LVLA), and "Low Valence-High Arousal" (LVHA). These categories were determined by partitioning the valence and arousal scales into two ranges: 0 to 5 and 5 to 9, as described in prior work [47].

To visualize the classification, Figure 5 illustrates the regions where both valence and arousal values exceed 5, labeled as "high," and regions where they are below 5, labeled as "low." Consequently, these labels effectively distinguish between emotions with higher or lower intensity levels. As a complementary step, we assigned two additional emotional classes to the first dependent variable: "High Valence" (HV) and "Low Valence" (LV), representing positive and negative emotions, respectively. This pragmatic approach enables straightforward comparisons with numerous other studies that have undertaken similar experiments and reported their findings [4,29,48-50]. By employing these well-defined emotional categories and labels, our study benefits from enhanced comparability with existing research, enriching the collective understanding of emotions in relation to valence and arousal levels.

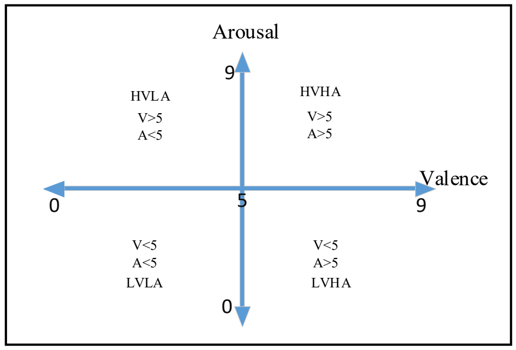

Figure 7: *Division of arousal and valence.*

3.5. Deep learning modeling for classification

Within the existing literature, a plethora of deep learning and machine learning algorithms have been explored for emotion classification. In our present research, we leverage the power of two distinct Convolutional Neural Network (CNN) models, alongside a hybrid CNN-LSTM model, to effectively classify EEG signals into four primary emotion classes: HVHA, HVLA, LVLA, and LVHA. Additionally, we extend our analysis to encompass two broader emotional classes: HV and LV emotions.

By employing these advanced neural network architectures, we aim to achieve more accurate and robust emotion classification, enriching the field of emotion recognition from EEG signals. Through this study, we contribute valuable insights into the potential applications of deep learning methodologies in understanding and discerning human emotions with enhanced precision.

3.5.1. CNN model

After completing EEG preprocessing, we obtain 1280 pre-processed segments, each containing thirteen channels with 7681 time series numbers per channel. Since feature extraction is omitted, we adopt a CNN architecture capable of automatically extracting relevant features. Thus, the input shape of the model is 13*7681. To optimize the CNN architecture for accurate emotion classification, we systematically explore various combinations of hyperparameter values. Consequently, we identify the top-2 performing models, namely CNN_1 and CNN_2, as illustrated in Figures 6 and 7, respectively.

CNN_1 comprises two convolutional and pooling layers, both utilizing Rectified Linear Unit (ReLU) as the activation function. Additionally, a one-dimensional Max Pooling layer with a kernel size of 2 is applied for pooling. To adapt to the number of labels, the last dense layer's units are set to either 2 for HV and LV or 4 for HVHA, HVLA, LVLA, and LVHA, corresponding to the considered class labels, as shown in Figure 6.

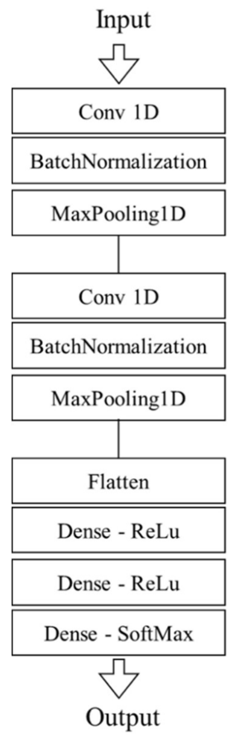

Figure 8: *Schematic overview of the CNN_1 model architecture.*

On the other hand, CNN_2 demonstrates a more complex architecture with three convolutional and pooling layers, each followed by a dropout layer to mitigate overfitting. ReLU serves as the activation function for each convolutional layer. Like CNN_1, the number of units in the last dense layer is adjusted based on the corresponding class labels, as depicted in Figure 7.

3.5.2. CNN_LSTM Model

Considering that CNN models excel at feature extraction and LSTM models are renowned for their accurate time series classification [51], we leverage the strengths of both architectures by integrating them into a single, powerful CNN-LSTM model. Our goal is to achieve the highest level of performance in emotion classification. The CNN-LSTM model is strategically designed, incorporating both CNN and LSTM layers to optimize its capabilities. For a clear representation of its architecture, please refer to Figure 8, which provides a schematic overview of the CNN-LSTM model.

These carefully designed CNN models with their distinctive architectures aim to enhance emotion classification accuracy by effectively capturing salient features from EEG signals. By considering the top-performing models, our study strives to contribute valuable insights to the field of emotion recognition and its potential applications.

By skillfully combining the complementary strengths of CNN and LSTM layers, we anticipate this hybrid model to outperform individual architectures and yield enhanced accuracy in classifying EEG-based time series data. Throughout our study, we meticulously tune the parameters of the CNN-LSTM model to maximize its potential and deliver superior results in emotion recognition.

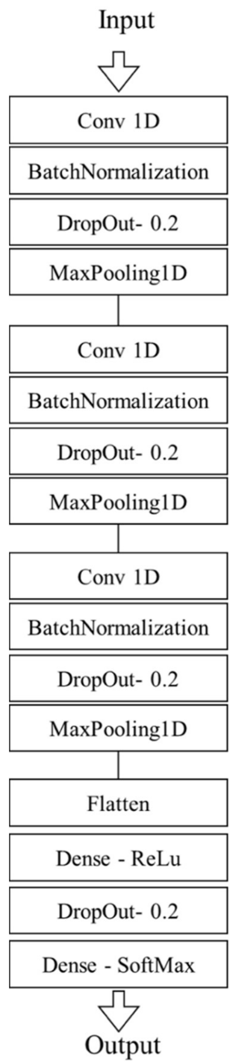

Figure 9: *Schematic overview of the CNN_2 model architecture.*

4. Experimental Results

In this study, we utilized the DEAP dataset, as detailed in the Material and Methods section. To address our research objectives, two distinct labels were defined and elaborated in Section A and Section B, respectively. Python programming language was employed for model implementation, and the models were executed on Google Colab with a 12-gigabyte GPU for efficient processing.

- **Scenario A: 2 categories**
  CNN_1, CNN_2, and CNN-LSTM were trained with various testing and training examples, repeated 10 times to ensure robust classification across different classes. While the network architectures remain consistent in both scenarios, the activation

function in the last layer of all three models in Scenario A is set to "Sigmoid." Detailed hyperparameters used in the models' architecture are provided in Table 3.

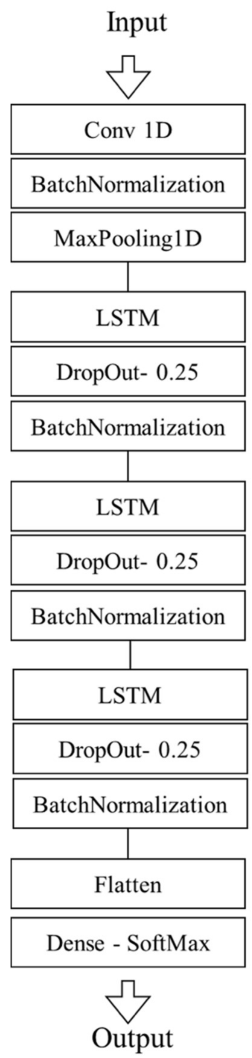

Figure 10: *Schematic overview of the CNN-LSTM model architecture.*

Table 3: *Parameter values used to create the CNN_1, CNN_2, and CNN-LSTM models.*

Parameters	CNN-1	CNN-2	CNN-LSTM
Optimizer	Adam	Adam	Adam
Learning Rate	0.001	0.002	0.001
Dropout Rate	-	0.2	0.25
Loss Function	binary_crossentropy	binary_crossentropy	binary_crossentropy
Batch size	256	512	256
Epochs	100	100	100

Remarkably, CNN_1 achieved the best performance with a remarkable 100% accuracy and 0.002 loss in the training examples, and equally impressive 100% accuracy and 0.009 loss in the testing examples. The performance metrics, including recall, precision, F1-score, and class accuracy values, are presented in Table 4. Notably, our proposed models outperformed other classifiers, establishing their superiority in emotion classification.

Table 4: *Comparison of accuracy, precision, recall, F1-score of CNN_1, CNN_2, and CNN-LSTM models.*

Performance Measures				
Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
CNN_1	100	100	100	100
CNN_2	98.8	100	97.9	98.9
CNN_LSTM	99.7	99.6	100	99.8

For further insights, Figure 9 displays the accuracy and loss curves of CNN_1, CNN_2, and CNN-LSTM models. The curve convergence rate of CNN_1 model is notably faster than that of CNN_2 and CNN-LSTM models, resulting in significantly higher final accuracy. Conversely, CNN_2 model demonstrates a quicker convergence rate for the loss value, closely matching CNN_1 and CNN-LSTM models in the final loss values.

To illustrate the classification performance specifically for high valence and low valence, Figure 10 depicts the confusion matrix for CNN_1, CNN_2, and CNN-LSTM models. Overall, our proposed approach showcases exceptional accuracy and robustness, surpassing existing methods, thus affirming its potential to advance emotion classification with EEG signals.

- **Scenario B: 4 categories**
  Similar to Scenario A, we conducted ten iterations of model training for CNN_1 with varying test and training examples. By the 10th iteration, the CNN_1 model achieved an impressive accuracy of 98.8%. Similarly, CNN_2 and CNN_LSTM models underwent the same training process as CNN_1. The proposed networks were initialized using the parameters defined in Table 5, ensuring a consistent and fair comparison (Table 6).

Table 5: *Parameter values used to create the CNN_1, CNN_2, and CNN-LSTM models.*

Parameters	**CNN-1**	**CNN-2**	**CNN-LSTM**
Optimizer	RMSprop	Adam	Adam
Learning Rate	0.001	0.001	0.001
Dropout Rate	-	0.2	0.25
Loss Function	categorical_crossentropy	categorical_crossentropy	categorical_crossentropy
Batch size	128	256	128
Epochs	100	100	100

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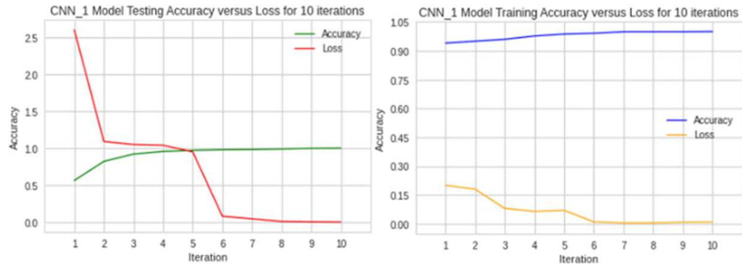
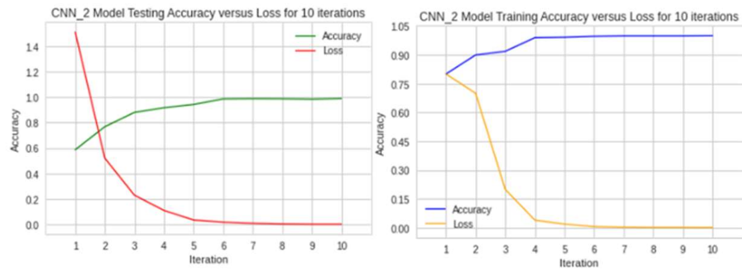
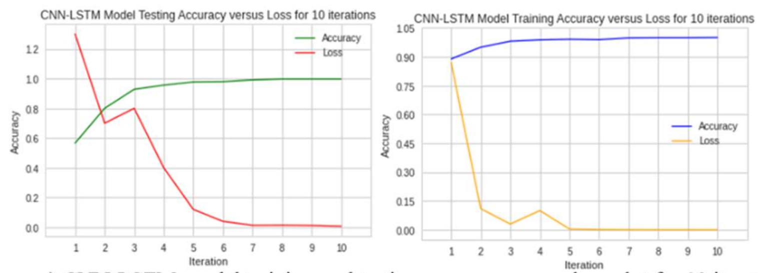


a) CNN_1 model training and testing accuracy versus loss plot for 10 iteration

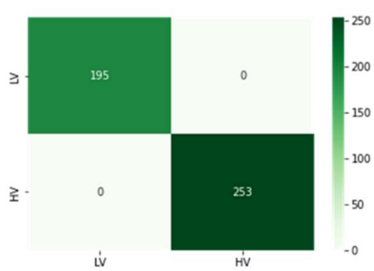


b) CNN_2 model training and testing accuracy versus loss plot for 10 iteration

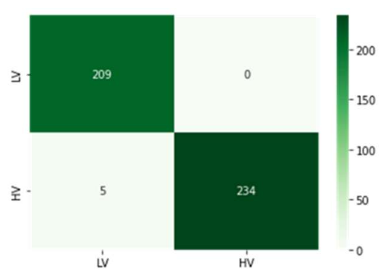


c) CNN-LSTM model training and testing accuracy versus loss plot for 10 iteration

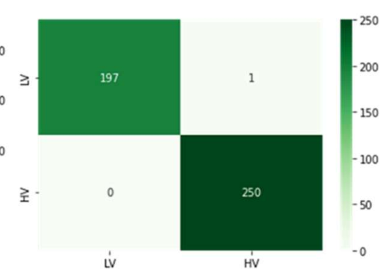
Figure 11: *Models accuracy versus loss plots for 10-fold cross-validation.*



a) Confusion Matrix of CNN_1



b) Confusion Matrix of CNN_2



c) Confusion Matrix of CNN-LSTM

Figure 12: *Confusion matrix for four emotions classification by CNN_1, CNN_2, and CNN-LSTM models.*

Table 6: *Comparison of accuracy, precision, recall, F1-score of CNN_1, CNN_2, and CNN-LSTM models.*

		Performance Measures		
Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
CNN_1	97.7	98.9	97.6	98.3
CNN_2	97.1	98.5	96.8	97.6
CNN_LSTM	99.5	99.6	99.6	99.6

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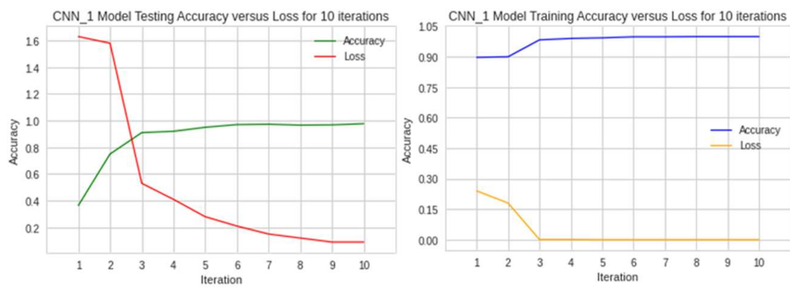
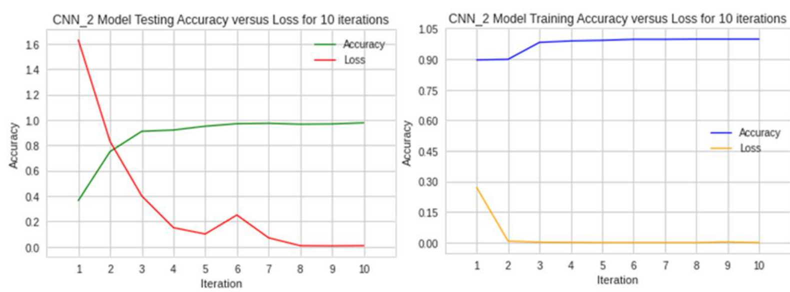
To assess the models' performance across the 10 iterations, Figure 11 displays the training and testing accuracy versus loss plots for 10-fold cross-validation. As depicted in parts a, b, and c of the figure, all models consistently minimized the loss function and maximized accuracy throughout the iterations.

Furthermore, Figure 12 presents the confusion matrix for the four emotion classes (HVHA, HVLA, LVHA, and LVLA) obtained by CNN_1, CNN_2, and CNN-LSTM deep learning models classifiers using a 33-67 sampling rate. This configuration involved 448 testing examples and 832 training examples, and 10-fold cross-validation was applied.

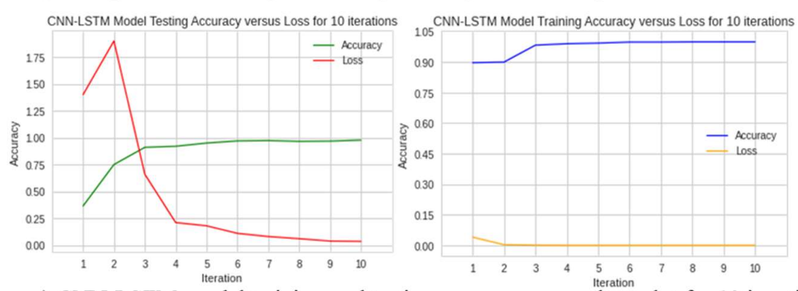
The results showcase the remarkable performance of our proposed deep learning models, demonstrating their ability to achieve accurate emotion classification across multiple iterations and 10-fold cross-validation. These findings underscore the robustness and reliability of our approach in effectively analyzing EEG signals to discern emotional states.



a) CNN_1 model training and testing accuracy versus loss plot for 10 iteration

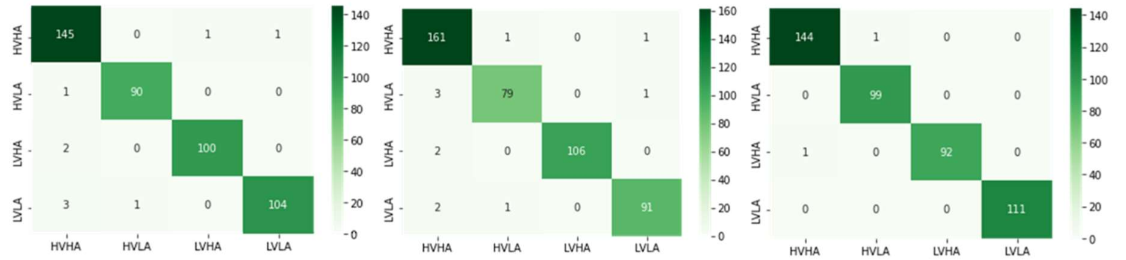


b) CNN_2 model training and testing accuracy versus loss plot for 10 iteration



c) CNN-LSTM model training and testing accuracy versus loss plot for 10 iteration

Figure 13: *Models accuracy versus loss plots for 10-fold cross-validation.*



a) Confusion Matrix of CNN_1 b) Confusion Matrix of CNN_2 c) Confusion Matrix of CNN-LSTM

Figure 14: *Confusion matrix for four emotions classification by CNN_1, CNN_2, and CNN-LSTM models.*

5. Conclusion

In this paper, we have introduced a method based on deep learning, for emotion recognition based on EEG signals. The EEG preprocessing steps, which included segmenting each EEG into 60-second trials, downsampling to 128Hz, and applying a bandpass filter of 3–47 Hz for noise reduction, effectively prepared all 1280 EEG samples for direct input into our proposed models, eliminating the need for manual feature extraction. Our proposed models, specifically the CNN and CNN-LSTM architectures, demonstrated exceptional performance in predicting the defined emotion classes and achieved minimal prediction error. Notably, in the case of two emotion labels, "high valence" and "low valence," the CNN_1 model excelled with an outstanding accuracy of 100%.

Additionally, for the more challenging task of predicting the four emotion classes, "High Valence-High Arousal," "High Valence-Low Arousal," "Low Valence-Low Arousal," and "Low Valence-High Arousal," the CNN-LSTM model exhibited remarkable accuracy, achieving 99.5%. Based on our results, it is evident that one-dimensional CNN and CNN-LSTM models are highly effective for emotion recognition using EEG signals. Importantly, the absence of manual feature extraction did not compromise the accuracy of our proposed models; instead, it expedited the learning process, allowing for faster and more efficient training.

This study contributes valuable insights to the field of emotion recognition from EEG signals, offering practical and accurate approaches to understanding human emotions. Our findings pave the way for further advancements in using deep learning methodologies for emotion recognition tasks and hold promising implications for applications in various domains, including healthcare, human-computer interaction, and affective computing. As this research opens up new avenues for future studies, we anticipate that our proposed models will serve as a foundation for continued exploration and refinement in the field of EEG-based emotion recognition.

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