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Using convolutional neural network to recognize emotions from scalp electroencephalography plot images

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ABSTRACT

Introduction: Real-time variations in brain activity are determined by electroencephalogram (EEG) data. EEG signals are commonly used in studies to analyze human emotional states. Emotions EEG signals vary from person to person because they each have different emotional responses to the same stimuli. The objective of this study was using EEG signals in emotion recognition.

Material and Methods: We specifically focused on employing convolutional neural network (CNN) for detecting image-based emotions in long-term EEG data. After filtering, the EEG data is divided into short sections based on a certain time window and they are converted into EEG plot images. Each of these is classified by convolutional neural networks.

Results: In comparison with the existing methods, the error rate has been reduced and the accuracy rate is better than the existing methods. The mean accuracy of the compared articles is 62.87, 70.50, 74.88, 82.88 and 68.11, but the average accuracy of the proposed method is 85.13.

Conclusion: This research demonstrates the potential and accuracy of CNN in recognizing emotions from scalp EEG plot images. The study contributes to the growing field of emotion recognition and paves the way for future advancements in utilizing CNN for analyzing EEG signals, ultimately aiming to use as an effective method for computer-aided recognition.

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INTRODUCTION

Emotions encompass conscious or unconscious feelings towards various phenomena or actions. Sound, language, gestures, facial expressions, and bio-signals are all examples of biological and physical reactions that are used to communicate emotions. Reacting to emotions is a crucial aspect of interpersonal communication [1]. Emotion detection, a subset of emotional computation, focuses on identifying human emotions using approaches that involve aural and visual expressions, body language, and physiological markers. Physiological signals such as electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), and others, in comparison to other techniques, have the benefit of being difficult to conceal [2].

In recent years, deep learning approaches have been presented for EEG-based emotion recognition. Deep learning approaches, in contrast to traditional machine learning methods [3-12] automatically extract features from huge amounts of data and can be used as a high-precision classifiers [13]. Some studies have demonstrated the superiority of deep learning approaches in emotion detection [14].

Convolutional neural networks (CNNs) are a type of deep neural network designed for image inputs. Rather than handcrafting intricate features, CNNs assign weights to different aspects or objects within an image. However, when employing CNNs for EEG-based emotion identification, achieving the desired outcomes becomes challenging. This is because the sequence in which input channels are fed into the CNNs must be relevant. By rearranging the EEG channels, the accuracy of the CNN can be improved [15]. In deep learning approaches, the EEG signal is typically fed directly into the models. However, some characteristics, such as power spectral density (PSD) and differential entropy, are extracted beforehand and utilized as input for the CNN [16].

As part of the literature review, we examined several related works. In [17], the authors used the cognitive model of the brain under emotional stress to select the appropriate EEG channels. Wavelet coefficients and chaos variables, such as fractal dimension, were employed to extract EEG signal characteristics. The authors demonstrated significant classification accuracy improvements using the Elman classifier, compared to similar works.

In [18], three types of features, namely power spectrum, wavelet, and nonlinear dynamic analysis, were extracted to evaluate the relationship between EEG data and emotion states. These features were smoothed using the linear dynamic system (LDS) method to eliminate irrelevant noise. The results of emotion classification using an SVM classifier showed that the LDS method can significantly improve the accuracy. Similarly, [19] proposed a new approach for classifying emotional stress in the valance-arousal space, using multimode biological signals. Visual stimulus images were selected from the International Affective Picture System (IAPS) database. The authors achieved a significant improvement in accuracy using the SVM classifier compared to previous studies by combining EEG and peripheral signals.

In [20], the authors presented an approach for classifying emotional stress states in the valance-arousal space using EEG signals. Feature extraction was performed using higher-order spectrum analysis. The best accuracy was obtained by using the radial basis function (RBF) SVM kernel.

In [21], an algorithm for EEG-based emotion detection was proposed. This algorithm decomposed emotion-related EEG signals using GaborSD functions and represented them in the spectral, spatial, and temporal domains. Effective features (R features) were obtained using discrete Fourier transform (DFT) and principal component analysis (PCA). At the end, the probabilistic neural network (PNN) classification was used to determine the optimal nonlinear decision boundary. The PNN classification utilizes a parallel structure and prevents premature convergence which can increase the sensitivity of the algorithm. The proposed algorithm was applied to classify the six main emotions. We will compare our proposed method with this method.

Lastly, in [22], an individual-independent emotion detection system based on EEG signals was proposed. In the proposed method, two features, the PSD peak value and the first difference from the intrinsic mode function (IMF), are used to classify emotions. It has been shown that the deep neural network classifier outperforms the SVM classifier in detecting individual-independent emotions. In [23] and [24], CNN was proposed for this purpose. In [15], CNN was used to reduce the manual effort on features and Pearson Correlation Coefficient has been applied to improve of the information related to neighboring channels. This study combined the Pearson Correlation Coefficient and CNNs through a dense layer to rearrange the channels effectively, yielding promising results in emotion detection.

As the number of identified emotions increases, the accuracy of EEG-based emotion identification systems tends to decrease. Additionally, electroencephalograms contain noise. To address these challenges, this paper focuses on the detection of image-based emotions in long-term EEG signals using convolutional neural networks. After filtering, the EEG data is divided into short sections based on a predefined time window. Subsequently, these sections are converted into EEG plot images that are individually classified using convolutional neural networks.

MATERIAL AND METHODS

This section introduces a novel approach for image-based emotion detection by applying CNN to long-term EEG. After filtering, the EEG data are divided into short sections using a predefined time window. These sections are then converted into EEG plot images, each of which is individually classified using CNN. Fig 1 shows the steps of the proposed method.

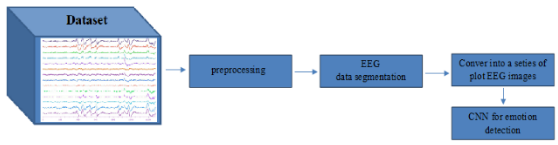

Fig 1: The steps of the proposed method

EEG preprocessing

A 0.3 Hz high-pass filter, a 60 Hz low-pass filter, and a 50 Hz notch filter are used to filter EEG data.

EEG data segmentation

EEG data is segmented and transformed into a series of 224 × 224 pixels EEG plot pictures using a suggested time window. The time frame is a variable that ranges from 0.5 to 10 seconds (0.5, 1, 2, 5 and 10 seconds). Assume a standard print resolution of 300 dots per inch (DPI), then the 0.5, 1, 2, 5, and 10 s time windows correspond to time intervals of 38, 19, 9.5, 3.8, and an1.9 mm/s, respectively.

Conversion to a series of EEG plot images

There are pre-trained CNNs available for usage and one of them is VGGNet. It was trained by Simonian and Zisserman [25]. Their best network consists of 16 CONV/FC layers and embraces a relatively homogenous design with just a 3.3 filter in the convolution layer and a 2.2 filter in the pooling layer. Because extremely tiny convolutional filters (3×3) successfully identify little EEG waves, VGG-16 was utilized as the CNN architecture in this research. Since the original VGG-16 was meant to differentiate 1000 classes, it was pre-trained using an ImageNet database, and classification errors in ILSVRC-2014 were 7.4 percent and output layer has 1000 nodes. We have four classes and the last two layers have 32 and 4 nodes, respectively (Fig 2).

The starting weights for the first 14 layers were pre-trained in the same way as VGG-16, while the weights of the last two layers were independent and random variables with a zero mean. In the case of the training optimizer, The Adam method is employed with alpha=0.001, β1 = 0.9 and β2 = 0.999. The model employs a small batch of 40 pictures for 50 epochs. An epoch is defined as a complete presentation of the training dataset that the CNN model must learn.

The trained CNN classifies each segment of the EEG, once every 0.5 seconds for the 0.5-second sector and once every second for the other segments. In leave-one-out testing (all but one), a model containing EEG data is trained on 23 instances out of 24 and tested with EEG data from the final remaining participant. In a paired comparison test, a model is generated using the same subject's data and evaluated independently with each subject's EEG data.

In this research, the best time frame for classifying plot pictures is 1 s, although epilepsy experts often utilize 10 s / page (30 mm / s). The reason for this is that the picture size in the CNN model employed in this work was reported to be 224 × 224 pixels, which was insufficient for plotting a 10-s EEG with obvious epileptic discharges. As a result, high-resolution CNN can increase performance in certain cases.

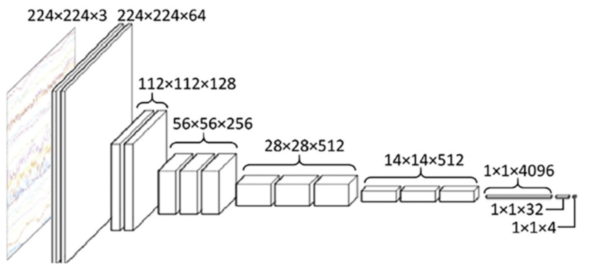

Fig 2: CNN structure

Dataset

The objective of this study is to develop a method for classifying emotion recognition based on EEG data. The EEG signal obtained from the SEED-IV was used in this study [26]. The SEED-IV dataset was gathered from 15 participants (seven of them were men) who were instructed to watch 15 film clips. Each film clip lasted around 4 minutes and was simple to understand in order to properly elicit the emotions of the 15 individuals who took part in the studies. Each participant had 15 trials, each lasting 305 seconds and consisting of a 5 second indication of commencement, a 4-minute video clip, a 45-second self-assessment, and a 15-second break. The SEED-IV dataset contains EEG data from 62 electrodes. Following data collection, EEG data were down sampled to 200 Hz and processed using a band pass filter ranging from 0 to 75 Hz. In this dataset, the data is filtered with a frequency filter ranging from 4.0 to 45.0 Hz in order to evaluate the suggested network fairly. Table 1 shows individuals' emotional states. This sequence is depicted in Fig 1. The signal for the 14 channels is seen in this picture.

According to the Fig 1, the EEG signal has a sequence of values that have been provided during the time. Hence, the horizontal axis represents the time and the vertical axis represents the signal amplitude. Each of the above signals indicates one of the electrodes. In Fig 3, the position of 62 electrodes on the scalp has been shown.

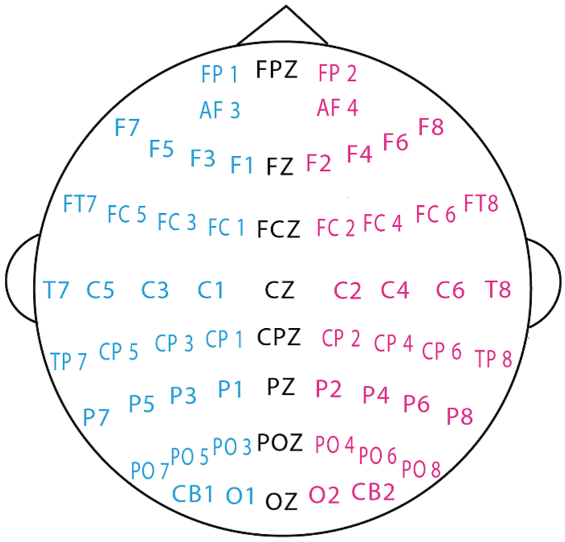

Fig 3: The position representation of the brain signal measurement electrodes

Table 1: Classes in the dataset used in the research

Class number	Emotion type
1	Happy
2	Sad
3	Neutral
4	Fear

RESULTS

The evaluation criterion was accuracy. Accuracy is positive samples that are correctly classified in the positive class (True Positive (TP)) and negative samples that are correctly classified in the negative class (True Negative (TN)) divide by sum of TP, TN, False Positive (FP) and False Negative (FN) (Eq. 1).

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

The results of the proposed improved convolutional neural network (CNN) are presented in Table 2. A comparison was conducted between the proposed method and the methods outlined in the papers [2, 7, 15, 16, 21]. Mean accuracy of these papers is respectively 62.87, 70.50, 74.88, 82.88 and 68.11 but mean accuracy of the proposed method is 85.13.

The VGGNet architecture was utilized, featuring convolution layers with a filter size of 3x3, a stride of 1, and zero padding with P = 1. The pooling layers had a filter size of 2x2, a stride of S = 2, and no zero padding.

To visualize the training progress, Fig 4 and 5 illustrate the increasing accuracy and decreasing losses over the course of 50 epochs.

Table 2: The comparison results of the proposed method with the compared methods in the SEED-IV dataset

Emotion	CNN [15]	CNN [16]	SVM [7]	RGNN [2]	PNN [21]	The proposed method
Happy	72.90	80.13	68.50	64.80	66.23	85.43
Sad	77.30	85.34	71.50	60.66	69.55	84.76
Neutral	75.50	80.89	72.50	63.14	68.74	85.37
Fear	73.85	85.03	69.50	62.90	67.92	84.96
Mean ACC	74.88	82.84	70.50	62.87	68.11	85.13

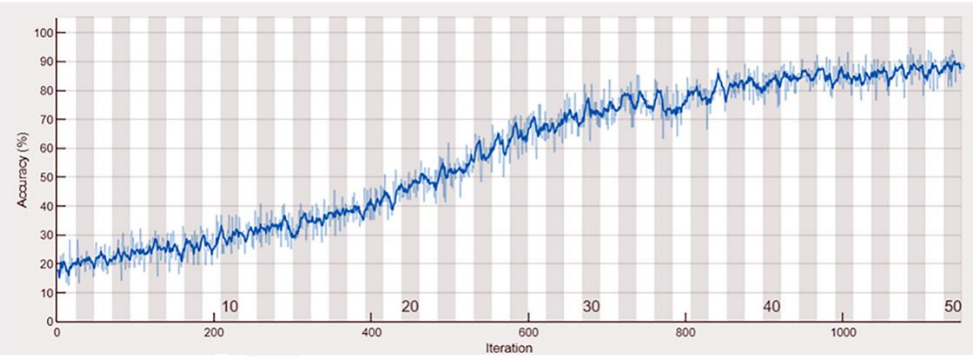

Fig 4: The accuracy results of the proposed method during 50 epochs

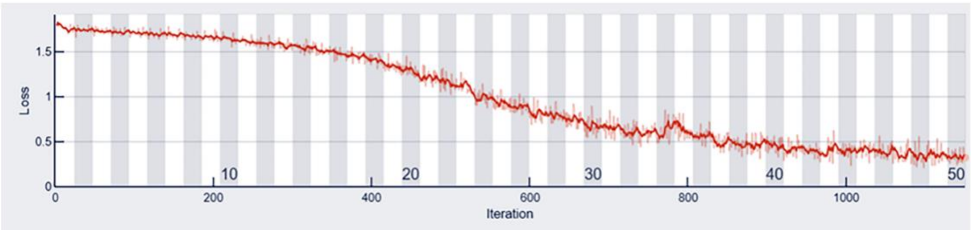

Fig 5: The loss results of the proposed method during 50 epochs

DISCUSSION

Upon comparing the proposed method with the existing approaches [2, 7, 15, 16, 21], it was found that our approach achieved a reduced error rate and higher accuracy. These results demonstrate the effectiveness of our approach in improving the accuracy of emotion recognition from EEG plot images. By utilizing the VGGNet architecture with appropriate parameter settings, the model effectively extracted meaningful features from the EEG data.

The superior performance of our proposed method signifies the potential of CNNs in recognizing emotions from EEG plot images. The reduction in error rate and increased accuracy highlight the ability of our approach to capture and classify emotional patterns accurately. By leveraging the power of deep learning and CNNs, the proposed model demonstrates its capability to learn complex representations and generalize the emotion recognition task.

To provide a visualization of the training progress, Fig 4 and 5 depict the increasing accuracy and decreasing losses over the course of 50 epochs. These plots demonstrate the learning capability of the proposed CNN model as it refines its predictions during the training process. The convergence of the accuracy curve and the decreasing trend of losses confirm the successful training of the model, indicating its ability to capture and recognize emotional features in the EEG plot images.

CONCLUSION

This study investigated the use of Convolutional Neural Networks (CNNs) for recognizing emotions from scalp Electroencephalography (EEG) plot images. The research aimed to develop an accurate emotion recognition system that could enhance computer-aided recognition.

Through the preprocessing of a comprehensive dataset of EEG plot images representing different emotional states, the CNN models were trained and optimized. The designed CNN architecture effectively captured and learned the relevant features from the EEG plot images, enabling the recognition of various emotions.

The evaluation results demonstrated the accuracy of the CNN-based emotion recognition system. The developed model achieved high accuracy in distinguishing different emotional states from EEG signals. The accuracy of the CNN models surpassed or showed comparable results to other existing methods for emotion recognition from EEG data, highlighting the potential of CNNs in this domain. These advancements can contribute to the development of various applications in mental healthcare and assistive technologies.

It is important to note that further research and exploration are needed to address certain limitations and challenges. For instance, incorporating larger and more diverse datasets, refining the preprocessing techniques, and exploring different CNN architectures and optimization strategies could enhance the performance of the emotion recognition system.

AUTHOR'S CONTRIBUTION

All authors contributed to the literature review, design, data collection and analysis, drafting the manuscript, read and approved the final manuscript.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest regarding the publication of this study.

FINANCIAL DISCLOSURE

No financial interests related to the material of this manuscript have been declared.

ETHICS APPROVAL

Not applicable.

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