EEG Emotion Detection Using Optimum Channels

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Abstract

Electroencephalogram (EEG) emotion recognition has been widely accepted in several applications, including intelligent thought, decision-making, behaviuor therapy, affective computing, etc. However, due to the EEG signal's insufficient amplitude change concerning time, emotion identification from this signal has become very difficult. Therefore, identifying the correct feature or feature set for a successful feature-based emotion identification system is typically substantial work. We have extracted differential entropy from five EEG channels in this proposed work. A CNN-LSTM network is used to evaluate spatio-temporal relationships from features and classify emotions. The results indicated that the 4-class classification accuracy for 32 channels is 80.2%, the accuracy for all channels situated in the frontal area is 79.52%, and the accuracy of the best four frontal channels is 76.9%. The result gives a fresh viewpoint for developing an EEG-based emotion detection system with fewer channels.

Index Terms Differential Entropy, CNN (convolution neural network), EEG, emotion classification, channel selection

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INTRODUCTION

Emotions are crucial in human interaction and interpersonal relationships [1]. Positive emotions support health and increase vitality, lifespan, happiness, and life satisfaction. Therefore, improving our comprehension of how the nervous system executes good feelings is crucial for developing interventions that enhance their well-being. On the other hand, existing health conditions might be worse by negative emotions. Furthermore, according to neurological and psychological research, emotions have a significant impact on rational conduct, and persons with those with emotional illnesses have trouble doing daily tasks [2]. Therefore, a substantial amount of research [3, 4] has focused on the neurological connections between pleasant or negative emotions and brain stimulation that promotes health be used to measure human brain activity, reflecting emotional Electroencephalography (EEG) may state. Different scales of emotion classification have been developed to analyze emotions automatically, but Russell's valence-arousal scale is extensively used [5]. According to this, each psychological state is represented by two dimensions: arousal and valence. Therefore, the subject's dependence on collecting EEG data and comparison with expert categorization or self-assessment is challenging. Consequently, channel selection efficiency is crucial. Literature indicates that comparable or identical performance might be achieved with fewer channels [6]. In addition, selecting electrodes may be vital for overcoming issues with sophisticated and obtrusive equipment. However, scientists disagree on the precise number and positions of EEG electrodes which is tough. In addition, EEG signals are collected from several brain regions and typically include 32, 64, or electrodes. A high number of electrodes affect the computing complexity of EEG data analysis. It also raises the likelihood of signal overlap and generates interaction issues.

Zheng et al. [7] suggested a technique based on deep neural networks for learning the standard total weight distribution to choose the appropriate EEG channels and get superior experimental outcomes. Gupta et al. [8] suggested a flexible analytic wavelet transform (FAWT) to find channel specific features. They used random forest and support vector machine media for emotion categorization. Wibawa et al. [9] described a method to combine emotion lateralization with ensemble learning. Temporal characteristics, frequency domain characteristics, and wavelet features were retrieved from EEG data using four distinct channel sequences and combinations. The DEAP dataset was subsequently categorized using random forest and got an accuracy of 75.6%. With wavelet packet decomposition (WPD), Mokatren [10] obtained energy and entropy features by splitting the EEG signal into five wavelet sub-bands. Considering the position of the EEG electrode, the channel mapping matrix is constructed. His accuracy for valence and arousal and CNN (convolution neural network) classifier for the DEAP dataset was 91.85 and 91.06 per cent, respectively. Zhong et al. [11] found an EEG spectrogram and then calculated inter-channel matrix using normalized mutual information. The reduced channels by applying thresholding and connection matrix analysis. He got 74.4% accuracy for the valance and 73% for arousal for eight and ten channels, respectively. W. Zheng [12] suggested a group sparse canonical correlation analysis where he found a correlation between emotion class and EEG feature. In addition, he discussed the significance of channel reduction for reducing complexity. K. Ansari Asl et al. [13] employed the technique of synchronization likelihood for emotion identification with reduced channels. Joshi and Ghongade [14] extracted features from four pre-frontal channels using the linear formulation of differential entropy and got an average accuracy of 73.37% with the Bi-LSTM (Bidirectional long short term memory) network. A Topic et al. [15] applied Computer-generated holography to create 2D feature maps for electrode selection and employed better significant channels to optimize model accuracy. They chose to use ReliefF and Neighbourhood Component Analysis (NCA). The generated 2D maps served as input for the CNN) and achieved an accuracy of emotion detection, with 90.76 % for valence and 92.92 % for arousal.

The primary objective of EEG channel selection is to pick a subset of channel in order to decrease computational cost and enhance the accuracy of emotion identification so that researchers can design a hand held, low cost user friendly equipment. However, most current research failed to use region-specific neuronal information at the network level. As revealed by recent analysis, EEG emotion processing and management can include time-varying complex neural networks instead of a distinct brain area [16, 17]. In addition, several studies have shown the importance of the frontal cortex for studying the emotion-related activity. They emphasized that the frontal cortex generates more EEG signal than other brain areas, such as the temporal, parietal, and occipital regions [18]. The analysis techniques look at how different parts of the frontal cortex interact over time and how other parts of the brain connect at the network level. It will help to determine the neural signatures of different emotional states and make automatic emotion recognition more accurate.

In this article, we suggest a strategy based on convolution neural network to develop a better EEG-based emotion identification system. Specifically, we assessed whether using a subset of EEG channels in the frontal brain area increases classification performance. Based on this, we determined the best EEG channel combination for emotion identification.

In addition, we examined how the dynamic functional network of the frontal cortex influences categorization ability. The contributions of the present study are as follows:

1) We propose a method to find differential entropy features from EEG signals.
2) We introduced a CNN-LSTM network to select appropriate features from given features to get better accuracy of classification.
3) We have contributed in the fact that the frontal cortex, especially a part of the frontal cortex, plays a crucial role in emotion realization.

MATERIAL AND METHOD

Figure 1 shows a typical flow diagram of emotion recognition process. It includes data collection, pre-processing and band separation, feature extraction and classification.

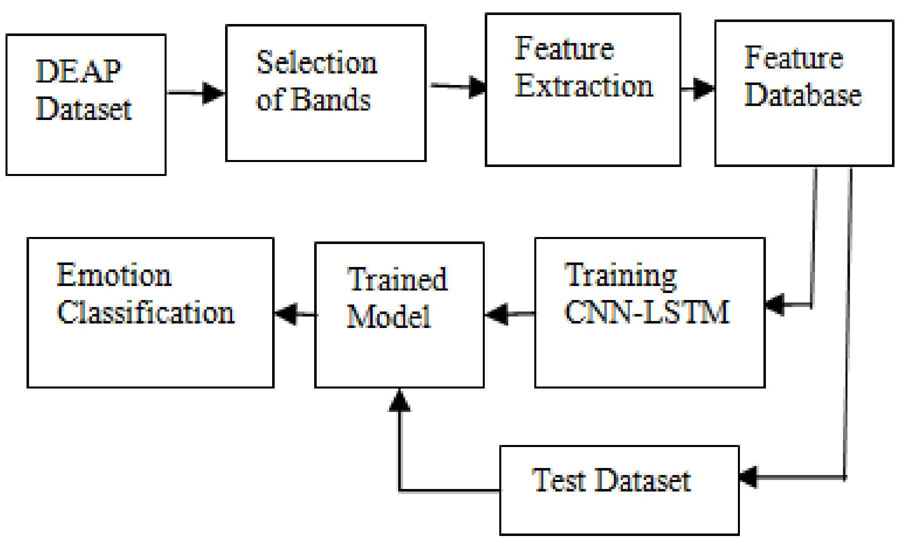

Fig. 1 Block diagram of work flow

A. Dataset

The existing open dataset DEAP [19] has been used for analysis. The data was collected in controlled illumination using Biosemi Active device. Thirty-two subjects were shown 40 music video clips of 1 minute each. At the end of each trial, participants did a self-assessment about valance and arousal. The valance scale varies from sad to joyful and arousal from calm to excited. EEG recording was done from 32 channels according to the 10-20 electrode system. A sampling frequency of 512 was used, and it was further down-sampled to 128Hz. EOG artefacts were removed using blind source separation and passed through a band pass filter of 4-45 Hz.

B. Feature Extraction

Cognitive thinking and emotional actions are the frontal lobes two main functions. EEG signals have non-stationary. Additionally, the valence of the emotion is asymmetrical in the forehead region, and arousal is connected to the activity of this region. Positive emotions are more evenly distributed and less intensely expressed than negative emotions in the low-frequency band of the emotional EEG, which is more completely activated than the high-frequency band [20]. The precise range of each frequency band varies significantly throughout the various investigations. One of the most important goals of EEG emotion detection research is to identify more specific emotional traits. Depending on the methods used for extraction, EEG characteristics may be categorized as either temporal or spatiotemporal. According to our research, differential entropy (DE) is one of the best features for recognizing emotions.

The differential entropy (DE) characteristic was suggested by Shi et al. [21]. It is a bigger version of the discrete Shannon entropy, which is used to figure out how complicated a system is. Duan et al. [22] said that differential entropy could better tell the difference between low-frequency and high-frequency EEG patterns than standard PSD characteristics. Here's how to figure out DE:

$$h(x) = -\int_x f(x)\log(f(x))dx \tag{1}$$

where x is a continuous variable and f(x) is the probability distribution for that constant variable. Since the probability distribution is unknown, it is hard to figure out the DE values.

If a random variable has a Gaussian distribution N (μ, σ^2) then we can use following formula to figure out its differential entropy:

$$h(x) = -\int_{-\infty}^{-\infty} \frac{1}{\sqrt{2\Pi\sigma^2}} e^{\frac{(x-\mu)^2}{2\sigma^2}} \log \frac{1}{\sqrt{2\pi\sigma^2}} \left(\frac{(x-\mu)^2}{2\sigma^2}\right)$$

$$= \frac{1}{2}\log(2\pi e\sigma^2) \tag{2}$$

where x is a variable, π and e are constants. Lu et al [21] demonstrated that the DE characteristics are similar to the logarithmic spectral energy for a certain frequency range and a particular length of EEG sample.

C. CNN-LSTM Network

CNN and LSTM neural networks are used to determine localized and comprehensive EEG signal characteristics. [23] The convolution layer is intended to manage a grid of X values. It can recognize a pattern of characteristics in which a single element derives from a few surrounding input elements. LSTM is typically competent to measure a sequence of rates X [24], and each component from the learned feature is a component of the earlier output results. The combination of CNN and LSTM enables the identification of salient traits, including local and extended contextual relationships. The most significant characteristics of the convolution layer are local spatial connections and shared weights [23]. Because of these qualities, the convolution layer has the potential to serve as the learning kernel. Deep neural networks can perform better and be more consistent thanks to a layer called the BN layer, which normalizes the output of the convolutional layer for each batch. Because of the batch normalization adjustment, the mean activation stays relatively near 0 while the standard deviation of activation stays very close to 1[25]. The RELU layer defines the BN layer's output. Positive values are produced by the RELU activation function, which speeds up the learning process in proposed networks and improves classification accuracy. In addition, the pooling layer reduces the amount of noise and distortion produced by the features. A well-known example of a nonlinear function is the max-pooling algorithm. It does this by separating the input into areas that do not intersect and then delivering the essential value from each sub region [26].

As a consequence of this, the function of the convolution network is to extract local features. Long-term contextual connections are learned using the LSTM architecture, a fundamental kind of recurrent neural network (RNN). [24]. Long-term correlations between sequences may be found using the LSTM network. Consequently, it is layered over CNN to infer contextual dependencies based on locally relevant feature series selected beforehand. The LSTM may either take away information from the block state or add information to it by using four components: an input gate, an output gate, an erase gate, and a cell having a link to itself that is self-recurrent.

IMPLEMENTATION DETAILS

In this section we describe our emotion recognition system. It elaborates details about feature extraction and actual CNN-LSTM model used for classification.

A. Feature Extraction

To extract features of EEG signals, we have chosen pre-processed python files of the DEAP dataset. Using 128-point short-time Fourier transform (STFT) and a Hanning window of 4s with 0.5s overlap, differential entropy is found for different frequency bands. EEG signals used in this study are categorized into five groups based on the differences in the frequency ranges of the signals: theta (4–8 Hz), alpha (8–12 Hz), low beta (12–16 Hz), high beta (16-25 Hz) and gamma (25-45Hz). In our experiment, we initially considered eight channels and finally selected four of them namely FP1, AF3, FP2 and AF4. We have also experimented with single-channel FP1. Thus we get 4*5, i.e. 20 samples per time slot and a total of 226560 × 20 samples with four channels. With a single channel, we got 5 samples per time slot.

B. Model implementation

This paper implements fusion of three 1D CNN and two LSTM layers. Each convolution module consists of 1DCNN layer with kernel size 3, max pooling layer with stride 2, a batch normalization layer and dropout layer. ReLU (Rectified Linear Unit) is used as an activation function in CNN layer. The output of third convolution unit is fed to first LSTM layer. Both LSTM layers use nonlinear function Leaky ReLU. Categorical cross-entropy is used to calculate the loss of system. It is given by:

$$Loss = -\sum_{i=1}^{n} x_i \log x_i \quad (3)$$

where Xi^ is ith scalar model output and Xi is the analogous target value of ith class. Optimization is done to tune the hyper parameters of the model so that loss of a neural network is reduced. Adam optimizer is used to update weights and bias. The learning rate of the Adam algorithm is 0.001. Zero padding is added in each convolution layer to avoid information from missing at the edges. The model implementation is done with the Tensor flow and Keras library.

The table I gives detailed configuration of CNN-LSTM model.

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Table I: Proposed CNN_LSTM model.

Layer	Output shape	Parameters
Convolution 1D	(None, 8, 128)	512
Max-pooling 1D	(None, 4, 128)	0
Batch-normalization	(None, 4, 128)	512
Dropout	(None, 4, 128)	0
Convolution 1D	(None, 2, 128)	49280
Max-pooling 1D	(None, 1, 128)	0
Batch-normalization	(None, 1, 128)	512
Dropout	(None, 1, 128)	0
Convolution 1D	(None, 1, 256)	33024
Max-pooling 1D	(None, 1, 256)	0
Batch-normalization	(None, 1, 256)	1024
Dropout	(None, 1, 256)	0
LSTM	(None, 1, 256)	525312
Dropout	(None, 1, 256)	0
LSTM	(None, 32)	36992
Dropout	(None, 32)	0
Flatten	(None, 32)	0
Dense	(None, 128)	4224
Dropout	(None, 128)	0
Dense	(None, 4)	516
Activation (softmax)	(None, 4)	0

RESULTS AND DISCUSSION

In the DEAP dataset, valance emotions are rated between 1 and 9. Most of the algorithms consider two-stage classification, namely valance (value > 5) and arousal (value > 5). We have considered all the values between 1 and 9 and generated a four-class category using low/high valance and low/high arousal: HVHA, HVLA, HALV, and LALV, respectively. After observing that the DEs of signals obtained from some electrodes were high, we treated them as bad channels and discarded subjects 4, 5, 24, and 27. We have considered only 24 subjects. We have experimented on all 32, 8, 4, and 1 (FP1) channels. From eight prefrontal channels, we selected 4 channels through random experimentation.

A. Performance Analysis

For quantitative analysis we have evaluated performance of our model based on four statistical metrics including accuracy, recall, F1 score and Kohen Kappa value.

$$accuracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \quad (4)$$

$$\mathrm{Re}call = \frac{Tp}{Tp + Fn} \quad (5)$$

$$F_1 score = \frac{2 * Precision * \mathrm{Re}call}{\mathrm{Pr}ecision + \mathrm{Re}call} \quad (6)$$

$$k = \frac{Po - Pe}{1 - Pe} \quad (7)$$

where Tp, Tn are true positive and true negative. Fp, Fn are false positive and negative. Po is the overall accuracy of the model and Pe is measures the agreement between model prediction and actual class value.

B. Results

In our experiment we have chosen 60% of dataset for training, 20% for validation and 20% testing after extracting features.

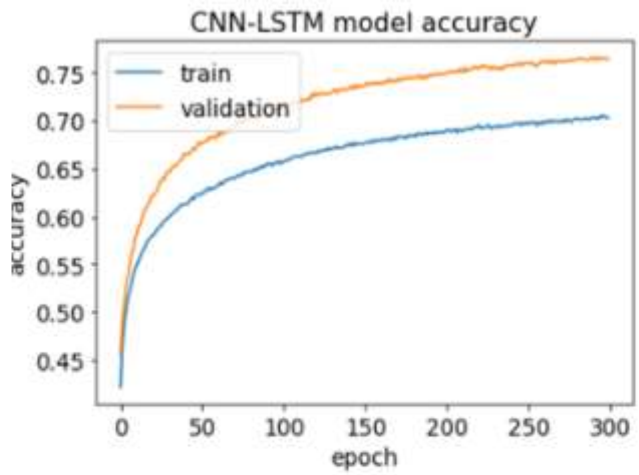

Fig. 2: Model training and validation accuracy curve for 4 channel

Fig.2 shows the model accuracy curve for all four emotion classes for four channels. It is observed that the number of epochs increases, accuracy increases, and approximately becomes stable from 230 epochs. From the figure, we can say that the probability distribution in validation data closely matches the distribution of training. The dropout layers while training is active to avoid overfitting, which has reduced accuracy. However, during the evaluation of validation and test data, dropout is not active, giving more accuracy.

Fig. 3: Confusion matrix for four channel data

The confusion matrix obtained from experimentation is shown in figure 3. It is the outcome of data from four channels. The confusion matrix visualization shows how much data is correctly predicted. It provides insight into the faults your classifier is making and the sorts of errors being produced. The performance evaluation is shown in table II.

Table II: Performance evaluation of CNN-LSTM model.

Emotion	Accuracy (%)	Recall	F_1 Score	Support
HVHA (joy)	80%	0.78	0.79	15395
HVLA (fear)	79%	0.74	0.76	9337
LVHA (calm)	72%	0.82	0.77	11777
LVLV(sad)	77%	0.71	0.74	8803

A high F1 score suggests that the significance of accuracy and recall were balanced and adequate for both procedures. The Kohen kappa value is 0.72. The value confirms that our classifier works better. Table III gives the accuracies of the model for different number channels.

Table III: Results of accuracy and F_1 score for different channels

Number of channels	Accuracy (%)	F_1 Score
32	80.2	0.79
8	79.5	0.78
4(FP1, AF3, FP2 and AF4)	76.9	0.75
1(FP1)	0.70	0.69

Overall, our results indicated that 8 frontal brain channels perform to 32channels in terms of classification ability, and the FP1, AF3, FP2 and AF4 channels together yielded the good classification accuracy. The results achieved utilizing the suggested single-channel technique are satisfactory. The suggested effort will significantly benefit society.

To validate the CNN-LSTM network's performance, we compare our model's accuracies with other recent deep learning models, as given in table IV. All these methods have used DEAP dataset and different number of channels.

C. Discussion

According to findings from recent studies, the left frontal brain is linked to joyful feelings, while the right frontal cortex is related to unhappiness. [27]. Following a similar line of thought, this research aimed to evaluate the influence of frontal EEG signals on the categorization of emotion states with low and high degrees of valence and arousal. We demonstrated that classification accuracy based on EEG channels in the frontal brain surpassed accuracy based on EEG channels from the whole head, which is consistent with results from earlier research.

Our results suggest that emotion processing may be intimately associated with certain parts of the frontal cortex, notably the lateral (AF3 and AF4) and anterior (Fp1 and Fp2) regions. According to recent research [28], the lateralized EEG inequality among the left and right hemispheres may adequately reflect the changes in emotional states, which may partly confirm our results. Aftanas et al. [29] demonstrated that the power of theta frequency of lateral channels like AF3 and AF4 was related to the valence and arousal scale. In addition, earlier research indicates that FP1 and FP2 are very accurate in identifying emotional states [30], the left frontal (FP1) is associated with unhappy emotion and the right frontal electrode (FP2) is pertinant with positive emotion [31]. Consistent with the literature, we observed that channels in the anterior portion of the frontal brain are favorable for emotion perception.

Table IV: Comparison of CNN-LSTM method with other methods

Name of Author	Features Extracted	Classifier	No. of channels	No. of Emotions classified	Accuracy (%)
S. Koelstra [19]	Spectral power	Gaussian Naïve Bayes	32	4	59.9
V. Gupta [8]	FAWT	KNN	32	2	86
E. S.Pane [9]	Time, frequency and wavelet	Random Forest	6	4	75
Zhong Min [11]	Spectrogram	CNN	18	2	74.4
K. Ansari [12]	Synchronization Likelihood	LDA	5	2	65%
V. Joshi [13]	Linear formulation Differential Entropy	Bi-LSTM	4	4	73.3
Proposed Method	Differential Entropy	CNN-LSTM	4	4	76.9

It should be emphasized, however, that channels in the front portion of the frontal cortex, such as Fp1 and Fp2, may be significantly influenced by ocular movement artifacts. Single-channel EEG devices with dry electrode FP1 are readily accessible, may be purchased at costs that are within a patient's budget, and are very simple to use. Less number of channels reduces the memory requirement and affordable hardware system can be designed.

CONCLUSION

In this paper, we have built a system using the CNN-LSTM network to identify EEG signals' emotions. This developed model has less computational complexity and requires less time for execution. It is observed that we can identify positive and negative emotions with a single EEG channel with good accuracy. The suggested effort will significantly benefit society. Using single-channel EEG equipment with a good degree of accuracy, diagnosis of diseases can be made. The efficacy of using these pathways to investigate emotional states requires additional investigation. Despite this, a practical suggestion based on our findings is that acquiring EEG signals from regional electrodes, particularly from the frontal regions, may aid in improving the performance of the emotion classification model and advancing the development of low-cost EEG devices with reliable performance.

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