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EEG Based Classification of Emotions with CNN and RNN

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ABSTRACT

Emotions are biological states associated with the nervous system, especially the brain brought on by neurophysiological changes. They variously cognate with thoughts, feelings, behavioural responses, and a degree of pleasure or displeasure and it exists everywhere in daily life. It is a significant research topic in the development of artificial intelligence to evaluate human behaviour that are primarily based on emotions. In this paper, Deep Learning Classifiers will be applied to SJTU Emotion EEG Dataset (SEED) to classify human emotions from EEG using Python. Then the accuracy of respective classifiers that is, the performance of emotion classification using Convolutional Neural Network (CNN) and Recurrent Neural Networks are compared. The experimental results show that RNN is better than CNN in solving sequence prediction problems.

KEYWORDS: *Emotion classification, SEED, EEG, CNN, RNN, Confusion matrix*

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INTRODUCTION

Emotions play a significant role in how we think and behave in daily life. They can compel us to take action and influence the decisions we make about our lives, both large and small. As technology and the understanding of emotions are progressing, there are growing prospects for automatic emotion recognition systems. There exists a successful breakthrough in facial expressions or gestures as simulative emotional recognition. As an advanced machine learning technique for emotion classification, neural network is considered as a machine used to simulate how the brain performs a specific task. It stimulates the brain as a concept of complex nonlinear and parallel computers, which can evaluate complex functions according to various factors. A new direction this paper is heading towards is EEG-based technologies for automatic emotion recognition, as it becomes less intrusive and more affordable, leading to ubiquitous adoption in healthcare applications. In this paper we focus on classifying user emotions from raw Electroencephalogram (EEG) signals, using various neural network models and advanced techniques. We particularly explore end-to-end deep learning approaches, CNN and RNN, for emotion classification from SEED dataset directly. Convolution neural networks are forward neural networks, generally including a primary pattern extraction layer and feature mapping layer, and can learn local patterns in data by a method called convolution. We found that CNN [1] is better, and deep neural models are more preferable in emotion classification and estimation for machine computer interface system that models brain signals for emotions. However, an RNN remembers the entire information through time. It is useful in time series prediction because it can remember previous inputs very well which is called Long Short-Term Memory. Also, recent developments in machine learning show that neural networks provide considerable accuracy in a variety of different tasks, such as text analysis, image recognition, speech analysis and so on.

Related Works

Automated classification of human emotion using EEG signals has been researched upon meticulously by various scholars. In related studies, there were many strategies proposed to perform emotion classification from EEG signals. It ranges from finding physiological patterns of emotions, identifying remarkable features, and any other combination of those strategies.

In [1] the research provides a concise evaluation for CNN classifier which was reasonably accurate in identifying the two criteria of pleasure (Valence) and arousal degree (Arousal) with an average accuracy of 84.3% and 81.2%, respectively but for an individual subject, the average classification accuracy was only 63%.

In [2] the paper showed, for both Valence and Arousal, DNN performs maximum classification accuracies of 75.78 and 73.281 respectively while their CNN model had classification accuracies of 81.41% and 73.35% respectively.

In [4] the research proved that the convolutional networks in comparison with the classic algorithms of machine learning demonstrated a better performance in the emotion detection in physiological signals, despite being conceived for the object recognition in images.

For classification of emotion, the most popular method, K-Nearest Neighbour algorithm [5] had achieved 62.3% overall accuracy by applying features namely, wavelet energy and entropy. The results showed 78.7±2.6% sensitivity, 82.8±6.3% specificity and 62.3±1.1% accuracy on the 'DEAP' database.

In [6] the paper showed that Hierarchical Structure-Adaptive RNN (HSA-RNN) for video summarization tasks, can adaptively exploit the video structure and generate the summary simultaneously.

In [7] the results showed that the proposed framework improves the accuracy and efficiency performance of EEG signal classification compared with traditional methods, including support vector machine (SVM), artificial neural network (ANN), and standard CNN by 74.2%.

In [8] the research proved that the TranVGG-19 obtains a good result with mean prediction accuracy is 99.175%.

In comparison to SqueezeNet, Residual Squeeze VGG16 of [9] can be more easily adapted and fully integrated with residual learning for compressing other contemporary deep learning CNN models since their model was 23.86% faster and 88.4% smaller in size than the original VGG16.

In paper [10], it was proved that the feature of mean gives the highest contribution to the classification using deep learning classifier, Naïve Bayes with the highest classification result of reached 87.5% accuracy of emotion recognition.

Proposed Work

A. Database Agglomeration and Description

The proposed method is conducted by SJTU Emotion EEG Dataset (SEED) which is a collection of EEG dataset provided by the Brain-like Computing and Machine Intelligence (BCMI) laboratory. This dataset contains the subjects' EEG signals when they were watching film clips. The film clips are prudently selected to induce different types of emotion, which are neutral, sad, fear and happy. 15 subjects (7 males and 8 females; Mean: 23.27, STD: 2.37) watched 15 video clips in the experiments. Each subject is experimented three times in about one week. The down-sampled, pre-processed and segmented versions of the EEG data in Matlab (.mat file) were obtained [2]. The detailed order of a total of 62 channels is included in the dataset. The EEG cap according to the international 10-20 system for 62 channels is shown figure [1].

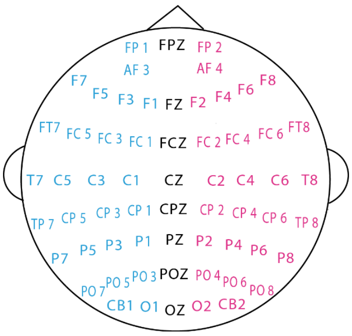

Fig.1 EEG cap according to the international 10-20 system for 62 channels

The differences and ratios between the differential entropy (DE) features of 27 pairs of hemispheric asymmetry electrodes give the differential asymmetry (DASM) and rational asymmetry (RASM) features. By using the conventional moving average and linear dynamic systems (LDS) approaches, all the features are further levelled.

B. Methodology

The project exhibits emotion recognition using EEG signals to detect emotions, namely, happiness, sadness, neutral and fear using SEED dataset. Two different neural models are used, a simple Convolutional Neural Network and Recurrent Neural Network (RNN) as the classifiers. Both models are augmented using contemporary deep learning techniques like Dropout technique and Rectilinear Units in order to introduce non-linearity in our model. Both models are implemented using Keras [1] libraries in Python.

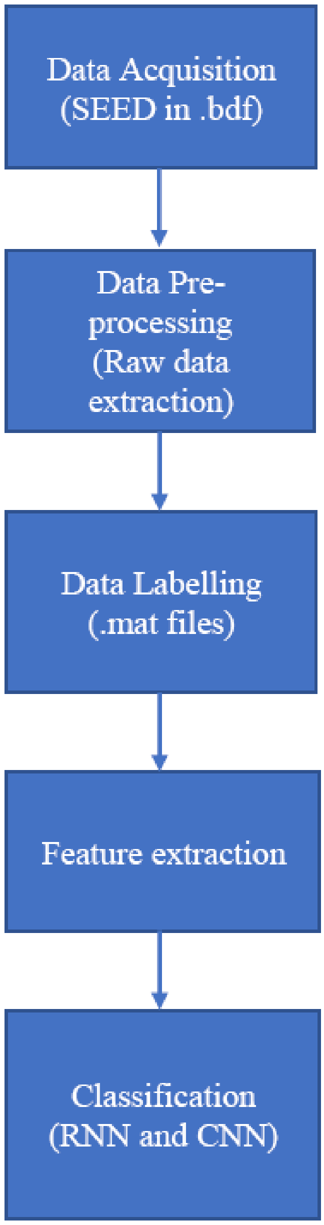

Fig.2 Proposed Method

RNN is a type of neural network which transforms a sequence of inputs into a sequence of outputs. An RNN can learn and detect an event, such as the presence of a particular expression, irrespective of the time, at which it occurs in a sequence. Hence, it naturally deals with a variable number of frames.

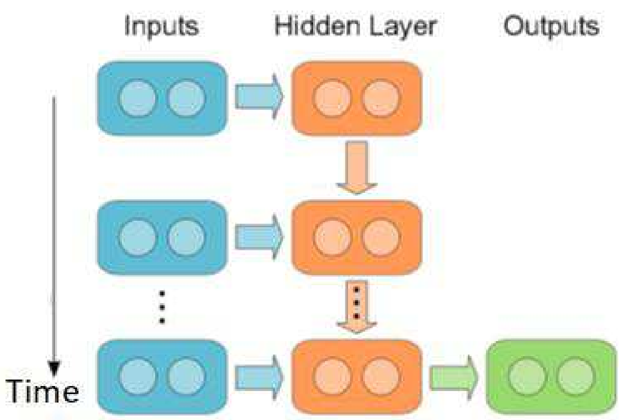

Fig.3 RNN Architecture

At each time step t, a hidden state ht is computed based on the hidden state at time t - 1 and the input xt at time t

$$ht = \sigma\ (Win\ xt{+}Wrecht{-}1)$$

where Win is the input weight matrix, Wrec is the recurrent matrix and σ is the hidden activation function. Each timestep also computes outputs, based on the current hidden state:

$$yt = f(Woutht)$$

where Wout is the output weight matrix and f is the output activation function.

We use a simple RNN with Rectified Linear hidden Units (ReLUs). We train the RNN to classify the emotions in a video agglomerated in the SEED dataset. Then using the confusion matrix, we measure the performance of each classifier in terms of accuracy, specificity, sensitivity, and precision.

C. Confusion Matrix Parameters

Confusion Matrix is a performance measurement table for machine learning classification where output can be two or more classes. It is composed of 4 different combinations of predicted and actual values.

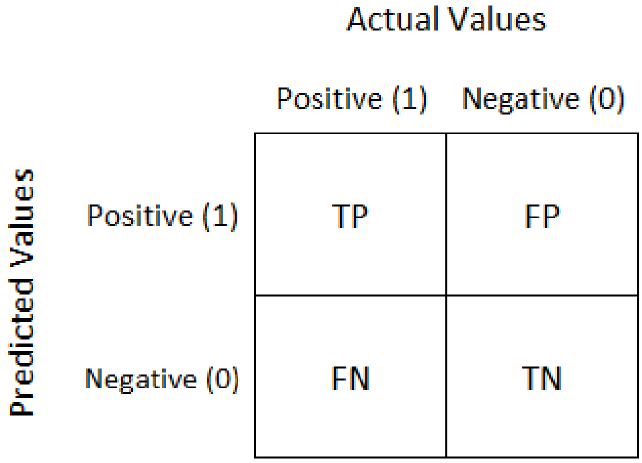

Fig.4 Confusion Matrix

True Positive (TP): Prediction is positive and it's true.

True Negative (TN): Predicted is negative and it's true.

False Positive (FP) – Type 1 Error: Predicted is positive and it's false.

False Negative (FN) – Type 2 Error: Predicted is negative and it's false.

Accuracy:

$$\mathrm{ACC} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FN}+\mathrm{FP}} \times 100\%$$

Specificity:

$$\mathrm{SP} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \times 100\%$$

Sensitivity:

$$\mathrm{SN} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \times 100\%$$

Precision:

$$\mathrm{PREC} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \times 100\%$$

Experimental results and analysis

RNN model is applied to construct EEG based emotion detection of four classes, namely Neutral, Sad, Fear and Happy. The dataset used here is SEED. The 62-channel EEG signals are recorded from 15 subjects while they are watching emotional film clips with a total of 24 trials. This data set is available with extracted features like Moving Average and PSD of Differential Entropy and LDS, differential and rational asymmetries, and caudal differential entropy. Further, these feature data belong to alpha and beta frequency bands are normalized with mean values and these have been used here.

Table1. Confusion matrix parameters for CNN and RNN

Confusion parameters	CNN				RNN			
Neutral	Sad	Fear	Happy		Neutral	Sad	Fear	Happy
Accuracy	95.53	88.13	88.01	87.89	96.50	89.88	90.85	89.61
Specificity	98.56	98.29	57.44	55.52	93.44	98.11	74.18	77.17
Sensitivity	94.54	83.57	96.68	97.20	98.29	84.01	98.14	98.34
Precision	85.50	72.85	83.07	85.08	94.38	81.37	90.43	88.74

With these features of preprocessed EEG data, the existing CNN and proposed RNN models are trained. Then classification is performed using trained models. The experimental results show that the pools of features that have been chosen can achieve relatively classification performance across all the experiments of different subjects.

From table (2) we see that RNN achieves the highest accuracy of 96.50%, 89.88%, 90.85% and 89.61% for Neutral, Sad, Fear and Happy while CNN model-based classification output gives 95.53%, 88.13%, 88.01% and 87.89% for the respective emotions.

A. CNN

For CNN, figure 5 shows the exponential behaviour of the accuracy during the training and testing for the 20 epochs. Similarly, in figure 6, the values of loss are displayed during the learning and testing that is decreasing for each epoch. The confusion matrix is showing the results of prediction for the four classes, respectively (figure 7).

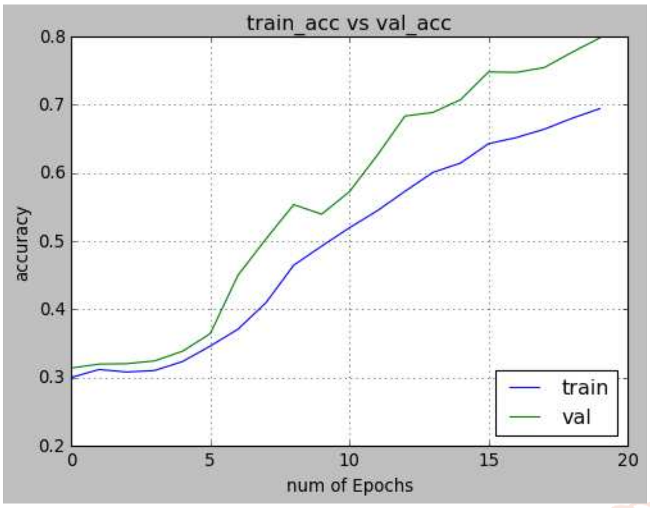

Fig.5. Accuracy result for CNN

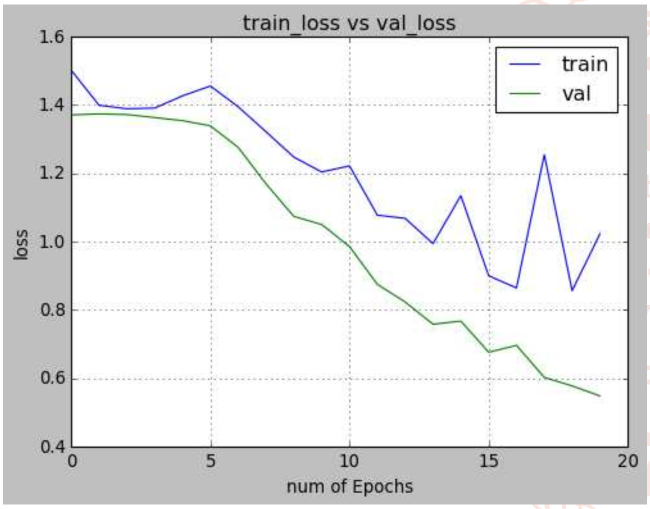

Fig.6 Loss result for CNN

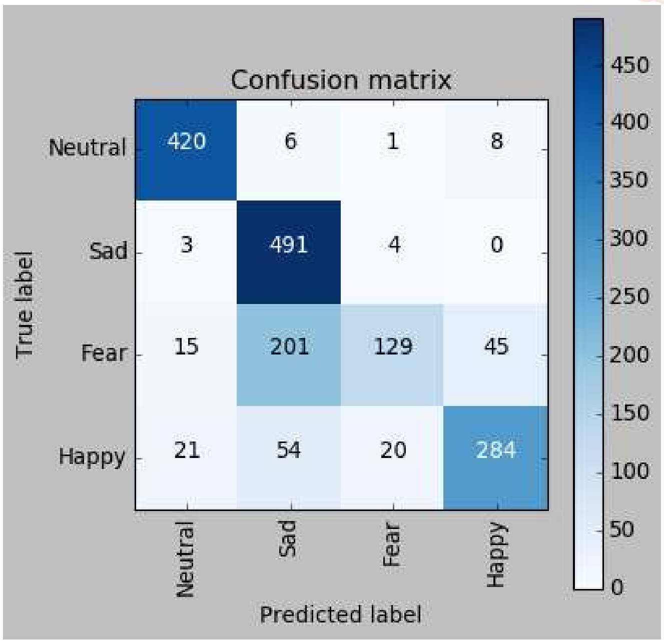

Fig.7 Confusion matrix of CNN for the prediction of four emotions

B. RNN

For RNN, figure 8 shows the exponential behaviour of the accuracy during the training and testing for the 20 epochs. Similarly, in figure 9, the values of loss are displayed during the learning and testing that is decreasing for each epoch. The confusion matrix is showing the results of prediction for the four classes, respectively (figure 10).

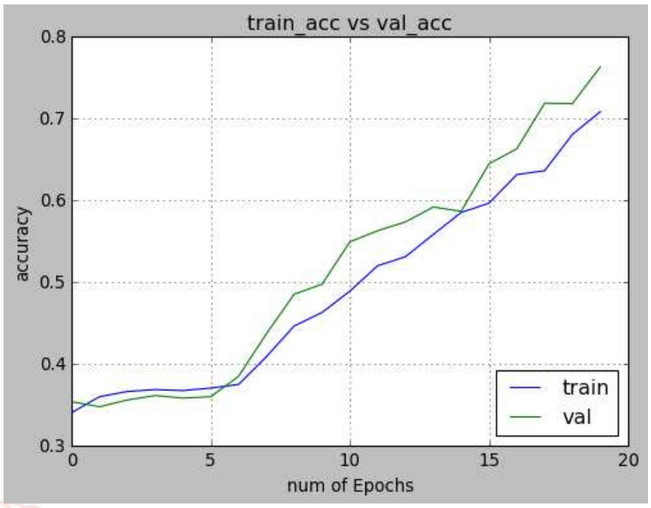

Fig.8 Accuracy result for RNN

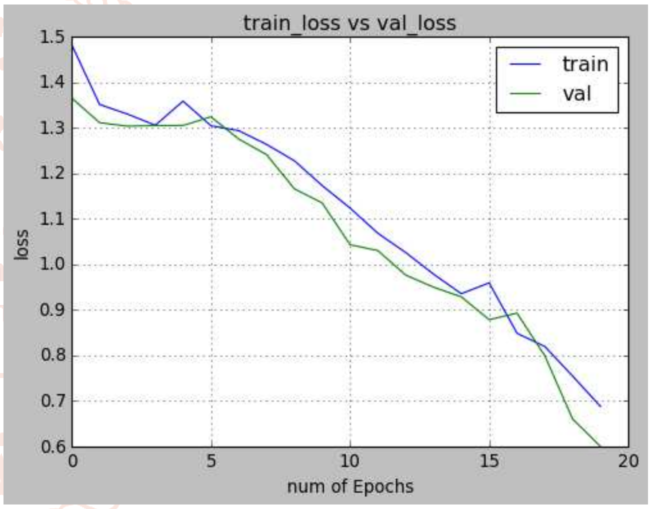

Fig.9 Loss result for RNN

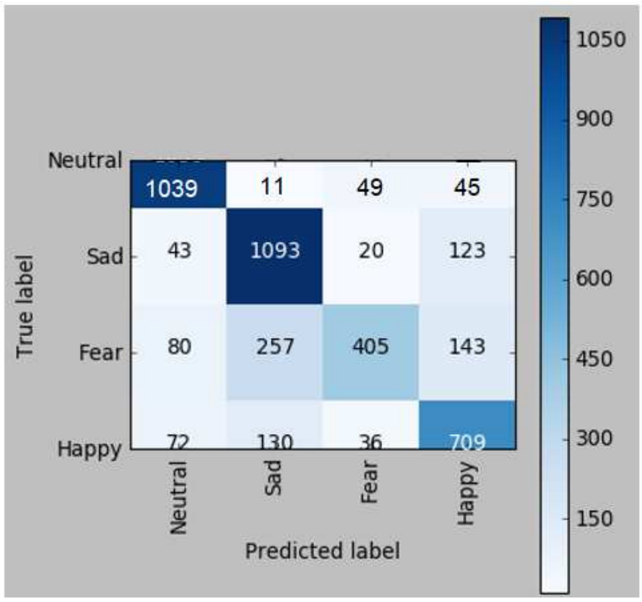

Fig.10 Confusion matrix of RNN for the prediction of four emotions

Hence, this paper shows that RNN figure (10) has made the highest prediction for the four classes compared to CNN figure (7).

Conclusion:

Based on the existing research in the field of emotion recognition, this study explores the effectiveness of the recurrent neural network. The experimental results show that the RNN model achieves higher precision to classify emotions with CNN based approach. The reliability of classification performance suggests that specific emotional states can be identified with brain activities. The learning by RNN suggests that neural signatures associated with Neutral, Sad, Fear and Happy emotions do exist and they share commonality across individuals. Thus, RNN provides an appealing framework for propagating information over a sequence using a continuous-valued hidden layer representation.

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