Human Emotions Classification Using Spectral Topography and Convolution Neural Network

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***Abstract*– Emotional state of a Human in real-time scenarios can be recognized by analyzing the Electroencephalography (EEG) signals. Human Emotion classification is a hot research topic of these days. From many decades efforts are being made in the field of brain computer interaction (BCI). This paper describes a way to use data obtained from EEG device to predict the current emotional state of person. We convert EEG time series signals into spectral topographic images after converting it into frequency domain. After that we implemented Convolution Neural Network (CNN) to classify these topographies. CNN was able to accomplish task giving about 98.12% accuracy. The study demonstrated that the matrices of spectral topographies carry important information about the emotional states, and the CNN model can extract the distinguishing features to differentiate the emotional states.**

***Keywords*– Electroencephalography (EEG), Convolution Neural Network (CNN), Signals, Classification, Features, Human Emotions and Spectral Topography**

I. INTRODUCTION

BRAIN of a human consists of billions of neurons, which are controlling their physical activities, mood, behavior and voluntary as well as involuntary movements. Electric potential is generated due to activity of these neurons [21]. Current state of these neurons can be detected by using electroencephalography (EEG) [19]. A wavelet is generated by EEG in result of electric potential. These EEG signals are worth to use in clinical findings include epilepsy diagnosis [9], [10], sleep analysis [13], emotional state [12], [20] and other medical usage [17], [19]. Commercial usages include brain-controlled wheelchair [23], brain activity level detection [16], communication [22], EEG-based games [14], human computer interaction [11], [15].

Emotions are intrinsic property of human being. Emotional state of human plays an important role in decision-making, intelligence, perception and interaction. Therefore, emotions are the drive force for human actions [27]. Emotions can be detected through text, speech analysis, facial expression and gestures. As EEG signals detect the original emotions arise from our brain and does not rely on external features. So EEG signals are real indicator of emotional state of person. The other reason for EEG being useful emotion recognition is it has low latency as compared to other techniques. It is also risk free and noninvasive technique.

EEG signals are acquired from the electrodes placed on scalp. Electrodes generate signals of very low strength which are further amplified using amplifier module. The EEG signals are in time series domain which is the composition of five main frequency band named as delta (1–3Hz), theta (4–7Hz), alpha (8–13Hz), beta (14–30Hz) and gamma ((31–50Hz) as show in Fig. 1. Analysis of these bands can provide information about cognitive and emotional state of person.

In this research, we took emotion dataset which contain their types of emotional states; positive, negative and neutral. We proposed a methodology to predict the emotional state of person on real-time bases.

The major contributions of this work are as follows:

- Exploration of spectral topographic based method for the classification of emotions.
- A high performing CNN to achieve 98.12% average accuracy.

The rest of this paper is structured as follows: The most related and previous works done are given in Section II. In Section III proposed method is explained in detail. Results are depicted in Section IV. The conclusion of research conducted is given in Section V.

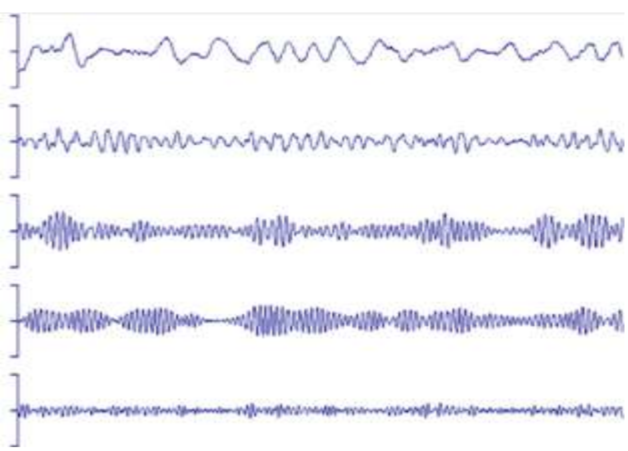


Fig. 1: Composition of EEG signals

II. LITERATURE SURVEY

There has been done a lot of work in EEG signal analysis and classification. Different feature extraction, visualization and classification techniques have been developed over time. Also these EEG signals have been used to conduct research and were able to perform successful jobs in different scenarios. A short survey is given below.

Orhan, et al. [1] worked on epileptic and healthy EEG signals to perform classification. They decompose signal into frequency sub-bands using discrete wavelet transform (DWT). K-mean clustering was also used to cluster wavelet coefficients. Finally Multi-layer Perceptron used to classify the input. They achieved accuracy of 95.60%.

Similarly, Subasi, et al. [2] in their paper utilized discrete wavelet transform (DWT) to decompose signal into frequency domain. Principle component analysis (PCS), Independent component analysis (ICA) and linear discriminant analysis (LDA) were carried out for dimensionality reduction. Then support vector machine (SVM) is applied for classification purpose. They proved that accuracy increases by using the feature extraction techniques.

Şen, et al. [4] in their work tried out different feature selection algorithms such as fast correlation-based feature selection (FCBF); minimum redundancy maximum relevance (mRMR); ReliefF; t-test; and Fisher score algorithms. Then these features are passed to five different classification algorithms feed-forward neural network (FFNN); (random forest (RF); decision tree (DT); radial basis function neural network (RBF) and support vector machine (SVM) to classify the signals. They achieved top accuracy of 97.03% by using RF algorithm. They were able to do sleep stage analysis by using this technique.

Empirical mode decomposition (EMD) method was used by Bajaj, et al. [3] to decompose signal into set of amplitude and frequency modulated (AM-FM) signals. Least squares support vector machine (LS-SVM) has been used for classifying seizure and non-seizure EEG signals. Their method achieved accuracy of 100 %.

Hsu, et al. [5] proposed a method to classify different sleep stages from the EEG signal data. In this method they first convert EEG signals of Fpz –Cz channels into energy features. Then they utilized recurrent neural network to classify these energy features. Classification of five possible sleep stages: wakefulness, NREM 1, NREM 2, SWS, and REM was done. They also tried out feed forward neural network (FNN) and a probabilistic neural network (PNN). But recurrent neural classifier achieved the better accuracy of 87.2%.

Mert et al. [6] conducted research to classify human emotions. They first used empirical mode decomposition (EMD) to analyze time series EEG signal. This converted signal into intrinsic mode functions (IMFs). Then these IMFs were analyzed using time and frequency domain techniques such as power spectral density, power ratio, correlation and entropy. They used DEAP multimodal dataset [7]. They used neural network and k-NN as classifier.

Bhardwaj, et al. [8] proposed a methodology to classify EEG signals to detect seven different types of emotions. They tried out independent component analysis (ICA) feature extraction technique followed by two different classifiers named as support vector machine (SVM) and linear discriminant analysis (LDA). They achieved average accuracies of 74.13% and 66.50% respectively.

All the work done previously in EEG signal classification is mostly based on traditional statistical and machine learning techniques. Which involve manual feature extraction by using Principal component analysis (PCS), Independent component analysis (ICA). And further any machine learning based classifier is implemented to classify signals.

III. METHODOLOGY

The normal pipeline for the classification of EEG signals includes five major stages: (1) acquisition of Raw EEG signals using electrodes. (2) Preprocessing to remove artifacts and normalize signal. (3) Feature extraction like using frequency domain. (4) Selecting useful features. (5) Classification using classifier like LDA or SVM.

In our technique we used 2D convolution neural network which are normally use for the classification of image data. The approach used is based on the face that fully convolution networks are better feature extractors than manual feature extraction techniques.

A) Dataset transformation

We have used the available on kaggle. Dataset have EEG signals recorded for three classes positive, neutral and negative. Two persons (one male, one female) recorded the dataset. Each emotion have 6 minutes of recorded EEG signals for each person. Total 12 minutes of record for each emotion and 36 minutes record for all the three emotions. The dataset was in raw form containing huge number of artifacts.

The dataset was available in CSV file. It was collected from four different channels named as TP9, AF7, AF8 and TP10 to get the measurement from different spatial location over the scalp. As EEG in time series carries less information and most useful features resides in frequency domain so we perform fast Fourier transformation (FFT) on time series data to get power spectrums. By applying FFT we get five main frequency bands described earlier in introduction section. But according to Bashivan, et al [24] the most useful information related brain memory operations reside in three frequency bands named as theta (4-7Hz), alpha (8-13Hz), and beta (13-30Hz). Now we transform these bands into 2-Dimentional image so it can preserve the spatial structure of data which is most important thing for classification purpose.

Just like RGB image three color channels were used to represent spectral dimensionality. A sequence of spectral topographic images is generated as shown in Fig. 2. Which was further used as input to train convolution neural network.

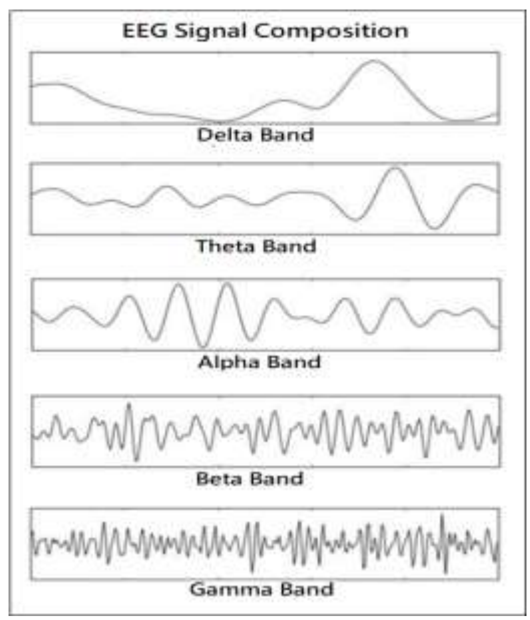


Fig. 2: evaluation graph based on loss

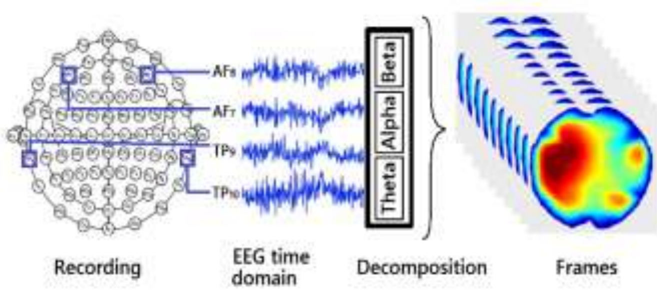
B) Architecture

We first tried out ResNet-50 [25] and VGG-16 [26]. But accuracy and loss graphs did not reach to optimal values for both networks due to spatial irreparability of frames. So, we built our own network on the base of available less deep neural network by tuning the classification layers.

Architectural Details

Fig. 3 depicts the details of proposed architectural in terms of number of parameters in each layer and output feature maps. It is clear from diagram that we used simplified network having only three convolution layers to extract features for achieving best performance in terms of response time and accuracy. After convolution layer the output feature map is flattened and input to dense layer for classification purpose. At the end of final dense layer softmax function is applied to predict class. First column gives information about layer name that can be convolution, pooling, flatten and fully connected. Secondly output dimensions of feature maps extracted from each layer are shown in column two.

Following this, number of parameters that each layer learns are provided in last column. Finally, total number of parameters are provided in two divisions of learnable and non-learnable parameters. Higher the number of learnable parameters, it took high memory space and time to train network. We have to manage these parameters so that network will be able to achieve high accuracy by consuming less time.



Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 32, 32, 32)	896
max_pooling2d_1 (MaxPooling2	(None, 16, 16, 32)	0
conv2d_2 (Conv2D)	(None, 16, 16, 64)	18496
max_pooling2d_2 (MaxPooling2	(None, 8, 8, 64)	0
conv2d_3 (Conv2D)	(None, 8, 8, 64)	36928
max_pooling2d_3 (MaxPooling2	(None, 4, 4, 64)	0
flatten_1 (Flatten)	(None, 1024)	0
dense_1 (Dense)	(None, 128)	131200
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 2)	258

Total params: 187,778
Trainable params: 187,778
Non-trainable params: 0

Fig. 3 provides the more detail in term of flow of features from input to output layer in our proposed convolution neural network as well as the size of filter used in each layer. Network take input image of size 32x32 having three channels. This input image is actually spectral topographic image as explained in dataset section. Each contributing feature extraction layer has an output of size m*n*c where m is height, n is width and c depict the number of channels. These output features are the result of filters convolving over the input and are shown above the layer in diagram. Hidden units in fully connected layers decides the output features. Last fully connected layer produces the probability for each representative class.

The Fig. 3 is showing two parts: feature extraction portion and classification portion. From that we can interpret that fully convolution network (FCN) performs the task of classification and multi-layer perceptron (MLP) do classification and give prediction end of network.

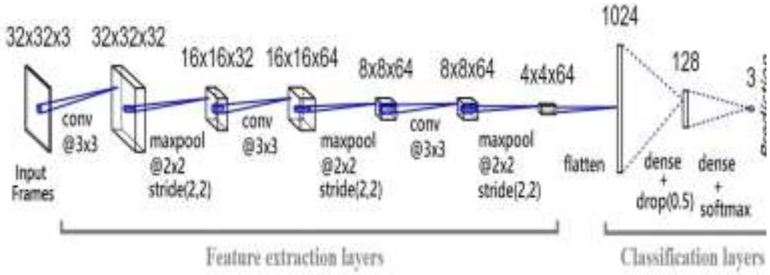


Fig. 3: Flow of Diagram

IV. RESULTS AND EVALUATION

We have trained the convolution neural network over 300 epochs. The training accuracy start from 48.12% and validation accuracy from 63.45% as it can be seen in Fig. 4. After a few epoch accuracy abruptly reaches above 90%. Which verifies the correctness of architecture of network and hyper-parameters. Both train and validation accuracies fluctuate throughout the epochs. But one thing here to be noted that both accuracies move hand in hand with very low distance which indicates model not over-fitting. This is due to dropout layer with 50% drop rate, applied after first dense layer.

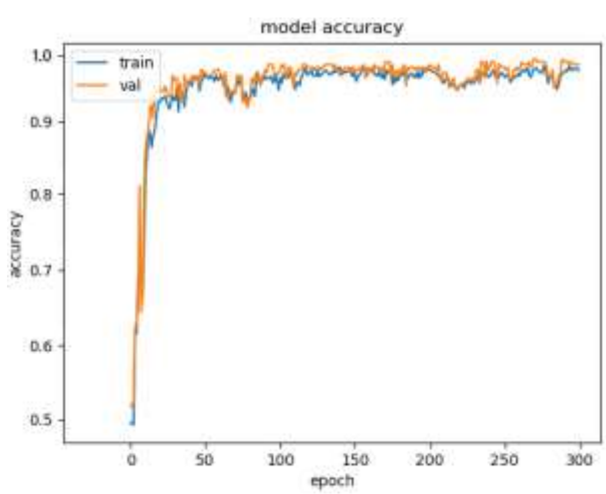


Fig. 4: Evaluation graph based on accuracy

Similarly, loss graph in Fig. 5 shows abrupt decrease in loss starting from 8 and reaches to 0.0023 as shown in Figure Y. We employed best save mechanism which saves best weights and updates them if loss is minimum than previously saved weights loss. We also employed shuffling mechanism to avoid model being biased.

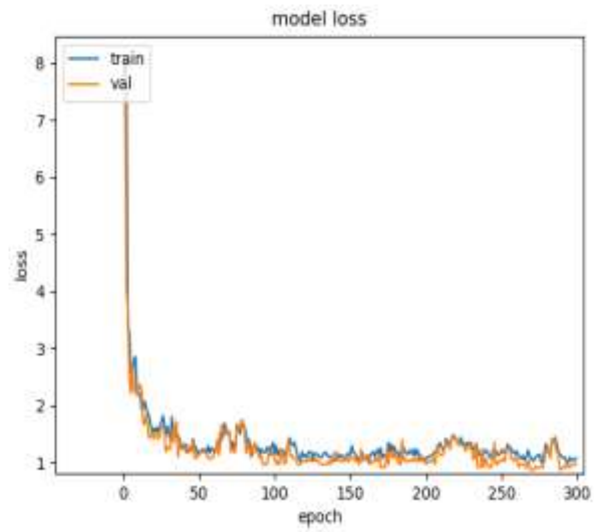


Fig. 5. Evaluation graph based on loss

Table I. Compares the results of our method with original paper of dataset [25]. We got the top average accuracy of 98.12% on the same dataset.

Table I. Comparison of results on same dataset

Study	**Methodology**	**Accuracy Achieved**
JJ Bird, et al [28]	InfoGain, MLP	97.89 %
JJ Bird, et al [28]	InfoGain, RandomForest	94.89%
This study	FFT, CNN	95.38%
This study	2-D topographic image, CNN	**98.12%**

The optimizer used was Adabost having initial learning rate value 1.0 to quickly converge the model. Learning rate decay value 0,001 was used which reduces the learning rate value after each epoch so the loss can reach to its global minimum value.

V. CONCLUSION

This work is aimed to use robust representations from EEG data, to perform analysis and classify into three different classes of emotions: positive, neutral and negative. We propose a novel technique to use spectral power representations from multi-channel EEG time-series, for emotion classification task. Our approach uses pictorial representations for classification task to get high accuracy of 98.12%. The work done is spatial domain. In future we would try to perform temporal analysis of these representations.

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