Emotion recognition using Electroencephalography (EEG) Signals

Baruri Sai Avinash
Department of Electrical Engineering
Indian Institute of Technology
Jodhpur, Rajasthan
avinash.1@iitj.ac.in

Himanshu Kumar Anand
Department of Mathematics
Indian Institute of Technology
Jodhpur, Rajasthan
anand.9@iitj.ac.in

Dr. Gaurav Harit
Department of Computer Science
Indian Institute of Technology
Jodhpur, Rajasthan
gharit@iitj.ac.in

***Abstract*—**

To recognize emotions using biological brain signals requires efficient and accurate feature extraction and signal processing methods. In this work by using discrete wavelet transform (DWT), EEG signals are decomposed into the gamma, beta, alpha and theta frequency bands. Next by using Principle component analysis (PCA) we will make features mutually uncorrelated. We have built model using Long short-term memory$(LSTM)$.

***Index Terms*—Recurrent Neural Networks, Discrete wavelet transform,Long short-term memory**

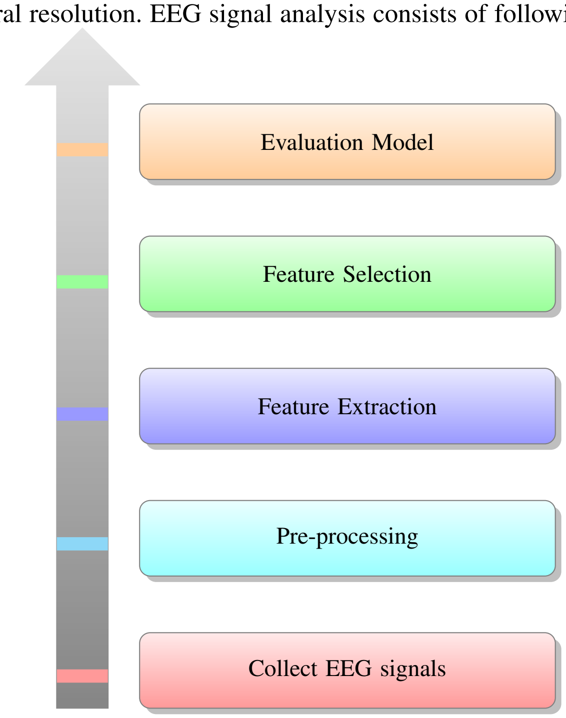
I. Introduction

The brain is a significant part of humans as it controls the entire body's movements or responses to external stimuli. Inside the brain, millions of neutrons act as messenger carriers between body and brain. Hence by analyzing signals, one can understand the cognitive behavior of the human brain.

Electroencephalography (EEG) helps acquire these brain signals categorized as delta, theta, alpha, beta, and gamma based on their frequencies ranging from 0.1 HZ to more than 100 Hz. In the EEG technique, the brain's electrical potential is measured by a device called an electroencephalogram. This device consists of electrodes, conductive gel, amplifier, and Analog to Digital converter.

In EEG Acquisition Phase, raw EEG signals are collected from the scalp of the brain. Then the processing stage begins, which consists of two processes, namely artifacts removal and data filtering. The next phase in the signal analysis is extracting features using various signal processing techniques like Fourier Transform, Wavelet, and Principal Component Analysis.

The EEG applications are increasing mainly to detect neurological diseases such as Parkinson's diseases and epilepsy and others. By continuously monitoring EEG signals we can observe the electrical activity of brain and it provides good temporal resolution. EEG signal analysis consists of following steps:



II. EEG DATA

We have take $emotion.csv$ data set from kaggle. It has total 2548 features and one target associated with it. The target has 3 class labels namely $positive$,$negetive$,$neutral$. There is no missing values in the data set. All the features has numeric data but the target labels are categorical.

III. Pre-processing EEG DATA

Here target labels are categorical. Categorical data is a type of data that is used to group information with similar characteristics. Most of the machine learning algorithms cannot handle categorical variables unless we convert them into numeric values. Some of the methods used are One-hot Encoding,Label Encoding,Frequency Encoding etc. In One-hot Encoding for each category we will have a feature with

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values 0 and 1 denoting the presence or absence of that category. In Label Encoding we will assign the values to each category. In this work we have used Label Encoding for conversion of categorical data to numerical data like $'NEGATIVE' : 0,' NEUTRAL' : 1,' POSITIVE' : 2$.

IV. Feature Extraction

In this section we will discuss about feature extraction using Wavelet transforms. We will use Discrete wavelet transform (DWT) for feature extraction. Let us consider an EEG signal X(Z) which will be decomposed into detailed and approximate coefficients using DWT. We will pass the EEG signal into high pass and low pass filters until we reach a desired level of decomposition. We will obtain detailed coefficients by passing EEG signal through high pass filter H(Z) and approximate coefficients are obtained by passing signal through Low pass filter L(Z). The number of decomposition levels is an hyperparameter. Let us say, we have used four level decomposition and for each channel we have obtained detailed and approximate coefficients [3].

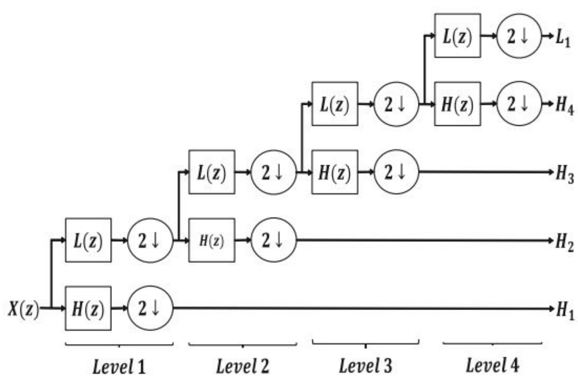

Fig. 1. Discrete wavelet transform. [2]

Frequency	Band	Wavelet level	Analysis constant
$Delta(\delta)$	0.1-3HZ	4	A4(L1)
$theta(\theta)$	4-7HZ	4	D4(H4)
$alpha(\alpha)$	8-12 HZ	3	D3(H3)
$beta(\beta)$	12-30HZ	2	D2(H2)
$gamma(\gamma)$	30-50 HZ	1	D1(H1)

Now we will extract features from these coefficients at each level. Some of features like mean , standard deviation, maximum, minimum . The mean feature is obtained by averaging all coefficients at each decomposition level.

$$Mean = \frac{1}{D_L}\sum_{i=1}^{D_L} X_i$$

D_L is the number of coefficients in a decomposition level and X_i is the value of coefficients i at each decomposition level. standard deviation is obtained by

$$STD = \frac{1}{D_L}\sum_{i=1}^{D_L}(X_i - mean)^2$$

It measures the deviation of coefficients from mean value. Minimum and maximum features are obtained by evaluating minimum and maximum values of coefficients at a given level of decomposition.

$$min = min_{L\in X} X_L$$

$$max = max_{L\in X} X_L$$

here X_L denotes the coefficients of detail or approximate part of signal.

V. Feature selection

To reduce the complexity of model we will reduce the number of features. One way to do dimensionality reduction is by using Principal Component Analysis (PCA) [5].

A. Principal Component Analysis

1) Standardization of data
2) Compute Covariance matrix
3) Compute Eigen Vectors and Eigen values of Covariance matrix
4) Identify Principal Components

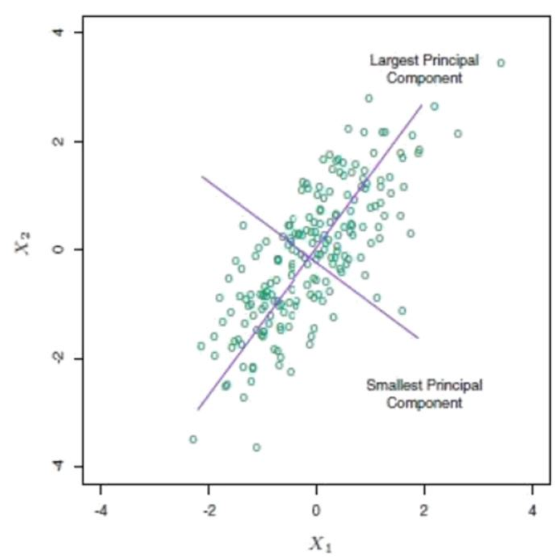

Fig. 2. Pricipal Component Analysis [5]

By using PCA, we are projecting data into low dimensional linear space. We have to work on number of features to be considered for better generalisation of model.

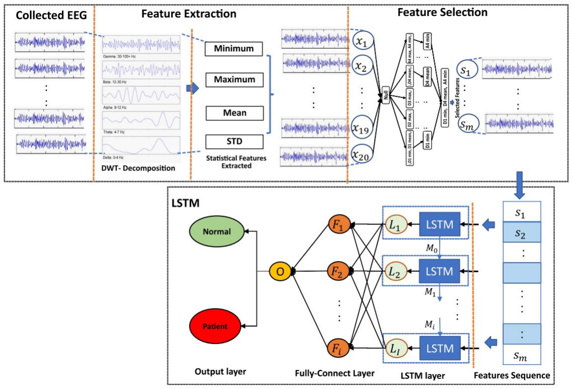

Fig. 3. System framework. The system consists of four major steps: EEG collection, feature extraction, feature selection and LSTM classification [2]

VI. Recurrent Neural Networks

Let us say if we want to speak a word we cannot utter it randomly as every word we speak has some connection with previous words. Normal Feed forward neural networks cannot do this. They consider only current input for the task and cannot memorize previous inputs. In order to predict next character in a sentence, network should remember information about its past history and RNNs are able to solve this problem of remembering input sequences with the help of hidden state. In recurrent neural network we can see broadly input X_t and output is h_t and the network is connected in loop from one step to next step. So we will use RNN if we want the present information to depend on previous one.

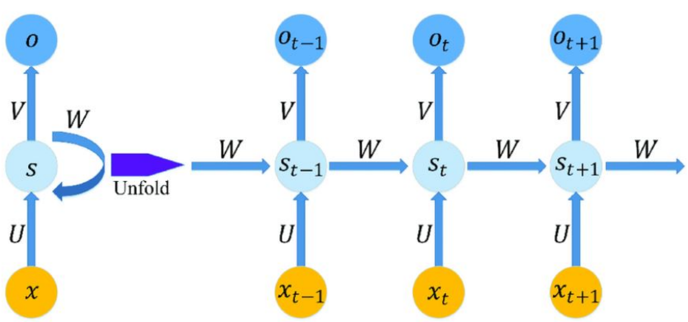

Fig. 4. Recurrent Neural Network.
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But main problem is, can RNN are able to do this task?. Let us take an example of sentence "I grew up in germany and i can speak..? If we want to predict the next word which is the language, network has to remember past information. But RNN cannot handle this long term dependencies. So we have different RNN architectures which can handle long term dependencies, they are Long short term memory units (LSTM). Like RNN, LSTM also have recurrent connections but in RNN we have single gate where LSTM have four gates. Let us now look at the LSTM briefly. The first gate in LSTM is the forget gate .This layer decides the information to be passed through cell state.

$$f_t = \sigma(W_f[h_{t-1}, x_t + b_f)$$

It will take h_{t-1} and x_t as inputs. Then the output will be a number between 0 and 1 for each number in cell state C_{t-1}. In the next step, if we want to add any new information to cell state is done here. The sigmoid layer decides which values we need to update and by tanh layer we will get C_t^* which needs to be added.

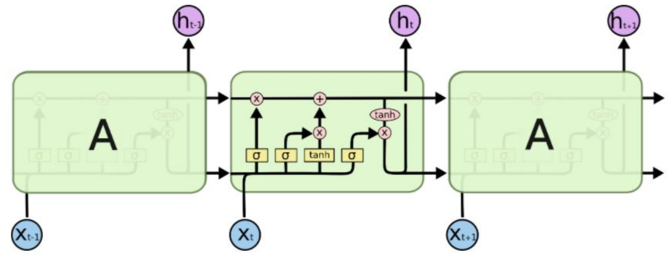

Fig. 5. LSTM [4]

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

$$C_t^* = tanh(W_c[h_{t-1}, x_t] + b_c)$$

Now we multiple old state with f_t forgetting things we need to forget and now we will add $i_t * C_t^*$ and we will get new updated value.

$$C_t = f_t * C_{t-1} + i_t * C_t^*$$

Now we will use sigmoid layer to decide which part of cell state we want to output and tanh layer is used to bring the cell state values between -1 and 1.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * tanh(C_t))$$

RNN has many structures as one-to-one, one-to-many, many-to-one, many-to-many. Thus RNN perform best in handling sequential data. LSTMs are mainly designed to avoid the long-term dependency problem.

A. LSTM Model

We have proposed LSTM model. We divided the data set into training and test data split. We have implemented the LSTM model on the Google Colab. Input has 5 neurons and the LSTM layer has 256 neurons and Dense layer has 3 neurons with 'Softmax' activation function. We use adam optimizer to minimize the loss and sparse categorical cross entropy as loss function. After performing 50 epoch with batch size of 32, got an accuracy of 94.531%.

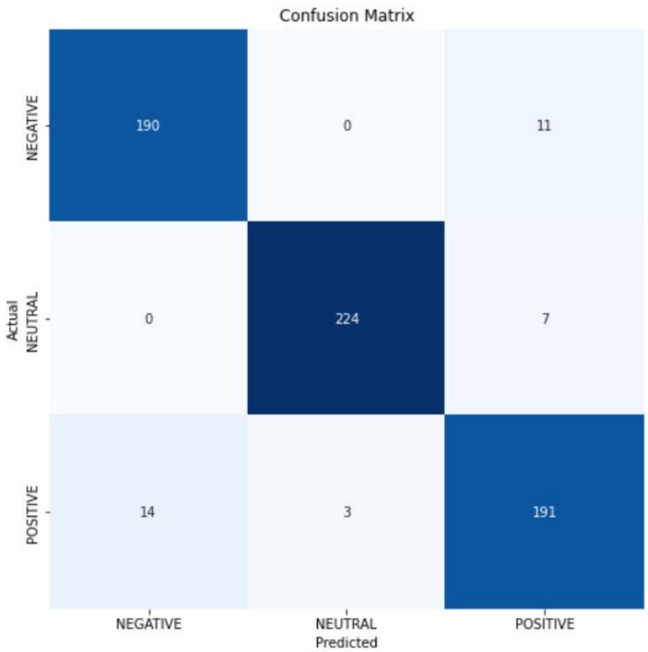

Fig. 6. Confusion Matrix.

Classification Report:

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	precision	recall	f1-score	support
NEGATIVE	0.93	0.95	0.94	201
NEUTRAL	0.99	0.97	0.98	231
POSITIVE	0.91	0.92	0.92	208
accuracy			0.95	640
macro avg	0.94	0.94	0.94	640
weighted avg	0.95	0.95	0.95	640

Fig. 7. Classification Report.

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