EEG Signal Analysis for Emotion Recognition

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1 Introduction

Emotions are fundamental for human beings and play an important role in human cognition. Emotion is commonly associated with logical decision making, perception, human interaction, and to a certain extent, human intelligence itself. With the growing interest of the research community towards establishing some meaningful "emotional" interactions between humans and computers, the need for reliable and deployable solutions for the identification of human emotional states are required. Emotion recognition has gained increasing importance in the field of brain-computer interface. Recognizing emotions using biological brain signals requires accurate and efficient signal processing and feature extraction methods. This classification is based on the brain signals- electroencephalogram (EEG) signals which get affected by the changes in the emotional state of a person. These brain signals communicate via electrical impulses and remain active all the time. EEG signals are non-linear and random in nature. Thus, feature extraction plays a major role for emotion detection. These features quantify the EEG signal and are used as attributes of the classifiers. Therefore, the performance of an emotional recognition system depends on the efficiency of the algorithms used for extraction of features, the feature selection algorithm itself and the classification process. Thus, the project aims to create an automated model for emotion recognition which involves the feature processing and feature extraction using wavelet filter bank technique, feature reduction using Principal Component Analysis and classification using various classifiers.

2 Related Work

Various methods have been proposed so far for the detection of emotions using electroencephalography (EEG) signals. Many of them rely on machine learning or deep learning-based methods. In [1] features extracted from the EEG are passed through to a Convolutional Neural Network (CNN), which are then sent to a Sparse Autoencoder for encoding and decoding after which, the output of the same is passed through as input features for a Deep Neural Network (DNN) for feature extraction. [2] Uses an artificial neural network for identifying six types of emotions after extracting special, temporal and spectral features with the help of wavelet transforms and Gabor filters. [3] Proposes a method to improve the detection of emotions from EEG signals by exploiting the fact that brain activities are unique and differ from person to person. It also involves identifying instances where the excitation in the signal is maximum whilst the person is experiencing the emotion. Combining various machine learning techniques for identifying emotions using EEG signals is also a recurring theme in this area of research. [4] Uses a combination of SVM, KNN and ANNs for detection of emotions. In [5], the authors propose the creation of an activation curve that describes the activation of emotions, from the classification results, correlation and entropy coefficients, which significantly improves the accuracy. [6] Proposes a novel signal processing method for processing EEG signals for emotion detection. [7] Uses two methods for feature extraction, namely the Fast Fourier Transform (FFT) and Auto Regression (AR) for feature extraction, followed by a classification stage, which uses an SVM. In [8], once again, three classifiers- namely KNN, SVM and quadratic discriminant analysis are used. This approach combines wavelet energy, modified energy, wavelet entropy and statistical features to classify a total of four emotions. Various baseline models implemented on the above features and classical ML techniques generally yield an accuracy of approximately 70%.

3 Dataset Description

The SJTU Emotion EEG Dataset (SEED), is a collection of EEG datasets provided by the BCMI laboratory, which is led by Prof. Bao-Liang Lu.

`https://bcmi.sjtu.edu.cn/home/seed/index.html`

The SEED dataset contains EEG signals recorded from 15 individuals when they were watching film clips. Fifteen Chinese film clips (positive, neutral and negative emotions) were chosen from the pool of materials as stimuli used in the experiments.

The selection criteria for the film clips are as follows:
(a) the length of the whole experiment should not be too long in case it will cause the subjects to have fatigue;
(b) the videos should be understood without explanation; and
(c) the videos should elicit a single desired target emotion.

The duration of each film clip is approximately 4 minutes. Each film clip is well edited to create coherent emotion eliciting and maximize emotional meanings. There are a total of 15 trials for each experiment. There was a 5s hint before each clip, 45s for self-assessment and 15s to rest after each clip in one session. The order of presentation is arranged in such a way that two film clips that target the same emotion are not shown consecutively. For feedback, the participants were told to report their emotional reactions to each film clip by completing the questionnaire immediately after watching each clip.

The preprocessed dataset contains downsampled, preprocessed and segmented versions of the EEG data in Matlab (.mat file). The data was downsampled to 200Hz. A bandpass frequency filter from 0-75Hz was applied. EEG segments were extracted according to the duration of clips. There are a total of 45 .mat (Matlab) files, one for each experiment. Each subject performed the experiment three times with an interval of about one week. Each subject file contains 16 arrays. 15 arrays contain segmented preprocessed EEG data of 15 trials in one experiment (eeg_1 - eeg_15, channel×data). An array named 'labels' contains the label of the corresponding emotional labels (-1 for negative, 0 for neutral and +1 for positive). The detailed order of the channels is included in the dataset. The EEG cap with 62 channels (according to the international 10 - 20 system) is used to collect the data.

4 Model Description and Analysis

Figure 1 shows the overall pipeline that we have implemented.

The key steps in our project are Feature Extraction, Feature Reduction and Classification.

1) Feature Extraction: The electroencephalogram (EEG) is a recording of the activity in the human brain and is measured in Hz. It is divided into five channels based on the frequency range – Delta, Theta, Alpha, Beta and Gamma. We are using the Alpha channel (focusing on extracting alpha channel, but delta, theta, beta and gamma are also extracted and are present) as its frequency falls under the range of 8-13 Hz, and studies have indicated that the changes in those frequencies are indicative of motor imagery-induced neural activation. After this, we are computing the discrete wavelet transform (DWT) of this data which will give us the approximation and detail coefficients. There are 62 electrode positions for which the EEG data is recorded, and 5 level decomposition is performed on the approximation coefficients obtained from the DWT. Using the detailed coefficients we calculated several features such as mean, variance, skewness, kurtosis, Shannon Entropy and

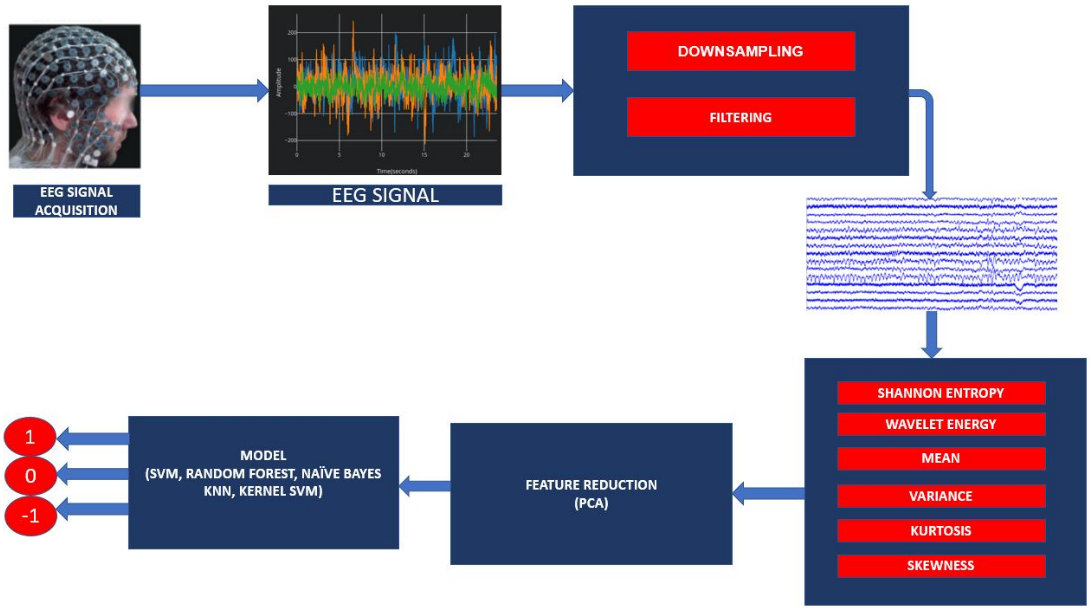

Figure 1:

Wavelet Energy. Table 1 shows the accuracies achieved by training the linear SVM on various combination of features obtained by 10 level wavelet decomposition of the detail coefficients. Using this, we came to the conclusion that Shannon Entropy and the Wavelet Energy are the best features that could be used to classify emotions. The Shannon entropy quantifies the uncertainty in the EEG signal which roughly relates to the three emotion states as mentioned. The Wavelet energy reflects the distribution of the principal lines, wrinkles and ridges in different resolutions (scales) of the EEG. In addition to this, the level of decomposition was also another parameter that we experimented on. After experimenting with different levels of decomposition we came to the conclusion that 10 level decomposition was giving the best test accuracy. Thus, we are calculating the wavelet energy and Shannon entropy for all the 10 detail coefficients, which results in a total of 1240 features.

Features	Test Accuracy - (Linear SVM/db8)
Mean and Variance	56.3
Mean, Variance, Shannon Entropy and Wavelet Energy	71.9
Kurtosis, Skewness	44.4
Kurtosis, Skewness, Shannon Entropy and Wavelet Energy	60.0
Shannon Entropy and Wavelet Energy	81.5

Table 1:

2) Feature Reduction: We are using principal component analysis (PCA) for feature reduction. It involves the following steps:
a. Normalizing the data
b. Calculating the covariance matrix of the normalized data

c. Applying Singular Value Decomposition on the covariance matrix
d. Selecting the top 'K' principal components

3) Model Tuning and Training: Initially we tried feature extraction using 5 level wavelet decomposition of detail coefficients after which the maximum accuracy achieved by the linear SVM was 77%. Because 5 level decomposition was used, the total number of features generated was 620. In a bid to increase the accuracy by generating more features, we used 10 level decomposition. This increased the total number of features to 1240. However, we noticed that training all the models and performing a hyperparameter search was becoming quite time consuming and computationally expensive. Hence, we employed principal component analysis, which involves projecting the data (1240 dimensions here) onto a lower dimensional space. This reduced the time taken to perform the hyperparameter search and the SVM model trained was able to achieve an accuracy of 81.5% using data that was projected on this lower dimensional subspace. It was found that the same accuracy could be achieved by projecting the data onto a 361 dimensional subspace as compared to using all the 1240 features.

Various models (SVM, Decision trees, KNN's) were trained for predicting the emotions from the output features obtained after performing feature reduction. The train/test set was split in the ratio of 80:20. In order to take into account and search for the best hyperparameters for each of the models being trained, grid search was performed systematically. For example, the hyperparameters we varied for SVM's were the regularization parameter C, the number of nearest neighbors in the case of K-nearest neighbors etc. The accuracies of all these trained models were evaluated on the test set later. After training and tuning all these models, linear SVM was found to achieve the highest test accuracy, peaking at 81.5%, which is much higher than the current benchmark (except neural networks, which are significantly more demanding in terms of memory, time and computational resources) of classification accuracies achieved on this dataset. The mathematical definition of the model we implemented (linear SVM) is:

$$
\begin{aligned}
&\min_{\boldsymbol{w},b,\xi} \frac{1}{2}\|\boldsymbol{w}\|_2^2 + C\sum_n \xi_n \\
&\text{s.t. } y_n\left[\boldsymbol{w}^\top \boldsymbol{x}_n + b\right] \geq 1 - \xi_n, \quad \forall n \\
&\quad\quad \xi_n \geq 0, \quad \forall n
\end{aligned}
$$

w is the weight parameter for the SVM Model
b is the bias term for the SVM Model
ξ is the slack variable
C is the regularization parameter
x are the features
y are the class labels

5 Results

As mentioned earlier, there are three states of emotion and the main objective was to classify the EEG signals into these three states. We trained our dataset on several models: Support Vector Machines (SVM's), an Ensemble method – Random Forests, KNN and Naive Bayes. Table 2 shows the accuracies of the various baseline models that have been implemented using the SEED dataset. Table 3 shows the accuracies of the various models that were trained on the extracted features. From these 2 tables, we can see that the Linear SVM model that we have implemented for this project gives significantly higher test accuracies than the baseline models. In addition to this, Table 4 shows the values of precision, recall and the F1-scores for the various models that were trained.

Model	Test Accuracy
SVM	59%
Deep Learning (Feature Extraction) + SVM (Classification)	82%
Deep Learning	96.7%

Table 2:

Model	Test Accuracy
Linear SVM	81.5 %
Polynomial SVM	29.6 %
Kernel SVM	29.6 %
Random Forest	48.1 %
KNN	53.3 %
Naive Bayes	40 %

Table 3:

	Precision			Recall			F1 score		
Model \ Class	-1	0	1	-1	0	1	-1	0	1
Linear SVM	0.79	.70	.94	0.72	0.78	0.94	0.76	0.74	0.94
Polynomial SVM	0.00	0.30	0.00	0.00	1.00	0.00	0.00	0.46	0.00
Kernel SVM	0.00	0.30	0.00	0.00	1.00	0.00	0.00	0.46	0.00
Gaussian NB	0.46	0.32	0.48	0.49	0.50	0.23	0.47	0.39	0.31
Random forest	0.48	0.38	0.64	0.26	0.65	0.56	0.33	0.48	0.60
KNN	0.54	0.39	0.79	0.45	0.60	0.56	0.49	0.47	0.66

Table 4:

6 Conclusion

Thus, EEG signals play an important role in emotion recognition. So, in conclusion, we implemented a linear SVM model where the EEG features were extracted using 10 level wavelet decomposition of the detail coefficients in the discrete wavelet transform. These coefficients are then used to calculate the features Shannon Entropy and Wavelet Energy that help in achieving the highest accuracy i.e 81.5%. The limitations in this model can be eliminated by using deep learning models or an ensemble of deep learning models and classical machine learning algorithms. Also a lack of publicly available datasets in this domain is a critical issue(requires special permission). Given the resources, we can create our own dataset with more subjects which can help improve accuracy. Finally, this project finds various applications. It plays a very crucial role in identifying early signs of mental illness, depression, anxiety and stress. It has also found application in improving gaming experience for people.

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