Classification of human emotions from EEG signals using SVM and LDA Classifiers

Aayush Bhardwaj
aayush.bhardwaj@yahoo.co.in

Ankit Gupta
mail.ankitgupta@yahoo.co.in

Pallav Jain
pallavjain292@yahoo.in

Asha Rani
ashansit@gmail.com

Jyoti Yadav
bmjyoti@gmail.com

Division of Instrumentation and Control Engineering
Netaji Subhas Institute of Technology
University of Delhi, Delhi, India

***Abstract*— Emotion Detection has been a topic of great research in the last few decades. It plays a very important role in establishing human computer interface. We as humans are able to understand the emotions of other person but it is literally impossible for the computer to do so. The present work is to achieve the same as accurately as possible. Emotion detection can be done either through text, speech, facial expression or gesture. In the present work the emotions are detected using Electroencephalography (EEG) signals. EEG records the electrical activity within the neurons of the brain. The main advantage of using EEG signals is that it detects real emotions arising straight from our mind and ignores external features like facial expressions or gesture. Hence EEG can act as real indicator of the emotion depicted by the subject. We have employed Independent Component Analysis (ICA) and Machine Learning techniques such as Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) to classify EEG signals into seven different emotions. The accuracy achieved with both the algorithms is computed and compared. We are able to recognize seven emotions using the two algorithms, SVM and LDA with an average overall accuracy of 74.13% and 66.50% respectively. This accuracy was achieved after performing a 4-fold cross-validation. Future applications of emotion detection includes neuro-marketing, market survey, EEG based music therapy and music player.**

Keywords—EEG; Emotion Detection; IAPS; ICA; LDA; Machine Learning; Neuro-marketing; SVM;

I. Introduction

Emotions play an important part in our daily life and will continue to do so in the future. Majority of future application will depend on brain computer interface where it is important to understand the human perceptions or emotions. .Major works of life which employ brain computer applications include neuro-marketing, market survey, medicine and defense. With increasing demand for such applications, it is imperative that we detect emotion with utmost accuracy. It allows humans to interact with computer devices which will form the foundation of all the future applications.

This has been the basis of several works. Many studies have employed various pattern recognition techniques to detect human emotions. M.Murugappan et al. [3] achieved a maximum accuracy rate of 79.174 using KNN. Viet Hoang Anh et al. [1] proposed a system which employed Russell's circumplex model which was able to predict emotions with an accuracy of 70.5%. Berkman et al. [2] used a two layered Arousal-Valence model and fractal dimension based algorithm which achieved an accuracy of 43%. Differentiation between different states of emotions such as happy and relaxed, relaxed and sad, happy and sad with performance rate of 90% was obtained in [4] using Relevant Vector Machine. In [5], an accuracy of 83.26% was achieved using k-Nearest Neighbors algorithm (KNN) and 75.21% using LDA while both classification techniques employed Discrete Wavelet Transformation (DWT) for decomposing the EEG signals into three frequency bands (alpha, beta and gamma). Researchers have relied on various features like energy, power, entropy etc. to detect emotions. Jamie F. Delgado Saa et al. [6] used power spectral features to classify EEG signals into two classes using LDA with accuracy as high as 86%.

Every classification technique has its own advantage and disadvantage. The choice of classifier generally depends on various factors leading to type of data and sample size to objective of classification. Sometimes a better data beats a better classification technique. Advantage of SVM includes high accuracy, prevents over-fitting and works very well with non- linear data with appropriate choice of kernel. LDA is generally not good with few category variables though it performs very well with linear data. The k-Nearest Neighbor works well on basic pattern recognition problems; however it is a slow learner in the sense that that it does not learn anything from the training data. It is also not efficient to noisy data.

The accuracies of all the classification techniques discussed have been a topic of great discussion. It is important to achieve a very high accuracy to enable applications to be built around human computer interaction in the future. In our model we have tried to use two techniques, SVM and LDA, to classify emotions into seven classes namely (happy, sad, anger, disgust, neutral, fear and surprised). Emotions were evoked in the subjects by showing them pictures and EEG signals corresponding to those events were recorded. These signals were then processed to extract relevant features and then fed to the two classifiers. The features considered for this study are Energy and Power Spectral Density (PSD).

This paper has been divided into different sections which are discussed below. Section II talks about the preliminaries required before we progress with this study. Section III talks

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about the pre-processing of the EEG signals and the machine learning techniques used to classify the emotions. In Section IV we talk about the respective accuracies achieved for the two techniques and their comparison. Finally in Section V we conclude this study.

II. PRELIMINARIES

In this section, we explain some basic terms and necessary theories used in this paper.

A. Electroencephalography (EEG)

Electroencephalography is the measure of the electrical signals generated by brain. These signals are recorded by placing electrodes on the scalp. In this experiment we have used the conventional 10 – 20 system for placing of the electrodes as shown in Fig. 1. To measure the EEG signals, we have placed 4 electrodes on the scalp namely, Fp1, F3, P3 and o1 electrodes.

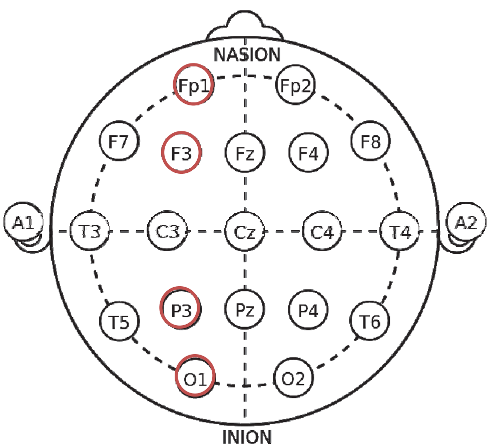

Fig. 1. Representation of 10-20 system for placing Electrodes, the red circled electrodes are the ones being used in this experiment.

B. Machine Learning

It is a branch of Computer Science and Statistics which deals with the formulation and study of complex systems and algorithms which can learn from data (information), without giving explicit instructions. The more they are trained, provided with data about the past results, the better they become, hence improving their ability to predict about the new inputs. Machine Learning is a very popular field now days, with its applications ranging from computer vision to pattern, speech and handwriting recognition. It is also employed in the field of Optical Character Recognition (OCR), in Search Engines, Stock Market analysis, Spam Filtering and also in many Recommender Systems.

In this paper, we have taken the help of Support Vector Machine and Linear Discriminant Analysis techniques to classify the features extracted from the subjects into seven different emotions.

- **Support Vector Machine:** Support Vector Machine is a very popular supervised learning algorithm, invented by Vapnik et al. [7], further modified by Corinna Cortes and Vapnik [8]. SVM is used to analyze data and recognize pattern.

SVM is a supervised learning algorithm, they infer a function or relationship from the given training data, this algorithm learn by analyzing data and recognizing patterns, and are frequently applied in the field of pattern regression analysis and classification. When provided with a set of training set, belonging to two different classes, an SVM algorithm design a model which can then efficiently assigns a new example point to one of the two classes.

- **Linear Discriminant Analysis:** Linear Discriminant Analysis is a technique which is used to describe the distinctive nature of two or more classes of objects or events by finding a linear combination of features, J. Ye et al. [9]. These combinations can be used for dimensionality reduction as a linear classifier for classification. Cases where class-frequencies are unequal can be easily handled by LDA. To get maximum separability, i.e. the ratio of between – class variance to the within- class variance is maximized.

C. IAPS Database:

To elicit various emotions in a subject we used images as stimuli. These pictures were taken from IAPS (International Affective Picture System). The IAPS was developed at The University of Florida, by P. J. Lang et al. [10]. The IAPS dataset has more than thousand photos, representing various scenarios, ranging from daily household like experiences to highly engrossing and extreme situations. The simplicity and adversity of these scenarios is what invokes such a dispersed array of emotions in a human.

D. Artifacts:

EEG detects electrical signal along the scalp, but the electrical signals that are generated from the non-cerebral activities (reasons other than activities of brain) are known as artifacts.

- Eye - induced artifacts (due to movements of eye, eye blinking, etc.)
- Electromyography artifacts (Induced due to muscular movements)

Our study was prone to these two artifacts, so we had advised subjects not to indulge in such movements. We had to perform Independent Component Analysis (ICA), to check for any such artifacts (explained further in Section III).

III. THE PROPOSED MODEL

Our model comprises of different phases namely Data Acquisition, Pre-processing of signals, Feature Extraction, Training (of classifiers) and Testing phases. Fig. 2 shows our proposed model and all the phases of this study.

A. Data Acquisition

This step is basically collecting the required EEG signals from a live subject. Emotions are evoked in a volunteer by showing them images from the IAPS dataset. While viewing an image EEG signals are generated in the brain which are recorded by the help of electrodes placed on the scalp and by using BIOPAC, MP – 150 EEG recording device, this is a 4

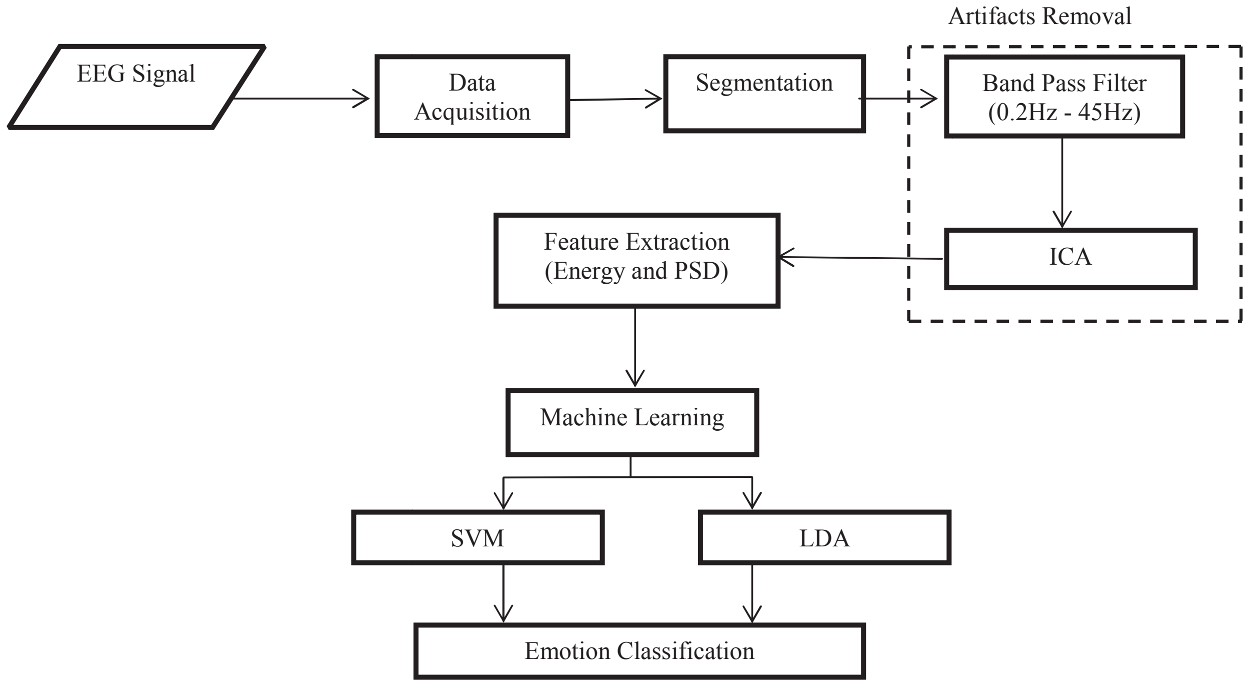

Fig. 2. Flowchart explaining the proposed model.

channel device with a sampling rate of 500 Hz.

We conducted this study on 32 healthy subjects. The participants were students who were 20 to 25 years old. Out of these 32, 14 were females and 18 were males. A typical Data Acquisition session lasted for about 20 minutes during which the subjects were given specific instructions about the complete process for the first 10 minutes and then the EEG recordings were made while showing the subjects emotion evoking stimuli. While recording the EEG the subjects were shown 5 images of each emotion (total 35 pictures for 7 emotions). One image of each emotion (total 7 images) was shown and each image was followed by a blank screen. This was followed by 7 sets of four images of each emotion and each set followed by a blank screen. The purpose of blank screen is to minimize the emotional contamination from previous emotion. There were 15 blank screens in total. The EEG signal for the complete session of a subject was recorded, which was later segmented into 35 different EEG signals corresponding to different images with the help of "AcqKnowledge 4.2 (software)", explained further in next section. Fig. 3 is a photograph of a subject while his EEG signals were being acquired, we can see him wearing the whole electrode setup.

Fig. 3. A subject wearing the electrodes, during Data Acquisition phase.

B. *Pre-processing*

- Segmentation: EEG signals were recorded for a total duration of around 590 seconds (per subject), this signal comprised of a total of 50 events, 35 corresponding to the EEG signals (8 seconds apiece) generated while viewing a picture and 15 were Greyed – Blank slides (15 seconds each). To separate these EEG signals segmentation process is done using the "AcqKnowledge 4.2 (software)".

- Band Pass Filter: The pattern of EEG signal spreads over the frequency range of 1-50Hz, comprising of various frequency bands namely Delta (1-4Hz), Theta (4-7Hz), Alpha (7-13Hz), Beta (13-30Hz) and Gamma (30-50Hz). In order to gather only the essential information from the gathered signals, we have filtered out the data by using a 0.2 - 45Hz band pass filter.

- Independent Component Analysis: This is a mathematical computational method which deals with removal of artifacts, which distort the recorded EEG signals by adding noise. ICA follows the principle of Blind Source separation and is used for separating a multivariate signal into its various sub-components. The recorded EEG signal can comprise of various disturbances. To perform ICA on an EEG signal, we used EEGLAB, a MATLAB toolbox. It is an open source environment and is freely available. Apart from various basic tools like filtering, windowing etc., this toolbox have a lot of distinct tools and features. EEGLAB is useful in performing ICA, in rejection of artifacts, time/frequency analysis, provides various modes of visualizing dynamic properties of components present in an EEG signal, etc. Fig. 4 gives the visual representation of the dynamic properties of independent components corresponding to all the four electrodes used (fp1, f3, p3 and o1). Here the red region represents muscle artifacts and blue region represents artifacts due to eye blinking.

C. Feature Extraction:

It is a type of dimensional reduction and is employed in applications like pattern recognition and image processing. When the size of input data is very large, it is prone to carry some unnecessary and irrelevant information. So to reduce the size of this data, we transform it into sets of feature. If performed correctly these feature sets should contain only the relevant information extracted from given input data and free from the redundant and irrelevant information. We have focused only on the Theta, Alpha and Beta frequency bands of the acquired EEG signals (i.e. 4–30Hz) and after the whole extraction process we were able to extract the following features from each EEG signals:

- Power Spectral Density
- Energy

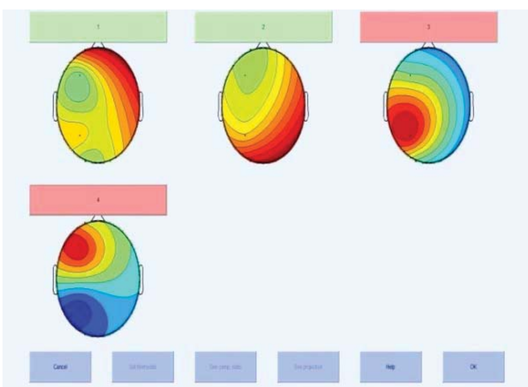

Fig. 4. Visual representation provided by EEGlab during ICA which helps in rejecting noisy components from the acquired signals.

D. SVM

-Training Phase: We extracted Energy and PSD as features from the acquired EEG signals. These features correspond to an already known emotion (images taken from IAPS database, used as a stimuli in data acquisition phase). So we train the SVM classifier using these features set against the known emotion matrix (referred as target matrix from here onwards), thereby formulating the emotions pattern which will then be used in testing phase.

We have taken features acquired from all the volunteers together and a known target matrix both of these taken together are used as an input of the SVM classifier.

- Testing Phase: In this phase we try to recognize the emotion using extracted features as an input to our model. We used the emotions matrix and target matrix to train the SVM. After training we use the test matrix (test set) as input to find the emotions corresponding to each input feature.
By comparing the result obtained with the known target matrix we calculate the accuracy.

E. LDA

Like the SVM classifier LDA classification also undergoes through training and testing phases.

-Training Phase: In the training phase the training set along with the extracted features are fed as input to the classifier and data points with similar frequencies are accumulated into different groups which is further transformed into 1-D Eigen vectors representing separate classes.

-Testing Phase: In the testing phase, the test matrix is fed to the classifier and Euclidean distance of the test data points with the Eigen vectors representing different classes is measured. The point which is closest to a particular Eigen vector belongs to that particular class.
Then accuracy is calculated by comparing the results with the known target matrix.

IV. Results & Analysis

Here we present results of the model implemented. First we will talk about the model where SVM and LDA are used as classifiers. The accuracy of each model is depicted and then their respective accuracies are compared. For each model the accuracy (Average and Best case) obtained in detecting each emotion is discussed in Fig. 5 and Fig. 6.

Before talking about the results it is important to understand the definition of accuracy. Each subject portrays a particular emotion corresponding to the image being shown to him/her. The purpose of the model is to accurately identify that emotion being depicted by the subject. Hence the accuracy discussed here is this ability of the model to correctly identify the emotions. This ability of the model varies from emotion to emotion.

Also it is important to know the true accuracy/error rate for a particular experiment. For this we use k-fold cross-validation. For our project we have used 4-fold cross-validation. In 4-fold cross validation the original dataset is divided into 4 equal sub sets. Out of these 4 sub sets, k-1, that is, 3 sub sets are used for training the classifier and 1 subset is used for testing the data.

One important thing to keep in mind is the accuracy obtained varies with the change in the training sample. For each set of training sample there will be a different set of accuracies. Here we will only talk about the maximum accuracy obtained for a particular training sample and average accuracy across different training samples. Total number of samples available for selection were 1120. Next we present the accuracy of the model:

A. SVM:

The maximum accuracy observed was 81.07%. This was obtained when the training samples used were 75% (840) of the total (1120). Overall the average accuracy observed was 74.13%.

B. LDA:

In case of LDA, the maximum accuracy observed was 72.14% when the training samples used were used were 75% (840) of the total (1120). Overall the average accuracy observed was 66.50%.

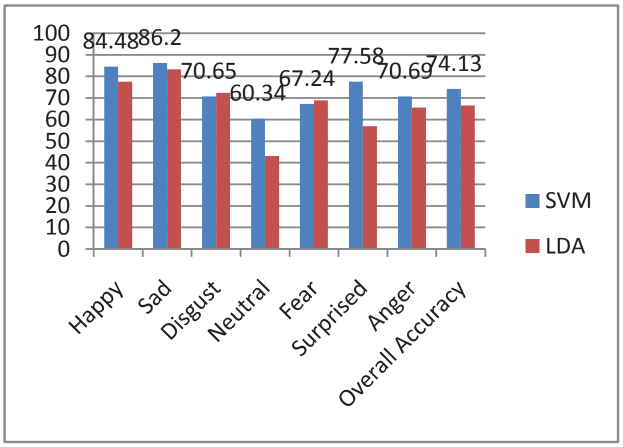

Fig. 5. Average Percentage Accuracy of the two Algorithms.

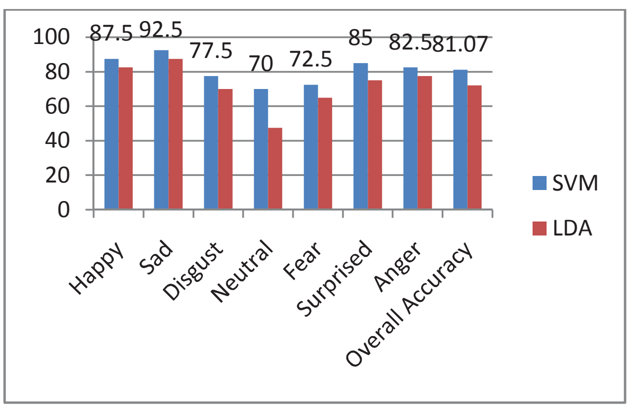

Fig. 6. Best Percentage Accuracy of the two Algorithms.

V. Conclusions

In this paper a model based on Independent Component Analysis, Support Vector Machine and Linear Discriminant Analysis is made. The general trend which is observed from the experimental results is that the accuracy increases with increase in number of training samples. From the class-wise accuracy analysis, it is observed that the Happy and sad emotions are recognized with best accuracy. SVM is able to recognize happy and sad emotions with an accuracy of 87.5% and 92.5% respectively whereas the accuracy fell to 82.5% and 87.5% respectively in the case of LDA. Also the SVM model is better as compared to LDA as a classifier.

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