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A Comparative Analysis of Emotion Recognition using DEAP Dataset

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***Abstract*—** Emotions play a crucial role in human communication and the Brain-Computer Interfaces (BCI) aid in emotion-based communication, similar to the way a mobile device aids in text-based communication. Emotions are expressed in myriad ways, including verbal, non-verbal and physiological signals. Most BCI systems accomplish this by using electroencephalography (EEG) signals. Before BCI systems are employed to practical use, efficient algorithms need to be developed in order to maximize efficiency. This paper proposes a method to map several emotional states using EEG signals collected from the publicly available Dataset for Emotion Analysis using Physiological signals (DEAP). It presents a comparative analysis of two different classification algorithms along with two different dimensionality reduction techniques. Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) are used in tandem with Support Vector Machine (SVM) and K-Nearest Neighbours (KNN). The objective of this paper is to weigh the results to find the most promising classifier and dimensionality reduction technique. The average accuracy of binary classification using KNN-LDA for each valence, arousal, dominance and liking was 97.98%, 96.21%, 98.24% and 96.19% respectively.

***Keywords*—** Emotion classification, EEG, Physiological signals, Signal processing, Pattern classification, Affective computing, DEAP Dataset, Machine Learning, Brain-Computer Interfaces (BCI), Electroencephalogram (EEG), Linear Discriminant Analysis (LDA), K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Principal Component Analysis (PCA).

I. INTRODUCTION

Emotions are one of the basic human traits. Even though no single definition of emotion is agreed upon by the experts, they shape nearly all the experiences in our lives. One feels happy when our favourite sports team wins, nostalgic when a song from our childhood is played, and angry when our possessions are harmed. Furthermore, these emotions strongly influence how a person responds to these events [1]. Emotions manifest in verbally through language, nonverbally through gestures, facial expressions, etc; and through physiological signals like electroencephalographic (EEG). There have been various attempts at classifying emotions. For both theoretical and practical reasons, emotions are defined according to one or more dimensions, for example, "pleasantness–unpleasantness" and "level of activation". These dimensional models of emotion interpret human emotions by describing where they lie in a multidimensional space. It indicates that a common and interconnected neurophysiological system is responsible for all affective states [2]. There are different models for classifying emotions, of which prominent ones include Russell's Circumplex model, Positive activation – negative activation (PANA) model and the vector model.

Recognising emotions is of use in a variety of purposes. Advertising industry works on eliciting an emotion related to a product for commercial benefits. The emotional reaction to products can help in better product design. Enhanced communication with other humans and machines are a possibility. Health care can exploit huge benefits from it, ranging from identifying various mental health disorders, effects of pharmaceutical drugs and can help identify relationships between physical and mental disorders.

With increasingly pervasive use of technology in our lives, brain-computer interfaces (BCI) are evolving to aid in much more comprehensive communications systems. BCI needs emotional intelligence, similar to a human. This can enhance human-computer interaction. As our knowledge of technology and emotions are improving, there are rising possibilities for use of emotion recognition systems. There are several successful studies on emotion recognition using text, speech, facial expressions or gestures as stimuli [3]. This paper focuses on the identification of emotions from EEG signals. The brain activity recorded using EEG provides non-invasive and passive measurement. It has been used extensively in cognitive neuroscience to analyse and investigate emotional states in the past decades.

The following sections illustrate our proposed classification methods for emotion recognition. In Section II, past research and work related to DEAP dataset and various machine learning techniques that were used are described. In section III, the description of dataset is covered. The detailed methodology for gathering the dataset and format is described. Section IV describes our proposed classification methods for emotion-recognition. Section V outlines the overall flow of research conducted for classification. Section VI illustrates the comparative results obtained for different classifiers and dimensionality reduction techniques used. Finally, in Section VII, we present the study's conclusions.

II. RELATED WORK

Emotions are known to have an important role in interaction and communication among people. In recent times recognition and classification of human emotions from Electroencephalogram (EEG) have led to the development of brain-computer interfaces which empowers computers in understanding human emotions. According to Plutchik [4], there are eight basic states of emotion as acceptance, anger, anticipation, disgust, fear, joy, sadness and surprise. Other emotions can be modelled using basic emotions like sadness and surprise make a disappointment. Garrett et al [5] in their paper compared the performance of linear and nonlinear classifiers for emotion classification. They observed that the nonlinear classifiers have superior performance. They obtained the average classification accuracy of 66% using Linear Discriminant Analysis (LDA), 69.4% using Neural Networks (NN) and 72% using Support Vector Machine (SVM). They have done this on a different dataset. Soleymani et al [6] in their paper used 32 channel electrodes to classify emotions based on valence and arousal values in response to video stimuli. The authors' calculated Power spectral density (PSD) from different bands using fast Fourier transform (FFT) and Welch algorithm and an SVM classifier with RBF kernel were employed to classify the samples using features from different modalities. They obtained the best classification accuracy of 68.5 % for valence and 76.4 % for arousal labels. Nivedha R et al [7] use feature selection using PSO. SVM classifier is used for classification. They experimented with different electrode combinations and observed that a good classification accuracy of 70.625% was obtained using a reduced set of 5 electrodes. A. S. Mali et al [8] develop music system which uses human emotions. Afzal Ahmad et all [9] review mood disorder prediction using machine learning.

III. DATASET DESCRIPTION

A multimodal dataset called the DEAP dataset for analyzing the human affective states is used [10]. It consists of EEG and other peripheral physiological signals collected from 32 healthy participants, aged between 19 and 32 (mean age 26.9), with an equal male to female ratio. Music videos were used to evoke emotions and the signals were recorded using a 32 channel BioSemi acquisition system at a sampling rate of 512 Hz. 32 Ag/AgCl electrodes were arranged according to the 10-20 international system. The participants are shown 40 one-minute long excerpts of these music videos. Participants subjectively rated their levels of arousal, valence, liking and dominance, and for 22 of the 32 participants, frontal face video is also recorded. The acquired signals were found to be distorted by eye blinking and muscular movements and thus were preprocessed. The signals were down-sampled to 128 Hz and a bandpass filter of 4-45 Hz was applied. EOG artefacts are removed using a blind source separation technique. Second harmonic of 50 Hz power line artefact is removed using a notch filter. The data was segmented into sixty-second trials and a 3-second pre-trial baseline removed. This segmented data free from all the artefacts are used.

IV. CLASSIFICATION METHOD

A. K- Nearest Neighbour

The K- nearest neighbour algorithm is one of the simplest supervised machine learning algorithms (non- parametric) which can be used to solve the problems such as regression and classification. A classification problem has a discrete value as its output and a regression problem has real value as its output. In K- nearest neighbour 'K' represents the number of training data points which will be considered for the classification of data points to a particular class. For each data points, the distance to the training data points is calculated. To find the nearest point different techniques are used such as:

1. Euclidean distance: The distance between two data points, say x and y using the formula given as

$$\sqrt{\sum_{i=1}^{k} (x_i - y_i)^2} \tag{1}$$

2. Manhattan distance: The distance between two points measured along axes at right angles.

$$\sum_{i=1}^{k} |x_i - y_i| \tag{2}$$

3. Minkowski distance: It is considered as a generalization of both the Euclidean distance the Manhattan distance.

$$(\sum_{i=1}^{k} (|x_i - y_i|)^q)^{1/q} \tag{3}$$

These distances of test data point to K nearest training data points are stored in a list and then voting for each class is done according to the distance measured. An object is classified by a majority vote of its neighbours, and the object is assigned to the class having the maximum vote. For the calculation of the distances between test data points to K nearest training data points Euclidean distance was used.

B. Support Vector Machines

Support vector machine (SVM) is one of the most popular supervised machine learning algorithms which can be used for the classification and regression problems in machine learning. The main purpose of the support vector machine algorithm is to find the optimized hyperplane in multidimensional space (multiple features) that helps to distinctly classify the data points. There may be many possible hyperplanes which can be selected but the objective is to find the hyperplane that has the maximum margin. The distance between the data points of both classes and the plane should be maximum. Maximizing the margin distance helps to classify the future data points more efficiently. SVM uses support vectors to select the optimized hyperplane. Support vectors are data points which are closer to the hyperplane and used to find the position and orientation of the hyperplane.

C. Linear Discriminant Analysis

Linear Discriminant Analysis is a supervised machine learning technique which can be used to avoid overfitting, where the machine learning model remembers all the training data including undesirable or unrelated features and the performance of the model highly decreases for the new dataset used. Reason for this overfitting is the too complex model. The model can be simplified using the feature selection algorithms. Features which are highly responsible for the classification should be used. In order to reduce the complexity of the model, dimension reduction plays an important role. Linear Discriminant Analysis projects the high dimensional dataset onto a lower dimensional space. LDA helps to reduce the dimensionality of the dataset while at the same time preserving the class discrimination. LDA finds the mean of each class and then it determines a new dimension which is an axis. The axis is created considering two parameters, first is the distance between the means and the second is the variation. The distance between the means of the classes should be maximum and the variation or scattering of the data points should be minimum.

D. Principal Component Analysis

Principal component analysis (PCA) is one of the most popular dimensionality reduction technique used in machine learning. It is used for linear dimension reduction. PCA can be used for feature elimination and feature extraction. Feature elimination is to remove some variable if they are redundant with some other variable. It is simple to implement and make our dataset small containing only variables which contribute to decision making.
Feature extraction is the formation of new variables using the old variables. PCA transforms the data by projecting it onto a set of orthogonal axes. It maximizes the variance of the dataset. It uses eigenvalues and eigenvectors of the covariance matrix, which is equivalent to fitting those principal components lines to the variance of the data. The line of variance is determined in the dataset which is called as the principal component. First principle component has the maximum variance, second having second maximum variance and so on. The first 20 components were used in our analysis. As the variance of the higher components were very small.

E. Russell Circumplex Model

Emotion classification is done so that different emotions can be distinguished from one another. This classification of emotion can be done using two approaches, first is that emotions are discrete and different second is that emotions can be classified on a dimensional basis of grouping. In a discrete emotion approach, only six emotions are considered to be basic. Six basic emotions are surprise, sadness, fear, happiness, disgust, and anger. Dimensional models of emotion classify emotions by defining them in two or three dimensions. Two-dimensional model mainly uses valence and arousal as its dimensions. Russell circumplex model is based on a two-dimensional approach.

The circumplex model of emotion was developed by James Russell [11]. Russell Circumplex model tells us how different emotions are related to each other. This model shows a unique relationship within a visual framework. To show the entire range of emotion two-dimensional circular model was used, in this emotion were divided into quadrants with arousal and valence as a crossed axis. The Vertical axis is represented by arousal and the horizontal axis is represented by valence. In this circular model, emotional states can be represented as a combination of arousal and valence. This model was selected because all the emotional states can be demonstrated along with their relative relationships also different emotions are equally spaced to show uniformity and precision.

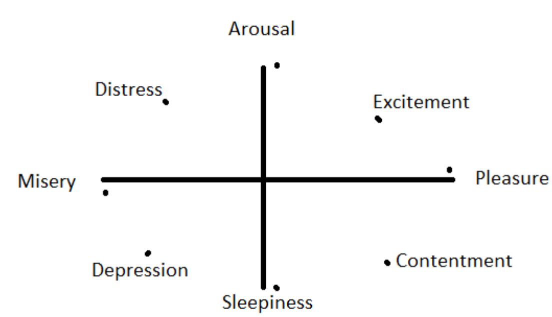

Fig. 1. A graphical representation of the circumplex model of affect with the horizontal axis representing the valence dimension and the vertical axis representing the arousal or activation dimension. [9]

V. FLOWCHART FOR EMOTION CLASSIFICATION

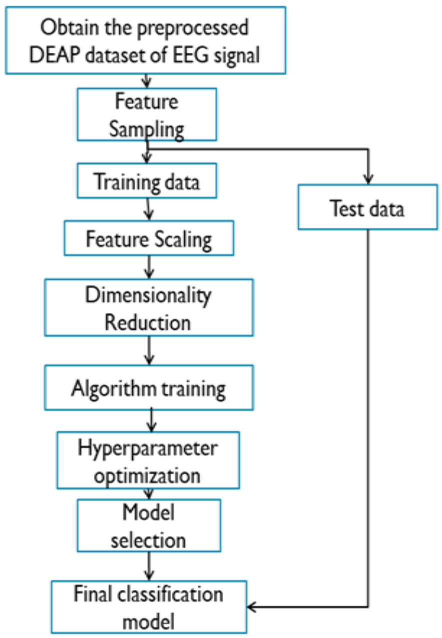

Fig. 2 Flowchart for emotion classification.

The first step was to obtain the publicly available DEAP dataset for emotion analysis. Feature sampling is done to reduce the number of features. The values of all the electrodes for one min are used as features and the number of features was too large therefore the features are downsampled. After this one hot encoding was done for each label valence, arousal, dominance and liking. All the four labels were encoded that is if the value was more than 4.5 then it was replaced by one. If the value was less than 4.5 then it was replaced by zero. Next, the whole dataset was divided into two parts that are test data and train data. This is done so that the performance of the model can be generalized for the new test set. Then feature scaling was done so that the mapping of input and output is proper. Feature scaling is done using StandardScaler, that is it will transform the data such that its distribution will have a mean value zero and standard deviation of one. After this the dimensionality reduction technique was applied, namely, Linear Discriminant Analysis and Principal component analysis are used. Cross-validation technique was applied for measuring the skill of the model for an unseen dataset. In this process the whole dataset is shuffled randomly then the dataset is split into k groups. Now for each group, the dataset was split into test data and train data. Then fit the model on the training set and evaluate it on the test set. Different classifiers are paired with different dimensionality reduction techniques. Simple KNN, simple SVM, SVM with PCA, KNN with PCA, SVM with LDA and KNN with LDA are applied. In the next step hyperparameters for the different algorithms were tuned. Hyperparameters are the parameters which are external to the model and whose value is not estimated from the data. Hyperparameters are specified by the users and there is no fixed formula to calculate its value. The Final model was selected with maximum accuracy and the four labels were classified as high valence and low valence, high arousal and low arousal, high dominance and low dominance and high liking and low liking. After this, the Russell circumplex model was applied and according to the valence and arousal level classification of emotion was done as happy, depressed, nervous and relaxed.

VI. RESULTS

Different classification algorithms with different dimensionality reduction technique were applied to the DEAP dataset. Simple KNN and SVM without dimensional reduction were applied. Different combinations of classifiers and dimensionality reduction techniques were applied. The results are summarised in table 1.

TABLE I. RESULTS FOR CLASSIFICATION OF ACCURACY FOR DIFFERENT EMOTIONAL STATES USING DIFFERENT CLASSIFIERS.

	Accuracy (in %)			
	Valence	***Arousal***	***Dominance***	***Liking***
KNN	56.64	56.25	67.58	65.23
SVM	63.44	64.86	67.66	67.19
SVM – PCA	64.87	64.3	69.58	64.07
KNN – PCA	53.52	58.59	68.75	69.53
SVM – LDA	97.64	97.16	98.35	95.84
KNN – LDA	99.61	97.27	99.60	96.87

Hyperparameter tuning was done in which accuracy for each value of K - neighbours in KNN-LDA was calculated, varying the value of k from 1 to 60. Graph of accuracy score versus K- values for valence, arousal, dominance and liking is shown in fig 3: (a), (b), (c) and (d).

Maximum accuracy was obtained with KNN classifier with LDA for dimensionality reduction, which was found to be 99.61% for valence, 97.27% arousal, 99.60% liking and 96.87% for dominance labels.

Accuracy score for Russell circumplex model that is the classification of emotions like happy, nervous, depressed and relaxed based on valence and arousal level was 83.59%.

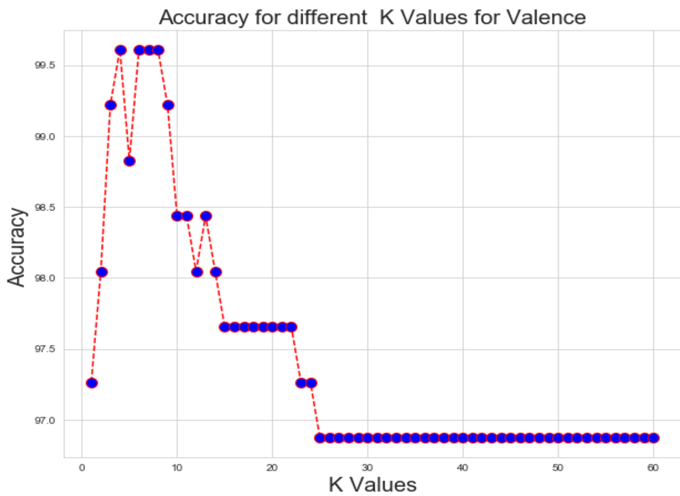

Fig. 3(a)

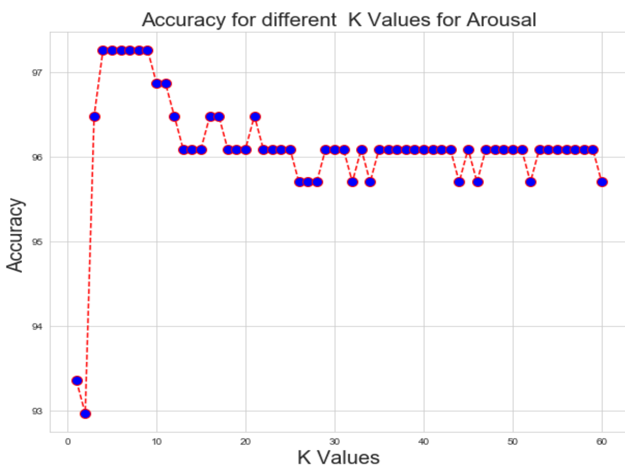

Fig. 3(b)

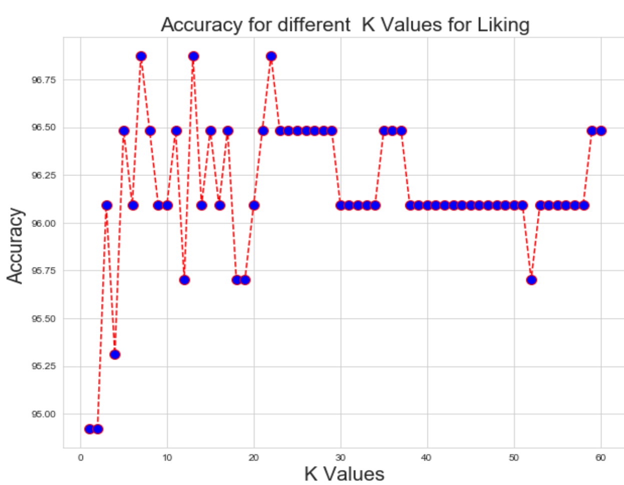

Fig. 3(c)

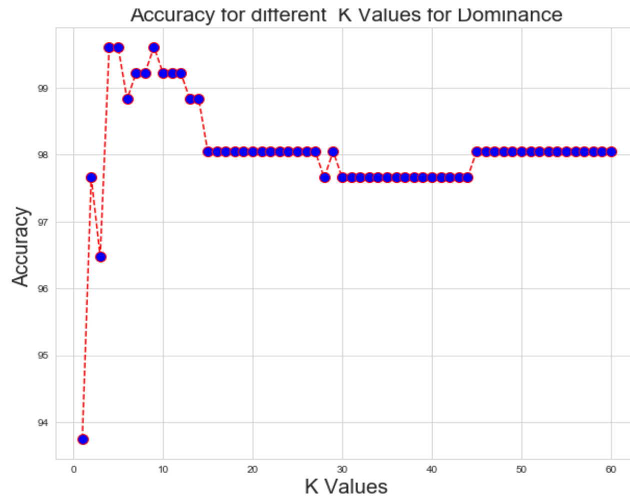

Fig. 3(d)

Fig. 3. Shows the graph of accuracy versus K-values for Valence, Arousal, Dominance and Liking respectively.

TABLE II. -RESULTS FOR CLASSIFICATION OF BINARY CLASSIFICATION OF VALENCE, AROUSAL, DOMINANCE AND LIKING USING KNN CLASSIFIER WITH LDA FOR DIFFERENT K VALUES (1-60).

Emotion	**Accuracy**		
	Maximum	***Minimum***	***Average***
Valence	99.61	96.87	97.98
Arousal	97.27	92.96	96.21
Dominance	99.60	93.75	98.24
Liking	96.87	94.92	96.19

VII. CONCLUSION

The pre-processed EEG signals from the DEAP dataset are classified into four discrete emotional states based on Russell's circumplex model. The comparative analysis of various combinations namely, SVM, SVM-PCA, SVM-LDA, KNN, KNN-PCA and KNN-LDA gave some interesting insights. Vanilla classifiers (without dimensionality reduction), SVM and KNN, gave the least performance, as was expected. LDA gives considerably better performance than PCA, in case of both the classifiers. This is due to the fact that LDA also takes class separability into account, in addition to variance, while reducing dimensionality.

KNN-LDA gave the highest performance heuristically. It can be seen that changing the neighbours can highly affect classification accuracy. After a certain value (k=35), the accuracy does not change much. Optimizing the numbers of neighbours is needed to maximize the performance of the model. The core element of this paper is LDA which optimizes the classifier thus providing higher classification accuracy.

In future more efficient feature extraction algorithm can be developed for improving the emotional classification. This model can be extended to implement some applications like to predict and explain employee Attrition, Brain-Computer Interface, Mental State detection, controlling devices, automatic music player control depending upon a person's emotions, etc.

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