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Emotion Recognition in EEG Data using Machine Learning

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Abstract- Understanding and classifying human emotions in electroencephalography (EEG) data has fascinated a large group of research community and human computer interaction in particular. In this article, various machine learning algorithms are explored for classifying human emotions such as positive, neutral and negative from EEG data. Thesealgorithms are applied to a publicly available EEG dataset comprising of 2 subjects, 3 different emotions with 2100 data samples acquired. The proposed model is trained and tested using different machine learning algorithms and finally tabulated the results of prediction values obtained using different classifiers. Experimental results demonstrate the performances of various machine learning algorithms in classifying human emotions.

Keywords – emotion recognition, EEG, classification, machine learning.

I. INTRODUCTION

Emotion recognition can be defined as a process of extracting and realizing the current state of human mind. Significant amount of research has been carried out due to its wide variety of applications in the field of Brain Computer Interface (BCI), computational neuroscience, cognitive and medical sciences, in recent years [3].

II.PROPOSED ALGORITHM

In this section, conventional and most effective machine learning techniques such as Naïve Bayes, Logistic regression, SVM & KNN are explained in detail.

A. Naïve Bayes-

This algorithm is based on Bayes theorem. It is an algorithm that helps structure a faster machine learningmodel that can predict faster. A classification is a probability, which means that from the probability of an event, we can predict or assume the occurrence of a known event without the occurrence of other characteristics. The Gaussian model is assumed that its features follow the concept of normal distribution. Meaning that the model takes values from the Gaussian distribution, if the continuous predictors take discrete values.

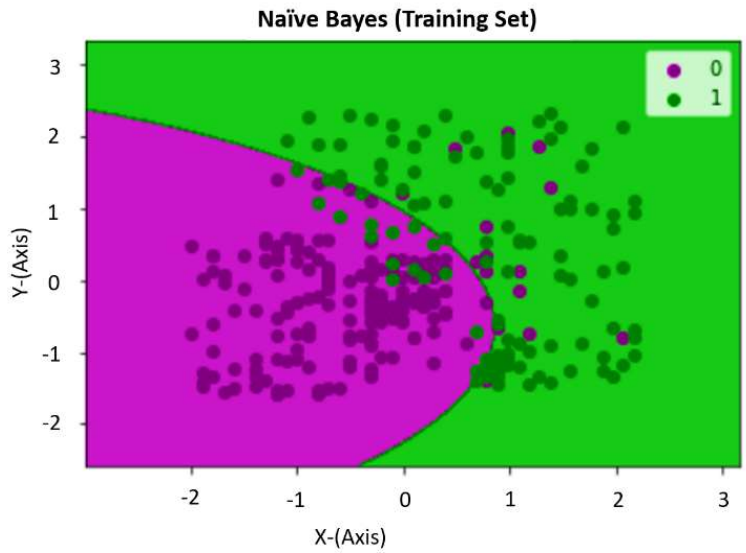

Figure 1: Naïve Bayes

1) *Conversion of the given dataset into frequency tables.*
2) *Generate a feasibility table by finding the probabilities of the given features.*
3) *Calculate the posterior probability,by using Bayes theorem. P(A|B) =*

$$\frac{P(B|A)P(A)}{P(B)} \quad (1)$$

B. Logistic Regression-

It is a predictable analysis algorithm which works on the concept of probability. It uses a more complex cost function, and its cost function can be referred to as the "sigmaoid function". Its hypothesis aims to reduce the cost function between 0 and 1. The horizontal axis represents the value of x and the vertical axis represents the probability of a particular classification. Apply the distribution y|x from the Bernoulli distribution. The linear model is given by y = ax + b. This function reduces the range of y to 0 to 1. This ML model can assign probabilities and insert new points using continuous and discrete data.

$$Y = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + \ldots + B_nX_n \quad (2)$$

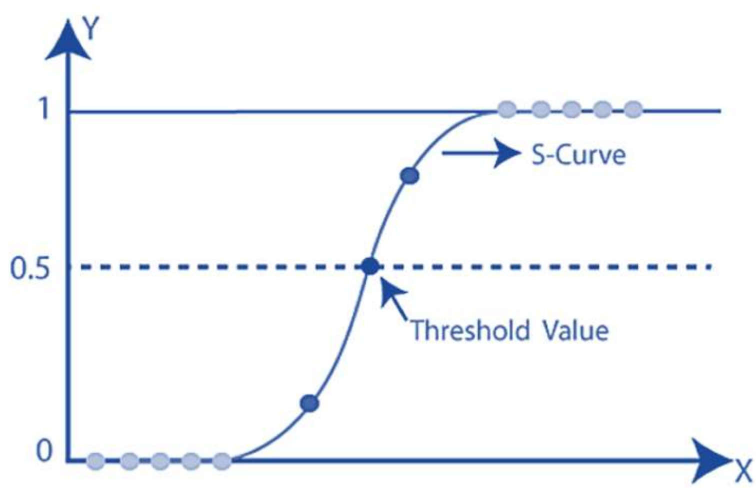

Figure 2: Logistic Regression

1) *Data Pre-processing*
2) *Fit Logistic Regression to the training set*
3) *Predict the test result*

4) *Create confusion matrix and test accuracy of the result*

C. Support Vector Machine (SVM):

A hyperplanein an N-dimensional space (N-number of features) that uniquely classifies data points, is chosen to separate the two classes of data points. A level having the maximum margin(H)between the data points of both categories is chosen. Support vectors are the points closest to the hyperplane that affect the orientation as well as the position of the hyperplane which can maximize the classifier margin. These points contribute to form the SVM.

1) *Pre-processing of data*
2) *Fit the SVM classifier to the training set*
3) *Predict the test result*
4) *Create the Confusion matrix & test the accuracy of the result.*
5) *Visualize test result.*

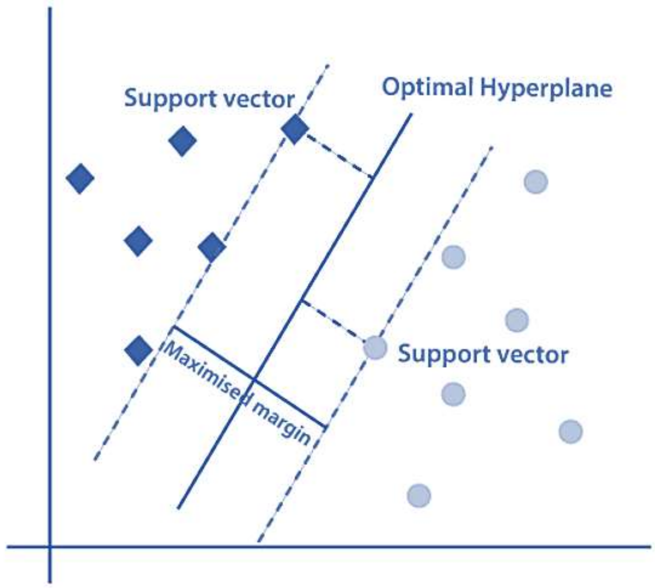

Figure 3: Support Vector Machine(SVM)

D. K-Nearest Neighbor (KNN):

It assumes similarity between the available point and new point and situates the new pointto that which comes closest to the available categories. This algorithm works by storing all the available data and then classifies or categorizes a new data point based on its similarity.

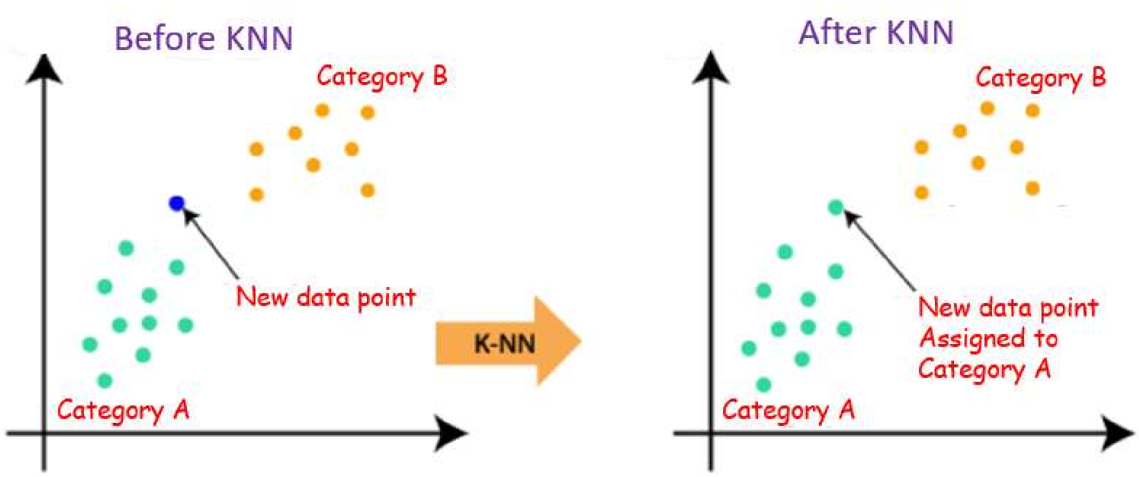

Figure 4: K-Nearest Neighbours(KNN)

1) Choose the number of neighbors
2) Calculate the Euclidean distance between the given points.(The Euclidean distance is the distance between two points).
3) Categorize the new data point based on the closest distance from the available categories.

By calculating the Euclidean distances,the closest neighbours near category A and B were found. As we can observe that, many neighbours are closer to category A, so this new data is assigned to category A. Euclidean Distance between A_1 and B_2 is given by

$$= \sqrt{(X_2-X_1)^2+(Y_2-Y_1)^2} \qquad (3)$$

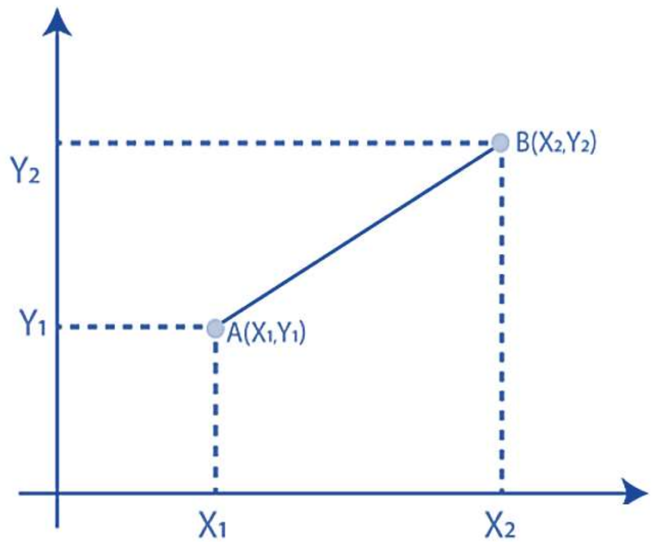

Figure 5: Plotting of data points from the categories

III. EXPERIMENT AND RESULT

Since emotions can be detecting using EEG signals the BCI technology can be due to emotions transforms the EEG signals produced by the brain into control signals which can be later recognized. Here we are going to use non-invasive detection of EEG signals to provide an extra dimension of detection between user and device. There are 3 stages involved in this methodology:

- Data collection
- Pre-processing
- Feature extraction and classification

Initially, we are going to acquire data. A subject is asked to wear a NIC2 EEG headband with a resolution of 4 electrodes. Positive and negative emotional states are invoked using film clips along with resting data for neutral state, with no stimuli involved, is recorded, all for one-minute per session. After acquiring raw EEG data, this data has to be pre proceed to acquire only useful data and also to filter any noise. Statistical extraction of brain waves alpha, beta, delta, gamma and theta waves are transformed to generate a large dataset, then it is reduced to small datasets by feature detection and ensemble classifiers such as random forest. A train and test ratio of 80:20 has been applied on the dataset by substituting as parameters in the ML algorithms

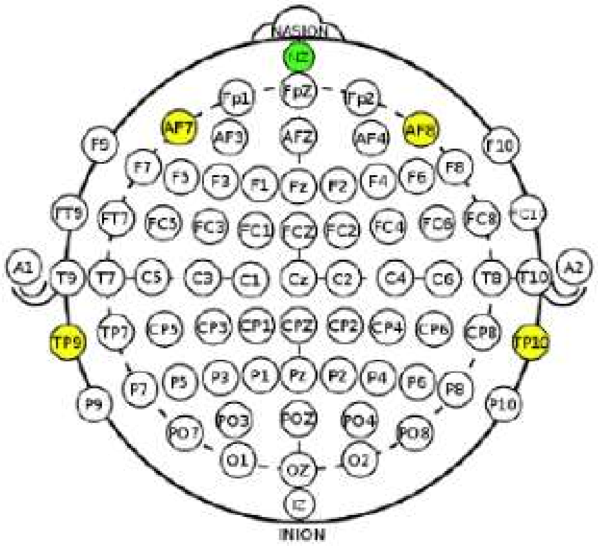

Figure 1 : EEG electrode placement (AF7, AF8, TP9 & TP10) of the Muse headband based on the international standard EEG placement system

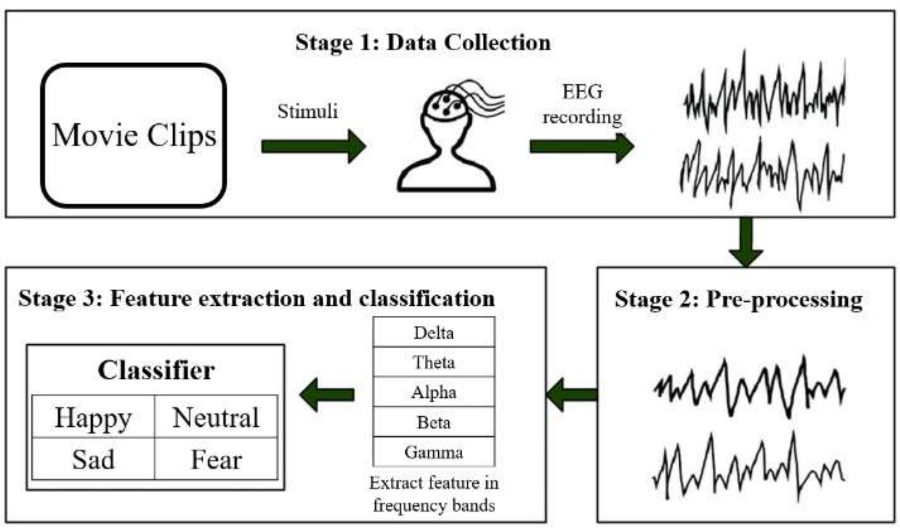

Figure 7: Experimental Procedure of Emotion Recognition using EEG signals.

TABLE I. RESULT OF DIFFERENT ML TECHNIQUES ON INDIVIDUAL PRE-PROCESSES (MALE & FEMALE)

	COR-F	COR-M	COVMAT-F	COVMAT-M	EIGN-F	EIGN-M
LOG REG	**65.34**	**66.51**	**86.42**	**78.69**	**66.28**	**68.38**
SVM	**70.56**	**71.03**	**74.9**	**71.73**	**69.5**	**69.03**
KNN	**93.61**	**94.08**	**92.26**	**92.55**	**81.7**	**80.18**
GNB	**56.72**	**56.72**	**50.21**	**47.16**	**45.28**	**45.92**
AVG	**71.5575**	**72.085**	**75.9475**	**72.5325**	**65.69**	**65.8775**

	ENTROPY-F	ENTROPY	STD	STD-F	MOMENT	MOMENT-F
LOG REG	**59.25**	**62.06**	**80.56**	**81.73**	**53.16**	**58.78**
SVM	**65.69**	**64.22**	**94.96**	**95.01**	**47.98**	**52.2**
KNN	**73.96**	**61.88**	**96.48**	**95.84**	**86.22**	**80.18**
GNB	**64.57**	**63.05**	**47.57**	**46.86**	**42.87**	**41.58**
AVG	**65.8675**	**62.8025**	**79.8925**	**79.86**	**57.5575**	**58.185**

	MIN	MIN-F	MEAN	MEAN-F	MAX	MAX-F
LOG REG	**90.16**	**89.7**	**88.76**	**89.46**	**74.71**	**77.05**

SVM	**97.24**	**96.72**	**93.14**	**93.9**	**88.27**	**87.98**
KNN	**93.96**	**94.66**	**96.66**	**96.72**	**85.69**	**85.57**
GNB	**66.98**	**71.85**	**83.34**	**82.93**	**54.78**	**54.66**
AVG	**87.085**	**88.2325**	**90.475**	**90.7525**	**75.8625**	**76.315**

	LOGM	**LOGM-F**	**FFT**	**FFT-F**	**LOGM**	**LOGM-F**
LOG REG	**82.9**	**83.84**	**86.18**	**85.01**	**82.9**	**83.84**
SVM	**92.38**	**92.38**	**97.3**	**96.72**	**92.38**	**92.38**
KNN	**81.35**	**81.23**	**96.6**	**96.6**	**81.35**	**81.23**
GNB	**74.31**	**74.25**	**71.73**	**70.15**	**74.31**	**74.25**
AVG	**82.735**	**82.925**	**87.9525**	**87.12**	**82.735**	**82.925**

TABLE II. AVERAGE RESULTS OF DIFFERENT ML TECHNIQUES

	COR	**COVMAT**	**EIGN**	**ENTROPY**	**STD**	**MOMENT**	**MIN**	**MEAN**	**MAX**	**LOGM**	**FFT**	**AVG**
LOG REG	**65.925**	**82.555**	**67.33**	**60.655**	**81.145**	**55.97**	**89.93**	**89.11**	**75.88**	**83.37**	**85.595**	**76.133**
SVM	**70.795**	**73.315**	**69.265**	**64.955**	**94.985**	**50.09**	**96.98**	**93.52**	**88.125**	**92.38**	**97.01**	**81.038**
KNN	**93.845**	**92.405**	**80.94**	**67.92**	**96.16**	**83.2**	**94.31**	**96.69**	**85.63**	**81.29**	**96.6**	**88.09**
GNB	**56.72**	**48.685**	**45.6**	**63.81**	**47.215**	**42.225**	**69.415**	**83.135**	**54.72**	**74.28**	**70.94**	**59.704**
AVG	**71.821**	**74.24**	**65.783**	**64.335**	**79.876**	**57.871**	**87.658**	**90.613**	**76.088**	**82.83**	**87.536**	

IV.CONCLUSION

The main goal of this article is to demonstrate the use of appropriate ML technique for emotion recognition in EEG signals. KNN technique outperforms the other algorithms and seems to be promising while handling higher ordered data enabling an efficient detection of emotion categories.

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