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Visual Task Classification using Machine Learning Algorithms with the help Breakout Game

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Abstract **Brain Computer Interface (BCI) research is growing now a days in many domains like gaming, health, marketing, advertising, performance measurement and enhancement etc. Games provide controlled environment to get the desired electroencephalogram (EEG) data till some degree. Many games that have easy controls are used for the research purpose like breakout, tennis, etc. These games have limited functionalities like left or right, up or down movement. In this paper breakout game have been used for data collection of 12 subjects and machine learning algorithms applied on this data to identify to the task (left or right) in subject's brain. Task in the game is to control the block movement, that move left or right at a time. Block movement is controlled by using EEG data and algorithms have been applied to calculate the distance in left or right direction. After data collection, Common Average Reference (CAR) is used for preprocessing and passed data to Decision Tree Classifier (DTC), K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) Classifier for classification task. Result shows that KNN is having highest accuracy in comparison to DTC and SVM.**

Keywords **—Brain Computer Interface (BCI), Common Average Reference (CAR), Decision Tree Classifier (DTC), Electroencephalogram (EEG), K-Nearest Neighbor (KNN), Support Vector Machine (SVM).**

I. INTRODUCTION

Brain computer interface is an interdisciplinary research domain that include psychology, neurology, rehabilitation engineering, machine-man interaction and signal processing. Now BCI could be used to command a machine to perform particular task by a paralyzed or healthy subject [1], [2]. Single task related research has been developed in early years like lift of an object, increasing speed, changing of colour according to the concentration or attention level [3], [4], [5], [6]. In this kind of work, attention or concentration EEG data is used, that is provided by EEG devices like Neurosky Mindwave, Emotiv Epoc. These devices provide different data channels like delta, theta, alpha, beta, and gamma. Tennis game is implemented by using only attention value that change the player location from bottom to top or top to bottom. Finding average attention value of healthy subject just by displaying attention value on screen. Blasting of an object if player is able to sustain at a particular attention level. All these are good examples for single task assignment but multiple task classification is not the same as single task [7], [8], [9] and in case of multiple task example are very few for EEG data. Labelling or classification is really difficult by using classical algorithms [10], [11], [12] but after the machine learning algorithms becoming popular, this thing has been relatively easy. Several machine learning algorithm are used for classification according to data size and domain of data [13], [14], [15], [16]. In this work we have used decision tree classifier, k-nearest neighbour and support vector machine classifier for classification of data in two classes [17], [18], [19], and [20]. This paper is divided into 6 sections. First section is introduction and second section is problem statement that describe about objective behind the work. Further third section is experiment setup and game, for data collection from different subjects has been discussed. Data and its pre-processing has been discussed in fourth section. In this order fifth section discuss about machine learning algorithms like DTC, KNN and SVM. Results has been discussed in sixth section and followed by conclusion.

II. PROBLEM STATEMENT

Visual task is really import in the scenario when real application developed is concerned for the physically disabled person like switch on/off any appliance in home environment or office environment. Even if healthy person want to use these application the same concept work. Entertainment or gaming domain is the domain where healthy and physically disabled person can participate and get benefitted from this domain. In this order we have used breakout game, in which a block movement is there, according to the attention value received from neurosky mindwave EEG headset. Our objective in this scenario is

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that how to classify or label the data between two classes that are left and right. Low alpha, high alpha, low beta and high beta EEG channels data is used in this work. Remaining channels are not suitable for this work because some of them are for sleep state, serious on high concentration state and that is not required in this scenario. Using all these things as problem basis, data has been collected from 12 subjects and machine learning algorithms are applied on this data for best classification. Each subject gone through a session for the purpose of data collection and objective of each player is to hit the block with ball, so only option is move block either left or right. Manual labeling is done on the data to prepare the dataset. Initially DTC, KNN and SVM algorithms are used for classification purpose. These algorithms are most commonly used for the purpose of classification in machine learning.

III. EXPERIMENT SETUP

International 10-20 system is used for the placing of electrodes on subject's brain as shown in figure 1. Neurosky mindwave EEG headset has been used in this work to take data from subject's brain.

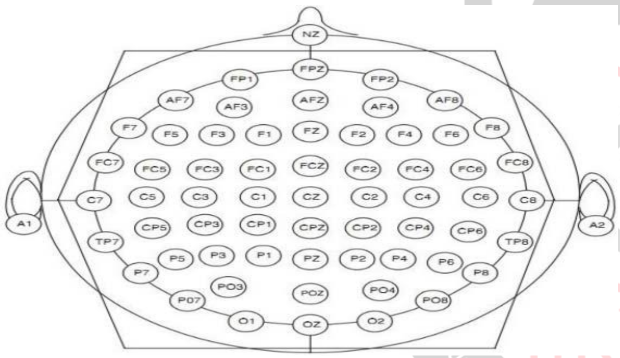

Fig.1 10-20 international system of electrode placement

Attention is primary value in the breakout game so subjects is focusing on the left or right direction so that he/she can score high [25], [26], [27], [28]. High attention by focusing on left or right direction gives us suitable data for our purpose of classification. Fp1 is the location in 10-20 electrode placement to take the data from brain by using mindwave EEG headset.

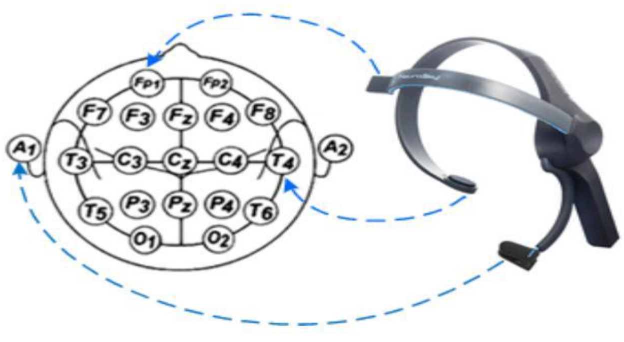

Fig.2 NeuroSky Mindwave headset electrode positioning based on 10-20 international system of electrode placement

Multiple frequency bands are provided by mindwave like delta, theta, alpha and beta from 0 to 50 Hz frequency. Delta varies from 0.1 to 3 Hz. Theta have the range from 4 to 7 Hz and 8 to 9 Hz is for alpha1 or low alpha frequency range. High alpha is in the range of 10 to 12 Hz. As like alpha, beta also having low beta and high beta varies from 13 to 17 and 18 to 30 Hz respectively as shown in Table 1.

Table 1: Neurosky mindwave EEG frequency band

EEG signal Type	Frequency Range (in Hz)
Delta	0.1-3
Theta	4-7
Low Alpha	8-9
High Alpha	10-12
Low Beta	13-17
High Beta	18-30
Low Gamma	31-40
High Gamma	41-50

Low frequency band provide data for the deep, dreamless sleep and theta beta is suitable to read data for imagination, fantasy and recall. Alpha and beta are suitable for our purpose because they provide data for relaxed but not drowsy state, thinking, aware of self and surrounding. Breakout game is used in this work after the going through literature work by gauttam j. and et. al. Figure 3 shown the breakout game layout, that have left and right label as shown.

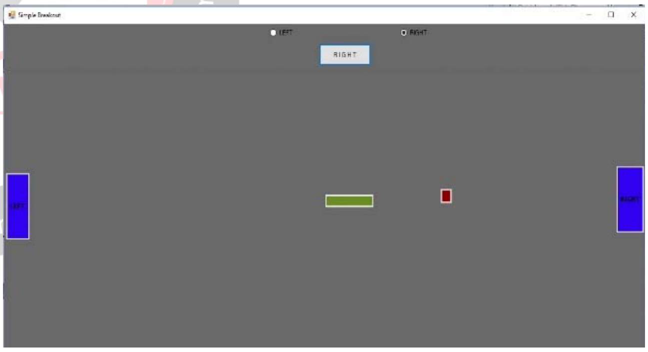

Fig.3 Breakout game layout

Initially subject settled down on chair in relaxed mode and EEG headset is placed on the head. Game is started on the computer screen and an alert is generated for the subject/player to play the game. Subject attention is received by the system and block is controlled with help of it. In between this process windowing based threshold (WBT) technique is applied on attention values. WBT algorithm pass this value to control the movement of block. Radio buttons are used to control the direction of block like left radio is selected then movement of block will be in left direction and same is true for right direction. In both the cases how much block will move is decided by the attention value that is received after the WBT processing on it. Objective of the player is to hit the block and ball, as ball is

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moving random from left to right, right to left, top to bottom and bottom to top in combination for a particular time period. The same process has been repeated for 12 subjects. Low alpha, high alpha, low beta and high beta channels data has been stored in separate file for each subject. All the subjects are healthy in the age group of 22-30 years old. Educational background of all the subject is technical education and a few instruction are given to them before the start of the game.

IV. Data and its Preprocessing

EEG data contains artifacts and that needs to be minimized. Common Average Reference (CAR) has been applied on data to reduce the artifacts effects [21], [22], [23], [24]. Common Average Reference (CAR) is used to overcome the effects of artifacts. CAR simple model can be described by using the following equation 1.

$$d_{k,t} = s_{k,t} + w_k * n_t \qquad \text{eq. 1}$$

Where k=1, 2,… k, $d_{k,t}$ is the recorded signal at time t from channel k. $s_{k,t}$ is expected signal and w_k is the coefficient and n_t is the artifacts. It takes input sample, one by one and sample average is used as global reference.

$$\hat{s}_{k,t} = d_{k,t} - \hat{n}_t \qquad \text{eq. 2}$$

where

$$\hat{n}t = \frac{1}{k}\sum_{k=1}^{k} d_{k,t} \qquad \text{eq. 3}$$

w_k is same for all for each channel.

$$\hat{n}t = \frac{1}{k}\sum_{k=1}^{k}(s_{k,t} + w_k * n_t)_{\approx} nt \qquad \text{eq. 4}$$

After preprocessing data passed to different machine learning algorithms. Four channel data has been used for this work and data behavior is shown in figure 4.

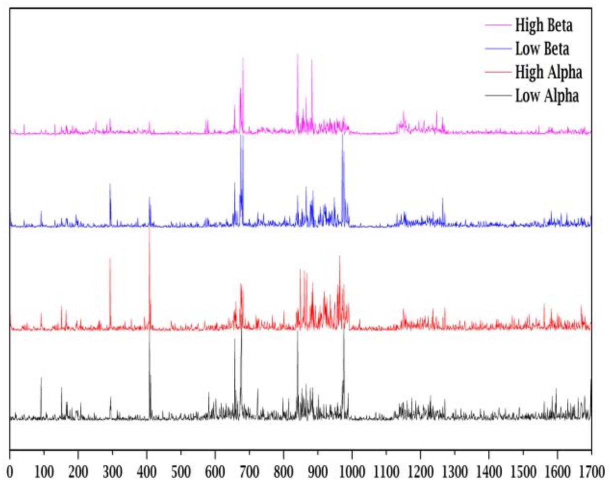

Fig.4 Complete Dataset

Common high values at 450, 650, 850 and 990 in figure 4 as it represents complete dataset that is further divided into training and testing data.

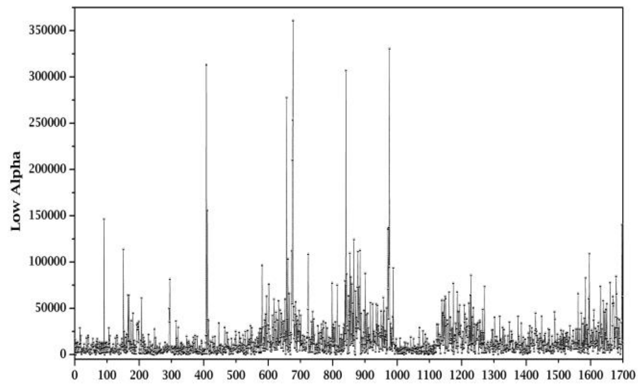

Fig.5 Low Alpha

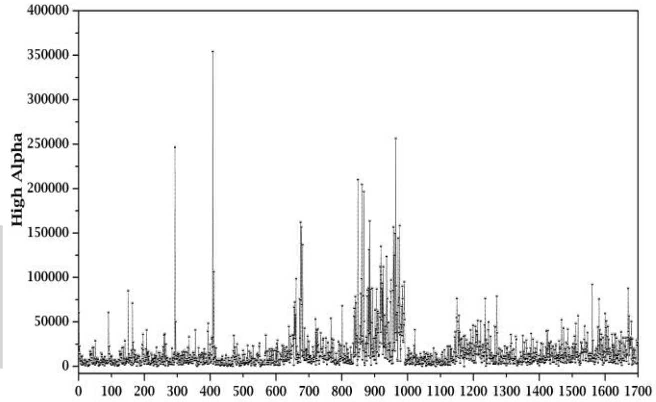

Fig.6 High Alpha

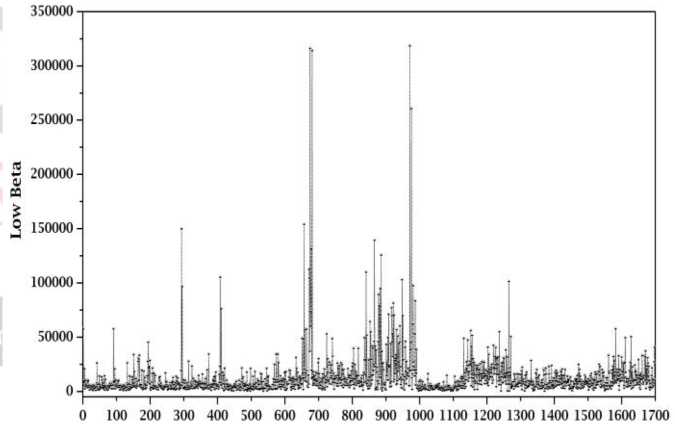

Fig.7 Low Beta

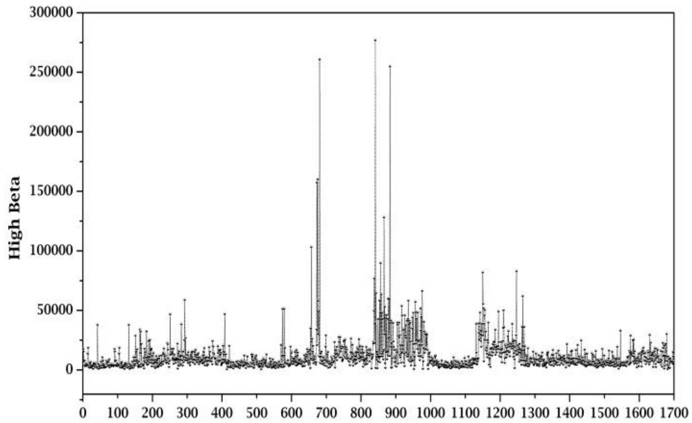

Fig.8 High Beta

Analysis on figure 4 describe that at point 650 and the range 850 to 1000, all channels giving very high values in

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comparison to remaining points and having similar behavior. Figure 5 represents the low alpha channel that show high value at points 400, 700 and the range 850 to 1000. In the similar manner figure 6 represents high alpha channel and high value at points 300, 400 and the range 850 to 970. Figure 7 represents the low beta channel and high value at points 300, 650 and the range 850 to 1000, continuously in the order figure 8 represents high beta and high value at 650 and the range 850 to 900. These high values indicates either artifacts effect or sudden response for particular time instance.

V. MACHINE LEARNING ALGORITHMS

Machine learning algorithms are used in many domains. Supervised and unsupervised are two major categories in machine learning algorithms. In this paper we have used Decision Tree Classifier (DTC), KNN (K-Nearest Neighbor) and SVM (Support Vector Machine) for the purpose of classification on brain data under the category of supervised machine learning algorithm.

1. Decision Tree Classifier

A Decision Tree is a Supervised Machine Learning algorithm which looks like an inverted tree as shown in figure 9, wherein each node represents a predictor variable (feature), the link between the nodes represents a Decision and each leaf node represents an outcome (response variable).

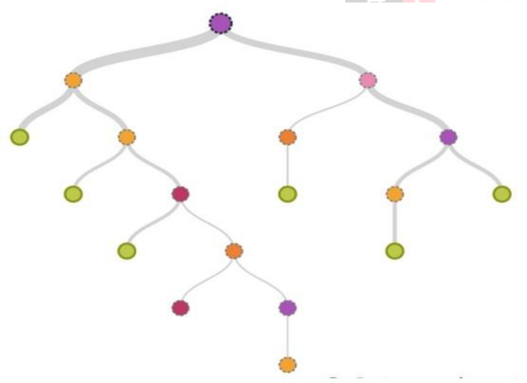

Fig.9 Decision Tree Classifier

The Decision Tree Algorithm follows the three steps:

Step 1: Select the feature (predictor variable) that best classifies the data set into the desired classes and assign that feature to the root node.

Step 2: Traverse down from the root node, whilst making relevant decisions at each internal node such that each internal node best classifies the data.

Step 3: Route back to step 1 and repeat until you assign a class to the input data.

2. K-Nearest Neighbor

KNN makes predictions using the training dataset directly. Predictions are made for a new instance (x) by searching through the entire training set for the K most similar instances (the neighbors) and summarizing the output variable for those K instances as shown in figure 10. For regression this might be the mean output variable, in classification this might be the mode (or most common) class value.

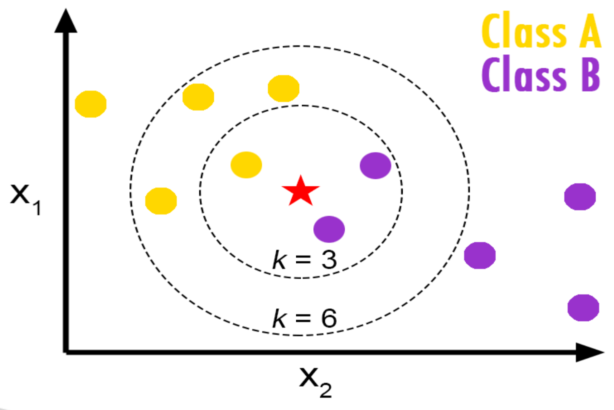

Fig.10 K-Nearest Neighbour

To determine which of the K instances in the training dataset are most similar to a new input a distance measure is used. For real-valued input variables, the most popular distance measure is Euclidean distance.

3. Support Vector Machine

In SVM, a hyperplane is selected to best separate the points in the input variable space by their class, either class 0 (yes/no) or class 1(yes/no) as shown in figure 11.

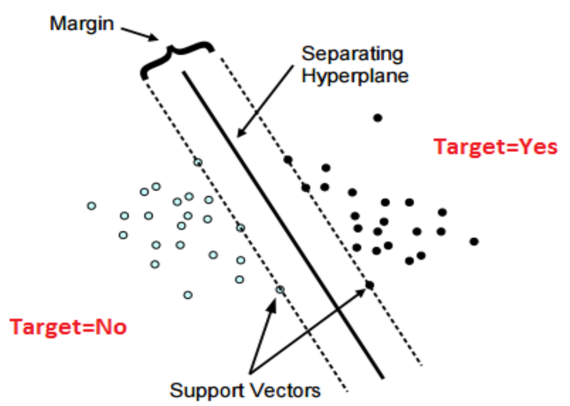

Fig.11 Support Vector Machine Classifier

In two-dimensions you can visualize this as a line and let's assume that all of our input points can be completely separated by this line.

For example:

$$B0 + (B1 * X1) + (B2 * X2) = 0 \quad \text{eq. 5}$$

Where the coefficients (B1 and B2) that determine the slope of the line and the intercept (B0) are found by the learning algorithm, and X1 and X2 are the two input variables. You can make classifications using this line. By

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plugging in input values into the line equation, you can calculate whether a new point is above or below the line.

Above the line, the equation returns a value greater than 0 and the point belongs to the first class (class 0). Below the line, the equation returns a value less than 0 and the point belongs to the second class (class 1). A value close to the line returns a value close to zero and the point may be difficult to classify.

VI. RESULTS

EEG data was divided into two sections as per requirement of machine learning algorithms. The ratio of training data and test data is 70:30. Test data is chosen from three different slots so that we can get actual result that can be used further for analysis. Test data is visualized in figure 12.

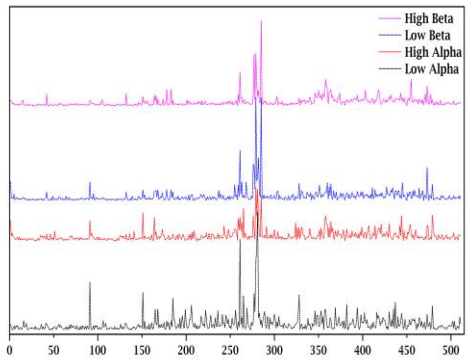

Fig.12 Test Data

Analysis on test data indicates that nature of test data and full data is similar.

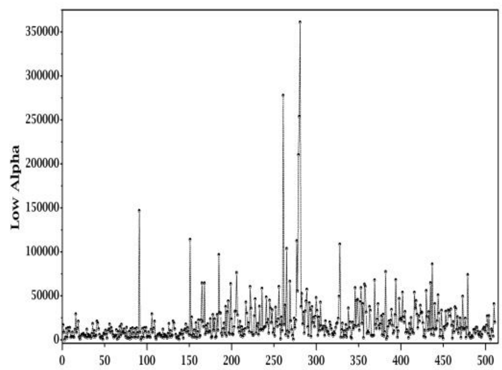

Fig.13 Low Alpha Test Data

Test data also contains high value in the range of 250 to 300. Similar behavior can be observed in all channels. Low alpha test data figure 13 indicates clearly that at data point location 260 and 270 are having high value, in the same order at some more point's high values can be observed like at 100, 150 and near to 200.

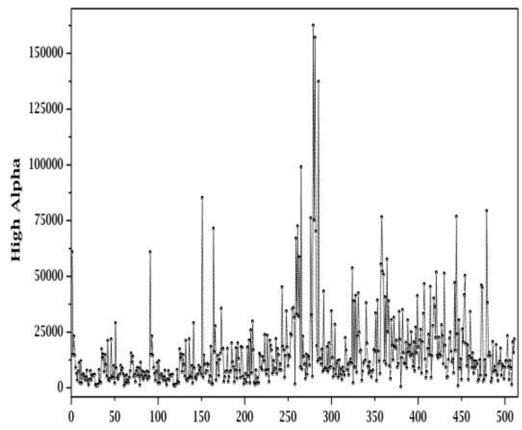

Fig.14 High Alpha Test Data

High alpha test data is visualized in figure 14 and high values are observed at locations 260, 270, 150, 360 and some more. Among all these data points, 270 location is having highest value as the same thing is visualized in test data graph of four channel.

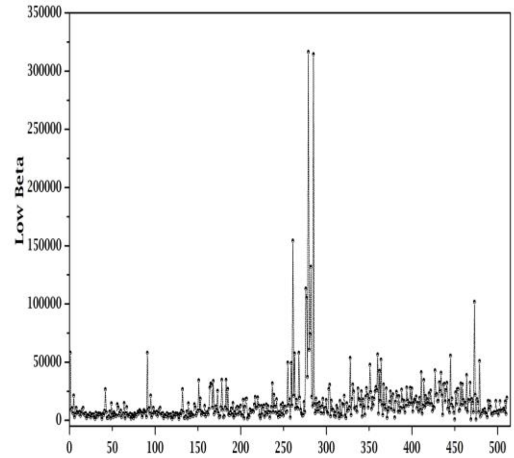

Fig.15 Low Beta Test Data

Low beta test data is presented in figure 15 and location range 260 to 280, indicates very high value. Location near by 480 and 100, also indicates some high value. High beta test data is presented in figure 16 and similar nature of test data is there. In the range of data point's location 260 to 280 very high value are observed. Some locations are having similar value like 180, 320, 460 and 260.

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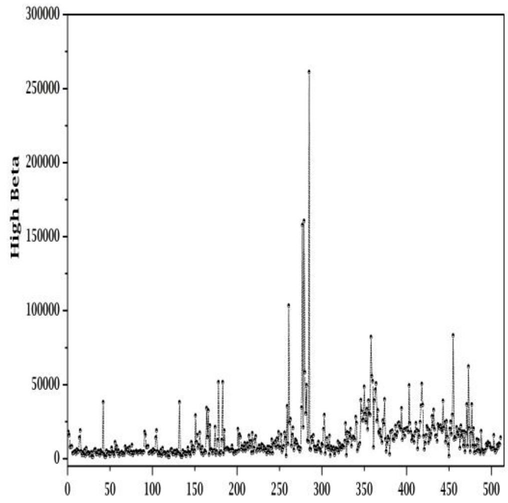

Fig.16 High Beta Test Data

Training and test data are same for all three algorithms. Results are presented in figure 17 of DTC, KNN and SVM algorithm for brain data classification into two classes either left or right.

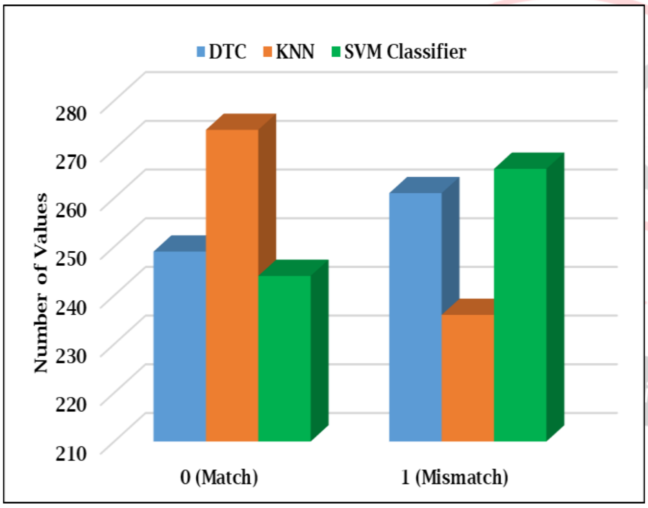

Fig.17 Result Comparison between DTC, KNN and SVM

Label 'LEFT' and 'RIGHT' were used to state the class of data. O (match) states that result is same as in the test data for that data point and 1 (mismatch) states that result is different from test data. As an example 'LEFT' label is there for some data point in test data and 'LEFT' label is there in result data then it is the case of 0 (match) and if the result label is 'RIGHT' then it is the case of 1 (mismatch) and vice versa it is also true. DTC results are there in blue color and observation on them indicates that mismatch case are more in comparison to match cases, and accuracy of this algorithm is 48.8%. KNN results are there in orange color and observation on them indicates that match cases are more in comparison to mismatch cases and accuracy of the algorithm is 53.7%. SVM results are there in green color and observation on them indicates that match cases are less in comparison to mismatch cases and accuracy of the algorithm is 47.8%.

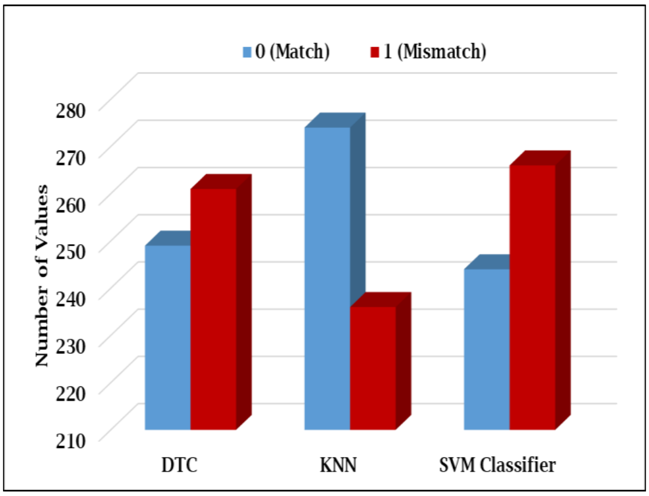

Fig.18 Accuracy graph for DTC, KNN and SVM

Accuracy graph is shown is figure 18 that have match and mismatch for DTC, KNN and SVM Classifier. Blue color bar represents match cases and red color bar represents mismatch cases. DTC accuracy is 48.8%, KNN accuracy is 53.7% and SVM accuracy is 47.8%. Analysis on them suggest that KNN is giving best result among DTC, KNN and SVM classifier. DTC and SVM are giving less than 50% accuracy that why these two algorithm are suggested for the classification or labeling of EEG data. KNN is performing well on this EEG data and having highest accuracy among these is 53.7%.

VII. CONCLUSION

This paper discussed about BCI and its role in different domains that further include visual task classification problem on EEG data. EEG data further processed by using machine learning algorithms like DTC, KNN and SVM after passing through CAR. Dataset was generate by using neurosky mindwave EEG headset from 12 subjects by playing breakout game. Data further divided into two sections training data and test data. Results from all three algorithms stated that KNN is giving better result over DTC and SVM, with accuracy 53.7%, 48.8% and 47.8% respectively.

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