**BTP REPORT**

**1.ABSTRACT**

This research work is about Electroencephalogram Brain Signal Processing for Chromatic Visual Impression Identification.

We conducted two types of experiments-

1.Bi-color: differentiate the brain signals from red and white color shown to the subject.

2.Tri-color: differentiate the brain signals from red, green and blue color shown to the subject.

as frontal, occipital and parietal lobe are more sensitive to and responsible for visual stimuli therefore we used fp1, fp2, p3, p4, o1, o2, c3, c4 lobe of headset of OpenBci device in both the experiments for collecting the visual stimuli through brain signals.

Data pre-processing is done by applying common average referencing, scaling factor, 50 hz notch filter, 0-40 band pass filter.

Some of the significant features we extracted from pre-processed data are statistical, DCT, Wavelet, bandpower, firstDiffMean, firstDiffMax, secDiffMean, secDiffMax, hjorth, maxPwelch.

Then Feature selection was done by experimenting on each possible combination of these.

Then different models we used for training with each of these features combination are Linear SVM, RBF SVM, Random forest, LDA, Decision tree, Gaussian NB, K-neighbour classifier, Adaboost classifier.

Highest accuracy of Bi-color experiment is 98.66%(when Random forest was trained with only DCT features)

Highest accuracy of Tri-color experiment is 72.56%(when K-neighbour classifier was trained with only Wavelet features)

This research work has pretty good application as if we are able to discriminate two different colors then we can use this as two control commands for controlling any dedicated computer application further It has also many applications in interior design, product development by visualizing psychological features of the brain activity.

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**2. INTRODUCTION**

The EEG is an electrophysiological technique for the recording of electrical activity from the human brain. By placing electrodes on the scalp, one can record these signals. EEG signals are mostly multicomponent and noisy signals. raw EEG signals do not provide useful information alone, and dedicated signal analysis is therefore required to extract relevant information contained within the signal and therefore Choosing suitable signal analysis method is a crucial step when extracting information from EEG data. Brain-computer interface (BCI) systems are able to record, analyse and transform electroencephalography (EEG) or bio-signals into computer data so that researchers can observe the signal.

The context of our research work is to use efficient pre-processing and features extraction techniques to differentiate the brain signals featuring (2 for first experiment and 3 for second experiment) colors using Electroencephalogram Brain Signal Processing. This research work has pretty good application as if we are able to discriminate two different colors then we can use this as two control commands for controlling any dedicated computer application further It has also many applications in interior design, product development by visualizing psychological features of the brain activity.

We conducted two types of experiments-

1.**Bi-color:**

The aim is to differentiate the brain signals from red and white color shown to the subject.

The data from 2 girls(between ages of 20-25) was taken in 3 sessions in total. in each session, 50 times(red or white) color was shown for 5 sec each with a baseline of 3 sec. in general total time of each session is 5.66 minutes.

as frontal, occipital and parietal lobe are more sensitive to and responsible for visual stimuli therefore we used fp1, fp2, p3, p4, o1, o2, c3, c4 lobe of headset of OpenBci device in both the experiments for collecting the visual stimuli through brain signals.

As we know raw EEG signals do not provide useful information therefore first of all we did data pre-processing as follows-

(Raw data -> common average referencing -> scaling factor -> 50 hz notch filter -> 0-40 hz band pass filter)

Then Some of the significant features extracted from pre-processed data are statistical, DCT, Wavelet, bandpower, PCA, CSP features.

Then Feature selection was done by experimenting on each possible combination of these. (there are total 18 feature selection combination)

2.**Tri-color:**

The aim is to differentiate the brain signals from red blue or green color shown to the subject.

From previous research , it is noteworthy that, three of the primary colors exhibit clearer complexity changes than the other colors in the spectrum. This supports the reasoning behind the usage of Red, Blue and Green in most of the studies in this field.

The data from 7 subject((between ages of 20-25),(6 males, 1 female)) on which was taken in 3 sessions in total.

in each session, 75 times(red,green or blue) color was shown for 5 sec each with a baseline of 3 sec. in general total time of each session is 10 minutes.

As frontal, occipital and parietal lobe are more sensitive to and responsible for visual stimuli therefore we again used fp1, fp2, p3, p4, o1, o2, c3, c4 lobe of headset of OpenBci device in both the experiments for collecting the visual stimuli through brain signals.

As we know raw EEG signals do not provide useful information therefore first of all we did data pre-processing as follows-

(Raw data -> common average referencing -> scaling factor -> 50 hz notch filter -> 0-40 hz band pass filter)

Some of the significant features we extracted from pre-processed tri-color data are statistical, DCT, Wavelet, bandpower, firstDiffMean, firstDiffMax, secDiffMean, secDiffMax, hjorth, maxPwelch.

Then Feature selection was done by experimenting on each possible combination of these. (there are total 3 feature selection combination we used)

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-Further as a result,

Highest accuracy of Bi-color experiment is 98.66%(when Random forest was trained with only DCT features)

- Highest accuracy of Tri-color experiment is 72.56%(when K-neighbour classifier was trained with only Wavelet features)

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**3. LITERATURE REVIEW**

I read these 11 papers to expand my knowledge related to this experiment and adapt any efficiency and techniques provided by these papers.

**PAPER NAME:** Analysis of brain activity and response to colour stimuli during learning tasks: an EEG study.

**AUTHOR NAME:** Raffaella Folgieri, Claudio Lucchiari, Daniele Marini

**PUBLISHING YEAR**: 2013

**SUMMARY**

The experiment is about analysing EEG data collected through BCI device from a sample of students during which they received visual stimuli based on colour variation of the text shown and its background on the screen and comes to the conclusion that which color has greater impact on remembering the words.

they organized four experimental sessions:

1. black words were shown on complementary and primary color backgrounds.
2. Primary and complementary colors words shown on white background.
3. Primary words shown on on primary background, complementary color shown on complementary background.
4. primary word shown on complementary or vice versa.

behavioural and EEG signal analysis was done.

As BCIs collect several cerebral frequency rhythms : Alpha,Beta,Delta,Theta,Gamma. The Pearson correlation index and the intra band synchronization index has been computed for all band couples and for each participant.

Finally as a conclusion the cyan background in the first experimental session, blue color words in the second experimental session, the red/blue blue/red combination, the cyan/magenta combination in the fourth experimental session had a greater impact on remembering the words.

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**PAPER NAME:** Brain response to color stimuli: an EEG study with nonlinear approach.

**AUTHORS NAME:** Souparno Roy, Archi Banerjee, Chandrima Roy, Sayan Nag, Shankha Sanyal, Ranjan Sengupta, Dipak Ghosh

**PUBLISHING YEAR**: 2021

**SUMMARY**

this paper attempts to explore the neural responses of the brain response change corresponding to each individual color of the VIBGYOR shown.

the corresponding EEG signals were analysed using two of the latest state of the art non-linear techniques (MFDFA and MFDXA) of dealing complex time series.

a comparative analysis of the multifractal spectral width using MFDFA technique and multifractal cross correlation coefficient using MFDXA technique was done for different pairs of experimental conditions, where each pair consists of a color from VIBGYOR and the adjacent grey just appearing before that particular color (for example, Violet—Grey1 or Green—Grey4).

Similarly, to identify the changes among the response from different electrodes corresponding to a particular color, a comparative study of spectral widths and cross-correlation was done for different electrode pairs.

Among all the electrode pair combinations some were from the homologous brain regions which in turn reflected the hemispheric differences in the neurona responses for a particular experimental condition, while the other electrode combinations indicated the nature of connectivity or correlations between different lobes of human brain during viewing a color.

As a result MFDFA revealed that for all the participants the spectral width, and the complexity of the EEG signals, reaches a maximum while viewing color Blue, followed by colors Red and Green in all the brain lobes.

MFDXA, on the other hand, suggests a lower degree of inter and intra lobe correlation while watching the VIBGYOR colors compared to baseline Grey, hinting towards a post processing of visual information.

the areas in the brain that are traditionally related to visual perception are Frontal and Occipital lobes, but their have indicated that Parietal lobe too plays key role in visual information processing.

The value of spectral width from their experiment is maximum in case of Blue, followed by Red and then Green. For all the subjects on which experiment was done.

From this research , it is noteworthy that, three of the primary colors exhibit clearer complexity changes than the other colors in the spectrum. This supports the reasoning behind the usage of Red, Blue and Green in most of the studies in this field.

F8, O2 and P4 has the highest complexity among the Frontal, Occipital and Parietal electrodes, respectively. So, the even electrodes show higher complexity than odd electrodes, which is an indicator that in our experimental setup, the long range correlations found during color perceptions are higher in the right hemisphere in the brain.

the complexity measures changes to Frontal > Occipital > Parietal.

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**PAPER NAME:** Analysis of Visual color perception using EEG spectral features.

**AUTHORS NAME:** *Paulraj* M P1, *Abdul Hamid Adom',* Hema *C R2, Divakar Purushothaman'*

**PUBLISHING YEAR**: 2012

**SUMMARY**

In this paper, a simple BMI system based on EEG signal was proposed based on the brain signal’s response on visualization of 8 colors (black, blue, cyan, green, magenta, red, white, yellow) was done.

The proposed MBI uses the color visualization tasks(CVT) and aims to provide a communication link using brain activity control signal.

EEG brain signals were recorded using Mindset-24 topographic neuro-mapping instrument is also called as 1.5 to 34 hz data acquisition system.

For each FFG signal, using spectral analysis, alpha, beta and gamma band frequency statistical spectral features such as spectral energy, mean spectral energy and standard deviation spectral energy are obtained.

The extracted features we then used to train the probabilistic neural network model.

As a result Visualization of classification accuracy of these three features (spectral energy, mean spectral energy and standard deviation spectral energy) individually are done.

MSE features performed well as compared to SE and SDSE features

This work has pretty good application for individual suffering from paralysis, quadriplegics, amyotrophic, lateral sclerosis brain stem stoke, and spinal cord injury to drive computers directly by brain activity rather than physical means.

As a conclusion, The proposed BMI using CVT is new in the development of BMI and it will be easy to implement, hence it involves less mental stress and no need of special training to control the BMI.

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**PAPER NAME:** Classification of color imagination using Emotiv EPOC and event-related potential in electroencephalogram.

**AUTHORS NAME:** Je-Hun Yu, Kwee-Bo Sim

**PUBLISHING YEAR**: 2016

**SUMMARY**

In the experiment. In the experiment, the subjects gaze at a non-flicker visual stimulus of color (i.e., red, green, blue, white, and yellow) and then proceed to imagine the color.

In the experiment, the subjects gaze at a non-flicker visual stimulus of color (i.e., red, green, blue, white, and yellow) and then proceed to imagine the color.

The flickered visual stimulus was made using an Arduino microcontroller board and LEDs with the purpose of prompting color imagination.

As a result,they obtained significant EEG responses of thoughts related to certain colors. The EEG response is classified using classification algorithms including a support vector machine (SVM) with linear discriminant analysis (LDA), an artificial neural network (ANN) with LDA, and an ANN without LDA.

they propose a method that classifies EEGs using non-flicker visual stimuli and EEGs when imagining a color.

Ten healthy volunteers participated (males: 10, age: 23–27) in this experiment. Only three subjects had previously participated in research involving any type of BCI system. Each subject was instructed to focus his sight on a fixed LED when the LED was on, and to imagine the LED color when hearing a beep from the speaker. Before the LED is turned on, the subjects have a rest period of 5 s.

The red LED is then turned on for 5 s, followed by another 5 s rest period, followed by 2 beeps with an interval of 7 s. During this period, the subject is asked to imagine the red color of the LED. The entire cycle, which is repeated 5 times in the following color progression: red, green, blue, white, and yellow.

a band pass filter was applied to the EEG data to avoid noise and distortion. The range of the filter is 1–30 Hz, which includes alpha and beta waves.

Additionally, linear discriminant analysis (LDA) was used to maximize the variance between the classes.

51.5%. In the case of ANN without LDA, the classification rate was greater than 61.5%. In addition, electrodes T7 and F4 have high values in the results of all classifiers.

The results of this research showed that, using a person’s simple perception of a basic color, a machine can recognize the person’s thoughts.

With further research and experiments, it will be possible to assist paralyzed individuals and the elderly using this technology. Thus, color imagination has the potential to be adopted in medical institutions and public areas.

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**PAPER NAME:** Classification of EEG from Black Color Stimuli to Command a Remote-Controlled Car: Ongoing Study.

**AUTHORS NAME:** Gerson Guillermo ∗, Bryan De Lama†, Christian Flores∗

**PUBLISHING YEAR**: 2023

**SUMMARY**

This paper presents a pilot study to use the black color stimuli and resting state to wirelessly control a remote-controlled car.

Power Spectral Density (PSD) was calculated on EEG signals to extract features and Multilayer Perceptron (MLP) was proposed to classify the EEG features using a 5-fold cross validation.

Their results reported that best score classification was on 100% for Delta band using six electrodes.

In this work, the dataset was recorded from a healthy subject aged 23 years old during he develops two mental activities i.e Sat in a comfortable chair during watching a black image (color stimuli) and resting condition with eyes-closed.

An acoustic stimulus indicates the beginning of the trial and a message was displayed for 1s to indicate the mental activity . After that the EEG data was recorded during 10 seconds per trial. According to protocol of the experiment consist of 3 sessions with 20 trials each which was separated by break of 3 minutes. In summary, 60 trials were recorded from 3 sessions and 30 trials for each task.

Six dry electrodes (FC6, P8, O2, O1, P7 and T7) we used.

As a preprocessing, An Elliptic filter of order five was used to filter twice (once forward and reverse) the EEG data to remove phase distortion effects and eliminate the artifacts.Then the analysis of the pass band spectral range of 1 − 4Hz (Delta), 4−8Hz (Theta), 8−15Hz (Alfa) and 15−30Hz (Beta) was done. Then The order of bandpass filter was calculated to obtain a -30 dB for frequencies 0.5 Hz.

As a feature extraction they calculated a Spectral Power Density (PSD) over each trial, brain band and electrodes to characterize EEG signals. Then they created two approaches of raw features: (i) five higher peaks of PSD (5-PSD) and (ii) five higher peaks of PSD and five higher peaks of histogram with 20 bins from PSD (5-Hist-PSD). These new parameters represent the features of each mental activity so feature extraction process converted EEG data into a new data set.

In the training process, A supervised learning called back propagation algorithm is used to training the Multilayer Perceptron (MLP) which is feedforward Artificial Neural Network (ANN).

In this work, MLP was used to classify EEG data related to two mental states. Different topologies with two-layer hidden were tested and we selected the best topologies. For both layers hidden, the numbers of neurons were calculated by means of all combinations since 5 until 100 neurons in multiples of 5 neurons.

In the testing process, The training processes of MLP was carried out in a computer using MATLAB and testing data was converted into commands to control our Arduino car.

The testing data were processed in MATLAB and the outputs were sent by means of bluetooth to Arduino plataform.

As future work, different color stimuli and mental states to control remote-controlled car will be explored and tested.

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**PAPER NAME:** Decoding visual colour from scalp electroencephalography measurements.

**AUTHORS NAME:** Jasper E. Hajonides, Anna C. Nobre, Freek van Ede, Mark G. Stokes

**PUBLISHING YEAR**: 2021

**SUMMARY**

Human scalp electroencephalography (EEG) and magnetoencephalography (MEG) are sensitive to synchronous activity in large neural populations, thus providing a macroscopic readout of brain activity.

This study is about to track visual colour processing by using Linear Discriminant Analysis on patterns of EEG activity. Building on other recent demonstrations, we show that colour decoding: (1) reflects sensory qualities (as opposed to, for example, verbal labelling) with a prominent contribution from posterior electrodes contralateral to the stimulus, (2) conforms to a parametric coding space, (3) is possible in multi-item displays, and (4) is comparable in magnitude to the decoding of visual stimulus orientation.

This work showed that while colour decoding can be sensitive to subtle differences in luminance, our colour decoding results are primarily driven by measured colour differences between stimuli. Colour decoding opens a relevant new dimension in which to track visual processing using scalp EEG measurements, while bypassing potential confounds associated with decoding approaches that focus on spatial features.

they showed that colour decoding is possible from scalp EEG measurements.

Building on this related recent work, we have now shown that this colour decoding reflects visual processing with a clear posterior-contralateral topography; that it conforms to a parametric colour-coding space; that it is possible in multi-item display; and that it is comparable to the decoding of stimulus orientation.

This opens a relevant new dimension in which to track visual processing using scalp EEG measurements.

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**PAPER NAME:** Discriminating Different Color from EEG Signals using Interval-Type 2 Fuzzy Space Classifier

**AUTHORS NAME:** Arnah Rakshit, Rimita lahiri

**PUBLISHING YEAR**: 2016

**SUMMARY**

This study employs four color stimuli; e.g. red; green; yellow and blue; that were shown to various subjects and EEG signal corresponding to the mentioned stimulus was acquired.

Power spectral density of each color was estimated and different activation areas of brain for each

Stimulus.

This paper also employs an Interval-Type-II fuzzy space classifier for distinguishing between different stimuli that are considered for the concerned experiment.

Neuro-marketing plays a vital role here; according to Lee. et al. neuro-marketing is a study discipline that concerns about application of neuroscientific procedure for analysing and understanding human psychology related to marketing.

the paper introduces the colour perception as new tool of neuro-marketing.

According to some studies; it has been found that colour perception of human brain is mainly caused due to activation of lingual and fusiform gyri situated in occipital lobes and further information about the color is processed in left inferior temporal; left frontal and left posterior parietal cortices.

As EEG signal is stochastic in nature; therefore uncertainty is always associated with it. Fuzzy logic has been applied here to take of the uncertainty. Type 1 Fuzzy space classifier uses a single membership function to represent variation in signal but EEG response evoked for same stimulus for same subject is different for different time; therefore

Type 2 Fuzzy space classifier employing secondary membership value has been used here. Interval Type 2 Fuzzy classifier uses constant and uniform secondary membership function [13].

context EEG signal has been acquired for four different colour stimuli and Power spectral density has been estimated by Welch method. Extracted features have been classified by IT2FS classifier.

Results showed that red color is the most responsible for mental arousal and cognitive activity followed by green; blue and yellow color.

It has got highest accuracy of 85.26% in case of red.

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**PAPER NAME**: Effects of colour towards underwear choice based on electroencephalography (EEG)

**AUTHORS NAME:** Fitri Aprilianty, Mustika Sufiati Purwanegara, Suprijanto

**PUBLISHING YEAR**: 2016

**SUMMARY**

The purpose of this paper is to investigate whether colours as stimuli can affect underwear choice based on consumers’ EEG recording as biological response to reveal preferences towards underwear products.

Twenty underwear buyers were asked to evaluate several underwear colours (red, white, blue, brown, grey and black) by using wireless EEG headset with 6 channels to collect EEG signals from participants’ frontal, temporal and occipital brain areas that can give us a measure to estimate consumers’ choice.

The result indicated there was a clear and significant change (p < 0.05) of EEG brain waves activities of right and left hemisphere in the frontal (F3 and F4), temporal (T7 and T8), and occipital (O1 and O2) brain areas when participants indicated their preferred colour.

Limitation is the study only focuses on colour and neglects other product cues and other psychographic variables that can influence consumers’ choice.

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**PAPER NAME**: ELECTROENCEPHALOGRAM (EEG) STUDIES ON HUMAN PERCEPTION IN COLOURS

**AUTHORS NAME**: S.H.N.S. Azwar1, M.K.M. Amin1, A.K.M. Muzahidul Islam2 and O. Mikami3

**PUBLISHING YEAR**: 2019

**SUMMARY:**

The aim of this study is to observe the human perception and its level of calmness in the brain.

Observation was made on the alpha band that was generated from various kinds of colors to different human.

This study further focused on the EEG frequency of Alpha brainwaves and its relation to the brain lobes.

Subjects were instructed to look into different colors displays during the experiment.

The EEG data was analyzed using the Fourier transform of Power Spectral Density (PSD).

Alpha wave was detected by the Electroencephalogram (EEG) and predominantly originated from

the brain lobe. When the strength of the alpha wave was high during observation, the participant is considered in relax mode and in calm condition.

The analysis result from this study showed that the alpha wave produced from different participants are affected through different colors. This observation further depicted that human are calm through their color of interest.

This observation depicted that human are calm through their color of interest.

In future, the study suggested to include several emotion parameters during implementing the experiment.

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**PAPER NAME**: Environmental Colour Impact upon Human Behaviour: A Review

**AUTHORS NAME**: Nurlelawati Ab. Jalila, Rodzyah Mohd Yunusb & Normahdiah S. Saidc

**PUBLISHING YEAR**: 2012

**SUMMARY:**

This paper analyses 40 previous colour studies selected from various disciplines discussing previous methods and colour effects in order to find its significant impact on humans.

It reviews factors such as type of setting, method of assessment, instruments and type of colours.

Secondly, it discuss how colours or coloured environment have influence working performances; causing certain behavior; creating negative or positive perception to surroundings and task given; and influencing moods and emotions.

Finally, this paper highlights the potential scientific approach in finding colour effects on human behaviour. The paper summarized factors to be included for further steps of current investigation.

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**PAPER NAME**: TOWARDS EEG-BASED SIGNALS CLASSIFICATION OF RGB COLOR-BASED STIMULI

**AUTHORS NAME**: Sara Åsly1, Luis Alfredo Moctezuma1, Monika Gilde1, Marta Molinas1

**PUBLISHING YEAR**: 2019

**SUMMARY:**

This research looks at the possibility to actuate devices by looking at primary colors, thought to be

especially useful for individuals having restricted motor control.

Analytic and empirical signal analysis methods for analyzing EEG signals produced by subjects exposed to primary colors (RGB) are presented.

Methods used are short time Fourier transform (STFT) and Empirical mode decomposition (EMD).

Intrinsic mode functions (IMFs) are obtained using EMD, three of which are used for feature extraction.

The features are used as inputs for the machine learning algorithms: random forest (RF), support vector machine (SVM), k-nearest neighbors (kNN), decision tree (DT) and naive Bayes (NB).

Using data from 7 subjects, a general model classifies RGB with 0.37 accuracy, while the best subject-specific model achieves an accuracy of 0.58, which is above the chance level of 0.33.

The classification accuracy between gray and any one of RGB is 0.98 with NB.

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**4.PROPOSED SYSTEM**

4.1Back-end-

Experimental Setup-

Setting the hardware part-----

we are using openBCI device to record the signals from the brain.

as frontal, occipital and parietal lobe are more sensitive to and responsible for visual stimuli therefore we used fp1, fp2, p3, p4, o1, o2, c3, c4 lobe of headset of OpenBci device in both the experiments for collecting the visual stimuli through brain signals.

make the subject wear this headset kit and make it comfortable on the subject’s head by adjust the supporting and non-supporting electrodes(which actually gives us data) to get the brain signals as a data properly.

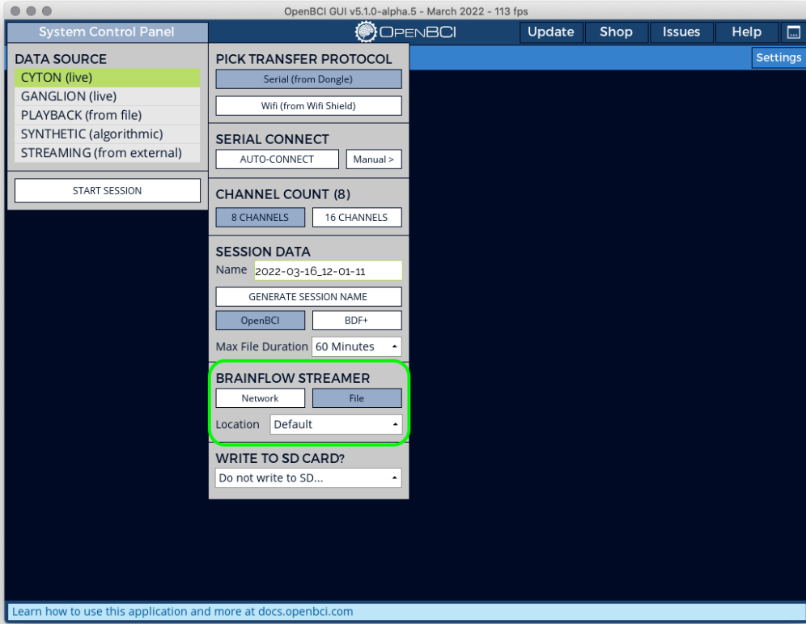
put the SRB pin clip to the right ear to get  all be measured against this reference pin.

connect dongle to the PC

Setting the software part-----

1.**installing Softwares -** a) OpenBCI GUI  b) driver for support < windows 11.

2.Open the openBCI GUI.    **Click on system control panel -> CYTON(live) ->Serial from Dongle .** and then   click on  **SERIAL CONNECT->AUTO-CONNECT.** to get the data from the electrodes in headset into the PC through the Dongle.



3.) Now session is started, completing the hardware settings:- set the **PGA gain=** 4 (…why…)and  **bias include = No** (….why…)  for all the 8 channels.



4.) Now for checking the signal quality :- Go to the FFT plot and try to put not railed for all the channels for good quality of signal. Now we are ready to collect the signals.



5.) for stop collecting the data click on stop data stream . Data for this session will get saved as .txt and .csv format and  events.txt file also got saved using the python script we wrote.

4.1.1 For Bi-color-

Motive-

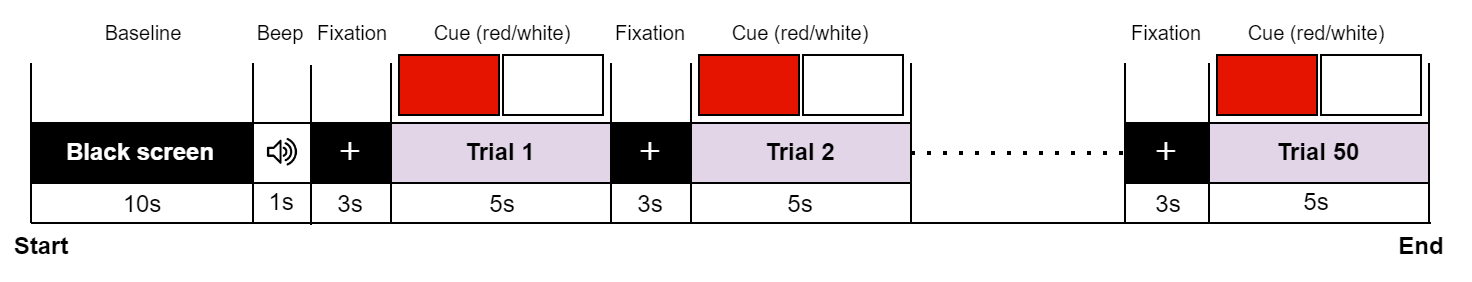
The aim is to differentiate the brain signals from red and white color shown to the subject using EEG with efficient techniques and accuracy as compared to other previous works.

DATA COLLECTION AND ITS DESCRIPTION-

The data from 2 girls(between ages of 20-25) was taken in 3 sessions in total.

in each session,50 times(red or white)color was shown for 5 sec each with a baseline of 3 sec.

in general total time of each session is 5.66 minutes.



Each session has:

**events.txt** – stores the time stamp information of red and white data in trial.txt.

**trials.txt** – contains brain signals data of all the 8 channels and their time stamps    using OpenBCI.

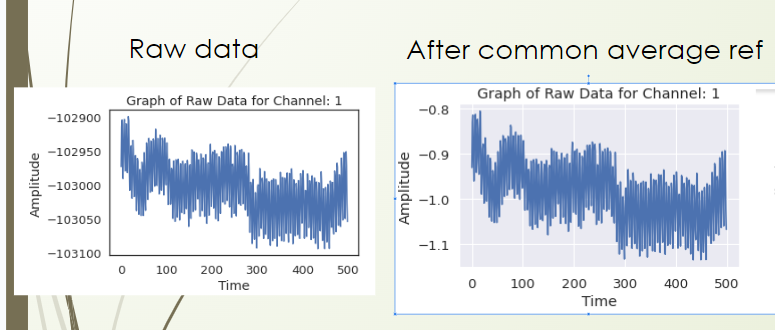
We filter out the data of only (all the 8 channels and the time stamp) from trials.txt.

DATA PREPROCESSING

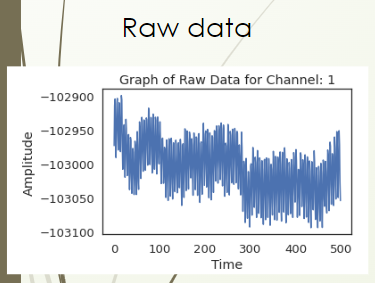
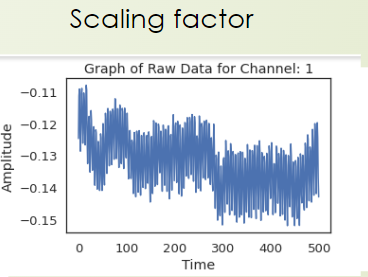
As we know raw EEG signals do not provide useful information therefore first of all we did data pre-processing as follows-

**Steps**- Raw data -> common average referencing -> scaling factor -> 50 hz notch filter ->  0-40 hz band pass filter

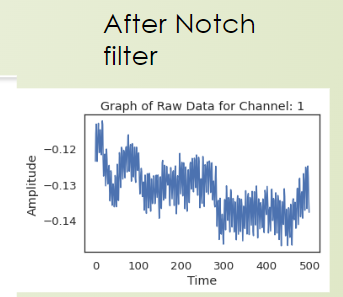
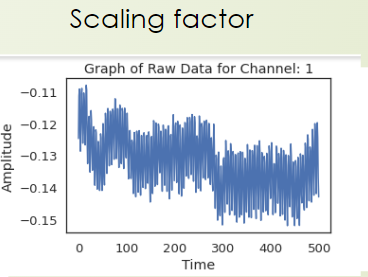
Common average referencing is done because taking a common average reference in the EEG data, also corresponds to taking a common average reference in the forward model. The consequence of subtracting the average potential (from each channel) is that the model error is averaged over all channels. Since there is no reason to assume that the model error is specifically positive or negative, the model error tends to average out and the forward solution at each channel will have a much smaller forward model error.



Scale factor correction of EEG spectra data improves the diagnostic accuracy for detecting pathological EEG spectra from an almost random level.

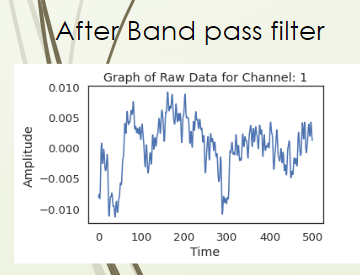
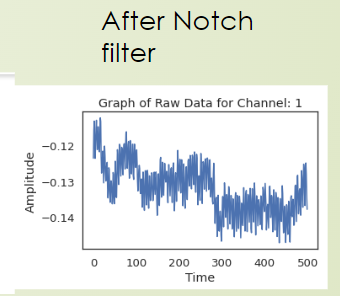
 

Notch filter is used when signals can often be exposed to strong power line interference at 50 or 60 Hz. A widely used method to remove line noise is notch filter. (here we used 50 hz notch filter)



bandpass filter is used to filter the eeg signals from noise i.e involuntary eye movements, unneccessary light from lamps, etc.

Studies generally use a bandpass filter from 1Hz to 40Hz on EEG signals because the literature does not report interest in data below 1Hz, and above 40Hz. Above the frequency of 40Hz, interferences of lamps and devices on EEG signals that operate at an approximate frequency can occur.

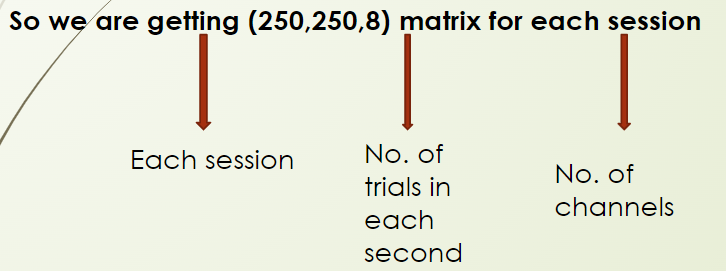


DATA EPOCHING

By filtering out  only the time stamps when the red or white color was shown.

Also each second 256 readings were recorded, by splitting the data secondwise and removing the last 5 readings from each of the seconds.

Further splitting the each of the 50 colours(which are of 5 sec each) into 5 readings.



Then we concatenated all the 3 sessions readings of subject\_1 concatenated all and 3 sessions readings of subject\_2 together.

Then we got (750,250,8) matrix for each of the subject\_1 and subject\_2

FEATURE EXTRACTION

Then the features we extracted from this kind of organized data-

1.)Statistical Features (mean, standard deviation, skewness, kurtosis)

2. )DCT Features (dct power)

3.) Wavelet Features (cA energy, cD energy)

4.) Band Power (delta, theta, alpha, beta, gamma)

5.) PCA (Principal Component Analysis) features

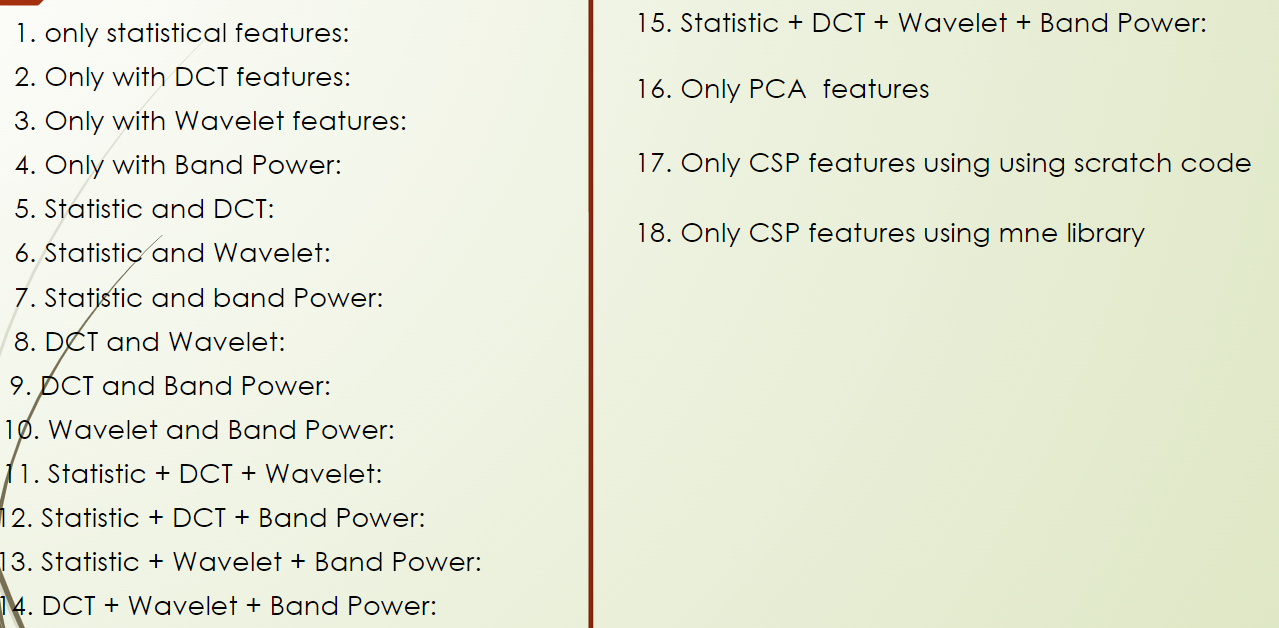
 6.) CSP (common spatial pattern) features using scratch code

7.) CSP (common spatial pattern) features using built in library mne

FEATURE SELECTION

different models we used for training with each of these features combination are Linear SVM, RBF SVM, Random forest, LDA, Decision tree, Gaussian NB, K-neighbour classifier, Adaboost classifier.

Then Feature selection was done by experimenting on each possible combination of model and the features combination.



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4.1.2 For Tri-color-

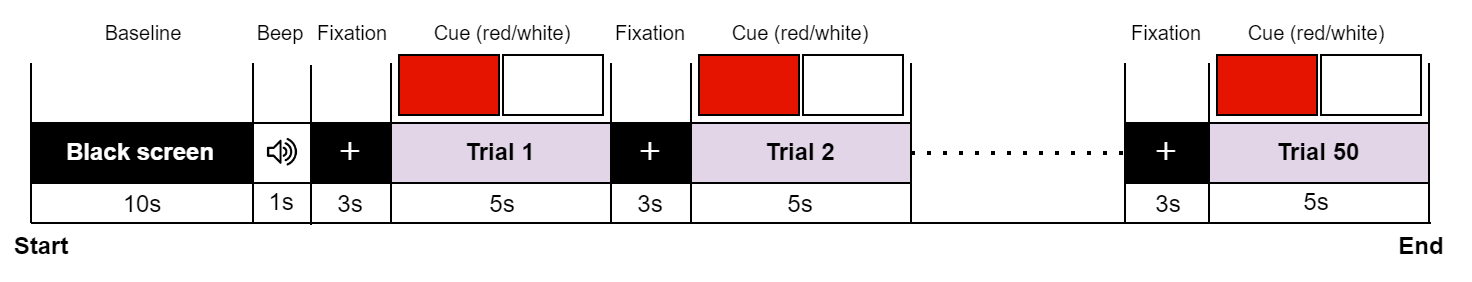
Motive-

The aim is to differentiate the brain signals from red, blue and green color shown to the subject using EEG with efficient techniques and accuracy as compared to other previous works.

DATA COLLECTION AND ITS DESCRIPTION-

The data from 7 subject((between ages of 20-25),(6 males, 1 female)) on which was taken in 3 sessions in total.

in each session, 75 times(red,green or blue) color was shown for 5 sec each with a baseline of 3 sec. in general total time of each session is 10 minutes.



Each session has:

**events.txt** – stores the time stamp information of red and white data in trial.txt.

**trials.txt** – contains brain signals data of all the 8 channels and their time stamps    using OpenBCI.

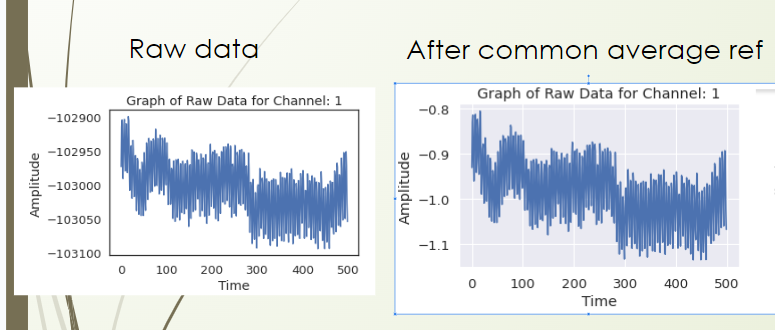
We filter out the data of only (all the 8 channels and the time stamp) from trials.txt.

DATA PREPROCESSING

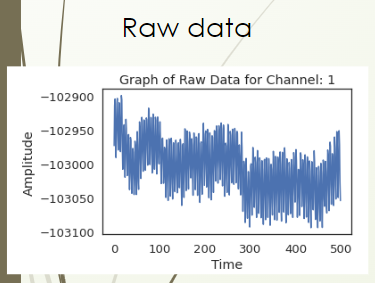
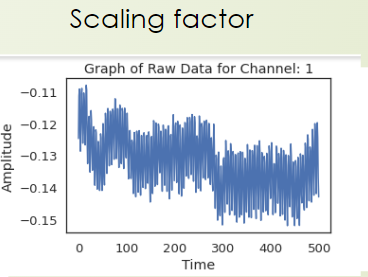
As we know raw EEG signals do not provide useful information therefore first of all we did data pre-processing as follows-

**Steps**- Raw data -> common average referencing -> scaling factor -> 50 hz notch filter ->  0-40 hz band pass filter

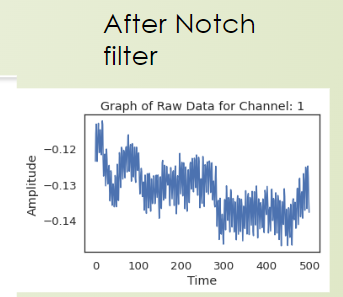
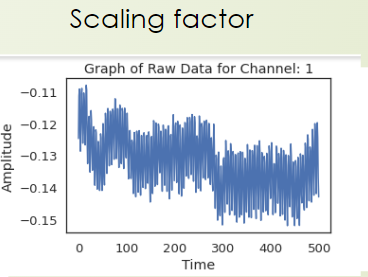
Common average referencing



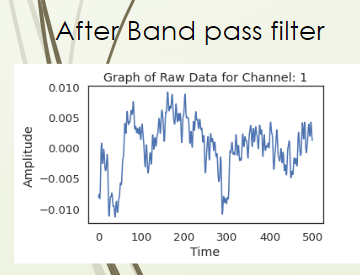
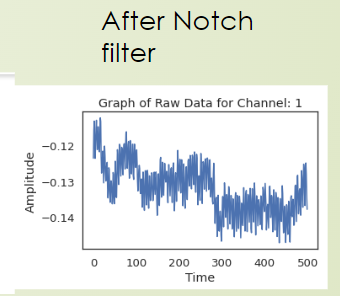
Scale factor

Notch filter (here we used 50 hz notch filter)



bandpass filter

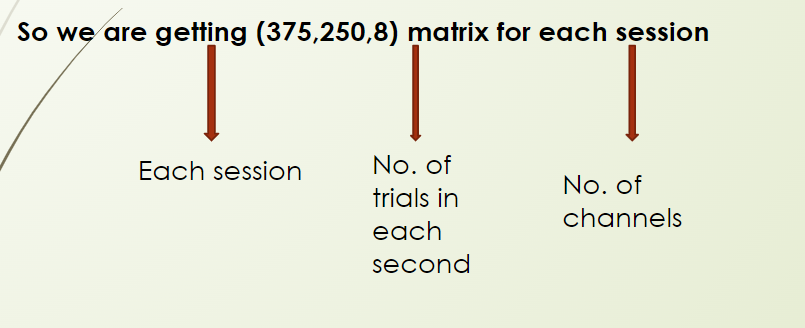


DATA EPOCHING

By filtering out  only the time stamps when the red or blue or green color was shown.

Also each second 256 readings were recorded, by splitting the data secondwise and removing the last 5 readings from each of the seconds.

Further splitting the each of the 75 colours(which are of 5 sec each) into 5 readings.



FEATURE EXTRACTION

Then the features we extracted from this kind of organized data-

1.)Statistical Features (mean, standard deviation, skewness, kurtosis)

2. )DCT Features (dct power)

3.) Wavelet Features (cA energy, cD energy)

4.) Band Power (delta, theta, alpha, beta, gamma)

5.) secDiffMean

6.) secDiffMax

7.) first\_diff\_mean

8.) first\_diff\_max

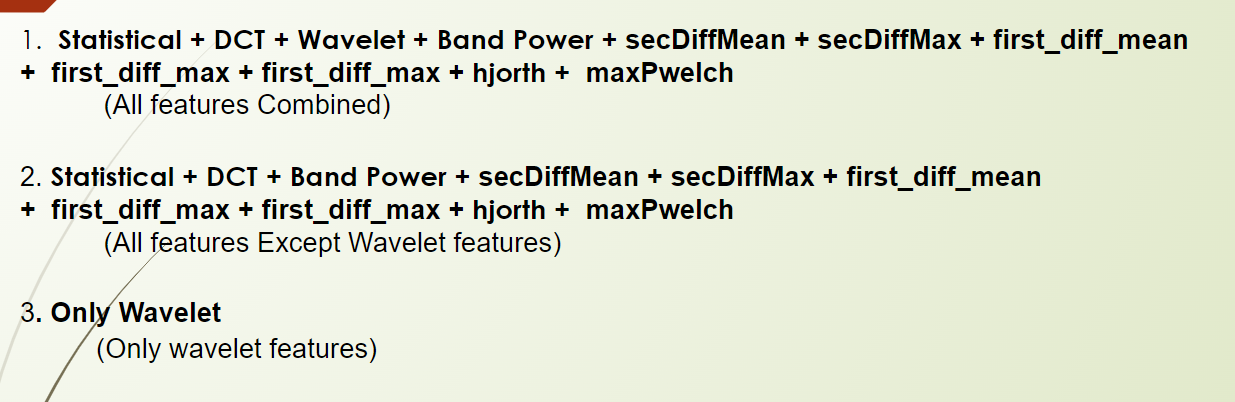
9.)hjorth

10.) maxPwelch

FEATURE SELECTION

different models we used for training with each of these features combination are Linear SVM, RBF SVM, Random forest, LDA, Decision tree, Gaussian NB, K-neighbour classifier, Adaboost classifier.

Then Feature selection was done by experimenting on each possible combination of model and the features combination.



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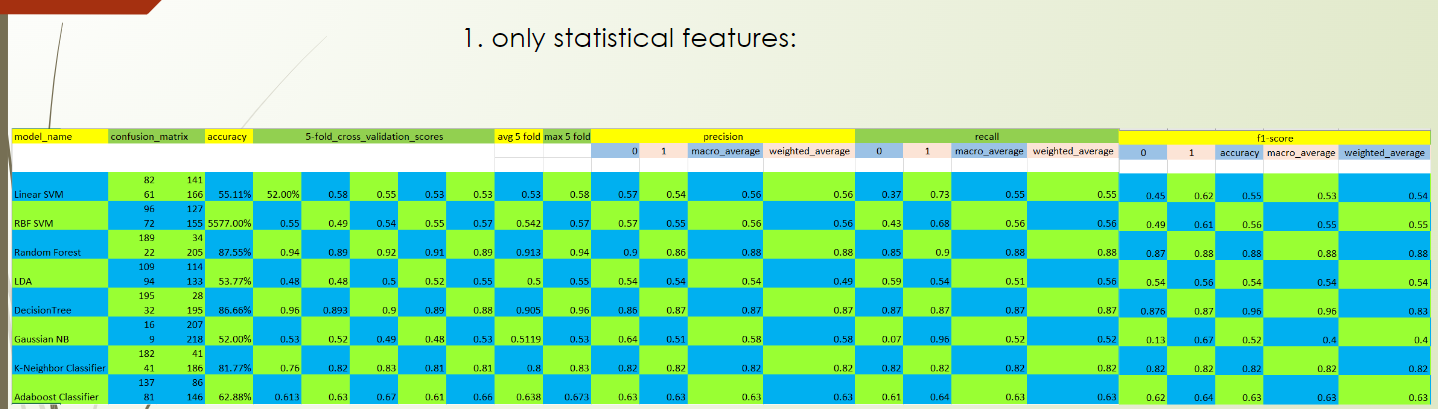
4.2Front-end

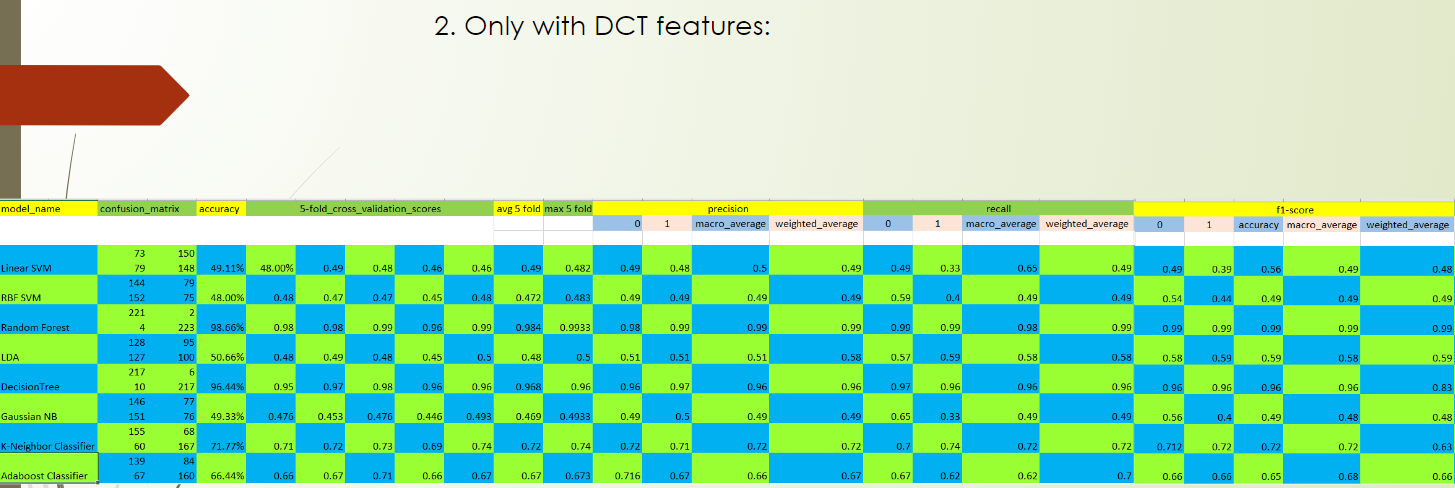
4.3Integrety

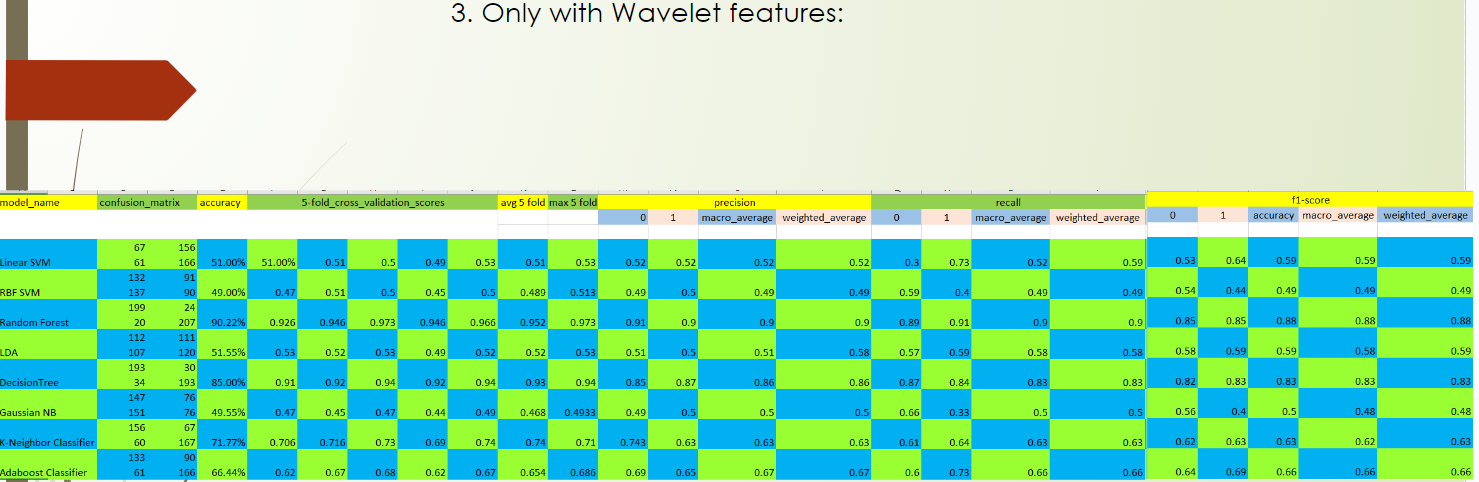
…………………………………………………………………………………………………………………………………………………………

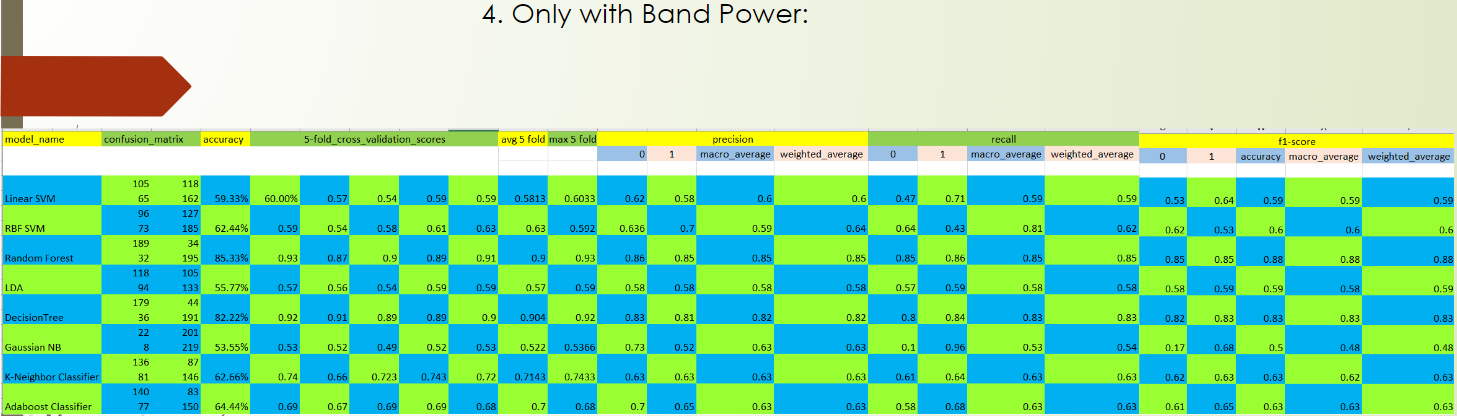
**5RESULTS AND DISCUSSION**

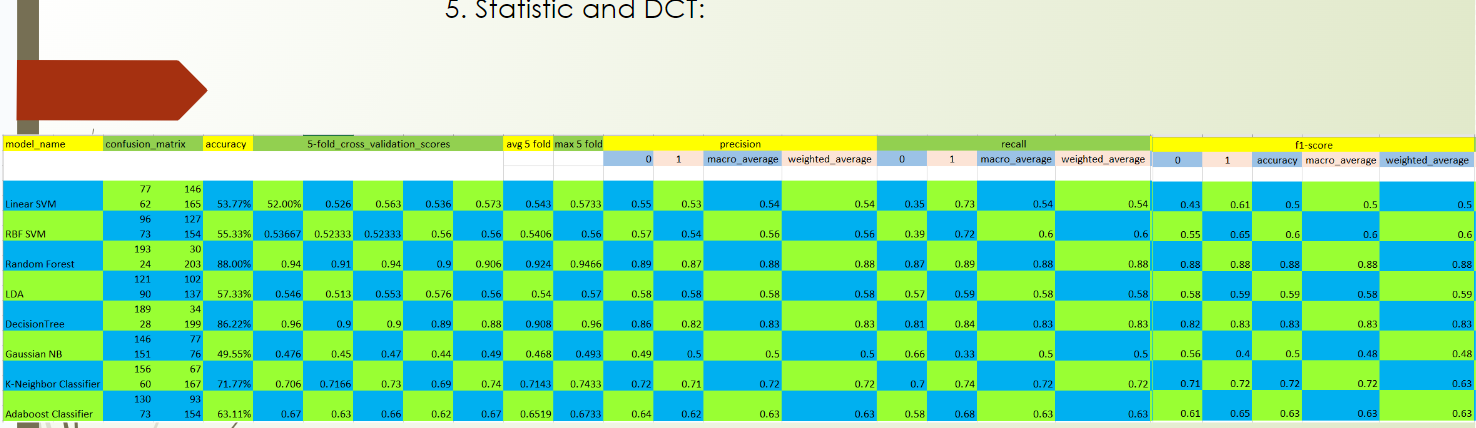
5.1For Bi-color experiment-

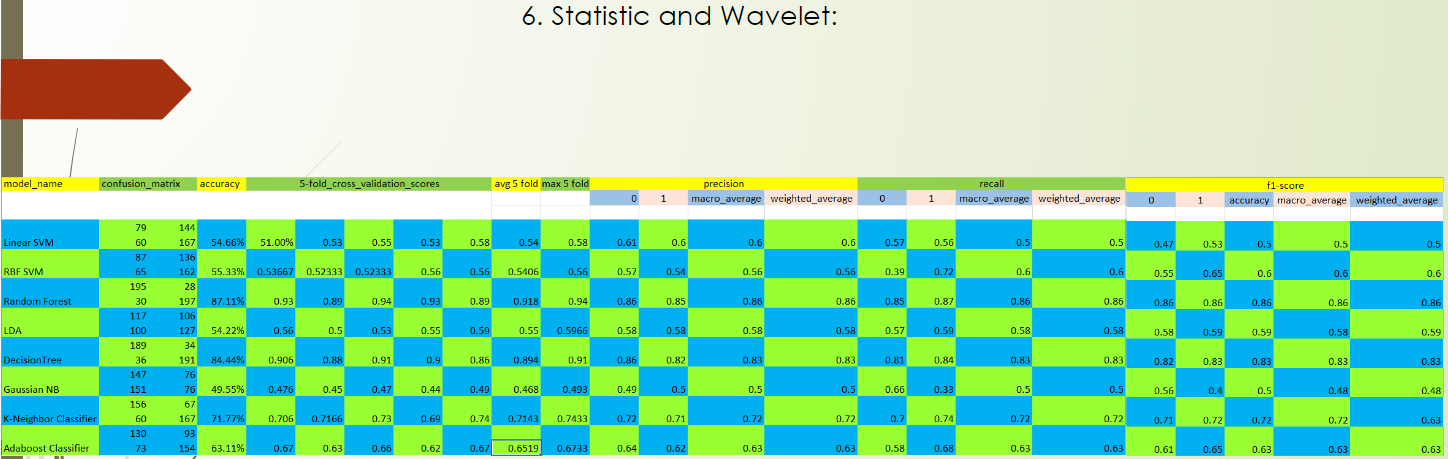


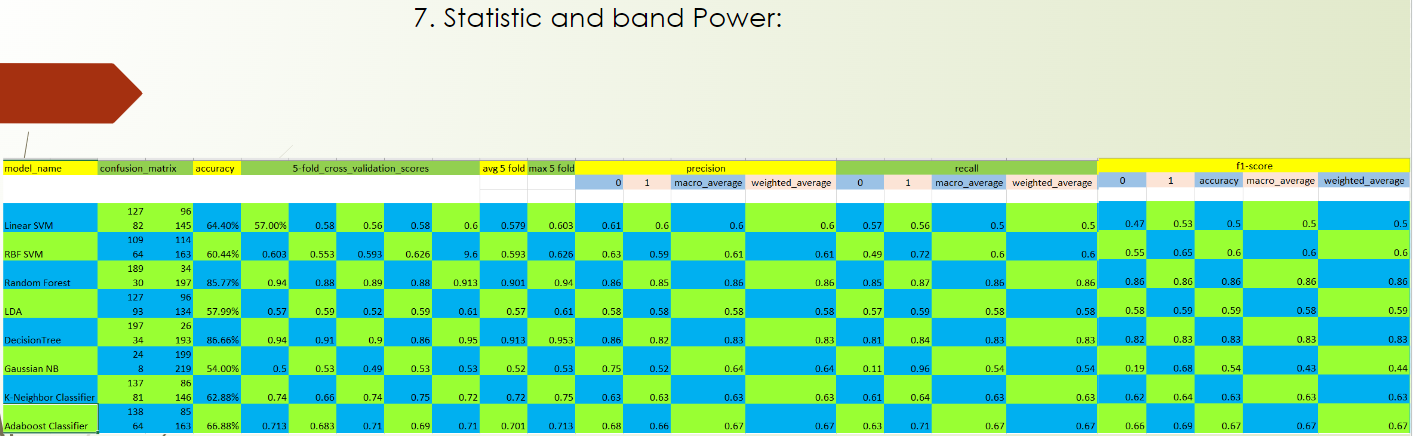


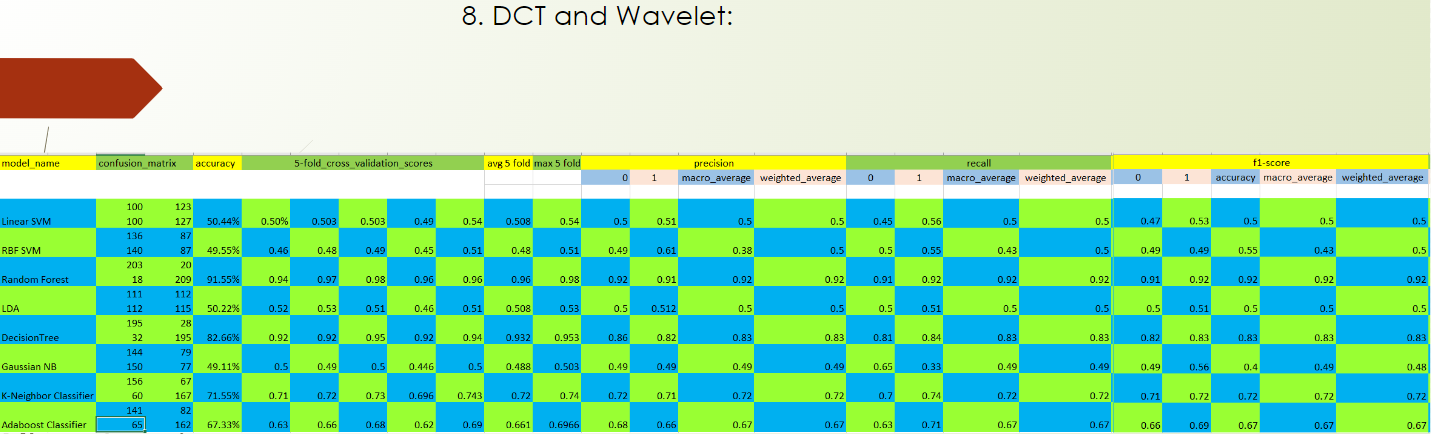


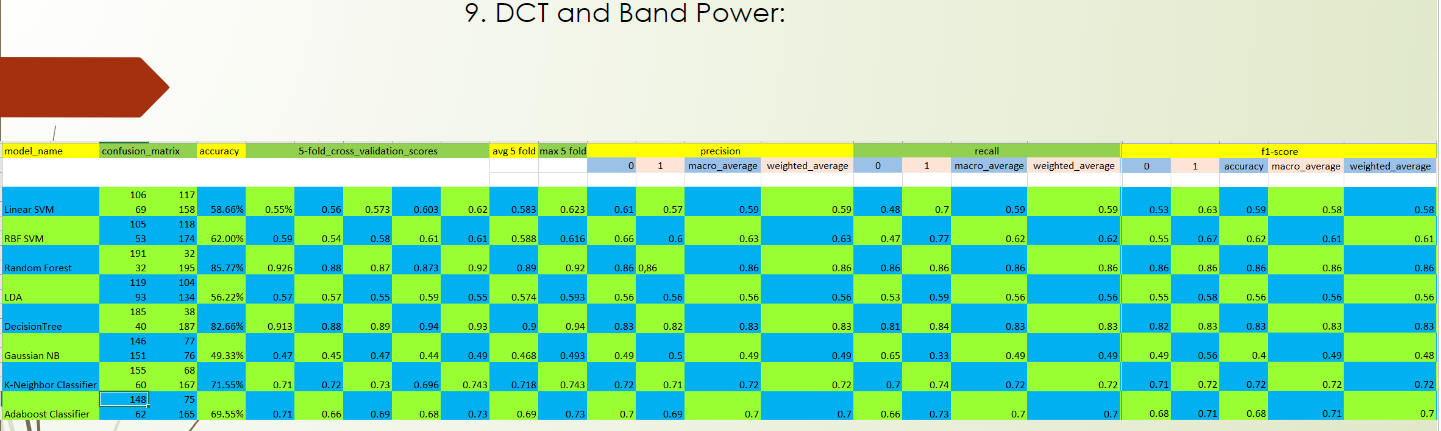


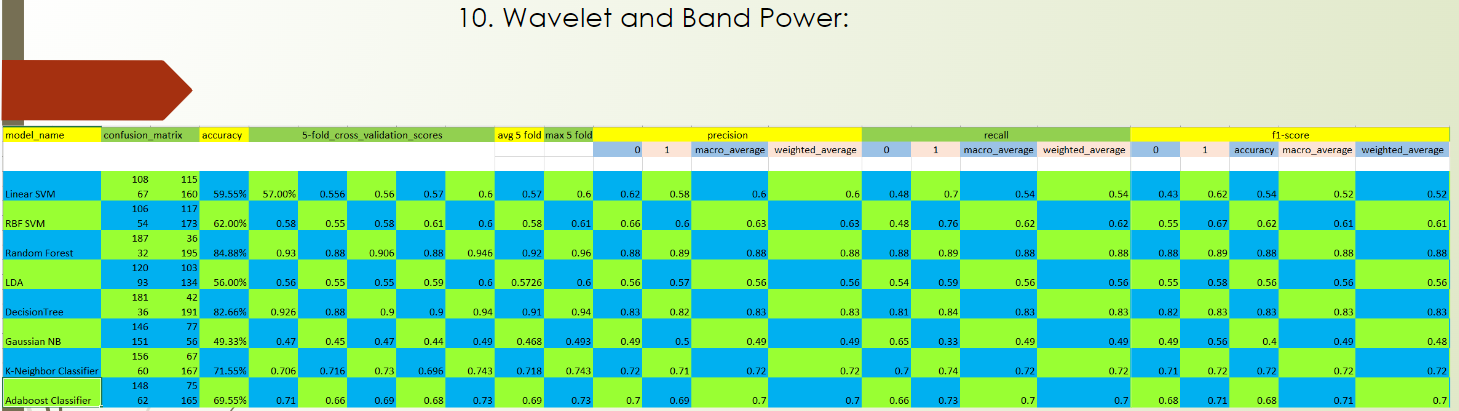


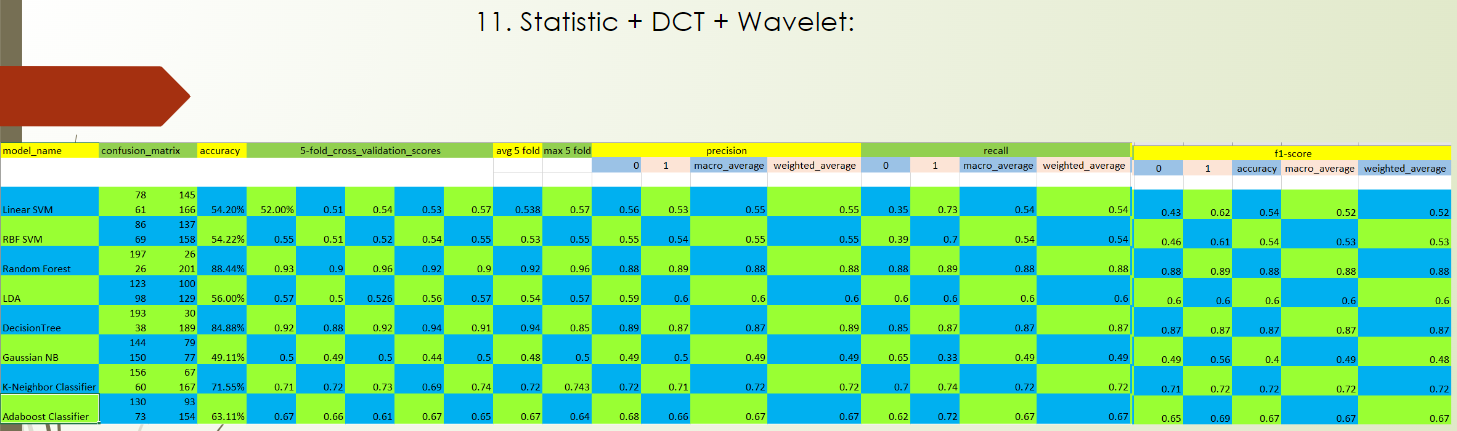


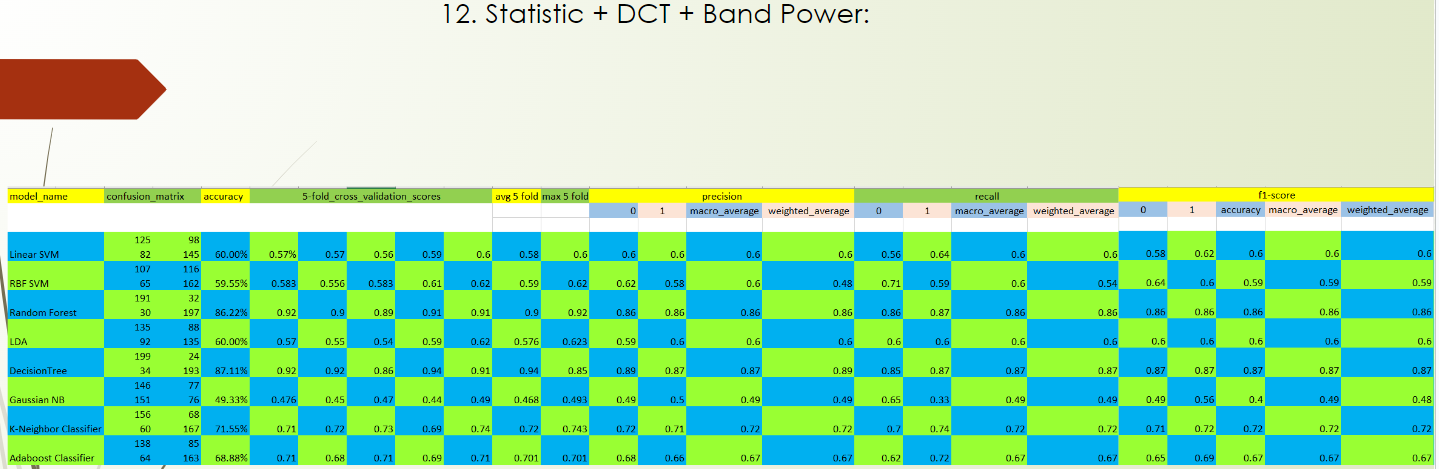


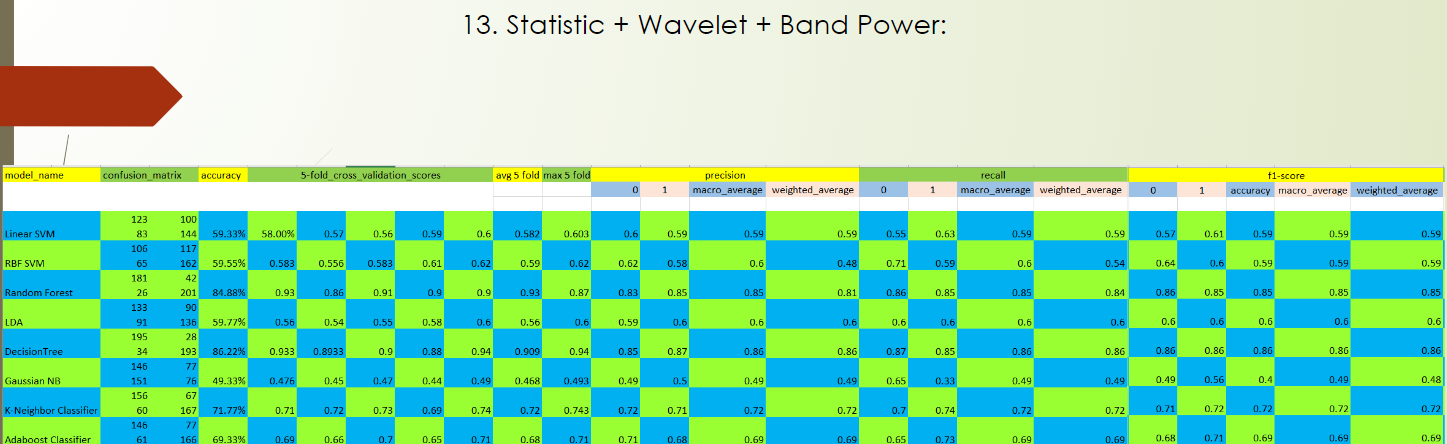


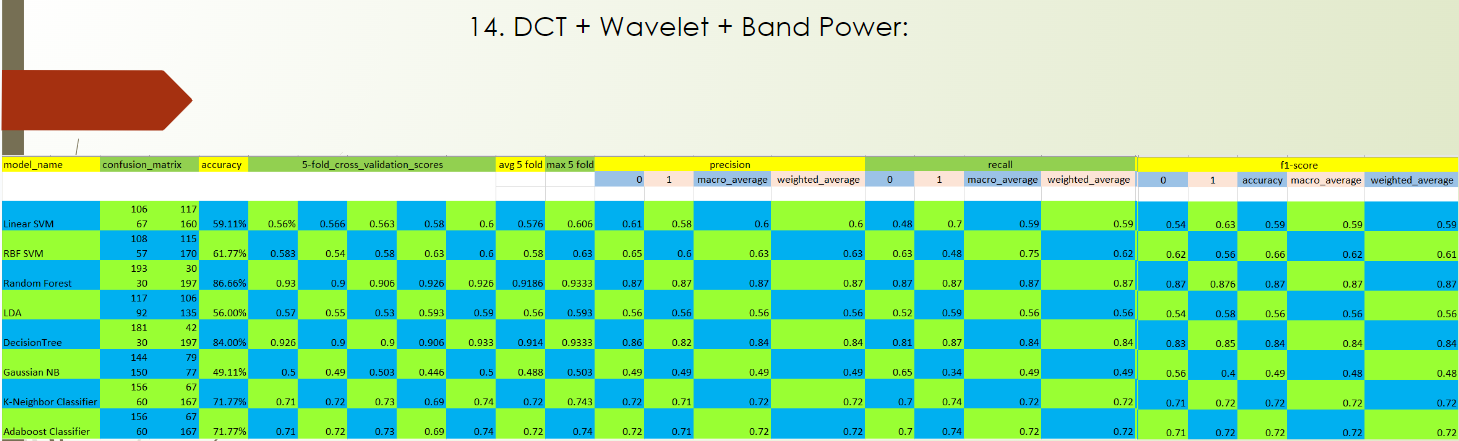


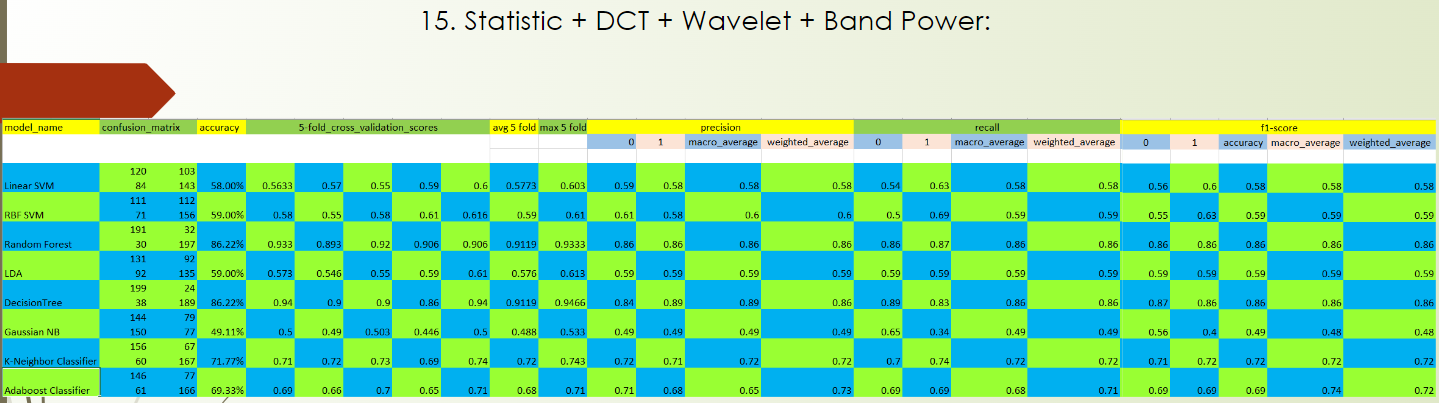


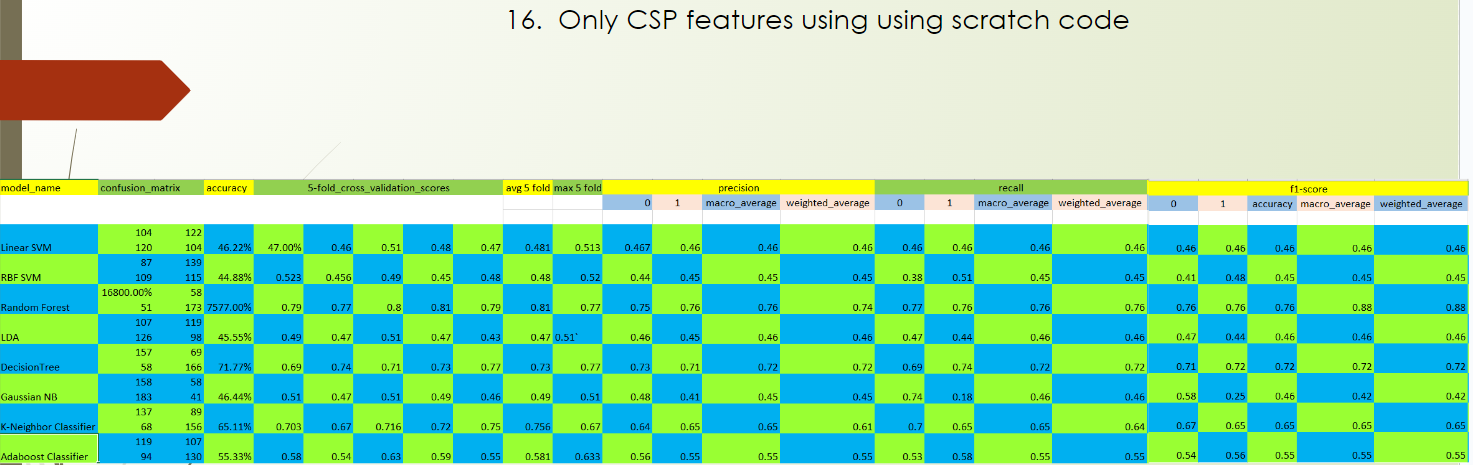


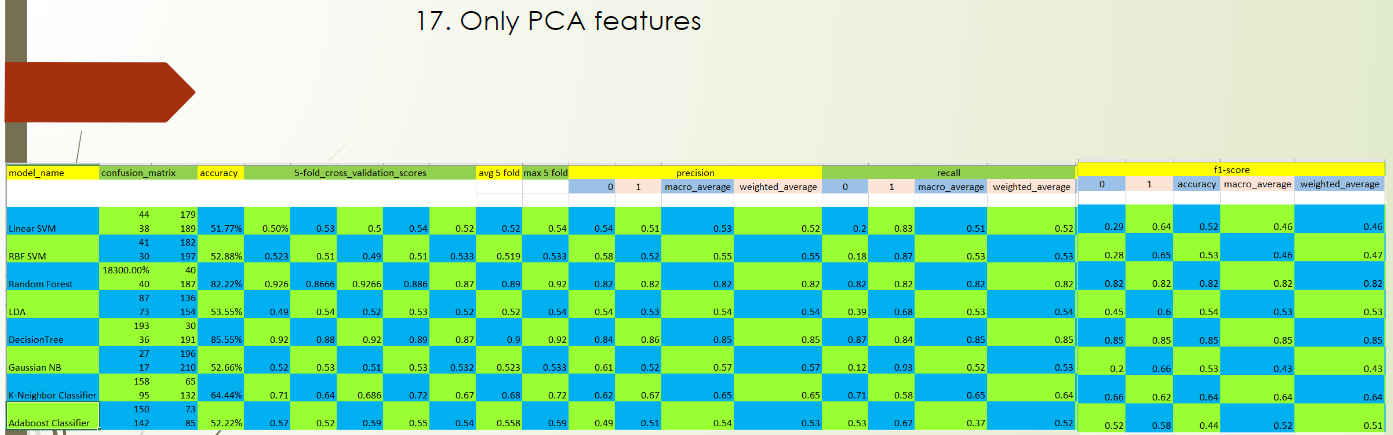


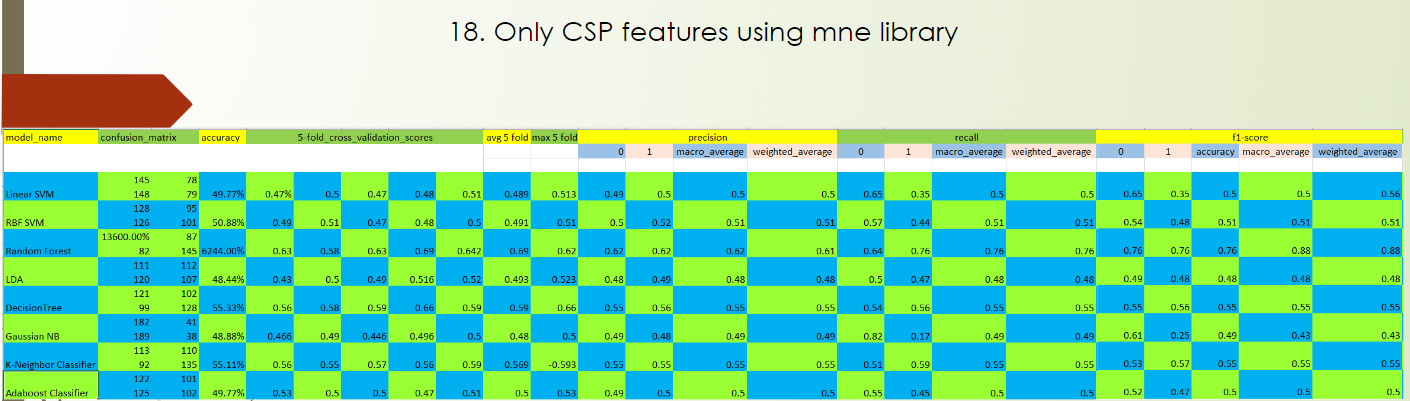




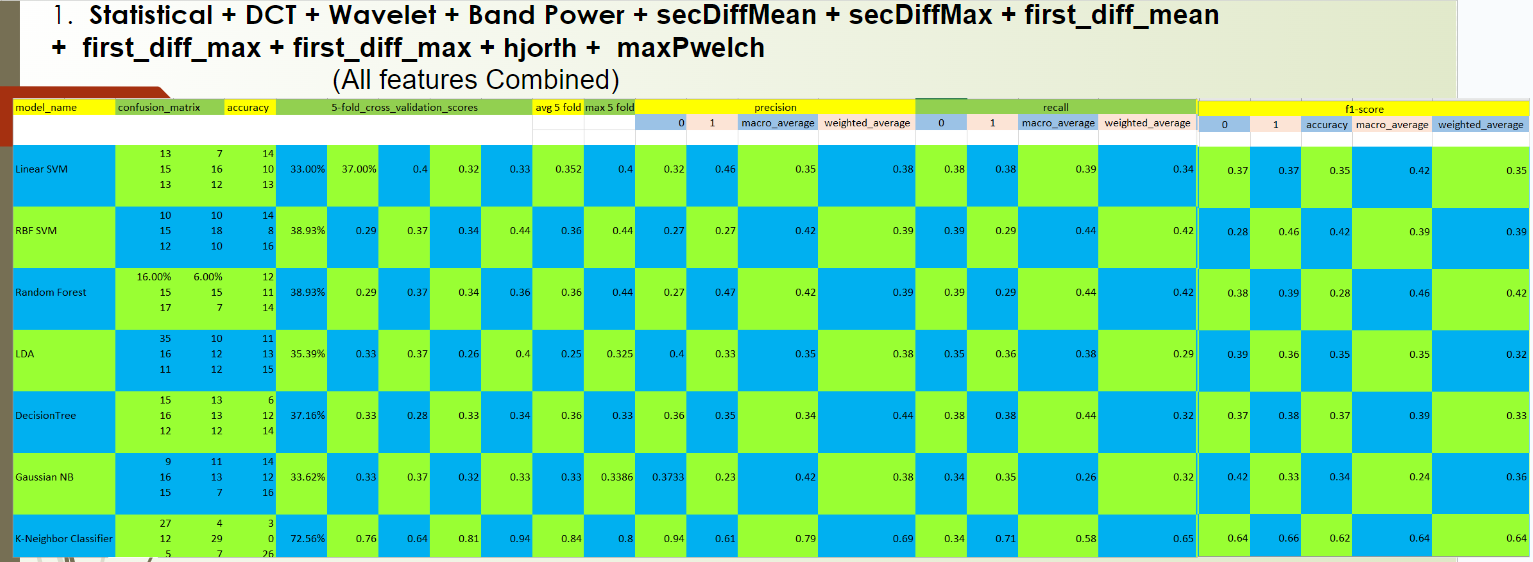


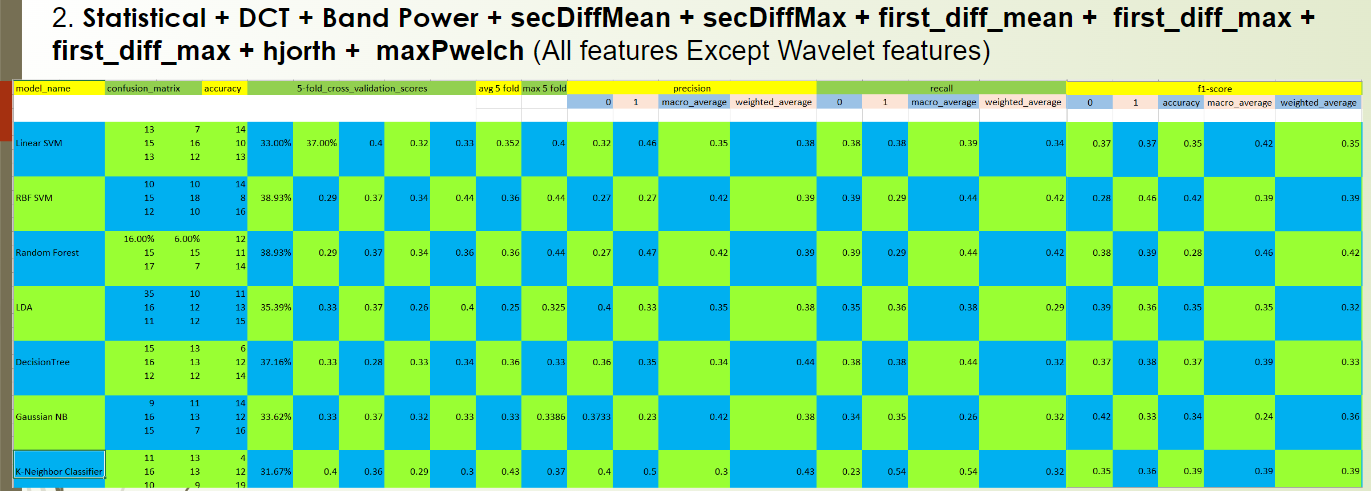


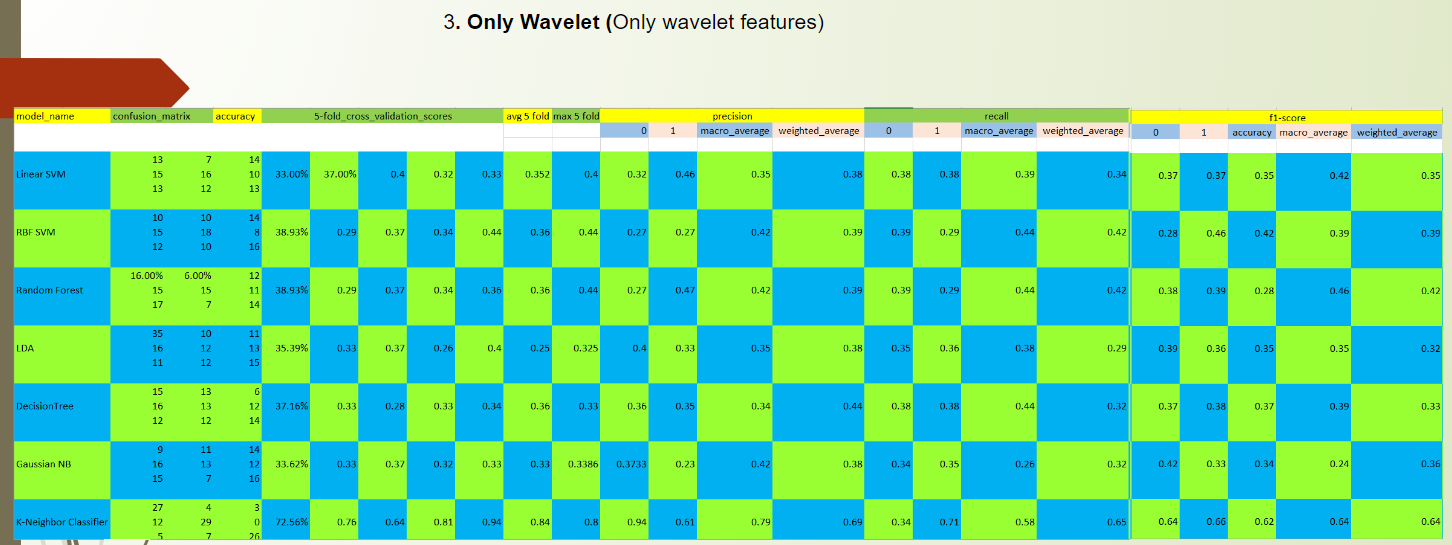




5.2For Tri-color experiment-







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**6.CONCLUSION AND FUTURE WORK**

In this paper, 2 experiments were conducted, one is for Bi-color and another is for tri-color.

In bi-color, we analysed and differeciated the brain signals from red and white color shown to the subject using a supervised learning approach.

in tri-color, we analysed and differeciated the brain signals from red, green and blue color shown to the subject again using a supervised learning approach.

We conducted various feature selection experiments to come to the conclusion below.

Highest accuracy of Bi-color experiment is 98.66%(when Random forest was trained with only DCT features)

Highest accuracy of Tri-color experiment is 72.56%(when K-neighbour classifier was trained with only Wavelet features)

This research work has pretty good application as if we are able to discriminate two different colors then we can use this as two or three control commands for controlling any dedicated computer application.

Further as a future work we would like to work on the broader way.

On a screen initially 3 boxes are shown, each box is having 3 letters and by seeing a some random box, that letters of thst box burthur expand to three boxes and now each box is having each of its letter. And by seeing at each of the box. That letter got selected.

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