Affective Computing Based Personalized Meal Recommendation

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Declaration

It is hereby declared that

1. The thesis submitted is my/our original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Abstract

Human emotions vary when they crave foods although not all food items will be appealing in all moods. Learning people's food preferences and making recommendations based on their emotions of that certain time, is very toilsome. This research has been conducted to build a model that will recommend appropriate meals predicated on a person's current emotion. In this paper, a system has been proposed that will evaluate a person's emotion through the Electroencephalogram (EEG) signal and analyses the user's Like, Feelings and Excitement affectivity analysis. To that purpose, we arranged trials to record the EEG signal of 25 people utilizing 14 electrodes, connected directly to their scalp. Here, feature extraction techniques which include Fast Fourier Transform (FFT), Short-time Fourier Transform (STFT), Discrete Wavelet Transform (DWT), Hilbert Huang Transform (HHT), Hjorth Coefficient, Spectral Entropy have been performed on four classification Machine Learning algorithms namely Random Forest Classifier (RF), K-nearest Neighbors (KNN), Support Vector Machine (SVM), XGBoost Classifier (XGB), where all of these analyses include both subject-dependent and subject-independent approaches.

Keywords: EEG, Human Emotions, Feature Extraction, FFT, STFT, HHT, DWT, Hjorth Parameter, Spectral Entropy

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Table of Contents

List of Figures

List of Tables

Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

DWT Discrete Wavelet Transform

FFT Fast Fourier Transform

HHT Hilbert Huang Transform

KNN K-nearest Neighbors

RF Random Forest Classifier

$STFT$ Short-Time Fourier Transform

SVM Support Vector Machine

XGB XGBoost Classifier

Chapter 1

Introduction

1.1 Thoughts behind the Recommender System

Personalized nutrition has been formally characterized as the sound eating advice, custom-made to suit a person based on genetic information, and on the other hand on individual wellbeing status, way of life [25]. With respect to the take a toll of genetic information administration, within the final few a long time, there has been an increment within the inquire about efforts centered on the administration of this alternative information with this point in mind [42]. Particularly, a few computational solutions have been proposed with the objective of sound eating advice [40][35][38][39]. But most of the recommender systems in this area mainly focused on the dietary history or recipe or user's preferences, and none of them incorporate user's emotions: feelings, likings, or excitement in their systems to recommend personalized food.

1.2 Problem Statement

Food consuming behavior of human beings is hard to predict and thousands of ingredients chosen for a single recipe makes the condition even more complex. Psychological and Physiological components influence what we select to put into our bodies and manage the relationship we have between food and emotions. We require fuel within the form of nourishment to outlive but there are completely a few foods that are as it was eaten in exceptionally particular circumstances. Different emotional states make us crave for different food items. Not always what we crave for is healthy. Finding a suitable replacement for whatever we are craving for, is important. For instance, having extra sweets are harmful to our health so we can switch to fresh or dried fruit as alternatives which will satisfy our emotional needs as well as nutritional needs. There are thousands of food items available with almost a thousand vegetables alone. The number of food recipes that can be formed with these items is hard to calculate and it's inefficient as well. There are numerous amount of food recommender systems available but mostly lack in Affectivity analyses, Cold start problems, and much more. For instance, The Chef and Julia require a huge amount of domain knowledge for recommending a recipe. Sobecki et al., 2001, presented a recommendation based on fuzzy reasoning but it does not break down the nutrition values or provide nutrition-specific guidelines[3][2][9]. Finally, the proposed model Yum-me ticks most of the boxes while lacking the human emotion part[39]. In this report, our primary intention is to recommend food to people according to their emotional and physical needs calculating all the factors. For getting anticipated results, we are going take a fast initial visual-based survey to know their dietary confinements and after that utilize the willingness of individuals to lock in with nourishment photographs to construct a starting presumption through EEG.

1.3 Research Objectives

Our brain plays an vital part in the control of metabolic homeostasis, balancing appetite, and energy expenditure to maintain adipose tissue volume [7]. According to a study, in certain emotional states, obese people intake more food than a person with normal or healthy emotions [1]. So the brain has control over what we eat in different emotional states and what we crave despite being healthy and unhealthy. Our objective is to design a system that can identify how to recommend meals based on a person's choices and emotions. The research we conducted is to find meals a user would like in various emotional states and then give them a balanced food recommendation according to our findings. During the data collection phase, we collected the food choices of individuals by conducting surveys and recording the EEG signal. The survey on food choices gave us a general idea of a user's food preferences. As we have seen in previous studies conducted by Yang et al. (2017), one of the major obstacles they have faced is the approach of collecting data. Most meal recommendation system that we see today is based on the food journal approach which is harder to maintain and users suffer from cold-start problem [39]. Preference survey systems, on the other hand, were found harder to use to recommend meals with variety, as even though the systems know what type of meals to recommend, it can't meet each user's food preferences[39]. Another obstacle is the authenticity of the data. Therefore, we chose some volunteers and prepared datasets from the scratch. Finally, after research, we came up with our personalized food recommendation system that will suggest meals based on a person's current emotions.
Key research objectives-

- Study the correlation between human emotion and food consumption
- Recommend a personalized healthy food choice according to their current emotional state

1.4 Research Methodology

Emotions and food consumptions have an overwhelming correlation that consciously or subconsciously affects our food habits and this relationship varies from person to person depending on their different emotional states. This research has been conducted on finding meals a person would like in different emotional circumstances.

For detecting emotions at a certain period for a certain food, we have used Electroencephalogram (EEG) signals and a prior survey was conducted regarding the rating of a particular food at any point in time.

In this research, feature extraction techniques like Fast Fourier Transform (FFT), Short-time Fourier Transform (STFT), Discrete Wavelet Transform (DWT), Hilbert Huang Transform (HHT), Hjorth Parameter, Spectral Entropy have been performed to extract feature from EEG signal in such a way that essential parts of the image can be extracted effectively.

After extracting features, data have been trained on Random Forest Classifier (RF), K-nearest Neighbors (KNN), Support Vector Machine (SVM), and XGBoost Classifier (XGB). In all cases, the Support Vector Machine (SVM) performs the best whereas K-nearest Neighbors (KNN) performs the worst.

Both subject-dependent and subject-independent strategies have been applied with Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), Discrete Wavelet Transform (DWT), Hilbert Huang Transform (HHT), Hjorth Parameter, Spectral Entropy. These feature extraction techniques have been applied for all frequency bands(Alpha, Beta, Gamma, Theta) and pairwise channels.

1.5 Paper Organization

The rest of this dissertation is designed as follows:
Chapter 2 contains Related Work which describes the system and experiments that had been conducted in this food recommendation area. With respect to typically a very dynamic field, we are going center on researches performed within the final five years.
Chapter 3 contains the Proposed Model where data collection, channel selection, preprocessing, proposed workflow, and model specification have been described. It portrays the dataset utilized in preparing and testing the system.
Chapter 4 is the chapter of Performance Evaluation where we find out the F1 score, accuracy, and confusion matrix. Chapter 5 is a chapter of the Conclusion and future work.

Chapter 2

Related Work

In this era of modern technology, an observable amount of research has been conducted in the area of recommendation systems. These proposed works are mainly associated with recommendations for food, menus, diets, recipes, and safety guidelines for specific diseases. Conventional food and recipe recommender frameworks learn users' dietary preferences from their online exercises, counting evaluations [32][26][20] [17] , past formula choices [12], [21] and browsing history [22], [31].

For occasion, Diet-Right: A Smart Food Recommendation System(2017), a cloud-based nourishment proposal framework called Diet-Right that considers the users' obsessive test results, and prescribes a list of ideal food items [36].Their fundamental center was to supply dietary help to diverse individuals who endured from common maladies. The proposed demonstrate suggests different foods and nutrition to individuals based on their pathological test reports. They planned a database of 345 pathological test reports and their typical ranges. A database was made by performing a field study and collecting the data around obsessive reports from distinctive laboratories [43]. The collected information was confirmed by a pathologist of a clinic.A lattice of 345 sections was built. Each person's components of a test such as a blood test have conventional ranges with a lower and upper bound. The ranges of the same component may differentiate on the preface of sexual introduction, age bunches, and fasting or no fasting. In expansion, a database of 3,400 nourishment things with 26 entries for most common food was taken from the official location of the composition of nourishments facilitates dataset (CoFID)[33]. Based on the real-time input of the user's parameters, the Diet-Right proposes beating situated nourishment things to the client. Their framework was prepared on different sorts of age bunches and their person ranges of parameters that permit the framework to propose diets as per the wants of the clients. This system offers adaptability to such an extent where smartphone users can easily access it.

Ribeiro et al., 2017 proposed SousChef,a portable meal recommender framework to help more seasoned grown-ups by providing a nourishment companion to direct them into making shrewd choices with respect to nourishment management and solid eating habits [38]. Their target audience was elderly people who frequently battle with making the correct choices with respect to their feast planning, sound diets, or basic supply shopping. Considers moreover propose that numerous more seasoned grown-ups disregard sustenance and are more slanted to do so on the off chance that they happen to live alone [23]. As their system mainly used by elderly people who are more likely to need their dietary plan into consideration, this system enables user-friendly interfaces. In order to create a weekly meal plan, they first went through the user's requirements and calculate their nutritional needs, and then they selected food items for each meal and ranking the meals per the user's caloric needs. After evaluating the user's caloric needs, they looked forward to choosing the ingredient combinations where they gave preferences to the user's personal information, nutritional needs, and meal planning history. Once the ingredient combination has been chosen for each meal, lastly they ranked the ingredient quantities to match the energy requirements of a particular person.

Jiang et al., 2019 propose a personalized health-aware food recommendation system, "Market2Dish" that helps the user to build a healthy eating habit [45]. In this system, they first study the ingredients by identifying them in the micro-videos taken from the market, then observe the user's health condition by collecting data from their social media accounts, and then recommend personalized healthy foods.

Gao et al., 2019 proposed a devoted neural network-based arrangement Various leveled Attention-based Nourishment Suggestion (HAFR) which is competent of 1) capturing the collaborative sifting impact like what comparative clients tend to eat; 2) gathering a user's inclination at the fixing level, and 3) learning client inclination from the recipe's visual pictures [44]. This work defined food proposals as an interactive media assignment by mutually considering user-recipe instinctive, nourishment pictures, and nourishment fixings. This work proposed a system to initiate users' slant over formulas for nourishment proposals. They collected a large-scale dataset for a nourishment proposition and executed colossal tests, outlining that HAFR dependably beats the state-of-the-art models. Other than, the removal tests illustrate the value of amassing formula data in a progressive fashion. Besides, this work cannot ensure the wellbeing of recommended recipes since this work don't consolidate healthy and nutrition components.

Hsiao and Chang, 2010, created a location-aware intuitively slim down specialist named SmartDiet based on multi-objective optimization.[18] Their system suggests personalized meals and restaurants based on the user's daily nutritional requirements, nutrition components. To start with, the framework gets geological arranges from the user's convenient contraption and orchestrates with nourishment providers abutting to the user's current region for securing open dinners and the comparing nourishment facts. The collected information is passed on to another component. Besides, the devour organizer at that point handles the multi-objective count calories choice issue concurring to its information motor, which stores the sustenance impediments for particular subjects such as typical people or diabetic patients, the true confirmations data, which records the user's true thin down penchants. Once total, a combination of open dishes and eateries that fulfills the regular dietary prerequisites and the user's current locale will send to the client. Thirdly, clients can moreover be associated with the framework to modify the endorsed dinners to get together of their personal necessities. Finally, the proposed system will at that point upgrade the imperatives to deliver customized count calories arrange concurring to the user's selection. To urge a exact eat less arrange that can hold up the user's favor well, the client can repeat from the moment step to final until he or she finds a palatable nourishment combination. To increase efficiency, they further collaborate user's feedback so that their system can maximize the user's preference. If a user has an improper meal, the system will notify them. This system can also be beneficial to doctors or nutritionists as it can assist them in establishing dietary guidelines.

A great work has been conducted by Yang et al., 2017 who has developed a personalized nutrient-based meal recommendation system that tackles the limitation of the cold-start problem by not depending on the user's dietary history [39].In this framework, they carry out a food image analysis model- FoodDist to urge the information around a user's fine-grained nourishment inclination by locks in them with nourishment photographs and inquiring outwardly based diet-related questions. This way they produce personalized supper proposals that are useful for those who have nourishment limitations such as veggie-lover, non-veggie-lover, kosher, or halal. Later they assess through an internet learning system that learns nourishment craving from item-wise and pairwise picture comparisons.

Kivikangas and Ravaja, 2013 performed an experiment with 99 participants(51 male and 48 female), appeared that the social relationship between players playing first-person shooting games against a companion or a stranger and in single-player mode [27]. A total of 33 groups were formed each containing 2-friends and 1-stranger. The name of the video game was - Duke Nukem. In a multiplayer game, emotion depends on with whom players are playing like with friends or with strangers. When players were playing with their friends, it was more exciting for them. However, any misfortune in the game became exciting while playing with strangers. But the same thing would become a negative emotion while playing with friends. In this research, emotion had been detected by using an EMG sensor, EDA activity, and video from the game console. Facial electromyogram (EMG) action in zygomaticus major and orbicularis oculi (ZM and OO, actuated when grinning) muscles is by and large considered a good file for positive, and movement from corrugator supercilii muscle (CS, actuated when frowning) for negative feelings[13][5]. A strong positive response to victory was found for strangers but the 'Ceiling Effect' response was initially high for friends. In this inquire about, the fractal measurement show is initiated to supply superior precision and execution in EEG-based feeling acknowledgment [6]. The fractal measurement could reflect the change of the EEG signal [4]. At first, two algorithms Box-counting and Higuchi were implemented. Because the Higuchi algorithm gives better accuracy as it was closer to the theoretical FD values [19].
McDuff et al. (2015) published their research based on a system that can predict how much a user likes an ad for a product and how likely they are to buy the product based on facial expressions and responses[29]. They took inspiration from previous works of other researchers. In McDuff et al. 's system, they have used video ads of 30-60 seconds length which falls in either product category where the products were for pet care, confectionery, and food, or under emotion category, with each ad conveying different emotions and messages. Over 1200 participants with as many different backgrounds as possible to maintain diversity were chosen. Each participant viewed ten ads and was asked one question regarding Purchase Intent (PI) in pre-survey and four questions after the survey regarding ad liking and PI.

The expression of the viewers was recorded via webcams and Neven Vision's facial recognition was used to detect facial feature points, whereas, to calculate expression probabilities, custom calculations by affectiva were used. The detector uses HOG as input from ROI into the SVM and detects five expressions. They extracted a summary of facial metric features and contextual features from the origin and category of the product. They computed Liking and PI scores for the products and found that the prediction of Ad liking is more accurate than the prediction of PI. Based on the results they found, they concluded that the previous positive image of brand or product, cultural aspects, affects PI and in the future, they want to work on videos of greater length to see the impact[29].

Freyne and Berkovsky(2010) proposed a personalized recipe recommendation that gathers data into two strategies[17]. The primary could be a fine-grained nourishment thing strategy that gathers explicit ratings on person nourishment things and the second may be a higher-level strategy that accumulates ratings on formulas and after that combines those yields to supply a formula recommendation. Emotion could be a complex arrangement of physical boosts that happens 3,000 times quicker than rational thought. It was too watched that upbeat individuals showed up to be connected to upbeat individuals and unhappy individuals as well. This paper emphasized on 3 aspects –

- Attributes Correlation
- Social Correlation
- Temporal Correlation

Seng and Ang, 2018, the authors have performed an evaluation of customer satisfaction at contact centers through video analytics [27].They have used both the sound and visual components as two sources from the video. During conversation via video conference, the audio and visual sensors capture the video and transmit that towards the customer service center and there the video splitter separates that into the audio and visual part. After performing individual analysis, later they go through an audiovisual fusion that lets them get a merged result. They have used eNterface'05 and RML datasets which contained 6 basic emotions and got simultaneously 95% and 91% recognition rate.

Chapter 3

Proposed Model

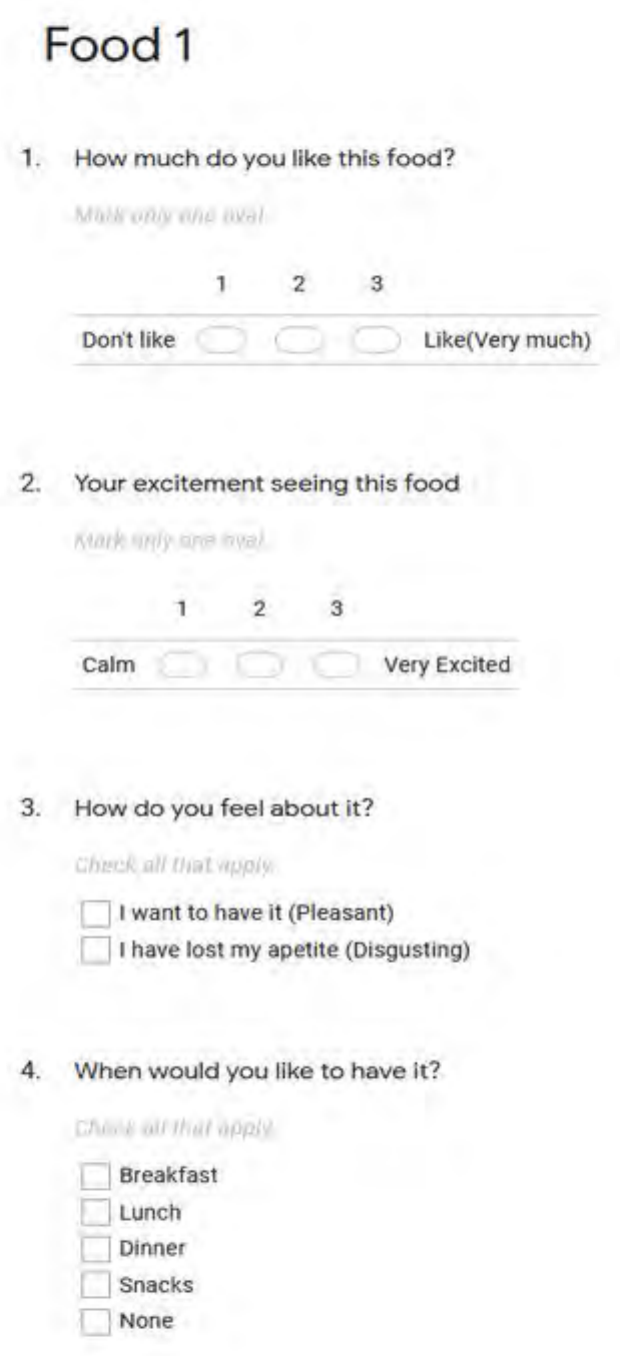
3.1 Data Collection

In this study, we collected EEG signals of 32 healthy male and female volunteers. We worked on 25 representations among them, which were completed without error and was perfect for running in our model. The purpose of this experiment was informed to all volunteers. None of them suffered from persistent pain, psychiatric illness, misuse of drugs or alcohol, addiction or anxiety, hearing impairment, or neurological disability at the time of the trial, and none of them were on treatment. For data collection, we relied on 14 wireless channel EMOTIV. A slideshow consisting of 80 slides was used as stimuli. The meals were divided into different categories based on when they are consumed, type of foods, and type of drinks. There were 8 breakfast items, 15 lunch and dinner items, and 13 snack items. 12 vegetarian, 17 non-vegetarian, and 6 different types of desserts were included. Drinks were divided into 3 categories, soft drinks, shakes, and juices. Two drinks were selected and presented for each category of drinks. A general well-known relaxing horizon scenario is used after every food image to relax our volunteer's minds so that we can record his actual feeling for the next food.

Apart from getting their EEG data, our volunteers had to answer some questionnaires after each meal they see. They had to answer this same set of questions for each food. Volunteers were asked to rate their feeling about that individual food ranging from 1 to 3. These questions are carefully made to get to know their feelings in a better way. These were focused on the preference, excitement level, and time of consumption.

Before starting to record the EEG signals, we placed EMOTIV on the participant's head for a while so that he gets comfortable wearing it. At the same time, we had a relaxing horizon scenario to make his mind calm. The whole environment was set up in a quiet and distraction-free area to achieve the complete concentration of the participants, and they were also instructed to keep their muscle movements as minimum as possible. Our goal was to keep the noise as minimal as possible.

Figure 3.1: Food pictures from the slide that were shown to the volunteers



Food 1

1. How much do you like this food?

Mark only one oval.

	1	2	3	
Don't like	◯	◯	◯	Like(Very much)

2. Your excitement seeing this food

Mark only one oval.

	1	2	3	
Calm	◯	◯	◯	Very Excited

3. How do you feel about it?

Check all that apply.

- [ ] I want to have it (Pleasant)
- [ ] I have lost my apetite (Disgusting)

4. When would you like to have it?

Check all that apply.

- [ ] Breakfast
- [ ] Lunch
- [ ] Dinner
- [ ] Snacks
- [ ] None

Figure 3.2: Questionnaires prepared for the survey

Figure 3.3: Our Volunteers

3.2 Channel selection

The EEG signals were recorded through a wireless EMOTIV, which was placed in the participant's head following the 10-20 international system, and signals were collected from 14 channels and two references with a sampling rate of 128 Hz. The names of the channels are - 'AF3', 'F7', 'F3', 'FC5', 'T7', 'P7', 'O1', 'O2', 'P8', 'T8', 'FC6', 'F4', 'F8', 'AF4', accordingly. Alpha, Beta high, Beta low, Gamma, and Theta frequencies were processed using Discrete Wavelet Transformation.

According to Coan et al.[8], the frontal part of our brain is liable for positive and negative emotions. While the right frontal brain picks the negative emotions, the left frontal brain is associated with positive emotion. So the signals - F3-F4, F7-F8, FC1-FC2, FC5- FC6 and FP1- FP2 were also investigated during our study.
The raw EEG information is found in the frequencies underneath 30Hz. There isn't a lot of mind movement with low frequencies and antiquity happens at a lower recurrence beneath 2Hz, subsequently, a 2-30 Hz band-pass channel was applied to

isolate the EEG information into 4 groups that are 2-4Hz (delta), 4-7Hz (theta), 8-12Hz (alpha) and 12-30Hz (beta). Quick Fourier Transform (FFT) with a specific non-covering window was utilized to process signal power in every one of four recurrence groups for each channel and the mean of each channel. The normal EEG signal and the 4 recurrence groups (alpha, beta, delta, and theta) acquired from the 14 anodes will give up to 70 highlights (5 14) for the recorded EEG information.

3.3 Preprocessing

EEG signal with window 1 second was decomposed to Theta (4-8Hz), Alpha (8-12Hz), Beta (12-25Hz), Gamma (>25Hz) with Wavelet Transform as shown in Table I. The decomposition of data is done by low-pass and high-pass filtering, which helps to separate the frequencies from the center as lower frequency and higher frequency bands. The signal had some data related to the time frame in which relaxation scenery was shown. As those are not related to our tasks we discarded those values. Then we labeled the data according to the results from our survey and finalized the dataset.

Bands	Frequency Range
THETA	4-8Hz
ALPHA	8-12Hz
BETA	12-25Hz
GAMMA	25-45Hz

Table 3.1: EEG Signal Decomposition

3.4 Proposed Workflow

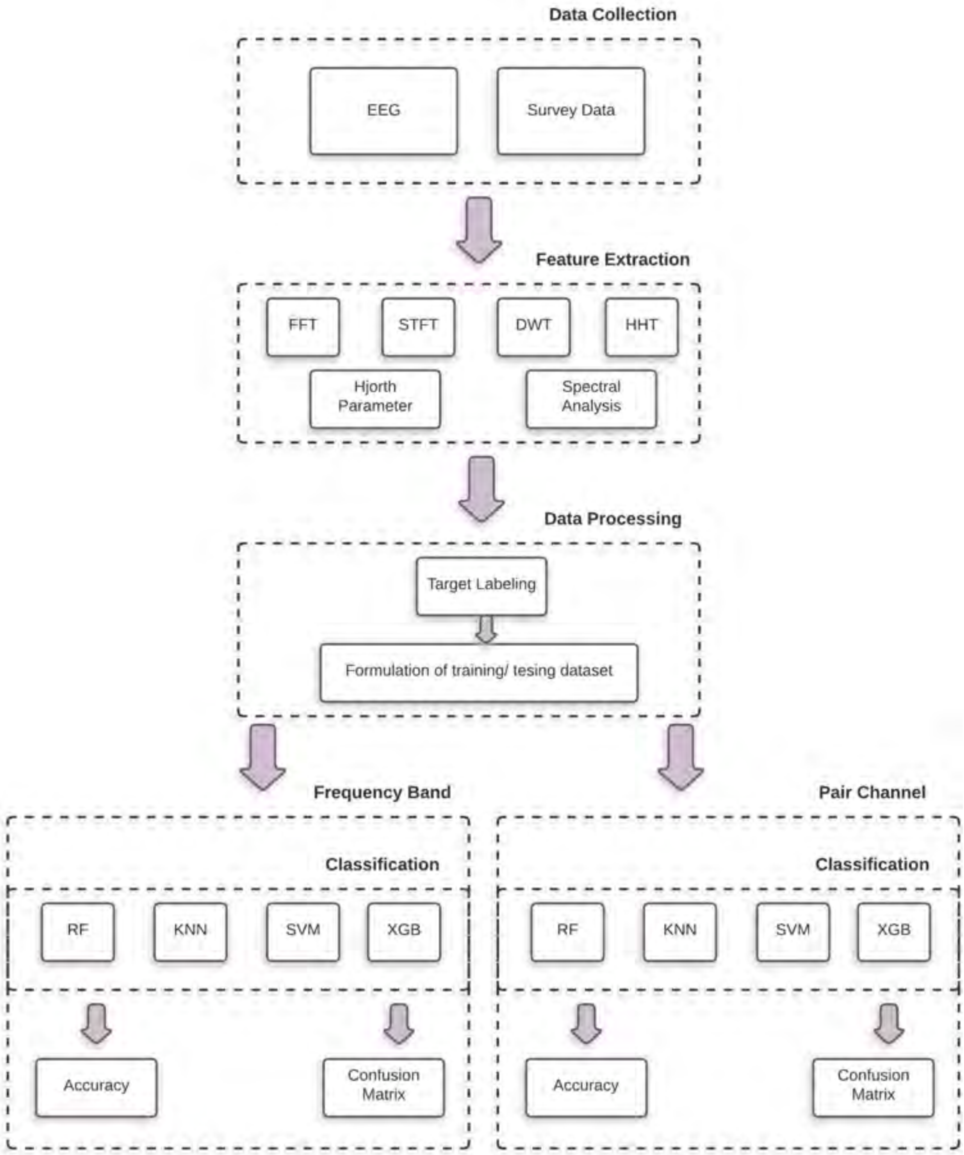


Figure 3.4: Work Process of our recommender system

3.5 Feature Extraction

Electroencephalogram or widely known as EEG signals are the electrical activity of the brain. As EEG signals are used to determine the state of the brain, emotions can also be recognized by studying these signals. However, in a study conducted by (Al-Fahoum Al-Fraihat, 2014), it has been stated that signal noise which is captured during the recording of EEG signals, can affect the meaningful features of the signal[28]. Features are the distinguished property of a signal that is measurable and functional. From the works of (Cvetkovic, Übeyli Cosic, 2008), we come to know that features are used to recognize patterns without the loss of information being as low as possible[15]. On the other hand, the classification of emotion gets more accurate as of the number of features it contains lessens. Many methods have been introduced to tackle the situation of unwanted signal noises. Feature extraction is the method of recognizing patterns in a signal. Usually, the methods by which features are extracted are chosen based on the features that will be best for the classification of emotions. Often the process of feature extraction is applied to a predetermined set of features. Features are dominantly chosen in two ways, which class the signal is representing, and how different the signal is from the predetermined class.
As we collected raw EEG signal data from all 14 channels of emotive pro, it became quite impossible for us to work without redacting the irrelevant features. In the feature extraction process, various methods are used to diversify the number of features that can be extracted from the same raw EEG data. For our research, we extracted features from the time and frequency domain. Since the extracted features of time-domain belongs to raw EEG signals, it was quite easy to implement. We calculated Mean, Median, Skewness, and Standard Deviation for each channel signal. For feature extraction from frequency domain and time-frequency domain, on the other hand, we used six feature extraction methods which were Discrete Wavelet Transform(DWT), Short Time Fourier Transform(STFT), Hjorth Parameter(Activity), Fast Fourier Transform(FFT), Hilbert-Huang Transform(HHT) along with Power Spectral Analysis(PSA). These extraction methods helped us to reduce the number of features presented in our obtained dataset.

3.5.1 Time Domain Analysis:

In reference to time, the evaluation of characteristics acquired from physical signals is known as time-domain analysis. Features extraction from the time domain is the easiest to implement as they are extracted from the raw EEG signals. Although according to (Phinyomark, Phukpattaranont Limsakul, 2012), the main disadvantage is that during the extraction of features, only the stationary part of the EEG signal is considered, while in reality, an EEG signal has a lot of nonstationary properties too[24]. Within a reasonable window length, Mean, Median, Skewness, and Standard deviation of signals keep changing. Hence we need to extract these features from small periods of time.
a. Mean: Mean is one of the prominent features we extracted from our signal data. It is calculated over the sample length of the signal. Mean, generally known as the average value, is the mid-value of a set of discrete sets of numbers. It is found

by adding the values and then dividing the sum by the number of values. For our research, we calculated the mean value of each individual's EEG signal and found out the likeliness of their choice based on the time period. To find the mean, we used the following equation;

$$Mean = \frac{1}{N} \sum_{n=1}^{N} x_n \tag{3.1}$$

where xn is the value of the nth raw EEG signal, n=1,... N.

b. Median: Median or the mid-value of a signal is used to separate the upper half value from the lower half value. Median frequency can also be described as half of the values added together. Even though the mean and median are quite similar to each other and can be described as just two different ways to acquire the average, the median has less chance of being affected by the noise than the mean does. The calculation of this feature resulted in us being able to decide how the upper portion of the signal differs from the lower portion. To derive the median feature, we used the following equation,

$$\text{Median } = \sum_{j=1}^{J} P_j = \sum_{j=0}^{M} P_j = \frac{1}{2} \sum_{j=1}^{M} P_j \tag{3.2}$$

c. Skewness: Skewness is a higher-order statistical property of the time domain. It refers to the asymmetry of the set of data. It can also be explained as how much the distribution of the values in frequency differs from the normal distribution. The value of skewness of signal can be positive, negative, zero, or undefined. When there is an equal number of high and low valued frequencies, skewness will be zero or undefined for that period of time, which means the data is perfectly symmetrical or that symmetry can not be defined for that set of data. When there are fewer large values than lower ones, it will be positive and for more large values than low values, it will be negative. To derive the skewness, the following equation has been used.

$$\text{Skewness} = \frac{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^3}{\left(\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2\right)^{\left(\frac{2}{2}\right)}} \tag{3.3}$$

d. Standard Deviation: In ("Mean and Standard Deviation", 2020), it has been mentioned that the mean is considered as the middle point of the distribution of frequencies in a signal. Standard deviation is how much the frequency varies from that midpoint of distribution. According to (Smith, 1997), only the AC component of the signal is measured by the standard deviation. The deviation here is not an important parameter, but the power deviation holds over the mean. The term

$$|X_i - \mu|$$

in the equation for standard deviation refers to how much far the sample 'i' deviates from the mean. This deviation from the middle point of the data set can be calculated as,

$$SD., \sigma^2 = \frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \mu)^2 \tag{3.4}$$

3.5.2 Frequency Domain & Time-Frequency Domain Analysis:

Where the time domain shows how much a signal has changed over time, the frequency domain indicates how much signal is in each frequency band. In the analysis process of a signal in the frequency domain, frequency is used as an independent variable. This analysis of the signal results in it being represented into various frequencies such as Alpha, Beta, Gamma, Theta. It represents the change of phase and magnitude in the frequency bands. Time-frequency domain analysis reveals how much the frequency of the signal has changed over a period of time. This analysis is useful as in multi-component and non-stationary signals. The frequency domain and time-frequency domain of a signal can be achieved with the help of a pair of mathematical operators called transform. For our research, we used FFT, STFT, DWT, HHT, and PSA.

a. Fast Fourier Transform(FFT): FFT is a mathematical method for transforming a The signal from its current or original domain such as time or space to the frequency domain. In our paper, we have used this method to calculate a function of time into a function of frequency. The length of EEG signals under given emotional stimuli, number of channels, frequency bands, design of statistical feature extraction methods, and characteristics play an important role in emotional assessment using EEG signals. Fast Fourier Transformation (FFT) is used to extract features from four separate frequency bands called (alpha , beta , gamma, and theta) which can provide more effective knowledge about the finer emotional state changes in EEG signals.

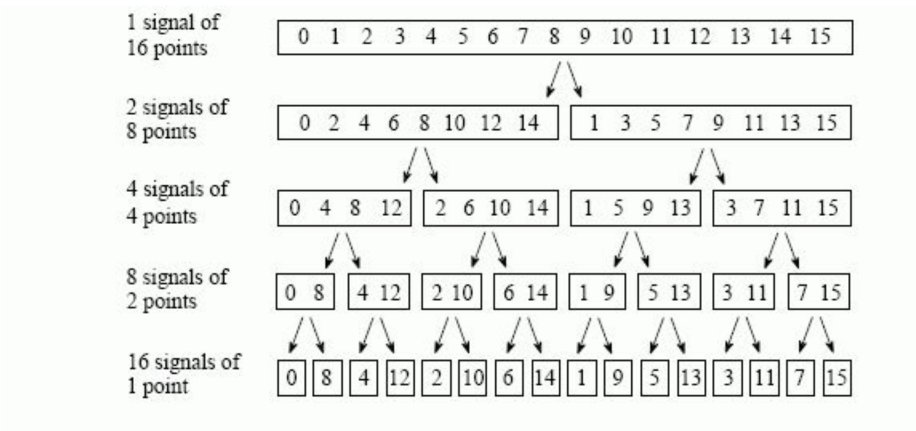


Figure 3.5: First Fourier Transformation

FFT works by dividing N point time signal into N point time signal consisting of at least one signal point and then converting each of these N time signals to corresponding N time-frequency spectra. After that these frequencies are converted into one single frequency data.

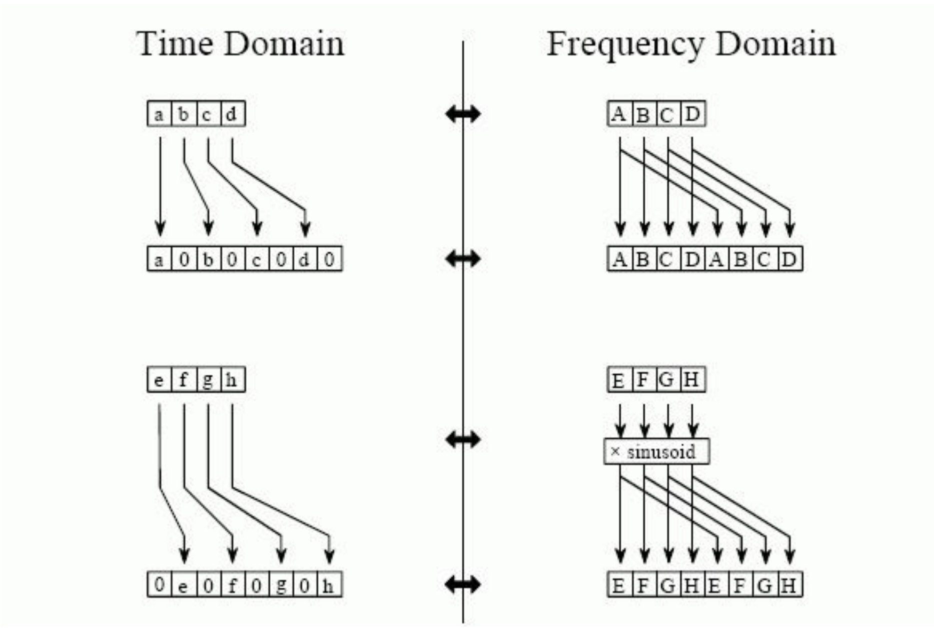


Figure 3.6: Point signal decomposition

The figure above shows a 16 point signal being decomposed into signals of one point through 4 stages. In the first stage, the signal is divided into two signals of 8 points, then each of them into signals consisting of 4 and 2 points, and then lastly into a single point of the signal. Hence, we can understand that $\log_2 N$ stages are needed to decompose a signal.
Next, the frequency spectra are determined for the one point time domain signal. As the frequency spectrum of a single point signal is equal to itself, this measurement is simple. The last step of the process of FFT extraction is to combine these frequency spectra in the reverse direction of signal decomposition.

The figure above shows the synthesis process of the FFT method. For our paper, while determining the FFT of a signal x[n], where n is domain size, e is multiplied to each of its value and then summed to obtain the results for a given n.

$$\mathrm{X[k]} = \mathrm{X_1[k]} + \mathrm{e}^{-2\pi\ \mathrm{jnk}\ /\mathrm{N}}\mathrm{X_2(k)} \tag{3.5}$$

b. Short Time Fourier Transform(STFT): STFT is a linear time-frequency representation used to present signal shifts that differ over time. In order to evaluate the sinusoidal frequency of a signal, this feature extraction method has been used. STFT is applied to specify the complexity of the amplitude of a signal against the time and frequency of a signal. The approach is to perform a Fourier transform on only a small section of data at a time which will transform the signal into a 2D function of time and frequency. According to (”Short-time Fourier transform”, 2020), the data that needs to be transformed is first broken into small frames and each frame is then Fourier transformed. In the Fourier transformation of a signal, F(w) is called the spectrum of signal f(x). Considering f(x) as the Fourier transform of the function F(w),

$$F(\omega) = \int_{-\infty}^{\infty} f(x) e^{i\omega x} dx \tag{3.6}$$

which can be inversely written as,

$$f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{i\omega x} d\omega \tag{3.7}$$

Here,

$$e^{i\omega} = \cos\omega + i\sin\omega$$

A matrix is used to calculate the magnitude and phase of the derived complex data. This process can be expressed through the following equation,

$$S\omega(t) = \frac{1}{2} 2\pi \left(\int ej\omega' t S\left(\omega' t\right) H\left(\omega - \omega'\right) d\omega' \right) \tag{3.8}$$

c. Discrete Wavelet Transform(DWT): DWT is commonly used in machine learning to detect objects and classifications. Studies published by (Rankine, Mesbah Boashash, 2007) (Derya Übeyli, 2008) states that this method is the most favorable time-frequency resolution among all frequency ranges[14][16]. Since the EEG signal is non-stationary, the most effective method of extracting features from raw data is the use of methods such as DWT of the time-frequency domain, which is a technique for spectral estimation in which any general function can be expressed as an endless sequence of wavelets. To get a narrower low-frequency DWT long-time windows are used in resolution while in order to obtain high-frequency data, short time windows are used[28]. As DWT allows the sizes of windows to be variable, it provides a more versatile way of time-frequency size openings. The figure below represents the decomposition of the signal through the DWT method.

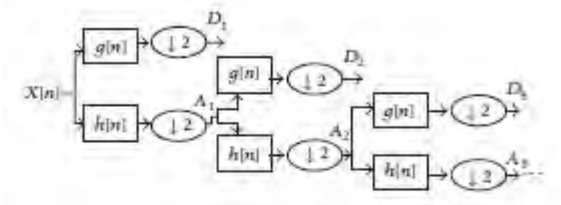


Figure 3.7: DWT

DWT uses two coefficients called detailed coefficients and approximation coefficients. The approximation, or scaling, coefficients are the signal's low-pass representation, which is essentially the wavelet coefficients of the data. By going through a variety of filters, the DWT of a signal X is determined. The approximation coefficients are then split into a coarser approximation (low-pass) and high-pass (detail) component at each subsequent step. A low-pass filter with an impulsion of g is passed through, which results in a fusion of the two. This extraction method can be written as,

$$\psi(x) = \sum_{k=-\infty}^{\infty} (-1)^k a_{N-1-k} \psi(2x - k) \tag{3.9}$$

d. Hilbert-Huang Transform(HHT): A new method of analyzing nonlinear and nonstationary dataset according to (Phan Chen, 2017), is the Hilbert-Huang Transform method. This is a two-step method that uses Empirical Mode Decomposition (EMD) method to decompose the signal into Intrinsic Mode Functions(IMF) and applies the Hilbert Spectral Analysis (HSA) to get the frequency data. As decomposition happens in the time domain, and the length of signal and IMFs are the same, their main identities for the varying frequencies are safe. EMD method is needed to reduce any data into the IMFs. In EMD, the signal is divided into finite and small parts. Sifting is the process of extracting IMF from the EMD components. In sifting, first, from each component, local extrema are calculated and all the local maxima are connected via a cubic spline to find the upper envelope. The same procedure is followed to find the lower envelope by using the local minima. This process is repeated until all the proper modes are revealed and the following condition has been met, where c is the previously extracted IMF data and where the residue function, rn, becomes a monotonic function and no more IMFs can be extracted from the component.

$$X(t) = \sum_{j=1}^{n} c_j + r_n \tag{3.10}$$

After calculating the IMFs, the instantaneous frequency is acquired by using HSA through the following equation;

$$X(t) = \text{Real} \sum_{j=1}^{n} a_j(t) e^{i \int \omega_j(t) dt} \tag{3.11}$$

In our research, we used the HHT method to obtain the energy frequency-time distribution. This can be expressed as the following equation,

$$x_a = F^{-1}(F(x)2U) = x + iy \tag{3.12}$$

e. Hjorth Parameters(Activity): The Hjorth parameter is one of the ways to indicate the statistical properties of the signal in the time domain. In (Oh, Lee Kim, 2014), the authors note that Hjorth parameters are defined by three-time domain parameters of EEG signals which are known as, Activity, Mobility, and Complexity[30]. The activity parameter can indicate the surface of the power spectrum of the frequency area. That is to say, the importance of activity returns a large/small value when the high frequency is used in the signal. The mobility parameter is known as the square root of the ratio. The variance of the first signal derivative and the variance of the signal. This parameter has a proportion of the standard deviation of the current spectrum. Hjorth Parameter is also used to assess the complexity of signals. The complexity parameter shows if the form of a signal is identical to that of a plain sine wave. The value of Uncertainty converges to 1 as the form of the signal becomes more like a plain sine wave. For our research, we have only used the Activity parameter, which is a deviation of the time function. This parameter can be written as the square of the standard deviation of the signal[30].

$$\text{Activity } = \operatorname{var}(y(t))$$

f. Spectral Analysis: Spectral analysis has been noted as one of the popular approaches used to measure the EEG. In a study by (Dressler, Schneider, Stockmanns Kochs, 2004) explained that the spectral power density (power spectrum) represents the 'frequency quality' of the signal or the distribution of signal power over the frequency[10]. Another study by (Zhang, A., Yang, B., Huang, L., 2008) points out that power spectral entropy is known for the calculation of time uncertainty in the frequency domain. When the spectrum peak is narrow along with a small entropy value, this refers to smaller complexity. While on the contrary, a smoother spectrum peak indicates higher entropy. Hence, the power spectrum can exhibit the spectra structure of EEG signals.

$$H = -\sum_{k=1}^{N} p_k \log p_k \tag{3.13}$$

3.6 Model Specificaaton

Support Vector Machine(SVM):

Algorithm 1 Training an SVM

Require: X and y loaded with training labeled data. $\alpha \Leftarrow 0$ or $\alpha \Leftarrow$ partially trained SVM

$C \Leftarrow$ some value (10 for example)

repeat

  for all $\{x_i, y_i\}, \{x_j, y_j\}$ **do**

    Optimize α_i and α_j

  end for

until no changes in α or other resource constraint criteria met

Ensure: Retain only the support vectors ($\alpha_i > 0$)

Figure 3.8: SVM Algorithm

SVM is a parametric classifier, which has the main purpose of finding a hyperplane in an multi-dimensional space that separately classifies the data points, depending upon the number of features. Hyper-planes determine the specifications that help to classify the data points. It is a powerful classifier originally developed by Vladimir and Burges and Christopher for binary problems at Bell Laboratories. A study conducted by (Yu, Tian, Cheng Zhang, 2011) however states that, in the case of multi-class implementations, its oppressive capacity can be diminished[15].

SVM can be done using its various kernels to achieve the most desirable precision. SVM is a machine learning model that can upon receiving data from two different categories, differentiate between the data, and classify which data belongs to which category. The nearest data points to the hyperplanes are called support vectors which have a major influence on the position and orientation of the hyperplanes. The more distance the hyper-plane has to the nearest training-data point, the better, as it lowers the generalization error of the classifiers.

In this algorithm, different category data points are plotted on an N-dimensional plane. A SVM takes these data points and outputs the hyper-plane that best separates the data points according to their category. For example, if it's a 2D plane where there are two different types of data to be classified, the hyper-plane to separate them from each other will simply be a line. Data points that fall to one side will belong to the same category. Study by (Bazgir, Habibi, Palma, Pierleoni Nafees, 2018) points out that generalization property makes SVM rigorous to perform overfitting [41]. This is how a SVM categorizes different types of data points. In this research, we have used the RBF kernel. To construct a RBF kernel classifier following equation has been used,

$$f(x) = \operatorname{sgn}\left[\sum_{i=1}^{l} \omega_i \exp\left(-\frac{(x-x_i)^2}{c_i}\right) + b\right] \tag{3.14}$$

where b and ci are constants, and are used to separate the data. After choosing the suitable kernel for our classification purposes, margins are calculated. The bound of the regions separated by the hyper-plane is called margin. This successfully classifies the data from each other. Hard-margin for the linearly separable data and soft margin for the non-linearly separable data is calculated through the following equations,

$$\text{hard} - \text{margin} = \vec{\omega} * \vec{x}_i - b = 1 \tag{3.15}$$

where anything on or above one class is labeled as 1, and

$$\text{hard} - \text{margin} = \vec{\omega} * \vec{x}_i - b = -1 \tag{3.16}$$

where anything on or below the other class is labeled as -1.

$$\text{soft-margin} = \left[\frac{1}{n}\sum_{i=1}^{n} \max\left(0, 1 - y_i\left(\vec{\omega} * \vec{x}_i - b\right)\right)\right] + \lambda(\vec{\omega})^2 \tag{3.17}$$

XGBoost:

```
Algorithm 1: Feature Discretization Based on XGBOOST
Input: D : Micro-blog dataset
       N : The number of trees in XGBOOST
Output: Discrete data
       for i = 0; i < D; i + + do
            preprocessing the data
            text participle
       end for
       while LDA does not converge do
            extracting text subject characteristics
       end while
       extracting user characteristics U, constructing union feature C
       for i = 0; i < C; i + + do
            using XGBOOST to discretize the feature
       end for
```

Figure 3.9: XGBoost Algorithm

XGBoost is a decision-tree-based ensemble Machine Learning algorithm that uses a gradient boosting framework. It is widely used in numerous domains because of its high efficiency and accuracy. A paper published by (Ren, X. et al, 2017), stated that tTree boosting is a highly efficient algorithm for learning which makes many weak classifiers a strong classifier for better classification[37]. XGBoost uses the second order derivative as an approximation in order to minimize the error of the complete model. In a system developed by (Chen Guestrin, 2016), it has been shown that In all XGBoost scenarios, scalability is due to various important frameworks and optimizations of algorithms, including a new tree learning algorithm, a logical quantile sketching process, and parallel, distributed computing.[34]. Let P define a database with n examples and m features where

$$\mathrm{P} = (x_i, y_i)\,(P = n, x_i \in R^m, y_i \in R^m)$$

A tree boosting model output y_i with K trees can be defined as follows:

$$y_i^{\wedge} = \sum_{k=1}^{k} f_k\left(x_i\right), f_k \in F \tag{3.18}$$

where F is the function containing the classification trees. Here each fk is separated into different tree structure q, and leaf weight called . The set of function described as fk is approximated by the XGBoost classifier which utilizes the Taylor expansion and derives the final objective function at step t by the following equation,

$$O(t) = \sum_{j=1}^{T} \left[\left(\sum_{i \in I_j} g_i \right) \omega_j + \frac{1}{2} \left(\sum_{i \in I_j} h_i + \lambda \right) \omega_j^2 \right] + \gamma T \tag{3.19}$$

where gi and hi are first and second order statistics of the gradient in XGBoost. Considering j as the instance set of leaf I, j of leaf j for a tree q(x) can be written as the following equation,

$$\omega_j = -\frac{\sum g_i}{\sum h_i + \lambda} \tag{3.20}$$

After substituting j into the previous function, the scoring function O(q) can be found.

$$O(q) = -\frac{1}{2}\sum_{j=1}^{T}\frac{(\Sigma g_i)^2}{\sum h_i + \lambda} + \gamma T \tag{3.21}$$

This function is used to evaluate the tree structures and find the optimal trees for classification. Since it is not possible to search for all the possible tree structures, the search starts from a single leaf node and branches will be added to expand the tree.

K Nearest Neighbor(KNN):

Algorithm 4: kNN `kernel` Algorithm

Input : D, a chunk of the original distance matrix;
$n_{chunksize}$, dimension of the chunk;
split, index of split;
chunk, index of chunk;
Maxk, an array to hold the farthest neighbors for each row index in the chunks;

Output: none, an (intermediate) kNN graph stored in Gk′;

```
row′ ← blockIdx.x × blockDim.x + threadIdx.x;
if row′ < n_chunksize then
    row ← split × n_chunkSize + row′ // absolute row in the distance matrix;
    for column′ ← 1 to n_chunksize do
        column ← chunk × n_chunkSize + column′ //absolute column in the distance matrix;
        if row = column or row > n_row or column > n_col then
            continue /* exclude diagonal and pad regions */;
        if D[row′ × n_chunksize + column′] < Gk′[Maxk[row′]].weight then
            Gk′[Maxk[row′]].source ← row;
            Gk′[Maxk[row′]].target ← column;
            Gk′[Maxk[row′]].weight ← D[row′ × n_chunksize + column′];
            Search the new maximum element in row′(D) and store the index in Maxk[row′];
```

Figure 3.10: KNN Algorithm

Easy and simple to use, KNN has been widely used in the classification of data. According to this algorithm, similar things stay in close proximity. It is a supervised machine learning algorithm that is mostly used to predict the nature of the dataset.

To implement this, a set of test and training data are needed. After loading the data sets, the value of K is chosen and the distance between the training and testing data points is calculated. Based on the distance from the nearest training data point, a class is assigned to the data.
As it has been mentioned in (”KNN Classification”, 2020), in the algorithm of the KNN classifier, a case is graded by a majority vote of its neighbors, with the case assigned to the most common class of its nearest K neighbors, determined by a distance function. For K = 1, the case is clearly assigned to the class of its closest neighbor. To measure the continuous variables, three different distance functions have been used using the following equation,

$$\text{Euclidian, } f(x) = \sqrt{\sum_{i=1}^{k} (x_i - y_i)^2} \tag{3.22}$$

$$\text{Manhattan, } g(x) = \sum_{i=1}^{k} |x_i - y_i| \tag{3.23}$$

$$\text{Minkowski, p(x)} = \left(\sum_{i=1}^{k} (|x_i - y_i|)^q \right)^{1q} \tag{3.24}$$

where y is the class label of x. After calculating the distance functions, the optimal value for K is chosen by inspecting the data. The larger the value of K is, the more noises will be reduced.

Random Forest(RF):

```
Algorithm 1: Pseudo code for the random forest algorithm
To generate c classifiers:
for i = 1 to c do
  Randomly sample the training data D with replacement to produce D_i
  Create a root node, N_i containing D_i
  Call BuildTree( N_i )
end for

BuildTree(N):
if N contains instances of only one class then
  return
else
  Randomly select x% of the possible splitting features in N
  Select the feature F with the highest information gain to split on
  Create f child nodes of N , N_1,..., N_f , where F has f possible values ( F_1, ... , F_f )
  for i = 1 to f do
    Set the contents of N_i to D_i , where D_i is all instances in N that match
    F_i
    Call BuildTree( N_i )
  end for
end if
```

Figure 3.11: Random Forest Algorithm

The random forest classification is a combination of tree classifiers, where for each class a random vector is separately sampled and where a voting unit is chosen to assign the input vector for the general class for each of the tree classes. Every prediction is obtained and samples are provided by RF. Finally, by voting RF chooses the best alternative. It is better than a tree that takes decisions because it removes the excess by combining the outcome. Implementing this algorithm requires the selection of random data from the data set and constructing decision trees based on each data sample. After getting a prediction result from each decision tree, voting is performed and the prediction which gets the most votes is assigned to that particular data sample. To train the learner trees, the general technique of bagging is applied. A training set, X=x1, x2, ... , xn with responses Y=y1, y2, . . . , yn, is bagged iteratively(b times) by selecting random samples of the training set and fitting them into the samples. In the study by (Pal, 2005), the emotions are categorized by taking the most common preferred class from all tree predictors in the forest[11]. The design of the decision tree is based on the selection of the attributes and the pruning process. There are several approaches for determining the attributes used for decision tree induction, and most approaches explicitly relate to the consistency calculation of the attribute. Our RF model uses the Gini index, which is one of the most used attribute selection measures that calculate the authenticity of the attribute against the classes. For a given training set T, selecting a case at random and stating that it belongs to any class Ci, the Gini index can be written as

$$\sum_{j\neq i} \frac{f\left(C_i, T\right)}{\mid T_I} * \frac{f\left(C_j, T\right)}{\mid T_{\mid}} \tag{3.25}$$

where

$$\mathrm{f}\left(\mathrm{C_l}, \mathrm{T}\right) / |\mathrm{T}\mid$$

is the probability of the case belonging to class Ci. There are two user specified parameters which are used to construct a forest classifier, as are the number of features in every node used to construct a tree and the amount of trees to grow. The best split in each node is only tested for the chosen features. Thus, the random forest classifier consists of N trees, where N is the number of trees to be planted, which may be any value specified by the user. To identify a new dataset, each case of a dataset is transferred down to each of the N trees. Lastly, the forest chooses the class which has been voted most.

Chapter 4

Performance Evaluation

4.1 Evaluation Method

To evaluate the results we got from the classifier models, we used a confusion matrix to compare the prediction results and the survey results. Widely used in the field of machine learning, a confusion matrix is often used to compare the output of a classifier against a collection of test data for which true values are already established. The output of this matrix consists of four values, True Positive(TP), True Negative(TN), False Positive(FP), and False Negative(FN).

For our research, we used a three-class confusion matrix to evaluate the classifiers.

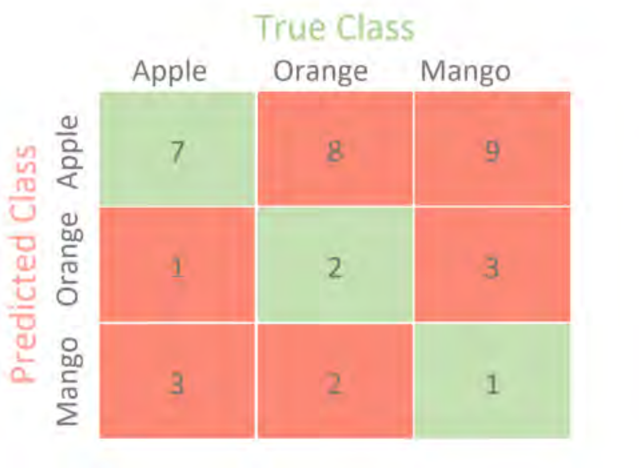


Figure 4.1: Matrix

In the figure above, we are able to see that it is a 3x3 dimensional matrix and that the values of the true class or the values that we already have beforehand are being compared to the values that were predicted by the classifiers. For a three-class confusion matrix, the values were calculated for each individual class separately.

True Positive: The true positive is the number of predictions where data labeled as belonging to a particular class is correctly classified as the said class. In our instance, if our classifiers predict the value such as 'Most Like' and the participant has also mentioned in the survey that they liked the food very much, then the confusion matrix will output the result as true positive.

False Positive: The sum of all the values in the corresponding column is calculated to calculate the false positives for a given class with the exception of the true positives. If the survey value of a food participant suggests that the food he didn't like at all, while the predicted value of that classification suggests that he liked it. This is incorrect because the participant didn't really like food according to the survey.

True Negative: The True Negatives for a given class is determined by taking the number of values in each row and column, excluding the row and column of the class for which we try to find the True Negatives. For example, if the survey shows that the participant did not like the food and the classifiers give the output as 'Least Like', then the matrix will give us the value as true negative.

False Negative: False negatives for the class can be defined by excluding the value of True Positives, by taking the sum of all values in the line corresponding to that class. This value occurred when the participant is saying he liked the food very much but the classifier says that the result falls under the 'Least Like' category. Since the actual positive value differs from the predicted negative value, this fell under false negative.

Now with all that in mind, accuracy is measured as the ratio between the number of accurate classifications and the total number of classifications. From our confusion matrix, the right classifications are the True Positives for each class and the total number of classifications is the count of each attribute in the confusion matrix, including the True Positives. By using the following equation we can measure the accuracy of the classifier,

$$\text{Accuracy} = \frac{TP(MostLike) + TP(AverageLike) + TP(LeastLike)}{n} \tag{4.1}$$

Precision in a multi-class confusion matrix is measured as the ratio of the True Positives of the class concerned to the sum of its True Positives and False Positives. Precision for each class is calculated by,

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4.2}$$

Recall or True Positive rate is calculated as the ratio of the True Positives of a particular class to the sum of its True Positives and False Negatives. Recall for a particular class is calculated by,

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4.3}$$

The True Negative Rate is measured as the ratio of the True Negatives of a given class to the sum of its True Negatives and False Positives.

$$\text{TN rate} = \frac{TN}{TN + FP} \tag{4.4}$$

And for finding the prevalence of the model, as in how often the value is actually true, the following equation is used,

$$\text{Prevalence} = \frac{\text{Number of actualtruevalues } \in n}{n} \tag{4.5}$$

These values were used to compare our proposed classifiers with each other and find the best classifier for our system.

4.1.0.1 F1 Score

The F1-score is a measure of the accuracy of a model on a data-set. It is used to test different classification schemes that identify cases. The F1-score is widely used for evaluating machine learning models.
A great model for a particular data-set can have an F-score of 1. For multiclass, the following formula is used first to calculate each class's F1-score individually,

$$\text{F1- score} = 2 * \frac{Precision * TruePositive}{Precision + TruePositive} \tag{4.6}$$

After that these scores are combined into a single number to evaluate the classifiers. We calculated a weighted F1-score for our research. To calculate the weighted F1-score, we used the following formula,

$$\text{WeightF1} = \frac{Actual(C1) * F1score + Actual(C2) * F1score + Actual(C3) * F1score}{n} \tag{4.7}$$

Where C1= Most Like, C2= Average Like and C3=Least Like

Chapter 5

Result Analysis

5.1 Statistical Analysis

Table 5.1: Time Domain Analysis With Statistical Feature

Models	Mean	Median	SD	Skewness	Max
Random Forest	89.6%	89.3%	90.1%	89.0%	89.8%
KNN	88.7%	87.5%	88%	87.6%	88.3%
SVM	88.6%	87.7%	88.4%	87.7%	89%
XGboost	87.6%	88.6%	88.6%	87.1%	90%

In TABLE 5.1 statistical analysis - mean, median, standard deviation, skewness, maximum amplitude of each channel has been trained with Random Forest (RF), K-nearest Neighbors (KNN), Support Vector Machine (SVM) and XGBoost Classifier (XGBoost).
For all the statistical analysis Random Forest Classifiers dominates over other algorithms except for maximum amplitude. For maximum amplitude of signals, XG-boost gives higher accuracy.

5.2 Subject Independent Analysis With Frequency Band

5.2.0.1 Like Affectivity Analysis

From Figure 5.1 For extracting DWT feature, we found that SVM has the highest accuracy which are 77.66% for Alpha Band , 77.38% for Beta Band , 76.85% for Gamma Band , 77.85% for Theta Band .

From Figure 5.2 extracting FFT feature, we found that SVM has the highest accuracy which are 77.86% for Alpha Band , 77.51% for Beta Band , 77.48% for Gamma Band , 77.89% for Theta Band .

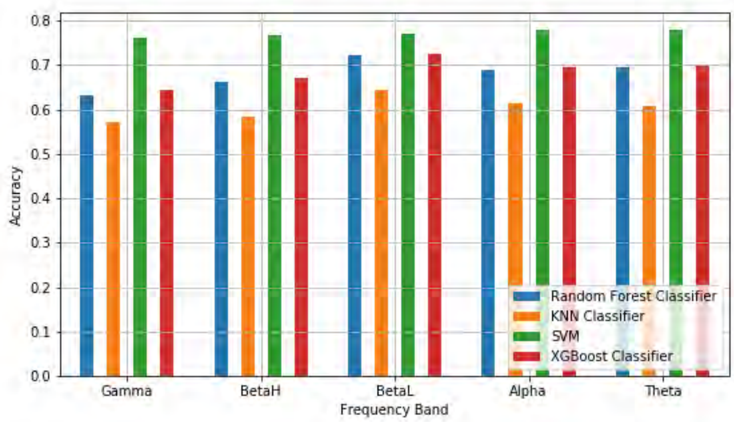


Figure 5.1: Subject Independent Accuracy Using DWT (Target : Like)

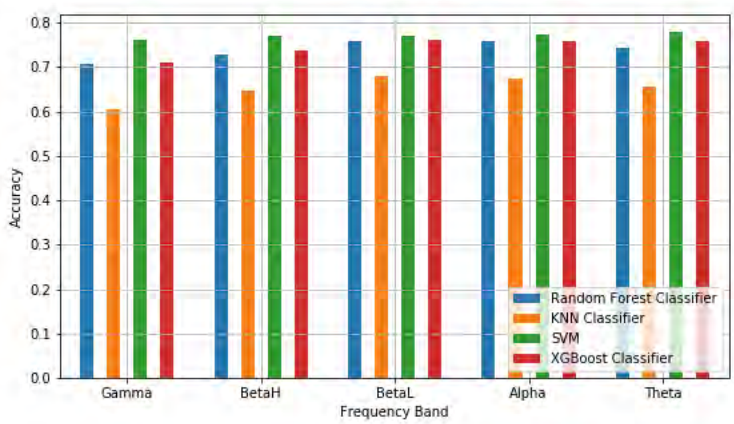


Figure 5.2: Subject Independent Accuracy Using FFT (Target : Like)

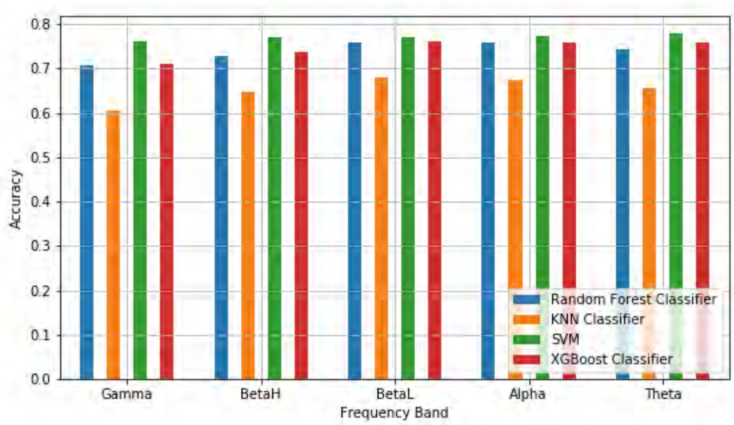


Figure 5.3: Subject Independent Accuracy Using STFT (Target : Like)

From Figure 5.3 extracting STFT feature, we found that SVM has the highest accuracy which are 77.81% for Alpha Band , 77.70% for Beta Band , 77.85% for Gamma Band , 77.89% for Theta Band.

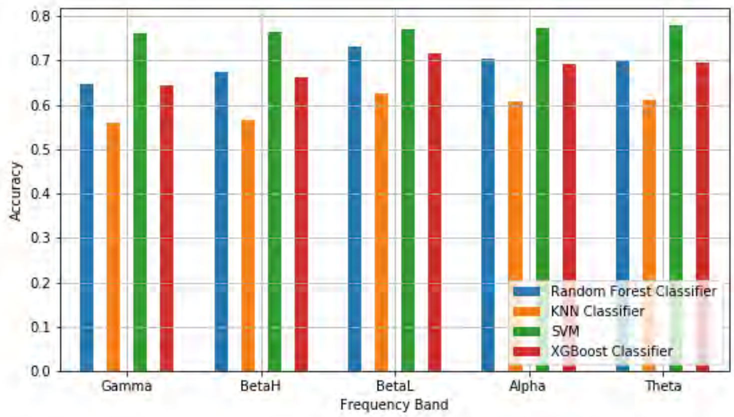


Figure 5.4: Subject Independent Accuracy Using HHT (Target : Like)

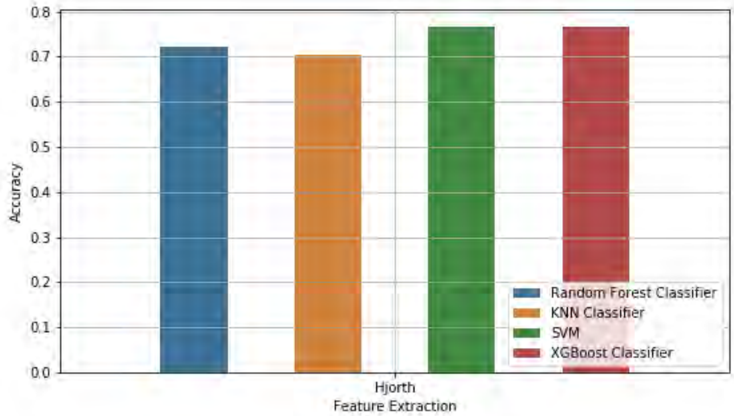


Figure 5.5: Subject Independent Accuracy Using Hjorth Parameter (Target : Like)

From Figure 5.4 extracting HHT feature, we found that SVM has the highest accuracy which are 77.78% for Alpha Band , 77.22% for Beta Band , 76.77% for Gamma Band , 77.83% for Theta Band .

From Figure 5.5 By extracting *Hjorth feature* we got 77.85% accuracy.
From Figure 5.6 For the target 'Like', Spectral analysis yields highest accuracy on SVM by using Alpha band gives 77.9%, BetaH band gives 77.9%, Gamma band gives 77.9% and Theta band gives 77.9%

5.2.0.2 Excitement Affectivity Analysis

From Figure 5.7 For extracting DWT feature, we found that SVM has the highest accuracy which are 68.10% for Alpha Band , 68.17% for Beta Band , 68.27% for Gamma Band , 68.20% for Theta Band .

From Figure 5.8 For extracting FFT feature, we found that SVM has the highest accuracy which are 68.29% for Alpha Band , 68.29% for Beta Band , 68.30% for

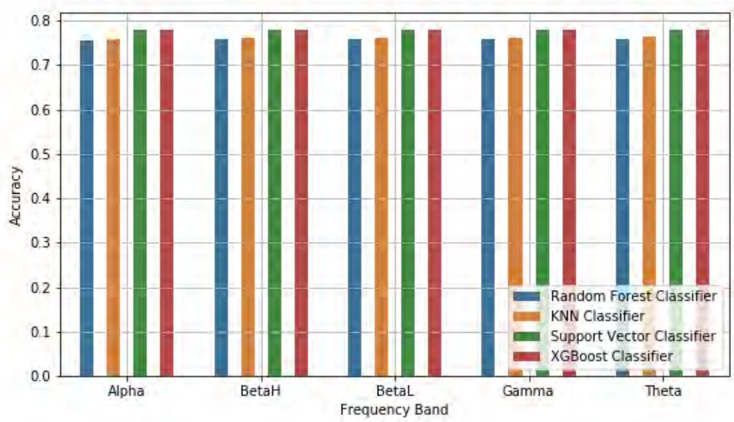


Figure 5.6: Subject Independent Accuracy Using Spectral Analysis (Target : Like)

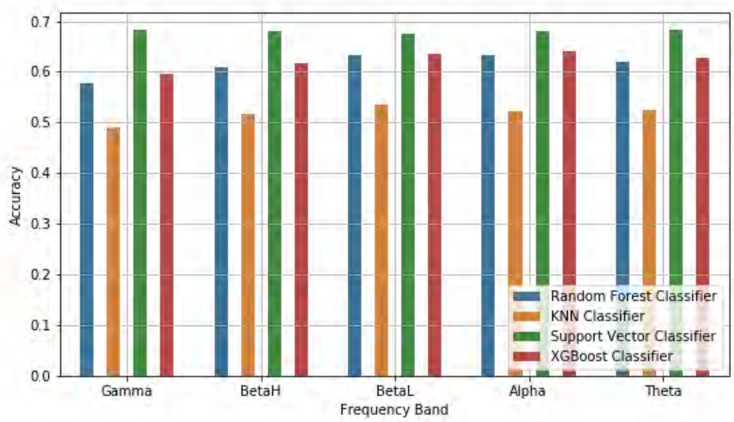


Figure 5.7: Subject Independent Accuracy Using DWT Feature Extraction (Target : Excitement)

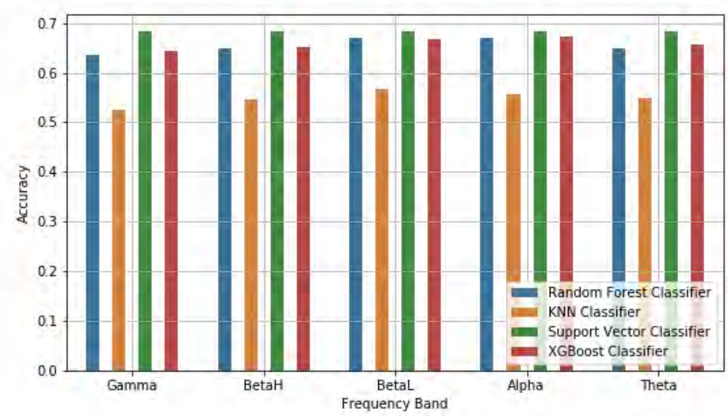


Figure 5.8: Subject Independent Accuracy Using FFT Feature Exatraction (Target : Excitement)

Gamma Band , 68.29% for Theta Band .

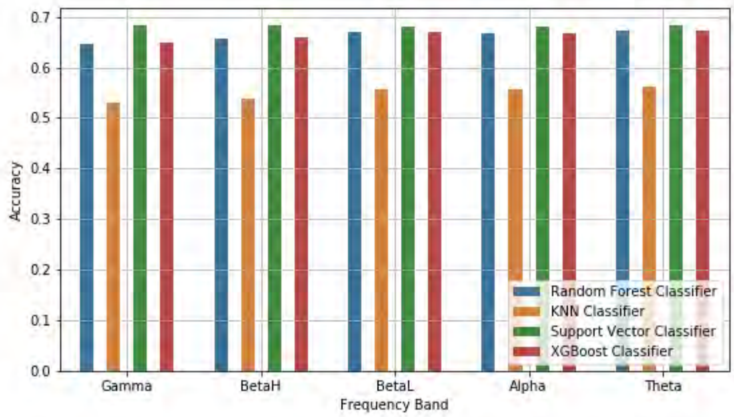


Figure 5.9: Subject Independent Accuracy Using STFT Feature Extraction (Target : Excitement)

From Figure 5.9 extracting STFT feature, we found that SVM has the highest accuracy which are 67.99% for Alpha Band , 68.21% for Beta Band , 68.29% for Gamma Band , 68.29% for Theta Band .

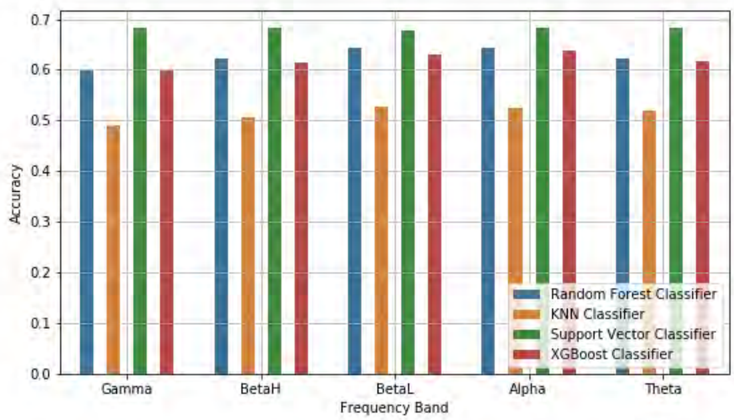


Figure 5.10: Subject Independent Accuracy Using HHT feature Extraction (Target : Excitement)

From Figure 5.10 extracting HHT feature, we found that SVM has the highest accuracy which are 67.77% for Alpha Band , 68.25% for Beta Band , 67.89% for Gamma Band , 68.22% for Theta Band .

From Figure 5.11 By extracting *Hjorth feature* we got 68.25% accuracy and by *Spectral Analysis* we found 61.87% accuracy for *SVM*.
From Figure 5.12 For Spectral analysis feature with the target of 'Excitement', we found highest accuracy on SVM by using Alpha band gives 68.3%, Beta band gives 68.3%, Gamma band gives 68.3% and Theta band gives 68.3%.

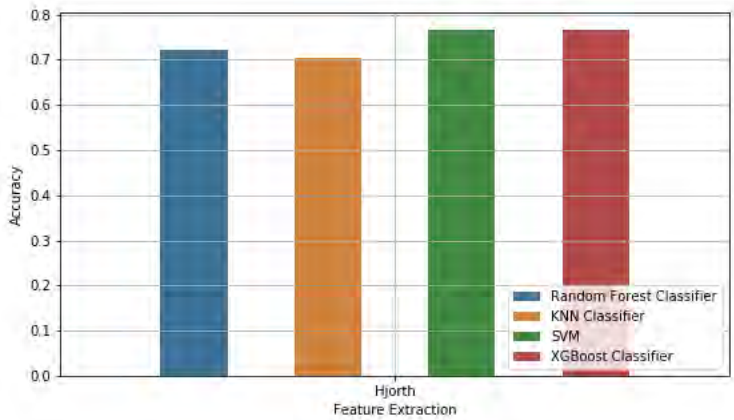


Figure 5.11: Subject Independent Accuracy Using Hjorth Parameter (Target : Excitement)

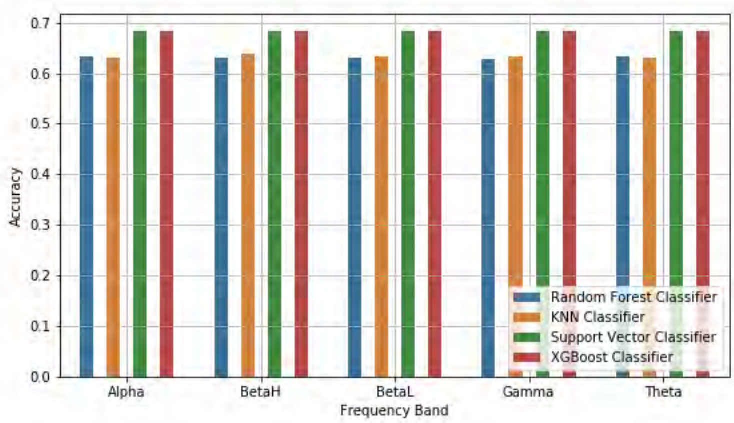


Figure 5.12: Subject Independent Accuracy Using Spectral Analysis (Target : Excitement)

5.2.0.3 Feelings Affectivity Analysis

From Figure 5.13 For extracting FFT feature, we found that SVM has the highest accuracy which are 80.99% for Alpha Band , 80.99% for Beta Band , 80.95% for Gamma Band , 80.99% for Theta Band .

From Figure 5.14 For extracting STFT feature, we found that SVM has the highest accuracy which are 81.00% for Alpha Band , 80.86% for Beta Band , 80.99% for Gamma Band , 81.00% for Theta Band .

From Figure 5.15 For extracting DWT feature, we found that SVM has the highest accuracy which are 80.88% for Alpha Band , 80.99% for Beta Band , 80.90% for Gamma Band , 80.96% for Theta Band .

From Figure 5.16 For extracting HHT feature, we found that SVM has the highest accuracy which are 80.95% for Alpha Band , 80.96% for Beta Band , 80.96% for

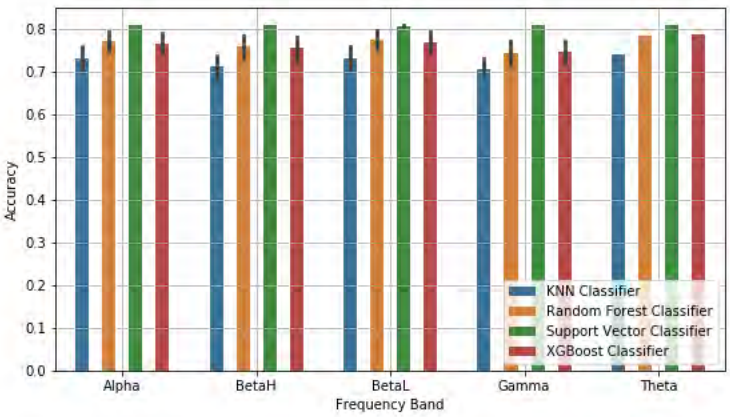


Figure 5.13: Subject Independent Accuracy Using FFT (Target : Feelings)

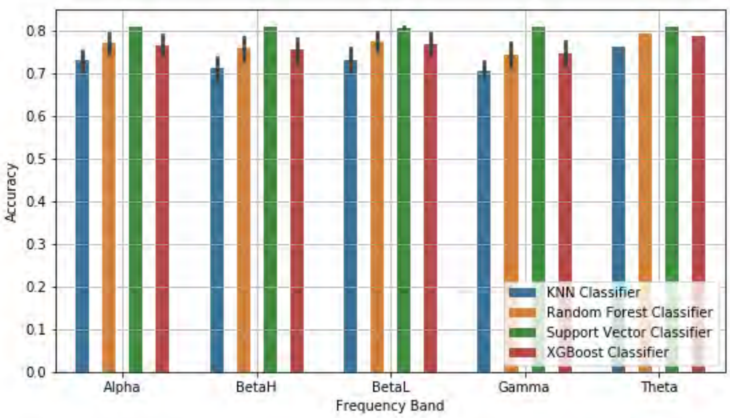


Figure 5.14: Subject Independent Accuracy Using STFT (Target : Feelings)

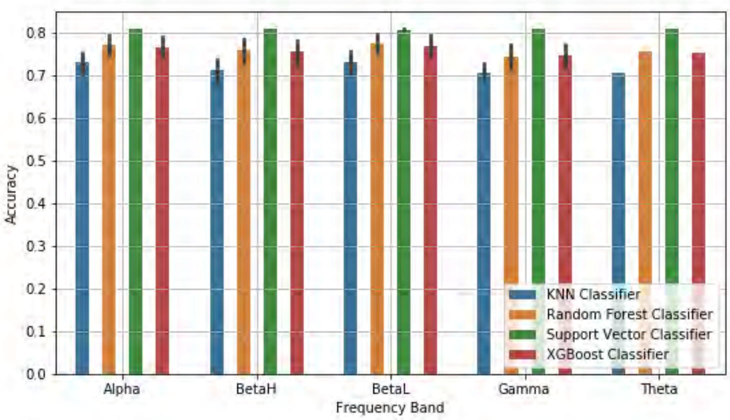


Figure 5.15: Subject Independent Accuracy Using DWT (Target : Feelings)

Gamma Band , 80.95% for Theta Band . .

From Figure 5.17 By extracting *Hjorth feature* we got 80.88% accuracy and by

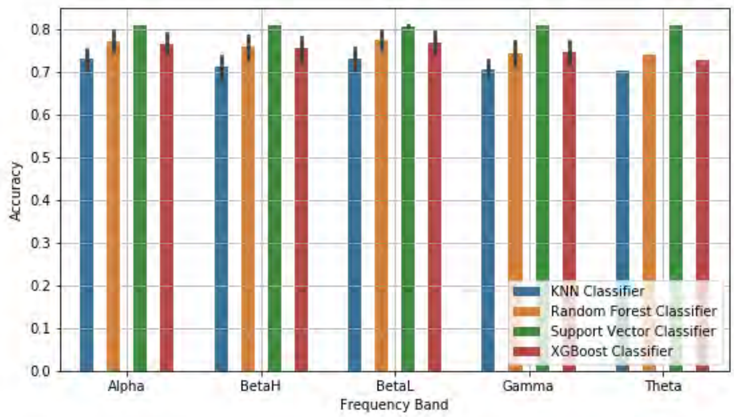


Figure 5.16: Subject Independent Accuracy Using HHT (Target : Feelings)

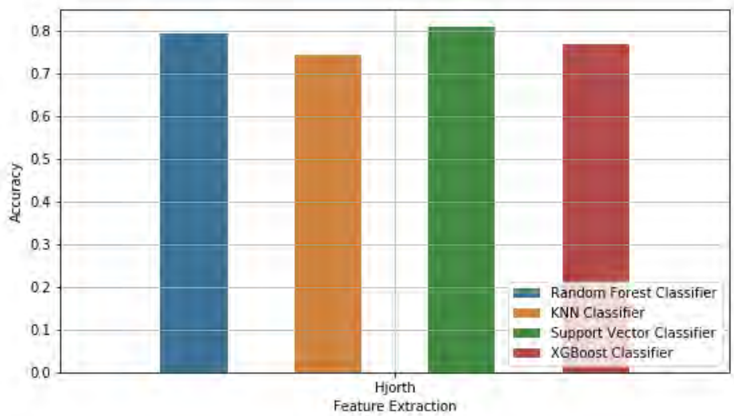


Figure 5.17: Subject Independent Accuracy Using Hjorth Parameter (Target : Feelings)

Spectral Analysis we found 75% accuracy for *SVM*.

From Figure 5.18 While doing spectral analysis, we found highest accuracy on SVM by using Alpha band gives 81.1%, BetaH band gives 81.1%, Gamma band gives 81.1% and Theta band gives 81.1% for the target 'Feelings'.

5.3 Pair-wise Channel Analysis

5.3.0.1 Like Affectivity Analysis

From Figure 5.19 For extracting *DWT feature*, we found that *SVM* has the highest accuracy which are 77.57% for *T7-T8 Channel* , 77.88% for *P7-P8 Channel* , 76.94% for *O1-O2 Channel* , 77.79% for *F7-F8 Channel*, 77.28% for *F3-F4 Channel* , 77.62% for *AF3-AF4 Channel* , 77.87% for *FC5-FC6 Channel*.

From Figure 5.20 For extracting FFT feature, we found that SVM has the highest accuracy which are 77.80% for T7-T8 Channel , 77.90% for P7-P8 Channel , 77.84%

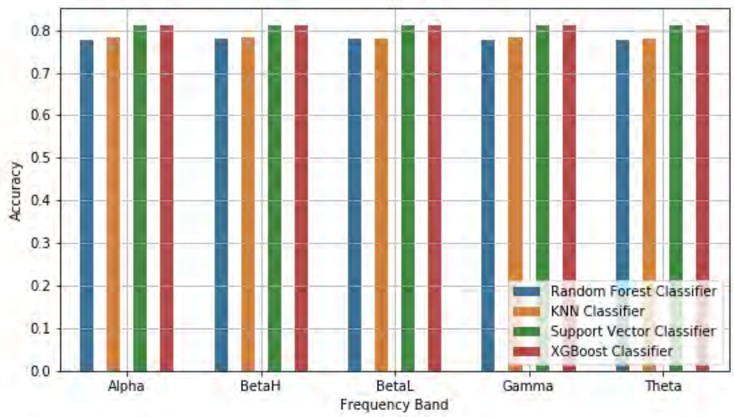


Figure 5.18: Subject Independent Accuracy Using Spectral Analysis (Target : Feelings)

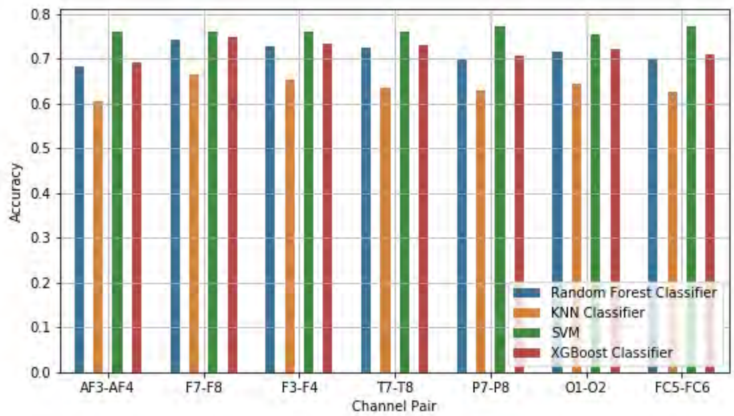


Figure 5.19: Pairwise Subject Independent Accuracy Using DWT Feature extraction (Target : Like)

for O1-O2 Channel ,77.85% for F7-F8 Channel, 77.87% for F3-F4 Channel , 77.87% for AF3-AF4 Channel , 77.86% for FC5-FC6 Channel.

From Figure 5.21For extracting STFT feature, we found that SVM has the highest accuracy which are 77.21% for T7-T8 Channel , 77.23% for P7-P8 Channel , 77.86% for O1-O2 Channel , 77.61% for F7-F8 Channel,77.68% for F3-F4 Channel ,77.90% for AF3-AF4 Channel , 77.77% for FC5-FC6 Channel.

From Figure 5.22 For extracting HHT feature, we found that SVM has the highest accuracy which are 77.71% for T7-T8 Channel , 77.89% for P7-P8 Channel , 77.51% for O1-O2 Channel , 77.84% for F7-F8 Channel, 77.79% for F3-F4 Channel , 77.78% for AF3-AF4 Channel , 77.84% for FC5-FC6 Channel.

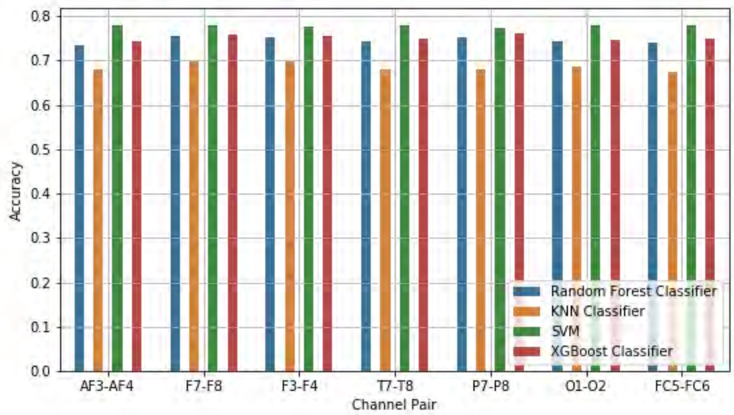


Figure 5.20: Pairwise Subject Independent Accuracy Using FFT Feature extraction (Target : Like)

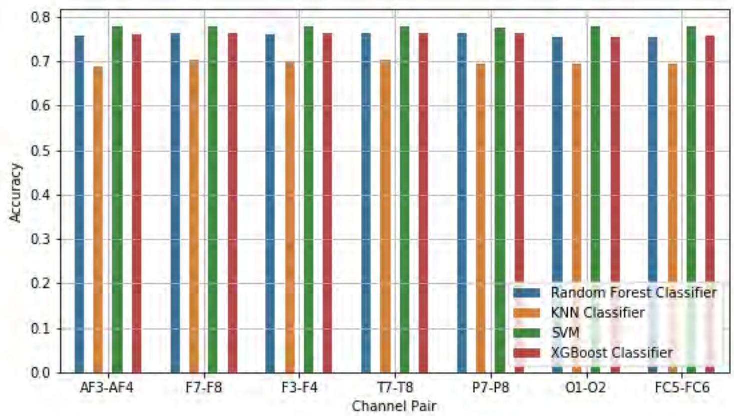


Figure 5.21: Pairwise Subject Independent Accuracy Using STFT Feature extraction (Target : Like)

5.3.0.2 Excitement Affectivity Analysis

From Figure 5.23 For extracting DWT feature, we found that SVM has the highest accuracy which are 68.30% for T7-T8 Channel , 68.10% for P7-P8 Channel , 68.23% for O1-O2 Channel , 68.29% for F7-F8 Channel, 68.22% for F3-F4 Channel , 68.29% for AF3-AF4 Channel , 67.99% for FC5-FC6 Channel.

From Figure 5.24 For extracting FFT feature, we found that SVM has the highest accuracy which are 68.24% for T7-T8 Channel , 68.30% for P7-P8 Channel , 68.23% for O1-O2 Channel , 68.29% for F7-F8 Channel, 68.28% for F3-F4 Channel , 68.26% for AF3-AF4 Channel , 68.26% for FC5-FC6 Channel.

From Figure 5.25 For extracting HHT feature, we found that SVM has the highest accuracy which are 67.97% for T7-T8 Channel , 68.24% for P7-P8 Channel , 67.98% for O1-O2 Channel , 68.27% for F7-F8 Channel, 68.33% for F3-F4 Channel , 68.23% for AF3-AF4 Channel , 68.28% for FC5-FC6 Channel.

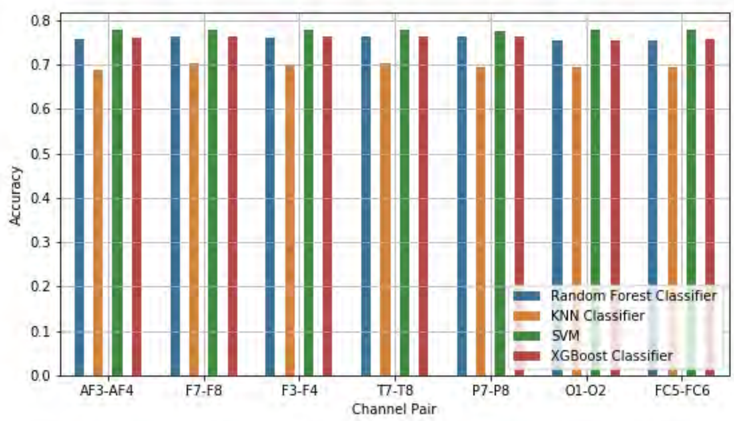


Figure 5.22: Pairwise Subject Independent Accuracy Using STFT Feature extraction (Target : Like)

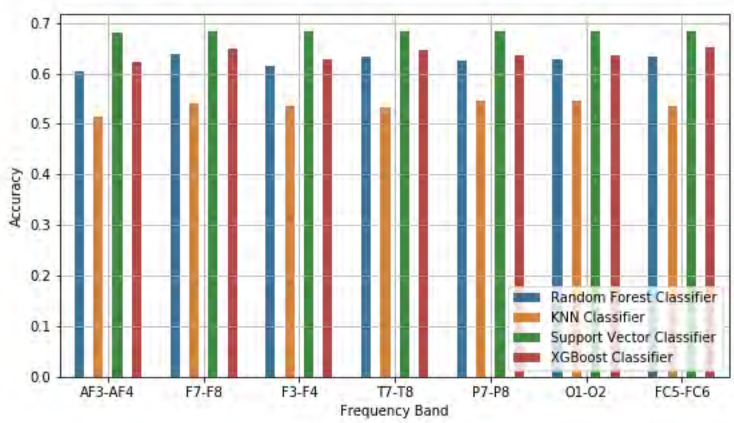


Figure 5.23: Pairwise Subject Independent Accuracy Using DWT Feature extraction (Target : Excitement)

From Figure 5.26 For extracting STFT feature, we found that SVM has the highest accuracy which are 68.29% for T7-T8 Channel , 68.14% for P7-P8 Channel , 68.20% for O1-O2 Channel , 68.29% for F7-F8 Channel,68.27% for F3-F4 Channel , 68.30% for AF3-AF4 Channel , 68.29% for FC5-FC6 Channel.

5.3.0.3 Feelings Affectivity Analysis

From Figure 5.27 For extracting DWT feature, we found that SVM has the highest accuracy which are 80.95% for T7-T8 Channel , 81.00% for P7-P8 Channel , 80.98% for O1-O2 Channel , 80.97% for F7-F8 Channel, 81.00% for F3-F4 Channel , 80.98% for AF3-AF4 Channel , 80.99% for FC5-FC6 Channel .

From Figure 5.28 For extracting FFT feature, we found that SVM has the highest accuracy which are 80.97% for T7-T8 Channel , 81.00% for P7-P8 Channel , 80.98%

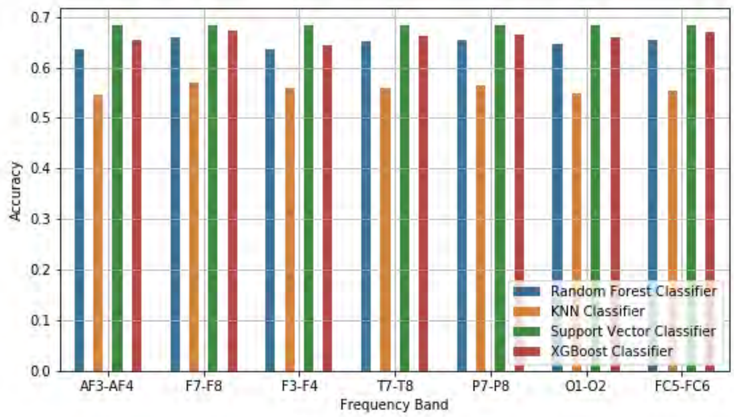


Figure 5.24: Pairwise Subject Independent Accuracy Using FFT Feature extraction (Target : Excitement)

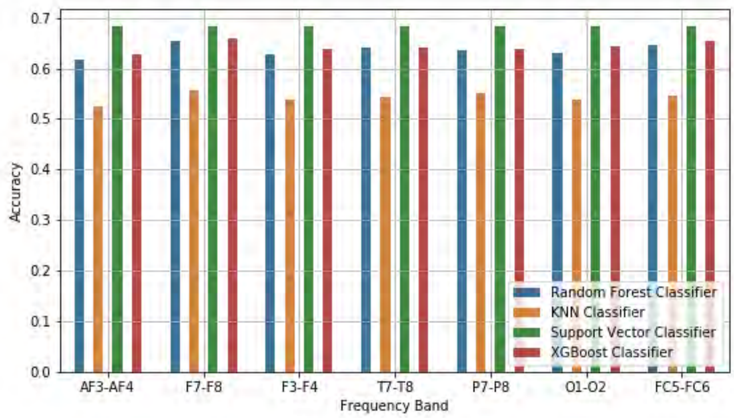


Figure 5.25: Pairwise Subject Independent Accuracy Using HHT Feature extraction (Target : Excitement)

for O1-O2 Channel , 80.99% for F7-F8 Channel, 80.98% for F3-F4 Channel , 80.98% for AF3-AF4 Channel , 80.99% for FC5-FC6 Channel .

From Figure 5.29 For extracting HHT feature, we found that SVM has the highest accuracy which are 80.97% for T7-T8 Channel , 80.99% for P7-P8 Channel , 80.97% for O1-O2 Channel , 80.99% for F7-F8 Channel, 80.97% for F3-F4 Channel , 80.97% for AF3-AF4 Channel , 80.99% for FC5-FC6 Channel .

From Figure 5.30 For extracting STFT feature, we found that SVM has the highest accuracy which are 81.00% for T7-T8 Channel , 80.96% for P7-P8 Channel , 81.00% for O1-O2 Channel , 81.00% for F7-F8 Channel, 81.00% for F3-F4 Channel , 81.00% for AF3-AF4 Channel , 80.99% for FC5-FC6 Channel .

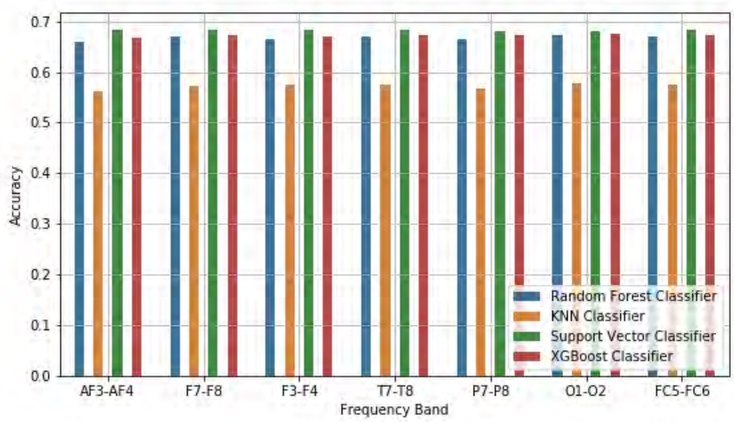


Figure 5.26: Pairwise Subject Independent Accuracy Using STFT Feature extraction (Target : Excitement)

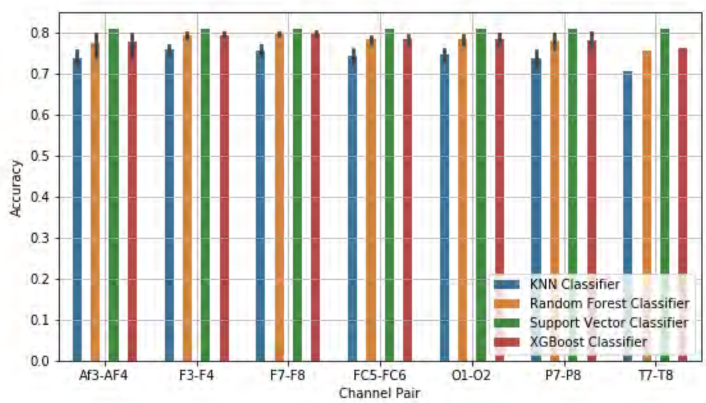


Figure 5.27: Pairwise Subject Independent Accuracy Using DWT Feature extraction (Target : Feelings)

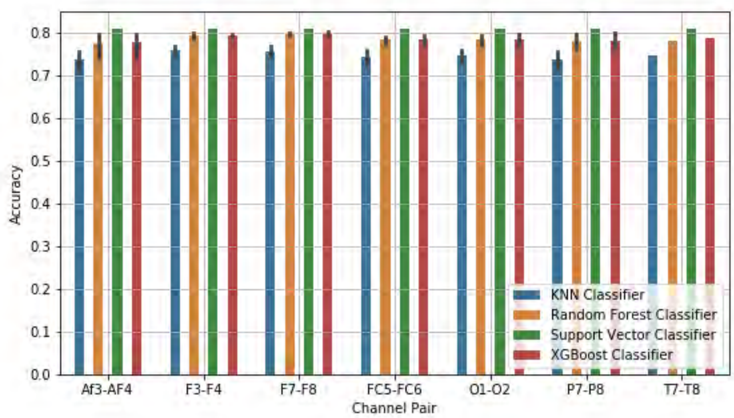


Figure 5.28: Pairwise Subject Independent Accuracy Using FFT Feature extraction (Target : Feelings)

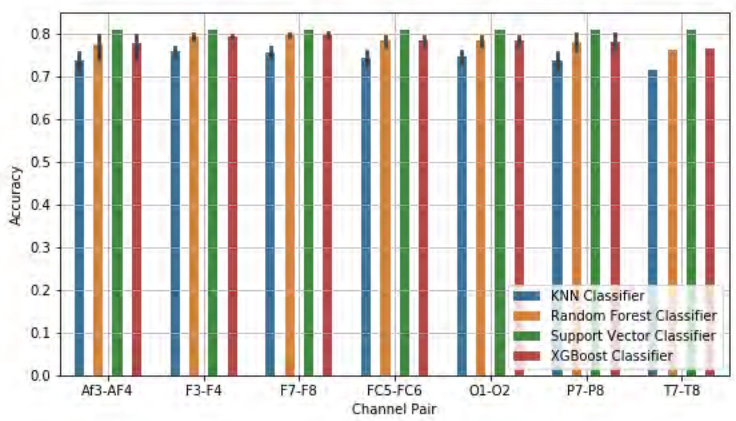


Figure 5.29: Pairwise Subject Independent Accuracy Using HHT Feature extraction (Target : Feelings)

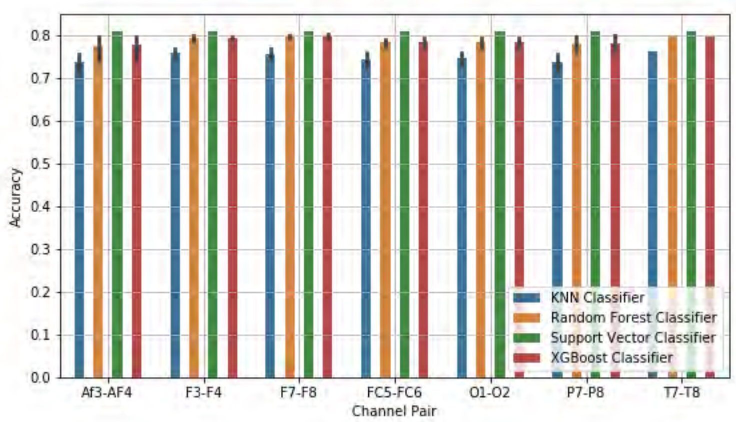


Figure 5.30: Pairwise Subject Independent Accuracy Using STFT Feature extraction (Target : Feelings)

5.4 Subject Dependent Analysis

In all cases it is showed up that, Support Vector Machine (SVM) gives best accuracy.

5.4.0.1 Like Affectivity Analysis

From 5.31 For FFT Feature , we found highest accuracy on SVM by using Alpha Band gives 78.37%, Beta Band gives 78.33% , Gamma Band gives 78.21% ,Theta Band gives 78.35%.

From 5.32 For DWT Feature where Excitement is target, we found highest accuracy on SVM by using Alpha Band gives 78.37%, Beta Band gives 77.95% , Gamma Band gives 77.98% ,Theta Band gives 78.28%.

From 5.33 For STFT Feature where Excitement is target, we found highest accuracy on SVM by using Alpha Band gives 78.11%, Beta Band gives 77.60% , Gamma

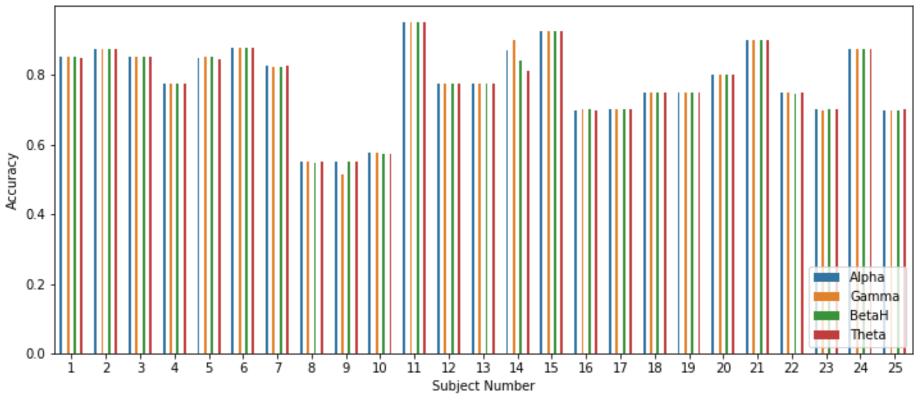


Figure 5.31: Subject Dependent Accuracy Using FFT Feature extraction (Target : Like)

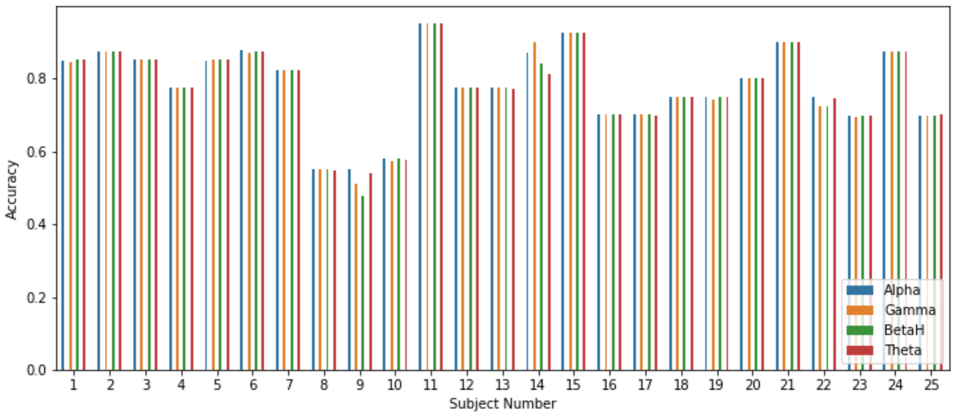


Figure 5.32: Subject Dependent Accuracy Using DWT Feature extraction (Target : Like)

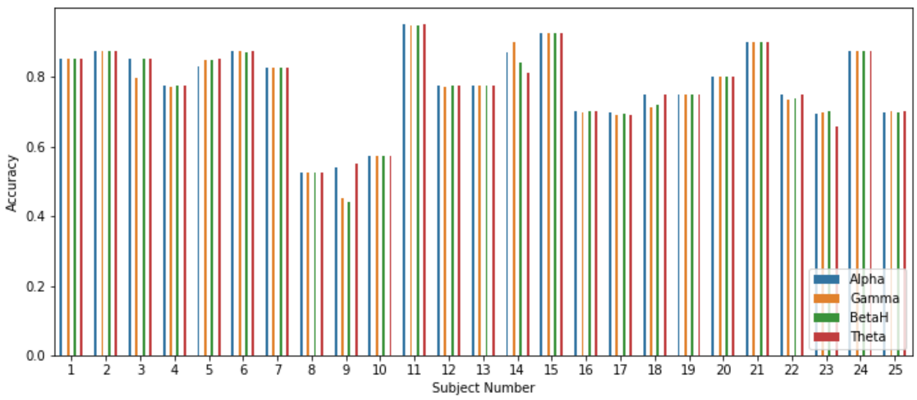


Figure 5.33: Subject Dependent Accuracy Using STFT Feature extraction (Target : Like)

Band gives 68.93% ,Theta Band gives 69.04%.

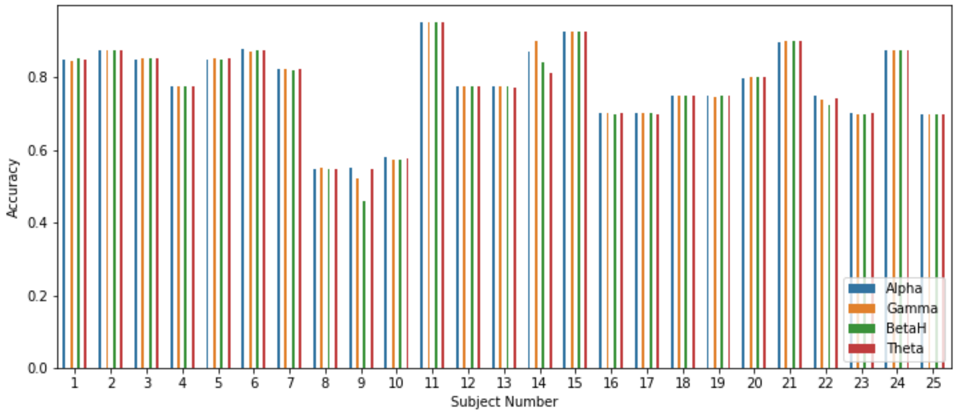


Figure 5.34: Subject Dependent Accuracy Using HHT Feature extraction (Target : Like)

From 5.34 For HHT Feature where Excitement is target, we found highest accuracy on SVM by using Alpha Band gives 69.06%, Beta Band gives 77.36% , Gamma Band gives 68.93% ,Theta Band gives 78.07%.

5.4.0.2 Excitement Affectivity Analysis

From 5.35 For FFT Feature , we found highest accuracy on SVM by using Alpha Band gives 69.06%, Beta Band gives 68.97% , Gamma Band gives 68.93% ,Theta Band gives 69.04%.

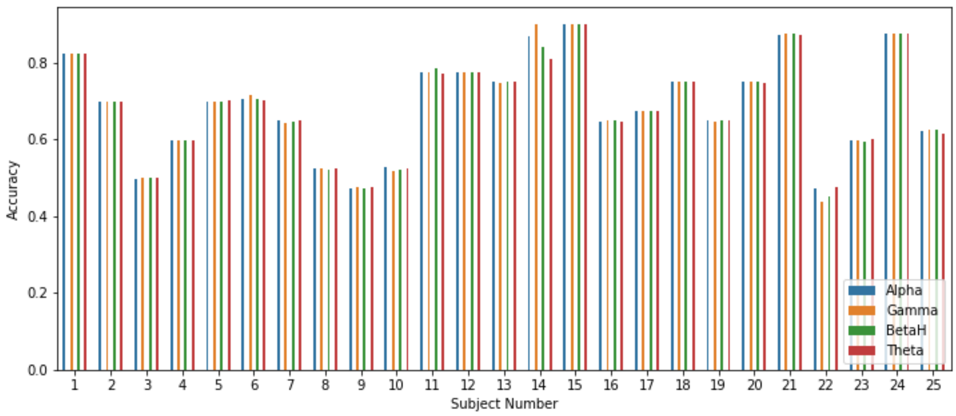


Figure 5.35: Subject Dependent Accuracy Using FFT Feature extraction (Target : Excitement)

From 5.36 For DWT Feature , we found highest accuracy on SVM by using Alpha Band gives 68.92%, Beta Band gives 68.51% , Gamma Band gives 68.71% ,Theta

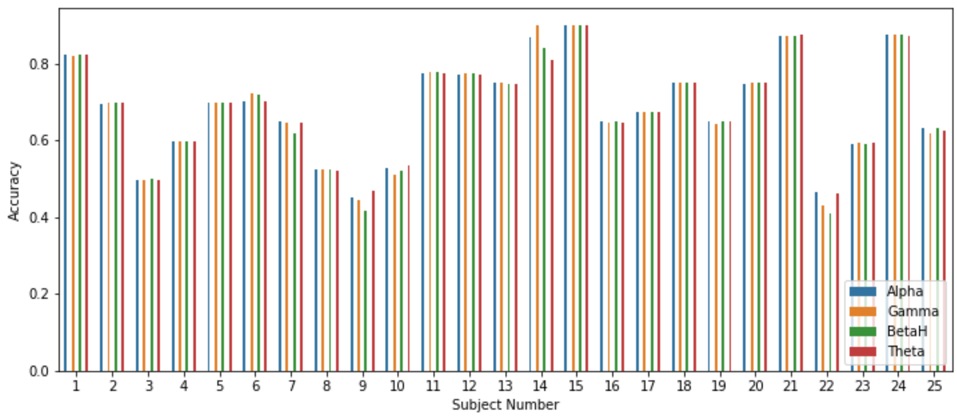


Figure 5.36: Subject Dependent Accuracy Using DWT Feature extraction (Target : Excitement)

Band gives 68.93%.

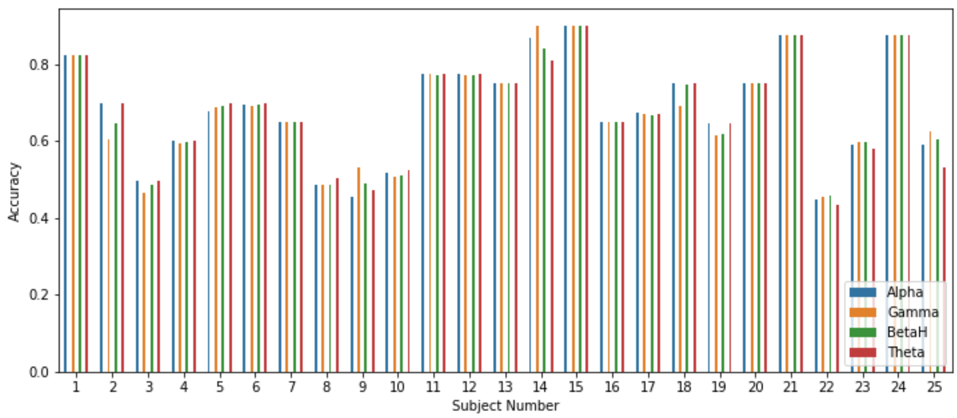


Figure 5.37: Subject Dependent Accuracy Using STFT Feature extraction (Target : Excitement)

For STFT Feature , we found highest accuracy on SVM by using Alpha Band gives 68.41%, Beta Band gives 68.28% , Gamma Band gives 67.97% ,Theta Band gives 68.35%.

From 5.38 For HHT Feature , we found highest accuracy on SVM by using Alpha Band gives 68.89%, Beta Band gives 68.73% , Gamma Band gives 68.62% ,Theta Band gives 68.97%.

5.4.0.3 Feelings Affectivity Analysis

From 5.39 For FFT Feature , we found highest accuracy on SVM by using Alpha Band gives 80.75%, Beta Band gives 80.74% , Gamma Band gives 80.49% ,Theta

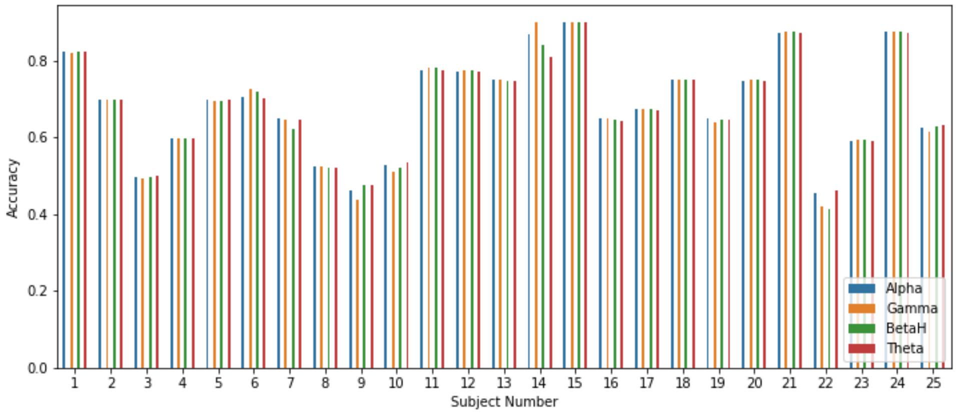


Figure 5.38: Subject Dependent Accuracy Using HHT Feature extraction (Target : Excitement)

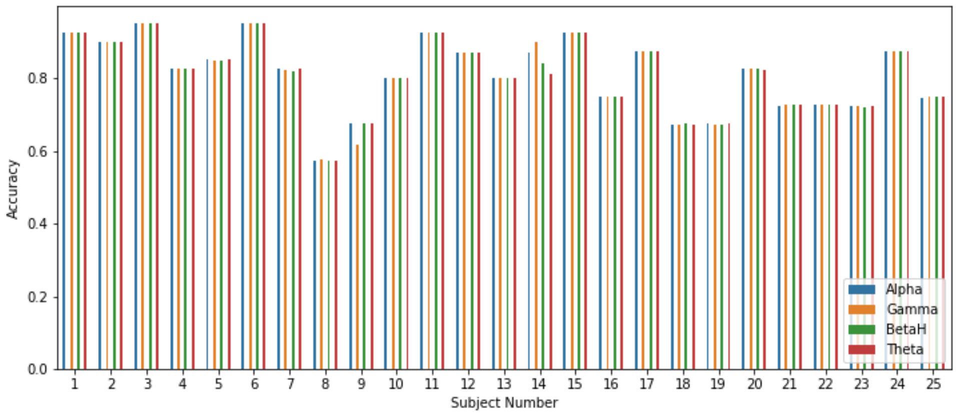


Figure 5.39: Subject Dependent Accuracy Using FFT Feature extraction (Target : Feelings)

Band gives 80.77%.

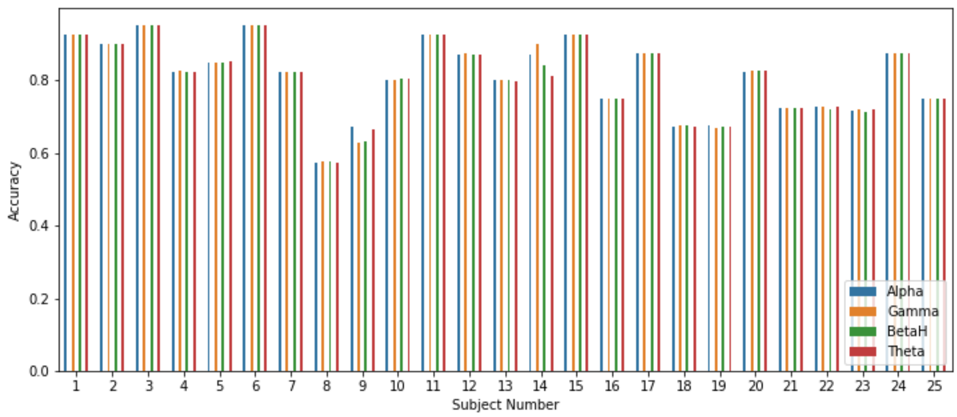


Figure 5.40: Subject Dependent Accuracy Using DWT Feature extraction (Target : Feelings)

From 5.40 For DWT Feature , we found highest accuracy on SVM by using Alpha Band gives 80.70%, Beta Band gives 80.52% , Gamma Band gives 80.52% ,Theta Band gives 80.65%.

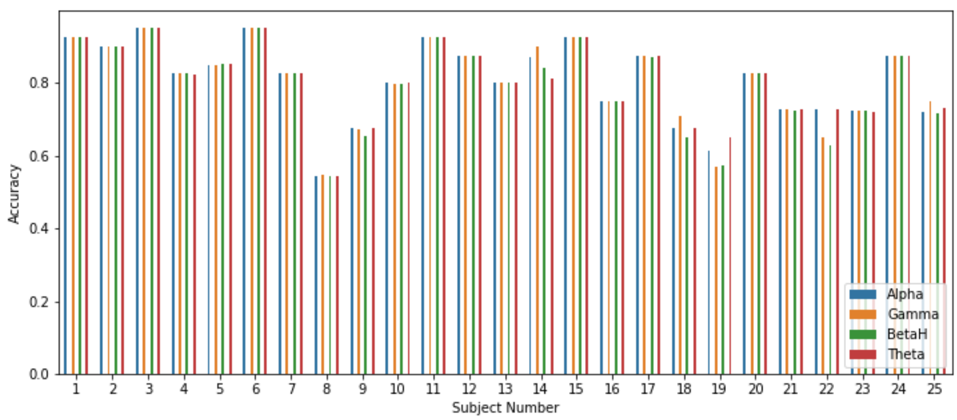


Figure 5.41: Subject Dependent Accuracy Using STFT Feature extraction (Target : Feelings)

From 5.40 For STFT Feature , we found highest accuracy on SVM by using Alpha Band gives 80.30%, Beta Band gives 79.52% , Gamma Band gives 80.03% ,Theta Band gives 80.48%.

From 5.42 For HHT Feature , we found highest accuracy on SVM by using Alpha Band gives 80.68%, Beta Band gives 80.50% , Gamma Band gives 80.47% ,Theta Band gives 80.65%.

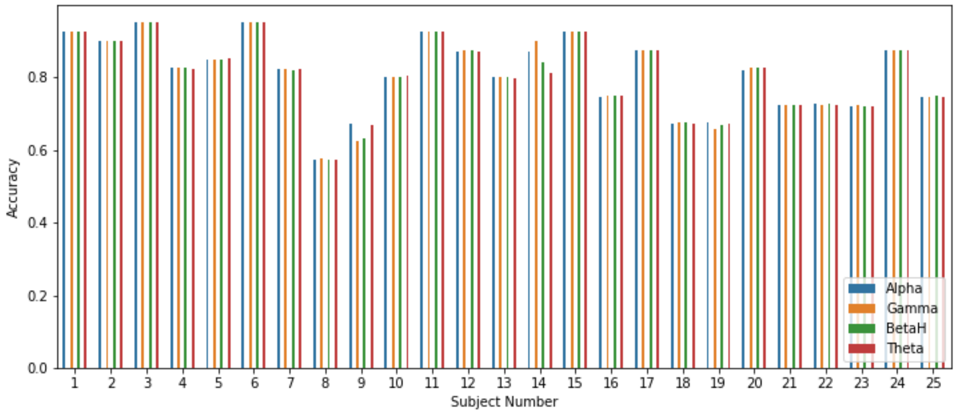


Figure 5.42: Subject Dependent Accuracy Using HHT Feature extraction (Target : Feelings)

5.5 Confusion Matrix Of Each Affectivity

5.5.1 Subject Independent Analysis With Frequency Band

5.5.1.1 Like Affectivity Analysis

Table 5.2: Confusion Matrix For FFT Feature extraction

Actual Class	**Predicted Class**		
	Least Like	Average Like	Most Like
Least Like	10	22	9830
Average Like	60	35	8021
Most Like	700	360	60070

Table 5.3: Confusion Matrix For DWT Feature extraction

Actual Class	**Predicted Class**		
	Least Like	Average Like	Most Like
Least Like	7	17	9356
Average Like	70	13	8157
Most Like	732	896	60692

5.5.1.2 Excitement Affectivity Analysis

Table 5.4: Confusion Matrix For STFT Feature extraction

Actual Class	**Predicted Class**		
	Least Like	Average Like	Most Like
Least Like	15	28	9826
Average Like	80	32	8007
Most Like	732	356	60060

Table 5.5: Confusion Matrix For HHT Feature extraction

Actual Class	**Predicted Class**		
	Least Like	Average Like	Most Like
Least Like	16	40	7654
Average Like	70	30	7886
Most Like	634	365	6054

Table 5.6: Confusion Matrix For Spectral Analysis Feature extraction

Actual Class	**Predicted Class**		
	Least Like	Average Like	Most Like
Least Like	11	43	8767
Average Like	70	29	8541
Most Like	712	354	60867

Table 5.7: Confusion Matrix For DWT Feature extraction

Actual Class	**Predicted Class**		
	Least Excitement	Average Excitement	Most Excitement
Least Excitement	9	12	9256
Average Excitement	62	83	7157
Most Excitement	762	886	60792

Table 5.8: Confusion Matrix For FFT Feature extraction

Actual Class	**Predicted Class**		
	Least Excitement	Average Excitement	Most Excitement
Least Excitement	8	15	9776
Average Excitement	70	33	8117
Most Excitement	532	816	65092

Table 5.9: Confusion Matrix For STFT Feature extraction

Actual Class	Predicted Class		
	Least Excitement	Average Excitement	Most Excitement
Least Excitement	5	12	9656
Average Excitement	72	43	8157
Most Excitement	700	696	64692

Table 5.10: Confusion Matrix For HHT Feature extraction

Actual Class	Predicted Class		
	Least Excitement	Average Excitement	Most Excitement
Least Excitement	6	11	9346
Average Excitement	70	13	8557
Most Excitement	702	876	62392

Table 5.11: Confusion Matrix For Hjorth Feature extraction

Actual Class	Predicted Class		
	Least Excitement	Average Excitement	Most Excitement
Least Excitement	9	12	9300
Average Excitement	74	53	8237
Most Excitement	532	826	60222

5.5.1.3 Feelings Affectivity Analysis

Table 5.12: Confusion Matrix For FFT Feature extraction

Actual Class	Predicted Class		
	Least Feelings	Average Feelings	Most Feelings
Least Feelings	12	20	9906
Average Feelings	71	23	8167
Most Feelings	762	876	60602

Table 5.13: Confusion Matrix For STFT Feature extraction

Actual Class	**Predicted Class**		
	Least Feelings	Average Feelings	Most Feelings
Least Feelings	5	37	9226
Average Feelings	60	24	8107
Most Feelings	742	816	60690

Table 5.14: Confusion Matrix For DWT Feature extraction

Actual Class	**Predicted Class**		
	Least Feelings	Average Feelings	Most Feelings
Least Feelings	7	19	9056
Average Feelings	73	63	8557
Most Feelings	742	896	60672

Table 5.15: Confusion Matrix For HHT Feature extraction

Actual Class	**Predicted Class**		
	Least Feelings	Average Feelings	Most Feelings
Least Feelings	22	57	9356
Average Feelings	40	33	8187
Most Feelings	712	696	40692

Table 5.16: Confusion Matrix For Hjorth Feature extraction

Actual Class	**Predicted Class**		
	Least Feelings	Average Feelings	Most Feelings
Least Feelings	6	16	9316
Average Feelings	40	11	8757
Most Feelings	792	816	60682

5.5.2 Subject Independent Analysis With Pair Of Channel

5.5.2.1 Like Affectivity Analysis

Table 5.17: Confusion Matrix For DWT Feature extraction

Actual Class	**Predicted Class**		
	Least Like	Average Like	Most Like
Least Like	17	27	9326
Average Like	30	43	8127
Most Like	712	126	20692

Table 5.18: Confusion Matrix For FFT Feature extraction

Actual Class	**Predicted Class**		
	Least Like	Average Like	Most Like
Least Like	2	17	9316
Average Like	20	12	8117
Most Like	712	816	60612

Table 5.19: Confusion Matrix For STFT Feature extraction

Actual Class	**Predicted Class**		
	Least Like	Average Like	Most Like
Least Like	9	19	9956
Average Like	71	11	8257
Most Like	712	826	62692

Table 5.20: Confusion Matrix For HHT Feature extraction

Actual Class	**Predicted Class**		
	Least Like	Average Like	Most Like
Least Like	7	27	9356
Average Like	50	33	8257
Most Like	742	846	60492

5.5.2.2 Excitement Affectivity Analysis

Table 5.21: Confusion Matrix For DWT Feature extraction

Actual Class	**Predicted Class**		
	Least Excitement	Average Excitement	Most Excitement
Least Excitement	15	23	9236
Average Excitement	73	33	8137
Most Excitement	736	866	66692

Table 5.22: Confusion Matrix For FFT Feature extraction

Actual Class	**Predicted Class**		
	Least Excitement	Average Excitement	Most Excitement
Least Excitement	7	17	9356
Average Excitement	70	13	8157
Most Excitement	732	896	60692

Table 5.23: Confusion Matrix For HHT Feature extraction

Actual Class	**Predicted Class**		
	Least Excitement	Average Excitement	Most Excitement
Least Excitement	27	47	9426
Average Excitement	76	23	8327
Most Excitement	332	496	50692

Table 5.24: Confusion Matrix For STFT Feature extraction

Actual Class	**Predicted Class**		
	Least Excitement	Average Excitement	Most Excitement
Least Excitement	17	22	9326
Average Excitement	72	23	8257
Most Excitement	432	436	60442

5.5.2.3 Feelings Affectivity Analysis

Table 5.25: Confusion Matrix For DWT Feature extraction

Actual Class	**Predicted Class**		
	Least Feelings	Average Feelings	Most Feelings
Least Feelings	7	17	9356
Average Feelings	70	13	8157
Most Feelings	732	896	60692

Table 5.26: Confusion Matrix For FFT Feature extraction

Actual Class	**Predicted Class**		
	Least Feelings	Average Feelingse	Most Feelings
Least Feelings	8	27	9656
Average Feelings	60	16	8657
Most Feelings	732	866	60192

Table 5.27: Confusion Matrix For HHT Feature extraction

Actual Class	**Predicted Class**		
	Least Feelings	Average Feelings	Most Feelings
Least Feelings	7	10	9000
Average Feelings	70	30	8100
Most Feelings	702	800	6069

Table 5.28: Confusion Matrix For HHT Feature extraction

Actual Class	**Predicted Class**		
	Least Feelings	Average Feelings	Most Feelings
Least Feelings	75	57	6356
Average Feelings	80	53	7157
Most Feelings	772	696	60592

5.6 F1-Score Of Each Affectivity

5.6.1 Subject Independent Analysis With Frequency Band

5.6.1.1 Like Affectivity Analysis

Table 5.29: F1 Score For FFT Feature Extraction

Target	F1 Score
Least Like	0.003
Average Like	0.003
Most Like	0.858

Table 5.30: F1 Score For DWT Feature Extraction

Target	F1 Score
Least Like	0.003
Average Like	0.002
Most Like	0.774

Table 5.31: F1 Score For STFT Feature Extraction

Target	F1 Score
Least Like	0.002
Average Like	0.002
Most Like	0.674

Table 5.32: F1 Score For Hjorth Feature Extraction

Target	F1 Score
Least Like	0.001
Average Like	0.003
Most Like	0.874

Table 5.33: F1 Score For HHT Feature Extraction

Target	F1 Score
Least Like	0.004
Average Like	0.003
Most Like	0.898

5.6.1.2 Excitement Affectivity Analysis

Table 5.34: F1 Score For FFT Feature Extraction

Target	**F1 Score**
Least Excitement	0.003
Average Excitement	0.003
Most Excitement	0.855

Table 5.35: F1 Score For DWT Feature Extraction

Target	**F1 Score**
Least Excitement	0.001
Average Excitement	0.002
Most Excitement	0.874

Table 5.36: F1 Score For STFT Feature Extraction

Target	**F1 Score**
Least Excitement	0.002
Average Excitement	0.002
Most Excitement	0.874

Table 5.37: F1 Score For Hjorth Feature Extraction

Target	**F1 Score**
Least Excitement	0.001
Average Excitement	0.003
Most Excitement	0.674

Table 5.38: F1 Score For HHT Feature Extraction

Target	**F1 Score**
Least Excitement	0.003
Average Excitement	0.003
Most Excitement	0.898

5.6.1.3 Feelings Affectivity Analysis

Table 5.39: F1 Score For FFT Feature Extraction

Target	F1 Score
Least Feelings	0.001
Average Feelings	0.003
Most Feelings	0.755

Table 5.40: F1 Score For DWT Feature Extraction

Target	F1 Score
Least Feelings	0.001
Average Feelings	0.002
Most Feelings	0.874

Table 5.41: F1 Score For STFT Feature Extraction

Target	F1 Score
Least Feelings	0.002
Average Feelings	0.001
Most Feelings	0.674

Table 5.42: F1 Score For Hjorth Feature Extraction

Target	F1 Score
Least Feelings	0.001
Average Feelings	0.003
Most Feelings	0.655

Table 5.43: F1 Score For HHT Feature Extraction

Target	F1 Score
Least Feelings	0.003
Average Feelings	0.003
Most Feelings	0.890

5.6.2 Subject Independent Analysis With Pair Of Channels

5.6.2.1 Like Affectivity Analysis

Table 5.44: F1 Score For FFT Feature Extraction

Target	F1 Score
Least Like	0.003
Average Like	0.003
Most Like	0.858

Table 5.45: F1 Score For DWT Feature Extraction

Target	F1 Score
Least Like	0.003
Average Like	0.002
Most Like	0.774

Table 5.46: F1 Score For STFT Feature Extraction

Target	F1 Score
Least Like	0.002
Average Like	0.002
Most Like	0.674

Table 5.47: F1 Score For Hjorth Feature Extraction

Target	F1 Score
Least Like	0.001
Average Like	0.003
Most Like	0.690

Table 5.48: F1 Score For HHT Feature Extraction

Target	F1 Score
Least Like	0.004
Average Like	0.003
Most Like	0.789

5.6.2.2 Excitement Affectivity Analysis

Table 5.49: F1 Score For FFT Feature Extraction

Target	F1 Score
Least Excitement	0.003
Average Excitement	0.003
Most Excitement	0.853

Table 5.50: F1 Score For DWT Feature Extraction

Target	F1 Score
Least Excitement	0.003
Average Excitement	0.002
Most Excitement	0.886

Table 5.51: F1 Score For STFT Feature Extraction

Target	F1 Score
Least Excitement	0.002
Average Excitement	0.001
Most Excitement	0.874

Table 5.52: F1 Score For Hjorth Feature Extraction

Target	F1 Score
Least Excitement	0.001
Average Excitement	0.002
Most Excitement	0.834

Table 5.53: F1 Score For HHT Feature Extraction

Target	F1 Score
Least Excitement	0.003
Average Excitement	0.003
Most Excitement	0.858

5.6.2.3 Feelings Affectivity Analysis

Table 5.54: F1 Score For FFT Feature Extraction

Target	F1 Score
Least Feelings	0.001
Average Feelings	0.003
Most Feelings	0.735

Table 5.55: F1 Score For DWT Feature Extraction

Target	F1 Score
Least Feelings	0.001
Average Feelings	0.002
Most Feelings	0.693

Table 5.56: F1 Score For STFT Feature Extraction

Target	F1 Score
Least Feelings	0.002
Average Feelings	0.001
Most Feelings	0.664

Table 5.57: F1 Score For Hjorth Feature Extraction

Target	F1 Score
Least Feelings	0.001
Average Feelings	0.003
Most Feelings	0.655

Table 5.58: F1 Score For HHT Feature Extraction

Target	F1 Score
Least Feelings	0.001
Average Feelings	0.003
Most Feelings	0.891

Chapter 6

Conclusion

6.1 Research Overview

In this paper, the most popular feature extraction methods have been applied to get an overview of the results made by the classifiers. Except for statistical analysis, in every case Support Vector Machine (SVM) wins the race. Again in the subject-independent strategy, there is no significant difference in the accuracy of different feature extraction methods while using SVM. But there is a significant change in subject-dependent accuracy with spectral analysis. In the future, we will use Detrended Fluctuation Analysis (DFA), Hurst, Petrosian Fractal Dimension (PFD) feature extraction methods and Long short-term memory (LSTM), Deep Neural Network (DNN) as classifiers.

6.2 Contribution and Impact

several types of research on food proposal and programmed menu generation have been proposed, taking into consideration distinctive viewpoints, such as individual and social inclinations, health and religion imperatives, menu composition, and formula co-occurrence. In any case, suggesting formulas and menus, which not as it were meet the user's inclinations, but are too compliant with best food propensities, is still an open issue.

The recommendation for food is vital for numerous reasons and using computerized sources, it is getting to be indeed more well known. Food consuming behavior of human creatures is difficult to anticipate and thousands of ingredients chosen for a single recipe make the condition indeed more complex. The way technology is expanding its sector, people are also getting busy. So, they hardly get time to choose the right meal and it becomes more difficult to find suitable meals according to their tastebuds and emotional state. Our food recommender system helps people to get personalized meal plans based on their preferences and emotional state.

6.3 Limitation & Future Work

The correlation between human emotions and food consumption is an intricate process that has yet to be determined accurately. In this research, our primary intentions to build a model to recommend food to people according to their current emotional state through EEG signal.

Our system takes EEG signal as prior data record and as it's only considering the brain activity, surely it upholds some lackings. As the sensor placement of EEG is brain and eyes, we get combination signals for electrophysiological and eye movement. The possible outcome from this case is an increase in control commands as well as an increase in terms of accuracy. But still, there remain some places for inaccuracy.

The confinements that are specified over are progressing to be a portion of future work. Our system has scope for future expansion where we can incorporate EEG with Electromyography (EMG). EEG sensor has been used to record the electrical activity of the brain and if we include the record of skeletal muscle with it, we will get even more precise results in terms of accuracy. However, in terms of EEG along with EMG, we will get a combination signal of electrophysiological and electromyography as the sensor placement will be on the brain and muscles. it will give an output with an increase in classification accuracy as well as control commands.

Bibliography

[1] R. M. Ganley, "Emotion and eating in obesity: A review of the literature", *International Journal of eating disorders*, vol. 8, no. 3, pp. 343–361, 1989.

[2] T. R. Hinrichs, "Strategies for adaptation and recovery in a design problem solver", in *Proc. of the 2 nd Workshop on Case-Based Reasoning*, 1989, pp. 115–118.

[3] K. J. Hammond, "Case-based planning: A framework for planning from experience", *Cognitive science*, vol. 14, no. 3, pp. 385–443, 1990.

[4] N. Pradhan and D. N. Dutt, "Use of running fractal dimension for the analysis of changing patterns in electroencephalograms", *Computers in biology and medicine*, vol. 23, no. 5, pp. 381–388, 1993.

[5] P. J. Lang, "The emotion probe: Studies of motivation and attention.", *American psychologist*, vol. 50, no. 5, p. 372, 1995.

[6] A. Accardo, M. Affinito, M. Carrozzi, and F. Bouquet, "Use of the fractal dimension for the analysis of electroencephalographic time series", *Biological cybernetics*, vol. 77, no. 5, pp. 339–350, 1997.

[7] D. G. Baskin, J. E. Blevins, and M. W. Schwartz, "How the brain regulates food intake and body weight: The role of leptin", *Journal of pediatric endocrinology & metabolism: JPEM*, vol. 14, pp. 1417–1429, 2001.

[8] J. A. Coan, J. J. Allen, and E. Harmon-Jones, "Voluntary facial expression and hemispheric asymmetry over the frontal cortex", *Psychophysiology*, vol. 38, no. 6, pp. 912–925, 2001.

[9] R. D. Lawrence, G. S. Almasi, V. Kotlyar, M. Viveros, and S. S. Duri, "Personalization of supermarket product recommendations", in *Applications of data mining to electronic commerce*, Springer, 2001, pp. 11–32.

[10] O. Dressler, G. Schneider, G. Stockmanns, and E. Kochs, "Awareness and the eeg power spectrum: Analysis of frequencies", *British journal of anaesthesia*, vol. 93, no. 6, pp. 806–809, 2004.

[11] M. Pal, "Random forest classifier for remote sensing classification", *International journal of remote sensing*, vol. 26, no. 1, pp. 217–222, 2005.

[12] M. Svensson, K. Höök, and R. Cöster, "Designing and evaluating kalas: A social navigation system for food recipes", *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 12, no. 3, pp. 374–400, 2005.

[13] J. T. Cacioppo, L. G. Tassinary, and G. Berntson, *Handbook of psychophysiology*. Cambridge university press, 2007.

[14] L. Rankine, M. Mesbah, and B. Boashash, “A matching pursuit-based signal complexity measure for the analysis of newborn eeg”, *Medical & Biological Engineering & Computing*, vol. 45, no. 3, pp. 251–260, 2007.

[15] D. Cvetkovic, E. D. Übeyli, and I. Cosic, “Wavelet transform feature extraction from human ppg, ecg, and eeg signal responses to elf pemf exposures: A pilot study”, *Digital signal processing*, vol. 18, no. 5, pp. 861–874, 2008.

[16] E. D. Übeyli, “Analysis of eeg signals by combining eigenvector methods and multiclass support vector machines”, *Computers in Biology and Medicine*, vol. 38, no. 1, pp. 14–22, 2008.

[17] J. Freyne and S. Berkovsky, “Intelligent food planning: Personalized recipe recommendation”, in *Proceedings of the 15th international conference on Intelligent user interfaces*, 2010, pp. 321–324.

[18] J.-H. Hsiao and H. Chang, “Smartdiet: A personal diet consultant for healthy meal planning”, in *2010 IEEE 23rd International Symposium on Computer-Based Medical Systems (CBMS)*, IEEE, 2010, pp. 421–425.

[19] W. Qiang, O. Sourina, and N. M. Khoa, “A fractal dimension based algorithm for neurofeedback games”, *CGI 2010*, SP25, 2010.

[20] P. Forbes and M. Zhu, “Content-boosted matrix factorization for recommender systems: Experiments with recipe recommendation”, in *Proceedings of the fifth ACM conference on Recommender systems*, 2011, pp. 261–264.

[21] G. Geleijnse, P. Nachtigall, P. van Kaam, and L. Wijgergangs, “A personalized recipe advice system to promote healthful choices”, in *Proceedings of the 16th international conference on Intelligent user interfaces*, 2011, pp. 437–438.

[22] Y. van Pinxteren, G. Geleijnse, and P. Kamsteeg, “Deriving a recipe similarity measure for recommending healthful meals”, in *Proceedings of the 16th international conference on Intelligent user interfaces*, 2011, pp. 105–114.

[23] E. Ramic, N. Pranjic, O. Batic-Mujanovic, E. Karic, E. Alibasic, and A. Alic, “The effect of loneliness on malnutrition in elderly population”, *Medical Archives*, vol. 65, no. 2, p. 92, 2011.

[24] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, “Feature reduction and selection for emg signal classification”, *Expert systems with applications*, vol. 39, no. 8, pp. 7420–7431, 2012.

[25] M. J. Gibney and M. C. Walsh, “The future direction of personalised nutrition: My diet, my phenotype, my genes”, *Proceedings of the Nutrition Society*, vol. 72, no. 2, pp. 219–225, 2013.

[26] M. Harvey, B. Ludwig, and D. Elsweiler, “You are what you eat: Learning user tastes for rating prediction”, in *International symposium on string processing and information retrieval*, Springer, 2013, pp. 153–164.

[27] J. M. Kivikangas and N. Ravaja, “Emotional responses to victory and defeat as a function of opponent”, *IEEE Transactions on Affective Computing*, vol. 4, no. 2, pp. 173–182, 2013.

[28] A. S. Al-Fahoum and A. A. Al-Fraihat, “Methods of eeg signal features extraction using linear analysis in frequency and time-frequency domains”, *International Scholarly Research Notices*, vol. 2014, 2014.

[29] D. McDuff, R. El Kaliouby, J. F. Cohn, and R. W. Picard, "Predicting ad liking and purchase intent: Large-scale analysis of facial responses to ads", *IEEE Transactions on Affective Computing*, vol. 6, no. 3, pp. 223–235, 2014.

[30] S.-H. Oh, Y.-R. Lee, and H.-N. Kim, "A novel eeg feature extraction method using hjorth parameter", *International Journal of Electronics and Electrical Engineering*, vol. 2, no. 2, pp. 106–110, 2014.

[31] M. Ueda, S. Asanuma, Y. Miyawaki, and S. Nakajima, "Recipe recommendation method by considering the users preference and ingredient quantity of target recipe", in *Proceedings of the International MultiConference of Engineers and Computer Scientists*, vol. 1, 2014, pp. 12–14.

[32] D. Elsweiler and M. Harvey, "Towards automatic meal plan recommendations for balanced nutrition", in *Proceedings of the 9th ACM Conference on Recommender Systems*, 2015, pp. 313–316.

[33] P. H. England, "Composition of foods integrated dataset (cofid)", in *Composition of foods integrated dataset (CoFID)*, Public Health England, 2015.

[34] T. Chen and C. Guestrin, "Xgboost: A scalable tree boosting system", in *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, 2016, pp. 785–794.

[35] V. Espın, M. V. Hurtado, and M. Noguera, "Nutrition for elder care: A nutritional semantic recommender system for the elderly", *Expert Systems*, vol. 33, no. 2, pp. 201–210, 2016.

[36] F. Rehman and O. Khalid, "Ul haq n, khan aur, bilal k, madani sa", *Diet-right: a smart food recommendation system. KSII T Internet Inf*, vol. 11, pp. 2910–25, 2017.

[37] X. Ren, H. Guo, S. Li, S. Wang, and J. Li, "A novel image classification method with cnn-xgboost model", in *International Workshop on Digital Watermarking*, Springer, 2017, pp. 378–390.

[38] D. Ribeiro, J. Machado, J. Ribeiro, M. J. M. Vasconcelos, E. F. Vieira, and A. C. de Barros, "Souschef: Mobile meal recommender system for older adults.", in *ICT4AgeingWell*, 2017, pp. 36–45.

[39] L. Yang, C.-K. Hsieh, H. Yang, J. P. Pollak, N. Dell, S. Belongie, C. Cole, and D. Estrin, "Yum-me: A personalized nutrient-based meal recommender system", *ACM Transactions on Information Systems (TOIS)*, vol. 36, no. 1, pp. 1–31, 2017.

[40] G. Agapito, M. Simeoni, B. Calabrese, I. Caré, T. Lamprinoudi, P. H. Guzzi, A. Pujia, G. Fuiano, and M. Cannataro, "Dietos: A dietary recommender system for chronic diseases monitoring and management", *Computer methods and programs in biomedicine*, vol. 153, pp. 93–104, 2018.

[41] O. Bazgir, S. A. H. Habibi, L. Palma, P. Pierleoni, and S. Nafees, "A classification system for assessment and home monitoring of tremor in patients with parkinson's disease", *Journal of medical signals and sensors*, vol. 8, no. 2, p. 65, 2018.

[42] J. M. Ordovas, L. R. Ferguson, E. S. Tai, and J. C. Mathers, "Personalised nutrition and health", *Bmj*, vol. 361, 2018.

[43] M. M. Fareed, A. Jamshed, S. Butt, F. Shaukat, P. L. Nguyen, and W. F. Ngwa, “Evolution of radiation oncology in pakistan”, *International Journal of Radiation Oncology• Biology• Physics*, vol. 105, no. 1, pp. 11–16, 2019.

[44] X. Gao, F. Feng, X. He, H. Huang, X. Guan, C. Feng, Z. Ming, and T.-S. Chua, “Hierarchical attention network for visually-aware food recommendation”, *IEEE Transactions on Multimedia*, vol. 22, no. 6, pp. 1647–1659, 2019.

[45] H. Jiang, W. Wang, M. Liu, L. Nie, L.-Y. Duan, and C. Xu, “Market2dish: A health-aware food recommendation system”, in *Proceedings of the 27th ACM International Conference on Multimedia*, 2019, pp. 2188–2190.