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Neuromarketing Analysis With Artificial Intelligence

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I want to thank my supervisor, Dr Andrew Harison, for helping me to do my best work by guiding through the project with his thoughts and recommendations. I not only learn about neuromarketing with artificial intelligence but also acquired useful skills. I would also like to thank my friends who always inspire and back me when I needed it. Without the unconditional support of my family my dream of studying in this university won't be possible, so lot of praises for them.

Abstract

Neuromarketing is an emerging field that combines neuroscience and marketing together. now a days brands publicity, tv commercials and products has great influence over the consumers. In this research we measure the attention, emotional engagement, and consumer behavior. This article proposed the literature review of neuromarketing tools, methods, and specific techniques. In this study emphasis about analysis on neuroimaging tools EEG, FMRI and physiology techniques Eye tracking, Facial emotional coding, and recency frequency monetary (RFM) analysis.

In EEG analysis brain signals were recorded and then it classifies into consumer feelings. In the experiment one male and female has shown different movies and response was recorded using EEG signal tracking device. Furthermore, analysis was performed on the consumer response and consider decision making of customers in a like/dislike task. Dataset is available on Kaggle. Features were extracted, one hot encoding was applied on labels, split the dataset with the ratio 80% and 20% into training set and testing set respectively. LSTM model was applied, accuracy was achieved 96%. We also compared our results by applying other machine learning models such as random forest, Guassian NB, Logistic regression and SVC. In FMRI analysis, we visualize the brain images to measure brain activity using signals recorded by MRI scan. To improve the scan, we find out the correlation and select the threshold. Echo-planner image (EPI) was created to see the part of brain where highest correlation coefficients are located. To improve the accuracy and remove distortion, we applied general linear model. Gaussian kernel also used to smoothen EPI images.

We created an application that can track customer eyes which is very helpful in neuromarketing analysis. It can track eye movement if subject looks in different directions, also control cursor on computer screen. Images dataset was downloaded from Kaggle, perform data preprocessing, feature extraction, split the dataset into training and testing set then apply deep learning model CNN to predict the accuracy of model. The accuracy of overall model was achieved 87%.

Facial coding performed to recognize consumer emotions towards products. The advantage of this application that we can recognize the consumer expressions, howâs they are feeling and what emotions they have about specific product. Eye images were collected from Kaggle. Inception and Xception model were used for features extraction. Training dataset was fed

into CNN model to classify into human expressions. Accuracy of the model was obtained 72%. We also compared our results without applying pretrained convolutional network Inception-v3 and Xception model, then accuracy was achieved just 13% with 185% loss on testing dataset.

Dataset between year 2010 - 2011 of retail online UK store was collected. Recency, frequency and monetary (RFM) analysis was performed. Did customer behavior segmentation base on their RFM score. Rating was assigned to the customers. Quantile method is used to calculate RFM score and then segment the customers. K means algorithm was also applied; 5 clusters were created due to the rating between 1star to 5star. Segment the customers based on clusters by calculating their RFM score.

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CHAPTER 1

Introduction

Neuromarketing comprises of two words, “neuro" means nerves or related to brain, and “marketing" means advertising or promotion of products by certain company or brand. In Neuromarketing there involved three things brain, science, and marketing. It tells that how marketing is affected by technology and medically [2].

Neuromarketing known as consumerâs neuroscience, reads consumer mind and turn its behavior and decision. Neuromarketing simply refers to the assessment of physiological and psychological signals of customerâs motivations, preferences, and decisions[3]. It scans brain, measures neural activity, and persuades the customer to the target [5].

In the previous last 100 years the marketing strategies has dramatically changed and in the marketing domain neuromarketing has emerged. It is gaining popularity due its speed and productivity, and it acquire less resources of the organization[8].

People wants to spend money, they want to buy, but they really do not know where that value comes from. Sometimes customer is so much confused what exactly they want to buy, so with the growing trend of analyzing consumer behavior, a study called neuromarketing can be applied to get an idea of marketing strategies.

If you want to spend less, and sell more, you must know how to reach your customerâs brain using simple, science-based techniques. "Roger Dooley" in his book "Brainfluence" writes 100 ways to persuade and convince consumers with neuromarketing[6].

About hundred years ago, companies in western world ran into the problem. Consumers had everything they needed. So, the companies came up with a great idea: persuade people that they need more things! Even things they didnât know they needed. Nowadays, companies are studying your brain to get you to keep buying more stuff. This is called neuromarketing.Company knows us better than we know ourselves. Brand exists nowhere else but in the mind of the consumers.

In 1950s, a clever marketer shocked the world with an astonishing experiment. He flashed the messages “Drink COCA-COLA" and “EAT POPCORN" on a cinema screen-too briefly for the audience to even notice. He claimed this had people rushing to the counters in droves to buy coke and popcorn [31].

Shopping has been evolved immensely because of internet. Now due to the facility of online shopping busy people can also buy and this made marketers to focus more on the involvement of brain of the customer. The focus of this study is to analyze the Fear of missing out in people from their friends and circle while opting for a course in neuromarketing and to be certified in the education system [7].

Neuromarketing it is the application of neuroscience to the understanding of consumer preferences towards products and services. It is considered as emerging area of research, approximately 400 billion dollars spent annually on advertisements and promotions. Traditional research methods of marketing like taking reviews, posters, getting feedback of the product and by asking consumers to fill the questionnaires, product rating, or review comments. But it is very time-consuming process, not enough to explain the decision-making process of consumers [12].

1.1 Motivation

As we all know in todayâs era marketing in the business process is very important. Organization applying different marketing strategies techniques to sell their products. Especially after Covid-19 there was a dramatic change in marketing campaigns, organizations using different techniques and tools for promoting certain brands. One of the intelligent marketing called neuromarketing means studying about consumer behavior in different scenarios and then applying on marketing strategies and decision-making process. I have used different neuroimaging and physiological tools and perform consumer behavior analysis to justify my research. It refers measurement of psychological and neuro signals, which can help for product creative advertising, development, pricing, and other marketing activities. The main motivation behind to measure neural activity using brain scanning, and psychological tracking which measures eye movement for understanding consumer behavior in the shopping terms [9].

1.2 History

The concept was first developed in 1990s by different psychologists at Harvard university. Gerald Zaltman is linked with the first experiment performed on neuromarketing. The term "neuromarketing" was given by Ale Smidts in 2002. In 2004 the first neuromarketing conference was held in Baylor College Houston. The foundation of neuromarketing was based on MEME. Meme is the unit knowledge stored in brain. Memes are affected, stimulated, and controlled by marketers. Neuroscience, psychology, physiology and even neurochemistry also have relevance in this regard[2].

1.3 Objectives

Neuromarketing research commonly used in brain scanning technology or physiological measurements to assess consumer behavior. The main objective of our review center is around the advancements and developments in neuromarketing as well as practices engaged with current era [2]. To learn neuroimaging tools EEG, FMRI brain scans and physiological techniques like eye tracking and facial coding. I collect datasets of each tool from internet, perform analysis on these datasets to justify my research. The primary objectives of this thesis are to prove the efficiency of the selected design solutions and to provide advice for future works. The aim to improve effectiveness of marketing and ultimately increase sales. We heard a lot about campaigns, tv ads and physical or traditional marketing but the neuromarketing brings neuroscience and marketing together known as intelligent marketing. It was an interesting and challenging for me to do research on this topic.

1.4 Challenges In Neuromarketing Domain

Neuromarketing is a big domain that includes both neuroscience and business marketing. Researchers continuously working in that domain because its not an easy thing to understand consumer behavior. Every person in this universe is unique, his feelings, emotions, way of thinking is also distinctive. Working on neuroimaging tools like electroencephalogram (EEG) to record brain activities. Despite of EEG based neuromarketing growing popularity, itâs difficult to collect the EEG signals. There should be no noise around the environment, otherwise it leads to error results. The area where EEG signals are to be recorded should ideally be sealed off from the outside environment [12]. The most difficult challenge in this field to collect accurate dataset and then achieved proper results, which is not an easy task. You need different devices to perform experiment, those are sometimes very expensive. Similarly functional magnetic resonance imaging (FMRI) is a machine that scans internal part of brain. I got datasets from internet and applied machine learning algorithms to obtain results that can justify my research was itself a big challenge. I worked on emotion classification, eye movement tracking and consumer behavior analysis using RFM linked together with neuromarketing that how we can improve our marketing strategies and decision making at organization level.

1.5 Neuromarketing Tools

Neuromarketing research tools are divided into two categories[3]:
1) **Neuroimaging tools**
2) **Physiological techniques**
In the neuromarketing research, it is discovered that electroencephalography (EEG) and functional magnetic resonance imaging (FMRI) are the most popular neuroimaging tool, while eye tracking and galvanic skin response (GSR) are the most physiological technique. [3]. Neuroimaging tools records the consumer's emotions, attention, and memory towards brand and ads. It includes functional magnetic resonance, positron emission tomography, single photon emission tomography, electroencephalography etc.EEG-FMRI integration is a new method for analyzing brain activity in people. We can better understand cognitive processes by using the information provided by simultaneous acquisition of EEG and FMRI data. We created a data collection system for simultaneous EEG and FMRI cognitive tasks [34].
Neuromarketing focuses on capturing the human response of actual state of mind (brain signals) at the time of purchase. Researchers use various techniques, such as Functional

magnetic resonance imaging (FMRI), electroencephalogram (EEG), SST, and TMS to measure changes in brain activity. But among all these neuroscience techniques EEG is the only technique that is most useful over the decision-making process of the customer. EEG stands undeniably prominent and the very deduction behind this is that EEG signal computation and calibration is an empirically constructive way to ascertain the consecutive and persistent changes of the brain activity without any considerably gauge able obstruction and time dawdling which is significant for comprehending both the unconscious reaction and afferent reaction of the customer. EEG has been used to explore reaction to TV advertisements in several ways to observe how peopleâs brains respond to a specific ad, packaging, packaging design, product design, etc[1].This article survey is on electroencephalography (EEG) tool used for neuromarketing strategies. We focused on EEG based marketing because now it relatively less expensive[11] and different devices are easily available in the market, can be connected to mobile devices[12].

Neuromarketing is mainly about predicting consumer behavior, perform analysis on it and then make decisions and strategies accordingly to make the product successful. In one more research EEG analysis is used to determine the influence of product brand and pricing. During experiment two similar product has shown to the customer, one is branded expensive product other is from cheaper from local brand. Customer asked to choose one of the products among those two he likes the most before and after being shown brands and prices to him. At that time BCI headset is used to record EEG brain signal which stimuli in his brain after watching the product [13].

I took the dataset of EEG brain signal from Kaggle, perform complete analysis on it. I trained the EEG dataset on LSTM model predict the accuracy and compare itâs results with the results of other machine learning models such as Guassian NB, SVC, Random Forest, and Logistic Regression.

Another neuroimaging instrument is FMRI used for brain image scanning while stimulus situation being presented. It is used to measure the oxygen level in the brainâs blood flow [10]. In the research scanned the consumer brain images and evaluated its behavior in a brand extension sample. We used FMRI technique that convert 3D-brain images to 2D image slices. We build deep learning model CNN to predict consumerâs response in a binary form (i.e., positive vs. negative) from FMRI data[35].I performed analysis on FMRI dataset to give you an idea of how data is generally structured. Find out correlation in the dataset and

visualize the brain image by applying general linear model.
Physiological techniques record physiological functions like heart beat and eye movement. It involves tools like eye tracking, facial expression coding etc. Eye tracking and gaze detection to measure customer attention, and facial expression coding to measure emotional response towards product. In the Neuromarketing with eye tracking research paper, an experiment was performed. Products are shown on the Microsoft power point presentation, and the subject is instructed to concentrate and select one of the two products shown. The subject can select the required object by dragging the mouse cursor across the screen. To record eye movement, an eye tracking device was positioned in front of the individual. The information is recorded are time spent on each product, few relative powers and finally product has chosen, then analysis performed on this recorded information [13].
In the analysis part of Eye motion tracking, I build an application that can track your eye movement using camera. When you will run the application itâs automatically on the webcam of your laptop, it takes an image of you face crop the region of interest (ROI) thatâs eyes fed into the trained CNN model and output the results. The application can recognize that person is looking at right, left, and center and track the blinking of eyes, it can control mouse cursor on the screen using human eyes.
This paper research discusses about various neuromarketing and emotion analysis techniques. If we perform sentimental analysis on different e commerce websites, find out about the customer feedback and opinions their emotions, attitudes, and expressions. The neuromarketing techniques can be merged with emotion analysis, human expressions towards anything are very important, we can extract the useful piece of information in our neuromarketing campaign. The objective of this research is review on emotion analysis classifier detecting human expressions using human facial coding (Face and eye emotion recognition) [16].
Sometimes its difficult to find out the human expressions, differentiate their emotions using human naked eye. For instance, if you are selling the product to someone itâs not an easy to read the personâs face that he/she is liking this product or not. I build an application that takes human face and eyes (image) as an input will classify into seven different types of emotions that can be Anger, surprise, neutral, happy, and disgust etc. This application will be helpful in extracting information about human expressions when they are doing shopping, howâs they feeling about the product. We can identify about the likeness and dislikeness of the person. So that gathers information can be used for making future market strategies and

in decision-making process.

We build emotion analysis classifier that can detect human expressions. Trained the images dataset onto the CNN model that takes Facial + Eyes images to classify into different human emotions [15].

We also include analysis on recency, frequency and monetary (RFM) segmentation in my report. It a technique used to categorized customers according to their purchasing behavior to find out best customers in a targeted marketing campaign. Recency is a recent transaction date when customer went on shopping and spend money for shopping. Frequency is total number of customers are visiting for shopping in the supermarket. It gives us information of frequency purchases of customers and monetary is the total amount spendings by the customers.

Researchers are getting more and more interested in consumer neuroscience because it offers more accurate data than conventional marketing strategies. It is also beneficial and useful for understanding consumer behavior and thought processes [10]. The main aspects of this report are the analysis on EEG, FMRI, EYE tracking, Facial coding and RFM. In chapter 2 we discussed about the **Literature Review**, chapter 3 is about **dataset explanation**, chapter 4 is about **algorithm implemented**, chapter 5 is about **Methodology**, chapter 6 is about **results and discussions**, and chapter 7 is mainly about **conclusion**.

CHAPTER 2

Literature Review

2.1 Electroencephalogram (EEG)

A studied was carried out by Wai and Zhen in 2018 for assessing the impact of advertisements on human brain by recording EEG signals. Advertisement attracts customers interest that tend to increase in sales. Many companies spending millions of budgets on advertising campaigns annually such as video advertising on Tv and web advertising which received wide viewership. EEG headbands used to record the brain signal stimuli by advertisements. 30 people were invited to participate in the experiment, and it performed by watching 220 various commercials [18]. SVM model is used to train the model, and then assess the influence of advertisements on human brain.

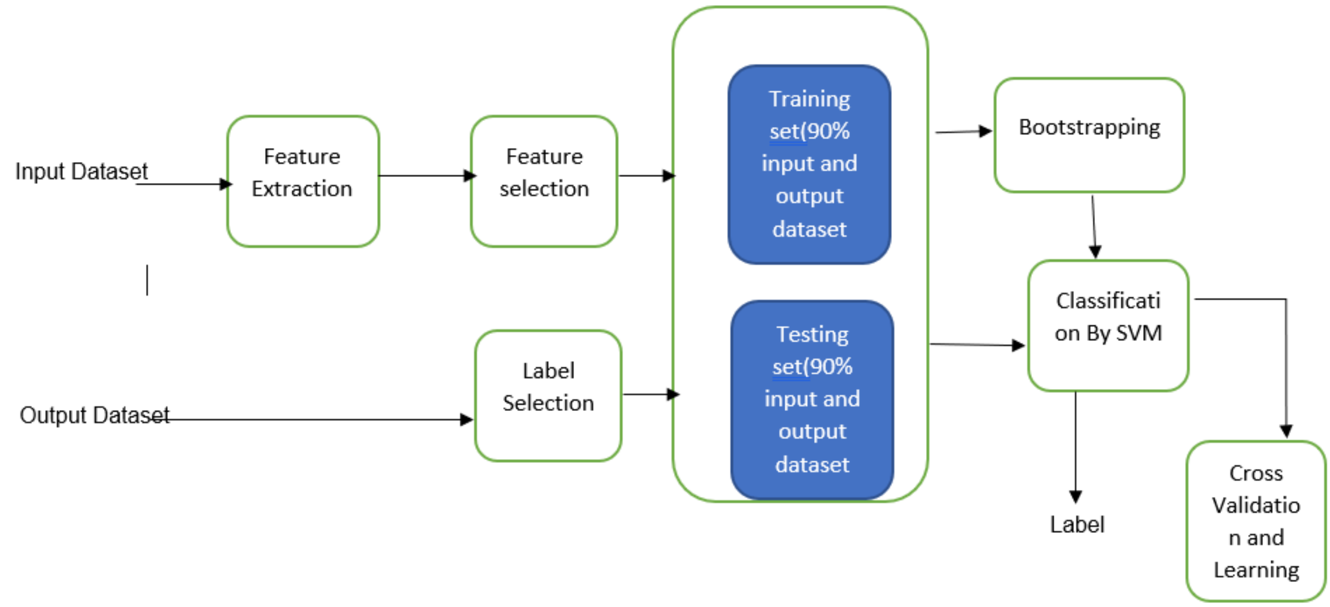

Figure 2.1: Flowchart of this research [18]

The training dataset is created by applying feature extraction and feature selection to the input dataset, then bootstrapping. On the testing dataset, label selection is used. Build an SVM classifier, then use a training set that was bootstrapped and a testing set. The classifierâs output is utilized to label the data and is fed into cross-validation and learning processes [18]. Another similar research was carried out on Neuromarketing study By Hassani. It has been investigated how customer decided like or dislike a product. EEG signals from 20 graduated students 10 men and 10 female who were aroused by seeing image of shoes. 16 images of various sizes and colors have been displayed. The screen shows each image for 15 seconds are shown in the Figure 2.2 below:

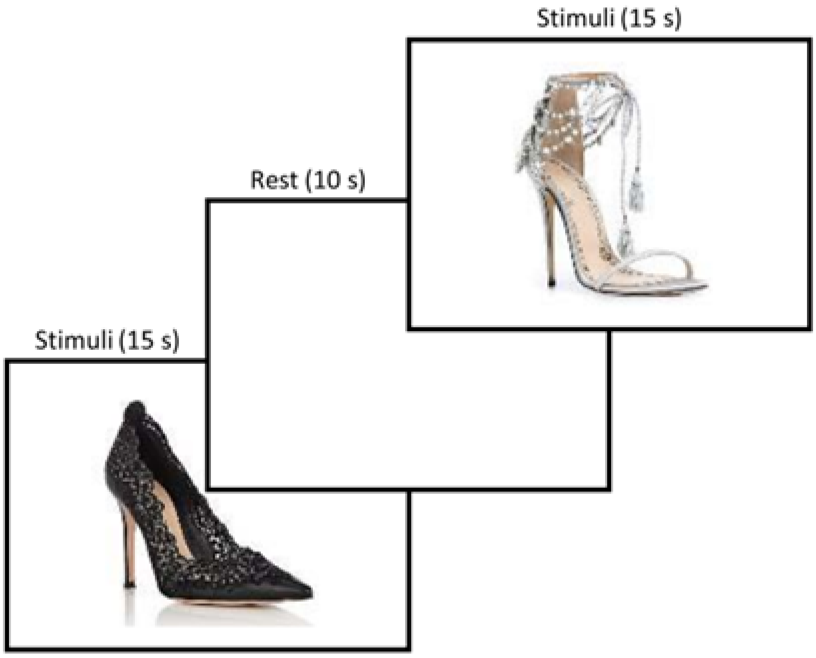

Figure 2.2: Flowchart of this research [19]

By clicking the "like" or "dislike" button, participants were asked to select one pair of shoes. The time responses were notes. The key question for women was: "Are you going to pay for the shoes for yourself?" The main question for males was: "Will you pay for your wife?". By training the model support vector machine, random forest, linear discriminant analysis and K-nearest neighbor classifiers, the customer identification like/dislike were categorized. The Rf classifier generated the highest accuracy for the female group, with a n accuracy rate of 71.51% and an error loss of 5.1%. Additionally, the RF classifier achieved the highest accuracy for femalesâ samples 71.33% with 14.07% loss [19].

To improve the performance and achieving more accurate results in Neuromarketing domain, a study was carried out on EEG signals.In the research explains different color of T shirst has shown to the customer, EEG brain signal is collected as a data set by the BCI devices. The data set is classified into customer feelings likeness/dislikeness. Perform analysis on brain signals, data pre-processing, then extract the features, train the model using ML or deep learning architecture based on emotions classification. Evaluate the model using test data brain signals. When model is ready, we can easily recognize the customer feelings. Take randomly EEG signals fed into the trained CNN model to predict that person "Like" or "Dislike" that product [12].

The scenario of neuromarketing has shown in the Figure 2.3: While a consumer is watching a product commercial, EEG brain waves are being captured. Whether a person would like or dislike a product is predicted by the BCI model.

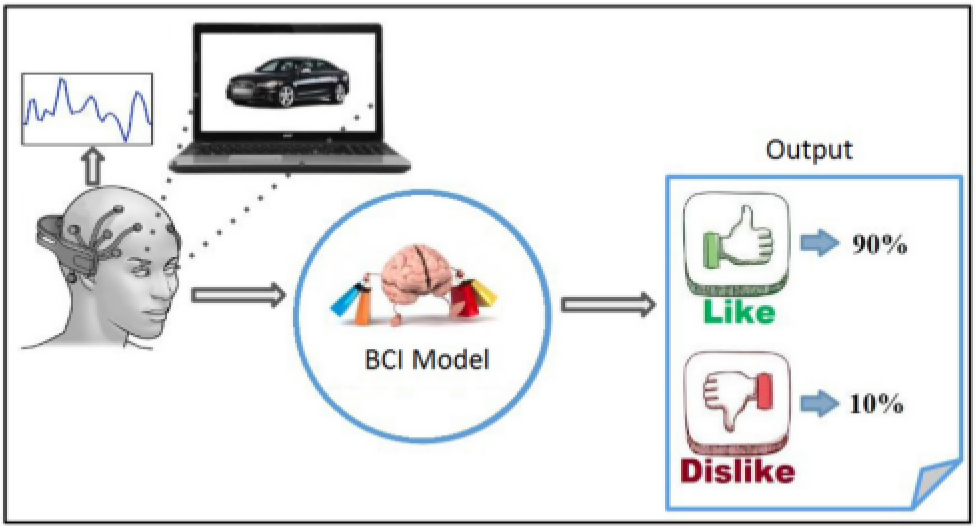

Figure 2.3: EEG and neuromarketing Architecture [12]

When EEG dataset were collected, there were lot of noise inside signals, sometime which may lead to wrong results, so we need to clean the data set. Noise has been removed from it, and extract the valuable information from the data. Used different filters like Savitzky-Golay to remove unwanted noise. Used filters to remove artifacts and used band pass filtering to improve signal predictions.Extract the features from processed signals, first transformed to the frequency domain and then passed through the Alpha, Beta, Gamma, Delta frequency band spectrum. After feature extraction we build the model for training to classify EEG emotion recognition. Trained a deep recurrent neural network (RCNN), achieved accuracy of 98.3%. Also used logistic dense neural network, with two dense layers with RNN accuracy achieved 92%. The 5 layers were trained, then two dense layers were added for achieving of the best accuracy of 95% [12].

2.2 Eye Motion Tracking

An experiment was performed at 15 Feb 2019 by Kellog's company use eye tracking technology for consumer behavior analysis in a virtual reality headset. With 845 mobiles at the VR platform, Accenture and Qualcomm technologies analyze VR merchandising. They permit customers to move randomly through areas of the store where goods are located, pick them

up, and put them in trolleys. It enables tracking of what consumers are viewing, It allows to record about what consumers are looking at, for how long, and why. Their findings were evaluated on the launch of food manufacturer's now pop tarts bites and analyze the deeper behavioral data. According to the results, products on lower shelves are 18% more efficient than those on higher levels [20].
Another study was carried out to find the best package in a retail setting based on the fastest search time. At the 2011 Pack Expo Las Vegas exhibition, a national packaging industry conference, experiments were run to time how long each "shopper" spent searching. The spacing of the items on the shelves was determined by the front elevation proportions of each box. The study examined the relationship between search time and package spacing using breakfast items under the Kellogg's brand name Pop Tarts[21].
Once IKEA performed experiment in 2016 to understand the shopper's attention and shopper's behavior. Various tools and technologies are used to monitor what customers are specifically looking for. Eye tracking offers a dynamic understanding of how customers move around or look around stores. Few moments later customer's picks up the hanger's pack. They analyze the consumer behavior based on the visual elements that consumers take in at various phases of the decision-making process. Floor signs were very helpful in directing the passenger and easing his journey. The eye tracking information shows how effective signage is in terms of attention and discovery. It is showing price on product itself can attract the attention. When the customer has reached the end of his shopping journey post interview was done that is regarding about his shopping experience and outcome. They asked different questions, for instance Did he find what he is looking for? anything unusual that happened. The material in shopping bag was also helpful for analyzing the eye tracking data, identifying the patterns, and finding correlation between interviews and eye tracking data [22].
Another experiment was carried out in which EEG signal used to analyze the cognitive behavior of a subject's preference on productâs brand and cost affects over the similar product. The Eye tribe device is used to monitor eye movement. The subject's movement is managed and recorded using eye tracking software. The information of the product was recorded in which person is interested in while controlling the mouse cursor on a computer screen [13]. Laptop was placed onto the desktop, person asked to look onto the screen. Series of Products were displayed on Microsoft power point slides. The items displayed are the same, yet they have various brand names and pricing ranges. The individual was instructed to concentrate

on one of the two products that were shown on each slide while the mouse was over the item they wanted. The movement of the subject was monitored using an eye-tracking equipment, and EEG data were captured using a BCI headset.

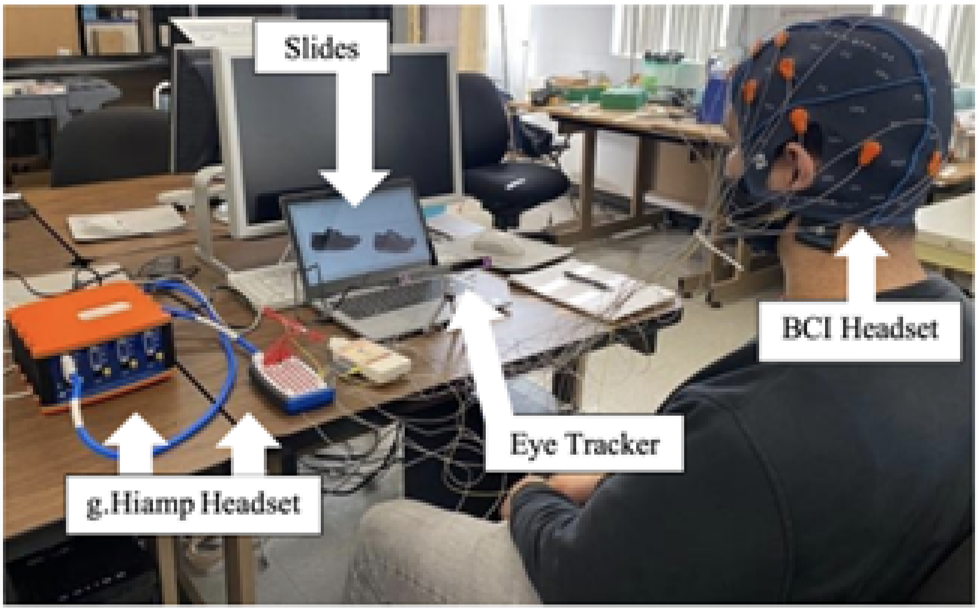

Figure 2.4: Eye Tracking Experiment [13]

The information below in the table 2.1 were recorded while experiment. If you compare both tables, it shows the time spend on each product there is more probability of the person will choose that product. If you see the table 1 1st row, time to watch left product is 14.86 sec and right product is 15.14 sec respectively, the relative theta and Alpha power is almost same, so product chosen is Right product. But, In the third-row time to watch left product and right product is 21.37 seconds and 8.63 seconds respectively, Alpha power is three times greater than the theta power, product chosen finally is Right product.

Slide	Left Product	Right Product	Relative Theta Power	Relative Alpha Power	Chosen Product on Questionnaire
1	14.86 seconds	15.14 seconds	0.2656	0.2911	Right
2	14.95 seconds	15.05 seconds	0.2688	0.3343	Right
3	21.37 seconds	8.63 seconds	0.5782	0.2187	Right

Table 2.1: Eye Tracking Experiment [13]

On the other hand, if you compare it with Table 2.3 person spend more time to watch the left product as compared to the right product so the product chosen is Left, but in the third row although time spent to watch the Left product is less as compared to the right product, but relative theta power is eight times greater than the alpha power, so the product is chosen Right.

Slide	Left Product	Right Product	Relative Theta Power	Relative Alpha Power	Chosen Product on Questionnaire
1	20.70 seconds	9.30 seconds	0.4139	0.2792	Left
2	16.35 seconds	14.35 seconds	0.5142	0.2189	Left
3	16.15 seconds	13.85 seconds	0.8769	0.1115	Right

Table 2.2: Eye Tracking Experiment [13]

Another study was carried to enhance the functionality of eye tracking model using a convolutional neural network (CNN). We created a crowdsourced gaze capture mobile eye tracking dataset with around 1500 participants. Using Amazon Mechanical Turk (AMT), we gathered 1103 data to encourage users to use our application. 141 subjects through our Appstore downloads and 230 subjects through UGA's in-class recruitment. As a result, fixed sites were used to capture the 2445504 total frame. 2.1M frames were produced as 1249 iPhone users and 255 iPad users combined. Our model achieves a prediction of 1.71 cm and 2.53cm without calibration on mobile phone and tablets respectively. This is decreased to 1.34cm and 2.12cm with calibration. We train our iTracker dataset using convolutional neural network (CNN) for gaze predictions. Input frame image, size is 224*224 pixels. Crop the original frame and get face image, left eye and right eye and the input these images into convolutional neural networks [23].

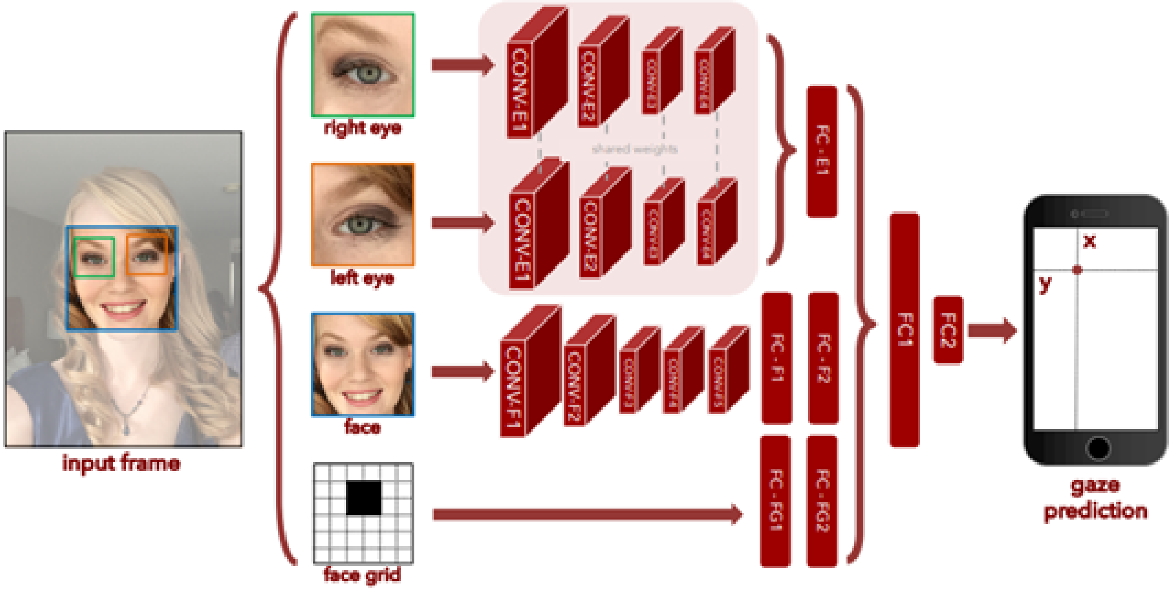

Figure 2.5: Gaze Prediction using CNN [23]

The 1490959 frames with both face and eye detections are chosen. In total 1471 subjects were chosen. The dataset was then divided into three groups: training, testing, and validation, each with 1271, 50, and 150 participants. There are 1251983, 59480, and 179496 in the train, validation, and test splits, respectively. Only subjects with a full set of points are chosen to guarantee consistent distribution in the validation/test sets. Increasing the dataset from current samples will increase the model's accuracy. Before input the data set for training and testing. We used the approach of image augmentation, shift, and rotate the eyes and face, change face grid appropriately.

The model underwent 150,000 iterations with a batch size of 256 using the gaze capture dataset. The learning rate was 0.001 at first, but after 85000 iterations, it drops to 0.0001. Weight decay was 0.0005 and the momentum was 0.9. we demonstrated error term of Euclidean distance from the gaze capturing position. Moreover, we used different screen sizes, use distances of phones and tablets, compare the performance and results of both devices (model used are perfectly same for both devices). Stream of frames of each fixation was processed rather than just single frame, that is known as dot error. In our case, classifier gave average predictions of all frames as compared to gaze point at a certain location. Results we obtained are shown in the table 2.3 below:

Model	**Aug.**	**Mobile Phone**		**Tablet**	
		error	**dot err.**	**error**	**dot err**
Baseline	tr + te	2.99	2.40	5.13	4.54
iTracker	te	1.84	1.58	3.21	2.90
iTracker	tr	1.86	1.57	2.81	2.47
iTracker*	tr + te	1.71	1.53	2.53	2.38
iTracker(no eyes)	None	2.11	1.72	3.40	2.93
iTracker(no face)	None	2.15	1.69	3.45	2.92

Table 2.3: iTracker Results [23]

Augmentation column, **tr** and **te** refers to train and test. Error and dot error values of itracker models are shown it is in centimeters. The support vector regressor (SVR) model are applied on features extracted using iTracker data set. Results are shown in the table 2.4 below:

The table 2.4 displays the information of Method used, Error came, and description of model used. If we see in the table when we applied SVR model error rate is 4.77, CNN error rate is 3.63 and when applied random forest it's 3.09. When used iTracker pretrained features and applied SVR it's 2.58 error rate.

2.3 Facial Coding

A studied was carried by Gill on Neuromarketing technique - Visual-Emotion mining in year 2020 to discuss about the human facial skin is used to recognize the human emotional state. He classified emotions into seven different types; Anger, surprise, neutral, disgust, happy,

Method	Error	Description
Center	7.54	Simple baseline
TurkerGaze	4.77	pixel features + SVR
MPIIGaze	3.63	CNN + head pose
AlexNet	3.09	eyes(conv3) + face(fc6)
iTracker(ours)	**2.58**	fc1 of iTracker + SVR

Table 2.4: iTracker Results [23]

surprised etc. Collect the visual images/vides based dataset, fed into the Machine learning or deep learning models. Train the model and then predict your results. The table 2.5 below shows the information about the different types of human expression to their corresponding action produced by the people [24].

Elementary Emotions	Produced Actions
Happiness	Closed eyelids mouth corners pulled upward and laterally
Surprise	Eyebrows raised; upper eyelid raised
Anger	Eyebrows raised Eyebrows lowered Raised upper eyelid
Sadness	Raised eyebrows Lowered eyebrows with depressing lip corners
Disgust	Raised upper lip Raised upper lip with wrinkled nasal skin

Table 2.5: Facial Emotions With Produced Actions [24]

The author mentioned about the previous work done in the field of emotion mining using neuromarketing techniques. In the table 2.6below represents some research, analysis and compare experiments done by different authors. Mostly researchers used EEG with other techniques. But as performing analysis on EEG is difficult and expensive, so authors proposed used eye tracking with facial emotion classification techniques[24].

Reference	Neuromarketing Techniques	Emotion Mining Techniques	Experimental Results	Type of Study
[25]	EEG signals and eye tracking	SVM	Accuracy 71.77% and 58.90% for EEG and Eye tracking respectively	Experimental Study
[26]	EEG, Facial analysis	SVM	53% Accuracy	Experimental Study
[27]	Eye-tracking, Facial expression	NA	NA	Analysis Study
[28]	EEG, Facial Analysis, eye tracking	NA	NA	Review

Table 2.6: Existing Research Using Neuromarketing Techniques [24]

In another study compares empirically the performance of eye-tracking against pupil diameter as the classification feature for emotion recognition in a virtual reality (VR) environment. In accordance with Russell's four quadrant circumplex Model of Affect, we divided emotions into four different categories. Participants in a VR environment are shown 360-degree films as emotional stimuli to elicit the userâs emotions. For the two selected eye features, support vector machine (SVM) was used as the classification algorithm. According to the data, pupil diameter had a 75% accuracy rate while emotion classification had a 57% accuracy rate [36].

Another research was caried out in which the proposed system introduces an emotion recognition system, based on human eye movement using electrooculography (EOG) signals. Emotions play a vital role in life as the person's response or reaction is solely based on feeling they are experiencing. EOG signals emotions are divided into happy, sad, angry, fear and pleasant. EOG signals emotions are classified as into happy, sad, angry, fear and pleasant. Machine learning model support vector machine is used for categorized the EOG signals that have been analyzed, and ICA is used to extract the features. Machine learning model Support Vector Machines is used for classifying the processed Electrooculography signals and for feature extraction ICA (Independent Component Analysis) is used. Using these techniques, human emotions are recognized and inputted in an augmented reality (AR) system where the humans can interact or respond to the system. These methods allow for the identification of human emotions [37].

2.4 Radio Frequency Monetary (RFM)

The studies was carried out on consumer behavior based on RFM analysis using classification model Support vector machine (SVM) for customer predictions. The SVM model is used because this model has good performance and predict accurately. Data samples are gathered from online retail stores. Recency, Frequency, and monetary (RFM) are chosen as the parameters. Weights of recency(R) and frequency(f) are calculated by using the value of monetary (M). the classification done through testing dataset [29]. The Table 2.7 below shows the results of SVM model applied:

counter	label	function	alpha	abs(alp...	support	R	F
0	17000	1591.301	0.500	0.500	supportv...	3.875	3.610
1	3000	1497.890	0.500	0.500	supportv...	0.331	- 0.375
2	4500	1546.705	0.500	0.500	supportv...	2103	1.867
3	1500	11500.000	0.500	0.500	supportv...	0.331	- 0.126
4	14000	1536.010	0.500	0.500	supportv...	1.217	2.365

Table 2.7: Support vector Table[29]

Another study was carried out in which k-means ++ clustering techniques are utilized to classify customers into five different segments. This classifies the suggested model using order data of Migo Claypot Restaurant in a takeaway platform in W city. The value of R(recency), F(frequency) and M(monetary) in consumer behavior segmentation is described by the traditional RFM model. To enhance the accuracy of customer classification, the traditional RFM model was modified, and the RFMT model was recommended. In this method, T stands for time between the first transaction in a customer's history and the most recent transaction. This article's weights indicator is determined using principal component analysis (PCA). The weights of each indicator is determined by its variance contribution rate [30]. Relative weights of four indicators of the R, F, M, and T are as follows:

$A_{m*i}(i = 1, 2, 3, 4)$ composed of four indicators of each user is

$$x_i = [x_{1i}, x_{2i}, ...x_{mi}], i = 1, 2, 3, 4,$$

Calculate the covariance matrix C of x_i,

$$C = \frac{1}{4}\sum_{i=1}^{4}(x_i - u)(x_i - u)^T \tag{2.4.1}$$

where $u = \frac{1}{4}\sum_{i=1}^{4} x_i$, is the region value matrix.Then the covariance matrix C is eigon decomposed as follows:

$$C = UAU^T$$

where $A = \begin{bmatrix} \lambda_1 & 0 & 0 & 0 \\ 0 & \lambda_2 & 0 & 0 \\ 0 & 0 & \lambda_3 & 0 \\ 0 & 0 & 0 & \lambda_4 \end{bmatrix}$, is the egion value matrix of C, U is the eigonvector of C and $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are the weights of the four indicators[30].

2.5 Functional Magnetic Resonance Imaging (FMRI)

The studied was carried out in which use spatio-temporal FMRI data to forecast buying decisions. When a consumer was presented with a sample of 24 distinct product categories and asked to make a purchase choice, a FMRI scan of the human brain was conducted. Eight regions of the human brain were clearly engaged in the FMRI scan findings report. We used spatiotemporal FMRI features that were supplied into recursive cluster elimination based on support vector machine (RCE-SVM) to forecast purchase decisions (RCE-SVM). When a participant made a purchasing decision during an experiment involving eight separate ROI, certain attributed were extracted using time series from those ROIs (buy or not buy). The features extracted by time series from eight different ROI that activated during purchase experiment when the subjectâs made purchase decision (but or not buy). The diagram 2.6 below displays the 8 ROIs that the analysis produced. RCE model is utilized as a feature selection strategy because it takes feature clusters rather than taking individual features into an account. We were able to be achieved 71% classification accuracy with this RCE-SVM model. 24 peoples were participated in an event related task. Images of 64 actual products from 32 different product categories were displayed to the subjects. The selection of the product images was made via behavioral testing. The subjects were shown 64 product images for 5 seconds before having further 5 seconds to decide whether to buy the product or not. They then pressed an MR-compatible button box to record their responses to all 64 stimuli. Echo planer imaging (EPI) sequencing with a 32-channel head coil was used to obtain FMRI data [33].

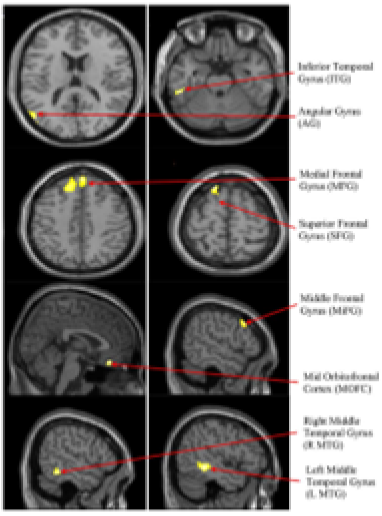

Figure 2.6: 8 Regions of Brain activated

The RCE SVM algorithm consists of three primary steps: the cluster step, the SVM scoring step, and the RCE step. Flow chart of RCE-SVM algorithm is shown in the Figure 2.7 below.

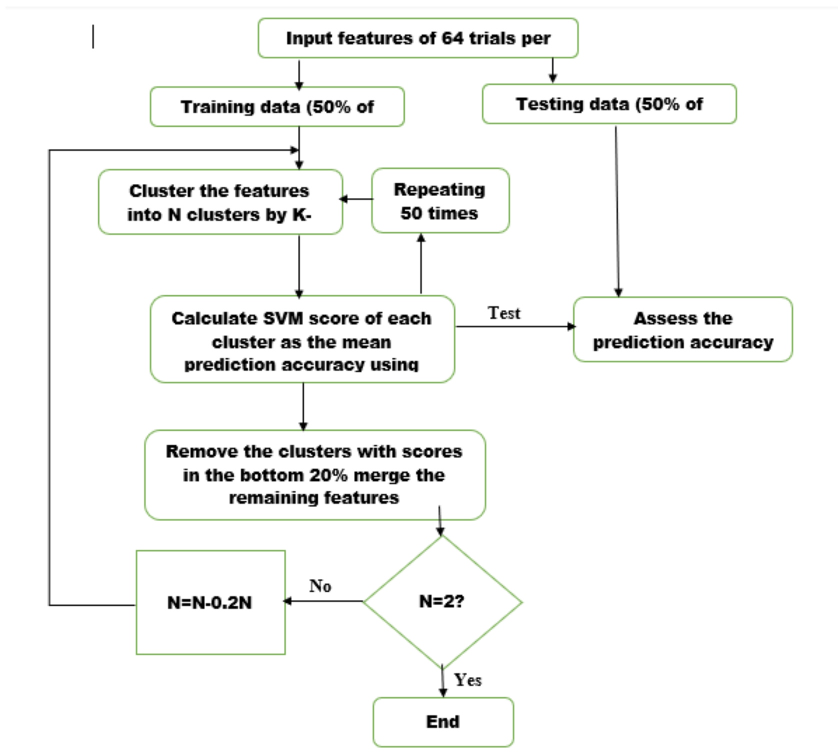

Figure 2.7: Flow Chart of RCE-SVM Algorithm

The results of the model accuracy were shown below. As the number of features decreases, model prediction accuracy increases and in the distribution of data in table x shows the only accuracy is higher when the p-value were less than 0.05. The model predicts the accuracy of 70.73% using 2 clusters and 4 features [33].

Number of features	Prediction accuracy (%)	P-value
64	55.70	0.1919
51	59.39	0.0517
18	66.28	0.0041
11	68.19	0.0018
5	69.76	0.0008
4	70.73	0.0003

RCE-SVM Model Accuracy table[33]

The FMRI studies was carried out that consumers' brain activity how they would assess brand extension. Brand extension is the use of an existing brand name to new products or services. Participants rated a brand extension sample's suitability for scanning with functional magnetic resonance imaging (FMRI). We preprocessed 3-D fMRI image data and generated 2-D feature images. A CNN model was used to classified FMRI images visual presentation of each brand extension sample. 94% overall model accuracy was attained [35].

CHAPTER 3

Dataset explanation

3.1 Electroencephalogram (EEG) Dataset

I have performed analysis on EEG brain signals, classify the people response into three different categories. The **EEG brainwave emotions dataset** was gathered from two individuals (1 male, 1 female) over the course of three minutes for each of the three possible reaction states: positive, neutral, and negative. We used an EEG headband that record the EEG signals TP9, AF7, AF8, and TP10 via dry electrodes. They observed the subjectsâ reactions by showing them variety of movie scenes, including emotional, funny, sad, death and nature etc. In this analysis combines ″Positive" and ″Neutral" responses that indicates people ″Like" the movie, while their ″Negative" responses indicate they ″Dislike" the film. It was simplified to a binary classification by combining labels into Neutral, Positive, and Negative reactions categories [17].The dataset of EEG brainwave data has been processed, extract the features consists of brain signals, try to predict the emotional state of a subject. The EEG dataset contains 2132 rows and 2549 columns. Length of each emotion signal is 750. You can see data distribution of EEG emotion signals plot in the Figure3.1 below.

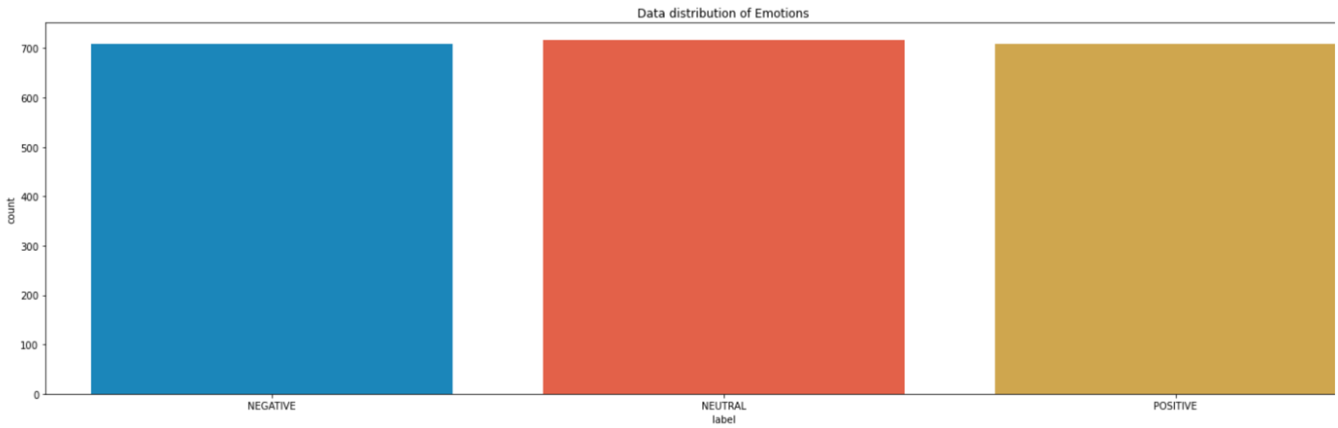

Figure 3.1: Data Distribution of EEG signals

The data frequency of Positive and Negative emotion is between 600 to -600, but the frequency of EEG brain signals of Neutral emotion is between 250 to -50 are shown in Figure 3.2 and 3.3.

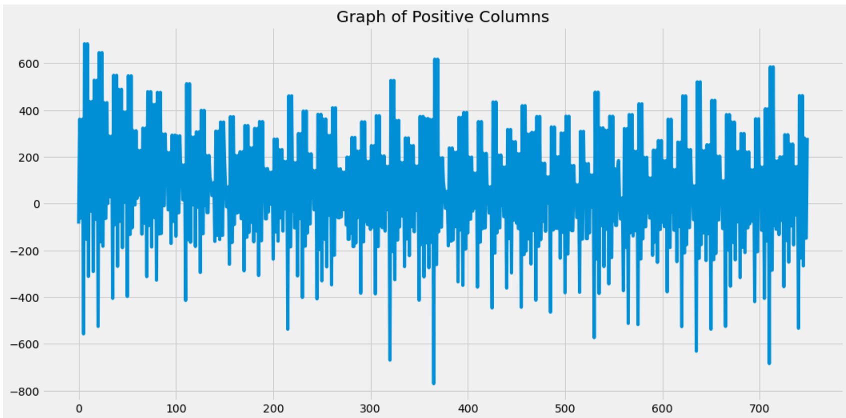

Figure 3.2: Frequency Distribution of Positive EEG features

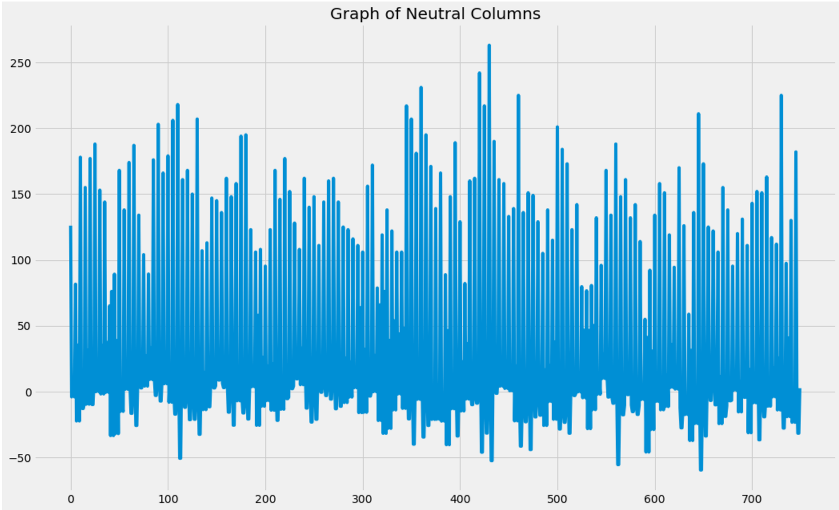

Figure 3.3: Frequency Distribution of Neutral EEG features

3.2 Eye Motion Tracking Dataset

Bunch of eye images are collected; CNN was applied on it. Data set was downloaded from Kaggle.com. There are two folders training images contain 2000 collections and test images contains 200 samples. Size of each image size is 50 * 100 pixels. I resized the Image to 48 * 48 using openCv library.

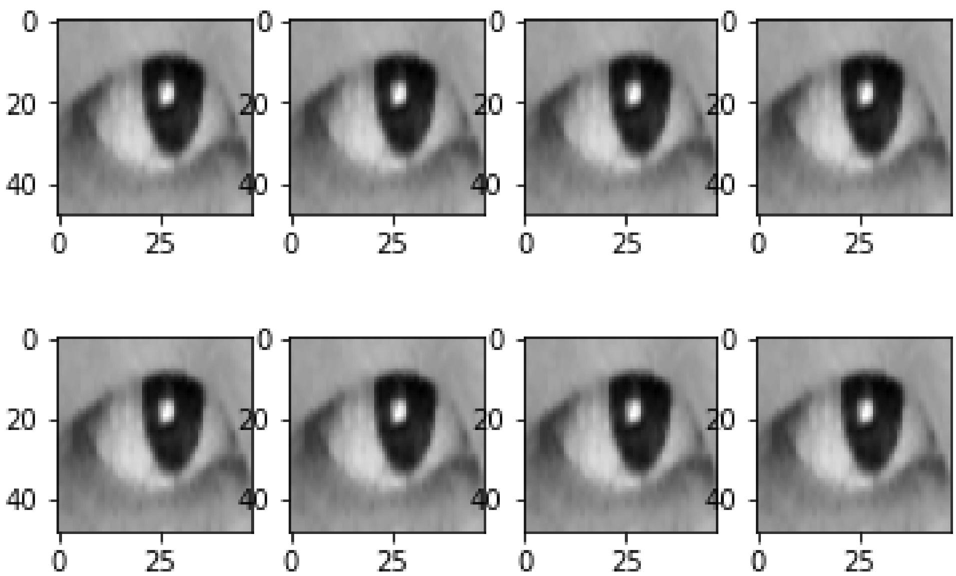

Figure 3.4: Eyes Images Dataset

3.3 Eye Emotion Classification Dataset

Dataset Eye Emotion DIU was downloaded from Kaggle.com. There were two folders, one is contained 270 training images and other one testing images contain 138 samples in the folder. Load the training images and store into variable train-x, with training labels into train-y. The length of labels was six, that contains six different human emotions. Similarly load the testing images and saved into the variable test-x and test-y, the length of those variables is 138 and 6 respectively. The type of the variables was list. Create the data frame function, convert the both labels into data frame by pd.DataFrame(). Plot the training dataset with label names and percentage of data distributed according to the emotions. Figure 3.5 shows the randomly selected images of eyes emotions.

Figure 3.5: Plot Images of Eyes Emotions

dataset with label names and percentage of data distributed according to the emotions. Figure 3.6 shows the training data distribution and Figure 3.7 shows the Testing data distribution.

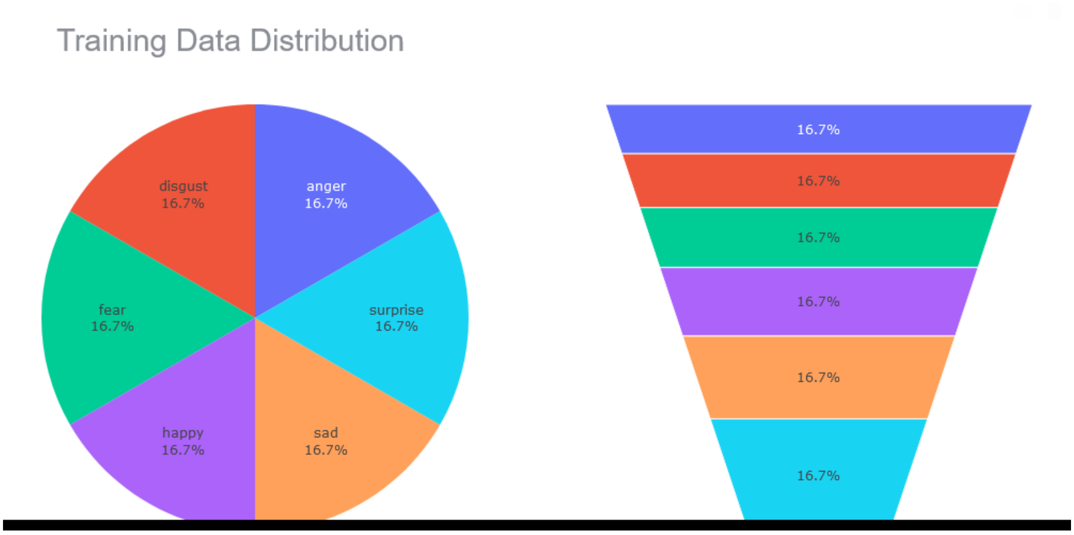

Figure 3.6: Data Distribution of Training Images

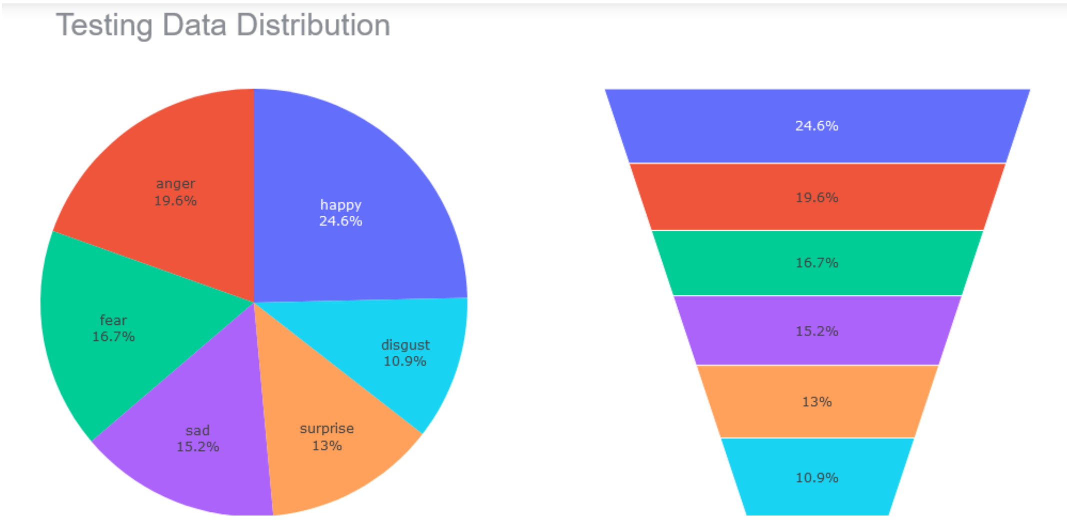

Figure 3.7: Data Distribution of Testing Images

You can see in the figure the training data set images is equally distributed to 16.7% of each expression, however testing data set is unequally distributed. The highest dataset is of happy emotion which is 24.6% and lowest one is disgust 10.9%.

3.4 RFM Dataset

I took the dataset **customer segmenattion using RFM** of e-commerce company from Kaggle.com, did segmentation based on customers behavior. It will be helpful for the company to making marketing strategies and decisions according to these segments. For instance, company will come to know about each category of customers and what steps need to take in terms of campaigns to retain profitable customers and different type of approach to attracts new customers. RFM analysis is important to increase revenue by targeting relevant or specific clusters of customers. The benefit of RFM analysis that it generates higher rates of response, increase loyalty and customer lifetime value.

The dataset Online Retail II downloaded from Kaggle.com, it's a data of online retail store based in the UK of year 2010 â 2011. The company mainly deal in souvenirs products. The majority of the company's customer are corporate customers. There is total eight variables in the dataset, and it contains 541910 rows. Invoice No is a unique number for each transaction, if it starts with C which means cancelled operations. Stock code is a unique product code, description is a product details, Quantity refers number of products in the invoices have been sold, Invoice Date, unit price is a product price in pounds, customer ID and Country. The Figure 3.8 below represents the first 5 rows of company's dataset.

```
data.head()
```

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

Figure 3.8: First 5 rows of company's dataset

3.5 Functional Magnetic Resonance Imaging (FMRI) Dataset

The dataset was obtained from the website Statistical Parametric Mapping (SPM). This is popular MATLAB toolbox is used to analyze FMRI experiments. This experiment was carried out under the supervision of Karl Friston and performed by Geriant Rees from the department of cognitive neurology. After importing the libraries, we downloaded the "Single subject epoch (block) auditory FMRI activation dataset". When I unzipped the file, got two directories. The first folder sM00223 contains structural scan of the subject in high resolution

and the second folder fM00223 contains the functional information.
To visualize the structural MRI data used NiBabel library to load the dataset. It has 4 dimmensions, first two dimensions represent x,y planes, 3rd dimension represent number of slices, 4th dimension has to be discarded it does not contain any data.

```
>>> print(data.shape)
(256, 256, 54, 1)
```

Figure 3.9: Dimension of structural MRI data

In each of 54 slices, the brain scanâs output displays 256*256 resolution. To plot 54 slices at once would be too excessive, so we will plot every tenth slice here. The brain skull is clearly visible in this image; it is displayed from lowest slice (0) to highest slice (50). You can clearly see the eyeballs in slice 20 in Figure 3.10.

Figure 3.10: Brain Image at different slices

In functional FMRI dataset, each acquisition was made up of 64 consecutive slices, 0r 64*64*64 3mm*3mm*3mm voxels. The volumes were required to 96. There are 96 .hdr files in the folder indicates that it contains all the slices for a single volume. Voxels have spatial dimensions of 3mm by 3mm by 3mm, we may rotate the data without distorting it. We displayed all three planes in the Figure 3.11 below that are commonly used to transect the brain: coronal, transversal and sagittal.

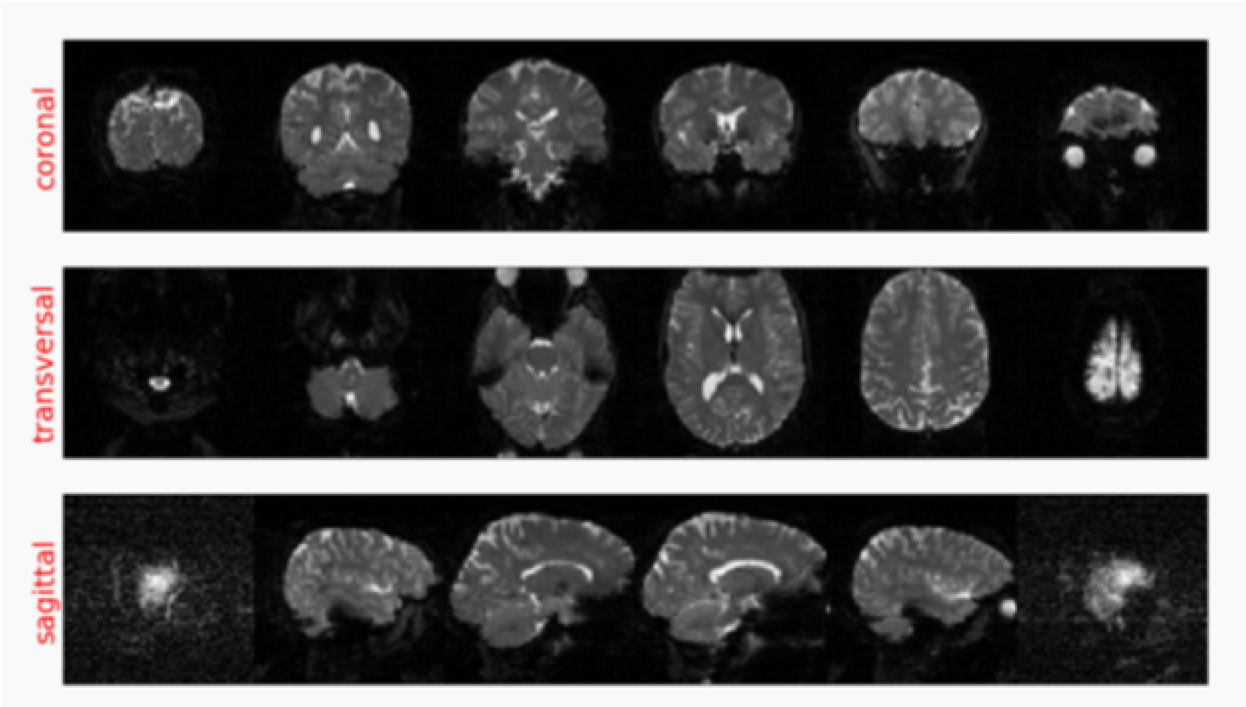

Figure 3.11: Transect of Brain

Doing for 6 slices from each automatic plane, you can see data will always undistorted due to same length of spatial dimensions. There are total 64*64*96 = 25165824 total data points, it is bit tricky to put all data set into one graph and shows as the brain visualization. Well Figure 3.12 is a time course, it is the scan of the brain image. It is not so meaningful and does not showing clear information what is going on in the brain.

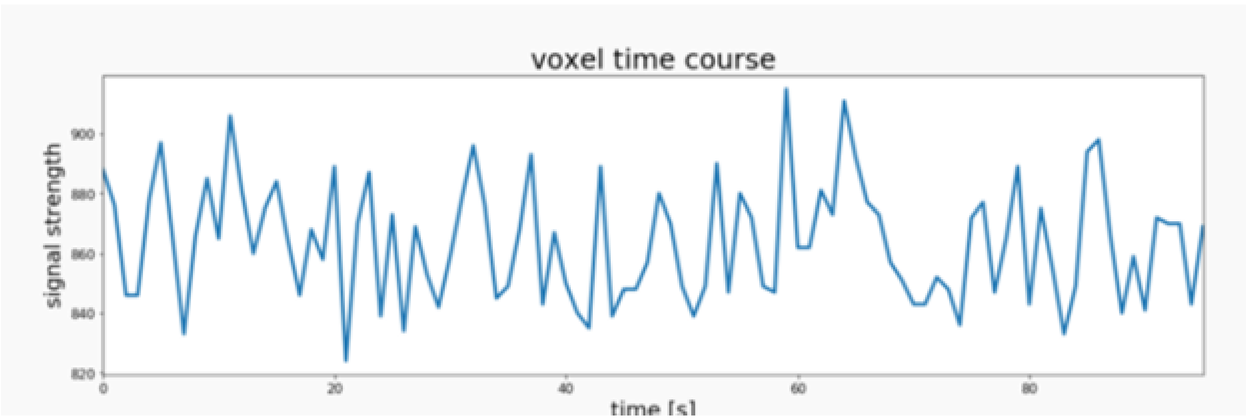

Figure 3.12: Voxel time course scan of brain image

CHAPTER 4

Algorithms Implemented

4.1 Convolutional Neural Network (CNN)

To analyze images, artificial neural networks are most frequently used. It recognizes patterns and interprets them. Convolutional layers are a type of hidden layer used by CNN. It has others non convolutional layers as well, but the basis of CNN is hidden layers. Convolutional layers receive input then transforms it into someway and then transforms the output to the next layer. This transformation is known as convolutional operation. Convolutional layers have different filters that able to detects the patterns in images some may detects circles, corners, edges, squares, and few are geometrical filters. There are two main portions in the CNN model first one is Feature extraction, and the second portion is Applying classification on those features to predict the output. For instance, In the Figure 4.1 below represent the feature extraction on the image and classifying the problem that Is this KOALA? To detect the Koala there are two main features head and the body. We further divided head into eye, nose, and ears. If our model detects these three features, we can say the input image contains Face. And for detecting the body we need to detect hands and legs of the koala in the image. So, extracting different feature we have different filters. After multiplying image matrix with head filter and body filter, aggregating the results of calculation we can say there is a head and body present in the image. We got two feature maps head and body, then we can flatten these numbers 2-d array into 1-dimmensional array. After joining both flatten layer make fully connected dense neural network for classification. The two other components are also used in CNN process one is ReLU activation used for to bring nonlinearity in our model. It takes our feature maps and if there are any negative values replaces with 0. We used max pooling to reduce the image dimension size. It also reduces overfitting and model is tolerant towards variations and distortions.

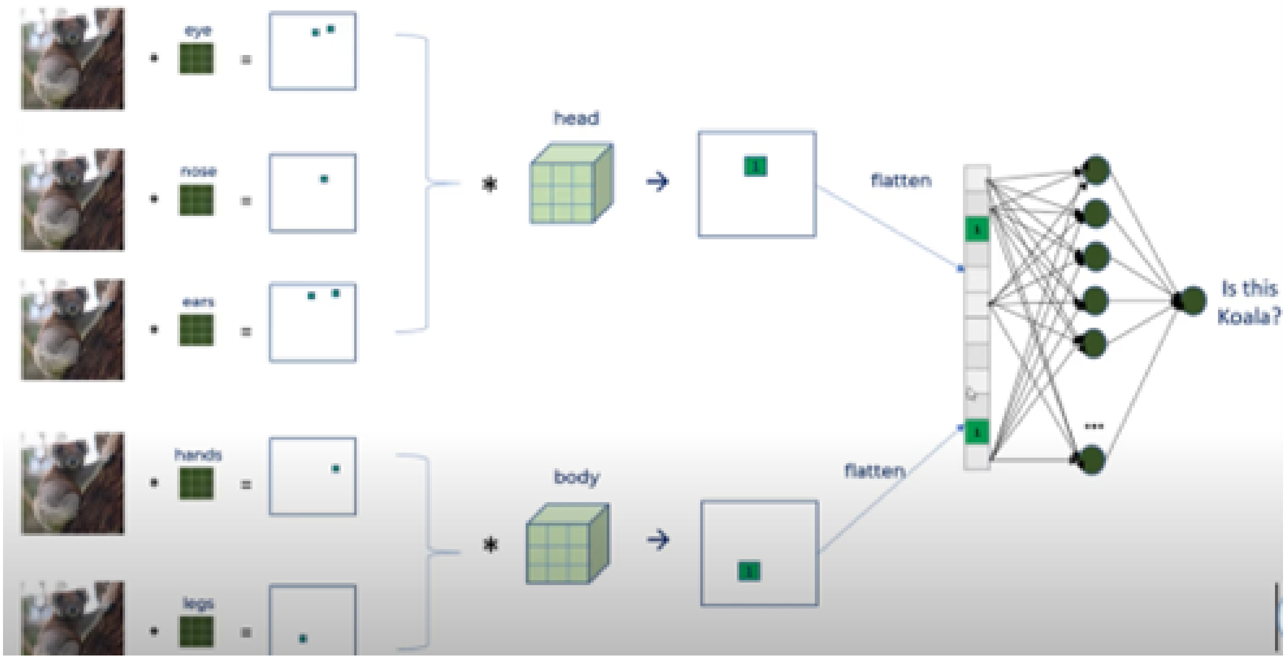

Figure 4.1: CNN model Architecture [39]

Convolution	$z^1 = h^{1-1} * w^1$
Max Pooling	$h^1{}_{xy} = max_{i=0...s,j=0...s} h^{1-1}(x+i)(y+j)$
Fully-connected layer	$z_l = W_l * h_{l-1}$
ReLu (Rectifier)	$ReLu(z_i) = max(0, z_i)$
Softmax	$softmax(z_i) = \frac{e^{zi}}{\sum_i e^{zj}}$

Table 4.1: CNN filters equation [38]

4.2 Long Short Term Memory (LSTM)

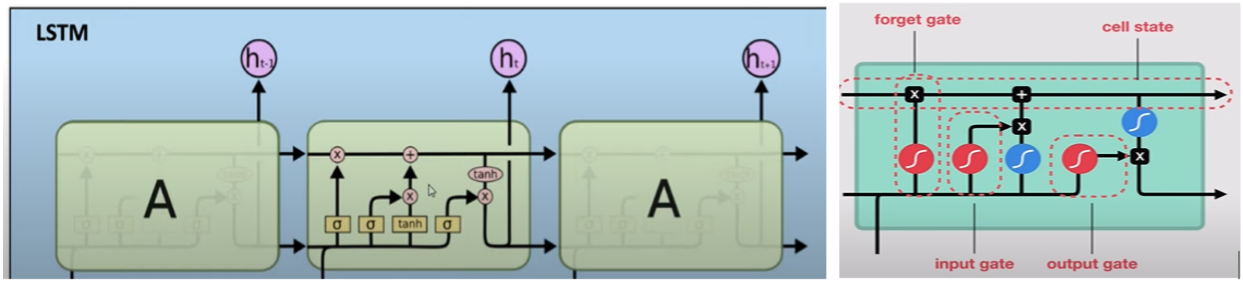

Figure 4.2: LSTM model Architecture

A unique variety of RNN is the long-short term memory (LSTM) model. Cells, forget gates, input gates, and output gates make up an LSTM unit. The first part in the LSTM model is a forget gate. It helps us in defining what information to forget, what information to remember. Next gate is input gate, it also controls the amount of information that passes through that gate and finally output gate. Information flowing through the cell and the gates letting the information through the cell state. There are three sigmoids and one tanh in the cell. Sigmoid output 0 to 1, it can be used to forget or remember the information. Tanh to overcome the gradient problem.

LSTM Math Equation [40]

Forget gate:

$$f_t = \alpha(W_f.[h_{t-1}, x_t] + b_f] \tag{4.2.1}$$

Input Gate:

$$i_t = \alpha(W_i.[h_[t-1], x_t] + b_i) \tag{4.2.2}$$

$$\tilde{C}_t = \tanh W_C.[h_{t-1}, x_t] + b_C \tag{4.2.3}$$

Output Gate:

$$O_t = \alpha(W_o.[h_[t-1], x_t] + b_o) \tag{4.2.4}$$

$$h_t = O_t * \tanh(C_t) \tag{4.2.5}$$

4.3 K-means Clustering

In data mining classification and clustering are two basics techniques used to categorize the target user. However, cluster analysis is the most popular technique used for segmentation. In the RFM consumer behavior analysis I applied the K-means clusters analysis on the dataset to segment into clusters.

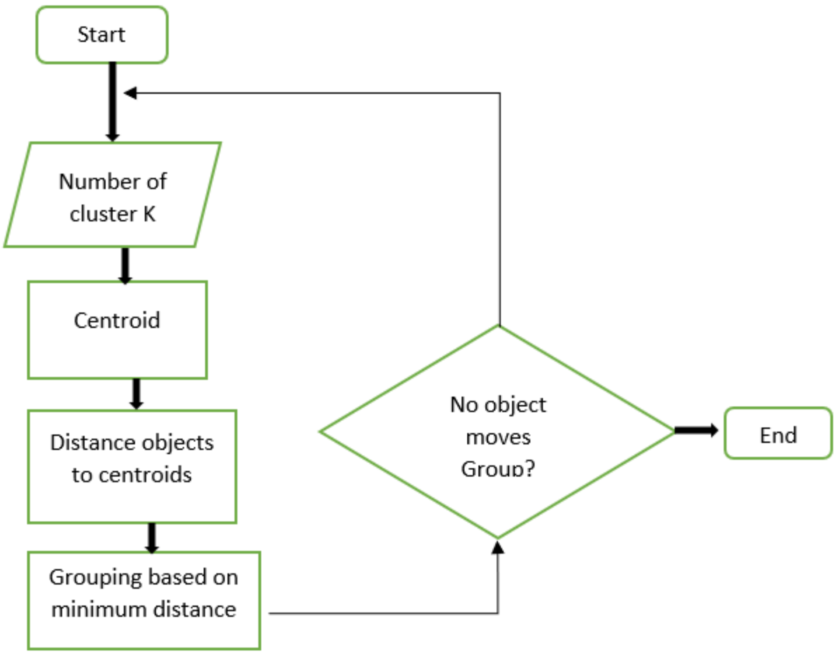

Figure 4.3: K-means Architecture Flowhart

Initialize the value of k means number of clusters. For instance, if K =2, randomly choose two centroids for two clusters. We will find the value of two centroids using Euclidean distance and fill the complete table. Divide the results into two clusters, because value of K = 2. Thus, we obtain two clusters, and then calculate new centroids by taking an average. Now will use new centroids compute the Euclidean distance of each object, keep performing the process until there is no change in the clusters. Thus, algorithm comes to a halt here and then obtain the results.

Euclidean distance Equation:

$$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{4.3.1}$$

Below in the Table 4.2 is an example of k-means clustering analysis:

Individual	Variable1	Variable2
1	1.0	1.0
2	1.5	2.0
3	3.0	4.0
4	5.0	7.0
5	3.5	5.0
6	4.5	5.0
7	3.5	4.5

Table 4.2: K-means Clustering Example table

The resulting centroids and clusters are shown in the Table 4.3 below:

Individual	Centroid 1	Centroid 2
1	1.0	1.0
2	1.5	2.0
3	3.0	4.0
4	5.0	7.0
5	3.5	5.0
6	4.5	5.0
7	3.5	4.5

Table 4.3: K-means Clustering Centroids

4.4 Support Vector Machine

It is the supervised machine learning algorithm used for classification problems. It works like mapping the data points and finding the optimal hyperplane that classify the dataset. We need to identify the right hyperplane, maximize the distance between the two nearest data points (classes). This distance is also called as margin. In the figure below you can see the example of linear SVM. Two classes star and circle are split through hyperplane A, B and C. Here, in three planes the right hyperplane is C because its margin is high as compared to A and B.

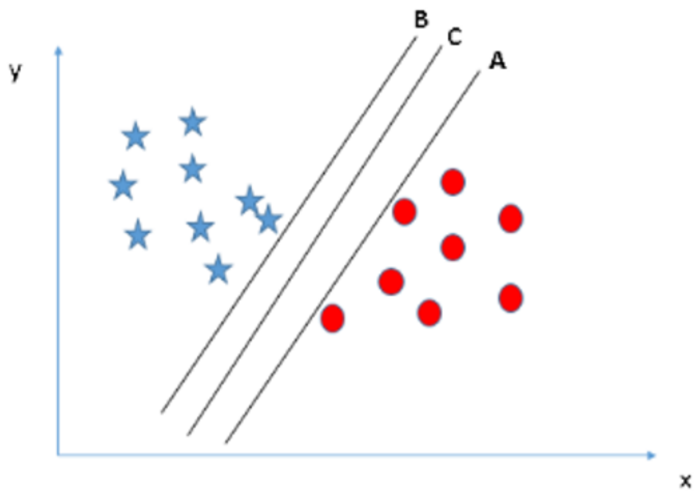

Figure 4.4: SVM Model Example Figure [42]

Different SVM kernel functions used that takes low input space and transforms into higher dimensions. Mostly it used for nonlinear dataset. For instance, Linear kernels, polynomial kernel, Radial Bias Function and Sigmoid functions.

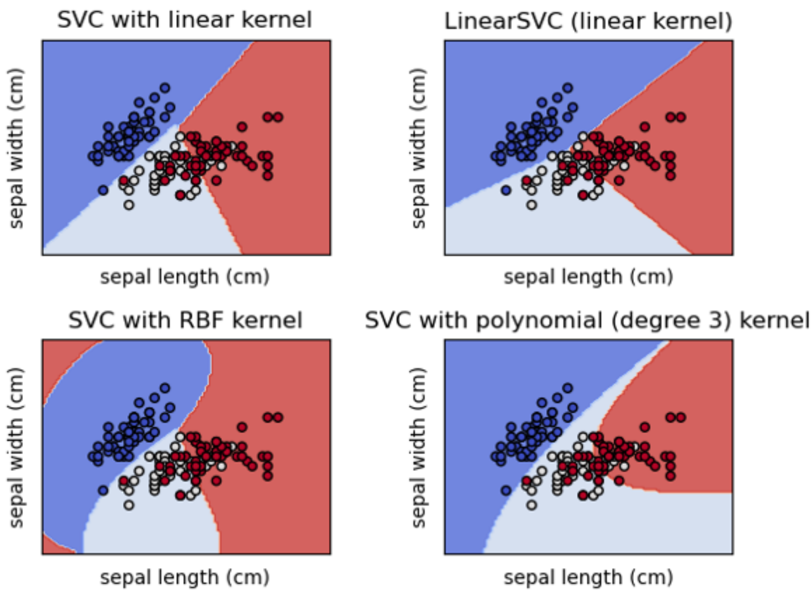

Figure 4.5: Different SVM Kernel Function [41]

If you see in the Figure 4.6 below data is distributed nonlinearly, so we split the two classes with the circle hyperplane.

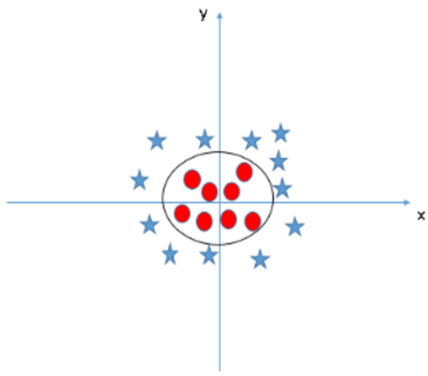

Figure 4.6: Nonlinear SVM Example

4.5 Techniques

4.5.1 Bootstrapping in SVM

It is the process of resamples a single dataset to create many simulated samples. Randomly selecting the data from original dataset and allowing for duplicates. Sampling with replacement means that we must has the same number sample values as the original dataset, this is called bootstrapped dataset. Creating bootstrapped dataset and then calculating mean, keeping record of that calculations is called bootstrapping. After creating 1000's of bootstrapped dataset, calculating their mean and adding them to the histogram. We can keep record of our calculation by calculating mean, standard deviation, median and Confidence interval etc. It is particularly useful for assessing the quality of machine learning models.

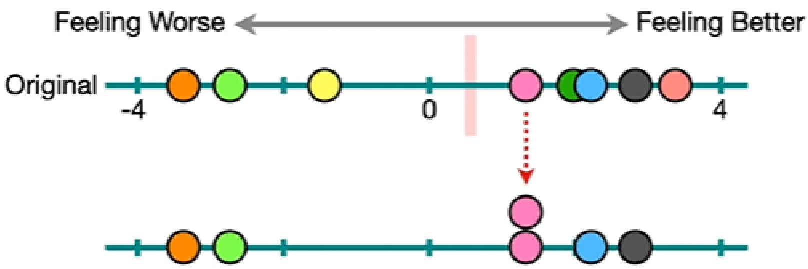

Figure 4.7: Bootstrappoing in SVM technique

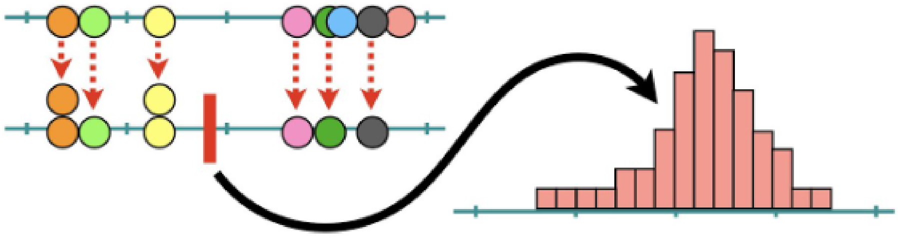

Figure 4.8: Bootstrappoing in SVM technique

4.5.2 Cross Validation

A method that requires dividing our dataset into subsets is cross validation. We divide the dataset into training and testing data; our model will learn from the training data while making predictions based on testing data. The purpose of employing this strategy is to increase the accuracy of our model, thus we will next choose a new block of data and retrain and reset it. This will repeat for the rest of the dataset by n times. For instance, K number of sections of data are used in K-cross validation. Pick one section to test, and the other to train. Then choose a new portion to test; the remaining sections will be used to train the model. Once each portion has been used as a testing set, the process will repeat K times. The average of the output measures from the K iteration will serve as the final performance metric [32].

$$FinalMeasure = Average(Measure1, Measure2, ...MeasureK)$$

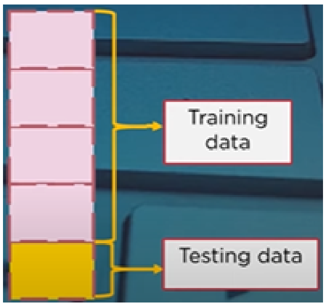

Figure 4.9: Cross Validation Technique

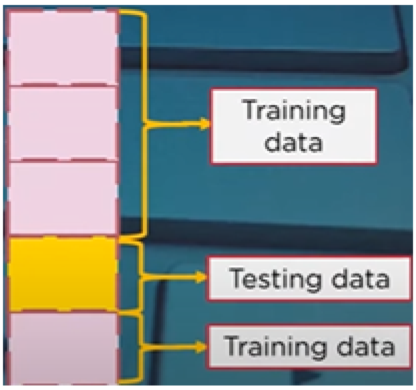

Figure 4.10: Cross Validation Technique

CHAPTER 5

Methodology

5.1 Electroencephalogram (EEG)

Data Pre-processing and Feature Extraction

Transform the data set, encode the labels into numbers. Get the brain signals into x variable and labels into y variable. Sklearn standard scaler function is applied on to the x variable. It useful for the feature that follow a normal distribution. It standardizes feature by subtracting the mean and then scaling to unit variance. One hot encoding is applied on labels. Split the training set and test data set with 80% and 20% respectively.

Import the TensorFlow and Keras layers library. Initialize the LSTM-MODEL. Input layer is added used Input shape of dataset which is according to number of columns. Hidden layer of brain signal is added to get the optimum solutions, expand the dimension, insert the input layer at index 2. Gated Recurrent units (GRU) layer was also used with 256 filters and set return sequence true. Flatten GRU layer to convert dataset into vector 1dimmensional array.

Classification

Classify the output dense layer with 3 neurons, activation function SoftMax is used. Print the model summary. Compile the model using Adam optimizer, whose metrics are accuracy and loss function was set to categorical cross entropy.

Starts the model training on dataset, total number of epochs is 10, validation split to 0.1 and steps per epochs is 48. After training the model, evaluate the model accuracy through testing data set. Accuracy achieved of overall model accuracy was 96% and loss was 11%. The model accuracy and loss is shown in the Figure 5.1 below:

```
#Loss and Accuracy of model on Testiong Dataset
print(f"Loss on testing: {loss*100}",f"\nAccuracy on Training: {acc*100}")

Loss on testing: 10.964921116828918
Accuracy on Training: 95.78454494476318
```

Figure 5.1: CNN model accuracy on EEG dataset

Comarison with Other Machine Learning Models

I used other machine learning and deep learning model for training and then compared their results with LSTM model through printing the classification reports and plotting confusion matrix of each model. I train the feature set on Gaussian naÃ¯ve bayes (GNB), support vector classifier (SVC), Logistic regression model, decision tree classifier and used random forest model to classify emotions from EEG brain signals. The accuracy achieved of GNB, SVC, Decision tree, Logistic Regression and Random Forest is 65%, 96%, 97%, 95% and 95% respectively.

5.2 Eye motion tracking methodology

In this project we build an application that is capable for recognizing the eye movements and detect when the person will blink the eye. Eye movement detection refers the gaze detection, where looking LEFT, RIGHT AND CENTER. OpenCv library used for live webcam, that takes your live picture predicts and detects the face using face landmark using dlib.shapePedictor(). The two main functions are used for **Gaze detection and recognizing eye blinking**.
If you see in the Figure 5.2 the structure of eyes there is sclera (white part), iris is the biggest circle, and the pupil is small circle in the iris.

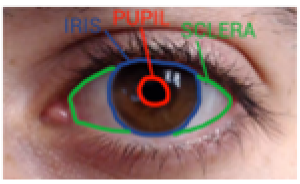

Figure 5.2: The structure of Eye

We the converted the image into grayscale and find the threshold exactly by the pupil. Using the threshold, find the biggest contours and remove the noise. After that we find the region of interest of both left and right eye. Then we detect the gaze, we need to understand how eyes appears when looking in different direction. If we look at right, the sclera (white part) will be on left side. If we look at left the sclera will be at on right side, but if we look to the center the white will balance between left and right.

Eye Gaze Ratio ()

Figure 5.3: Division of Eye for Gaze detection

In the Figure 5.3 we focused on the white part for calculating the gaze ratio. We split our eye like that as shown in figure. If we look at left side, sclera will be more visible on right part. I calculate the threshold of both eyes, then find the white pixels of both eyes respectively, divide the pixel of left eye to the right eye we will get the gaze ratio. I passed the eye points and face landmarks of both eyes as a parameter in the gaze detection which returns the gaze ratio. Took the average for both left and right eye. If the gaze ratio is smaller than 1 that means person is looking at right, if ratio is greater than 1.7 person is looking at left and if the ratio between 1 and 1.7 means looking at the center.

EYE BLINKING Ratio ()

Let's thing that there are how many ways, we can find the eye is blinking. There is total three ways. For instance, if eyelid is closed, we cannot see eyeball anymore and bottom and upper eye lashes comes closer. Human can blink eye just happen for short amount of time, approximately 0.3 to 0.4 seconds. We created the two lines on an eye horizontal and vertical line. The horizontal line will remain constant not matters eye is closed or open, but the vertical line fluctuates. The vertical line is maximum when eye is open and gets shorter when the upper and bottom eye lashes come closer. See in the Figure 5.4 below:

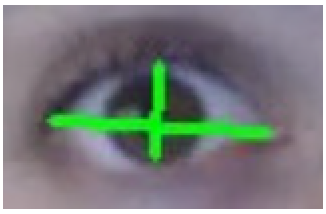

Figure 5.4: Blinking of Eye

So, we calculate the ratio between horizontal line and vertical line. If the ratio gets below to the specific number that means eye to be closed, otherwise is open. We insert the eye points and face landmarks to get the ratio between the lines. Take the average of both left and right eye. Through experiment we came that most reliable threshold is 5.7, if the blinking ratio is greater than this threshold that means eyes are blinking, otherwise not.

Controlling cursor on screen using eyes

We build an application that can control the movement of cursor on windows screen. This application very helpful for tracking consumer eye while performing neuromarketing analysis. According to the research we've read, an eye tracking device and an HCI headset were to collet customer data for the analysis. On Microsoft power point slides, several items were displayed. The user was instructed to concentrate on one of two products while the cursor tracked their eye movements and recorded the data. For instance, the amount of time spent considering each product, its relative theta power, and the chosen product (right or left)[13] [19].

Model Architecture And Analysis

Load all the data from eyes folders and Test Eyes directory to train the models. Apply the convolutional neural networks for eye motion tracking. Build the class of CovNet, train my model on two CNN layer. In the first layer, contains 4 filters with activation function RELU, kernel seize used 5,5, padding was 2 and stride used 1. 16 filter used on the second layer, with

kernel size 5*5, padding and stride was used same. Bach normalization 2d and max pooling was also done before every layer in the network. Add fully connected dense layers. I compile the model with total number of epochs is 10, steps per epoch is 2000. Initially learning rate (LR) was set to 0.001. The optimizer Adaptive Moment Estimation (Adam) used for tunning the CNN model. Weights and bias of model keep update during the forward and backward propagation process. Loss function used was categorical cross entropy. Evaluate the model with comparison to both training set images and test set images. Find the best final score, if final score is less than the 150 save that updated training CNN weights into the xModels folder. The accuracy of the model achieves is 87%, which is quite good accuracy.
In the Table 5.1 below shows the details of the model parameters used.

Hyper Parameters	Set value
Batch size	16
No of Epochs	10
Steps per epochs	2000
Momentum	0.9

Table 5.1: Model Architecture Parameters

Eye Track jupyter file responsible to detect the eye movement. We collect the pupil data by moving eyes. Detect the face landmarks, then our region of inetrest which is our left eye. Mark the circle on the left eye rigion of interest. We used live webcam, from the input frame(image), recognize the face accurately, and then detect the left eye, mark the circle on it. **MLtrcaking** jupyter file I write the code for control the mouse movement on windows using left eye. With the help of trained CNN weights files predict the cursor movement. Open cv library used for live webcam, detect the face and eye landmarks accurately.

5.3 Eye Emotion Recognition

This analysis is about research and approach of image processing domain. The application mainly detects the human eyes (ROI) and then classify it into the desired human expressions. I have already done task analysis on human expressions using facial images dataset and submitted my research paper in the module of MA902 to university of Essex. But now I am using the images of human eyes to recognize different human expressions. I merged it with neuromarketing techniques as a consumer behavior analysis. Classifying human expressions, it's not an easy task, because its very difficult to predict between similar pattern emotions. For instance, differentiate between Fear and surprise emotion correctly because it seems like similar pattern. We need to train the model on larger data set to improve the accuracy.

Facial Emotion Recognition

In facial recognition system used the Faced images downloaded the data set from Kaggle.com. Data set was divided into train images contains 28709 samples and test images contains 7178 samples. I used different ML and deep learning model, compared the results to each other. Based on results, recommend the best model. I trained the dataset on SVM, just achieved the 60% accuracy. I applied K-Nearest Neighbor obtained 72% accuracy, but model was predicting incorrect results. So, then I tried deep learning architecture CNN, the performance, speed, and accuracy in recognition process was very good. The trained model predicts correct results during evaluation, CNN is much feasible because it reduces the effects of variations and noise. Before training to CNN model, during data processing Image Augmentation is done to enhance the data set to train the CNN weights and bias for increase the accuracy. Image augmentation means increase the size of data set by rotating, flipping, shift the image and normalizing the data. Feature extraction process was done through convolutional layer, pooled features were extracting through max pooling process. The feature extracted from pooling process is transferred into 1D array form through flatten layer then this data is used as an input to Artificial neural network for classification. The process is involved forward and backward propagation to update the weights and bias which can correctly classify the human emotions [15].

Eye Emotion Recognition

Data Pre-processing

The type of labels is list nonnumeric labels, to normalize the labels transformed nonnumeric labels into numeric labels, we converted into array form and then fit into label encoder to apply one hot encoding for processing categorical features for applying machine learning models.

One Hot Encoding

```
train_y = np.array(train_y)
train_x = np.array(train_x)
test_y = np.array(test_y)
test_x = np.array(test_x)
encoder = LabelEncoder()
train_y = encoder.fit_transform(train_y) # transform non nemeric labels into numerical labels
train_y = to_categorical(train_y)
test_y = encoder.fit_transform(test_y)
test_y = to_categorical(test_y)
```

Figure 5.5: One Hot Encoding

Feature Extraction

Features are extracted using deep learning model with pre-trained convolutional neural networks using the Keras library. The network is already trained on more than a million images from the imageNet dataset to train model **inceptionV3 and exception**. We extract features with both inceptionv3 and Xception model then concatenate both features. This is used for model optimization and improve the accuracy of the model.

Classification

Build the CNN model with three dense layers. All layers used activation function RELU. Input shape was used 4096. In the first, second and third layer I used 1020, 900 and 800 filters respectively. Dropout layer was added with frequency rate 0.5 ideal for large networks, which helps prevent overfitting during the training process. Fourth dense layer is also added, that contains 6 neurons with activation function SoftMax. Model is compiling on optimizer Adaptive momentum estimation (Adam), loss function was used categorical cross entropy and metrics sets to accuracy. Initially the learning rate was set to LR = 0.001. Then fit the model, starts feature training with batch size was 5, total number of epochs was 22 and steps per epoch was 54.

```
model = Sequential()
model.add(layers.Dense(1020,activation= "relu",input_shape= (features.shape[1],)))
model.add(layers.Dense(900,activation = "relu"))
model.add(layers.Dense(800,activation="relu"))
model.add(Dropout(0.5))
#model.add(layers.Dense(700,activation="relu"))
model.add(layers.Dense(6,activation="softmax"))
model.compile(optimizer = "adam" ,loss = "categorical_crossentropy" , metrics = ["accuracy"])
history = model.fit(features,train_y,batch_size = 5,epochs = 22)
```

Figure 5.6: Build CNN Model

Hyper Parameters	Set value
Batch size	5
No of Epochs	22
Steps per epochs	54
Momentum	0.8
Training Images	270
Testing Images	138

Table 5.2: CNN Model Parameters of Training

Extract the testing features with pretrained convolutional network InceptionV3 and Xception model. Concatenate both features and save into the test feature variable. Evaluate the model accuracy through testing dataset and test labels. We got 72% accuracy of overall model.

```
eva = model.evaluate(features_test,test_y)
5/5 [==============================] - 0s 8ms/step - loss: 1.1889 - accuracy: 0.7246
```

Figure 5.7: Accuracy achieved on testing dataset

ANN Vs InceptionV3 And Xception CNN Model

For comparison to show the difference in results come without using the approach of features extraction using InceptionV3 + Xception model. I used the same approach, upload the same dataset but perform training on different deep learning model without extracting features using InceptionV3 and Xception model. I trained my model on artificial neural networks (ANN) and predicts the results. On model evaluation obtained 13% accuracy and loss on testing is 1.85. On previous model I extract features using pretrained CNN InceptionV3 and Xception model, obtained about to 75% accuracy on testing data set, but on this deep learning architecture the accuracy reduced to 13%.

```
loss,acc = model.evaluate(x_test,y_test, verbose=0)
print("         Using ANN           ")
print(f"loss on testing is {loss}\naccuracy on testing {acc}")
```

```
         Using ANN
loss on testing is 1.8593820333480835
accuracy on testing 0.1304347813129425
```

Figure 5.8: Dataset Trained on Artificial Neural Network (ANN)

5.4 RFM Methodology

Data Preprocessing

I dropped the duplicates from the country and Customer Id dataset, sort the data in descending order of customer Id. Checked the missing values in the dataset and validate if there are any negative values in the quantity column. Introduce the RFM class, add the method name **data-cleaning()**. The purpose of that function is to rename the dataset variables, if it found the country equals to United Kingdom drop that records and reset the index. Remove missing values from customer Id and ignore from description column. Filter out the records by applying the condition quantity should be greater than 0. Initially the datatype of date was string, so convert it into datetime. Calculate the total amount by multiplying quantity with unit price.

Add method of calculate RFM, set the latest date 10/12/2011 as the last invoice date was 09/12/2011 this is to calculate the number of days from recent purchase. Calculate the RFM modelling scores for each customer ID. Recency is calculated by calculating number of days from recent purchase, Frequency of customer is calculated by counting total number of invoices of each customer and monetary through doing sum of total amount. Rename the columns invoice date, invoice number and total amount to recency, frequency and monetary respectively.

Segmentation using Quatile Method

Add methods for to do recency, frequency, and monetary segmentation. Scores are calculated through quantile method, split into four segments quantile [<=0.25, <=0.5, <=0.75 and >=0.75] to categorize each customer. Add two methods to calculate the scores recency, frequency and monetary. Less recency number means customer visited for shopping like few days ago, so itâs better. And more frequency, monetary means frequently customers visited and spending higher on shopping, so higher value of frequency and monetary are better. I calculate recency score using quantile method, if quantile is less than 0.25 will return 1, less than 0.50 will return 2, less than 0.75 will return 3 and else will return it 4. In calculating frequency and monetary score, if quantile is less than equals to 0.25 return 4, less than 0.50 will return 3, less than 0.75 will return 2 and else will return 1.

```
def recency_score(self,x,p,d):
    if x <= d[p][0.25]:
        return 1
    elif x <= d[p][0.50]:
        return 2
    elif x <= d[p][0.75]:
        return 3
    else:
        return 4
#more freqynecy and monetory are better
def frequency_and_monetory_score(self,x,p,d):
    if x <= d[p][0.25]:
        return 4
    elif x <= d[p][0.50]:
        return 3
    elif x <= d[p][0.75]:
        return 2
    else:
        return 1
```

Figure 5.9: Code for calculating RFM score using Quantile Method

Define the method to assign the rating to the customers. Calculate the value of recency, frequency and monetary from existing dataset and saved into R, F, M data frame. RFM score is calculated by combining the value of each RFM column, total sum of RFM values. Rating between 1start to 5star is assign to customers on the basis of RFM score, rating labels and length of rating array passes as an arguments in **pd.qcut()** function.

5.5 FMRI Methodology

The primary goal of FMRI scans is to obtain information from MRI scanners about the dynamics of brain functions, which is performed by MRI scanners. The blood-oxygen-level-dependent (BOLD) signal, which is an indirect indicator of brain activity in FMRI is captured by the MRI machine.

By conducting a correlation analysis between the data and an idealized response profile, we may determine the region of the brain that was stimulated during the FMRI scan. During auditory stimulation, we observed activity in the auditory cortex. However, the map appeared a bit noisy, so we used the general linear model to enhance our findings.

We build the design metrix. The total number of volumes was acquired 96, each rest or stem was 6 volumes long. This means that there were 16 blocks recorded in total, 8 with stimulation and 8 at rest, always alternating. The time between each acquisitions was 7 seconds (that allows us to convert volume into seconds).

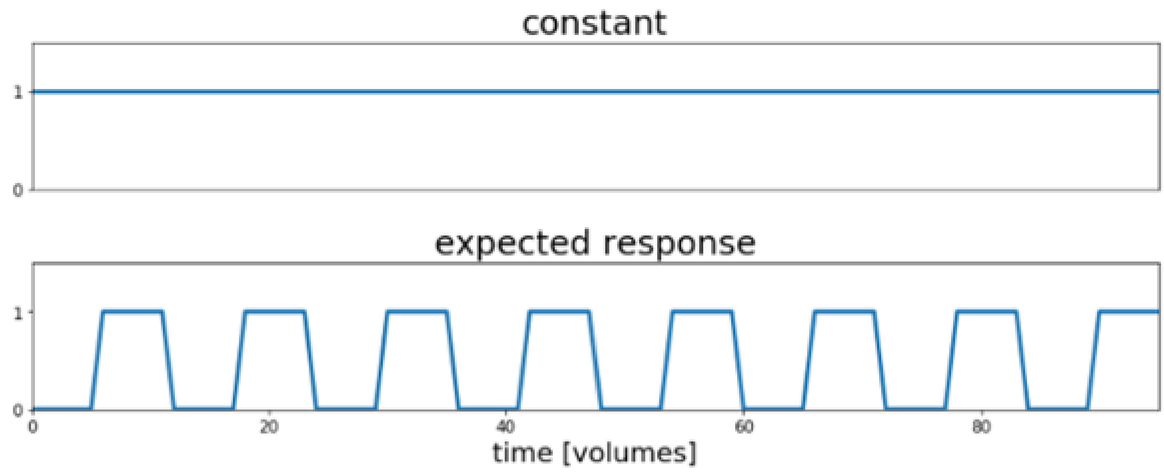

Figure 5.10: Bold signal expected reponse time

This is our design matrix look like, while there is no stimulation the bold signal is at base line level and during stimulation the signal increases. Neglect the constant part, only look at our expected response. Previously random voxel it does not seem like expected response.

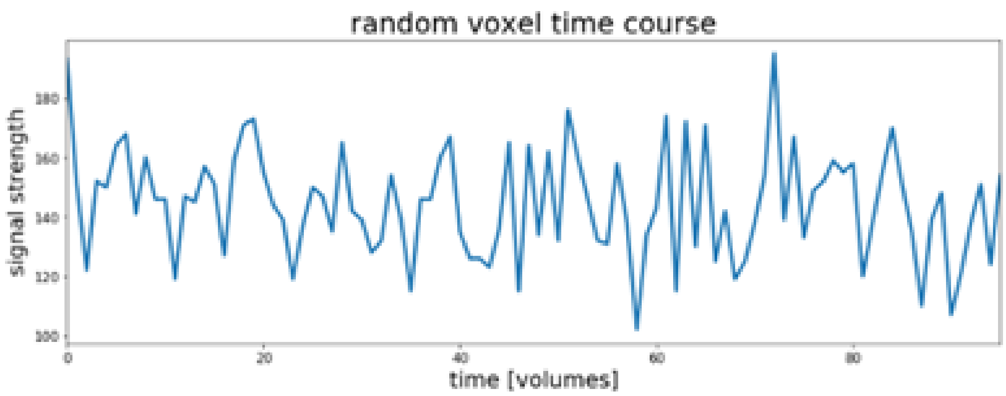

Figure 5.11: Voxel time course

Even this voxel 5.11 not giving proper information. So, we calculate the correlation between expected response and the time course of every voxel in the dataset.
For each slice, a data.csv file containing both the spatial and temporal dimensions is created. We will reshape each slice into a M*N matrix because .csv file only has two dimensions, and M = y-size * x-size and N = n volumes. We import the data file of one slice "Slice-36.csv". Reshape the data to 2 spatial and 1 temporal dimensions, calculate the correlation coefficients to identify the voxels with the highest correlation coefficients. To plot the voxel time course, we scale the signal to the range 0 to 1 min-max scaling 6.27.

$$scaledx = [(x) - min(x)]/[max(x) - min(x)] \tag{5.5.1}$$

The FMRI images were acquired by an imaging sequence called "Echo-planner Imaging" (EPI). We created 1st EPI image 6.28, reshape the correlation coefficients to match the dimensions of the EPI image and visualize the resulting correlation map. Finally, we select the threshold for the correlation map and overlay the thresholded map with first image in the scan to see were the regions with the highest correlation coefficients are actually located with respect to the brain anatomy.
Un-threshold maps the voxels with high correlations are not randomly distributed across the map. The region where they are located the auditory cortex which is involved in processing auditory information. However, the map still looks noisy, so to improve the noise level of maps, I applied general linear model (GLM).

General Linear Model

$$y_i = \sum \beta_j x_{ij} + \epsilon_i \tag{5.5.2}$$

This is the linear combination of bold signal, two regressors we define in our design matrix (constant and expected response).

i : is observation

j-th regressor (constant or expected response).

E is error term.

The bold signal **y** is the sum of the constant part * b0 and the expected part * b1, plus sum error term E.

$$y = Xb + e$$

Our voxel with 96 dimensions, and our design matrix is a matrix with dimension 96*2. X denotes our 96*2 design matrix and b the 2-dimensional weights vector.

$$e = y - Xb \tag{5.5.3}$$

$$e'e = (y - Xb)'(y - Xb) \tag{5.5.4}$$

In order to minimize the error to fit the GLM is the sum of the squared errors:

$$b = (X'X)^{-1}X'y \tag{5.5.5}$$

We can easily find the weights b through simple matrix multiplication. The parameter r is the correlation coefficient of our fitted model and the data, meaning that square of r is the percentage of variance explained by the model 6.29.

z-score has been calculated to improve the results by adding more regressor and modify design matrix shows in Figure 6.30 and 6.31 .

$$z = \frac{x - \mu}{\sigma} \tag{5.5.6}$$

x : sample of time course

$\mu : is mean of the signal$

$\sigma : Standard deviation$

Gaussian kernel used for spatial smoothing of EPI images. Basically, it blurs images by averaging the neighboring voxels with different weights. As you can see, we reduce the noise in our EPI images as compared to the other maps in Figure 6.32.

Chapter 6

Results and Discussions

6.1 EEG Results

Plot the confusion matrix using LSTM model predicted on the test dataset. Predicted labels on the x-axis and actual labels on the y-axis. The figure below shows the confusion matrix of LSTM model. Total test set was 427, as you see in the figure model predict 150 brain signals neutral emotion and 3 positives in the first row, In the second row 3 neutral, 129 positive and 10 negative emotions, and in the third-row model predicts 2 positive and 130 negative emotions respectively.

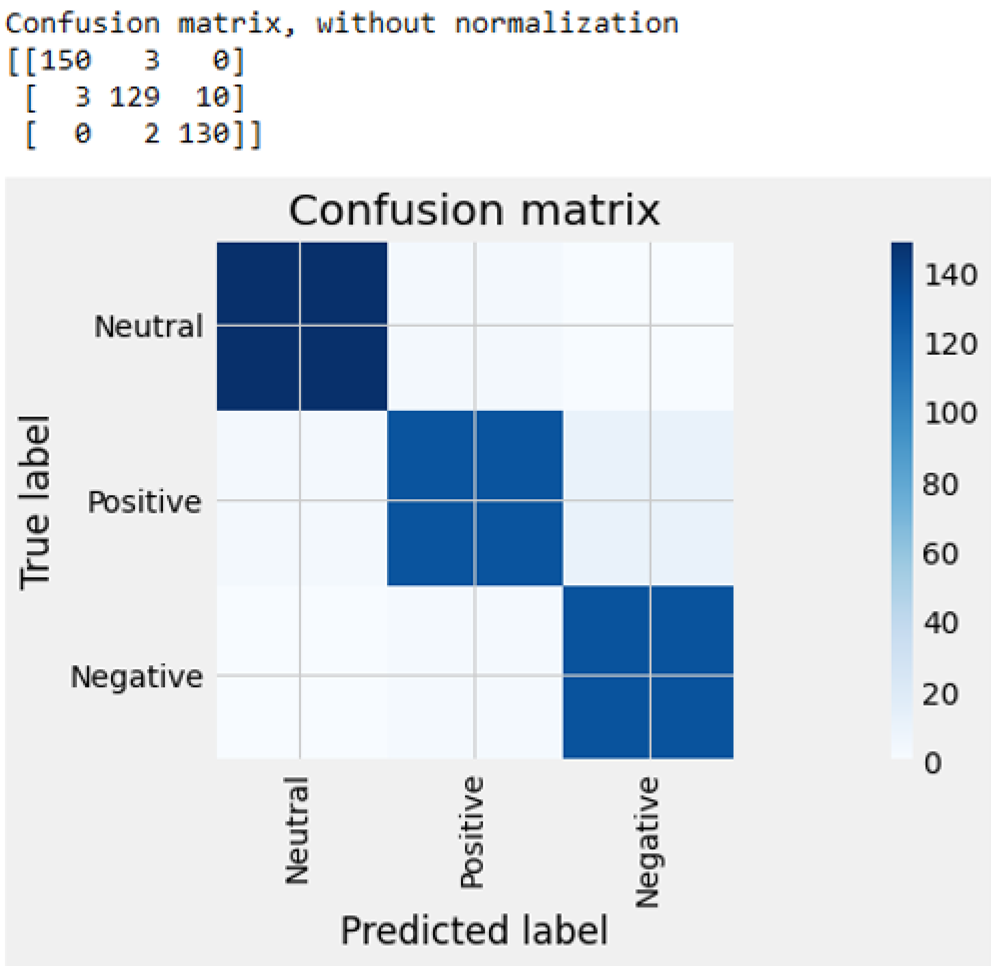

Figure 6.1: Confusion matrix of LSTM-Model

Train the LSTM classifier, evaluate the model and has plot of accuracy vs loss in Figure6.2. The training dataset results are represented by the blue line, and the testing dataset results are represented by orange line.

Figure 6.2: Accuracy-Loss plot of LSTM-Model

The Figure 6.3 below shows obtained classification report of LSTM model.

* Classification Report OF Brain Waves LSTM:

	precision	recall	f1-score	support
0	0.98	0.98	0.98	153
1	0.96	0.91	0.93	142
2	0.93	0.98	0.96	132
accuracy			0.96	427
macro avg	0.96	0.96	0.96	427
weighted avg	0.96	0.96	0.96	427

Figure 6.3: Classification report of LSTM-Model

The Figure 6.4 below shows the classification report and Figure 6.5 shows confusion matrix of GNB, SVM, Logistic Regression, Decison Tree and Random Forest.

Classification Report GNB:

	precision	recall	f1-score	support
0	0.65	0.97	0.78	153
1	0.46	0.30	0.36	142
2	0.81	0.66	0.73	132
accuracy			0.65	427
macro avg	0.64	0.64	0.62	427
weighted avg	0.64	0.65	0.62	427

Classification Report SVM:

	precision	recall	f1-score	support
0	0.95	0.99	0.97	153
1	0.98	0.89	0.94	142
2	0.94	0.99	0.97	132
accuracy			0.96	427
macro avg	0.96	0.96	0.96	427
weighted avg	0.96	0.96	0.96	427

Classification Report LR:

	precision	recall	f1-score	support
0	0.97	0.99	0.98	153
1	0.99	0.93	0.96	142
2	0.96	0.99	0.97	132
accuracy			0.97	427
macro avg	0.97	0.97	0.97	427
weighted avg	0.97	0.97	0.97	427

Classification Report Deccsion Tree:

	precision	recall	f1-score	support
0	0.99	0.98	0.98	153
1	0.94	0.93	0.93	142
2	0.93	0.95	0.94	132
accuracy			0.95	427
macro avg	0.95	0.95	0.95	427
weighted avg	0.95	0.95	0.95	427

Classification Report Random Forest:

	precision	recall	f1-score	support
0	0.99	0.98	0.98	153
1	0.94	0.93	0.93	142
2	0.93	0.95	0.94	132
accuracy			0.95	427
macro avg	0.95	0.95	0.95	427
weighted avg	0.95	0.95	0.95	427

Figure 6.4: Classification report of all machine learning models

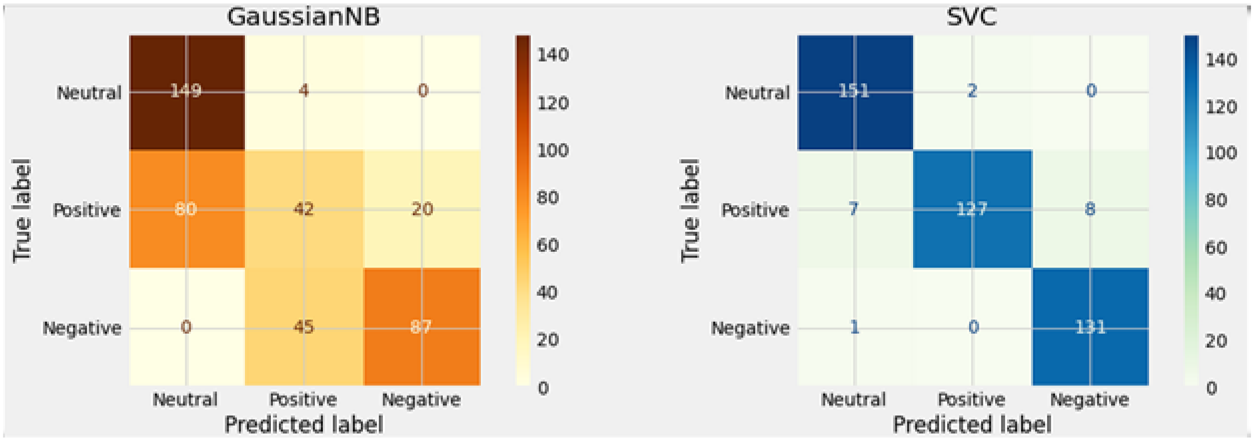

Figure 6.5: Confusion Matrix of GuassianNB and SVM machine learning models

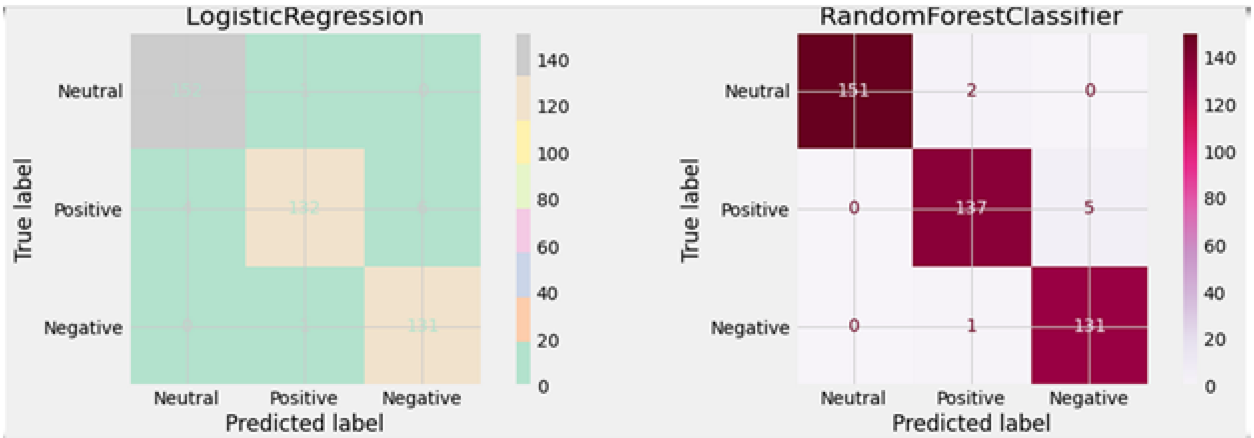

Figure 6.6: Confusion Matrix of LogisticRegression and RandomForest machine learning models

6.2 Eye Motion Tracking Results

The Figure 6.7 below is an output of my gaze detection. I used live webcam of my laptop to test my model. As you can see in the figure, I was looking at right side so model predicts and shows the text on the screen 'Right', and then to test eye blinking, I closed my eyes model showed test 'Eye Blinking'.

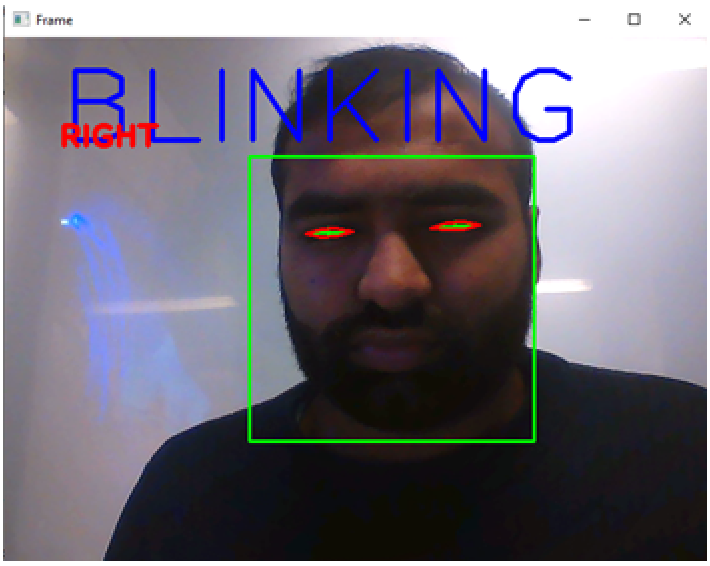

Figure 6.7: Output of eye gaze detextion

I build an application that can control the mouse cursor on computer screen through eye. The output is shown below n the Figure 6.8 and 6.9. Open the paint document and draw lines by controlling cursor on screen through eyes.

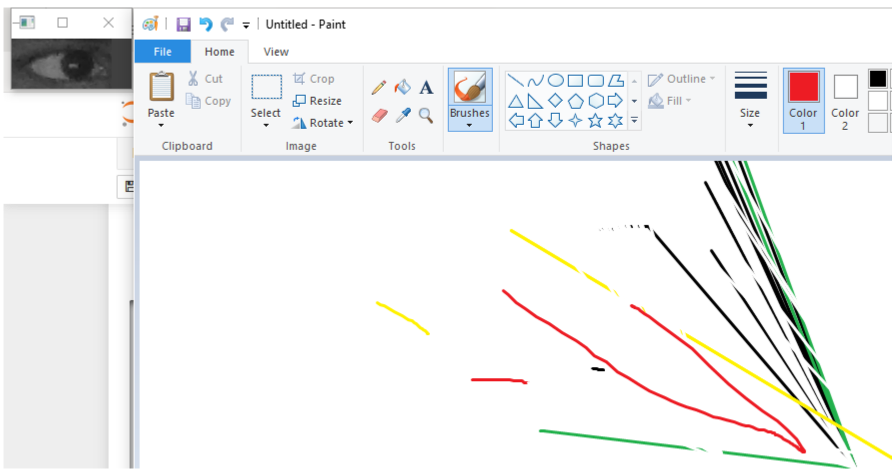

Figure 6.8: Controlling Cursor on screen by Eyes

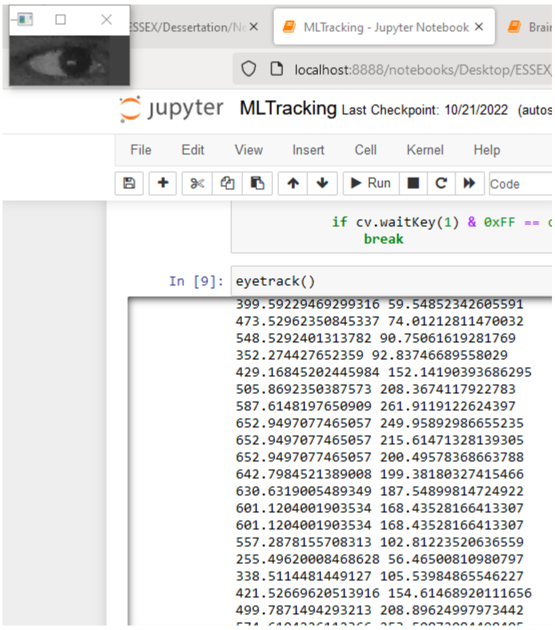

Figure 6.9: Controlling Cursor by Eyes

6.3 Facial Coding Results

Classifying Human Expressions Using Facial Images

After training the CNN model over 48 epochs, I evaluate the model on test dataset. Overall accuracy of the model was 70%. The Figure 6.10 below shows the plot of accuracy vs loss of Facial emotion recognition. The blue line represents the results achieved on training data set and orange line represents the results achieved on testing data set. I used live webcam to predict the results with OpenCV library. The application classifies the specified emotions on different human expression images[15].

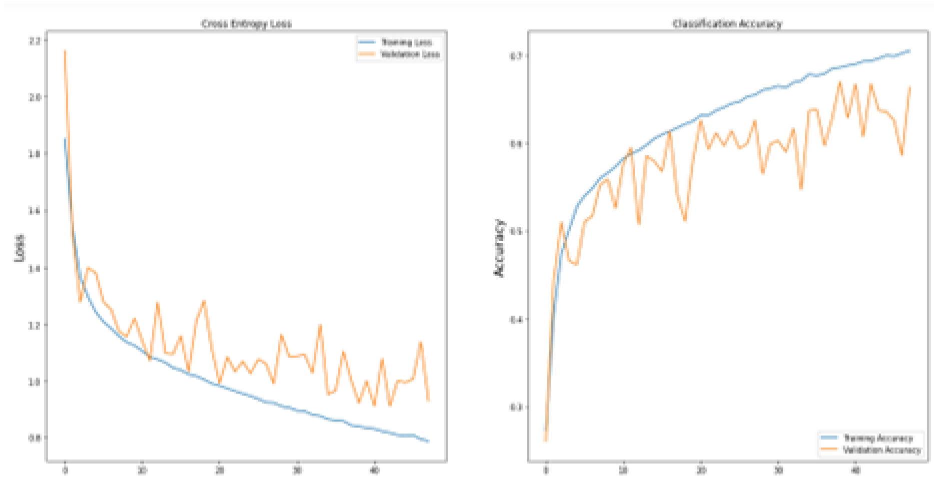

Figure 6.10: Facial Recognition Accuracy vs Loss Plot [15]

The Figure 6.11 below shows the results achieved through Facial Emotion Recognition model:

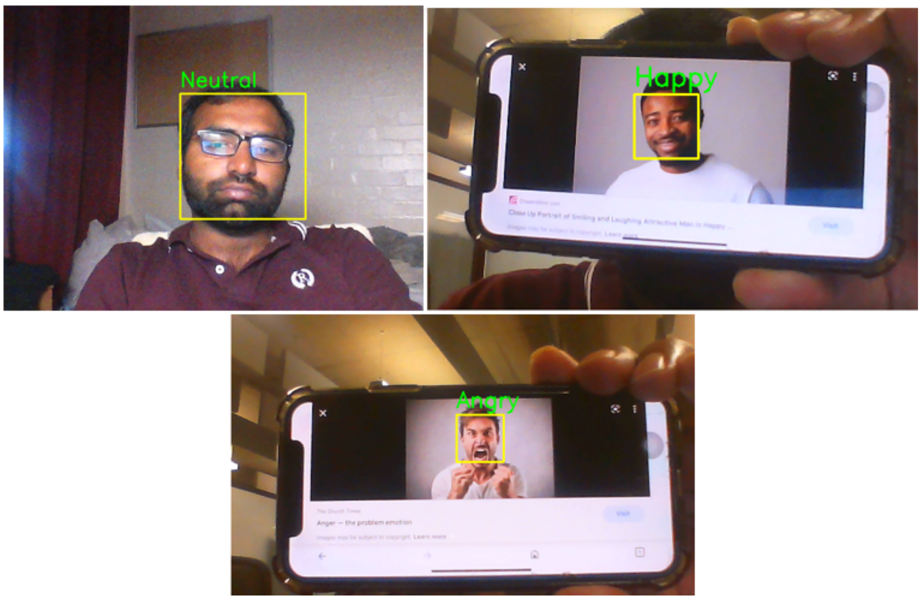

Figure 6.11: Facial Emotion Recognition Output [15]

Classifying Human Expressions Using Eyes Images dataset

I trained the data set on pretrained CNN model InceptionV3 and Xception, extract the features. Below fig shows the model loss vs accuracy plot after training. I got 72% accuracy, which is quite impressive. Now weights are trained and updated, I can use updated weights file for predicting the results. In Figure 6.12 below shows model accuracy vs loss plot:

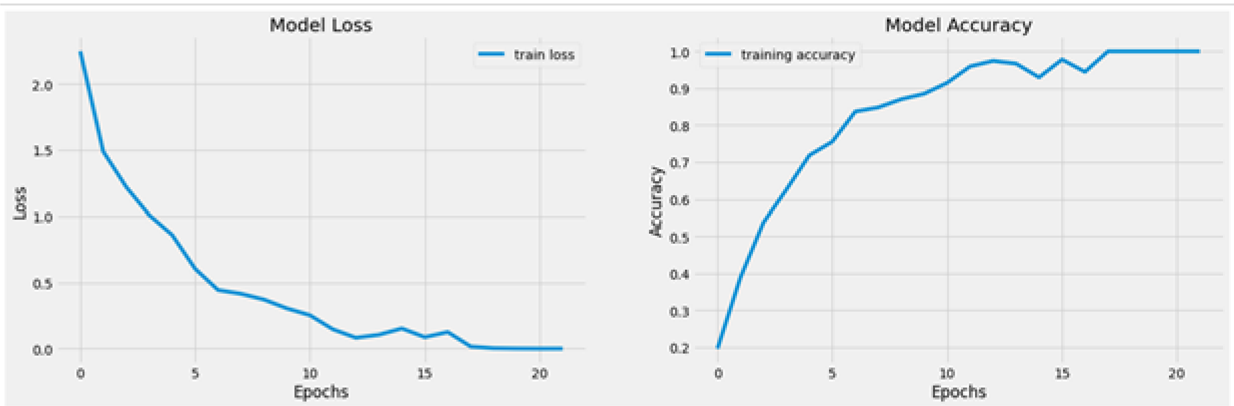

Figure 6.12: Model Accuracy vs Loss Plot

I build another Jupiter file that allows live webcam using OpenCV library takes as an input image and then classify the emotions based on eyes expressions. The camera of my laptop was not good, so did not getting proper results due to bad image quality. I downloaded good quality eyes emotion random image from internet, fed into the model and the predict the results as shown below.

Figure 6.13: Model Classified into Human Expressions

Input the image of human face into model to classify into emotions classification, first of fall model detect the face landmarks, and then cropped to its region of interest (ROI), as you can see third image is the copped image of desired region which we fed into the trained CNN model to predict the results. Our model predicts the Fear emotion according to these eyesâ expressions.

Figure 6.14: Input Image into the Model

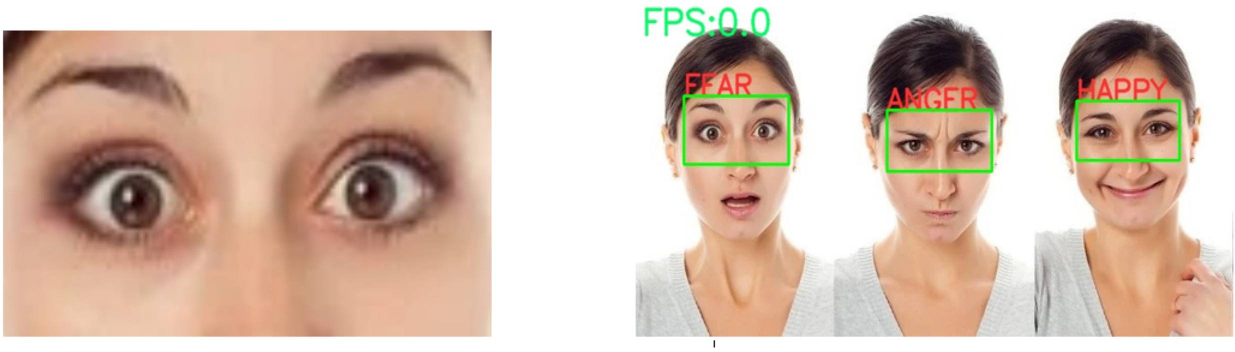

Figure 6.15: Output Image Obtained after Classification

6.4 RFM Results

Apply the RFM class method to calculate the rating of the customers. The Figure 6.16 below shows the column **rfm-rate-customers**, calculated through RFM score. Rating is assigned to each customer, based on their RFM score.

```
data1
```

	index	CustomerID	Recency	Frequency	Monetary	R	F	M	score	rfm_rate_customers
0	0	12346.0	325	1	77183.60	4	4	1	9	3stars
1	1	12747.0	2	103	4196.01	1	1	1	3	5stars
2	2	12748.0	0	4596	33719.73	1	1	1	3	5stars
3	3	12749.0	3	199	4090.88	1	1	1	3	5stars
4	4	12820.0	3	59	942.34	1	2	2	5	5stars
...	...	...	...	...	...	...	...	...	...	...
3916	3916	18280.0	277	10	180.60	4	4	4	12	1star
3917	3917	18281.0	180	7	80.82	4	4	4	12	1star
3918	3918	18282.0	7	12	178.05	1	4	4	9	3stars
3919	3919	18283.0	3	756	2094.88	1	1	1	3	5stars
3920	3920	18287.0	42	70	1837.28	2	2	1	5	5stars

3921 rows × 10 columns

Figure 6.16: Rating assigned to each Customer based on RFM score

To represent the RFM analysis results, I plot different charts. For instance, Customers Rating wise chart, pie chart is draw of rating between 1star to 5start. You can differentiate ratings with easily and percentage is clearly representing each segment of rating in Figure 6.17.

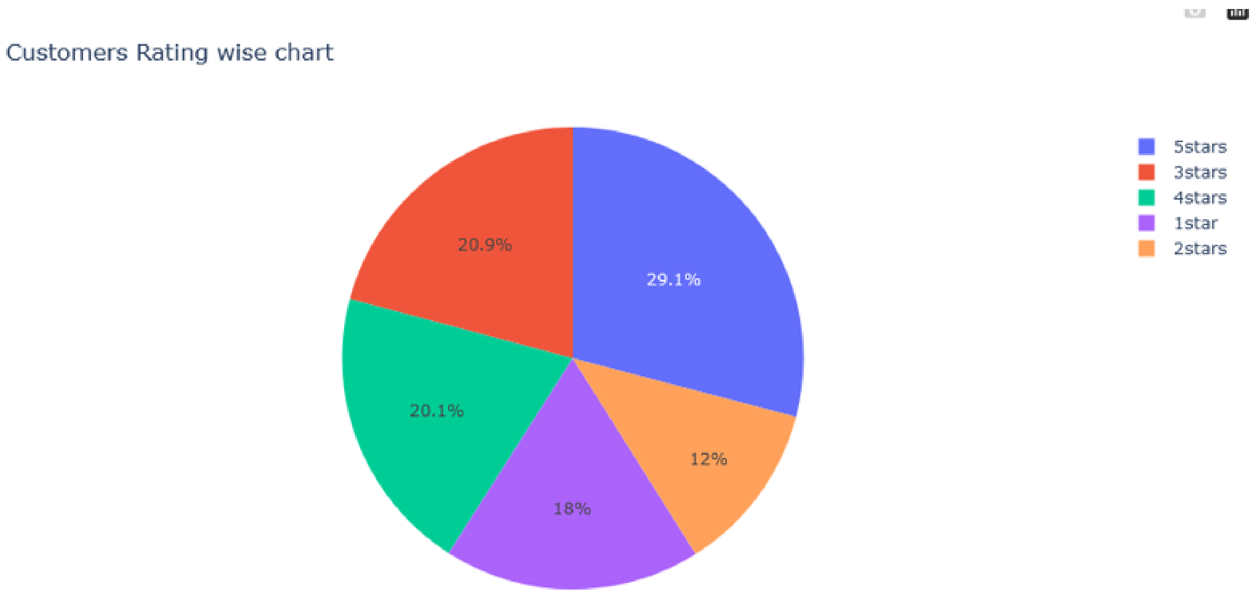

Figure 6.17: Cutomers Rating Wise Chart

The below code used to plot Frequency, Monetary and Recency charts based on their ratings.

21]:

```
df_local =  data1.groupby('rfm_rate_customers').agg({"Frequency" : "sum"}).reset_index()
fig = px.pie(df_local , values='Frequency', names="rfm_rate_customers", title='Customers Ratings Frequency wise segmentatior
fig.show()

df_local =  data1.groupby('rfm_rate_customers').agg({"Monetary" : "sum"}).reset_index()
fig = px.pie(df_local , values='Monetary', names="rfm_rate_customers", title='Customers  Ratings Monetary wise segmentation'
fig.show()

df_local =  data1.groupby('rfm_rate_customers').agg({"Recency" : "sum"}).reset_index()
fig = px.pie(df_local , values='Recency', names="rfm_rate_customers", title='Customers Ratings Recency wise segmentation')
fig.show()
```

Figure 6.18: Plotting RFM Data on Charts Code

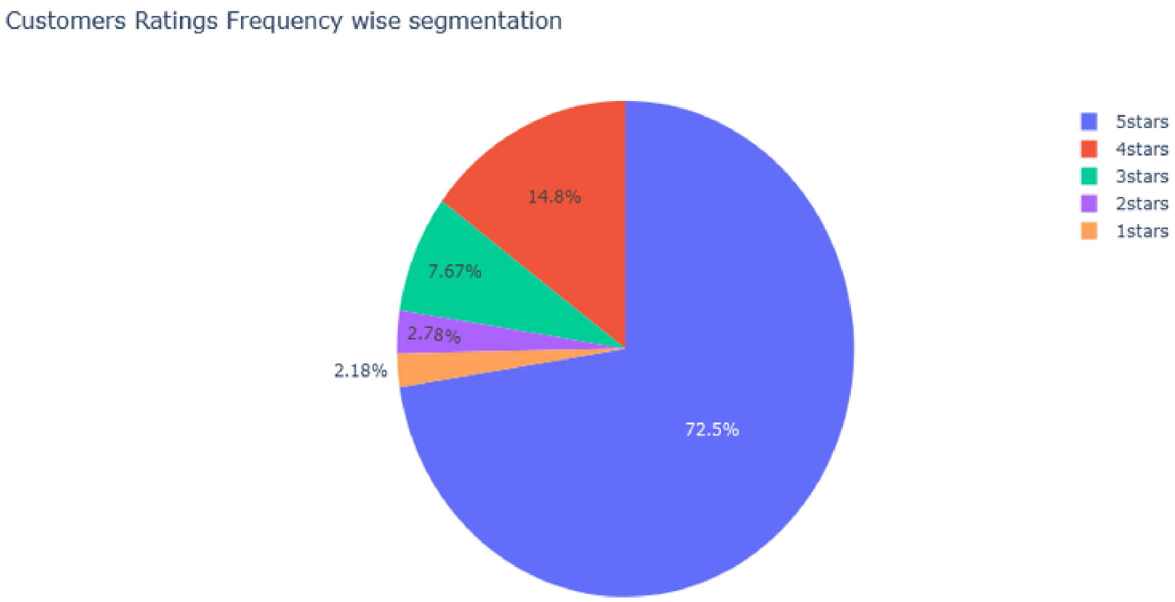

Figure 6.19: Cutomers Ratings Frequency Wise Segmentation

Grouping customer ID's and plot it into frequency wise segmentation. In the below pie chart shows top 15 frequent customers. The most frequently who visited to for shopping his ID is 12748, and he visited 4596 times to the shopping center.

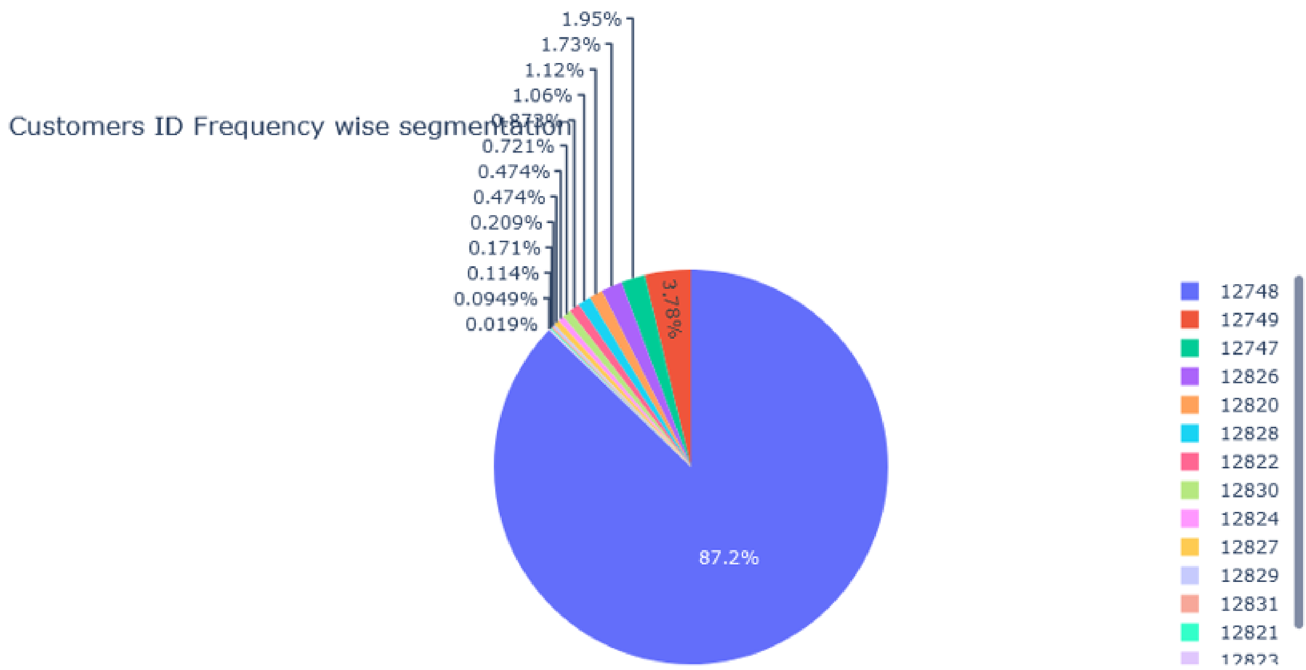

Figure 6.20: Customers ID Frequency Wise Segment

This is the code to plot the density graph, we plot it to show the distribution of recency, frequency, and Monetary dataset.

```
plt.style.use('dark_background')
# plt.style.use('fivethirtyeight')
f,ax = plt.subplots(figsize=(20, 12))
plt.subplot(3, 1, 1); sns.distplot(data1.Recency, label = 'Recency')
plt.subplot(3, 1, 2); sns.distplot(data1.Frequency, label = 'Frequency')
plt.subplot(3, 1, 3); sns.distplot(data1.Monetary, label = 'Monetary')

plt.tight_layout()
plt.show()
```

Figure 6.21: Code For To Plot Density Graph

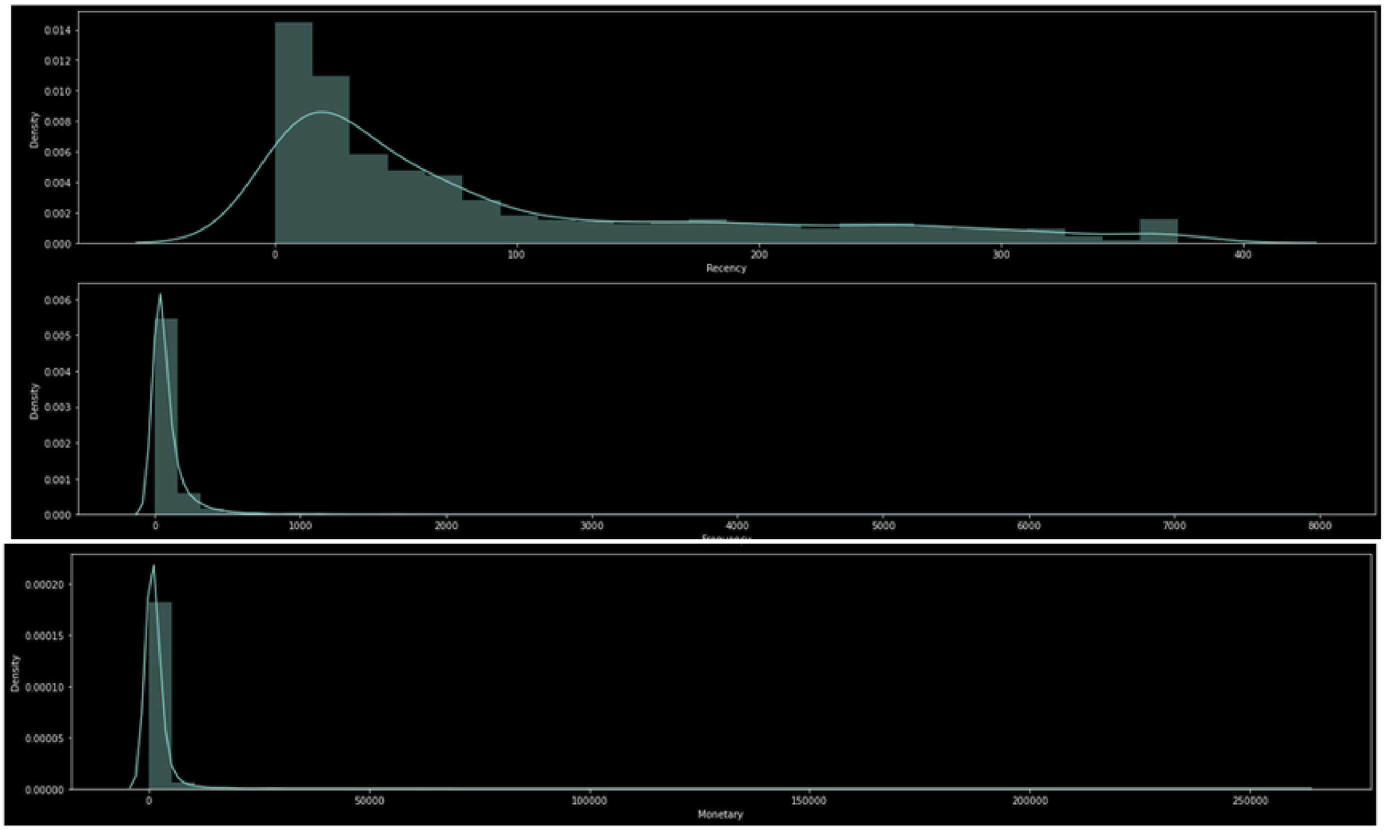

Figure 6.22: Distribution of RFM Data on Density Plot

I also applied k means cluster model on the dataset. Number of clusters used 5, clusters are representing labels. Create recency, frequency, and monetary scatter plots with relationship to each other with clusters.

```
kmeans= Kmeans(data1)
data1 = kmeans.apply_kmeans()
data1.head()
```

	index	CustomerID	Recency	Frequency	Monetary	R	F	M	score	segment	rfm_rate_customers	Clusters
0	0	12346.0	325	1	77183.60	4	4	1	9	9	3stars	4
1	1	12747.0	2	103	4196.01	1	1	1	3	3	5stars	1
2	2	12748.0	0	4596	33719.73	1	1	1	3	3	5stars	1
3	3	12749.0	3	199	4090.88	1	1	1	3	3	5stars	1
4	4	12820.0	3	59	942.34	1	2	2	5	5	5stars	1

Figure 6.23: Kmeans Model Outcomes

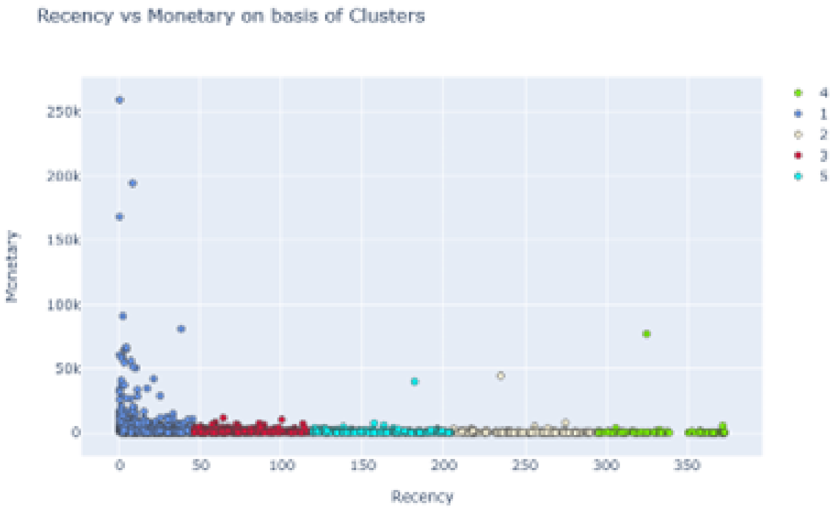

Figure 6.24: Recency Vs Monetary clusters segementation based on RFM Customers Rating

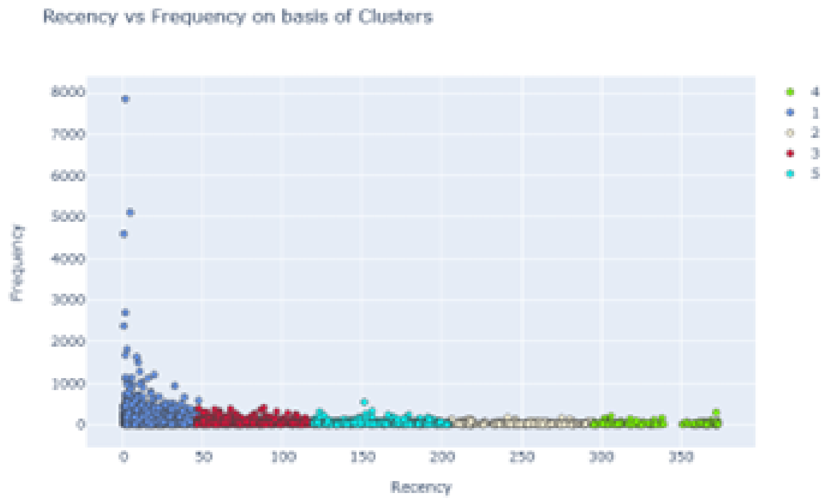

Figure 6.25: Recency Vs Frequency clusters segementation based on RFM Customers Rating

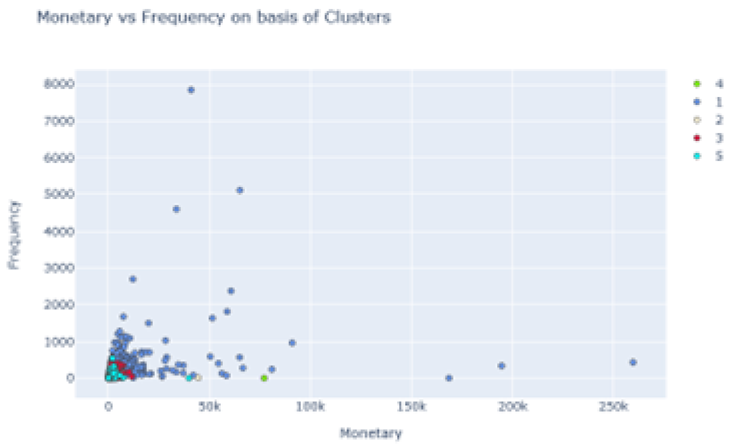

Figure 6.26: Monetary Vs Frequency clusters segementation based on RFM Customers Rating

6.5 FMRI Results

This response is quite better than previous random voxel. So, we can easily see where this voxel and others with high correlation coefficients are located.

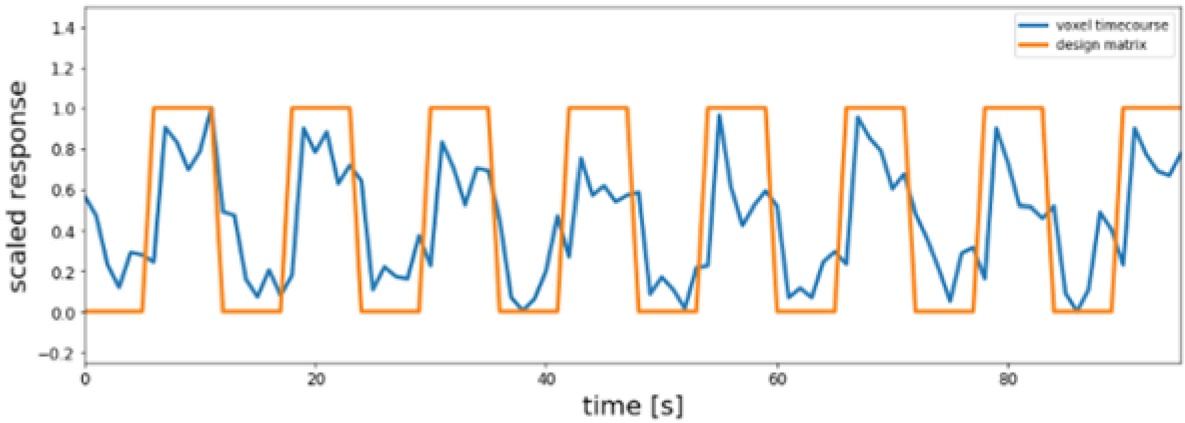

Figure 6.27: Correlation time course and design matrix

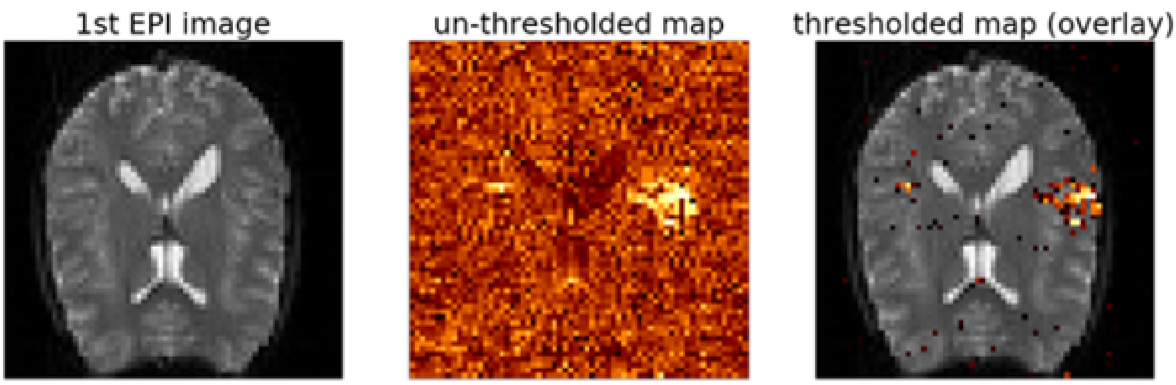

Figure 6.28: First Correlation map EPI Image

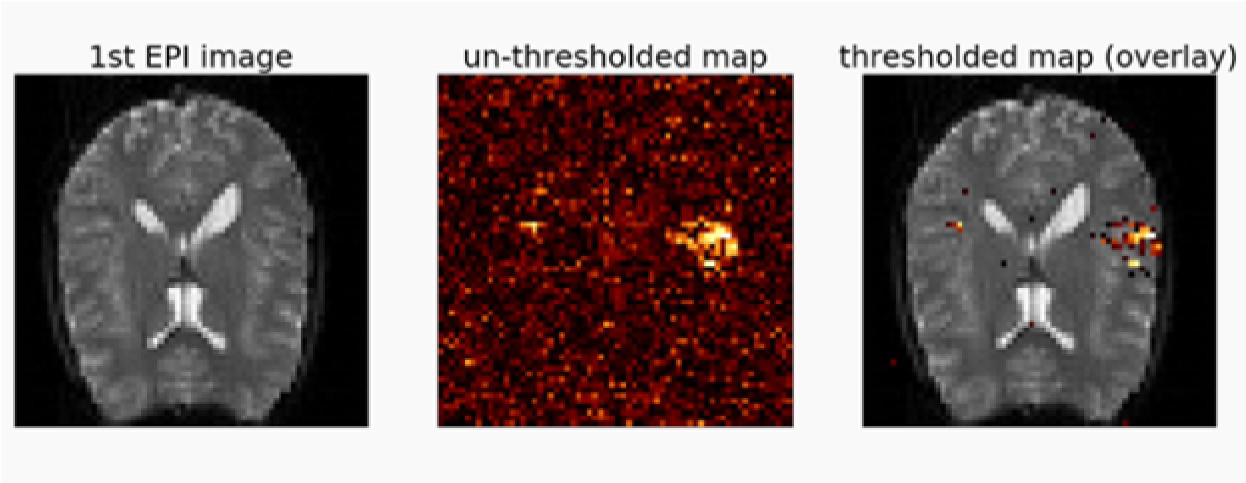

Figure 6.29: General Linear Model has applied, EPI Image

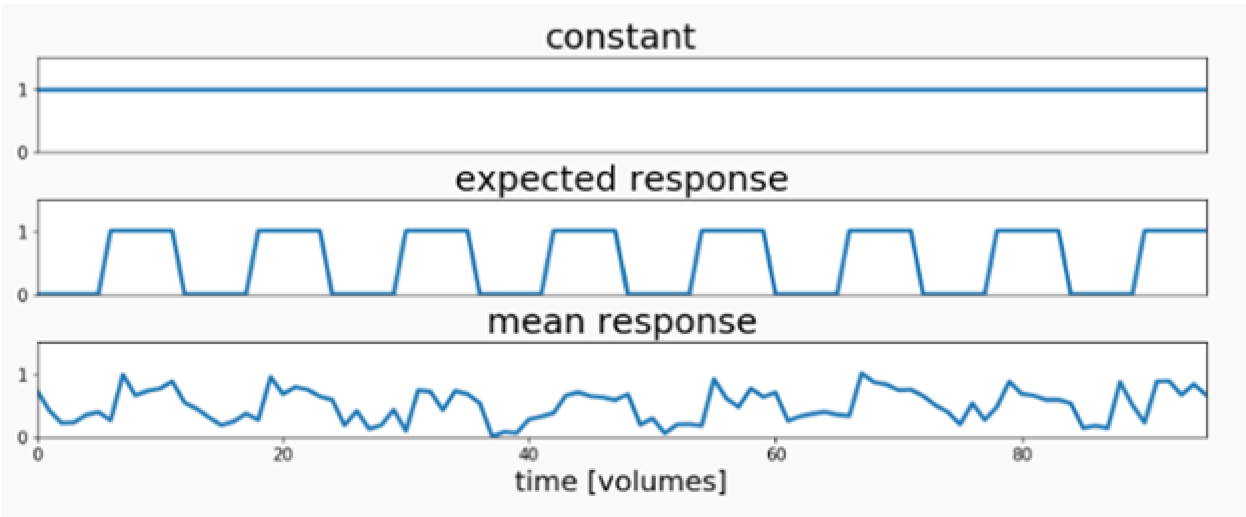

Figure 6.30: Modified design matrix

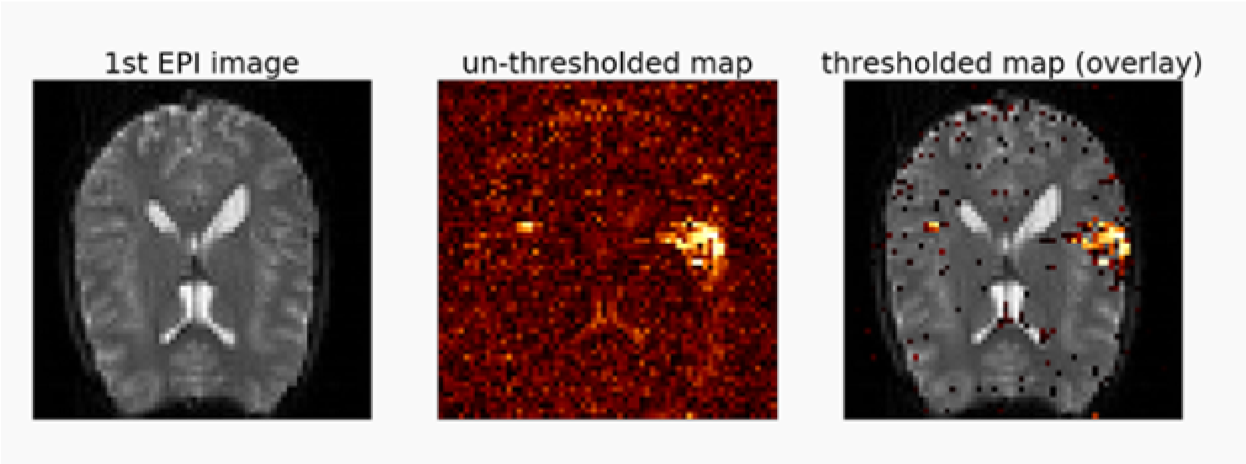

Figure 6.31: Modified EPI Image

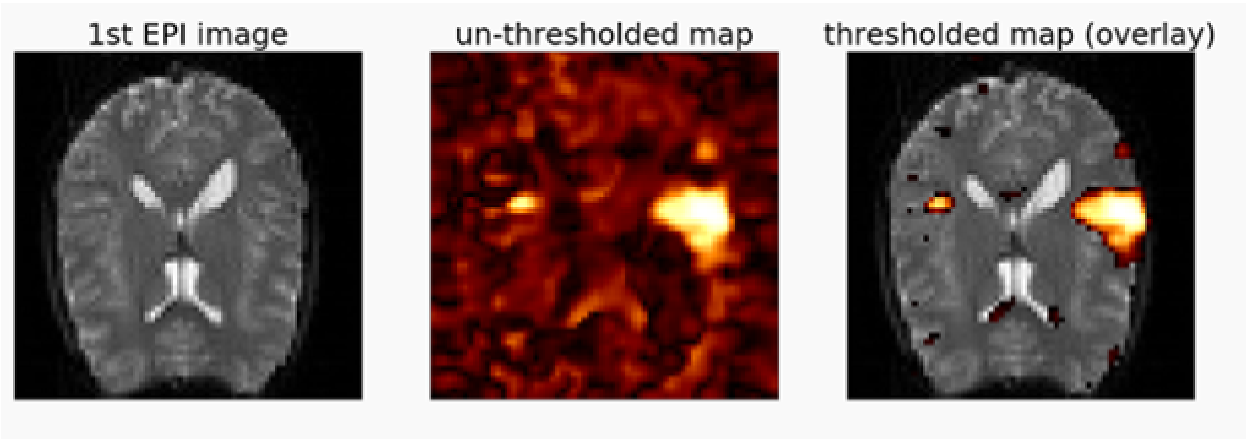

Figure 6.32: Gaussian Kernel Applied on EPI Image

CHAPTER 7

Conclusions

In conclusion, the primary objective to perform an analysis on neuromarketing tools and methods. This study proposed how data from EEG signals and eye tracking devices can be used to better understand the consumer's behavior. Also used the FMRI technique to scan the brain's image and classified customer behavior based on their RFM score. Mainly it is finding out about the consumer behavior, tracking their eye movements, recognizing emotions and how does they feel about the product, taking feedbacks and improve the product quality. In experiment it proves that when customer make purchase decisions will (buy or not buy), specific ROI of brain stimuli signals, so we use BCI headset to record EEG signals. Eye tracking devices used to record or design path of the customer eye movement and then extract the valuable information from it for analyses. FMRI scans used to get the scan of specified brain region which was activated while customer make purchase decisions. In **EEG analysis**, while individuals watched emotional film clips, we created an emotion experiment and recorded their emotional response EEG signals (positive, negative, and neutral). Here, dataset has been processed, extract the feature, and predict the emotional state of the subject. The training dataset is applied on LSTM-model with GRU layer. Accuracy of the model achieved 96%. To evaluate the model, we plot confusion matrix and generate classification reports using testing dataset.

I build an **eye motion tracking** application to find out that what customers are looking for extract the useful information for future analysis for making strategies and decision making. There are two functionalities in application. First one is gaze and eye blinking detection in which we calculate eye gaze ratio to detect direction of eye movement for instance, he/she is looking at âRight, Left, and Centerâ. For eye blinking, we calculate the eye blinking ratio. So, when we close our eyes, the system will detect and show the person is blinking his eyes. In the other part, we can control mouse cursor on laptop screen using our eyes. We take the dataset of eye images available of Kaggle, perform data preprocessing, feature extraction. Training dataset fed into the CNN model. Accuracy of the model achieved 87%. This system works like it creates the path of consumer eye movements from which analyst extract the useful information which is beneficial for their business processes. We used **eye emotion dataset** DIU available on Kaggle. Build an application that can take human eyes as an input, with the help of trained CNN model will classify the image into human expressions. Data preprocessing was done, one hot encoding was applied on labels. InceptionV3 and Xception pretrained CNN model was used for feature extraction. CNN model was built, and train dataset was fed into model. Accuracy of the model achieved 72%. I build another Jupiter file that allows to use live webcam of your laptop using OpenCV library, it takes human face as an input image, crop the image to region of interest and classify the human expressions.

Functional magnetic resonance imaging is one of the neuroimaging tools. This technology also used for assessing consumer behavior. The main objective to get FMRI scans, so we can get reports of specified ROI of brain that are involved and activated, while when consumer make purchase decisions (buy or not buy). So, I used structural and functional dataset available on SPM website. Visualize the brain scan in 3-d dimensions, divide it into slices. We created the EPI image. Calculate the correlation coefficients and find out the region with highest correlations. Results were bit noisy, so to improve the results I applied general linear model and get the smooth EPI images.

In **RFM analysis** mainly focused consumer behavior through their RFM values. We categorized the customers by extracting the information for instance, number of customers are coming in the store, how much frequent they are. How much total they are spending on shopping and finding the date of last invoice. Using this information, we calculate the RFM score, assign the ratings between 1star to 5star to the customers. The main advantage of RFM analysis to organizations in making strategies and companyâs future decisions. When we categorize each customer, then it will be easy that what approach is required in terms of campaign to achieve milestones. I used the dataset of online retail store based in UK. Used the quantile method, split into four segments and assign the rating labels to customer by finding R, F, M score separately using **pd.qcut()** function. And applied k-means algorithm, 5 clusters were made to categorized customers based on their assigned ratings.

This research is mainly on four different topics. I worked on image processing and big data to analyze the consumer behavior. In image processing I trained my dataset on Convolutional neural networks, although I got quite impressive results but for future task, we can enhance model accuracy by expand our data set with a greater number of real images, applying image augmentation technique, extracting features on pretrained CNN model or use VGG16 model technique for classification problems.

APPENDIX A

Code Links

EEG Code

https://github.com/abdullahayub/EEG-Analysis.git

Eye Emotion Recognition

https://github.com/abdullahayub/Eye-Emotion-Recognition.git

Eye Emotion Tracking

https://github.com/abdullahayub/Eye-Motion-Tracking.git

FMRI Code

https://github.com/abdullahayub/FMRI-Analysis.git

RFM Analysis Code

https://github.com/abdullahayub/RFM-Analysis.git

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