Machine Learning-based Approach on Predicting Online Shopping Addiction using EEG Signals

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A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science and Engineering

Department of Computer Science and Engineering
BRAC University
May 2022

Declaration

It is hereby declared that

1. The thesis presented is our own original work while pursuing bachelors degree at BRAC University.
2. Except as properly referenced through thorough and correct referencing, the thesis does not contain information already published or produced by a third party.
3. The thesis does not contain any material that has been approved or submitted for any other university or other institution's degree or certificate.
4. We have acknowledged all main sources of help.

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Ethics Statement

We, hereby, declare that this thesis has been found based on our study findings. In the document, all additional sources of information have been mentioned. The following thesis has never been submitted to any other university or institute for the purpose of obtaining a degree, in whole or in part.

Abstract

According to experts, shopping addiction is often a coping mechanism for those who are experiencing mental pain. As a result, to research online shopping addiction, researchers must look at changes in brain activity during emotional processing. For decades, electroencephalography (EEG) one among the most popular technologies for detecting psychological states by measuring various brain activity. Following this line of thought, we suggest a dual-track approach for predicting behavioral addiction in this research. We have at first collected EEG dataset and treat it by eliminating noise and encoding it. Furthermore, in order to achieve the highest degree of accuracy, we have proposed a six classification framework utilizing six distinct machine learning algorithms. The suggested model includes Multi-Layer Perceptron Classifier (MLP), Stochastic Gradient Descent (SGD), Support Vector Machine (SVM), Random Forest Classifier (RFC), Decision Tree (DTC) and Gated Recurrent Unit (GRU). The accuracy levels of those models have determined our ultimate conclusion and we have achieved the best performance based on accuracy of Multi-Layer Perceptron in our research that is 78% on Alpha bands, 82% on Beta bands and 85% on Gamma bands. In the end, we have suggested the severity of both Beta and Gamma bands in predicting Online Shopping Addiction precisely based on the cross-research analysis since the test accuracies of Beta (SVM-68%, MLP-82%, RFC-70%, SGD-61%, DT-59%, GRU-62.85%) and Gamma (SVM-81%, MLP-85%, RFC-77%, SGD-75%, DT-61%, GRU-76.91%) bands have been higher that that of Alpha bands (SVM-66%, MLP-78%, RFC-68%, SGD-61%, DT-57.99%, GRU-61.81%) in every classification model.

Keywords: Shopping Addiction; Machine Learning; Electroencephalography; Support Vector Machine; Gated Recurrent Unit; Decision tree; Random Forest

Dedication

We dedicate our dissertation to our beloved families, respected faculties and friends. A special gratitude to our loving parents whose words of support and motivation were significant.

This dissertation is also dedicated to our friends who have supported us throughout the process. We shall always be grateful for what they have done.

Acknowledgement

Foremost, we give thanks to Almighty Allah for allowing us to finish our thesis without any major interruption.

Without the expertise of Dr. Amitabha Chakrabarty, our esteemed thesis supervisor, we would not have been able to complete this work. We would like to express our sincere gratitude for his patience, motivation, enthusiasm and immense knowledge.

Moreover, a debt of gratitude is owed to Dewan Ziaul Karim sir, our co-supervisor, for his invaluable assistance and suggestions.

Finally, without our parents' unwavering support, it may not be conceivable. We are currently on the verge of graduating for which we are thankful to their kind support and prayer.

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Nomenclature

The following list contains several symbols & abbreviations that will be used later in the document

BSAS Bergen Shopping Addiction Scale

DT Decision Tree

DWT Discrete Wavelet Transformation

EEG Electroencephalogram

FFT Fast Fourier Transformation

GRU Gated Recurrent Units

MLP Multilayer Perceptron

OSA Online Shopping Addiction

RF Random Forest

SGD Stochastic Gradient Descent

SVM Support Vector Machine

Chapter 1

Introduction

In recent years, as retailers have shifted their focus to online sales, widespread consumerism has grown. Merchants are rapidly migrating away from brick-and-mortar stores and toward online purchases as global internet usage develops. In addition, the recent COVID-19 epidemic has undoubtedly contributed to the rapid expansion of e-commerce business by delivering safer and fast purchasing than traditional retail. Thus, "one-click purchase" makes shopping addiction more likely. As a result, consumer behavior experts have seen substantial changes in buying behaviors, which includes a greater proclivity for online shopping in terms of frequency and value. The following addiction is characterized by an insatiable need to shop and buy things, which has severe social, economical and personal consequences. Like other addictive behaviors, the fundamental purpose of this type of addiction is to exhibit the ability to withstand unpleasant emotions like sadness and concern.

According to research, the major cause of internet shopping addiction is connected to one's psychology. Since the birth of civilization, emotion has always played a crucial role in people's reactions to diverse activities. Because brain functioning regulates emotions, it's vital to look into the inner workings of the human brain while looking at something directly related to emotions. Again, when consumers engage in consuming activity, personality traits have a clear and decisive impact on their psychological characteristics because personality traits have a deep impact on an individual's psychological characteristics. Regardless of the cause, OSA may have a substantial influence on a person's daily and social life, as well as their financial circumstances. Online buyers with high neurotic scores are said to be emotionally unstable, impulsive, and prone to impulsive purchasing [46]. As a reason, it's vital to identify OSA early and treat it properly. Therefore, an accurate and valid OSA prediction is needed which offer the impetus for the following thesis: the ability to predict Online Shopping Addiction in early stages.

1.1 Problem Statement

In the rapid development of online business, consumer choice activities identification from visual data is one of the most crucial study fields. Excessive shopping addiction is one of the problematic behaviours in terms of shopping online. Because it is easier to purchase things through e-payment without even realizing the addiction. Due to the worldwide epidemic, the ability to buy and sell items or services online without forcing clients to visit in person is at an all-time high. In 2019, global e-commerce sales increased to $26.7 trillion, and the lockdown caused by the spread of Covid-19 is driving it even higher. People are becoming shopaholics as a result of the sales and advertising of this already popular e-commerce, even while staying at home and keeping social distance. This online buying addiction is becoming difficult to categorize as required purchasing. If someone is addicted to online shopping, the typical technique of classification is simple ”yes” or ”no” surveys which may demonstrate inaccuracy. As a result, the question ”Is there any appropriate way of classifying Online Shopping Addiction?” may emerge. Our proposed study will use EEG signals and Machine Learning-based Classification Algorithms to solve the aforementioned issue.

1.2 Aims and Objectives

The goal of our study is to construct an EEG-based model that can identify online shopping addiction. After obtaining EEG recordings of brain waves, the purpose is to evaluate the data using different machine learning and deep learning classifiers to figure out which frequency bands (Alpha, Beta, Gamma, Delta and Theta) are more efficient for detecting Shopping Addiction. This study seeks to offer a quick overview of which EEG channels are more useful, as well as which brain areas (frontal, parietal, temporal, and occipital) might be used to detect addictive behavior in online purchases.

1.3 Thesis Outline

The purpose of this paper is to develop a prediction model that examines the differences in brain signals in order to detect Online Shopping Addiction using pre-recorded EEG signals. The results of the experiment have been examined in the report highlighting the significance and relevance of the findings and assesses the strengths and weaknesses of the proposed model. In this regard, the document is divided into five chapters.

Chapter 1 - The introduction of our study report is included in this chapter. It gives an outline of Online Shopping Addiction and how it relates to brain signals. It also emphasizes the significance of evaluating OSA.

Chapter 2 - The next chapter offers a summary of previous studies on consumer behavior and brain signal alterations due to addiction.

Chapter 3 - The architecture of our suggested model is briefly described in the next chapter, which also demonstrates the models we used to achieve the needed accuracy.

Chapter 4 - The dataset that we used may be found here. We pre-processed the raw dataset described before in this chapter for better accuracy.

Chapter 5 - The implementation and gained output of the proposed model for Online Shopping Addiction Prediction has been analyzed here.

Chapter 2

Related Work

The following section gives an overview of prior research papers on the identification of online shopping addiction. The use of GRU, LSTM and other deep learning algorithms have been used by researchers to defend their claim. Here, we examine some of the significant methodologies that have been used in the past to extract human emotions from an EEG dataset and changes in brain signals as a result of addiction. Foremost, we will start by examining the interpretation of consumer decision making process with the help of EEG.

2.1 OSA and its proposed predictors

We have studied previous researches based on Online Shopping Addiction Interpretation which was constructed by developing a conceptual model of the addiction [10]. The study used an experimental methodology that includes watching online customers execute different purchasing actions such as searching, adding things to their shopping carts, and paying for their purchases. Data was collected both during and after the buying experience, revealing major differences between obsessive and non-compulsive shoppers. The author emphasized the points by pointing out particular aspects of the online retail medium that may promote OSA. The proposed model has been incorporated in figure 2.1. Again a study compares multiple models for detecting online shopping addiction and finds that the MLP model has an accuracy of 90.9% [48]. Furthermore, the mediating and buffering effects of online-shopping addiction on academic procrastination and negative emotions were investigated in a study conducted by Capital Normal University in Beijing, China, which found that online-shopping addiction has a strong positive predictive influence on negative emotions [44]. Another similar study, using the Bergen Shopping Addiction Scale, discovered a favorable connection between compulsive buying behavior and online shopping addiction [29].

2.2 Consumer Decision-Making Interpretation

The two major aims with the new finding of consumer decision-making interpretation [28] were to use EEG to project customer preference and to understand the

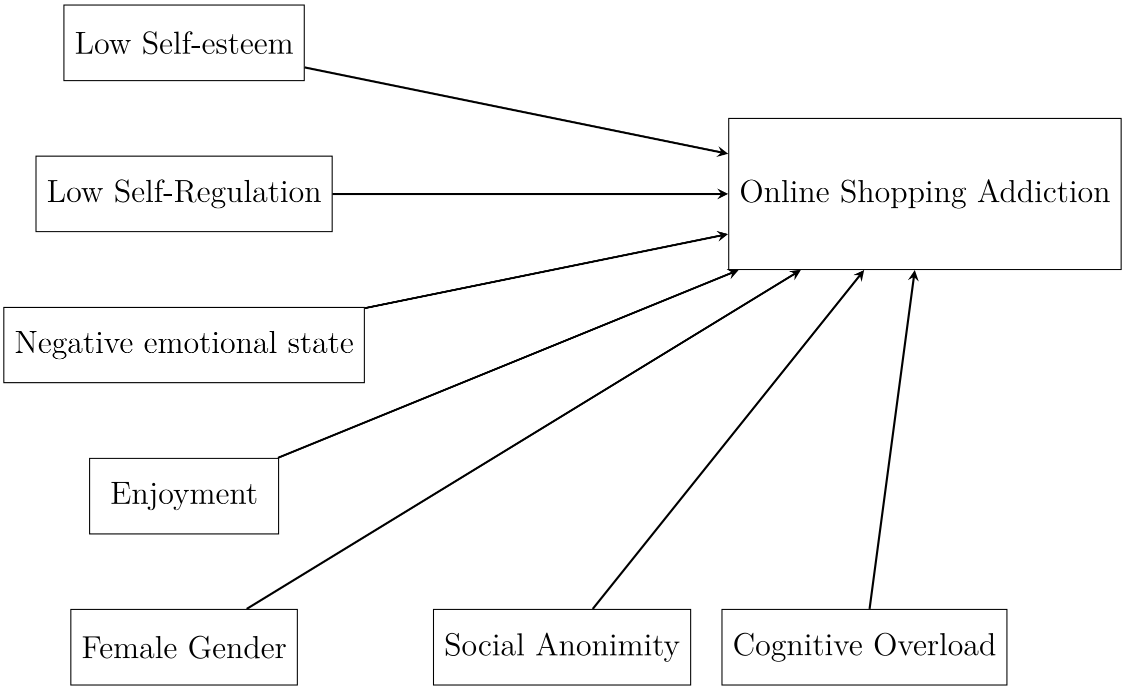

Figure 2.1: A conceptual model of Online Shopping Addiction conceived in [10]

change in consumer decision in the course of altering advertisement, backdrop color, and promotions. The author at first marked ”Like,” ”Dislike,” ”Buy,” and ”Neutral” to categorize all trials. In the following study, the average power of the right frontal (FP2, F4, F8, Ft8, FC4) and left frontal (FP1, F3, F7, Ft7, FC3) electrodes were used to compute the ”Dislike” and ”Like” preferences. While using SVM (Support Vector Machine) classifier with RBF kernel, the accuracy rate: ”Like” vs ”Neutral” 87.06% with FP1, ”Dislike” vs ”Neutral” 95.96% with CP3 and ”Buy” vs ”Neutral” 93.87% with FP1. For LDA (Linear Discriminant Analysis) classifier, the accuracy rate is as follows: ”Like” vs ”Neutral” 89.62% with CP3, ”Dislike” vs ”Neutral” 95.46% and ”Buy” vs ”Neutral” 90.06% with CPZ; which clearly depicts that the frontal region (CP3, CPZ and FP1) and centro-parietal region can be used for predicting decision making. Thus the author substantiated a hypothesis that Theta band increments in the left frontal area correspond to like preference, whereas those in the right frontal area refer to dislike preference.

Another research about sentiment analysis [30] by using EEG response in order to predict customer behavior proposes the usage of Discrete Wavelet Transformation (DWT) for detecting changes in the EEG signals. The DB4 decomposes the signal into five wavelet coefficients: D1, D2, D3, D4 and A4 which are identified as γ(32–100 Hz), β(13–22 Hz), α(8–13 Hz), θ(4–8 Hz), and δ(1–4 Hz) frequency bands of EEG spectrum, respectively. After evaluating several sentiment analysis classifiers such as Naive Bayes, SVM, and HMM on three distinct datasets, the authors discovered that the SVM test results exhibit the greatest performance, with accuracy levels of 87%, 92.32%, and 93.30% accordingly with F1 scores.

In addition, we investigated the accuracy of OpenBCI (an open-source consumer-grade EEG amplifier) in detecting emotional changes in consumer-grade brain sensing [31]. In comparison to the traditional ground truth labeling approach, the author recommended K-means clustering to achieve good classification performance. After that, Greenhouse-Geisser-Correction has been executed for statistical analysis. In terms of EEG-based emotion categorization, however, a model of hierarchical bidirectional Gated Recurrent Unit (GRU) exhibits more robust classification performance than baseline models [26]. Another BCI-VR Rehabilitation Design project based on drug addiction severity [49] elaborates the utilization of a Decision Fusion-based Bimodal signal processing architecture. The authors have used an optimized FBCSP, an MI-EEG decoding algorithm and performed a frequency domain filtering.

To understand emotional process better, we have further studied emotion detection using EEG signals and facial expressions [11]. In order to analyze facial expressions, researchers employed Compute Unified Device Architecture (CUDA) technology. The authors utilized four regression models for continuous emotion detection in their study: LSTM-RNN, SVR, MLR, CCRF. Log-magnitude Fourier spectra were used in another investigation to provide multiscale dynamic descriptions of data that defined global and local face appearance and head movements [6].

2.3 Addiction Detection

In order to better understand the human brain's addiction process, we have looked into previous works on detecting addictions using brain signals. According to a comprehensive study, supervised learning is increasingly being employed for the categorization of addiction and has demonstrated its effectiveness [32]. Looking at the comparison of detecting addiction by both clinical diagnosis and machine learning, there is no significant difference on average, but using machine learning models with high accuracy will aid in the whole classification process [33]. Quantitatively recorded EEG (QEEG) has been used to explore a variety of illnesses, including addiction, using spectral and coherence studies [5]. A research on Cross-Validated Predictive model of Addiction, although anatomical sites and directions of relationships have varied among research, largely supports the idea that individual differences in brain function and structure are linked to treatment outcomes discrepancies [41].

A research on Cross-Validated Predictive model of Addiction, although anatomical sites and directions of relationships have varied among research, largely supports the idea that individual differences in brain function and structure are linked to treatment outcomes discrepancies [41]. Dominik's research work on the influence on brain signals due to Binge Eating Disorder (BED) [40] using Random Forest (RF) clearly demonstrates the existence of increased Beta activity when a person is addicted. Again in [15], it has been stated that The 'obesity neural brain activity' is made up of the dorsal and pregenual anterior cingulate cortex, posterior cingulate extending into the precuneus/cuneus, as well as the parahippocampal and inferior parietal regions. However, in order to prevent produced sounds in EEG data, the authors recommend preprocessing the data utilizing Independent Component Analysis (ICA) which we have been seen in previous section as well. Another research of changes in brain signal due to being addicted to Tobacco [42] conceived the combination of temporal and frequency domain characteristics in which the accuracy ranges from 86.5% to 91.3% where RF shows the best performance. Because this combina-

Research	Data Preprocessing	Feature Extraction	Used Classifier	Accuracy(%)
Application of EEG to interpret consumer decision-making [28]	performed ICA to remove eye blink & eye movement and visual inspection to remove bad segments	PSD using the Welch method	SVM and LDA	>87%
EEG-based preference prediction [34]	down-sampled data to 128 Hz, applied a (4.0-45.0 Hz) bandpass filter, used ICA to remove EOG artifacts	used PSD to extract bands from EEG signals	DNN and DTL	DNN (87%) DTL (93%)
Emotion recognition using consumer-grade brain sensing [31]	notch-filtering using iirnotch, finding the reference signal with Common Average Reference, and removing artifact components with ICA	extracted the bands using PSD	K-means clustering and GMM	71.57%
Using a Generative Adversarial Network to visualize human thinking [24]	On the 10 second EEG recording, I used a sliding window with overlap to separate the data into pieces with an overlap of 8	Generative Adversarial Network	CNN and LSTM	72.35%
Fusion of EEG to predict customer satisfaction [30]	S-Golay filter to smooth the noisy channels and DWT to detect changes in EEG signals	3 statistical features: Mean, SD and Energy for each band waves	ABC based RF regression	70.33%
EEG-based decoding semantic categories in silent speech imagination [43]	To reduce power line noise and epoching, use a second-order Butterworth notch filter with a lower cutoff frequency of 48Hz and a higher cutoff frequency of 52Hz	Common Spatial Patterns (CSP)	SVM and RF	84.61%
EEG-based Consumer Behavior Analysis [35]	running average to smooth out short-term fluctuations	5 level decomposition of DWT	Decision Tree	95%

Table 2.1: Previous researches on interpretation of decision-making

tion increases classification performance, the author suggests employing frequency domain characteristics to diagnose addiction. In a research of Cocaine Use Disorder (CUD) [19] demonstrated the result measuring analysis of variance (ANOVA) and Spearman rank correlation analyses.

Previous study on the EEG features of Online Shopping Addicts has revealed aberrant brainwaves in test participants when there is a consumption conflict as compared to the EEG brainwaves of healthy adults [46]. When the two groups of participants did not use the Internet, the author found that those who abuse the Internet had considerably weaker short-term memory than those who did not, implying that online shopping addicts must have a strong urge to use the internet excessively. In this regard, we have examined diagnosis of Internet Addiction where it has been highlighted that the ten most relevant electrodes in terms of the addiction diagnosis process are: C6, CPz, F1, F3, F6, FC3, O2, PO4, PO7, PO8 [38].

Moreover, according to the findings of a neurophysiological study on excessive Gaming Disorder point out that individuals with Gaming Disorder had increased Delta and Theta activity and decreased Beta activity, with coherence studies revealing abnormalities in brain activity in the mid-to-high frequency range; whereas, individuals with Internet Addiction had higher gamma activity but lower beta and delta activity [37]. Again, a study on excessive Alcohol Addiction shows higher absolute Beta activity can be marked as Alcohol Addiction Detector [18]. Anyway, the authors in [23] calculated PSD for electrodes near the motor cortex in the Beta frequency range by measuring the intensity of energy fluctuation as a function of beta frequency range. Additionally, another research about Insomnia Disorder has suggested that a valid and objective biomarker of cortical hyperarousal might be higher Beta activity [47]. In summary, all of the publications listed above employed Power Spectral Analysis (PSA) across numerous frequency bands to study the link between impulsivity and rapid frequency (Beta, Gamma) activity in various addict types.

Furthermore, according to the findings of another study on Internet Gaming Disorder, stimulation of the dorsolateral prefrontal cortex changes inhibitory control over addiction-related signals and motivation [45]. Again, a study utilizing neurofeedback to reduce cravings in nicotine-dependent smokers was conducted [16] processed rtfMRI using the Siemens research mode and analyzed data using Statistical Parametric Mapping. Their data preparation includes normalization to Montreal Neurological Institute (MNI) space and smoothing with an isotropic 8 mm3 Gaussian kernel. A research of predicting smartphone addiction [21], followed a different approach by using Emotion Regulation Scale for Adolescents to study effects of emotions in addiction. Here the addiction was determined through multiple linear regression analysis. On the other hand, a study of predicting Cigarette craving in Nicotine Addiction suggested a hypothesis that low-theta EEG Coherence might be marked as smoking cue response and predict addictive behavior [25].

Method	Data Preprocessing	Feature Extraction	Used Classifier	Accuracy(%)
Diagnosis of Tobacco Addiction [42]	FIR filter (0.5-44 Hz) to remove non-linear trends	SD, skew (sk), kurtosis (k), PSD, FFT	LR, KNN, RF and SVM	max - RFC (91.3%)
Diagnosis of Binge Eating Disorder [40]	noise removal by ICA	EEG spectral analysis using FFT	RF	81.25%
Diagnosis of Premature Internet Addiction [38]	split of data into EC/EO, the digital finite-impulse-response filtering, ICA using Information Maximization Approach	k-fold cross validation	RF	94.17%
Prediction of Drug Addiction [36]	outlier quantile to eradicate noisy value	applied PCA and split the data into train and test	KNN, LR, SVM, Naive Bayes, DT, RF, MLP, ADA boosting classifier and gradient boosting classifier	97.91%
Detection of Betel Nut Addiction [39]	data cleaning, data transformation using OrdinalEncoder	applied PCA and χ^2 for feature selection	KNN, LR, SVM, Naive Bayes, DT, RF	99%
BCI+VR Rehabilitation Design based on the Degree of Drug Addiction [49]	Band filtering on Filter banks and CSP Spatial Filtering	Feature Selection based on Mutual Information	Naive Bayes Parzen Window (NBPW)	between 67% to 80%

Table 2.2: Diagnosis of several Addictions using ML Techniques

2.4 Thoughts behind the Proposed Model

We have looked at prior studies on consumer behavior and predicting compulsive buying among online shoppers in order to develop a better prediction model [10]. However, those studies are primarily psychological in nature. They rely heavily on self-report questionnaires and the validation of the Bergen Shopping Addiction Scale (BSAS) [12] that can easily be falsified. However, a technique that delivers functionality based on objective parameters is necessary to make a meaningful and objective assertion regarding Online Shopping Addiction. Besides, it is worth remembering that one of the primary concerns of Hans Berger, the creator of electroencephalography, was providing the solution to the difficulty of linking brain electrical activity to psychological events [1]. In this way, the Electroencephalogram (EEG) is a well-known and widely used tool for monitoring a person's brain activity. As a result, we've looked at new research using the Brain-Computer Interface (BCI) to decode useful patterns from brain waves.In this regard, we've been inspired to investigate the consequences of brain activity in shopaholics. In our research, we will be using EEG recordings of electric potentials produced by neurons to capture brain activity.

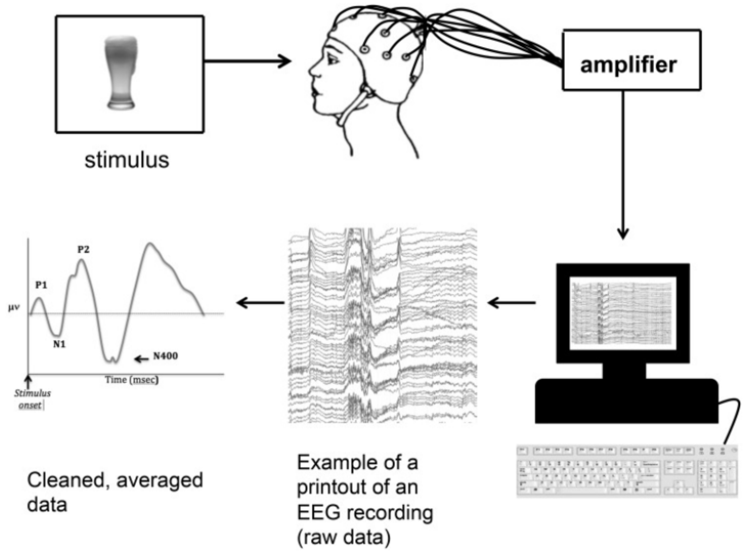

Figure 2.2: Experimental setting of EEG that enables the electrical brain activity [17]

Chapter 3

Proposed Method

The model we will be using to predict Online Shopping Addiction has been demonstrated in the following section.

3.1 Model Architecture

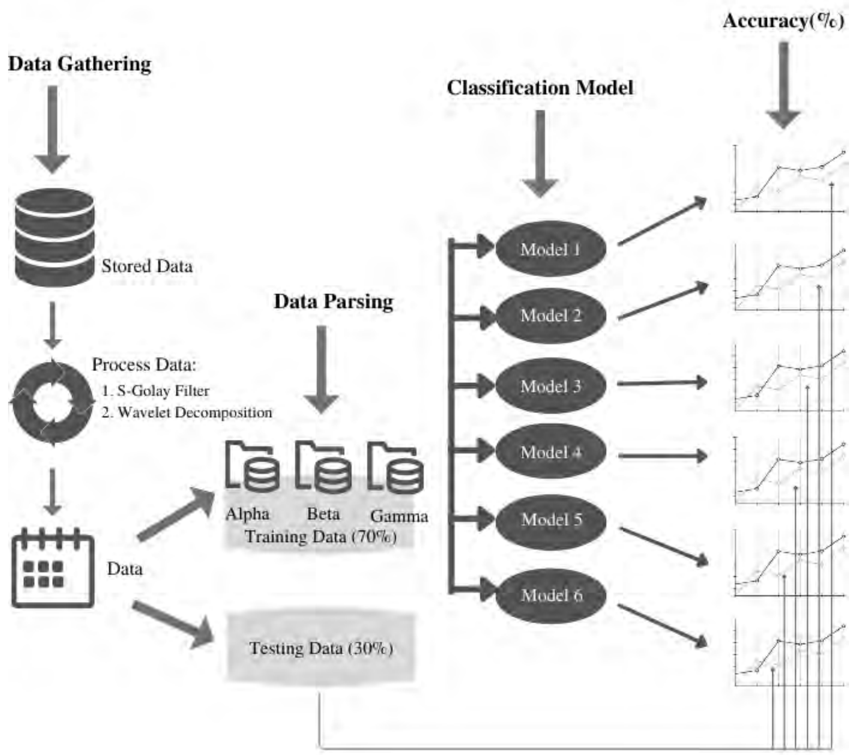

Figure 3.1: The Architecture of the proposed Online Shopping Addiction Prediction

The proposed four-stage architecture contains: Data Gathering, Data Parsing, six distinct Classification Models and Accuracy Testing. The dataset we have collected contains raw EEG signal values. That is why, at first, we have processed the data to our convenient in the second step to apply the later classifications. To decrease and smooth out high-frequency noise, the preprocess incorporates a signal smoothing procedure. We propose using the Savitzky-Golay Filter to each raw EEG data to achieve this. Later, we used Discrete Wavelet Transformation since it allows for simultaneous time and frequency domain localisation. Subsequently, the dataset has been separated into three frequency bands after wavelet decomposition in the feature extraction section: Alpha, Beta, and Gamma.Then, in a 7:3 ratio, each of the three data files was separated into training and testing data. The data files of mentioned frequency bands are passed into six different classification models from [7] for testing accuracy. The framework of the proposed Prediction of Online Shopping Addiction has been displayed in figure 3.1.

3.2 Six Classification Models

Six categorization models are used in our suggested model. Support Vector Machine (SVM), Multi-layer Perceptron Classifier (MLP), Random Forest Classifier (RFC), Stochastic Gradient Descent (SGD), Decision Tree, and Gated Recurrent Unit (GRU) are some of the algorithms we have suggested. We developed six classifiers so that we could compare them and see which one produces the best results.

3.2.1 Support Vector Machine

Because the primary goal of the Support Vector Machine (SVM) is to identify a hyperplane that separates the two classes with the greatest margin, it is commonly employed in binary classification [27]. As we are to deal with non-linear data, we will need a kernel function that takes a nonlinear problem and converts it into a linear problem in a higher-dimensional space. The Radial Basis Function (RBF), the default Kernel in sklearn's SVM classification method, has been employed as the kernel function in this study shown in eq. 1 to non-linearly map samples into a higher-dimensional space, which also helps to reduce the hyper-parameter in the computation. We used the following kernel function:

$$\chi(x_i, x_j) = \exp(-\frac{||x_i - x_j||^2}{2\sigma}) \tag{1}$$

where σ is the RBF function width.
When there are non-separable cases, a parameter ξ is added to tweak the classifier once again. To alter the ability to modify, a new parameter C, in the range (0, +), with the minimization error function called C-SVM has been given in eq. 2:

$$\frac{1}{2}\omega^\tau \omega + C\sum_{i=1}^{m} \xi_i \tag{2}$$

After the addition of two more parameters υ and ρ, ρ-SVM is constructed which can control the number of support vectors, where the error function has been shown in eq. 3:

$$\frac{1}{2}\omega^\tau \omega - \upsilon\rho + \frac{1}{m}\sum_{i=1}^{m} \xi_i \tag{3}$$

3.2.2 Multilayer Perceptron Classifier (MLP)

Each node among the three levels of nodes in an MLP i.e. an input layer, a hidden layer and an output layer, with the exception of the input nodes, is a neuron with a non-linear activation function. MLP neurons employ a non-linear activation function that is given in eq. 4 and 5:

$$y(v_i) = tanh(v_i) \tag{4}$$

$$y(v_i) = (1 + e^{-v_i})^-1 \tag{5}$$

In our study, we have used the rectifier Linear Unit, simply known as ReLU, as shown in eq. 6 where the rectifier activation function is defined as:

$$f(x) = x^+ = max(0, x) \tag{6}$$

where x is the input to a neuron, that is analogous to half-wave rectification. A measure is elaborated in [2] that is capable of predicting the number of classifier training epochs for achieving optimal performance in an essemble of MLP classifier.

3.2.3 Random Forest Classifier

Another technique we used in our research was Random Forest, which picks characteristics or a combination of attributes at each node at random. The random forest classifier consists of many tree classifiers, each of which is built using a random vector chosen independently from the input vector, and each tree votes for the most popular class to categorize an input vector. The standard deviation of all the predictions from all of the different regression trees on x' was used to calculate the prediction's uncertainty:

$$\sigma = \sqrt{\frac{\sum_{b=1}^{B}(f_b(x') - f)^2}{B-1}} \tag{7}$$

B as discovered in eq. 7 is the number of trees is a free parameter. Cross-validation or the mean prediction error on each training sample may be used to find the ideal number of trees, B.

3.2.4 Stochastic Gradient Descent

In Stochastic Gradient Descent, the acual gradient of $Q(w)$ as given in eq. 8 is approximated by a gradient at a single sample:

$$w : -w - \eta \nabla Q_i(w) \tag{8}$$

The algorithm executes the aforementioned equation for each training sample as it sweeps across the training set. Several runs over the training set can be conducted until the algorithm converges. To avoid cycles, the data can be randomized for each iteration if this is done. In most cases, an adjustable learning rate is used to ensure that the algorithm converges.

3.2.5 Gated Recurrent Unit

A GRU, or Gated Recurrent Unit, is a recurrent neural network. It's comparable to an LSTM except that it just has two gates: a reset gate and an update gate, and it doesn't have an output gate. GRUs are easier and faster to train than LSTMs since they have fewer parameters.

The algorithm of GRU we implemented in our research has been given in algo. 1:

Algorithm 1 GRU Algorithm

$m_0 \leftarrow 0$
$v_0 \leftarrow 0$
$i \leftarrow 0$
while $!\Theta_i$ **do**
    $i \leftarrow i + 1$
    $g_i \leftarrow \nabla_\Theta f_i(\Theta_{i-1})$
    $m_i \leftarrow \beta_1 m_{i-1} + (1 - \beta_1) g_i$
    $v_i \leftarrow \beta_2 v_{i-1} + (1 - \beta_2) g_i^2$
    $m'_f \leftarrow \frac{m_i}{(1-\beta'_1)}$
    $v'_i \leftarrow \frac{v_i}{(1-\beta'_2)}$
    $\Theta_i \leftarrow \Theta_{i-1} - \alpha \frac{m'_f}{\sqrt{v'_f} + \eta}$
end while
return Θ_i

3.2.6 Decision Tree

The information gain strategy is commonly employed in the decision tree method to find appropriate properties for each node of a created decision tree [9]. In our research, we used ID3 method where we may choose the property with the biggest information gain with maximum level entropy reduction as the current node's test attribute. The information gain function has been discovered in eq. 9:

$$InformationGain = Entropy(before) - \sum_{j=1}^{K} Entropy(j, after) \tag{9}$$

where the entropy is calculated as shown in eq. 10:

$$E(S) = \sum_{i=1}^{c} -p_i log_2 P_i \tag{10}$$

3.3 Accuracy Testing

After implementing the six classification methods, we have compared the accuracy of each models in this sub-section.

Chapter 4

Dataset

4.1 Dateset Description

The paper uses the pre-recorded EEG dataset from 25 participants mentioned in [20]. Here, EEG signals were recorded while they were watching commercials on a computer screen, using all 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F7, F8, AF4). The participants range in age from 18 to 38 years old. There were 14 different products chosen, each with three possible modifications, resulting in 42 product photographs. After exhibiting the image for 4 seconds, a total of 1050 EEG data were captured for all individuals, as well as the user's selection. Each second, 128 wavelet instances are gathered, for a total of 512 wavelets for each product. The researchers have made the dataset available to the general public for future investigation.

4.2 Data Preprocessing

Because EEG recording is extremely susceptible to many types of noise, evaluating EEG data to intercept the characteristics is challenging. There are many existing strategies for properly dealing with noise [35], [40]. Smoothing data is a technique for removing noise from a dataset that allows signal patterns to stand out. The specifics of the signal smoothing approach used to preprocess the signal for feature extraction are presented in this section. Following that, a wavelet analysis based on the Discrete Wavelet Transform (DWT) has been used to extract valuable characteristics from the recorded signals.

4.2.1 Savitzky-Golay (S-Golay) Filter

To eliminate noise from the dataset's recorded data, we have used Savitzky-Golay filter where applying Savitzky-Golay to a series of digital data-points enhances accuracy without altering the signal trend. In this paper, we utilized S-Golay to smooth the noisy sinusoid using a fourth-order polynomial and a frame length of five for further usage of the dataset. From a signal Y_j as shown in eq. 11, where j ranges from 1 to n (i.e n is the length), the S-Golay filter can be represented as the given expression:

$$Y_j = \sum_{i=\frac{1-m}{2}}^{\frac{m-1}{2}} C_i y_{j+i}; \frac{m+1}{2} \leq j \leq n - \frac{m-1}{2} \tag{11}$$

Here, m stands for the frame span and C_i represents the number of convolutional coefficients. The smoothed channel is represented as Y_j.

The below figures depict the signal smoothing procedure, with figure 4.1 depicting one of the participant's (Abhishek) raw EEG data signal and figure 4.2 depicting the corresponding smooth signal after applying the described filter.

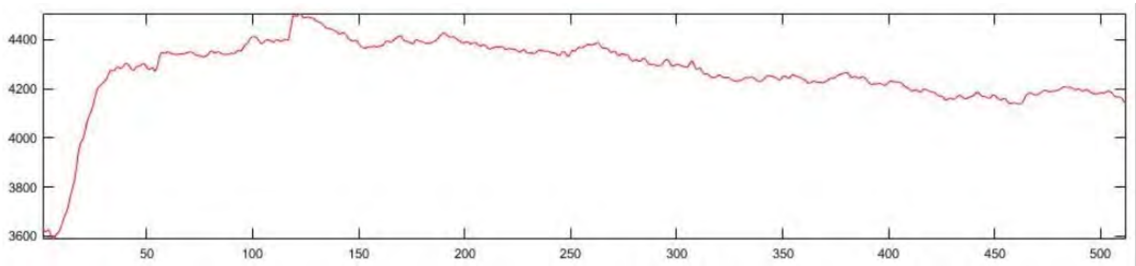

Figure 4.1: Signal before applying S-Golay Filter

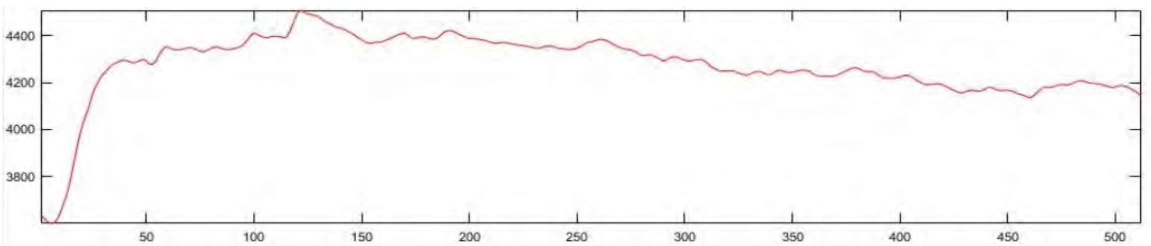

Figure 4.2: Smooth output signal after applying S-Golay Filter

4.2.2 Discrete Wavelet Transformation (DWT)

We have applied DWT to divide each signal into a number of sets, each of which is a time series of coefficients characterizing the signal's temporal evolution in the associated frequency band. The reason behind applying DWT is that Wavelet transforms, unlike short-time Fourier transforms, evaluate signals at numerous resolutions for distinct frequencies, rather than a single resolution for all frequencies. [4] Here, the output signal from S-Golay first passes through two layer of digital filters, that is High pass filter and Low pass filter denoted as H and L respectively. The first one removes the slow trends from the signal and provides wavelet coefficient, D. Again, the second one removes high frequency fluctuation from the signal and provides an approximation, A.

In figure 4.3, the process is depicted as a binary tree in different levels, with each node indicating a distinct time-frequency localization of a subspace.

Frequency Band	**Brain States**
Gamma	Concentration
Beta	Anxiety dominant, active, external attention
Alpha	passive attention, very relaxed
Theta	Deeply relaxed
Delta	Sleep

Table 4.1: Characteristics of the Five Basic Brain Waves [14]

The algorithm has been completed for all 14 channels of EEG data, yielding a 14 dimensional feature vector matching to each band. To be noted, we have used four levels of EEG signal decomposition by using the Coiflet 2 (Coif2) wavelet decomposition technique [8] that results in a group of five wavelet coefficients D1, D2, D3, D4, A4 which refer to Gamma, Beta, Alpha, Theta and Delta respectively.

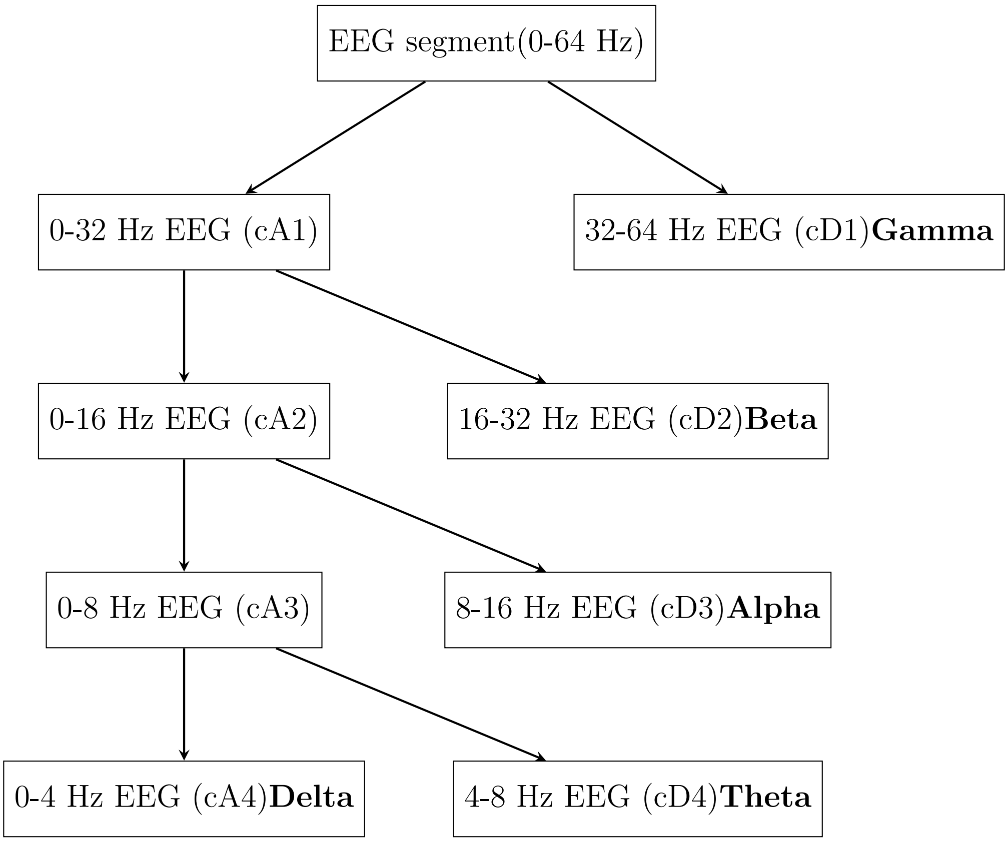

Figure 4.3: Multi-level decomposition tree by Wavelet Transformations

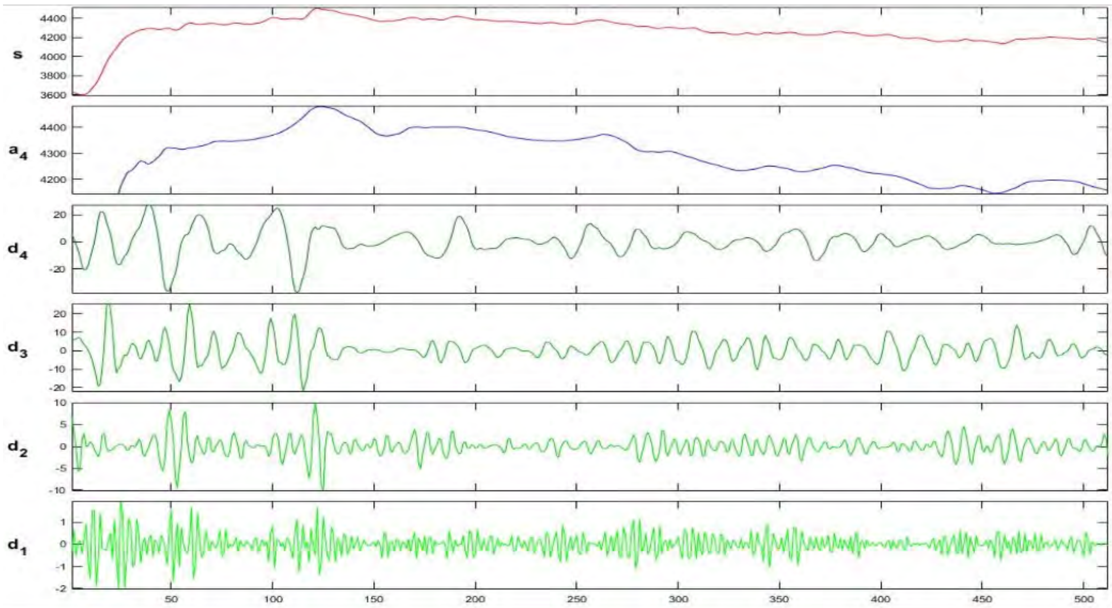

Figure 4.4: Feature Extraction in the form of different waves for a smoothed signal of channel FC5

In figure 4.4, the result is obtained at 4^{th} level of decomposition. The appeared output waves were based on the results obtained from the tool MATLAB for the corresponding smoothed signal of channel FC5 of figure 4.3. In the following figure, d1 denotes Gamma band oscillations, d2 denotes Beta band oscillations, d3 denotes Alpha band oscillations, d4 denotes Theta band oscillations, and a4 denotes Delta band oscillations.

Furthermore, we have studied about the characteristics of the five bands from [14] in order to interpret which bands are crucial in predicting addiction. The characteristics of the five basic brain waves in Table 4.1 demonstrates that sleeping or dreaming is the major brain state in which Theta and Delta bands are monitored. Whereas, the major characteristics of other three frequency bands include concentration, problem solving, busy, reflective and active mind. According to this information, Theta and Delta values are redundant in our study. Therefore, in this stage we have shortlisted our dataset which contains only three frequency bands (Alpha, Beta, Gamma).

4.3 Feature Selection

As mentioned in [38] that 10 of the most important channels (C6, CPz, F1, F3, F6, FC3, O2, PO4, PO7, PO8) in terms of predicting addiction from brain signals, we have only extracted four of them that are present in our collected dataset. Unfortunately, out of the 10 relevant channels, only two (F3,O2) are included in our chosen dataset. However, when we looked at the typical location of EEG electrodes in figure 4.5, we have discovered that the nearby channels of FC3 and PO8 are FC5 and P8 respectively which are both present in our dataset. Finally, we have extracted the values of these four channels (F3, FC5, O2 and PO8) manually from from Alpha, Beta, and Gamma band oscillations.

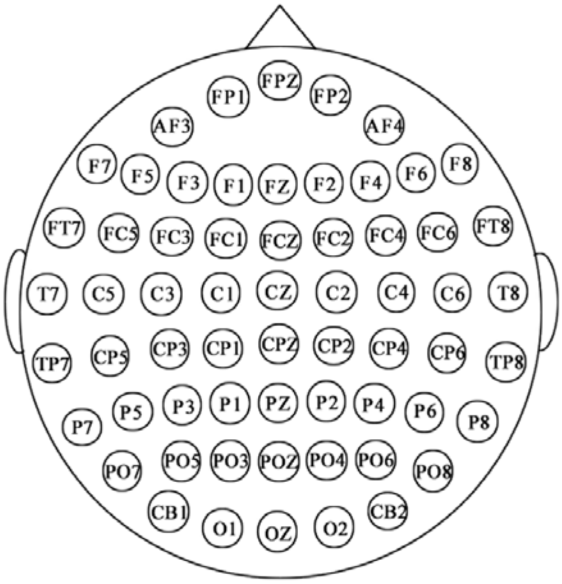

Figure 4.5: Placement of EEG electrodes shown in [13]

For instance, the signals of four aforementioned channels (F3, FC5, O2 and PO8) of one of the participants (Abhishek) has been shown in figure 4.6.

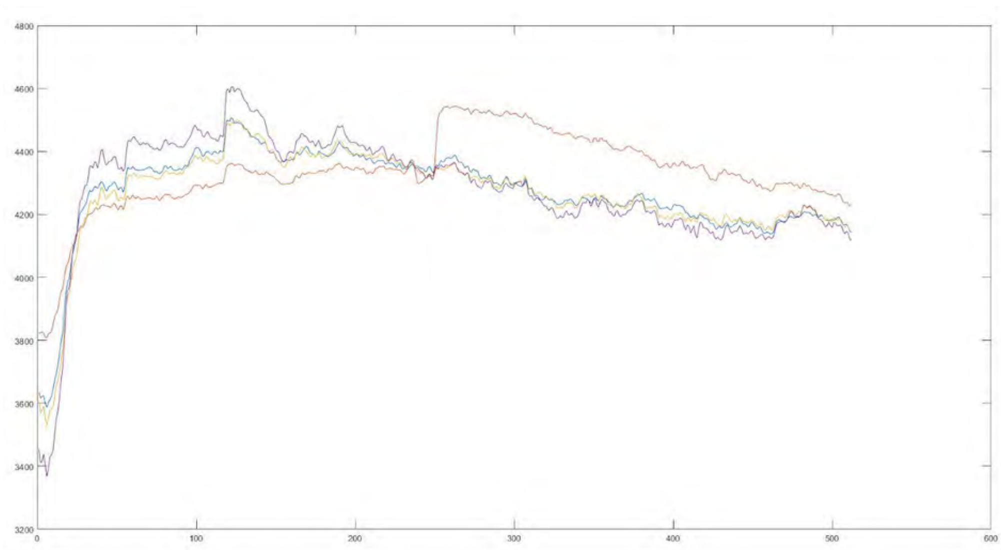

Figure 4.6: Four extracted signals of a participant (Abhishek)

Chapter 5

Implementation and Result

The following chapter explains the implementation of our suggested approach for predicting Online Shopping Addiction. The proposed model has been trained and tested using Python Tensorflow, Keras and other libraries in Google Colaboratory. This section summarizes the training procedure. Following that, a brief comparison among the results of the mentioned six models had been exhibited.

5.1 Implementation

This section presents the outcomes of putting the prediction model to the test. The test has been done by importing libraries from Python Tensorflow.

5.1.1 Training Methodology

The trained and tested models were displayed at this step. The trained models were built using three separate data files including Alpha, Beta, and Gamma oscillations, each of which contains data for four different channels: F3, FC5, O2, and P8. Support Vector Machine (SVM), Multi-Layer Perceptron Classifier (MLP), Random Forest Classifier (RFC), Stochastic Gradient Descent (SGD), Decision Tree (DTC) and Gated Recurrent Unit (GRU) are the classification models we previously proposed in the following paper in order to determine Shopping Addiction. The accuracy of these classifiers have been discussed in the below sections.

5.1.2 Metrics

The efficacy of the suggested model was evaluated using the following criteria.

Train & Test Accuracy: The accuracy of our proposed six classification models have been exhibited in this segment.

5.2 Experimental Results

A summary of obtained accuracies of the six classification architecture has been displayed in table 5.1. Support Vector Machine (SVM) was the initial classification model in our proposed model. The accuracy we obtained using the SVM classifier on our data is shown in figure 5.1. The figure shows that the accuracies on Alpha, Beta and Gamma bands are 66%, 68% and 81% respectively.

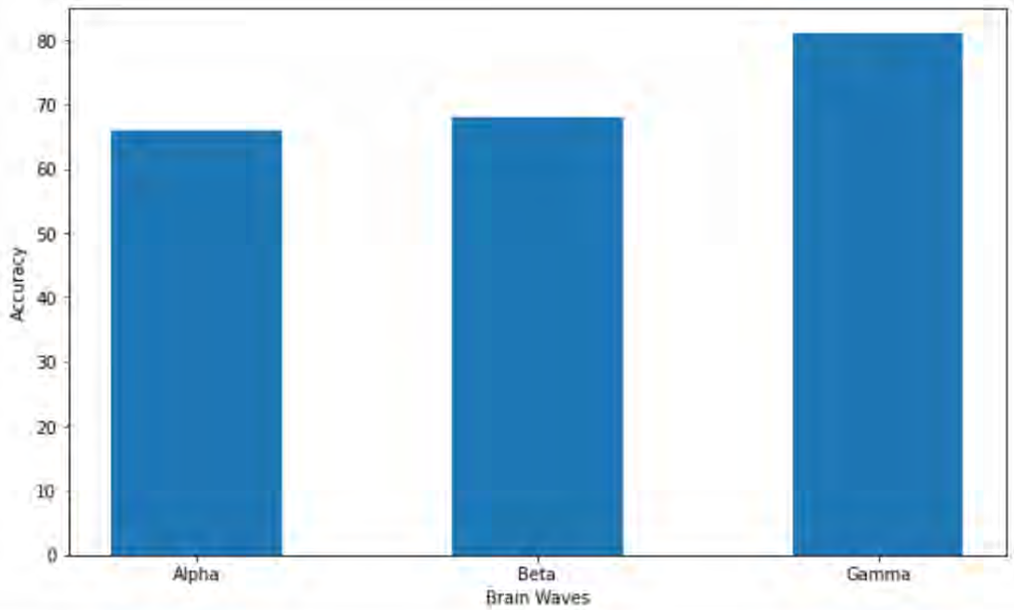

Figure 5.1: Test Accuracy of SVM

Following that, Multi-Layer Perceptron (MLP) was the second classifier of the proposed framework. Figure 5.2 exhibits the accuracy we obtained when we used MLP classifier on our data. The accuracy on the Alpha, Beta, and Gamma bands is 78%, 82%, and 85%, respectively, as seen in the mentioned figure.

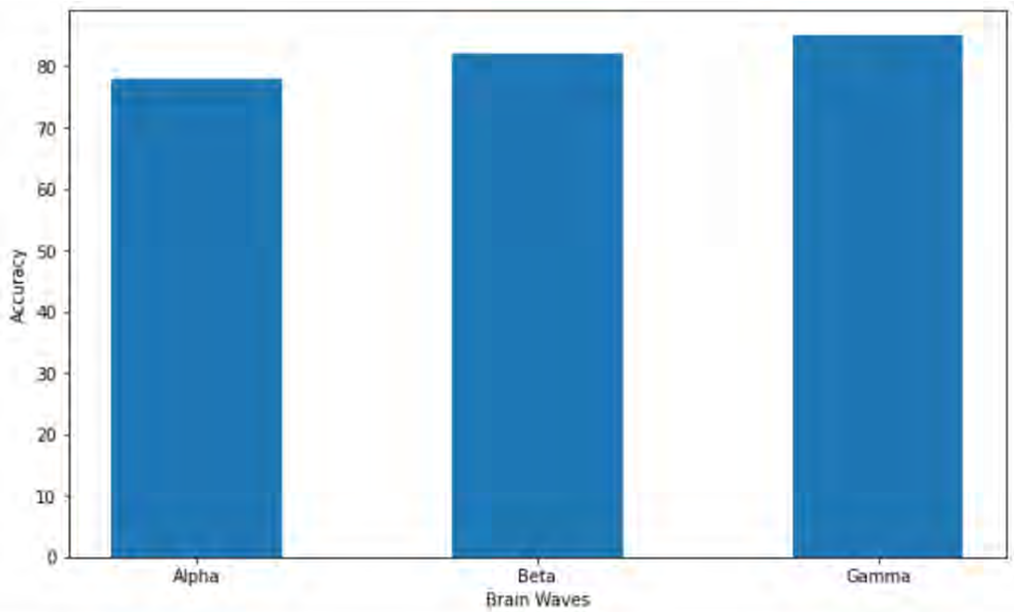

Figure 5.2: Test Accuracy of MLP

In the classification models, we selected Random Forest Classifier (RFC) as the third one. The accuracy shown in figure 5.3 follows: 68% on Alpha band, 70% on Beta band, 77% on Gamma band.

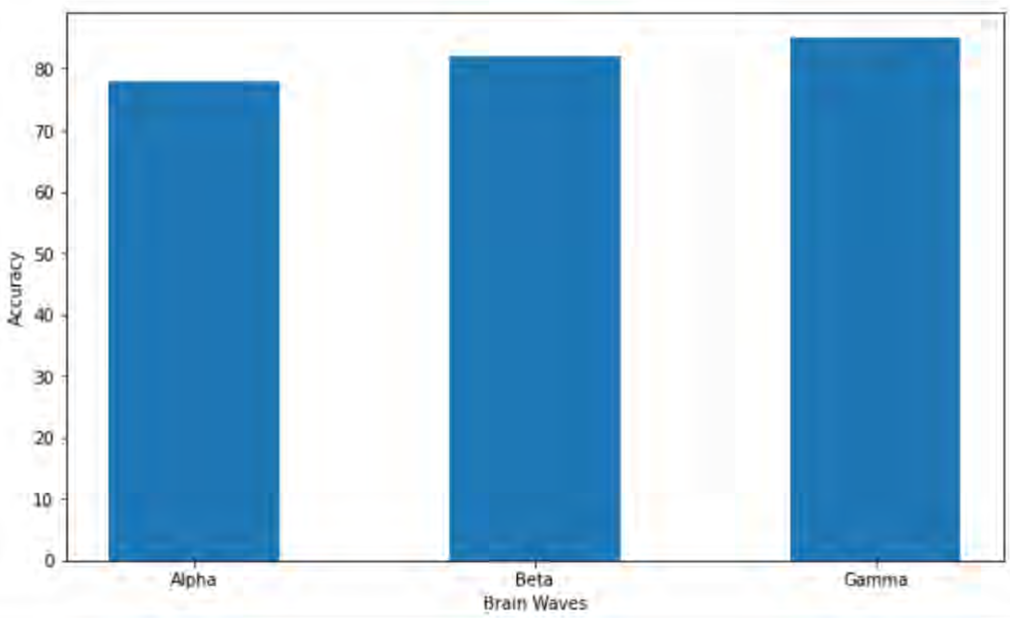

Figure 5.3: Test Accuracy of RFC

Additionally, as shown in figure 5.4, the accuracy of Stochastic Gradient Descent (SGD) is as follows: 61% on Alpha band, 61% on Beta band, 75% on Gamma band.

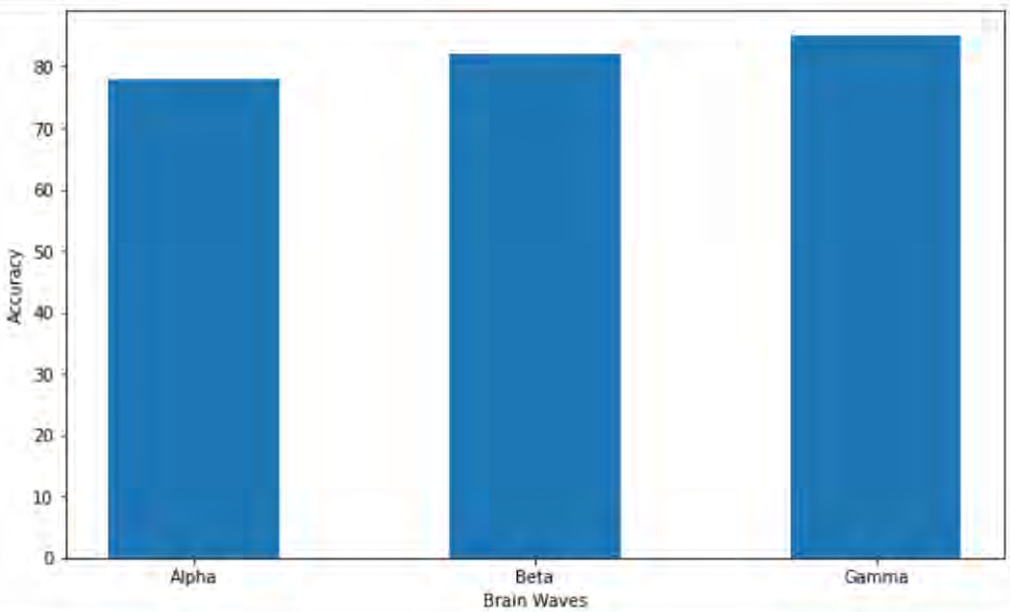

Figure 5.4: Test Accuracy of SGD

The Decision Tree was the fifth classification model in our mentioned architecture. Figure 5.5 shows the accuracy we obtained using the DT classifier on our data. The accuracy on the Alpha, Beta, and Gamma bands is 57.99%, 59%, and 61%, respectively, as seen in the graph.

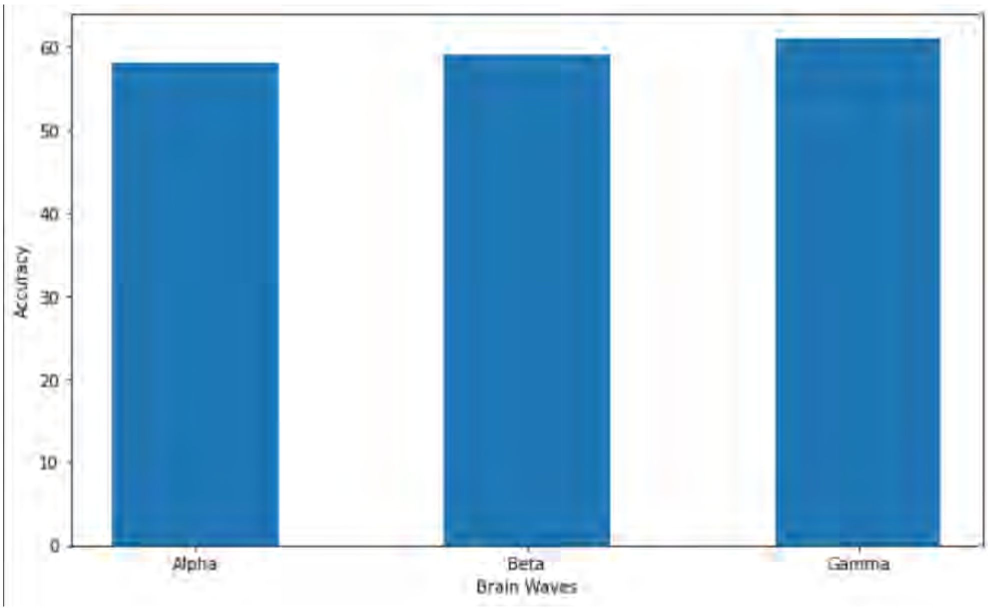

Figure 5.5: Test Accuracy of DTC

Lastly, we applied a Neural Network algorithm that is Gated Recurrent Unit (GRU) on our data. Figure 5.6 shows the accuracy on Alpha band is 61.81%, figure 5.7 shows the accuracy on Beta band is 62.85% and figure 5.8 shows the accuracy on Gamma band is 76.91%

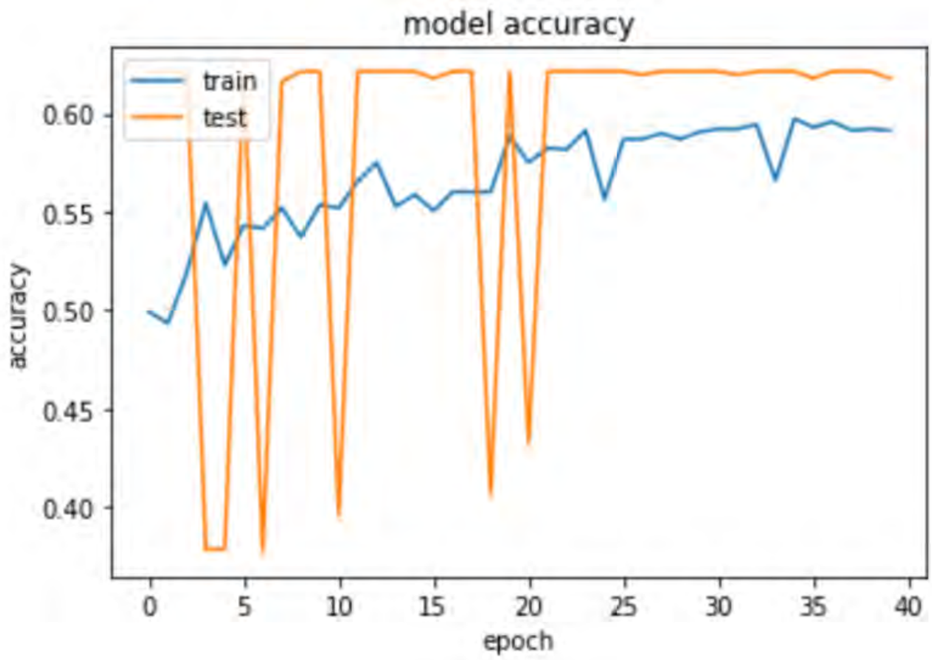

Figure 5.6: Train and Test Accuracy of GRU on Alpha frequency band

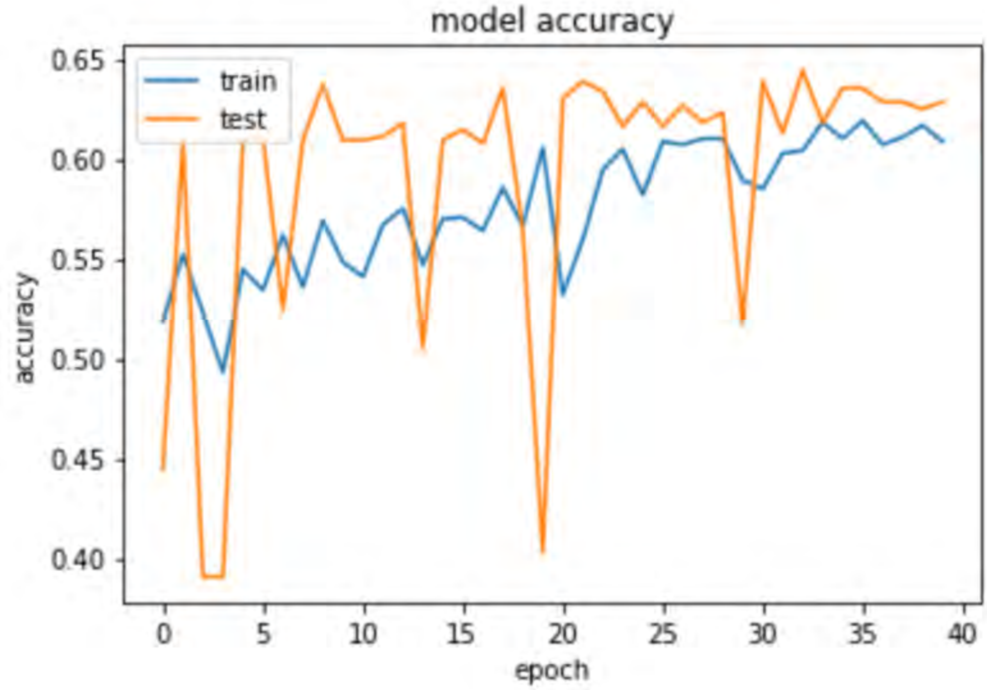

Figure 5.7: Train and Test Accuracy of GRU on Beta frequency band

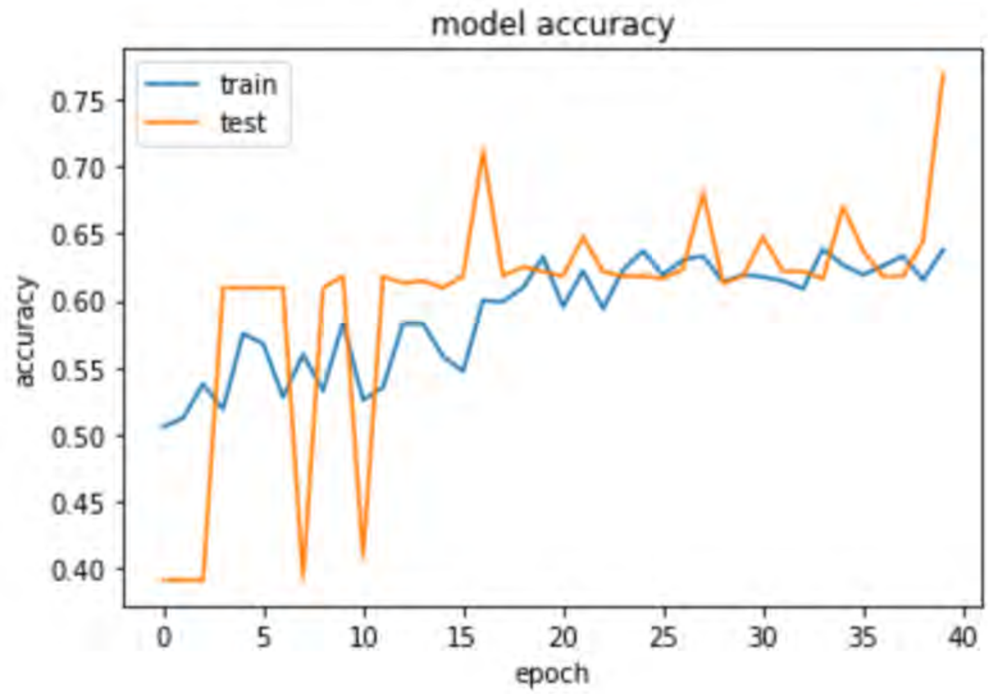

Figure 5.8: Train and Test Accuracy of GRU on Gamma frequency band

Frequency Bands	Classifier Model	Accuracy(%)
Alpha	SVM	66%
	MLP	78%
	RFC	68%
	SGD	61%
	DT	57.99%
	GRU	61.81%
Beta	SVM	68%
	MLP	82%
	RFC	70%
	SGD	61%
	DT	59%
	GRU	62.85%
Gamma	SVM	81%
	MLP	85%
	RFC	77%
	SGD	75%
	DT	61%
	GRU	76.91%

Table 5.1: A summary of classification accuracies

5.3 Comparative Analysis

The following section examines algorithm performance and accuracy of our model in predicting Online Shopping Addiction. Based on the accuracy results, we've determined that the Beta and Gamma frequency bands are more important than the Alpha frequency band in accurately forecasting Online Shopping Addiction. Needless to say, we have found relevance of our hypothesis in [38] which looked at the link between impulsivity and high-frequency Beta and Gamma activity in addicts. We could suggest that we limit ourselves to simply utilizing Gamma bands to accurately forecast Shopping Addiction because they have the best accuracy. However, it will not be relevant to implement prediction algorithms on Delta and Theta bands since their characteristic mostly lies in deeply relaxed activities such as: sleeping or dreaming as shown in 4.1. Additionally, in [38], it has been stated that C6, CPz, F1, F3, F6, FC3, O2, PO4, PO7, PO8 are the ten most important EEG channels to predict addiction among people. However, our proposed model can predict Online Shopping Addiction only using four channels from the above mentioned channels that are: FC5, P8 O2, F3. Here, FC5 is the neighboring channel of FC3 and P8 is the neighboring channel of PO8. Therefore, it can also be conceived that the characteristics of the neighboring EEG channels are quite similar. Based on these, it can be stated that the frontal-occipital and parietal areas of the human brain are more active to Shopping Addiction behaviors.

Besides, the accuracy of predicting addiction was substantially lower when we applied the models to the dataset before pre-processing. Table 5.1 suggests that among

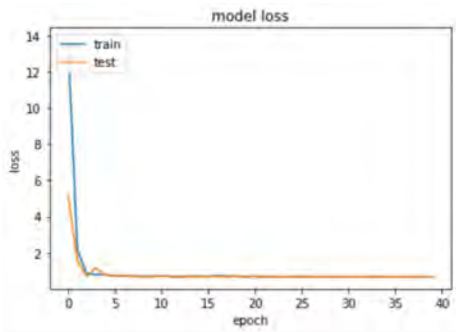

Figure 5.9: GRU Training & Testing loss on Alpha bands.

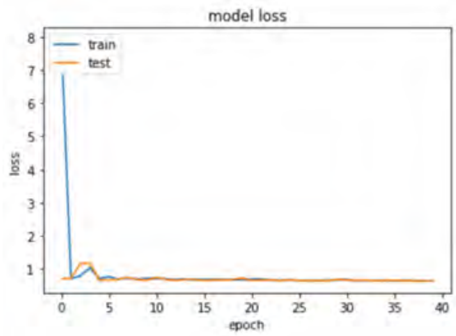

Figure 5.10: GRU Training & Testing loss on Beta bands.

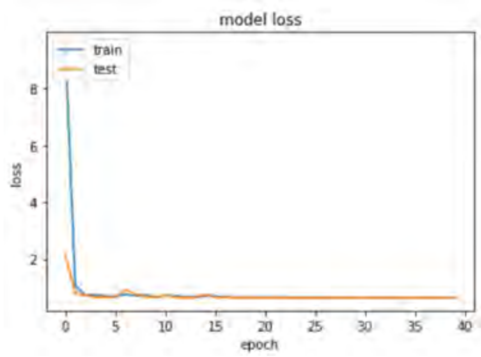

Figure 5.11: GRU Training & Testing loss on Alpha bands.

the six classification models, MLP Classifier has given the best outcome in our proposed framework. The accuracy rate of SGD on the Alpha and Beta bands, however, is the same. Again, when GRU algorithm was implemented, the highest accuracy was on Gamma bands. The GRU training and testing loss has been shown in figure 5.9, 5.10 and 5.11.

The summary of the classification models in table 5.1 clearly depicts that in almost every categorization layer, the Beta (SVM-68%, MLP-82%, RFC-70%, SGD-61%, DT-59%, GRU-62.85%) and Gamma (SVM-81%, MLP-85%, RFC-77%, SGD-75%, DT-61%, GRU-76.91%) bands have more accuracy than the Alpha band (SVM-66%, MLP-78%, RFC-68%, SGD-61%, DT-57.99%, GRU-61.81%).

Chapter 6

Conclusion

The major goal of this study is to use electroencephalogram recordings of brain activity to look at internet shopping addiction in people (EEG). The following addiction is classified as a subset of Compulsive Buying Disorder (CBD) and is characterized by an irresistible-uncontrollable preoccupation with shopping and purchasing activity that results in severe social, personal, and financial consequences. Two-thirds of the people (31.5 percent) had high CBD levels, according to data published in World Psychiatry, the official journal of the World Psychiatric Association.

If we examine the causes of shopping addiction, it is clear that emotion plays a significant part. As a result, it has been significant to identify changes in brain signals to analyze the occurrence of shopping addiction. Many publications describe how to extract Spatio-temporal information from brain signals using OpenBCI and GAN architectures. The electroencephalogram (EEG) is a non-invasive technology for monitoring the brain that is frequently utilized [22]. The cerebral cortex, which is assumed to be mainly responsible for our individual ideas, emotions, and behavior, generates the majority of EEG signals [3]. However, in this work, we have demonstrated a two-way approach based on an EEG dataset of 25 participants' EEG recordings. I) noise reduction in the dataset II) six classification models to get the highest level of accuracy. The test accuracies suggest the significance of Beta and Gamma frequency bands over Alpha band in terms of predicting Online Shopping Addiction efficiently. Since characteristics of Delta and Theta include relaxed activities like sleeping or dreaming, we have excluded those frequency bands from our dataset in the processing segment.

We may conclude our research by stating that the ten most significant EEG channels in terms of the addiction diagnosis process are: C6, CPz, F1, F3, F6, FC3, O2, PO4, PO7, PO8. From these, our suggested framework is able to predict Shopping Addiction using only four of them which are: FC5, P8 O2, F3. As a result, it is reasonable to suppose that the frontal-occipital and parietal areas of the human brain are more important in predicting addiction. In this way, our suggested technique outperforms theoretical addiction prediction models in terms of precision.

6.1 Future Work

TechnologLimitations and y and contemporary science have made our lives simpler and faster in recent years. With the help of previous researches in this field, we have been able to predict Online Shopping Addiction with a high degree of accuracy in the following study. However, we encountered certain constraints while doing study on predicting Online Shopping Addiction, which we want to solve in the future. To begin with, the dataset we utilized was not sufficiently enriched and had not been created according to our recommended structure; as a result, we had to spend a lot of time pre-processing the data to meet our requirements. Therefore, we would like to generate our own EEG dataset for the future model we have already thought of so that we may edit the data as we see fit.

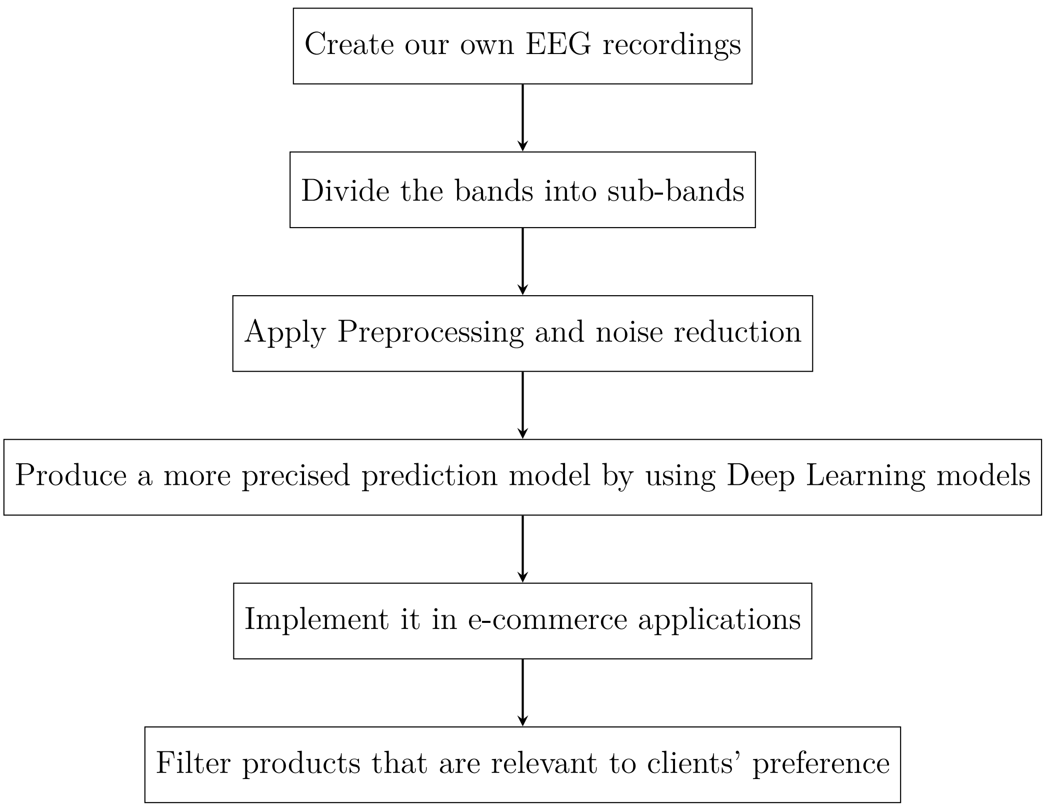

Figure 6.1: Work plan for future

In this paper, our research was limited to predicting Online Shopping Addiction using four distinct channels (FC5, P8 O2, F3) of three EEG bands (Alpha, Beta, Gamma). In the future, we hope to investigate the sub-bands of the EEG bands indicated above in order to narrow the scope of the research and determine which sub-bands are more effective in accurately predicting OSA. We'd also like to find out which genders and age groups are most susceptible to OSA in the future. To assure a much more exact model, we plan to apply several Deep Learning algorithms on the dataset comprising data about EEG sub-bands. Afterwards, we would like to implement our more precised prediction model of Online Shopping Addiction on an e-commerce application for advanced product filtering to continue the use of information technology so that if the application contains the EEG dataset of its regular customers, the application will only recommend products that the client is more likely to buy. An initial workflow of our future model has been shown in figure 6.1.

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