A Dissertation Report

on

Exploring the impact of Age and Gender on Sentiment Analysis

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Presented By:

Monika Gahalawat

M.Tech (CSE)

16535024

Under the Guidance of

Dr. Partha Pratim Roy

(Assistant Professor)

Department of Computer Science and Engineering

Indian Institute of Technology Roorkee

Roorkee – 247667, India

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AUTHOR'S DECLARATION

I declare that the work presented in this dissertation with title **"Exploring the impact of Age and Gender on Sentiment Analysis"** towards fulfillment of the requirement for the award of the degree of **Master of Technology** in **Computer Science & Engineering** submitted in the **Department of Computer Science & Engineering, Indian Institute of Technology Roorkee, India** is an authentic record of my own work carried out during the period of **May 2017 to May 2018** under the supervision of **Dr. Partha Pratim Roy**, Assistant Professor, Department of Computer Science and Engineering, Indian Institute of Technology Roorkee, Roorkee, India. The content of this dissertation has not been submitted by me for the award of any other degree of this or any other institute.

Date: ....

Place: ROORKEE

Monika Gahalawat

M. Tech CSE (16535024)

Indian Institute of Technology Roorkee

CERTIFICATE

This is to certify that the statement made by the candidate is correct to the best of my Knowledge and belief.

Date: ....

Place: ROORKEE

Sign: ....

DR. PARTHA PRATIM ROY

(Assistant Professor)

Indian Institute of Technology Roorkee

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MONIKA GAHALAWAT

ABSTRACT

Sentiment Analysis is a rapidly growing field of research due to the explosive growth in digital information, there is a need to filter out unnecessary information and get meaningful results out of this huge information. Sentiment Analysis focuses on finding polarity of the expressed sentiment. The main objective of this paper is to find the impact of age and gender of the user on the subjectivity of the expressed opinion by examining the differences in the way of expression taking in consideration user's age and gender separately.

Psychologically it is always said that different gender and age groups have different ways of expressing their opinion. Multiple studies have been done to support these claims and in most of the studies, these differences have been highlighted. Based on these psychological differences, we create a dataset by collecting reviews on books from facebook users along with their age and gender information. Different data sets on the basis of age groups (Below 20, 21 - 34, 35 - 50 and Above 50) and gender (male, female) are extracted from this dataset and sentiment analysis is done using different machine learning approaches along with a dictionary based approach, Vader. The results are in align with the previous studies on the psychological differences in different gender and age groups.

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Chapter 1 INTRODUCTION

The growth of Internet has led to huge influx of data that holds vast and valuable insights about the public opinion. Each and every internet user that expresses their opinion on the web becomes a part of this information circuit where other users benefit from these public reviews and hence make an informed decision. After the complete process of data collection (reviews, posts, comments) from different sources such as social websites (facebook, twitter, amazon, goodreads, imdb) or blogs, the task of using these reviews to find the polarity of public (positive, negative or neutral) opinion is called Sentiment Analysis. Sentiment analysis is generally performed on movie reviews ([54], [20]), restaurant or food reviews ([42], [64]) along with data from microblogs ([14], [26]) providing some useful insights to different organizations so that they can improve their business strategies to attract new customers.

Sentiment Analysis has evolved over the years with different dictionary-based and machine learning techniques implemented on the data to obtain better accuracy from the results. Starting from simpler methods that provided a good accuracy, the state of art methods contain deep learning algorithms implemented for sentiment analysis on the textual data that result in a much higher accuracy. Along with improved accuracy, the number of labels of data classification has also improved from just positive or negative to a range of labels from extremely positive to neutral to extremely negative. With the advent of deep learning techniques in sentiment analysis, prior information has also played a great role in adequately expressing the polarity of the opinion. Li et al. [51] in 2013 studied sentiment analysis using microblog websites dataset to propose a framework providing an abstract of the opinions expressed in the blog. The authors have taken into consideration the opinion subjectivity and user credibility in their proposed approach.

We try to analyze whether the opinions expressed by people from different gender and age groups align with their psychological differences as illustrated by different research groups. Even before the advent of internet, there have been multiple research studies on how different individuals handle different emotions and the way these individuals express their emotions. Today there are stereotypes that women are generally more expressive than men, different stereotypes on co-occurrence of negative and positive emotion on basis of age. Fabes and Martin examined gender differences in [23] conducting a study on 400 college students in five age groups from preschoolers to adults. The study aligned with the stereotypes of gender and age emotional expressiveness like the males expressing lesser as compared to females. Another

research by Stoner et al. [70], done in 1987 taking people of both genders and in different age groups to study their anger expressing ability. The research showed that young adult group expressed anger more as compared to old adult age group. Though they did not find out much differences on basis of gender in this aspect.
A research by Teresa D. on gender differences in negative emotions showed that boys displayed a greater negative effect as compared to girls when they were disappointed. Brody R. researched more on gender and emotional expression and showed that gender differences in emotional expressiveness were culturally specific in Asian international students. Another study by Kring Ann et al. [43] in which they showed emotional videos to a group of students and reaffirmed that women are generally more expressive than men even in case of experienced emotions. A study by Birditt in 2003 [12] examined age and gender differences in description of emotional reactions. It contained 185 individuals as 85 males and 100 female ranging from 13 to 99 which showed that adolescents and young adults are reported more likely to describe anger and giving more intensive aversive reposes as opposed to the male adult group. Woman rated their distress more intensely than men and they experienced it for a longer amount of time. Similar studies have been done time and again like the one done by Lockenhoff et al. [53] in which they analyze how different age groups express their emotions. It was found that older adults described the positive emotions better than their negative emotions as compared to younger adults. Another research by Zimmermann et al. [85] for estimating emotion control based on age and gender of the person as per which person was able to handle emotions better. The results showed that people in middle adolescence showed the least emotional regulation as compared to other age groups. Even gender differences were also encountered as either under or over estimating a particular emotion. Based on these established psychological differences between people of different age and gender, we aim to find out whether these differences can also be observed in the opinions that the individuals express on on-line platforms.

Fig. 1.1 explains the basic flow diagram of the framework that we have used for sentiment analysis where the data collected from social media is used to extract two datasets on basis of age and gender and then the different sentiment analysis approaches are implemented on the data.

1.1 Contribution

The main contribution of this work are as follows:

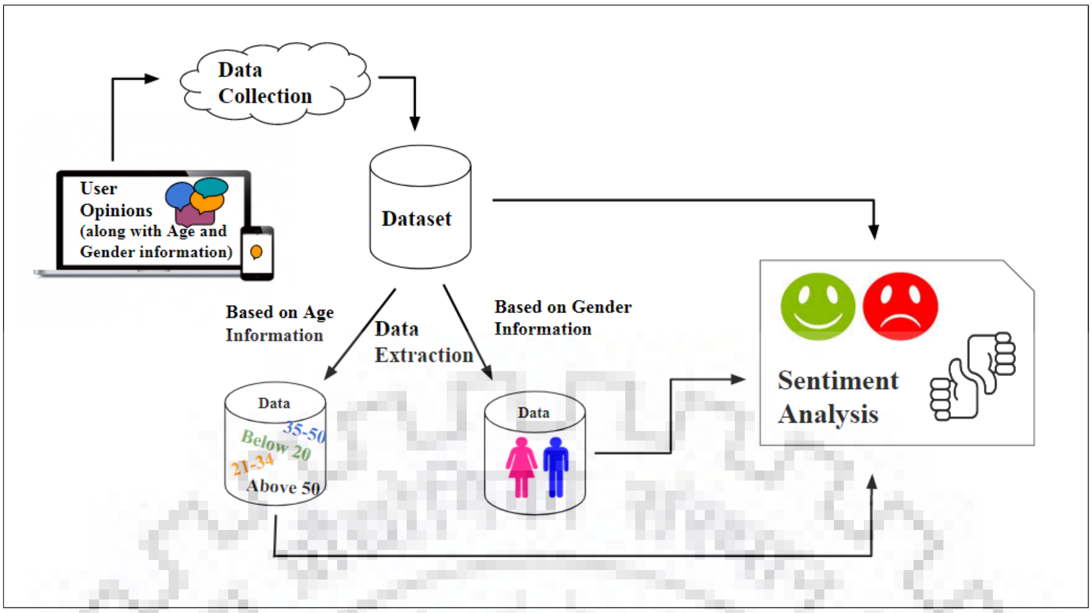

Figure 1.1: Data is collected from the social media along with the user's age and gender information that is then used to extract data. Sentiment Analysis is then performed on the newly created data sets.

- We collect a dataset containing user reviews along with the their age and gender information.
- Secondly, we study difference in user expression based on age and gender using different feature extraction methods like bag of words and word2vec on the collected data. Next, we compare different machine learning based classifiers and a dictionary based classifier for sentiment analysis.

1.2 Motivation

The study explores the differences in sentiment expressing abilities of different groups and their subsequent impact on the sentiment review of the complete data. Analyzing the smaller amount of data that is concentrated on a particular group helps in finding impactful results for that group. This can be extremely helpful for economic applications as they can focus directly on a particular audience that is more receptive towards their product rather than making a generalized marketing strategy, which will further help in differentiating their brand from other companies leading to better customer support. Multiple studies have focused on age and gender statistics such as [59] by Oh et al. in 2016 where they study the market segmentation on basis of gender and age of users to find the travel potential of different groups based on their incomes and available leisure time. Another recent study has been performed by Keshari et al. in [35] to understand the effectiveness of advertising appeals on different gender and age groups based on how the consumers respond to these advertisements.

1.3 Dissertation Outline

The rest of the report is organized as follows. In the next section, we have surveyed some related works in sentiment analysis. In Section 3, the methodologies implemented on the dataset have been discussed, along with a comparison of these machine learning based approaches with dictionary based approach. Section 4, we first describe the dataset that we have collected and then the experimental results have been discussed. Next, in Section 5 the work has been concluded along with discussion of some future improvements. Finally the report is concluded with some additional work that consists of a survey paper on EEG and Neuromarketing.

Chapter 2 LITERATURE REVIEW

2.1 Review of Previous Work

In this section, we discuss some of the recent works of sentiment analysis as the research continues in multiple domains where the researchers try to find a better approach to predict the sentiment polarity. Twitter and facebook has been the most consistent data sources as people express their opinion about each and every topic on these networking sites that greatly help in understanding public sentiment. Appel et al. [6] have used twitter sentiment and movie review datasets to implement a hybrid approach based on Ambiguity Management, Semantic Rules, Sentiment Lexicon, Linguistic Variables and Negation Handling. The authors have compared this proposed hybrid system's results with the standard supervised algorithms such as Naive Bayes and Maximum Entropy and found out that the proposed system achieves higher precision score and accuracy than the standard methods. Similarly, Zainuddin et al. [83] have used twitter dataset of aspect-based sentiment analysis to perform a fine-grained analysis. They have proposed a hybrid approach using a feature selection method that performs better than the standard methods.

Blogs have been a relevant source of data in sentiment analysis with posts containing reviews and the comments on these blogs that can be used for analysis such as Fan et al. [24] have analyzed blog text so as to improve the quality of advertisements in the blogs that are more relevant to the user. To find the blogger's overall emotions towards any particular topic, Kuo et al. [44] create a Social Opinion Graph as generally every blogger is somewhat influenced by its social circle. So their social interactions can be used to find the overall sentiment orientation of the blogger. Li et al. [50] have used opinions expressed on the web such as blogs, reviews and comments to design a new technique to further enhance the accuracy of clustering based approaches and the approach proves to more suitable in noticing neutral opinions. In [5], Ali et al. have used the web information to propose a system that reforms the queries that user's feed into the search engine to extract the target hotel that is required by the user along with it's customer reviews.

Apart from using products, movie, restaurants or book reviews for sentiment analysis, researchers have also focused on analyzing sentiment in other languages than English. Pak et al.[61] have proposed a technique that works quite well for other languages as well, though they have not tested their algorithm on multilingual data which is performed in [18], where the author has implemented a methodology to find sentiment polarity within a multilingual framework and the testing is performed using movie reviews in German language collected from amazon. Similarly, Zhou et al. [84] have translated Chinese reviews to English language and then used English language corpus to perform sentiment analysis on these translated reviews. The authors have also presented separate analysis of English translated and original Chinese reviews and compared their results to establish that translated reviews outperform original reviews and finally to further enhance the performance, the author has combined the two analysis. Another study on Chinese public figures has been performed in [15] to analyze the opinion polling of public figures.

Chapter 3 SENTIMENT ANALYSIS METHODOLOGIES

The basic framework of the study is shown in the Fig. 3.1 where initially the dataset is used to extract data into two sets on basis of age and gender and then divided into categories based on the specific age and gender, then each particular data group is divided in training data and testing reviews.

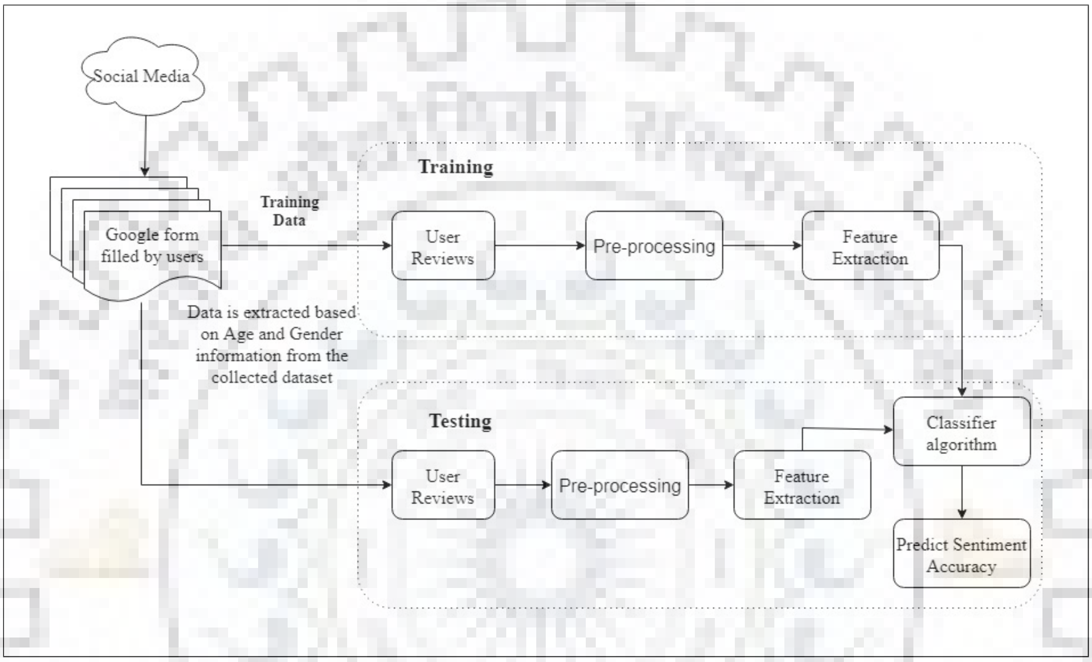

Figure 3.1: Flow Diagram representing the steps taken for sentiment analysis where the classifier algorithm is implemented at the end of training after the data preprocessing and feature extraction and it used in testing step to produce the final results. The user reviews need to go through pre-processing and feature extraction in the testing phase as well before being passed on to the classifier algorithm.

The reviews are preprocessed, so as to remove the unnecessary information from the reviews that has no effect on the polarity of the sentence. Then, the feature extraction step is performed as explained in the further sections. Finally, the classifier algorithm predicts the label which when compared to the ground truth gives the accuracy of the classifier. We have collected data regarding people's preference in books (hard bound, kindle ebooks or audio books) along with their age and gender information. We implement different algorithms for sentiment analysis on each set of data separately and the results are then compared to identify the respective differences between the groups. Also, a dictionary based approach called Vader sentiment analysis has been implemented on the data according the distribution already done.

Table 3.1: Pre-processing steps that have been performed on the user reviews for doing data cleansing and removing uninformative parts that has no effect on the sentiment score of the sentence.

S.No.	Description of noisy and uninformative parts in reviews
1.	Removing punctuations, numbers and symbols since they do not add any substantial meaning to the sentence that may affect it's sentiment score.
2.	Removing stop words as they make no impact on the sentiment score of the expressed opinion.
3.	Replacing the acronyms of a word with the actual word.
4.	Transforming the text to lowercase.
5.	Replacing emoticons with the sentiment that the emoticon expresses.
6.	Tokenize the review.

3.1 Preprocessing and Feature Extraction

3.1.1 Preprocessing

Data preprocessing is a very important step as it involves converting unstructured data obtained from different sources to a structured, more understandable and uniform format. The raw data contains multiple errors that may lead to inaccuracies during the result [36]. To avoid that we perform data cleansing through the steps, briefed in 3.1.

After preprocessing the dataset, we try to transform the complete dataset to a concise set of features. Through this, the redundant features in the text are eliminated and we extract the most distinctive aspects of the processed dataset. These features are then used in the further step to identify the sentiment of the sentence as positive or negative. In case of deep learning techniques, feature extraction focuses on processing the text and converting the key features to feature vectors which are then further used for classification tasks. One of the limitation of this model is that it does not preserve the ordering of words appearing in the sentence which in some cases, change the basic meaning of the sentence hence affecting it's polarity.

3.1.2 **Feature Extraction**

Next we discuss two feature extraction methods that we have used in different machine learning classifiers. Bag of words feature extraction is used in NB, ME and SVM methods while word2vec creates a feature vector using either Continuous bag of words or Skip gram model which is further used in LSTM and CNN. The methods are explained below.

3.1.2.1 **Bag-of-Words**

A feature extraction method, Bag of words is a very flexible and simple model used in Natural Language Processing. As the name suggests, the model keeps a track of number of occurrences, also called term frequency of every word that appears in the sentence. Also, a specific subjectivity score is assigned to each word of the sentence. The score for each word is added up to find the total score. Depending upon this total score, the polarity of each sentence is decided.

3.1.2.2 **Word2Vec**

Word2Vec model is used for forming word embeddings. Created by Tomas Mikolov at Google, it is a two-layer neural network that is trained to process text. It takes the text dataset as an input and then outputs a set of vectors [78]. Word2Vec is a combination of two techniques i.e. Skip-gram model and Continuous bag of words (CBOW) model. This model is very useful as it detects similarities of words in its vector form rather than textual format. These similarities are detected on the basis of word's meaning guessed through its past appearances and its association with other words.

3.2 Dictionary Based Classifier

Vader Sentiment Analysis [27] is a dictionary based approach that uses word matching for sentiment classification. In dictionary based approach, each word present in the sentence is assigned a score as per the meaning of that word in the dictionary. A final cumulative score is calculated of the sentence that represents whether the sentence is positive or negative. The cumulative score for each sentence in the dataset is combined and an average score for the whole document signifies the polarity of the document. To compare it with the other machine learning approaches, we convert the average score to accuracy by dividing the score of the whole document by the total number of reviews in that particular data set. Vader focuses on the words used in the sentence and then assigns polarity to each word based on whether is perceived as positive or negative usually. Though being a dictionary based approach, it does not require training of a model as in machine learning based classifiers.

3.3 Machine Learning Based Classifiers

In machine learning based approaches, the computer algorithm trains itself from the data input given to the algorithm. We have used 5 algorithms to determine the sentiment accuracy, these algorithms are explained further.

3.3.1 Naive Bayes

A supervised algorithm, the Naive Bayes method is the most frequently used method for sentiment analysis owing to its simplistic approach. This is a probabilistic model that is based on the Bag-of-words module, that is, to store only the frequencies of each word and ignore their positioning with respect to each other. By using Bayes Theorem, it estimates the probability that a feature set will belong to a particular predefined label. Naive Bayes classification model, based on the distribution of words present in the document or sentence, it computes the posterior probability that this document or sentence will belong to a particular class. The probability is heavily based on the distribution and frequency of the words rather than their positioning with respect to each other.

$$P(label|features) = \frac{P(label) * P(features|label)}{P(features)} \tag{3.1}$$

where P(label|features) determines the probability that a feature set will belong to a particular label. P(label) is the prior estimate of the label. P(features|label) is the probability that the given feature set belongs to this particular label and P(features) is the prior estimate that this given feature set occurred.

3.3.2 Maximum Entropy

Another probabilistic classifier, Maximum Entropy (MaxEnt) belongs to the class of exponential models. Due to the simplistic approach in Naive Bayes where we assume all the features are independent of each other just on basis of their frequency which is never true as when we write a sentence, its polarity is more based on the positioning of words rather than their frequencies. So, MaxEnt does not assume that all the features are independent of each other. It is based on the Principle of Maximum Entropy where from all the models, we pick the one that has the largest entropy. The MaxEnt classifier uses encoding to convert the feature sets into vectors. Then for computation of most likely label for each feature set, we combine the calculated weight for each feature [33].

3.3.3 Support Vector Machine

Another model with supervised learning, Support Vector Networks can be used for multiple machine learning problems such as regression and classification etc. The main principle that works behind SVM is finding that particular linear classifier that separates all the classes in the search space in the best possible manner. There can be multiple linear classifiers that divide the search plane in a particular manner but we have to identify the hyperplane that maximizes the margin of separation between the linear classes. After identifying this plane, we map the new examples or the data in the test cases in the same search plane and predict the class to which the data example has more probability of belonging [57]. SVMs can also be used to classify non-linear data using kernel function that maps the non-linear dataset into another surface where the data can be linearly separated using a hyperplane.

3.3.4 Long Short Term Memory

Recurrent Neural Networks focus on the issue of considering the past information so as to understand the meaning of current and next words. This is more similar to human thinking as compared to previous methods as humans also keep the past data in mind while making an image of the current and future data. RNNs contain loops within them so as to keep the past information to better understand the future information.LSTM network is a type of RNN that is capable of handling long term dependencies as otherwise it was difficult for RNNs to connect multiple long term dependencies [32].

First introduced by Hochreiter and Schmidhuber in 1997, LSTMs have gone through multiple changes throughout the years. LSTM also solves other problems occurring in Recurrent Neural Networks such as vanishing and exploding gradient. LSTM solves the problem of long term dependencies by introducing a cell inside the network that can also be called a memory unit that passes through each cell and contains the previously loaded information making information flow relatively easy. This way each cell can use prior information if required and can make changes by adding or removing appropriate information regulating this information exchange through gates. There are three gates that handle and control the flow of information to maintain the cell state.

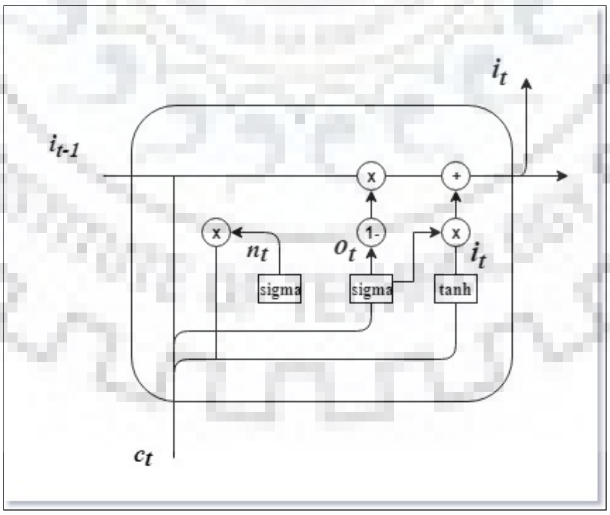

Figure 3.2: Long Short Term Memory cell, the data flow is from left to right with c_t being the current cell input and i_{t-1} being the output from the previous cell, both these values are concatenated based on the parameters giving the output value as i_t

The steps of LSTM are defined as: The first step is to decide the information that is going to be deleted from the memory cell. This decision is executed by a sigmoid layer after looking at prior information i_{t-1} and current input c_t and outputs a number between 0 and 1 that determined what amount of information needs to be retained based on weight W_o where o_t represents the output of the current cell

$$o_t = \sigma(W_o * [i_{t-1}, c_t] + b_o) \tag{3.2}$$

Next, it decides the new information that is to be updated into the memory cell.It is done through two steps, a sigmoid layer to decide the values to update and a $tanh$ layer to create a vector of new values, $\tilde{V}_t$ that is to be included in the current state information which will be done in the further step. An LSTM cell is shown in Fig. 3.2.

$$n_t = \sigma(W_n * [i_{t-1}, c_t] + b_n) \tag{3.3}$$

$$\tilde{V}_t = tanh(W_V * [i_{t-1}, c_t] + b_V) \tag{3.4}$$

Now this information is to updated into the next cell V_t by multiplying the old state with o_t.

$$V_t = o_t * V_{t-1} + n_t * \tilde{V}_t \tag{3.5}$$

In the last step, we again implement a sigmoid layer to find which information is to be updated and the $tanh$ layer to update the required parts.

$$f_t = \sigma(W_f * [i_{t-1}, c_t] + b_f) \tag{3.6}$$

$$i_t = f_t * tanh(V_t) \tag{3.7}$$

This output from the cell serves as prior information for the next cell to find out its cell state.

3.3.5 Convolution Neural Network

Convolution neural network was originally developed for computer vision and its applications, it makes use of local features of the image on which multiple layers with convolving features can be implemented [45]. To implement CNN on the textual reviews, we train a simple CNN model [41] with a single layer on top of the features extracted from the sentences using the word2vec model. Next, there is Convolution layer where we slide multiple filters of different sizes over the word embeddings. Max-pooling layer follows this by convolving the results of previous layer into one long feature vector. Finally after dropout regularization, we use softmax layer to classify the result. This network is shown in Fig. 3.3

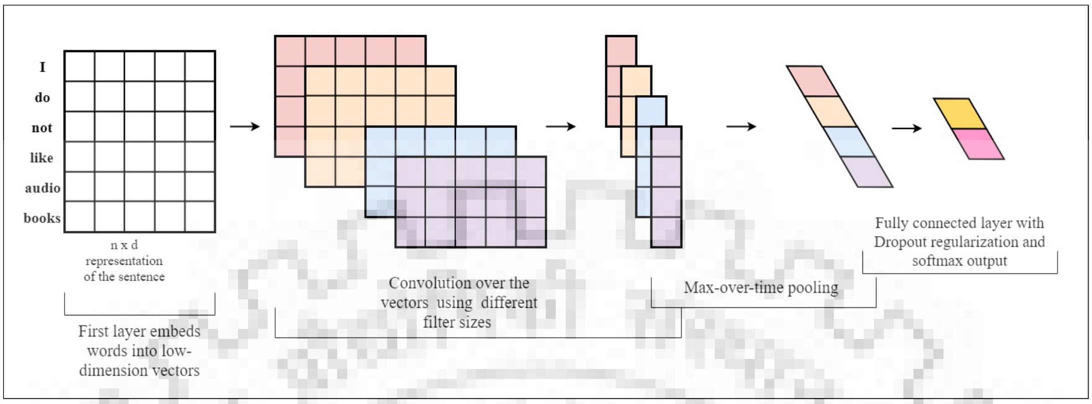

Figure 3.3: First layers of the model form low-dimensional vectors from the sentence words. The convolution is done by the next layer, using multiple filter sizes such as sliding over 3 or 4 words at a time. Next, the result is max-pooled into a long feature vector and the final results is given using a softmax layer after adding dropout regularization.

Chapter 4 EXPERIMENTATION AND RESULTS

Dataset description is done in the first part of this section. We have explained the process of data collection and its further processing that we have done in our experiment. The next part presents an analysis of the results obtained from the feature extraction methods and different classifiers that we have implemented, as discussed in the previous section.

4.1 Dataset Description

One of the most crucial part of this study is data collection. Generally, dataset for sentiment analysis are easily available on the internet which can not be used here as along with the expressed opinion, we also require the reviewer's age and gender information. This information is not present in any of the available sentiment datasets, so we create a new dataset that contains all the required information. Also, micro-blogging sites that usually are the biggest source of data like twitter and facebook containing comments, posts and tweets can not be used here as twitter does not have accurate information in this regard while facebook and other sites like amazon, goodreads and imdb do not divulge their user's personal information due to privacy concerns.

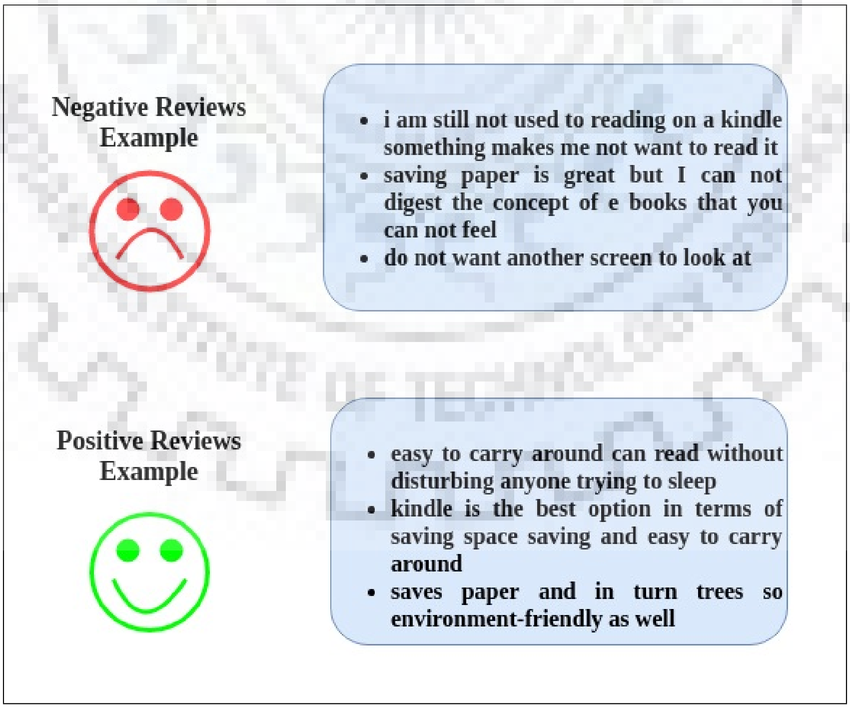

Figure 4.1: Example of the recorded reviews divided into positive and negative reviews.

We collect the data from people using a Google form who filled the form and stated the age and gender information voluntarily. We circulated this Google form in different facebook Groups while requesting the group users to fill the form. The Google form recorded the user's opinion about the types of books that he/she prefers along with the gender (male or female) and the specific age group (Above 50, 35 - 50, 21 - 34, Below 20) they belonged to. We have received nearly 900 reviews containing some positive and some negative reviews on whether they like a book reading medium or not. An example of the positive and negative responses has been shown in Fig. 4.1. Also, the ground truth of each review has been collected from the reviewer as well about whether he/she expresses his/her opinion to be positive or negative.

Next, from the recorded data we extract the data into separate groups, first on the basis of gender of the person giving the opinions. Two categories of male and female data are formed and then we divide the whole data into four groups with respect to the age group that the reviewer belonged to. We have created four categories in the age group as in Below 20, 21-34, 35-50 and lastly, the Above 50 age group. Finally in the next section, the accuracies are compared with each other and with the accuracy of combined group of data that contains mixed reviews both from different age and gender groups.

4.2 Result Analysis

Here, we present the result analysis in this section as the effect of age and gender. We have shown the result of all the machine learning classifiers and dictionary based classifier, Vader, on basis of dataset that is distributed using age and gender information. We evaluate the results using accuracy as a measure which is estimated on the basis of True Positives, True Negatives, False Positives and False Negatives. These terms are defined below, with the example that we wish to create a classifier that selects all positive reviews from the dataset.

True Positives: True positives are the correctly predicted positive values. E.g. Classifier predicts actual positive reviews as positive.

True Negatives: True negatives are the correctly predicted negative values. E.g. Classifier predicts actual negative reviews as negative.

False Positives: False positives are the cases when the actual class value and predicted value contradict each other. E.g. Classifier predicts actual negative reviews as positive.

False Negatives: Similar to false positives, these values are predicted incorrectly. E.g. Actual positive reviews that the classifier predicts as negative.

Based on these parameters, we find other values that give us an estimate of how well a classifier works.

Accuracy: Accuracy is a simple ratio of the correctly predicted values and the total values present for observation. E.g. finding the ratio of correctly predicted results with all of the observations gives us the percentage of correctly predicted results.

$$Accuracy = \frac{TruePositives + TrueNegatives}{TotalObservations} \tag{4.1}$$

where Total Observations = True Positives + False Positives + True Negatives + False Negatives

4.2.1 Effect of Age

As discussed previously, the extracted dataset based on age is divided into 4 sections on the basis of age of the person giving the opinion as one group with age below 20, second with age from 21 to 34, from 35 to 50 and last one with age above 50. So, a total 4 sections are created containing positive and negative responses from people of that particular age group. Another group containing reviews from all the age groups is formed so as to compare its results to the other age group results.

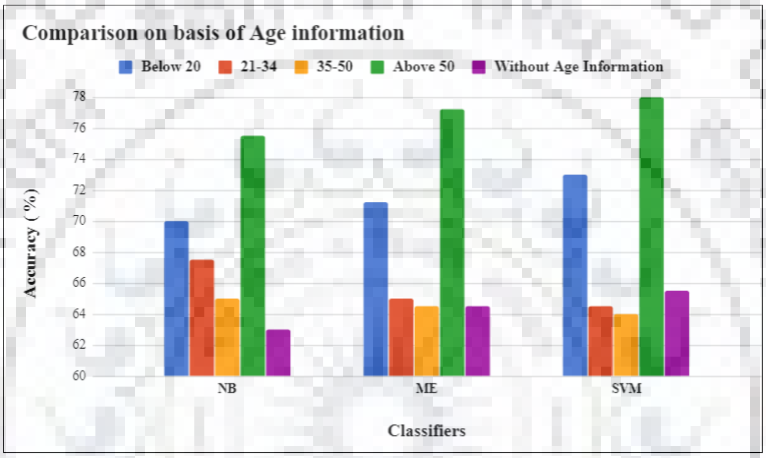

Figure 4.2: Comparison on basis of Age between different Machine Learning classifiers using Bag-of-words feature extraction method

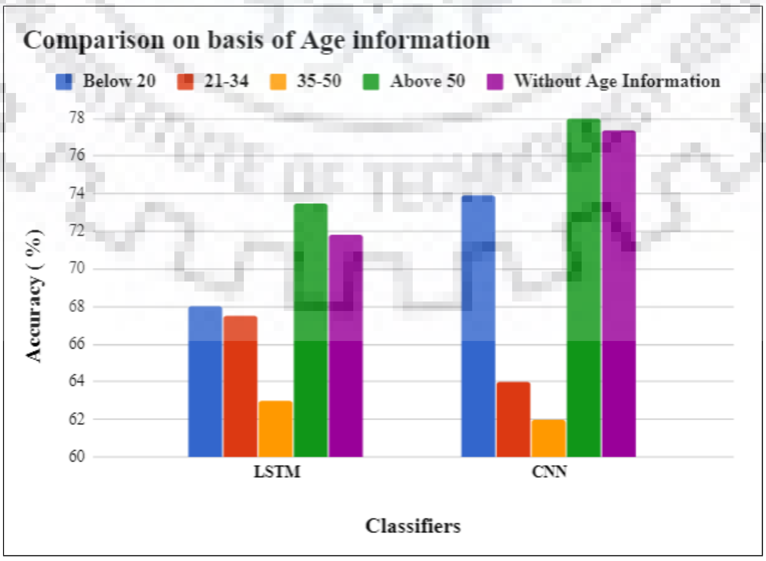

Figure 4.3: Comparison on basis of Age between different Machine Learning classifiers using word2Vec feature extraction method

Pre-processing of all the reviews is performed individually by removing the punctuations, symbols and the stop words from the user reviews. Feature extraction methods are implemented on this pre-processed data. Bag-of-words model is used to create feature vector which is then used in classifiers Naive Bayes, Maximum Entropy and Support Vector Machine while low dimensional vectors are formed from sentences using word2vec model which are then used in LSTM and CNN methods.

Dictionary based Vader classifier is also implemented on the pre-processed data. After these approaches are implemented on the separated groups of data individually, the results are recorded. For evaluating the results of Vader sentiment analysis on the measure of accuracy, we have implemented Vader on the textual reviews to find the number of positive and negative reviews from the total amount of reviews.

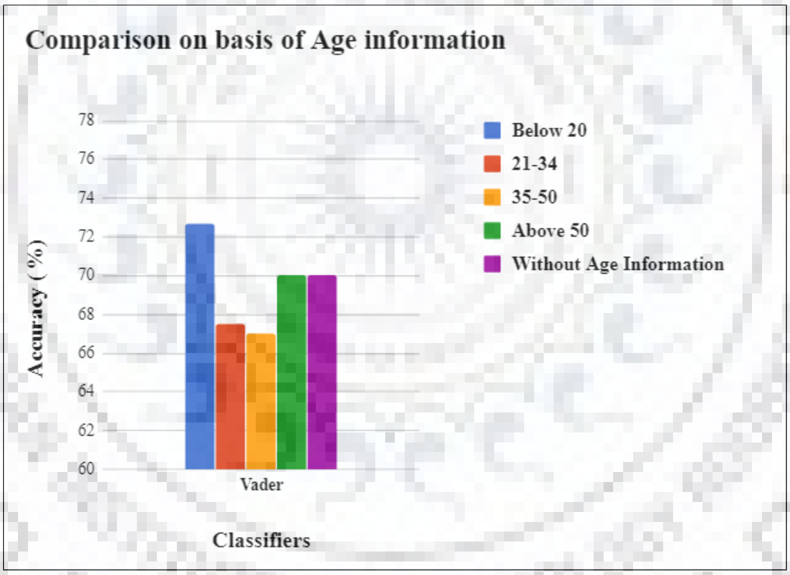

Figure 4.4: Comparison on basis of Age using Dictionary based classifier technique

For accuracy of the multiple sections, we divide the number of positive reviews that has been predicted correctly and the number of negative reviews predicted correctly. Then after finding the true positives and true negatives, we divide the sum of these values from the total number of observations i.e. the total number of reviews that we have fro that particular section.

As seen from the above images, the 'Above 50' age group performs better as compared to all other age groups in all the classifiers with the highest accuracy of 78% in CNN classifier.

’Below 20’ age group has better accuracy compared to th other two middle age groups where the age group ’21 - 34’ performs better than the other age group in all instances, even though the difference between these two age groups is not considerable. Better performance of the eldest age groups shows that the sentiment analysis approaches are able to predict the sentiment in this age group more easily as compared to others. The section of data without any age information performs better in LSTM and CNN as compared to other machine learning approaches where it performs worse than the sections with age information.

4.2.2 Effect of Gender

Similar to the above distribution of data on basis of age, here we divide the whole dataset into 2 sections as female and male data containing their positive and negative reviews about their reading device. Preprocessing, feature extraction and the classifiers are implemented on these data section similarly as explained in the above section. The results are represented below

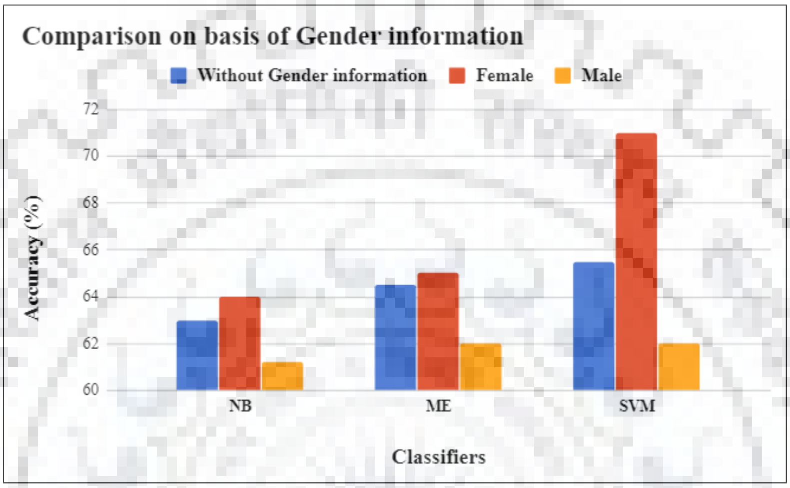

Figure 4.5: Comparison on basis of Gender between different Machine Learning classifiers using Bag-of-words feature extraction method

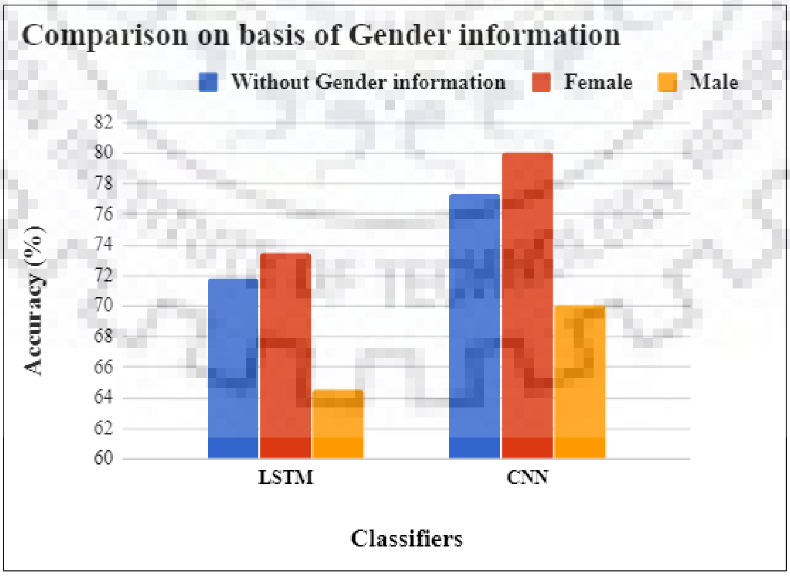

Figure 4.6: Comparison on basis of Gender between different Machine Learning classifiers using word2Vec feature extraction method

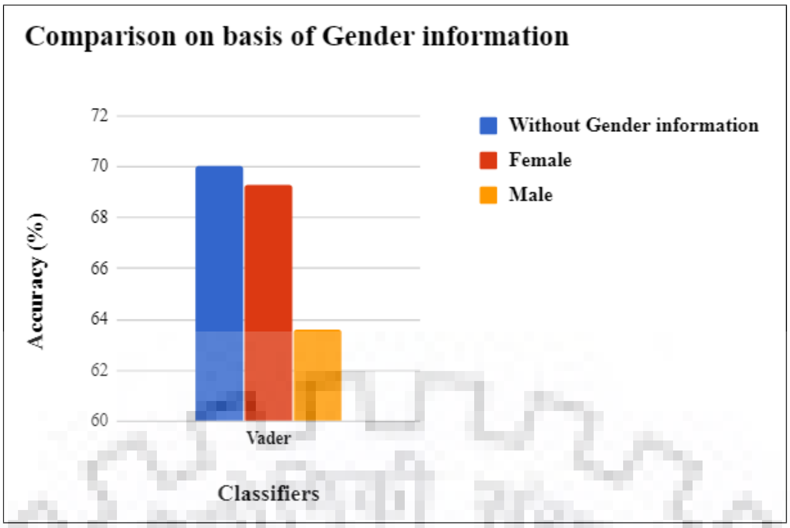

Figure 4.7: Comparison on basis of Gender using Dictionary based classifier technique

It can be clearly seen that female data generates better accuracy as compared to the data without gender information and the male data. Female data has the best accuracy in CNN classifier of 80% which is better than the other classifiers. This result aligns with the psychological studies that females express their opinion better as compared to their male counterparts and hence the sentiment in female data is easier to predict, hence giving a better accuracy. The same pattern of female data having the better accuracy can be observed in all the machine learning approaches and also male data has the least accuracy when compared to the other two data sections.

4.2.3 Combined Effect of Age and Gender

To understand the combined effect of age and gender we divide the whole dataset into multiple sections on the basis of their age and gender.

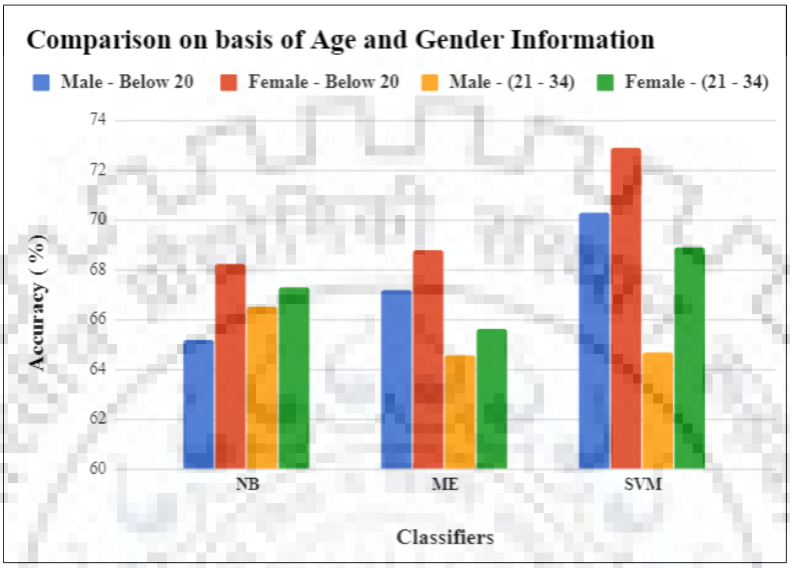

Figure 4.8: Comparison on basis of Age and Gender between different Machine Learning classifiers

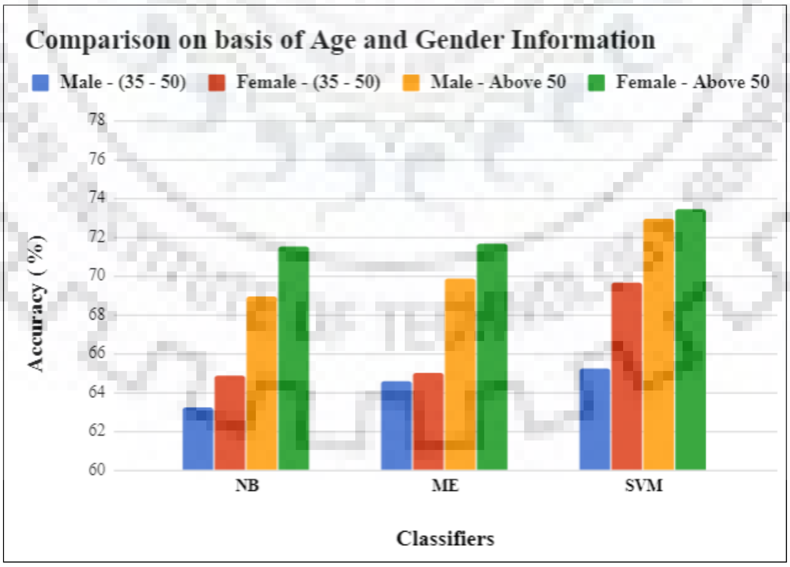

Figure 4.9: Comparison on basis of Age and Gender between different Machine Learning classifiers

For each of the age data section, we further divide it according to whether the review has been given by a female or male user. After dividing these data sections we perform the steps of preprocessing, feature extraction after which the classifiers are implemented on these data section similarly as explained in the above section. The results are represented above.// It can be clearly seen that even in this case, female data generates better accuracy as compared to the data without gender information and the male data. In Fig. 4.8 we can see that the Age group of Below 20 females performs better than all the other categories for all the machine learning approaches. Where as in the second figure, Above 50 age group performs better than all other age groups and specifically female dataset has the best accuracy amongst the other age and gender groups.

Chapter 5 CONCLUSIONS AND FUTURE WORK

In this paper, we have implemented multiple sentiment analysis techniques on the dataset collected from social media along with the user's age and gender information which is then used to bifurcate the data into multiple sections on basis of age and gender to analyze the impact of age and gender on the way the user expresses his/her opinion. In this, we have implemented machine learning based classifiers such as NB, ME, SVM, LSTM, CNN and dictionary based approach, Vader sentiment analysis. We have recorded data from nearly 900 facebook users, males and females ranging over different age groups where they express their opinion (positive or negative) on their reading devices along with their age and gender information. Female data has recorded the best accuracy while 'Age 50' age group has the better accuracy as compared to all other age groups. The results can be further improved by collecting more data for both male and female and different age groups and consider different levels of reviews from extreme positive to neutral to extreme negative.

Future work also includes exploration of reviews in audio and visual format [73] to detect emotions from the way of speech and facial expressions of the user as that will provide better result since it is not always possible to detect the emotions through textual reviews because of use of sarcasm, contradictions or frequent change of topic within the same sentence.

Chapter 6 ADDITIONAL WORK

6.1 A Survey on Neuromarketing using EEG Signals

6.1.1 Abstract

Neuromarketing is the application of neuroscience to understand consumer's preference towards marketing. It studies how the change in the market stimulus presentation affect the reaction of the human brain. Neuromarketing is considered as an emerging area of research. Promoters invest around 400 billion dollars every year for advertisement. Therefore, it is required to be performed efficiently by targeting focused market. Traditional approaches consider only the later feedback of the user but not at the time of purchase. The response during purchase provides the exact snapshot which cannot be altered. Various techniques can be used to learn about the decision making of the consumers. These may include brain imaging techniques (fMRI, EEG, SST, TMS) and various biometric sensors. The use of EEG in neuromarketing field is highly promising. EEG detects the sequential changes of brain activity without time delay, which is very important to know both the unconscious reaction and sensory reaction of the customer. Various types of EEG devices are available in the market. Each one has its advantages and disadvantages. Wireless EPOC+ device is highly used nowadays by various researchers. Researchers have conducted the experiment on different age group people showing different categories of products by using different EEG devices. But the neuromarketing field of research is still taken as research area with a warning from consumer protection groups that there should not be any intentional neurological effect of the advertisement on consumers. This paper discusses about the various neuromarketing strategies, what type of information can be gathered using these strategies, how the marketing stimulus is presented to consumers, what effect it has caused to the consumer in terms of pleasantness and memorization, available machine learning techniques used in this field, various challenges faced, different ethics that must be taken care of and the applications of neuromarketing. It has been suggested that neuromarketing has the capability to improve the effectiveness of advertisements on customers.

6.1.2 Introduction

Neuropsychology studies the relationship between the brain activity of consumer and his behavior. It determines the effectiveness of a particular product to promote sale by linking the choices of consumer and his decision-making process with the marketing research. This is referred as neuromarketing. Neuromarketing is a field to understand consumers' likeliness and choices by applying the neuroscience principles to consumers' response for the marketing stimuli. It is an emerging field which relates all, neuroscience, psychology and marketing with each other [8]. Neuromarketing not only focuses on impact of small change in market stimuli on the sales but also explains how changes in the stimuli presentation affect the reaction of brain which is related to consumer's choices. Promoters invest around 400 billion dollars every year for advertisement [56]. Therefore, it is required to be done efficiently by targeting the correct market.

Traditional research methods focus only on the attitude of consumer towards products by asking the customers to fill the questionnaires which is not exactly related to the actual state of mind at the time of purchase[2]. That is an important factor for failure of various newly launched products in the market. Neuromarketing focuses on the latter by considering the brain signals at the time of purchase. Fig. 6.1 shows how the neuromarketing process workflow goes. Researchers use various techniques like functional Magnetic Resonance Imaging (fMRI), Electroencephalography (EEG), Steady State Topography (SST) and Transcranial Magnetic Stimulation (TMS) to measure changes in brain activity and biometric sensors to measure changes in physical state of customers like respiratory rate, heart rate, facial expression, skin response for emotion analysis and eye tracking for focal attention analysis, to figure out why and how customers make the decisions about the products and which brain areas are responsible for that decision [2].

Human brain is made up of neurons and those neurons communicate with each other via electrical impulses [37]. EEG signal measurement is a practical way to detect the sequential changes of brain activity without time delay, which is very important to know both the unconscious reaction and sensory reaction of the customer. The neuromarketing field overcomes the challenge of heterogeneity within and across consumer groups which affects consumer preferences and decisions. This heterogeneity may be based on age, gender, various biological factors like hormones and genes, and various physiological factors.

Using neuromarketing, marketers can choose the best strategies like celebrity endorsement or linking with social cause for their product promotion and avoid wastage on inefficient campaign or failed celebrity endorsements. In literature, researchers have focused on different marketing

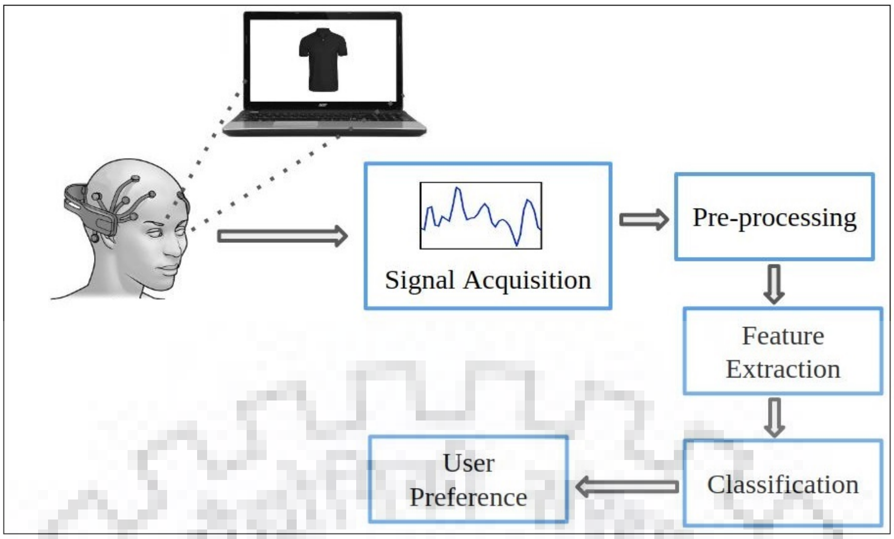

Figure 6.1: The process of neuromarketing where EEG response towards a product is recorded and processed to get the his/her preference.

parameters such as brand perception [52, 55], brand evaluation decision [21, 22, 68], brand relationships [3, 66], brand preferences [11, 77, 81], pricing [62], product packaging [67, 69], brand naming [31], green consumption [46], store illumination [10], advertisement [72, 76], and new product development [7], etc.

In this paper, we have focused on neuromarketing using EEG because EEG devices are relatively inexpensive, wireless, robust, can be connected with mobile devices, can be used outside the laboratory and are comfortably wearable by users, making this EEG technology of great interest for the evaluating the marketing stimuli. Also, we discuss the effect it has caused to the consumer in terms of pleasantness and memorization, available machine learning techniques used in this field, various challenges faced, different ethics that must be taken care of and the applications of neuromarketing.

6.1.3 Problem Definition

According to [48], the definition of neuromarketing in scientific literature is given as the study and analysis of human behavior relating to market exchange. Neuromarketing is another application of neuroimaging technology that emerged in mid 1980s, along with different fields such as neuropsychology, neurophysiology, neuroethology and neuroanatomy. Neuromarketing as a term was coined in 2002 and has gained tremendous popularity in the last few years with researchers focusing on consumer behavior on how they feel when exposed to certain advertisement or how and why they react the way they do for particular products. As per [56] one of the reason behind increasing neuromarketing research is that it does not require conscious participation of the consumer.

Neuromarketing and consumer neuroscience are generally used interchangeably as both the terms refer to intersection of marketing, psychology and neuroscience. Consumer neuroscience is more focused on the academic research while neuromarketing refers to curiosity in neurophysiological tools [2] like skin conductance, eye tracking, EEG, fMRI and Event Related Potential (ERP), where the researchers conduct commercial market research using these tools [63].

6.1.4 Computational Approaches for Neuromarketing

This section contains the detailed analysis of the techniques used for preprocessing, feature extraction and classification of EEG signals in the recent research work done in the field of neuromarketing using EEG. The Tables 6.4, 6.5 and 6.6 show the related work done in the field of neuromarketing.

6.1.4.1 Pre-processing

Various sources of artifacts like muscular activities, blinking of eyes, and electrical power line noise, etc. come into picture while capturing EEG signals [4]. These artifacts badly affect the useful features in the original signal, so they are required to be separated. Different researchers have used different pre-processing techniques as per their requirements. Table 6.1 shows different filters used in the preprocessing step by various researchers in the field of neuromarketing.

6.1.4.2 Feature Extraction

EEG signals are time domain signals in unprocessed form, so they are first transformed to frequency domain, otherwise they require highly trained professionals for their investigation. Different researchers have extracted different features for further evaluation as per their requirements. To convert the EEG signals from time domain to frequency domain, researchers have used various techniques and got the frequency band spectrum as Gamma (32-100 Hz), Beta (13-22 Hz), Alpha (8-13 Hz), Theta (4-8 Hz) and Delta (1-4 Hz). Yadava et al. [79] have applied DB4 (Daubechies 4) wavelet decomposition technique where each one of the resultant five

Table 6.1: Preprocessing filters used in the field of neuromarketing

Filter	Details	References
Savitzky-Golay (S-Golay) filter	frame span = 5 with a quadratic polynomial	Yadava et al. [79]
Moving-Average filter	average number of points = 5	Gauba et al. [25]
Notch filter	Frequency = 50 Hz in [58, 71] and 60 Hz in [47]	Teo et al. [71], Murugappan et al. [58], Lee et al. [46]
Surface Laplacian filter	–	Murugappan et al. [58]
Butterworth bandpass filter	Order = 4 with a cut off frequency between 0.5 Hz and 60 Hz	Murugappan et al. [58], Gupta et al. [30]
Elliptical bandpass filter	Order = 10	Rakshit et al. [65]
Common average referencing spatial filter	–	Rakshit et al. [65]
Bandpass filter	cut-off frequency between 0.01 and 30 Hz in [9], 0.5 Hz to 40 Hz in [38], 4 to 50 Hz in [46], 0.1-45 Hz in [40]	Bastiaansen et al [9], Khushaba et al. [38], Lee et al. [46], Khushaba et al. [40],
FIR1 bandpass filter	100th degree cut off frequency 1 and 45 Hz	Yilmaz et al. [81]
ICA(Independent Component Analysis)	–	Gauba et al. [25], Kawasaki et al. [34], Ohme et al. [60] and Khushaba et al. [40]
PCA(Principal Component Analysis)	–	Khushaba et al. [38]

coefficients corresponds to a frequency band whereas Kawasaki et al. [34] have used wavelet transformation by using Morlet wavelets with a Gaussian shape. The researchers in [38] have used FFT and logarithmic transformation as the extracted power feature of the EEG changes less linearly in the normal scale than in the logarithmic scale whereas in [19], they have used FFT with 50% overlap window to improve lobes fluctuations. In [46, 58, 60], the researchers have also used FFT. In [40], FFT with zero padding has been used. In [71], STFT technique and in [65], DFT technique has been used. Table 6.2 shows various feature extraction techniques used by various researchers in neuromarketing.

Different statistical features have been extracted by researchers. Yadava et al. [79] have

Table 6.2: Feature Extraction Techniques used in the field of neuromarketing

Feature Extraction Techniques	References
DB4 (Daubechies 4) wavelet decomposition technique	Yadava et al. [79]
Wavelet transformation by using Morlet wavelets with a Gaussian shape	Kawasaki et al. [34]
FFT	Khushaba et al. [38], Djamal et al. [19] Lee et al. [46], Ohme et al. [60], Murugappan et al. [58], Khushaba et al. [40]
STFT	Rakshit et al. [65]
DFT	Teo et al. [71]

extracted Mean (M), Standard Deviation (SD), Root-Mean-Square (RMS) and Energy (EN) as statistical features whereas in [25], just the statistical mean for all 14 electrode channels has been extracted. Rakshit et al. [65] have extracted features in such a normalized way that its mean is zero and variance is unity, using welch method for power spectral density estimate whereas in [81] power spectral density using the Burg method has been used. In [9, 34], the authors have taken the average mean across participants. Guo et al. [29] have extracted the averaged relative power and then generated the ratings accordingly. Khushaba et al. [38] have used spectral moments extracted by power spectral analysis as features. In [8, 46, 60, 75], the power spectral density has been extracted . Khushaba et al. [40] have extracted Moving-average power spectral density feature with normalized averaged power spectrum on logarithmic scale. Murugappan et al. [58] have extracted other statistical features such as, Spectral Centroid and Spectral Energy with Power Spectrum Density. Table 6.3 shows the extracted features used by various researchers in neuromarketing.

6.1.4.3 Classification and Results

Research work in neuromarketing is focused around the study of customer's preference of images, video advertisements or color visuals and subsequent brain activations in accordance with the preference. In this section, we have listed different classification techniques being used in recent research papers and brain activations for frontal, parietal regions. Frontal region brain activations has been investigated in [60] in which the author has used mean classifier on the alpha power in ipsilateral electrodes. They have aimed to study the reaction of frontal cortex activation to different TV advertisements. The actual results of dominant reactions in only seen

Table 6.3: Extracted Features used in the field of neuromarketing

Extracted Features	References
Statistical Mean	Yadava et al. [79], Gauba et al. [25], Bastiaansen et al. [9], Kawasaki et al. [34]
Standard Deviation	Yadava et al. [79]
Root-Mean-Square	Yadava et al. [79]
Relative Power	Guo et al. [29]
Energy	Yadava et al. [79]
Power Spectral Density	Rakshit et al. [65], Yilmaz et al. [81],Balconi et al. [8], Lee et al. [46], Ohme et al. [60], Vecchiato et al. [75],Khushaba et al. [38], Khushaba et al. [40]
Spectral Centroid and Spectral Energy	Murugappan et al. [58]

Table 6.4: Related work done in the field of neuromarketing considering "Product Images" as dataset

Author, Year	Approach Used	Dataset	No. of subjects	Channels
Khushaba et al. [39], 2012	Bandpass filter, PCA, FFT, Mutual Information Classifier	Choice sets of images that vary in color and pattern	18 participants, Aged 25 to 65 years	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4)
Khushaba et al. [38], 2012	Bandpass filter, ICA and DWT for denoising, FFT with zero padding, Mutual Information Classifier	Used objects pictures to choose as screen background	18 Participants, Aged between 25 and 65 years	14 channels(AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, 01, 02)
Yilmaz et al. [82], 2013	FIR1 and bandpass filter, Logistic regression, GLM	Powerpoint slide of images containing women's shoes in different styles and colors	15 participants, No male and 15 females, Aged 20 to 40	21 channels; 19 of them used for like/dislike analysis(Fp1, Fp2, A1, A2, O1, O2, C3, Cz, C4, F3, Fz, F4, F7, F8, T3, T4, T5, T6, P3, Pz, P4)
Bastiaansen et al. [9], 2016	Bandpass filter, automatic artifacts removal	photos of the tourist destination Bruges	32 participants, 8 male and 24 females, Aged 18 to 26	61 electrodes
Yadava et al. [79], 2017	S-Golay filter, DB4 wavelet decomposition, HMM Classifier	14 different product images with 3 varities of each	40 participants, 25 male and 15 females, Aged 18 to 38	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4)

in one of the selected advertisements as compared to the expected left hemispheric dominance in accordance with the theoretical methods. The author has presented the detailed analysis of which advertisement's emotional content bought forth higher left frontal activation. An interesting and distinct concept is discussed in [1] where the authors try to understand the true impact of

Table 6.5: Related work done in the field of neuromarketing considering "Advertisement Video" as dataset

Author, Year	Approach Used	Dataset	No. of subjects	Channels
Vecchiato et al. [74], 2010	Average classifier	Different commercial video advertisements about a naturalistic documentary	A mannequin as subject	Brain Amp (61 channel system)
Ohme et al. [60], 2010	ICA, FFT, Mean classifier	3 Video advertisements from same product	45 Participants, 21 male and 24 females, Aged 26 to 45	16-channel
Lee et al. [46], 2013	60 Hz Notch filter, Bandpass filter, FFT, General Linear Model (GLM)	Written description of products with their prices without visual depiction of the product	19 university students, 12 male and 7 females, Mean age 23.4	Niteen channel(Fp1, Fp2, A1, A2, O1, O2, C3, Cz, C4, F3, Fz, F4, F7, F8, T3, T4, T5, T6, P3, Pz, P4)
Murugappan et al. [58], 2014	50 Hz Notch filter, Butterworth 4th order bandpass Filter, Surface Laplacian filter, FFT, KNN, Probabilistic Neural Network(PNN)	Video clips of four Malaysian automotive brands	12 Participants, 9 male and 3 females, Aged 22 to 24	14 channels(AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, 01, 02)
Gupta et al. [30], 2017	Butterworth 4th order bandpass filter	Video clips of 4 soap brands, namely, Lux, Pears, Dove and Cinthol	18 subjects, 9 male and 9 females, Aged 22 to 24 years	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4)
Esmeralda et al. [19], 2017	FFT with windowing, non-linear SVM	TV Advertisements	30 subjects, Aged 20 to 25 years	4 channels (AF3, AF4, T7, and T8)
Gauba et al. [25], 2017	Moving Average filter, ICA, Random Forest Regression	Video advertisements from different promotional categories(home, shopping, sports, automobiles)	25 participants, Aged 20 to 42 years	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4)

mobile applications the brand perception and popularity. With focus on the pre-frontal cortex of brain to understand left-right alpha asymmetry with respect to the subjects' emotional response as recorded in the feedbacks that were filled before and after the experiment. As a result of the experiments the authors emphasize on the importance of clarity and simple interface of the application for better user experience. Also the results present that excessive browsing in the application leads to a negative emotional engagement possibly due to complicated interface that spoils the user experience. Another study of frontal brain waves has been done in [46] where they have introduced the concept of Green Consumers. The consumers who try to choose environment-friendly products so as to fulfill their economic responsibility are called green

Table 6.6: Related work done in the field of neuromarketing considering "Color Visuals and 3D Virtual Products" as dataset

Author, Year	Approach Used	Dataset	No. of subjects	Channels
Kawasaki et al. [34], 2012	ICA, Wavelet Transformation, Mean classifier	Color visuals, choose color from 2 colors presented simultaneously	19 participants, 11 male and 8 females, Aged 18 to 27 years	60 electrodes
Guo et al. [28], 2013	Adapted Collaborative Filtering for making recommendation on basis of EEG ratings	3D virtual website where the user can easily interact with the interface	–	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4)
Rakshit et al. [65], 2016	elliptical bandpass filter of order 10 and Common average referencing spatial filter, DFT, SVM, T1FS, BPTT Neural Network	visual stimuli consisting of four colors (Red, Yellow, Green, Blue) and each color appearing randomly on the screen	7 subjects, 4 male and 3 females, Aged 22 to 30 years	10 channels (F3; F4; Fz; P3,Pz; P4; 01; 02; T7; T8)
Teo et al. [71], 2017	50 Hz Notch filter, Automatic Artifacts removal, STFT, Deep Neural Network	3D visual jewellery type objects stimul	16 subjects, 8 male and 8 females, Mean age 22.44	9 channels (POz, Fz, Cz, C3, C4, F3, F4, P3 and P4)

consumers and a study to identify green consumers is done in this paper. Lee et al. [46] try to identify green consumers by finding differences in the frontal theta brain waves. General Linear Model (GLM) for multivariate analysis has been used for analyzing the frontal brain waves and the results find a significant difference between the frontal theta activations of the green consumers and non-green consumers.

Apart from focus on frontal brain region, some researchers have focused on complete brain activations with respect to human preferences and the inter-dependencies between these regions. One such study is done in [40] where the authors investigate the psychological process of decision making by the participants with focus on the different brain regions' cortical activity and their inter-dependencies using mutual information analysis.

While most of the research in neuromarketing and EEG is focused on like/dislike of the consumer, the authors here focus on the qualitative features of the product that result in the subject taking a particular decision. The results show that better cognitive processing was initiated by some particular attributes of the crackers' shape, topping or flavor. A combination of two non linear classifiers namely Probabilistic Neural Network (PNN) and k-Nearest Neighbor (KNN) is used in [58] for understanding the objective of participant's decision making process. The authors intend to study the human behavior on basis of spectral features of alpha wave while purchasing marketing products.

6.1.5 Datasets

The process of collecting EEG signals is very time consuming as each participant's recording of signals can take a significant amount of time. Further, it requires careful preparation of the environment where the signals are to be recorded as any noise or interference during the data collection may lead to erroneous results. Therefore, the lab where the EEG signals are to be collected should be insulated from outside noise and there should be very less disturbance while recording signals. Moreover, the researcher should run some initial pilot experiments so as to minimize the chances of mid failure of the experiment.

6.1.5.1 Dataset Description

Available Datasets To analyze and study EEG signals, there are multiple EEG datasets available on line which can be used directly for analysis such as LSW-neuromarketing[1] [49]. Another dataset that can be used for neuromarketing is NAS dataset[2] where the authors have shared their data of Neuro Against Smoking collected by different participants from all over the world. Another EEG dataset is published by Delorme et al. in EEG/ERP free public Dataset[3] [16] [17] that contains EEG data of 14 participants (7 females, 7 males) which is collected using the Neuroscan software. Similar dataset for EEG signals is available in EEG Database[4] that contains data measured using device with 64 electrodes in three version that can be used as per the requirements of the researcher. Multiple datasets relating to EEG signals and their usage in advertisement ratings are available online[5].

Device Used Various devices are available in the market for acquisition of EEG signals. The devices are different in terms of the way data is collected and the number of electrodes used for that. Various available devices and the placement of electrodes according to International 10-20 system have been shown in Fig. 6.2 and 6.3, respectively. EEG signals can be collected by placing the electrodes on human scalp which capture the brain activity in terms of the weak

[1] https://old.datahub.io/dataset/lsw-neuromarketing
[2] http://www.nmsba.com/neuro-against-smoking/data
[3] https://sccn.ucsd.edu/~arno/fam2data/publicly_available_EEG_data.html
[4] https://archive.ics.uci.edu/ml/datasets/eeg+database
[5] https://sites.google.com/site/iitrcsepradeep7

electrical potentials generated by the brain.
In [25, 79], 14 channels Emotiv EPOC+ device has been used. Whereas in [29, 38], 14 channels Emotiv EPOC device is used. In [30, 40, 58], the researchers have used 14 channels Emotiv EPOC Wireless EEG device.

Figure 6.2: Various EEG devices that have been used in research. All devices has varying number of electrodes from 5 to 128.

In [82], 21 channels of EEG 1200, Nihon Kohden Corporation, Japan has been used where only 19 of them were used for like/dislike analysis. In [46], 19 channel have been used also, but of a different device i.e. WEEG-32, a multichannel EEG acquisition system.
In [60], 16 channels of 16 channel Contact Precision Instruments Amplifier have been used. In [65], 10 channels out of 19 channel EEG amplifier Neurowin have been used. In [71], 9 channels ABM B-Alert X10 device has been used and in [19], just 4 channels of wireless EEG have been used.

Bastiaansen et al. [9] have used 61 electrodes of active Ag-AgCl electrodes mounted in an elastic cap device whereas Kawasaki et al. [34] have used 60 electrodes of electro cap where

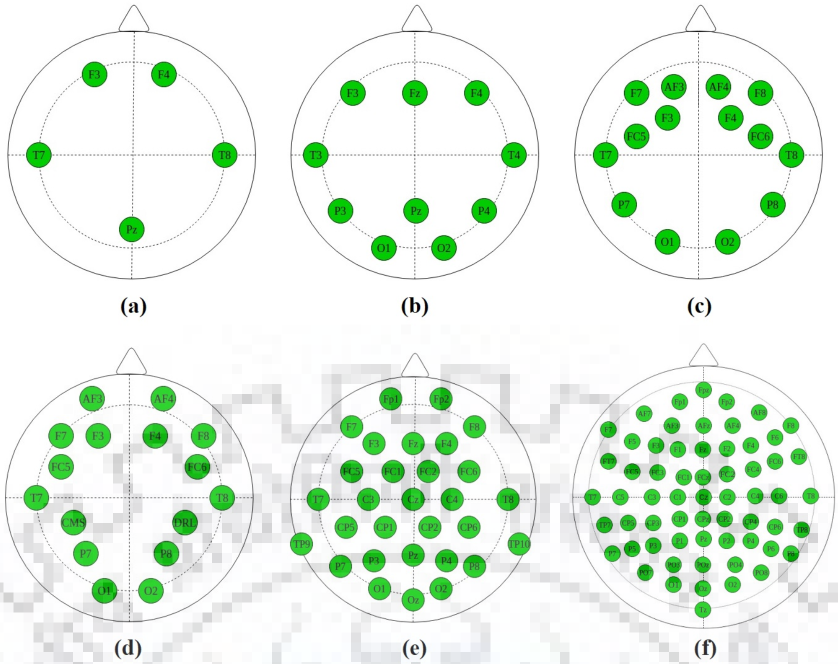

Figure 6.3: Placement of EEG electrodes over skull as International 10-20 system: (a) 5 electrodes device [13], (b) 10 electrodes device [65], (c) 14 electrodes device [25], (d) 16 electrodes device [79], (e) 30 electrodes device [80] and (f) 61 electrodes device [9].

signals amplified by using Neuroscan (Compumedics, Charlotte, NC). In [75], also 61 channels of Brain Amp device have been used.

It has been observed that more is the number of electrodes collecting EEG signals, more accurate are the results. But the number should not be that large that the noisy signals are captured more than the original signals. Also the correct placement of electrodes is a major task. If the electrodes are not placed correctly, even then there can be more noisy signals. Now a days, most of the researchers are using 14 channel Emotiv EPOC+ device, as it has various advantages over the other available devices in the market like, it is easy to handle and use both by researchers and users, as it has compatibility with different operating systems (Windows, Linux, Android, iOS) and is comfortable to be worn by the users as it fits easily over scalp because of its flexible design and also it has salined wet sensors which ensures no use of sticky gels. Also, it is wireless with battery backup of 12 hours with continuous use, so can even be used outside laboratory. The dense array spatial resolution of the device makes the device to capture complete brain signals [37].

6.1.6 Conclusions

Neuromarketing is an evolving field of research that helps to understand the actual logic about what goes on in the consumer's cognitive mind when they choose a particular product over the other. This is important because of its direct implication on market as the companies can improve their marketing strategies according to what pleases users and what has adverse effect on consumers' minds. The various neuromarketing strategies, kind of information possible to be gathered with these strategies, how the marketing stimuli is presented to consumers, what effect it has caused to the consumer in terms of pleasantness and memorization, available machine learning techniques used in this field, various challenges faced, different ethics that must be taken care of and the applications of neuromarketing has all been discussed.

As the current scenario witnesses the drift from television to web that requires subsequent change in the marketing strategies which means the advertisement length needs to be shorter. This poses a challenge to show eye catching important content to users in a small time frame which further intensifies the importance of neuromarketing field. It has been observed that due to the potential ethical issues, it is not opted as a field of research by various researchers. However, in future, neuromarketing can reach critical effectiveness using modern devices and techniques.

Chapter 7 LIST OF PUBLICATIONS

- **Monika Gahalawat**, Sudhanshu Kumar, Kanjar De, Partha Pratim Roy, Exploring the impact of Age and Gender on Sentiment Analysis, Applied Intelligence *(Submitted)*
- Vaishali Khurana, **Monika Gahalawat**, Pradeep Kumar, Partha Pratim Roy, A Survey on Neuromarketing using EEG Signals, IEEE Transaction Affective Computing *(Submitted)*

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