SENTIMENT ANALYSIS OF PRODUCT REVIEWS

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By

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ABSTRACT

During the past decades, online market places have been popular and most of the sellers also request the customers to express the reviews of the products. Nowadays individual and groups depend heavily on website for consumers' reviews in their agreement on buying the product. User generated opinioned data are increasing day by day as consumer left opinions about the product they bought. Product manufacturers also need to take time for analyzing the huge amount of opinions. With the increasing amount of text data, sentiment analysis is becoming more and more important. Sentiment analysis is commonly used with Natural Language Processing. This paper expresses about the sentiment analysis, which is the process of mining the texts, in order to distinguish the extract written by the user. So, the paper proposes a framework for reviews data using hybrid approach used in lexicon and machine learning approach to classify the review text whether they are positive opinion, negative opinion, and neural opinion. The approach describes a guideline for training data using Vader lexicon and testing data using machine learning algorithm and demonstrates the classification approach of supervised learning using Multinomial Naïve Bayes on Amazon product review dataset. The paper presents the evaluation results as positive reviews are found the most and negative reviews are found the least.

Keywords: Sentiment analysis, Vader lexicon, text classification, opinion mining, supervised learning

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CHAPTER 1
INTRODUCTION

Nowadays, Twitter, Facebook, Blog and Amazon have become a vital role in daily lives of the people. People can share their opinion (sentiment analysis) on each and every happening of the life. Thus sentiment analysis is useful to extract and understand their attitudes on certain topics. The combination of lexicon and machine learning approach is a hybrid approach. In this system, hybrid- based approach is used to analyze the sentiment analysis.

Lexicon-based approach is a straightforward and factual approach to Sentiment Analysis. Lexicon-based approach signif~~y~~ the numbers of positive and negative words in the text and the most frequently used will be counted. Lexicon gives off recommendations for eliminating the negative aspects of individuals.

Machine learning approach is a classification model, which is trained using the pre-labeled dataset (positive, negative and neutral) before it can be applied to actual classification task. Machine learning uses classifiers such as Naïve Bayes, SVM, etc.

The system uses both lexicon and machine learning approach to classify product review data set. This approach may provide compliments in order to bind the tough and dispose of the flaws of the individual technique and the more the size of training data, the higher the accuracy.

1.1. Motivation

With the development of web, people make their transactions on internet such as searching information, shopping, banking and so on. And People left their opinions on the product they bought on that site. Therefore, user-generated opinionated data are increasing day by day. The more the increasing amount, sentiment analysis is becoming more and more important. In order to extract valuable insights from a large set of reviews, classification of review into positive and negative sentiment is required.

1.2. Objectives of the Thesis

The objectives of this thesis are as follows:

- To study sentiment analysis based on opinion mining
- To identify the attitude and opinion of customers according to the polarity of the reviews and comments that they left
- To classify the polarity of product reviews datasets
- To analyze all the reviews of product buyers' opinions within a short time.

1.3. Organization of the Thesis

This thesis is composed of five chapters. In Chapter (1), the introduction of the thesis, motivation and objectives are presented. Chapter (2) describes the theoretical background and literature review concerning the classification process. Chapter (3) mentions the related worked of the thesis. In Chapter (4), the system design and implementation are presented with the figures. Moreover, Data Collection, Data Cleaning, Labelling Process using Vader, Compound Score, Explanation of Double Negative Sentences and Input Review Text are included. Multinomial Naïve Bayes algorithm is used for feature extraction in computing term weight and Naïve Bayes classifier classifies the data based on the training data into predicted sentiment (positive, negative or neutral). Chapter (5) concludes the thesis with further extension.

CHAPTER 2

THEORY BACKGROUND AND LITERATURE REVIEW

Electronic commerce is becoming increasingly popular as e-commerce websites allow purchasers to leave reviews on different products. Many of reviews are being given everyday by costumers which makes it difficult for product manufacturers to keep track of customer opinions of their products. Thus, it is very vital to classify such large and complex data in order to derive useful information from a large set of data. Classification methods are the way to tackle each problems. Classification is the process of categorizing data into groups or classes based on common traits. Organizations common concern is the ability to automate classification process when large datasets are being processed.

2.1 Sentiment Classification and Analysis

Sentiment analysis, opinion mining, is a natural language processing (NLP) problem that means identifying and extracting subjective information of text sources. The aim of sentiment classification is to analyze the written reviews of users and classify them into positive or negative opinions, so the system does not need to fully understand the semantics of each phrase or document.

In different fields such as movie reviews, travel destination reviews and product reviews, sentiment classification has been attempted. For sentiment classification, two main approach,lexicon- based methods and machine learning methods are usually used. Sentiment analysis, opinion mining is also a natural language processing problem and used to extract subjective information from texts and to analyze people's opinion, sentiments, evaluation towards entities such as materials, servicing, organization. The aim of sentiment classification is to classify positive, negative and neutral words in the reviews. It applies a machine learning approach, a lexicon -based approach and hybrid approach in this paper. There are three levels in sentiment analysis: Document level, Sentence level and Aspect level. Document level is used to classify a whole document which expresses a positive or negative sentiment. Sentence Level is used to classify each sentence that expresses a positive, negative or neutral opinion. Aspect Level is used to classify based on the facts. Sentiment classification analyze the written reviews of the users and classifies them into positive, negative and neutral opinions.

2.1.1 Natural Language Processing

Sentiment analysis, *opinion mining*, is a natural language processing problem which means:

- To identify and extract feedbacks and information from dataset.
- To analyze people's opinion, sentiments, evaluation, attitudes and emotions towards entities such as products, services, organization and so on.
- The aim of sentiment classification is to analyze the written reviews of the users and classify them into positive, negative and neutral opinions.

2.1.2 Lexicon-Based Approach

Lexicon-based method is another unsupervised approach, which relies on word and phrase annotation. To compute a sentiment score for each text, this method uses a dictionary of sentiment words and phrase. The simplest approach for determining the sentiment of a review document in lexicon based method is to use a count-based approach. If there is a text and lexical resource containing the positive and negative annotation of words and phrases, can be assigned the polarity of the reviews. This means that if the number of positive words is more than the negative ones the polarity of the review is positive. If there are more negative sentiment words than positive sentiment words, the overall sentiment of the text is then negative.

However, using only sentiment words and phrases for sentiment classification is not enough. Sentiment lexicon for sentiment analysis is necessary but it is not sufficient. There are some issues involved with this method.

- A lexicon- based approach is a simple, viable and practical approach to Sentiment Analysis without training data.
- Lexicon-based approach counts the number of positive and negative words in given text and the larger count will be the sentiment of text.

2.1.3 Vader Lexicon

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon. It uses a combination of a sentiment lexicon is a list of lexical features (e.g., words) which are generally labeled according to their semantic orientation as Positive, Negative or Neutral. The approach maps words to *sentiment* by using a lexicon or a 'dictionary of sentiment. It is a rule-based sentiment analysis used for text sentiment analysis. The system uses this dictionary to assess the sentiment of product review text.

2.2 Compute Positive, Negative, Neutral Score

The following figure shows computing positive, negative and neutral scores.

Algorithm 2.1

Compute Positive, Negative, Neural Scores

```
        postivie_sum=0
        negative_sum=0
        neutral_count=0
    for valence_score in sentiments:
    if  valence_score > 0 then
        postivie_sum  += valence_score + 1
    else if valence_score < 0 then
        negative_sum += valence_score -1
    else if valence_score ==0 then
        neutral_count += 1
    endif
end for
    total= positive_sum + negative_sum + neutral_count
    pos_score= positive_sum/total
    neg_score= negative_sum/total
    neu_score= neutral_count/total
```

2.2.1 Total Score

The total score (sentiment score) is computed by summing the sentiment (valence) scores of each word in the lexicon. Calculate the total score of all positive valence scores and all negative valence scores: total score, x.

$$x = \sum_{i=1}^{n} pos\_valence\_score + neg\_valence\_score \qquad 2.1$$

The total score is adjusted according to the rules, and then normalized to be between -1 (most extreme negative) and +1 (most extreme positive). Normalize the score to get compound score:

$$norm\_score = \frac{x}{\sqrt{x^2+\alpha}} \qquad 2.2$$

where x = sum of valence scores and α = Normalization constant value is 15.

Algorithm 2.2

Compute Compound Score

```
norm_score= x/math.sqrt(score*score)+alpha
if norm_score < -1.0 then
        compound_score= -1.0
else if norm_score > 1.0 then
        compound_score= 1.0
 else
         compound_score=norm_score
endif
```

2.2.2 Compound Score

Typical threshold values are:

(compound_score >=0.05) positive sentiment:

(compound_score>-0.05) and (compound_score<0.05) neutral sentiment:

(compound_score<=-0.05) negative sentiment:

The *positive, negative,* and *neutral* sentiment scores are texts that fall in each category.

2.2.3. Explanation of Double Negatives

A double negative is using two negative words or phrases in a sentence. A double negative is produced when two negative words in a clause are used so that it would create a positive effect. This is not a simple sentiment problem, it's total natural language understanding (negation, context, etc.). Negation Handling is important part while sentiment analysis. Many sentences contain the negation word that shifts the polarity of the sentence. This approach solves the problem when the system finds any negation term in sentence. And the system multiplies the negation scalar value to valence scores of sentiment word. (Neg-scalar= -0.74)

2.3 Sentiment Classification Using Machine Learning Approach

There is a large number of papers that have been published in the field of machine learning. One of the most used approaches for sentiment classification is machine learning algorithms. In order to optimize the performance of the system, machine learning develops an algorithm by using example data. The solution that machine learning provides for sentiment analysis involves two main steps. The first step is to “learn” the model from the training data and the second step is to classify the unseen data with the help of trained model. Machine learning algorithms can be classified in different categories:

- supervised learning
- semi-supervised learning
- unsupervised learning

In Supervised Learning the process where the algorithm is learning from the training data can be seen as a teacher supervising the learning process of its students. The supervisor is somehow teaching the algorithm what conclusions it should come up with as an output. So, both input and the desired output data are provided. It is also required that the training data is already labeled. If the classifier gets more labeled data, the output will be more precise. The goal of this approach is that the algorithm can correctly predict the output for new input

data. If the output were widely different from the expected result, the supervisor can guide the algorithm back to the right path. There are however some challenges involved when working with supervised. The supervised learning works fine as long as the labelled data is provided. This means that if the machine face unseen data, it will either give wrong class label after classification or remove it become it has not "learnt" how to label it.

The difference between Unsupervised learning and Supervised learning is training on unlabeled data with no corresponding output. The algorithm should find out the underlying structure of the data set on its own. This means that it has to discover similar patterns in the data to determine the output without having the right answers. One of the most important methods in unsupervised learning problem is clustering. Clustering is simply the method of identifying similar groups of data in the data set. For sentiment classification in an unsupervised manner, it is usually the sentiment words and phrase that are used. This means that the classification of a review is predicted based on the average semantic orientation of the phrases in that review. This is obvious since the dominating factor for sentiment classification is often the sentiment words.

Finally, the benefit of both supervised and unsupervised learning, semi-supervised learning refers to problems in which a smaller amount of data is labelled, and the rest of the training data set in unlabeled. This is useful for when collecting data can be cheap but labelling it can be time consuming and expensive. This approach is highly favorable both in theory and practice because of the fact that having lots unlabeled data during the training process tends to improve the accuracy of the final model while building it requires much less time and cost. Semi-supervised learning was experimented in which 2000 documents as unlabeled data and 50 randomly labeled data. Develop a classification model, which is trained using the pre-labeled dataset (positive, negative and neutral) before it can be applied to actual classification task. Machine learning uses classifiers such as Naïve Bayes, SVM, etc.

2.3.1 Naïve Bayes

Naïve Bayes is a classification technique based on Bayes's Theorem with as assumption of independence among predictors. A Naïve Bayes classifier assumes that

the presence of a particular feature in class is unrelated to the presence of any other feature. Ever if these features depend on each other or upon the existence of the other features, all of these properties independently contribute to the probability that this fruit is an apple and that is why it is known as 'Naïve'.

Naïve Bayes model is easy to build and particularly useful for very large data sets. Along with has been simplicity, Naïve Bayes is known to outperform ever highly sophisticated classification methods. The simplest solutions are usually the most powerful one and Naïve Bayes is a good example. It has been successfully used for many purposes but it works particularly well with natural language processing problem.

Naïve Bayes is a family of probabilistic algorithm that take advantage of probability theory and Bayes. Theorem to predict the tag of a text (like a piece of news or customer reviews). They are probability of each tag for a give text and the output the tag with the highest one. The way they get these probabilities is by using Bayes' Theorem, which describes the probability of a feature based on prior knowledge of conditions that might be related to that feature.

Naïve Bayes algorithm converts the data set into a frequency table. It creates likelihood table by finding the probabilities like overcast probability = 0.29 and probability of playing is 0.64. Then, Naïve Bayes equation is used to calculate the posterior probability for each class. The class with the highest posterior probability is the outcome of prediction. Naïve Bayes uses a similar method to predict the probability of different class based on various attributes. This algorithm is mostly used in text classification and with problems having multiple classes.

Naïve Bayes has pros and cons, respectively. It is easy and fast to predict class of test data set. It also performs well in multi class prediction. When assumption of independence holds, a Naïve Bayes classifier performs better compare to other models like logistic regression and you need less training data. It performs well in case of categorical input variables compared to numerical variable(s). For numerical variable, normal distribution is assumed (bell curve, which is a strong assumption).

If categorical variable has a category (in test data set), which was not observed in training data set, then model will assign a 0 (zero) probability and will be unable to make a prediction. This is often known as "Zero Frequency". To solve this, we can use the smoothing technique. One of the simplest smoothing techniques is called Laplace estimation. On the other side Naïve Bayes is also known as a bad estimator, so the probability outputs from predict- proba are not to be taken too seriously. Another

limitation of Naïve Bayes is the assumption independent predictors. In real life, it is almost impossible that we get a set of predictors which are completely independent.

Real time Prediction: Naive Bayes is an eager learning classifier and it is sure fast. Thus, it could be used for making predictions in real time. Multi class Prediction: This algorithm is also well known for multi class prediction feature. Here the probability of multiple classes of target variable (can be predicted.). Text classification / Spam Filtering / Sentiment Analysis: Naïve Bayes classifiers mostly used in text classification (due to better result in multi class problems and independence rule) have higher success rate as compared to other algorithms. As a result, it is widely used in Spam filtering (identify spam e-mail) and Sentiment Analysis (in social media analysis media analysis, to identify positive and negative customer sentiments) Recommendation System: Naïve Bayes Classifier and Collaborative Filtering together builds a Recommendation System that uses machine learning and data mining techniques to filter unseen information and predict whether a user would like a given resource or not. Gaussian is used in classification and it assumes that features follow a normal distribution. Multinomial is used for discrete counts. The binomial model is useful if your feature vectors are binary (i.e. zero and ones). Based on your data set, you can choose any of above discussed model. If continue features do not have normal distribution, transformation or different methods should be used to convert it in normal distribution. Naïve Bayes is another machine learning technique that is known for being powerful despite its simplicity. This classifier is based on Bayes theorem and relies on the assumption that features (which are usually words in text classification) are mutually independent. In spite of that this assumption is not true (because in some cases the order of the words is important), Naïve Bayes classifiers have proved to perform surprisingly well. The first step that should be carried out before applying the Naïve Bayes model on text classification problems is feature extraction. Naïve Bayes is a statistical classification technique based on Bayes Theorem. It is currently experiencing a renaissance in machine learning has long been a core technique in information retrieval. It is one of the simplest supervised learning algorithm and its classifier is the fast, high accuracy, speed on large datasets, thus Naïve Bayes algorithm is reliable algorithm.

$$\boldsymbol{P(h|D)} = \frac{P(D|h)P(h)}{P(D)} \qquad 2.3$$

- P(h): the probability of hypothesis h being true (regardless of the data) This is known as the prior probability of h.
- P(D): the probability of the data (regardless of the hypothesis) This is known as the prior probability.
- P(h | D) = the probability of hypothesis h given the data D. This is known as posterior probability.
- P(D | h) = the probability of the data d given that the hypothesis h was true. This is known as the posterior probability.

2.3.2 Multinomial Naïve Bayes

Multinomial naïve Bayes (MNB) is a popular method for document classification due to its computational efficiency and relatively good predictive performance. It has recently been established that predictive performance can be improved further by appropriated data transformations. It is the version of Naïve Bayes that is commonly used for categorization problem.

$$\hat{P}(w_i \mid c) = \frac{count(w_i, c)}{\sum_{w \in V} \left(count(w, c) \right)} = \frac{count(w_i, c) + 1}{\left(\sum_{w \in V} count(w, c) \right) + |V|} \qquad 2.4$$

w = word/term/feature

c = class/category

wi = No of Occurrence of feature in all document

v = Total number of unique feature in all document

Machine learning based feature extraction is used in computing term weight using Multinomial Naïve Bayes algorithm. Finally, Naïve Bayes classifier classifies the data based on the training data into predicted sentiment (positive, negative or neutral).

CHAPTER 3

RELATED WORKS

The purpose of this paper is to classify amazon reviews as positive, negative and neutral opinions. It uses two approaches such as lexicon -based approach and machine learning approach.

Lexicon -based approach performs sentiment analysis at document level by calculation the sentiment score of the product reviews that are already defined in lexicon to obtain training set.

Machine learning approach includes SVM, NB, Maximum Entropy and KNN. This paper uses hybrid- based approach. By Removing the punctuations, emoji and transformation of upper case to lower case. Vader sentiment analysis tool is used and training data is obtained.

There are four related papers dealing with the thesis. The first two is Based -Approach and the last two are Hybrid -based approach.

The first one is "Twitter Sentiment Analysis for Product Using Lexicon Method". Its datasets are downloaded from twitter API. Dictionary -based approach is used in the system. The experimental result can be found as positive, negative and neutral. The second one is "Sentiment Analytics: Lexicons construction and analysis". Datasets are from Amazon engine oil product reviews. Lexicon based approach is used in the system. The results show that compare the combination of sentiWordNet with three lexicon. The third is "Twitter Sentiment Analysis Using Hybrid Approach". Its datasets are downloaded from twitter API. Lexicon- based method and Support Vector Machine are used in the system. The result proposed algorithm is highly effective and better for sentiment analysis of twitter message. The four is "Sentiment Analysis on IMDb Movie Reviews Using Hybrid Approach". IMDb Movie Reviews Dataset is used in the proposed work. Lexicon- based method and Naïve Bayes, Support Vector Machine, Maximum Entropy, KNN are used in the system. The results obtained by this method are promising both in term of accuracy, F-measure and complexity. The five is "Twitter Sentiment Analysis Using Vader ". Its datasets are downloaded from twitter API. This system used Naïve Bayes Support Vector Machine, Artificial Neutral Network and Lexicon -based method. VADER distinguishes itself from others in terms that it is more sensitive to sentiment expressions in social media contexts while also generalizing

more favorably to other domain. The last one is "Sentiment Classification on Amazon reviews using machine learning approaches". Amazon beauty product reviews is used for this system. Naïve Bayes and Support Vector Machine Approach are used in this work. The accuracy SVM compares with that Naïve Bayes classifier. When the dataset is large, SVM method is better results than Naıve Bayes method. However, both algorithms reached at least 80%. in promising accuracies.

CHAPTER 4
SYSTEM DESIGN AND IMPLEMENTATION

In order to improve the performance of sentiment analysis, the following figure is used.

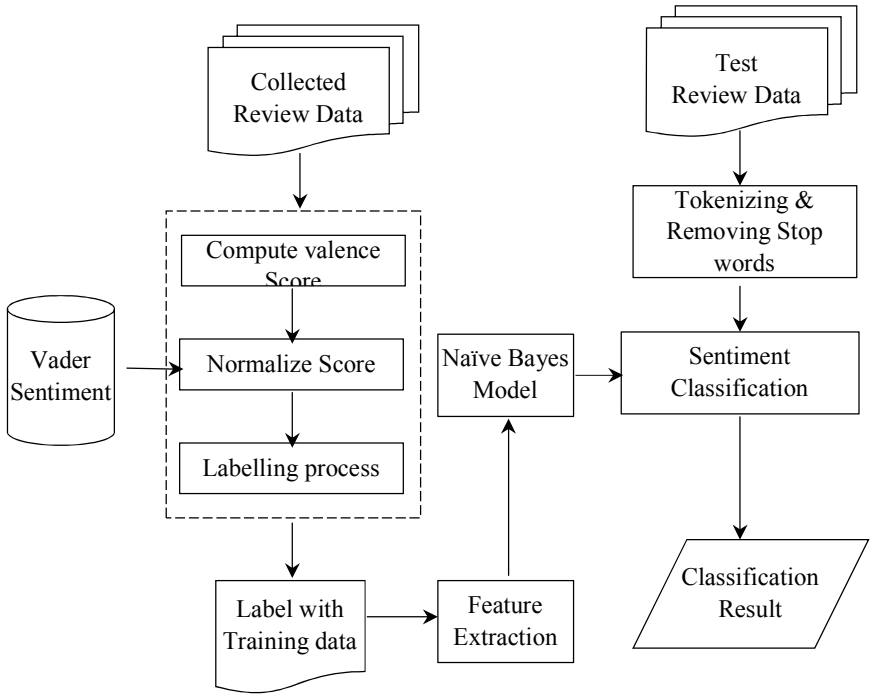

Figure 4.1. Workflow for sentiment Analysis

There are five steps of the proposed approach. The Sentiment Analysis of reviews includes the following steps.

- Step One - Reviews Data Collection
- Step Two - Data Cleaning

- Step Three - Labeling process using Vader
- Step Four - Classification of Navies Bayes Machine Learning Algorithm
- Step Five - Sentiment result output

4.1 Data Collection

The data is obtained by scraping with google chrome web scraper and manually to store required data into review data collection. To get raw data, the user may enter at Chrome, firstly and then https://www.scrapehero.com/amazon-review-scraper. Next, Web Scraper extension can be downloaded from the Chrome Web Store. After downloading the extension you will a spider icon in your browser toolbar.Google Chrome Browser (49 + version)is necessary to do this task. Secondly, you may choose right click right click anywhere at Browser Page, inspect at Popup dialog box, click Web Scraper, click Create new sitemap and then choose Import sitemap. Now, the user may copy and Paste the JSON below into the Sitemap JSON box. Click Import Sitemap Button and Sitemap button. You may choose Edit metadata option and paste the new URL as the Start URL. To start scraping, Click Sitemap and Scrape from the drop down.

4.2 Environments in Programming

In machine learning and data science, Python is one of the most widely used programming language. Python has a large set of libraries that can be used for handling and various machine learning algorithms. Python is used in this study is because of its wealth of libraries and ease of use. Scikit-learn is Python's one of libraries, that features a variety of supervised machine learning algorithm. It provides different classification and offers techniques for feature extraction.

4.2.1 The Dataset

This stage classifiers to complete the project include data collection for training and testing the reviews. These data collection were converted to the Comma Separated Values (CSV) format, and therefore it is more convenient for python to solve these data collection. The example review in Json file is as follow:

For unknown labelled shoe reviews data

{
" reviewer ID": " R3P2HIOQCIN5zU",
" asin": "B000XB31CO",
" customerID": "18069663",
"helpful": [1,2,3,9],

"reviewText": "Do not buy: really didn't start to wear them until May of 2016. Junk, they are falling apart. The outer sole is so thin that although I wear them almost completely in the house on rugs the inner padding is showing through in the heel. My previous pair from the same company lasted 5 years before I threw them out. I'm sorry I didn't wear them more often when I first got them as I would have returned them immediately."
"overall": 5,1,
"summary": "Minnetonka Men's Double Deerskin Softsole Moccasin",
"reviewTime": "8 13 2015"}

where

reviewer ID - ID of the reviewer, e g R3P2HIOQCIN5zU
asin - ID of the product, e gB000XB31CO
customer ID - ID of the customer
helpful - helpness of rating of the reviews, eg 1/9
reviewText – text of the review
overall – rating of the product
summary - product of the title
reviewTime - time of the review(raw)

Shoes Product dataset

marketpla	customer	review_id	product_i	product_p	product_t	product_c	star_ratin	helpful_v	total_vote	vine	verified_p	review_h	review_bo	review_da
US	18069663	R3P2HIOC	B000XB31	2.65E+08	Minneton	Shoes	1	0	0	N	Y	.	Do not bu	########
US	16251825	R12VVR0	B00CFYZH	2.59E+08	Teva Men	Shoes	5	0	0	N	Y	super flip	provides	########
US	20381037	RNCCKB6	B00S8JNN	6.66E+08	Anne Klei	Shoes	4	0	0	N	Y	Great clut	It's perfec	########
US	108364	R2NZXYIV	B00XFBPC	4.48E+08	adidas Me	Shoes	5	0	6	N	Y	Badass	Getting w	########
US	45449350	R2EQ1TG9	B00SW64Y	7853171	OverBling	Shoes	3	0	0	N	Y	Three Star	small	########
US	19324665	R1WXA9J	B011F9E6	14311457	MESSI 15.	Shoes	5	1	1	N	Y	Five Stars	My 13 yea	########
US	50073594	R12ENYLF	B00HAUP	2.65E+08	Hoka One	Shoes	5	1	1	N	Y	Finally, so	Ok, I have	########
US	21706057	R2R07E5P	B00L1RKO	7.67E+08	Olukai No	Shoes	4	0	0	N	Y	good deal	I went a fu	########
US	13708216	R27BA52A	B00SWA9	8.14E+08	Carolina N	Shoes	5	0	0	N	Y	... would h	I would ha	########
US	40542649	RLF8DOID	B00BEYQI	6.61E+08	Alegria W	Shoes	3	0	0	N	Y	Too small	The size is	########
US	13409446	R369CEXH	B00EYAFT	3.32E+08	Naturalize	Shoes	5	0	0	N	Y	Five Stars	These sho	########
US	9451727	R171PPUX	B00I0QHY	49243908	Forever Li	Shoes	5	0	0	N	Y	Five Stars	I love the	########
US	193731	R2JDNM8	B010FZZK	1.61E+08	Versace C	Shoes	4	1	1	N	Y	Four Stars	Good qua	########
US	34798634	R2W977F	B00V8B30	7.6E+08	Twisted G	Shoes	5	0	1	N	Y	Good sho	My daugh	########
US	37235551	R3AM24Q	B00LAVB1	9.1E+08	Travel Sm	Shoes	2	1	2	N	Y	Two Stars	It's okay .	########
US	27081399	REDVX5FY	B003C1P8	7.63E+08	Saucony C	Shoes	5	0	0	N	Y	Love these	Love these	########
US	120678	R14AIIK7	B000W3U	1.24E+08	Dr. Marte	Shoes	5	0	0	N	Y	Five Stars	Good	########
US	22272389	R3B1NUR	B00LX65P	8.49E+08	Skechers	Shoes	3	2	2	N	Y	Three Star	I like the g	########
US	19584241	R14Q1GZ	B00BEE7N	2.12E+08	Hi-Tec Kid	Shoes	4	0	0	N	Y	Four Stars	Kids love	########
US	12334573	R9BHBB0	B008NCH	1.39E+08	Foot Sox	Shoes	1	2	2	N	Y	Tissue pa	Tissue pa	########
US	28744432	R3HVI8OI	B00MFXF2	2.01E+08	RYKA Wor	Shoes	4	0	0	N	Y	Fit small	Had to ret	########

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Figure 4.2 Shoe Reviews dataset

For labelled electronic reviews data

{

" reviewer ID": "AVqklhwDv8e3D10-lebb",

" asin": "B0IAHB9CN2",

" customerID": "841667104676",

"helpful": [1,2,3,9]

"reviewText": "It's a great tablet for the price. Don't expect it to be as fast more expensive ones. It's meant for casual use and it does a great job at that. For the price, you can't beat it. Get a nice large micros card and you don't have to worry about space. It runs a little slow on certain things if you are multitasking but it's a simple tablet. I've run plenty of 720p videos without fail. It's great for e-books or other files. Some more elaborate pdfs take a while to load if they have a lol of graphics. Battery life seems good for a small table too. The only real Issue I have is the Amazon App store being limited. It is an offshoot of Android but not all the same apps are available. There is a way around it but I wish they would just allow it access to Google Play or at least offer the same apps. So, it's a nice inexpensive table that works great. For the money, you will love it but don't get upset that is doesn't run as fast as a $500 tablet. That's not its job."

"overall": 5,1,

"summary": "http:// reviews.bestbuy.com",

"reviewTime": "12. 01. 2017"}

where

reviewer ID - ID of the reviewer, e g R3P2HIOQCIN5zU

asin - ID of the product, e gB000XB31CO

customer ID - ID of the customer

helpful - helpness of rating of the reviews ,eg 1/9

reviewText – text of the review

overall – rating of the product

summary - product of the title

reviewTime - time of the review(raw)

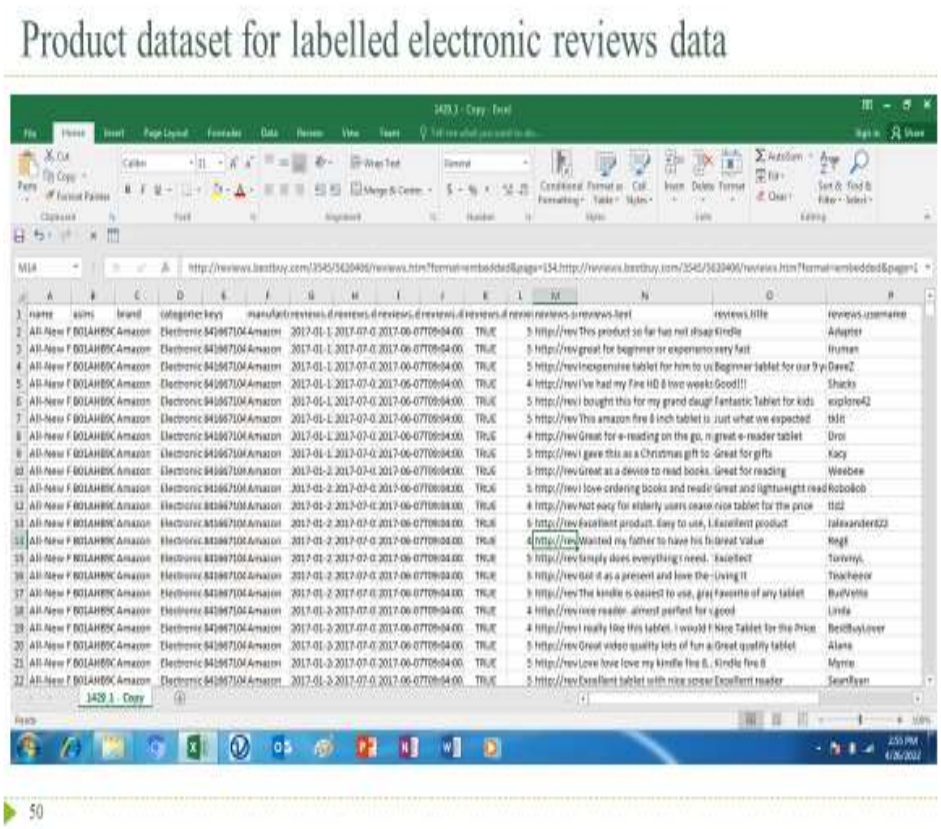


Figure 4.3 Electronic Reviews dataset

4.2.2 Data preparation

The following table is sample reviews for training.

Table 1: Product Review Content

Review ID	Content
Review 1	The shoe is pretty good.
Review 2	It wastes your money buy this defective shoe.
Review 3	I received faulty piece
Review 4	This is a really smart shoe, the quality of the leather is amazing.
Review 5	Expensive, but is a comfortable shoe with advance method.
Review 6	It is a product.
Review 7	It is simple shoe.

4.2.3 Data Cleaning

This stage comprises of removing the punctuations, emoji and transformation of upper case to lower case. Unnecessary data will need to be cleaned from the reviews data. This stage comprises of removing the punctuations, emoji and transformation of upper case to lower case. Then, we use the method word-tokenize ( ) to split a sentence into words. A stop word is a commonly used word (such as "the", "a", "an", "in"). After noise removal, we obtain the training set by using Vader sentiment analysis tool. The process of stemming reduces the inflection words in the language. This thesis (research paper) contains and uses 179 stopwords. There are i, me, my, myself, we, our,ours,ourselves,you,you're,you've,you'll,you'd,your,yours,yourself,yourselves,he,him,his,himself,she,she's,her,herself,it,it's,its,itself,they,them,their,theirs,themselves,what,which,who,whom,this,that,that'll,these,those,am,is,are,was,were,be,been,being,have,has,had,having,do,does,did,doing,a,an,the,and,but,if,or,because,as,until,while,of,at,by,for,with,about,against,between,into,through,during,before,after,above,below,to,from, up,down,in,out,on,off,over,under,again,further,then,once,here,there,when,where,why,

how,all,any,both,each,few,more,most,other,some,such,no,nor,not,only,own,same,so,than,too,very,s,t,can,will,just,don,don't,should,should've,now,d,ll,m,o,re,ve,y,ain,,aren,aren't,couldn,couldn't,didn,didn't,doesn,doesn't,hadn,hadn't,hasn,hasn't,haven,haven't,isn,isn't,ma,mightn,mightn't,mustn,mustn't,needn,needn't,shan,shan't,shouldn,shouldn't,wasn,wasn't,weren,weren't,won,won't,wouldn,wouldn't.

Vader lexicon contains (7516) words and Vader lexicon includes (3351) positive words and (4165) negative words.

4.3 Labelling process using Vader

Positive values are positive valence and negative values are negative valence.

Table 2: Valence score of sentiment word

Sentiment Word	Valence score
good	1.9
smart	1.7
pretty	2.2
bad	-2.5
terrible	-2.1
faulty	-1.3
comfortable	2.3
amazing	2.8
poor	-2.1

Example: Input Review Text: ("The shoe is pretty good.")

Two emotional words**:** *pretty and good*

Lexicon ratings (sentiment score) for *pretty* and *good* are: 2.2 and 1.9.

Compute the positive, negative, neutral and compound score:

sentiments_score= [0, 0, 0, 2.2, 1.9]

pos_sum =6.1

neg_sum=0

neu_count=3

Pos_score= 6.1/9.1=0.670

Neg_score= 0/9.1= 0

Neu_score= 3/9.1= 0.329

total_score= 2.2+1.9=4.1

norm_score= $\frac{4.1}{\sqrt{(4.1)^2+15}}$ **=0.726946,**

compound_score= 0.726

Table 3:Compute the positive, negative, neutral and compound score

Review	Sentiment Metric	Score	label
The shoe is pretty good.	Positive	0.670	pos
	Neutral	0.329	
	Negative	0.0	
	Compound_score	0.726 (0.726>0.05)	

4.4 Explanation of Double Negative Sentence

A double negative means the use of two negative words or phrases in a sentence. A double negative is produced when two negative words (are used) in a clause so that it would create a positive effect.This is not a simple sentiment problem, it's total natural language understanding (negation, context, etc.).

Some examples of double negatives are :

- She is not incorrect.
- Time is not unlimited.
- The phone is not poor.
- I do not mean that this product is not good.
- I never recommend to buy this bad quality product.

4.4.1 Explanation of Negatives Sentences

Negation Handling is major issue while sentiment analysis. Because many sentences contain the negation word that shifts the polarity of the sentence. The approach solves this problem, when the system finds any negation term in sentence then the system multiplies the negation scalar value to valence scores of sentiment word. (Neg_scalar= -0.74)

Example: Input Review Text: **("**I do not mean that this product is not good. **")**

Lexicon ratings (sentiment score) for good is 1.9.

Compute the positive, negative, neutral and compound score

Neg_scalar= -0.74

sentiments_score= [0, 0, 0, 0, 0, 0 ,0, 0, 1.9] = > = [0, 0, 0, 0 , 0 , 0, 0, 0 , 1.04]

pos_sum = 2.04

neg_sum = 0

neu_count = 8

Pos_score = 0.203

Neg_score = 0

Neu_count = 0.796

total_score= 1.04

norm_score= $\frac{1.04}{\sqrt{(1.04)^2+15}} = 0.259$

compound_score= 0.259

Table 4: Compute the positive, negative, neutral and compound score

Review	Sentiment Metric	Score	label
I don't mean that this product is not good	Positive	0.203	pos
	Neutral	0.796	
	Negative	0	
	Compound_score	0.259 (0.259>0.05)	

Example: Input Review Text: (I never recommend to buy this bad quality product.)

Lexicon ratings (sentiment score) for recommend and bad are 1.5 and -2.1 .

Compute the positive, negative, neutral and compound score.

Neg_scalar= -0.74

sentiments_score= [0, 0, 1.5,0, 0, 0,-2.1,0,0] = > = [0, 0, 1.5, 0 ,0, 0, 1.554,0,0]

pos_sum =5.054

neg_sum= 0

neu_count= 7

Pos_score= 0.419

Neg_score= 0

Neu_score=0.580

total_score= 3.054

norm_score= $\frac{2.664}{\sqrt{(2.664)^2+15}}$ **= 0.619**

compound_score= 0.619

Table 5: Compute the positive, negative, neutral and compound score

Review	Sentiment Metric	Score	label
I never recommend to buy this bad quality product.	Positive	0.419	pos
	Neutral	0.580	
	Negative	0	
	Compound_score	0.619(0.5>0.05)	

4.5 Labelling process using Vader

Table 6: labelling reviews text

Review Text	Pos-score	Neg-score	Neu-score	Norm-score	Compound-score	label
Review 1	0.674	0	0.33	0.7269	0.7269	pos
Review 2	0	0.325	0.675	-0.5228	-0.5228	neg
Review 3	0	0.535	0.465	-0.3182	-0.3182	neg
Review 4	0.43	0	0.57	0.7778	0.7778	pos
Review 5	0.389	0	0.611	0.6652	0.6652	pos
Review 6	0	0	1	0	0	neu
Review 7	0	0	1	0	0	neu

Table 7: Labelled review data set: Training set

Review	Content	Category
1	The shoe is pretty good.	Positive
2	It wastes your money buy this faulty shoes.	Negative
3	I received faulty piece.	neg
4	This is a really smart shoe, the quality of the leather is amazing.	pos
5	Expensive, but is a comfortable shoes with advance method.	pos
6	It is a product.	Neutral
7	It is a simple shoes.	neu

Table 8: Testing data set

Review	Content	Category
8	It is a simple one.	?
9	Faulty product.	?
10	Nice smart perfect one.	?

Table 9: After removing stopwords and tokenizing

Review	Content	Category
1	[shoe / pretty/ good]	pos
2	[wastes / money / buy / faulty /shoe]	neg
3	[received / faulty / piece]	neg
4	[really /smart /shoe / quality / leather / amazing]	pos
5	[expensive/ great/ shoe / advance / method]	pos
6	[product]	neu
7	[simple / shoe]	neu

4.6 Feature Extraction

Feature extraction has two stages namely – lexicon based feature extraction and Machine learning based features extraction. Machine learning based feature extraction is used in computing term weight using Multinomial Naïve Bayes algorithm. Finally, Naïve Bayes classifier classifies the data based on the training data into predicted sentiment (positive, negative or neutral).

4.6 Classification with Naïve Bayes

Classification is the process of assigning labels to the reviews. In the proposed work, data collection, pre-processing, feature extraction using multinomial Naïve Bayes and sentiment classifier using Naïve Bayes. It is independent of the number of features in the feature space. It is a statistical classification technique based on Bayes theorem.

Table 10: Feature category count

Word	Positive	Negative	Neutral
pretty	1	0	0
good	1	0	0
wastes	0	1	0
money	0	1	0
buy	0	1	0
faulty	0	2	0
shoe	2	1	0
received	0	1	0
piece	0	1	0
really	1	0	0
smart	1	0	0
quality	1	0	0
leather	1	0	0
amazing	1	0	0
expensive	1	0	0
comfortable	1	0	0
shoe	1	0	0
advance	1	0	0
method	1	0	0
pretty	1	0	0
good	1	0	0
wastes	0	1	0
money	0	1	0
buy	0	1	0

faulty	0	2	0

Naïve Bayes classifier currently experiencing a renaissance in machine learning, has long been a core technique in information retrieval. Naïve Bayes is one of the simplest supervised learning algorithm and its classifier is the fast, high accuracy, speed on large datasets, thus Naïve Bayes algorithm is reliable algorithm. Further, it assigns the label of nearest neighbor to the unlabeled reviews. We calculate term weight values using multinomial Naïve Bayes. Classification process use Naïve Bayes. It sets standardized thresholds for classifying text as either positive, neutral or negative.

Typically, threshold values are compound score values greater than 0.05 and it is positive, compound score values between 0.05 and 0.05 is neutral compound score values less than 0.05 and it is negative.

- P(negative) = $\frac{2}{7}$ = 0.33
- P(positive) = $\frac{3}{7}$ = 0.42
- P(neutral) = $\frac{2}{7}$ = 0.33

$$P(f_i i) = \frac{\text{no. of } f_i \text{ occurs in } ci_{+1}}{\text{total feature in each } ci + \text{ total no. of unit feature}} \qquad \textbf{2.4}$$

Feature	No. of Occurrence of featurein Positive	Total feature in Positive	Conditional Probability of Given feature in Positive	No. of Total unique word in All Document
shoe	3	14	0.1	26
pretty	1	14	0.05	26
good	1	14	0.05	26
wastes	0	14	0.025	26
money	0	14	0.025	26
buy	0	14	0.025	26
faulty	0	14	0.025	26
received	0	14	0.025	26
piece	0	14	0.025	26
really	1	14	0.05	26
smart	1	14	0.05	26
quality	1	14	0.05	26

Feature	No. of Occurrence of featurein Positive	Total feature in Positive	Conditional Probability of Given feature in Positive	No. of Total unique word in All Document
leather	1	14	0.05	26
amazing	1	14	0.05	26
expensive	1	14	0.05	26
comfortable	1	14	0.05	26
shoe	1	14	0.05	26
advance	1	14	0.05	26
method	1	14	0.05	26
product	0	14	0.025	26
simple	0	14	0.025	26
shoe	0	14	0.025	26
one	0	14	0.025	26
perfect	0	14	0.025	26

Feature	No. of Occurrence of featurein Negative	Total feature in Negative	Conditional Probability of Given feature in Negative	No. of Total unique word in All Document
shoe	1	8	0.06	26
pretty	0	8	0.03	26
good	0	8	0.03	26
wastes	1	8	0.06	26
money	1	8	0.06	26
buy	1	8	0.06	26
faulty	2	8	0.09	26
received	1	8	0.06	26
piece	1	8	0.06	26
really	0	8	0.03	26
smart	0	8	0.03	26
quality	0	8	0.03	26

Feature	No. of Occurrence of featurein Negative	Total feature in Negative	Conditional Probability of Given feature in Negative	No. of Total unique word in All Document
leather	0	8	0.03	26
amazing	0	8	0.03	26
expensive	0	8	0.03	26
comfortable	0	8	0.03	26
shoe	0	8	0.03	26
advance	0	8	0.03	26
method	0	8	0.03	26
product	0	8	0.03	26
simple	0	8	0.03	26
shoe	0	8	0.03	26
one	0	8	0.03	26
perfect	0	8	0.03	26

Feature	No. of Occurrence of featurein Neutral	Total feature in Neutral	Conditional Probability of Given feature in Neutral	No. of Total unique word in All Document
shoe	0	3	0.03	26
pretty	0	3	0.03	26
good	0	3	0.03	26
wastes	0	3	0.03	26
money	0	3	0.03	26
buy	0	3	0.03	26
faulty	0	3	0.03	26
received	0	3	0.03	26
piece	0	3	0.03	26
really	0	3	0.03	26
smart	0	3	0.03	26
quality	0	3	0.03	26

Feature	No. of Occurrence of featurein Neutral	Total feature in Neutral	Conditional Probability of Given feature in Neutral	No. of Total unique word in All Document
leather	0	3	0.03	26
amazing	0	3	0.03	26
expensive	0	3	0.03	26
comfortable	0	3	0.03	26
shoe	0	3	0.03	26
advance	0	3	0.03	26
method	0	3	0.03	26
product	1	3	0.07	26
simple	1	3	0.07	26
shoe	1	3	0.07	26
one	0	3	0.03	26
perfect	0	3	0.03	26

4.7.1 Input Review Text:

The following sentences are used for testing.

Review 8	It is simple one.

P(Review 8 | positive) = P(positive) *P(simple | positive)* P(one | positive)

= 0.43 * 0.025 * 0.025

= 0.00026875

P(Review 8 | negative)=P(negative)*P(simple | negative)*P(one | negative)

= 0.29 * 0.03 * 0.03

= 0.000261

P(Review 8 | neutral) = P(neutral) *P(simple | neutral)* P(one | neutral)

= 0.29 * 0.07 * 0.03

= 0.0006

Review 8 **is neutral.**

The input review text results are 0.00026875 for positive, 0.000261 for negative and 0.0006 for neutral. Neutral result value is maximum thus the input reviews text result is neutral.

Review 9	faulty product

P(Review 9 | positive) =P(positive) *P(faulty | positive)* P(product | positive)

= 0.43* 0.025 * 0.025

=0.000268

P(Review9 | negative)=P(negative) *P(faulty | negative)* P(product | negative)

= 0.29 * 0.09 * 0.03

=0.000783

P(Review 9 | neutral) =P(neutral) *P(faulty | neutral)* P(product | neutral)

= 0.29* 0.03* 0.07

=0.000609

Review 9 **is negative.**

The input review text results are 0.000268 for positive, 0.000783 for negative and 0.000609 for neutral. When Negative result value is maximum, the input reviews text result is negative.

Review 10	Smart shoe perfect one.

P(Review10 | positive)=P(positive)*P(smart | positive)*P(shoe | positive)*
P(perfect | positive) *P(one | positive)
= 0.43 * 0.05 * 0.1 * 0.025 * 0.025
= 0.00000134375

P(Review10 | negative) = P(negative)*P(smart | negative)*P(shoe | negative) *
P(perfect | negative) *P(one | negative)
= 0.29 * 0.03 * 0.06 * 0.03* 0.03
= 0.0000004698

P(Review10 | neutral) =P(neutral)*P(smart | neutral)*P(shoe | neutral)*
P(perfect | neutral) *P(one | neutral)
= 0.29 * 0.03 * 0.03 * 0.03 * 0.03
= 0.0000002349

Review 10 **is positive.**

The input review text results are 0.00000100781 for positive, 0.0000004698 for negative and 0.0000002349 for neutral.

Positive result value is maximum thus the input reviews text result is positive.

4.8 Performance Evaluation Result

There are so many comments or reviews in Amazon. Among them, the comments reviews data for shoes 1400 obtained. We collected reviews from 1400, 1100 reviews use for training data and 300 reviews use for testing data. F-measure, Precision, Recall, and Accuracy (are used) to analyze the performance of reviews. F-measure is a value between the balances of Precision and Recall. Accuracy focuses on the aggregates of exact prophecies. Precision and Recall are effective ways to evaluate the correction of classes.

- Accuracy of the performance reviews can be calculated by using F-measure, Precision, Recall.
- F-measure is a value between the balances of Precision and Recall. Accuracy focuses on the aggregates of exact prophecies.
- Precision and Recall are effective ways to evaluate the correction of classes.
- PR represents precision, RE is Recall, FM is F-measure.

$$PR=\frac{TP}{TP+F} \quad 2.5$$

$$RE=\frac{TP}{FN} \quad 2.6$$

$$FM=2\frac{PR.RE}{TP+FP} \quad 2.7$$

$$ACC=\frac{TP+T}{TP+FP+TN+FN} \quad 2.8$$

- TP is True Positive,
- TN is True Negative
- FP is False Positive,
- FN is False Negative,
- ACC is Accuracy Respectively

Table 11: Performance Evaluation Result for shoes reviews data

Class Label	No of training sentiment	No of testing sentiment	Precision	Recall	F-Measure	Accuracy
Pos	322	159	82	92	87	93
Neg	236	92	70	97	82	90
Neu	142	49	100	56	72	88

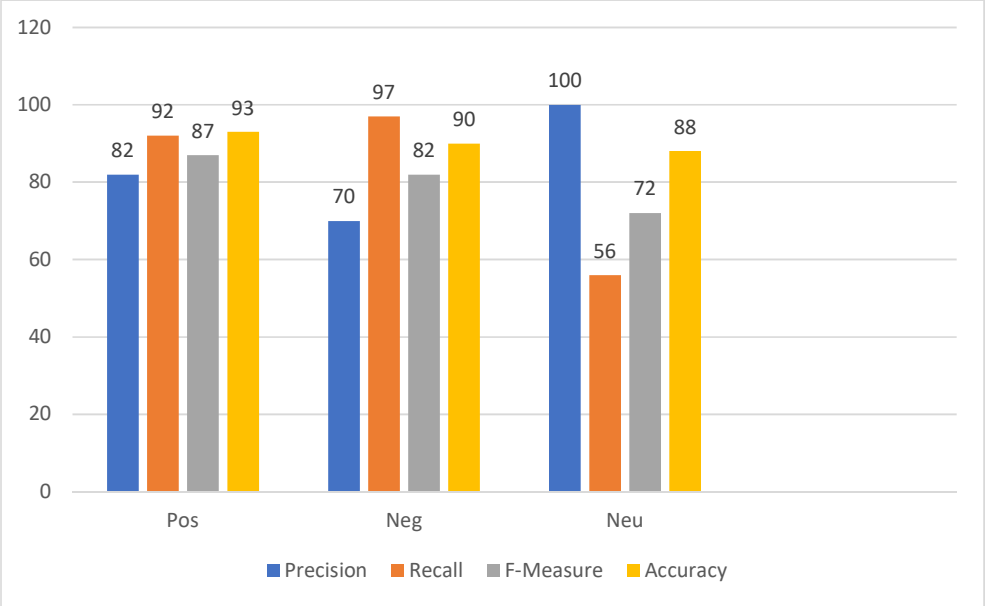
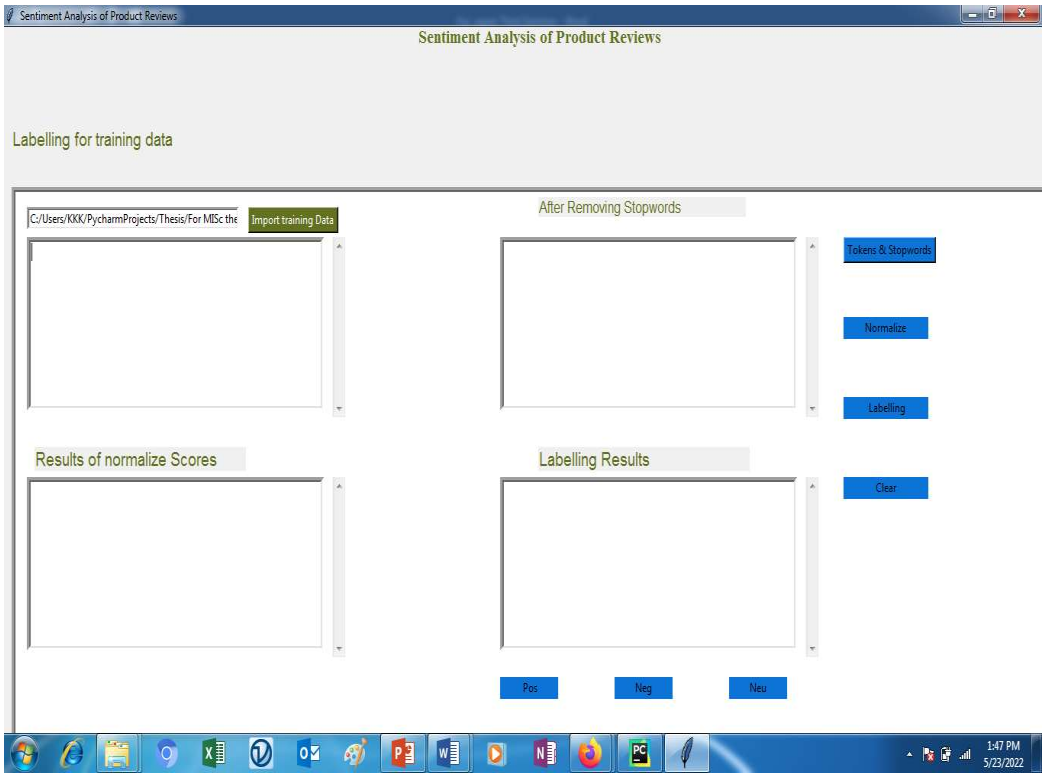
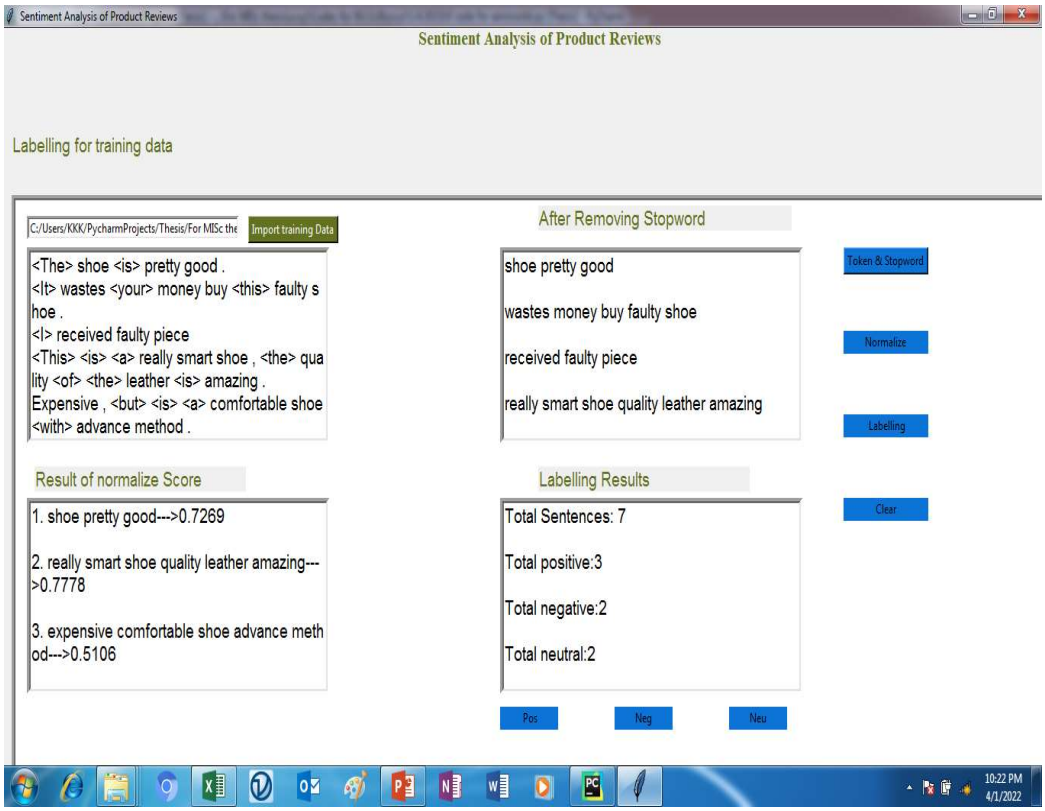


Fig 4.4 Result of Accuracy for testing shoes reviews data

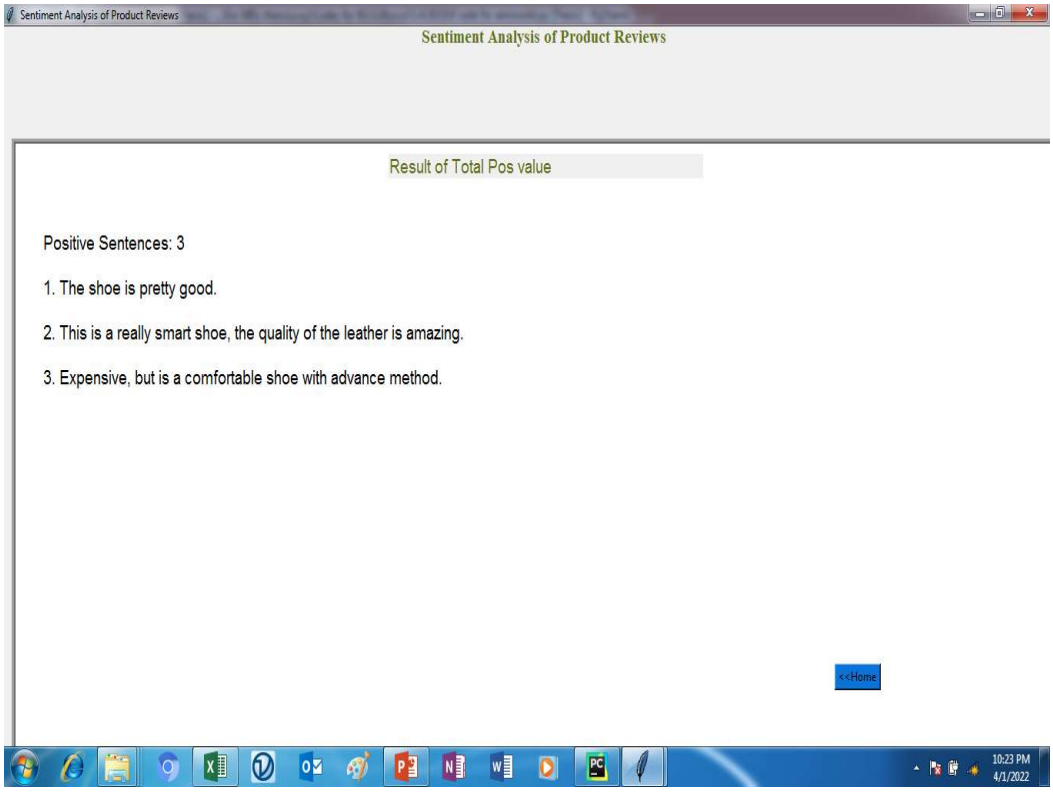
4.9 User Interface of the proposed system for shoes reviews data

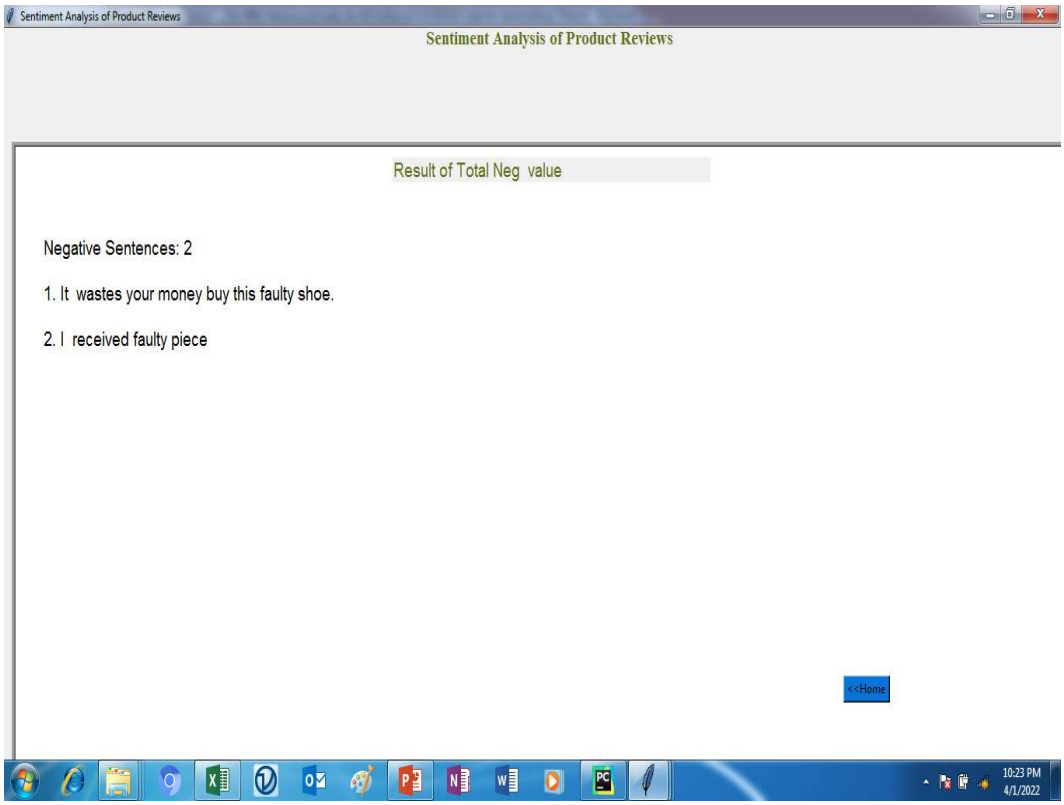
To label for training data, firstly the user may import training data, secondly click Token and Stopwords button which makes the removal stopwords from training data. Thirdly, the user may select Normalize button and then Result of normalize Score can be achieved. Next, if the user may click labelling, labelling results (would have been seen).

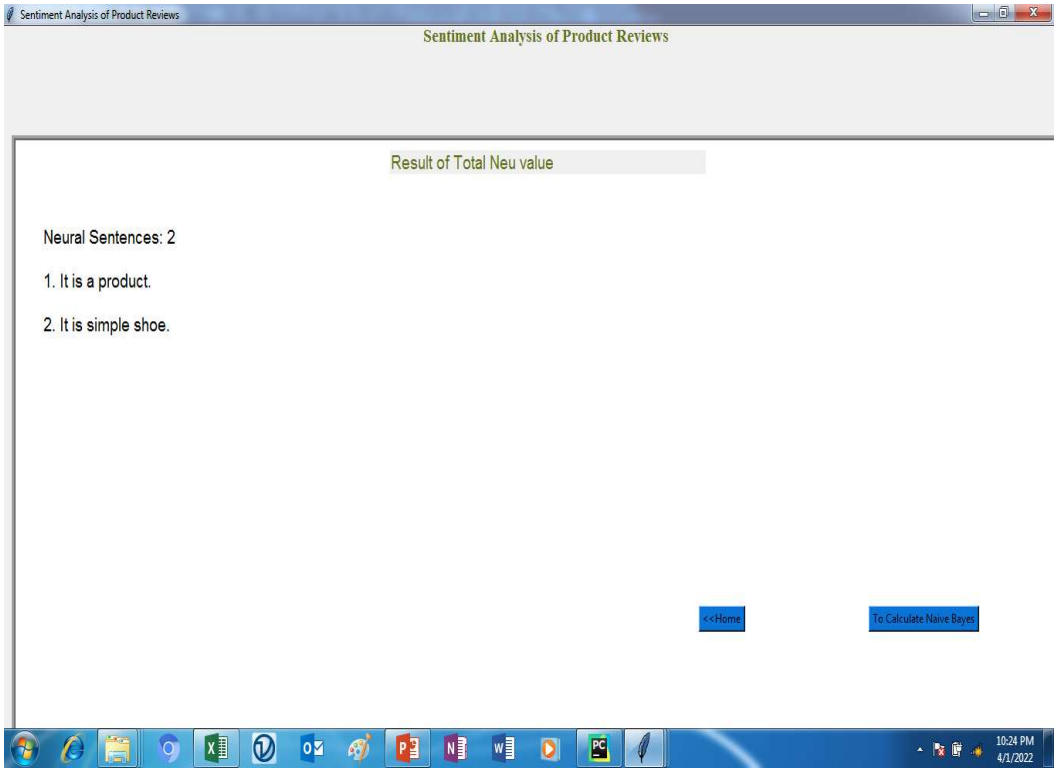


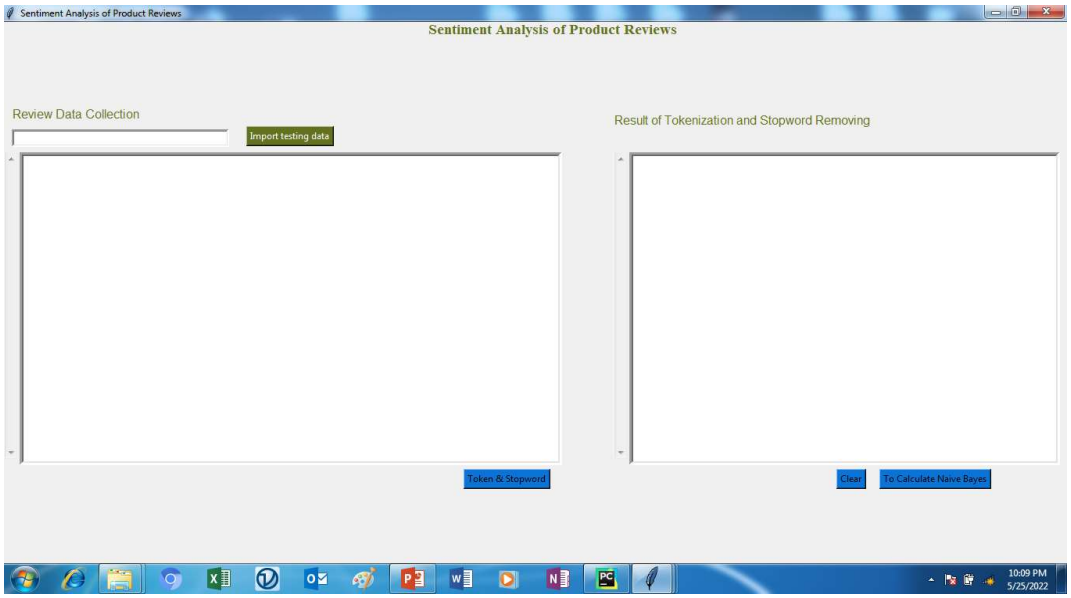


And then, the user may get positive sentences if the user click positive button, negative sentences if the user click negative button and neutral sentences if the user click neutral button.

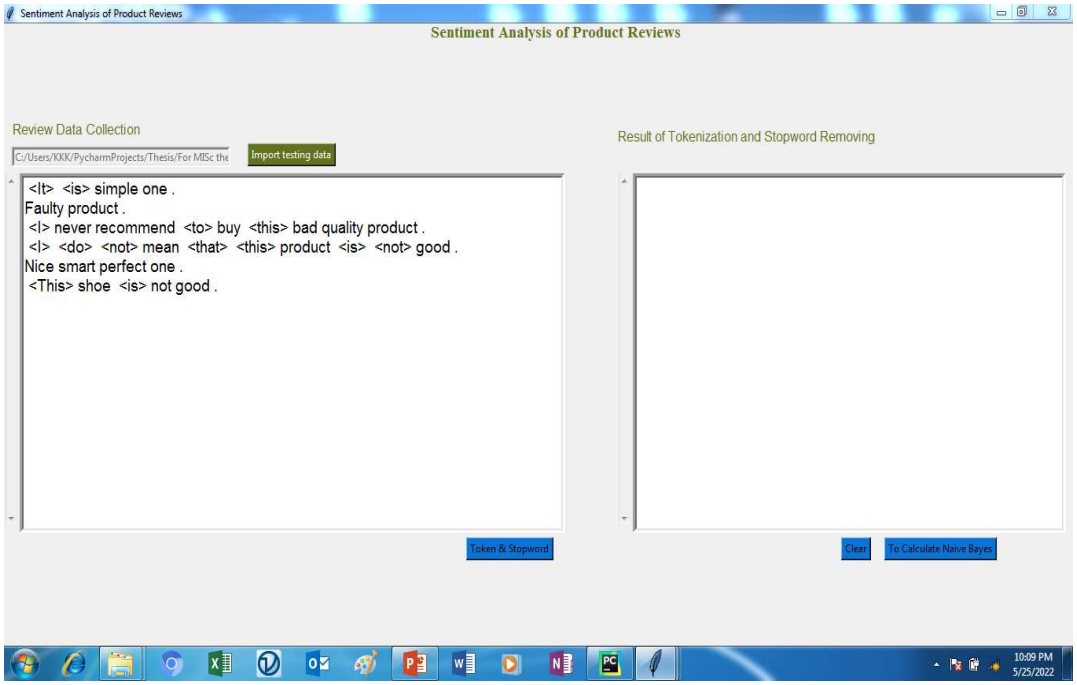


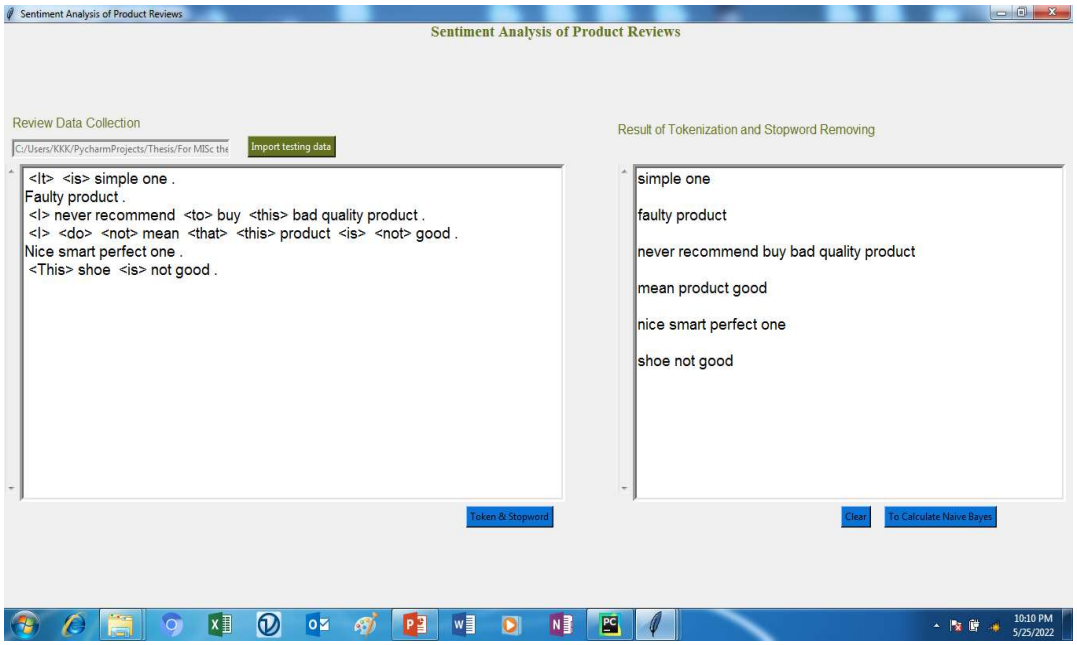

Sentiment Analysis of Product Reviews
Sentiment Analysis of Product Reviews
Result of Total Neg value
Negative Sentences: 2
1. It wastes your money buy this faulty shoe.
2. I received faulty piece
<<Home
10:23 PM
4/1/2022

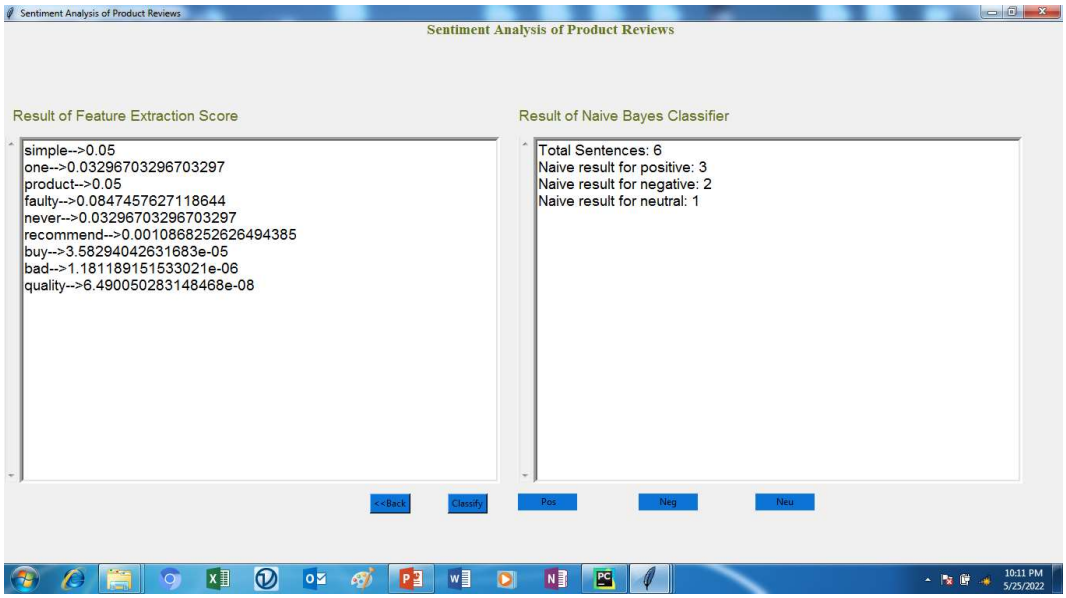

Sentiment Analysis of Product Reviews
Sentiment Analysis of Product Reviews
Result of Total Neu value
Neural Sentences: 2
1. It is a product.
2. It is simple shoe.
<<Home
To Calculate Naive Bayes
10:24 PM
4/1/2022



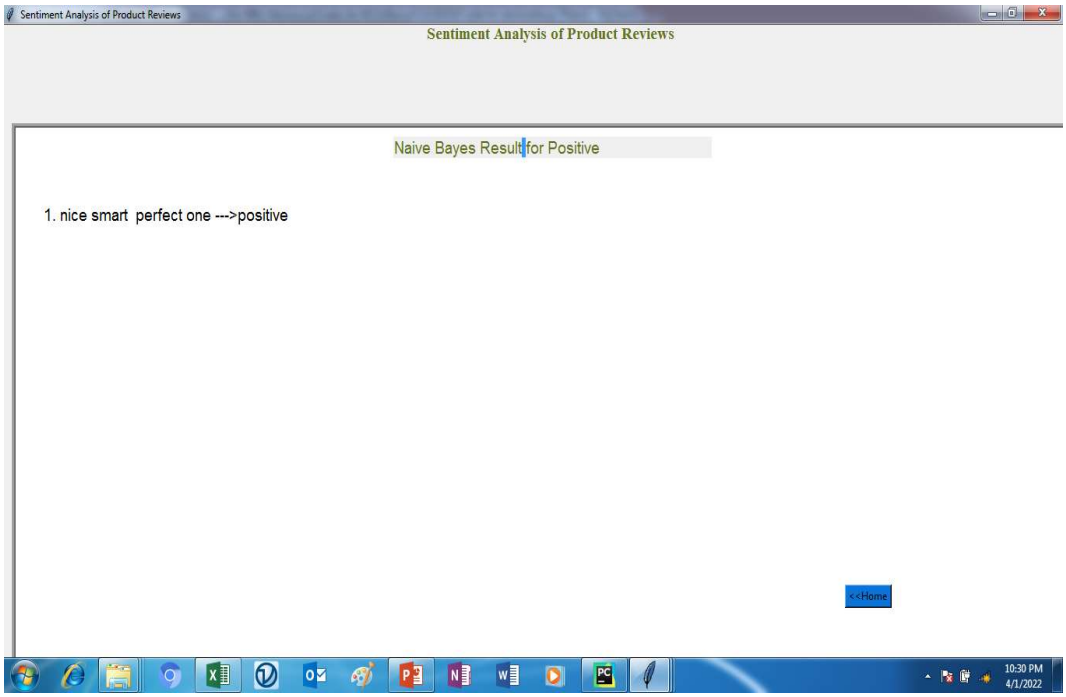
To classify for testing data, the user may firstly import testing data, secondly click Token and Stop word button which removes the stopwords. And the user need to choose 'To Calculate Naïve Bayes 'which gives result of Feature Extraction Score. And then, the user may click Classify which shows the result of Naïve Bayes Classifier.

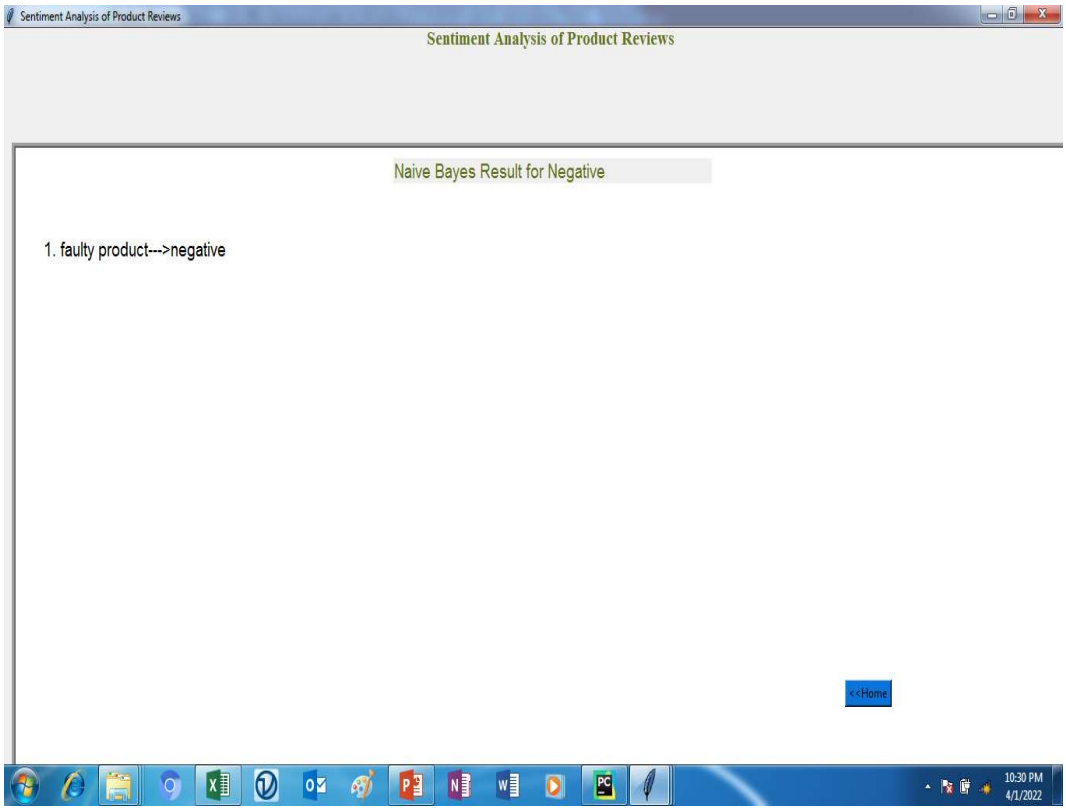






If the user click positive, the user may get Naïve Bayes Result for positive, if you click negative, the user may get Naïve Bayes Result for negative, and then if you click neutral button, the user may get Naïve Bayes result for neutral.


Sentiment Analysis of Product Reviews
Sentiment Analysis of Product Reviews
Naive Bayes Result for Positive
1. nice smart perfect one --->positive
<<Home
10:30 PM
4/1/2022


Sentiment Analysis of Product Reviews
Sentiment Analysis of Product Reviews
Naive Bayes Result for Negative
1. faulty product--->negative
<<Home
10:30 PM
4/1/2022

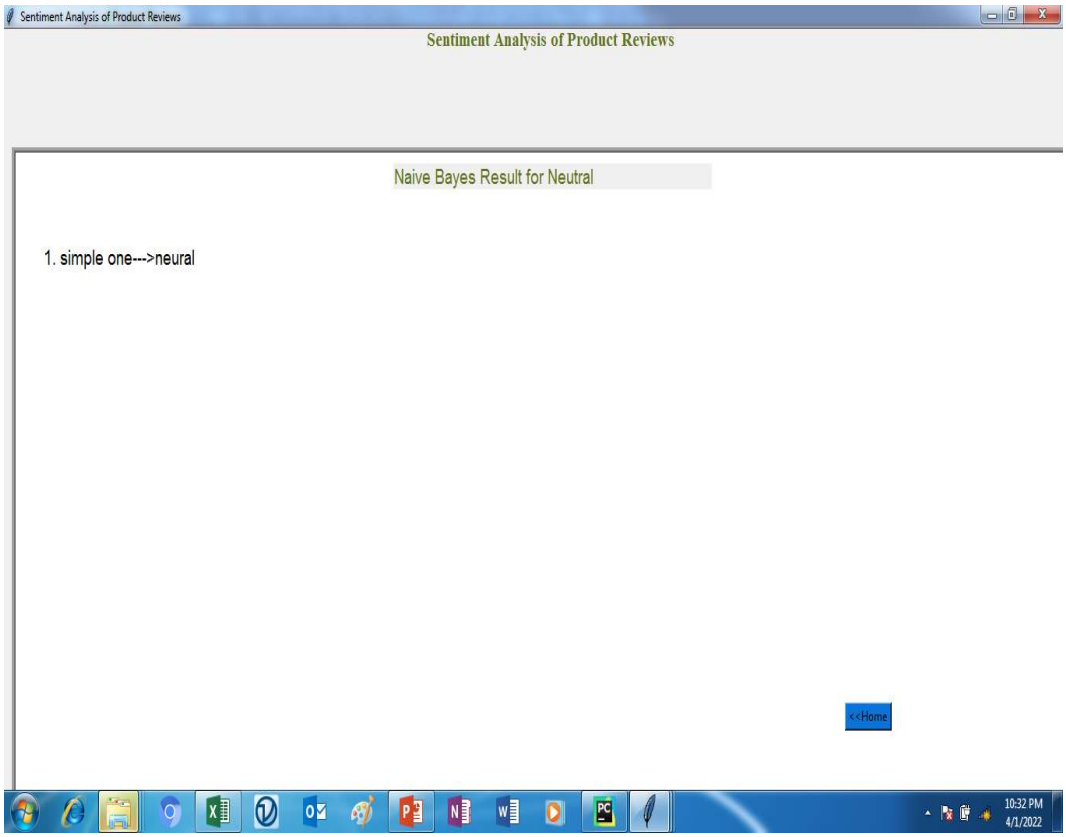


Table 12: Performance Evaluation Result for labeled electronic reviews data

Class Label	No of training sentiment	No of testing sentiment	Precision	Recall	F-Measure	Accuracy
Pos	544	287	82	92	87	93
Neg	113	6	70	97	82	90
Neu	44	7	100	56	72	88

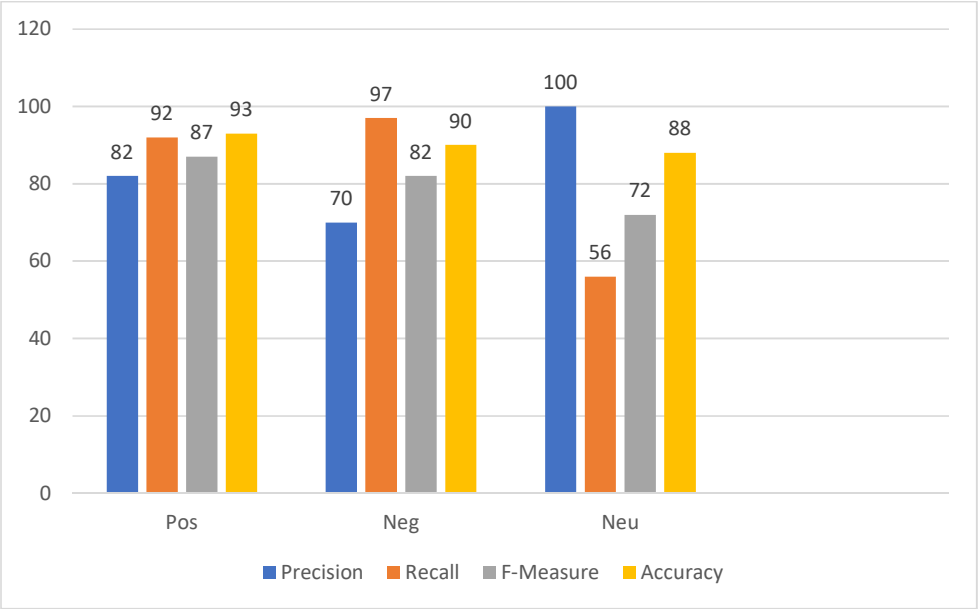
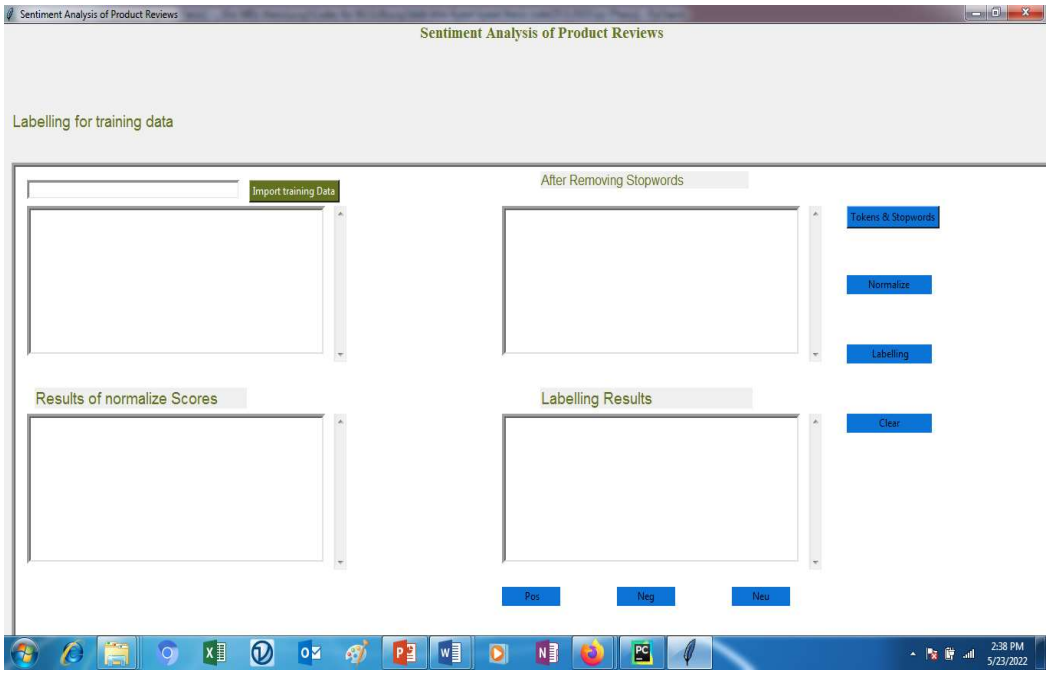


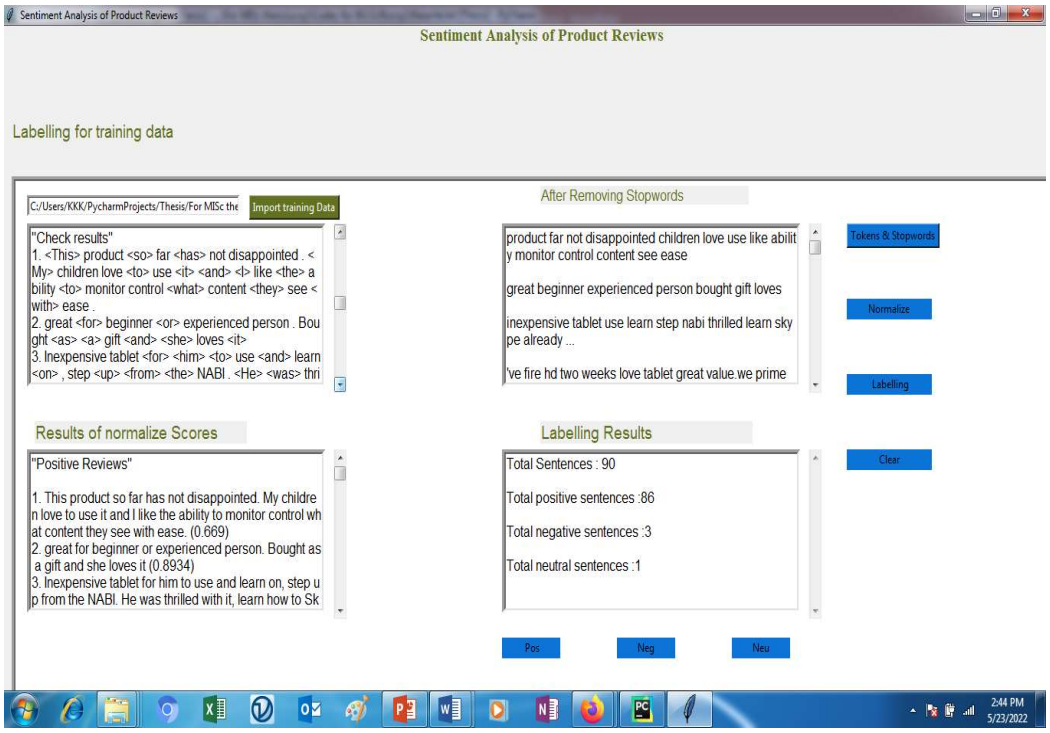
Fig 4.5 Result of Accuracy for testing labelled electronic reviews data

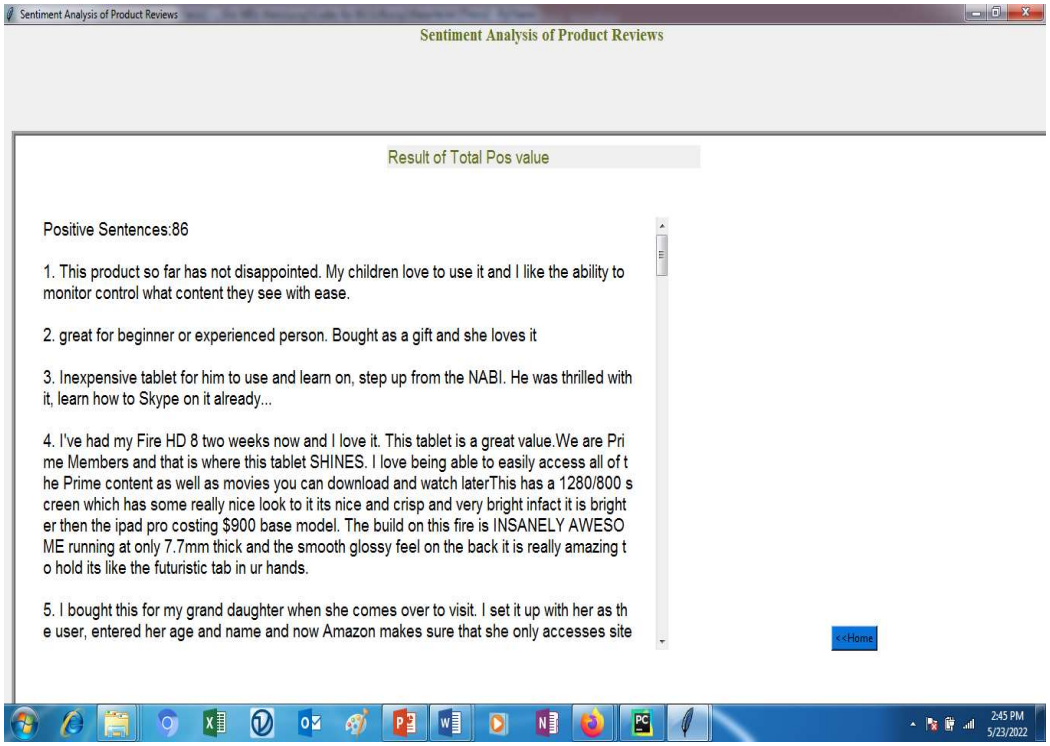
4.10 User Interface of the proposed system for labeled electronic reviews data

To label for training data, firstly you may import training data, secondly click Token and Stopwords button which makes the removal stopwords from training data. Thirdly, the user may select Normalize button and then Result of normalize Score can be got. Next, if you may click labelling, you would have seen labelling Results.



And then, the user may get positive sentences if the user click positive button, negative sentences if the user click negative button and neutral sentences if the user click neutral button.




Sentiment Analysis of Product Reviews
Sentiment Analysis of Product Reviews
Result of Total Pos value
Positive Sentences:86
1. This product so far has not disappointed. My children love to use it and I like the ability to monitor control what content they see with ease.
2. great for beginner or experienced person. Bought as a gift and she loves it
3. Inexpensive tablet for him to use and learn on, step up from the NABI. He was thrilled with it, learn how to Skype on it already...
4. I've had my Fire HD 8 two weeks now and I love it. This tablet is a great value.We are Pri me Members and that is where this tablet SHINES. I love being able to easily access all of t he Prime content as well as movies you can download and watch laterThis has a 1280/800 s creen which has some really nice look to it its nice and crisp and very bright infact it is bright er then the ipad pro costing $900 base model. The build on this fire is INSANELY AWESO ME running at only 7.7mm thick and the smooth glossy feel on the back it is really amazing t o hold its like the futuristic tab in ur hands.
5. I bought this for my grand daughter when she comes over to visit. I set it up with her as th e user, entered her age and name and now Amazon makes sure that she only accesses site
<<Home
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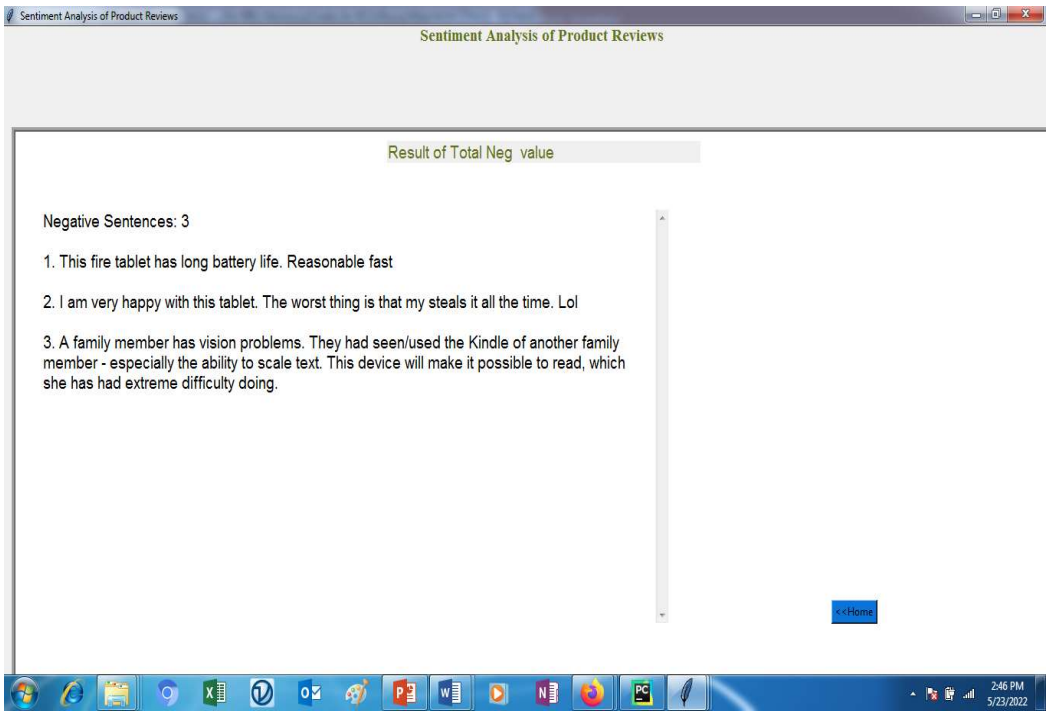
5/23/2022


Sentiment Analysis of Product Reviews
Sentiment Analysis of Product Reviews
Result of Total Neg value
Negative Sentences: 3
1. This fire tablet has long battery life. Reasonable fast
2. I am very happy with this tablet. The worst thing is that my steals it all the time. Lol
3. A family member has vision problems. They had seen/used the Kindle of another family member - especially the ability to scale text. This device will make it possible to read, which she has had extreme difficulty doing.
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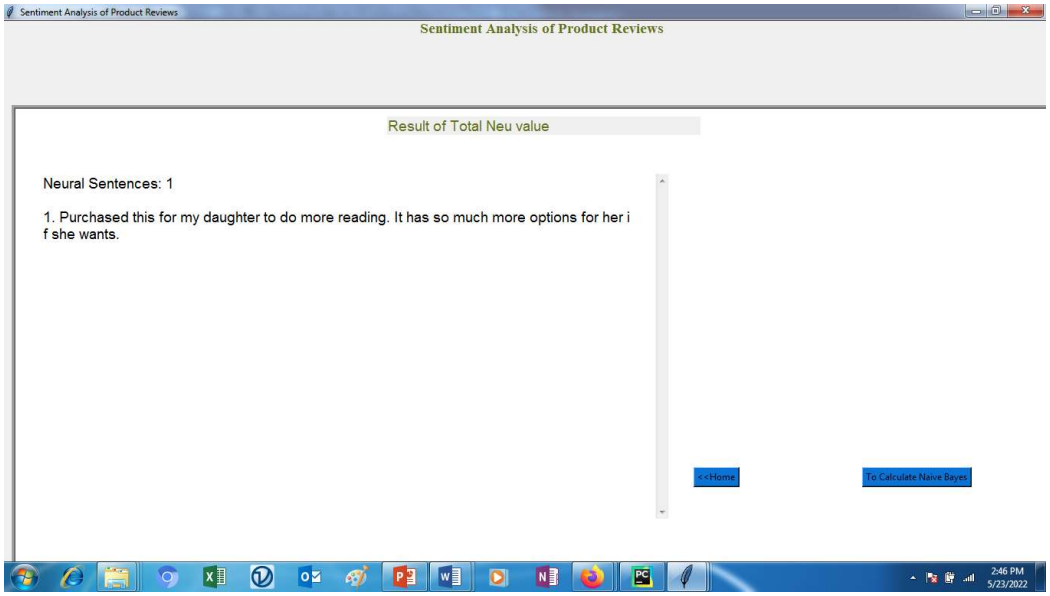
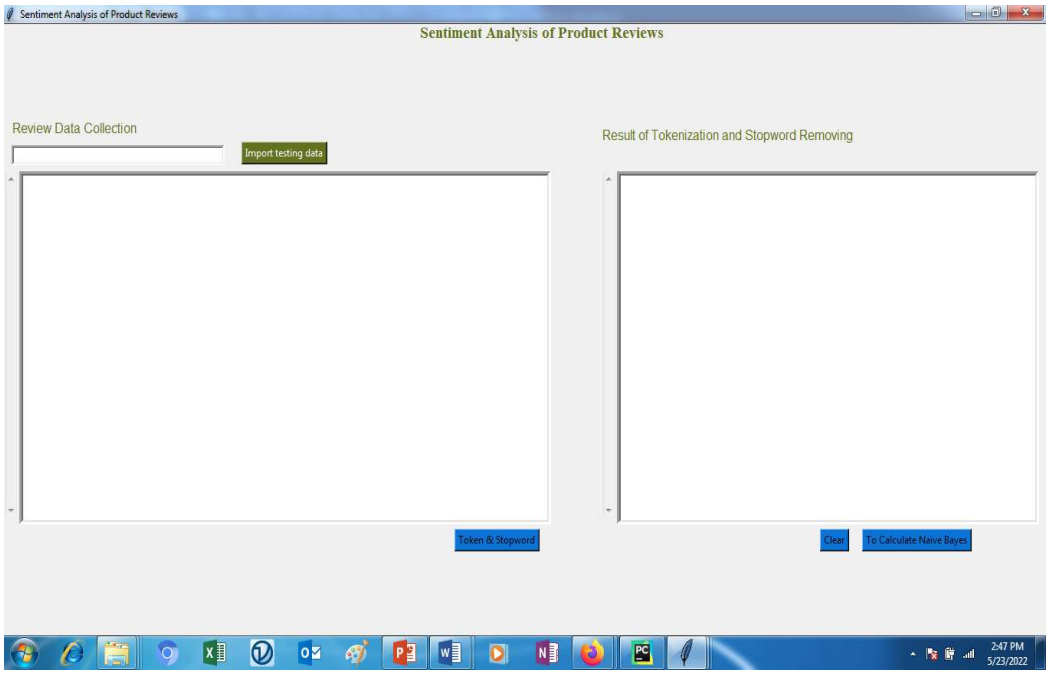
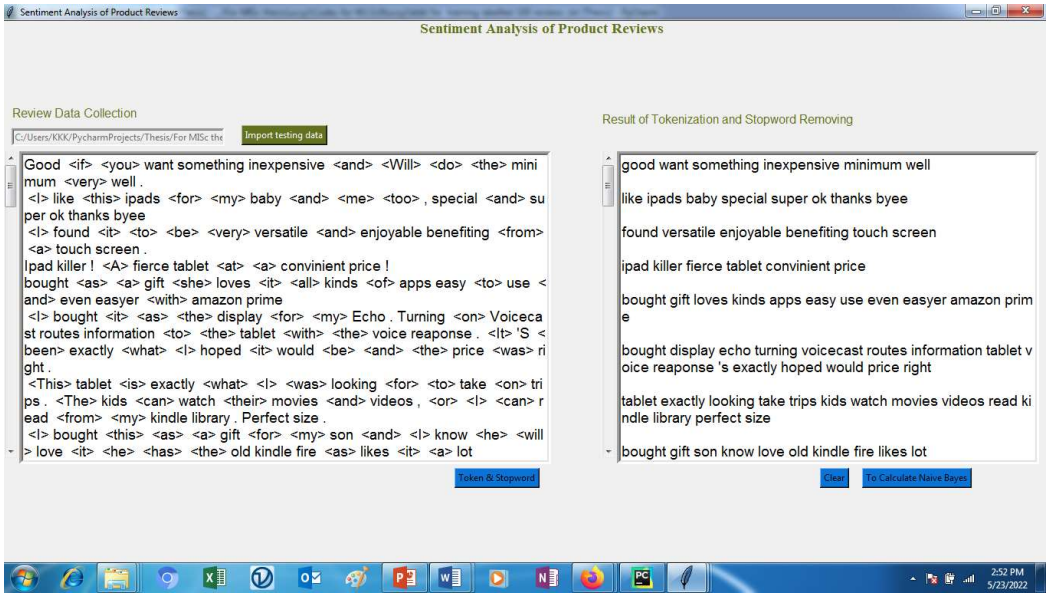
5/23/2022



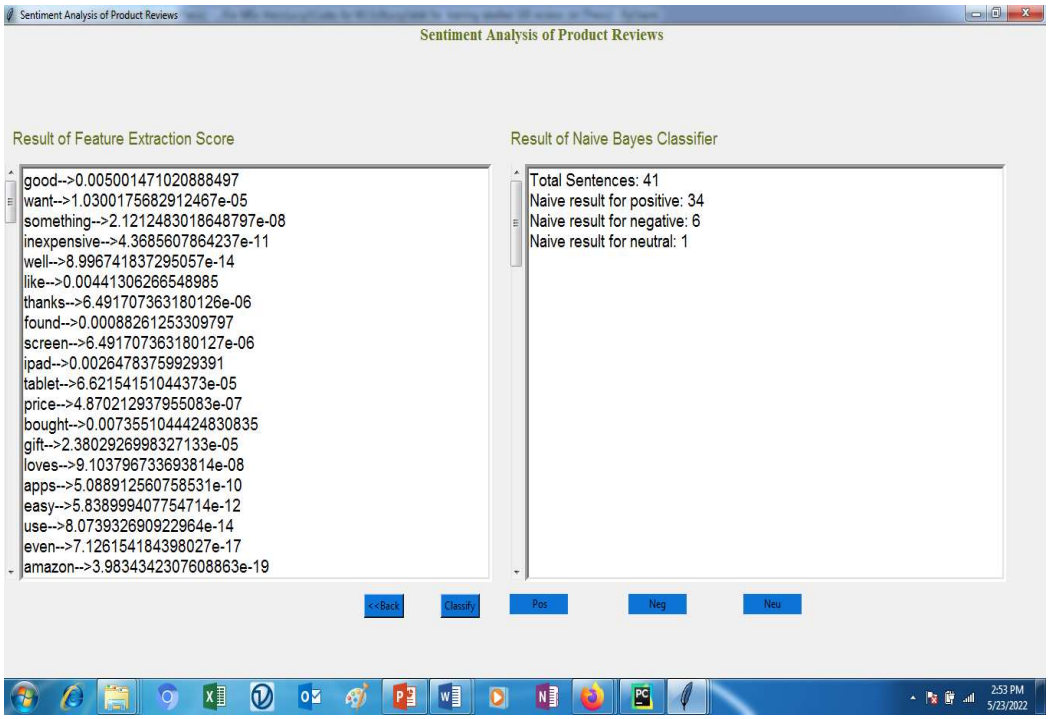
To classify for testing data, the user may firstly import testing data, secondly click Token and Stop word button which removes the stopwords. And the user need to choose

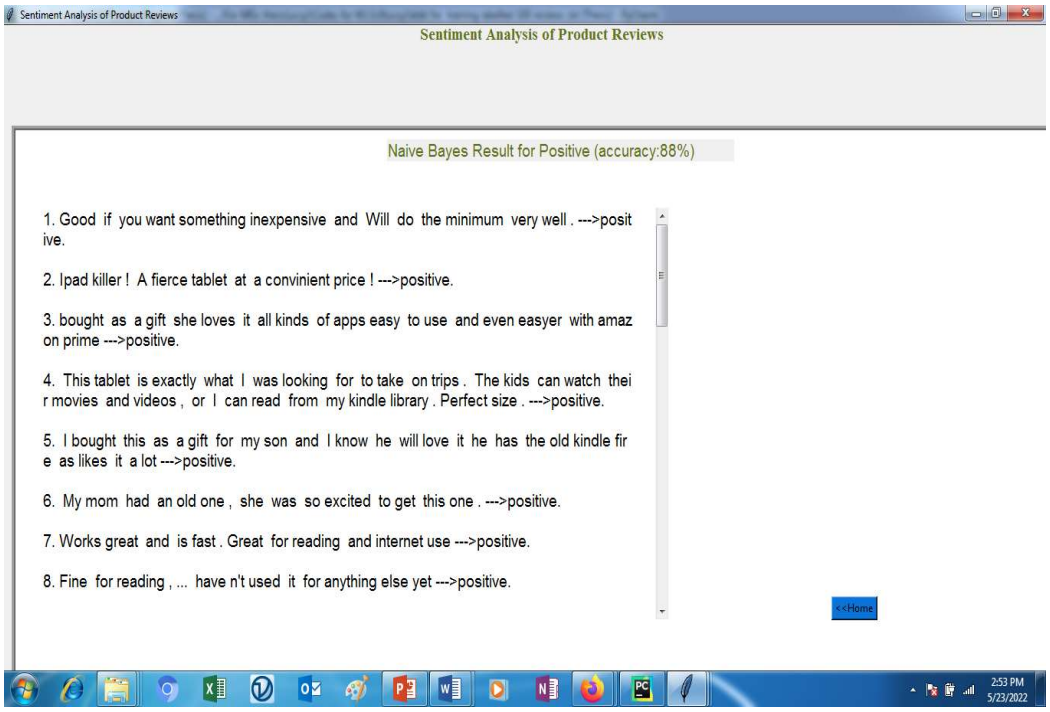
'To Calculate Naïve Bayes' which gives result of Feature Extraction Score. And then, the user may click Classify which shows the result of Naïve Bayes Classifier.





If you click positive, the user may get Naïve Bayes Result for positive, if you click negative, the user may get Naïve Bayes Result for negative, and then if you click neutral button, the user may get Naïve Bayes result for neutral.




Sentiment Analysis of Product Reviews
Sentiment Analysis of Product Reviews
Naive Bayes Result for Positive (accuracy:88%)
1. Good if you want something inexpensive and Will do the minimum very well . --->positive.
2. Ipad killer ! A fierce tablet at a convinient price ! --->positive.
3. bought as a gift she loves it all kinds of apps easy to use and even easyer with amazon prime --->positive.
4. This tablet is exactly what I was looking for to take on trips . The kids can watch their movies and videos , or I can read from my kindle library . Perfect size . --->positive.
5. I bought this as a gift for my son and I know he will love it he has the old kindle fire as likes it a lot --->positive.
6. My mom had an old one , she was so excited to get this one . --->positive.
7. Works great and is fast . Great for reading and internet use --->positive.
8. Fine for reading , ... have n't used it for anything else yet --->positive.
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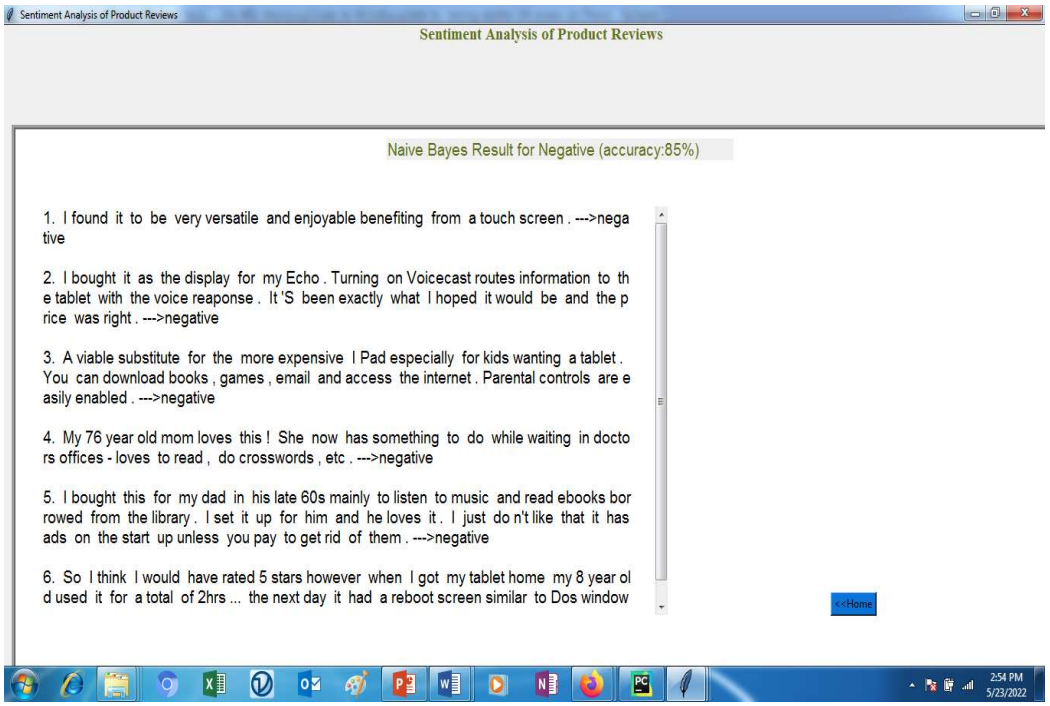
Sentiment Analysis of Product Reviews
Sentiment Analysis of Product Reviews
Naive Bayes Result for Negative (accuracy:85%)
1. I found it to be very versatile and enjoyable benefiting from a touch screen . --->negative
2. I bought it as the display for my Echo . Turning on Voicecast routes information to the tablet with the voice reaponse . It 'S been exactly what I hoped it would be and the price was right . --->negative
3. A viable substitute for the more expensive I Pad especially for kids wanting a tablet . You can download books , games , email and access the internet . Parental controls are easily enabled . --->negative
4. My 76 year old mom loves this ! She now has something to do while waiting in doctors offices - loves to read , do crosswords , etc . --->negative
5. I bought this for my dad in his late 60s mainly to listen to music and read ebooks borrowed from the library . I set it up for him and he loves it . I just do n't like that it has ads on the start up unless you pay to get rid of them . --->negative
6. So I think I would have rated 5 stars however when I got my tablet home my 8 year old used it for a total of 2hrs ... the next day it had a reboot screen similar to Dos window
<<Home
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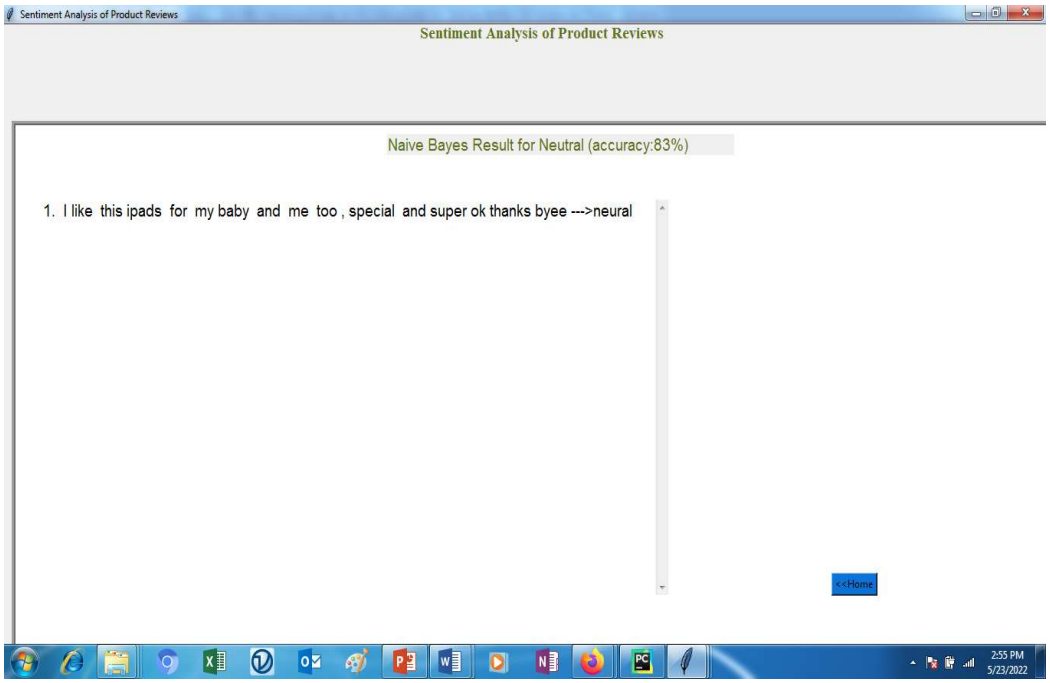
5/23/2022



If the reviews which are positive, negative and neutral have been labelled manually by Vader, the results of reviews would have been got exactly and correctly. So Vader is a reliable and trustful system.

CHAPTER 5

CONCLUSION

This paper has explored the sentiment analysis of the product reviews from Amazon use Hybrid Based Approach. It is noted that the importance of the Sentiment Analysis. And this paper aims to conduct Sentiment Analysis of product reviews by classifying reviews into positive, negative and neutral sentiment. Based on results of this paper, positive sentiment is mostly found and the least one is negative sentiment. Moreover, Sentiment Analysis enables the company to find out the customer's opinion about its product. Sentiment Analysis helps to obtain the solutions and satisfactions from customers.

5.1 Conclusion of the System

Sentiment analysis is also known as opinion mining. In its simplest form, it's a way of determining how positive or negative the content of a text document is, based on the relative numbers of words it contains that are classified as either positive or negative. Sentiment analysis is a useful tool for any organization or group for which public sentiment or attitude towards them is important for their success - whichever way that success is defined.

The results from sentiment analysis help businesses understand the conversations and discussions taking place about them, and helps them react and take action accordingly. They can quickly identify any negative sentiments being expressed, and turn poor customer experiences into very good ones. They can create better products and services, and they can formulate the marketing messages they send out according to the sentiments being expressed by their target audience or customers.

Businesses can compare their results with those of their competitors to better understand people's attitude to their business. They can identify where they may be excelling, or identify where there's room for improvement compared to the competition. They can also conduct market research into general sentiment around key issues, topics, products, and services, before developing and launching their own new services, products or features.

Hybrid System has been tested with unlabeled shoe reviews dataset and labelled electronic review dataset. The accuracy of shoe reviews dataset is positive (93%), negative (93%), neutral (91%).The accuracy of electronic reviews dataset is positive (93%), negative (93%), neutral (90%).The accuracy between shoes reviews dataset and electronic reviews dataset is not very different.

5.2 Limitation

Sentiment analysis tools can identify and analyze many pieces of text automatically and quickly. However, computer programs have problems recognizing things like sarcasm and irony, negations, jokes, and exaggerations - the sorts of things a person would have little trouble identifying. And failing to recognize these can skew the results.

'Disappointed' may be classified as a negative word for the purposes of sentiment analysis, but within the phrase “I wasn't disappointed", it should be classified as positive. The proposed system cannot analyze for double negative sentences, for example:

- Ko Ko didn’t see anyone in the park.
- There aren’t no fruit in fridge.
- The driver can’t find no place to stop.
- I cannot find my purse nowhere.

The percentage of error results in this system is 12.

Therefore, automated sentiment analysis tools do a really great job of analyzing text for opinion and attitude, but they're not perfect.

5.3 Further Extension

This system determines the sentiment of the text, whether it is positive, negative or neutral, which is extended to strength of the dilemma of the sentences. This thesis focuses on analyzing the sentiments of Amazon reviews and presenting the result under different sentiments sentences. These results can be used to train a machine learning model in the future to predict customer behavior for product, service or expectation of people in regard to particular political party. People use social media widely not only to sell their products, but also to buy products. So they express their opinions about the products. That is why, this thesis describes the sentiment analysis using Hybrid to

understand the customers' behavior. So the study of the sentiment analysis using Hybrid becomes a vital role to analyze the attitudes for each object in the text.

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