Detecting And Characterizing Online Product Reviews

Mr.D. Ramana Kumar[1], Madichetti Sritha[2], Vanguri RajaPrasad[3], Surnar Vyshnavi [4]

[1]Assistant Professor, Department of Computer Science and Engineering,

Anurag Group Of Institutions

[2,3,4] Department of Computer Science and Engineering,

Anurag Group Of Institutions, Hyderabad, India

Abstract— **The rise of e-commerce sites has led to an increase in customer reviews, which can provide valuable insight into customer sentiment and preferences. However, not all reviews are created, or extreme reviews (i.e. very positive or very negative reviews) can have a disproportionate impact on customer perceptions and decisions. Therefore, detecting and characterizing extreme reviews is an important task for companies to deeply understand customers and improve products or services. It is also difficult and time-consuming for product manufacturers to analyze so many opinions. This project considers the problem of classifying reviews according to their global semantics (positive or negative). Conduct research on two different supervised machine learning techniques. SVM, Logistic Regression, Random Forest, Tree-Based Pipeline Optimization Tool (TPOT) classifiers, Multinomial Naive Bayes, and Decision Tree were tested on Amazon's vacuum cleaner product. Then compare their accuracy. The results show that the TPOT method outperforms state-of-the-art methods as it optimizes the code based on the generations of the data.**

Keywords: E-commerce website, Supervised Machine Learning Techniques, Decision-making, Characterizing, Extreme Reviews, SVM, Random Forest, Logistic Regression, TPOT classifier, Multinomial Naïve Bayes, Decision Tree.

I. INTRODUCTION

As the commercial site of the world is almost fully undergone in online platform, people is trading products through different ecommerce website. And for that reason, reviewing products before buying is also a common scenario. Also now a days, customers are more inclined towards the reviews to buy a product. So analyzing the data from those customer reviews to make the data more dynamic is an essential requirement. In this age of increasing machine learning based algorithms reading thousands of reviews to understand a product is rather time consuming where we can polarize a review on particular category to understand its popularity among the buyers all over the world.

"It's a virtuous circle: the more reviews, the more purchases. The more purchases, the more reviews. The more purchases, the more you rank well in search results and the more sales you make," said by Alice, owner of online cosmetic brand Elizabeth Mott[1] in their shopping budget online. [2] In 2017, e-commerce store sales were $2.3 trillion and are expected to reach $4.5 trillion by 2021.Today, there are nearly 12 to 24 million e-commerce stores in the world. Research has found that 61% of Amazon reviews in the electronics category are fake [3]. Detecting and characterizing extreme reviews is an important task for companies to deeply understand customers and improve products or services. By identifying key issues and themes in extreme reviews, companies can prioritize the areas of improvement most important to customers. The purpose of this article is to rank positive and negative customer reviews for different products and build a supervised learning model to polarize a large number of reviews. A study by Amazon last year showed that more than 88% of online shoppers trust reviews as much as personal recommendations. Any article online that has a high number of positive reviews makes a strong statement about the legitimacy of the article. Conversely, a book or other online article without a review puts potential customers in a state of distrust. Simply put, more reviews seem more compelling. People value the endorsement and experience of others, and material reviews are the only way to know other people's impressions of a product. Opinions gleaned from a user's experience with a particular product or topic directly influence the buying decisions of future customers. Likewise, negative reviews often result in lower sales. The goal is for those who understand customer feedback and polarize accordingly based on amounts of data. Similar work was done on the Amazon dataset. In our project, we conduct opinion mining on a large data set of Amazon product reviews to understand polarized attitudes towards products.

II. Literature survey

As a preliminary part of the work, an elaborative literature survey was carried out.

Viresh Gupta, Aayush Aggarwal, Tanmoy Chakraborty [4] This paper focus on opinions collected from the Amazon product website which are of 923 reviewer groups and are manually labelled. These clusters are extracted using regular article crawling based on brand similarity, so users can be grouped together if they view (from) multiple brands with each other. It assumes that the nature of the population of consultants depends on 8 characteristics specific to a couple (group, brand). The authors develop a supervised feature-based model to classify candidate groups as extremist entities. They use the kmultiple classifier to classify groups based on reviews written by users of that group to determine if the group displays membership. A classifier based on a 3-layer perceptron seems to be the best classifier. They then looked in detail at the behavior of these groups to better understand the dynamics of opinion fraud at the brand level. These behaviors include rating consistency, review sentiment, verified purchases, review dates, and upvotes a review has received. Surprisingly, they noticed that there were many verified reviewers showing extreme sentiment, and upon further investigation, they found a way to circumvent existing mechanisms to prevent unofficial inducements on Amazon.

Ata-Ur-Rehman, Nazir M. Danish, Sarfraz M. Tanzeel, Aslam Muhammad, et.al [5] With the growing trend of online shopping, more and more people want to buy the products they need from online stores. This type of purchase does not take the customer much time. The customer goes to the online store, searches for what he needs and places an order. But the problem that people face when buying products from online stores is that the quality of the products is poor. Customer places an order only by viewing ratings and reading reviews related to a particular product. Such reviews from others are a source of satisfaction for buyers of new products. Here, a single negative review may change the customer's perspective of buying this product. In this case, this review may be wrong. Therefore, in order to remove such fake reviews and provide users with the original product related reviews and ratings, we offer the Fake Product Review Monitoring and Removal System (FaRMS), which is an intelligent interface using unified integration with Amazon, Flipkart, and Daraz (URL) and product-related resource locators analyze reviews and provide customers with raw ratings. The unique quality of the proposed system is that it works with three e-commerce sites analyzing not only reviews in English but also reviews written in Urdu and Roman Urdu. Previous work on fake reviews does not support features to analyze reviews written in languages such as Urdu and Roman Urdu and cannot handle reviews from more than one business website electronic. The proposed work of this paper uses intelligent learning techniques to achieve an accuracy of 87% in detecting fake reviews written in English, which is higher than the accuracy of previous systems.

Q. Ye, Z. Zhang, and R. Law [6] In this study, sentiment classification methods are used to extract travel blog reviews. For sentiment classification of seven famous travel locations in the United States and travel blog reviews in Europe, we investigate three supervised machine learning algorithms: Naive Bayes, SVM, and N-gram models based on characters. SVM and N-gram techniques outperform than Naive Bayesian strategies.

J. Rout, S. Singh, S. Jena, S. Bakshi [7] This paper proposed that, the availability of millions of products and services on e-commerce sites makes it difficult to find the most suitable product for your needs, as there are so many options. The most popular and useful way to get out of this situation is to follow the comments of other people who have already tried it on opinionated social networks. Almost all e-commerce sites offer users the opportunity to view and learn about the products and services they have experienced. Customer reviews are increasingly used by individuals, manufacturers and retailers for their purchasing and business decisions. Since there is no review of comments received, anyone can write anything unanimously, which will definitely lead to comment spam. Additionally, driven by the desire for profit and/or publicity, spammers generate synthetic reviews to promote certain products/brands and disparage competitors' products/brands. Misleading comment spam has increased significantly over time. In this work, we apply supervised and unsupervised techniques to identify comment spam. The most efficient feature set is compiled for model building. Sentiment analysis is also included in the tracking process. To get the best performance, some well-known classifiers are applied to labeled datasets. Also, for untagged data, clustering is used after calculating the attributes required for spam detection. Moreover, comment spammers are also likely to be responsible for content pollution in multimedia social networks, as many users today use their social network credentials to post comments. Finally, this work can be extended to find suspicious accounts responsible for posting fake media content on their respective social networks.

M. Chelliah and S. Sarkar, [8] This paper mainly focused on product reviews written by users include a wealth of information about user preferences for product features, as well as helpful explanations that shoppers often use to make purchasing decisions. experiences have been recorded in product reviews. In this course, authors show how to use various strategies to help recommender systems on e-commerce sites to get the most out of customer reviews. and distributed representations that bridge the vocabulary gap between user reviews and product descriptions are examples. They described recommendation algorithms that solved the cold start problem by using revision information to create recommendations and explanations. They discussed cases and lessons learned from online marketplaces i.e. Flipkart.

S. Xie, G. Wang, S. Lin, and P. S. Yu [9] They suggest that by examining reviews correlated with normal arrival patterns of rater and error rater arrival patterns, they observe that normal arrival patterns of rater are stable and uncorrelated over time with their rated patterns. In contrast, spam attacks are typically burst and are positively or negatively correlated with scoring patterns. The dataset they took was snapshots of a review website on October 6, 2010. It includes 4,444 and 408,469 reviews written by 343,629 reviewers, of which 4,444 are reviews of 25,034 stores on a certain website. For each comment, they collect information such as the rating, the date the was posted, and whether it is a Spammer Review (SR). During the evaluation process, they selected 53 stores, of which had more than 1000 reviews. If two or more reviewers declare a store to be SR, the human reviewers decide if the store is spammy, not the system considers the store dishonest in its sales. Out of 53 stores, 34 are suspicious and the rest are normal stores. At least two of the 4,444 votes were suspicious in 22 of the 34 stores. The recall related to the system was 75.86%, indicating that the system detected most of the stores attacked by SR spam. The accuracy associated with the proposed method is 61.11%. Since the model is trained using a large number of exams that have SR in its data set, the proposed system performs well in training its model to find the SR that are related.

Z. Wang, Y. Zhang, and T. Qian [10] The authors have worked with the intention of filtering out fake reviews from the original review as this has become a need of the moment. The proposed system classifier takes the exam text and other information and indicates whether the exam is trustworthy. The dataset used in this project comes from Yelp.com. They used 16282 comments and divided them into 0.7 training sets, development 0.2 sets and 0.1 test sets. Extracting predictive features from reviews is the hardest part of this project. Basically, they extract two types of functionalities: review-centric functionality and reviewer-centric functionality. First, they calculated percentages of each unigram and bigram tag for fake reviews and non-fake reviews. They then find the top 100 single-letter s and bigrams with the largest percentage difference between false s and non-false notices. The second approach leads to better performance for because it handles all unigrams and bigrams. They tested several algorithms for machine learning, but using a neural network, they achieved the highest accuracy for , around 81.92%.The system does a good job of detecting fake reviews, but still needs to improve the accuracy of filtering reviews.

Sanjay K.S, Dr. Ajit Danti [11] This article states that online reviews are one of the most important factors for a customer to buy a product or obtain a service and come from many sources of information that can be used to determine the public's perception of a product. Fake reviews will be posted intentionally to drive web traffic to a particular product. These fake reviews distract buyers by misleading customers. The behavior of reviewers is extracted based on the semantic analysis of their review content, with the aim of identifying whether the review is fake or not. In this work, the reviews of a specific product are extracted from the web, along with the reviews, various other reviewer information is also extracted to identify the fake reviewers using a decision tree classifier and d gain of information. Use information gain to check the importance of features for decision making. Experiments are carried out on a complete set of reviews extracted from the web and demonstrate the effectiveness of the proposed method.

P. Rosso, D. Cabrera, M. Gomez [12] As these days, there are tons of opinion pieces posted on the web. These reviews are a very important source of information for customers and businesses. The former rely more than ever on online reviews to make their purchasing decisions, while the latter are sensitive to customer expectations. Unfortunately, as companies have fallen behind, there has been an increase in misleading opinions, that is, fictitious opinions written deliberately to ring true in order to mislead consumers into promoting a product of poor quality (misleading positive opinion) or by criticizing a potentially superior product. (negative misleading sexual opinion). In this article, they focused on detecting two types of misleading opinions, positive and negative. Since there are few examples of misleading opinions, they proposed to use PU learning to solve the misleading opinions detection problem. PU learning is a semi-supervised technique to build binary classifiers based only on positive (i.e. false opinions) and unlabeled examples. Specifically, they proposed a new method which, compared to its original version, is more efficient in the selection of negative samples (eg.i.e. not a misleading opinion) is not marked. The obtained results show that the proposed PU learning method systematically outperforms the original PU learning method. In particular, the results show an average improvement of 8.2% and 1.It outperforms the original method by 6% in detecting positive and negative misleading opinions, respectively.

A. Mukherjee, B. Liu, and N. Glance [13] This paper mainly focuses on spotting fake review groups, finding fake reviews and a fake review group that works on writing fake reviews on e-commerce sites to promote or demote the products of sellers. The developer has used the "Frequent Itemset Mining (FIM)" method to search for fake reviewer groups. The system uses behavioral and relational models to find relationships between groups of fake reviewers (also known as "spam groups") . Prior to this work, no labeled datasets were available, so to examine their method, they generated labeled datasets using expert human judgment. This system uses a new ratio-based model, called "GSRank", which detects fake reviewers and ratios between groups of spammers. In this technology, the collection of items I is the collection of reviewer IDs, and each transaction is a collection of IDs for specific product reviews, then the system uses the FIM method to find several different product combinations for the given group.

V. K. Madhura N Hegde, Sanjeetha K Shetty, Sheikh Mohammed Anas [14] This article focuses on using sentiment analysis to detect spam and fake comments, and to remove comments containing profanity and vulgarity. In the proposed system web crawler, it is used to explore the data on the website. During pre-processing, the data is transformed into the desired format, and then fake reviews are removed from the mix of raw and spam reviews. The fake review detector detects fake reviews. Each review must pass through a classifier which calculates the sentiment score of the review. Cosine similarity method is applied to measure this type of similarity. If the calculated cosine value is greater than 0.5, the revision is considered a bad revision. The developed system revealed that 111 out of 300 reviews were fake. However, the datasets used to train the models were too small to find suspicious patterns more accurately.

III. System Design

Previous researches would build a clear classifier by using different techniques like semi-supervised or unsupervised learning techniques from machine learning but in proposed system to classify the sentiment of the product reviews we used a group of supervised classifiers and compared their performances in terms of accuracy, precision, recall, f1-score.

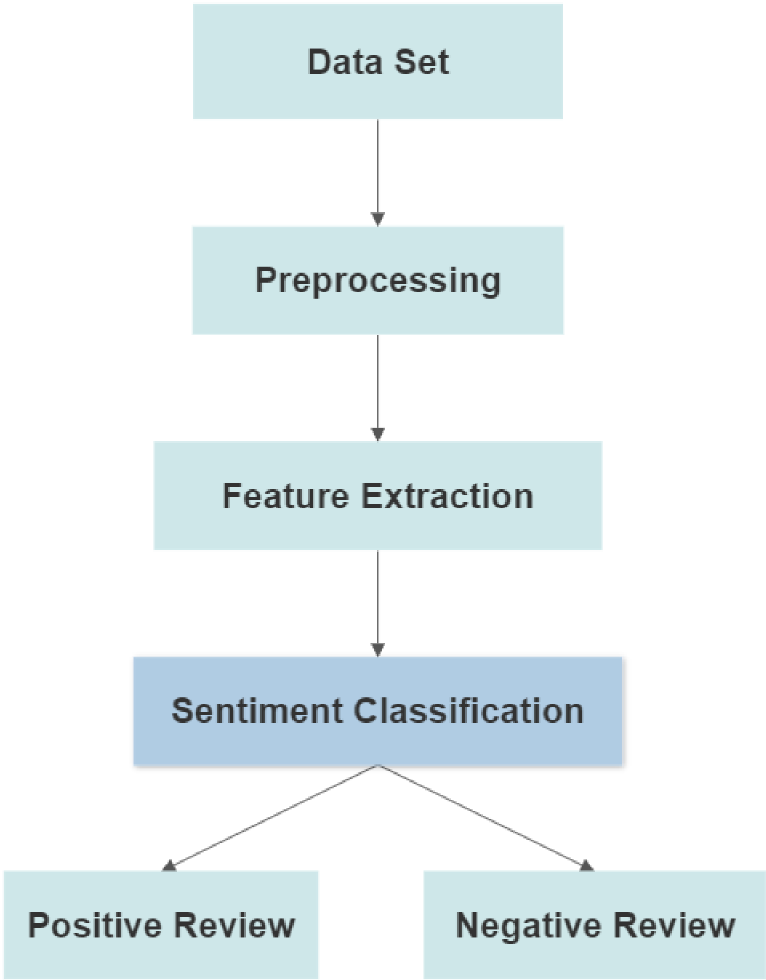

Fig 3.1. System Architecture for detecting and characterizing the online product reviews

Fig 3.1 describes the overall architecture of model, as an initial step is collecting the dataset. The data set is gathered from Kaggle (an online website) in the format of CSV file. Then we run the application by importing all the necessary libraries and performs data pre-processing and feature selection. We split the data into testing and training data which will be 20 and 80 percent respectively and generate the model. The next step is to build the Classifiers using Support Vector Machine (SVM), Decision Tree, Random Forest, Multinomial Naïve Bayes, Logistic Regression, Multilayer Perceptron and then compared their accuracies. As it is the classification of reviews according to their sentiment the result will be classified into two class labels such as Positive and Negative Reviews.

- Loads the Dataset and imports all the necessary libraries.
- Explores the dataset and performs data preprocessing.
- Performs feature extraction using Natural Language Processing (NLP) techniques.
- Applying the Support Vector Machine (SVM), Decision Tree, Random Forest, Multinomial Naïve Bayes, Logistic Regression, and Multilayer Perceptron algorithms.
- Builds the model by splitting the data into training and testing phases.
- The result gets displayed as the review belongs to positive or negative class.

3.1.1. Data Collection:

In the very first data collection stage, we have collected the reviews on product, delivery and packaging of vacuum cleaners from Amazon. The dataset has been taken from the official website of Kaggle. This Dataset consist of 41,042 rows and 4 columns. The dataset is further split into 80% for training and 20% for testing the algorithms. Furthermore, in order to obtain a representative sample, each class in the full dataset is represented in about the right proportion in both the training and testing datasets.

3.1.2. Data Pre-processing and Data Analysis:

The data which was collected might contain missing values and that may lead to inconsistency. To gain better results data need to be pre-processed to improve the efficiency of the algorithm. The outliers must be removed and variable conversion needs to be done. In order to overcome all these issues, we used pandas library in python.

- Handling outliers
- Handling missing values

- Dropping unwanted columns.
- Fixing spelling and syntax errors

No. of Records	41,042
No. of Columns	4
Names of the columns	ProductId, UserId, Review Text Rating
Train data	80%
Test data	20%

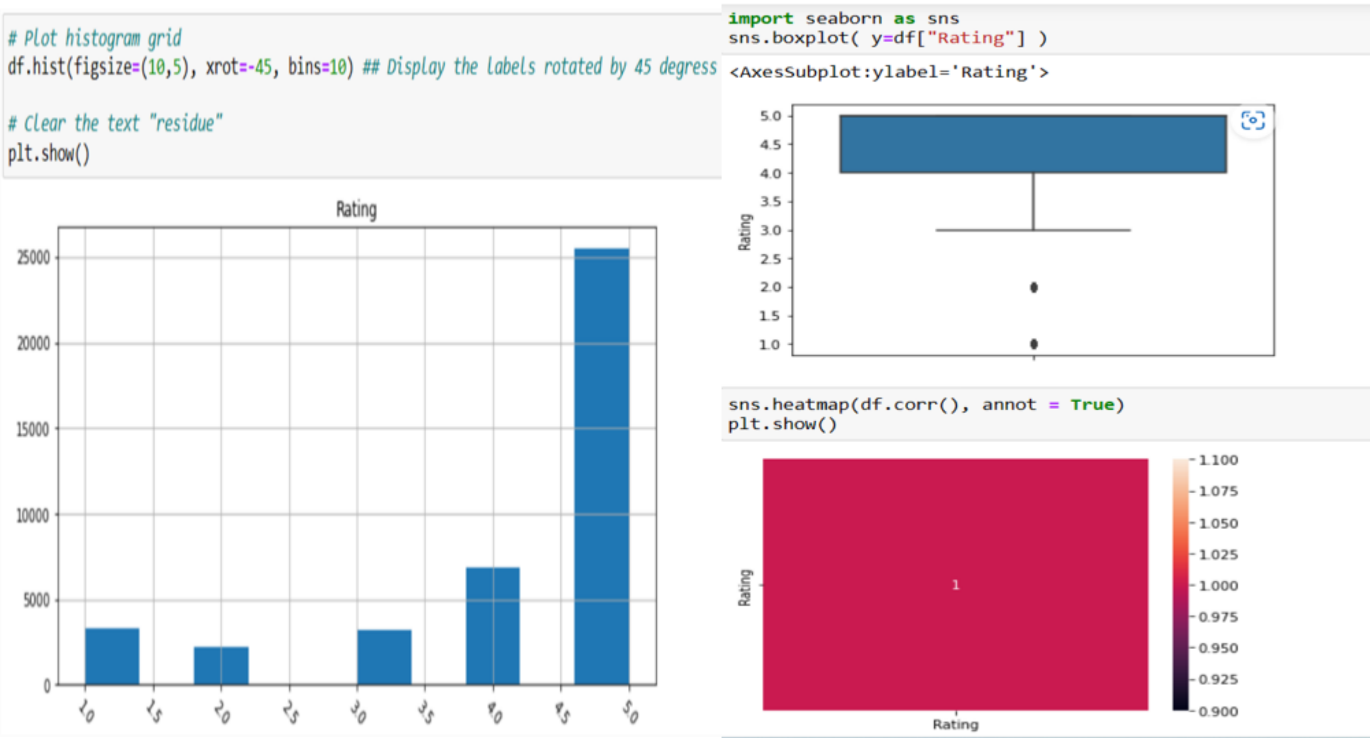

Fig 3.2. Data Analysis of the collected review dataset

3.1.3. Feature Extraction:
Feature selection is a process of feature reduction. Unlike feature extraction, which ranks existing features based on their predictive importance, feature extraction actually transforms the features. The transformed attributes or characteristics are linear combinations of the original attributes. We have used module on Natural Language Toolkit library of Python.
These are following techniques used in feature extraction:

- Tokenization
- Stemming
- Lemmatization
- Vector Space Model

Tokenization:

For written natural language processing, it is unavoidable to break text into smaller units called tokens. Computers must distinguish individual entities from text and use tokenization to create them. Typically, tokens represent single words, which are the smallest independent units of natural language. Additionally, token parses consist of idioms or hyphens, such as "User-Generated". Tokenization decomposes running text into short textual entities and is the first task in any text preprocessing cycle. In addition to splitting small units, whole sentences can also be the output of the tokenizer. A simple word generator can be implemented in multiple languages by splitting text on the occurrence of space symbols. This simple basic approach has some drawbacks due to the lack of recognizable words that go semantically together. However, a simple tokenizer divides the phrase, which was introduced below, is into the following five tokens:

the best fox is running

By using tokens, it is possible to create so-called n-grams, representing sets of tokens of length n. Gramma" is the Greek word for a letter or a symbol. When we talk about a set of n letters in a word, it is the n-gram character. The removal of stop words is a very important way in NLP to reduce large raw input spaces (SWR). Most languages have specific words that appear more frequently than others, or do not contain much information about the content of the text, e.g. 'is', 'are', 'the', 'a'. Therefore, it often makes sense to exclude these so-called stop words in further analysis. In English, such a word could be "the", "a" or "an". Elimination can be done by comparing the words to a normalized list of stop words. These lists are available in the literature and are often implemented in different software packages. In our example, "the" and "is" have been removed. Stop word removal should be used with caution, especially in sentiment analysis that attempts to predict the positive or negative intent of text. Deleting will exclude words that may change the entire statement, such as "not" or "none".

~~the~~ best fox ~~is~~ running

Stemming:

In addition to stop word removal, tuning is a useful technique for mapping words to their roots and further reducing input dimensionality. This helps extract the true meaning from text and makes unstructured data more accessible to machines. The first stemming algorithm based on removing longest suffixes and misspellings was developed in 1968. Porter's stemming algorithm is by far a modern method that removes suffixes from words to preserve the stem. Although this approach works well in English, it has some drawbacks in German, since German words are generally not constructed by adding suffixes. However, there is a German equivalent based on Porter's ideas and the Snowball string processing language. Using the English Porter Stemmer, assign the words "best", "fox", and "run" to the following words:

Best → best fox →fox running →run

Lemmatization:

Lemmatization is the process of mapping each word in a text according to its dictionary type or expected source structure. Verbs are transformed into infinitives, nouns are restructured in their singular form, and adverbs or adjectives announce their positive form. The method is based on lexical analysis, usually using a dictionary, such as WordNet, where the lemmas of each modified word form can be found. This preprocessing step is similar to alignment, reducing the input space by mapping different word forms to their common representation. Dictionary entries support natural language processing lemmatization; it is able to map "best" to its "good" lemma:

Best → good fox→ fox running→ run

Vector Space Model:

Besides, preprocessing the words themselves, their representations have to be changed into a machine readable format. Meanwhile, a couple of different approaches have been developed to transform texts into different kinds of numerical representations. Some of them only represent statistics of a word, such as the one-hot-encoding, and other formats also include the word's context, e.g. word2vec.The Vector Space Model is an approach that transforms a text into one vector. It is based on one-hot-encoding of words. Given a set of textual documents (corpus), it is possible to create a vocabulary with the length of N. The one-hot-encoded word vector represents a word by1at the corresponding vocabulary entry.

3.1.4. Model Selection:

Machine learning is about predicting and recognizing patterns and generate suitable results after understanding them. ML algorithms study patterns in data and learn from them. An ML model will learn and improve on each attempt. To gauge the effectiveness of a model, it's vital to split the data into training and test sets. So before training our models, we split the data into Training set which was 80% of the whole dataset and Test set which was the remaining 20%. Then it was important to implement a selection of performance metrics to the predictions made by our model. We have applied algorithms like SVM, Random Forest, Logistic Regression, Multinomial Naïve Bayes, Decision Tree Classifier, Tree-Based Pipeline Optimization Tool (TPOT) classifier.

Support Vector Machine is one of the popular machine learning algorithm, generally used for the classification task. SVM algorithm finds a hyperplane that optimally divides the classes. It is best used with a non-linear classification solver which best suits to classify the reviews into positive or negative class labels.

Random Forest is an ensemble algorithm that combines multiple decision trees to improve the accuracy and generalization of the model. In the context of e-commerce websites, Random Forest can be trained on a large dataset of reviews to classify them as positive, negative, or neutral. The algorithm learns to identify patterns in the text of reviews that are associated with each sentiment category.

Multinomial Naive Bayes is a probabilistic algorithm that is particularly effective at processing text data. It is particularly useful in detecting extreme reviews because it can effectively handle sparse data and outliers. Extreme reviews often use unique or rare language, which can be difficult to classify using other algorithms. Multinomial Naive Bayes can handle these types of reviews by treating each word as a separate feature and calculating the probability of each word occurring in each sentiment category.

The Tree-Based Pipeline Optimization Tool (TPOT) is an automated machine learning package in python that uses a version of genetic programming to automatically design and optimize a series of data transformations and modeling models. It is a machine

learning library that seek to improve classification accuracy for a given tree monitor to maximize the dataset. It automates the most tedious parts of machine learning by intelligently exploring thousands of possibilities to find the best settings for our data.
A Decision Tree is a highly interpretable classification or regression machine learning algorithm that divides data feature values into branches at decision nodes (for example, if the feature is a color, each possible color becomes a new branch) until the final decision is made which is suitable for the easy classification sentiments of the reviews collected.
Logistic regression is one of the machine learning algorithm used for classification problems where the output is a binary or categorical variable. It is an extension of linear regression for classification tasks. The output class label is binary (e.g. only black or white) rather than continuous.
We compared the accuracies of above classifiers used. TPOT classifier got high accuracy of 97%, as it pipelines the data into number of generations and maximizes the performance of the model.

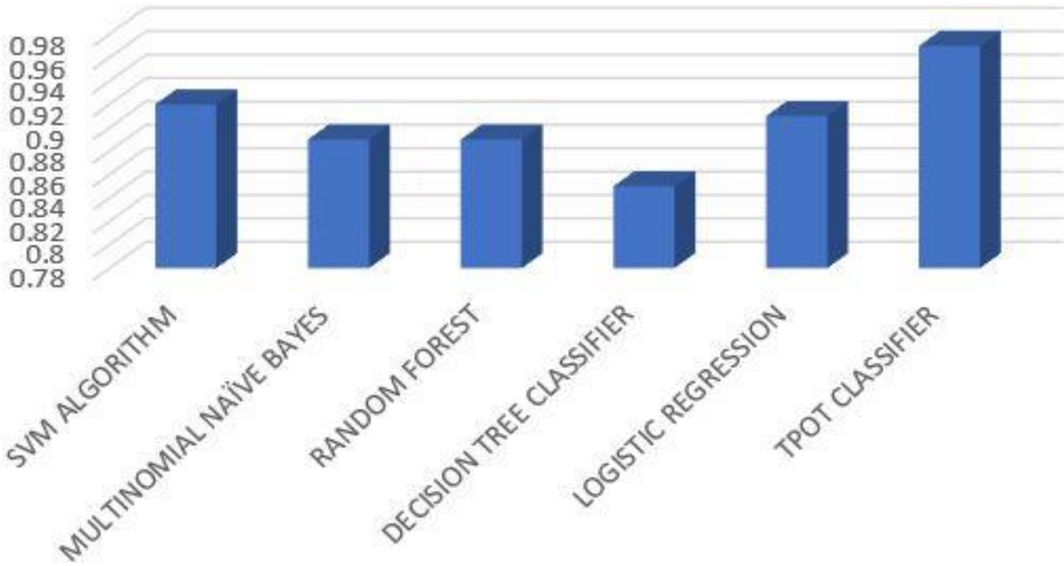

Fig 3.1.4. Accuracy Graph for Detecting and Characterizing Online Product Reviews

IV. RESULTS

Algorithms Used	Precision	Recall	F1-Score
SVM	0.94	0.96	0.95
Logistic Regression	0.92	0.98	0.95
Random Forest	0.88	0.99	0.93
Decision Tree	0.91	0.91	0.91
Multinomial Naïve Bayes	0.80	1.00	0.89

Table 4.1 Report on Precision, Recall, F1-Score

The table 4.1 provides information about precision, recall and f1-score of proposed approaches. As observed these values are high when calculated with the techniques such as SVM and logistic regression classifiers when compared with other proposed approaches. Although, in order to increase the efficiency of the algorithm we have used a tree-based pipeline optimization tool which helps in optimizing the code and has resulted with performance of 97-99% of accuracy based on the generations of the data.

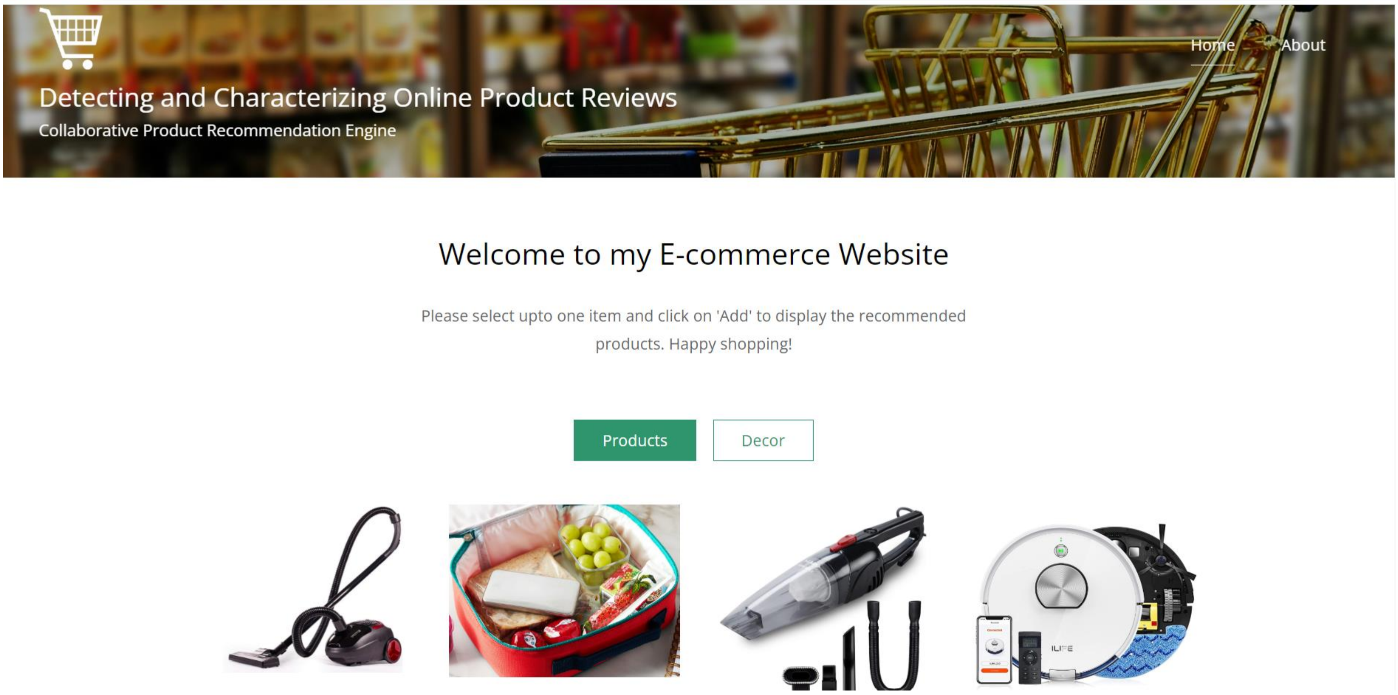

Fig 4.2. Home Page for Detecting and Characterizing Online Product Review

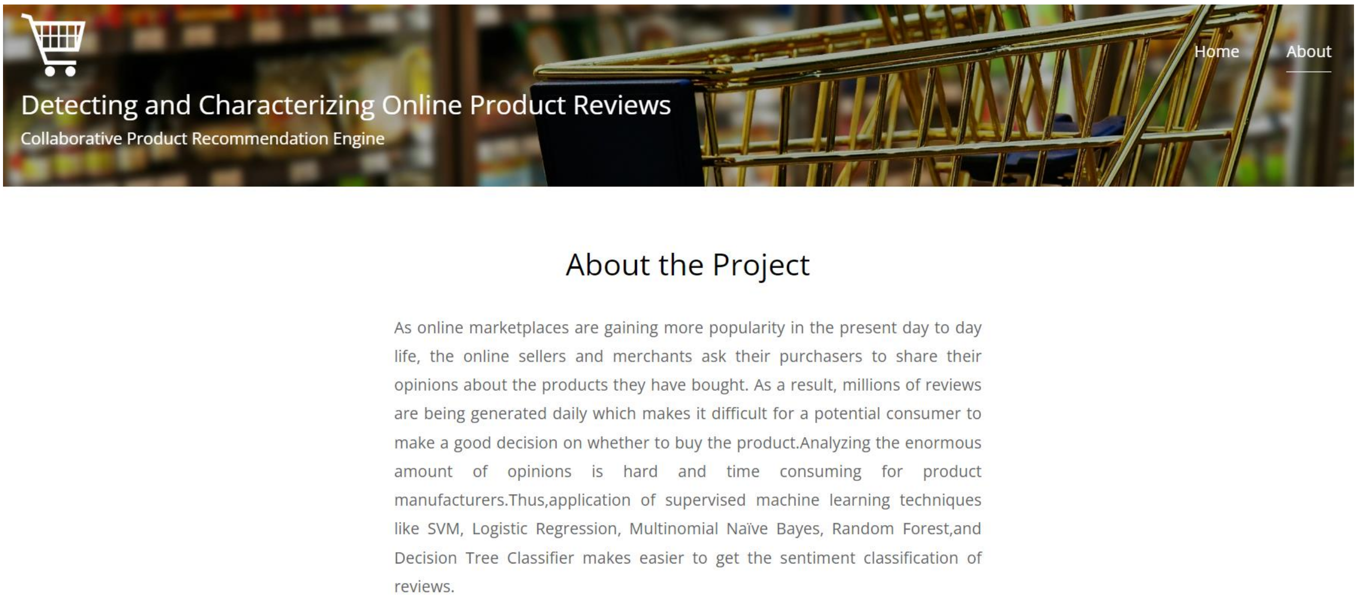

Fig 4.3. About Page for Detecting and Characterizing Online Product Reviews

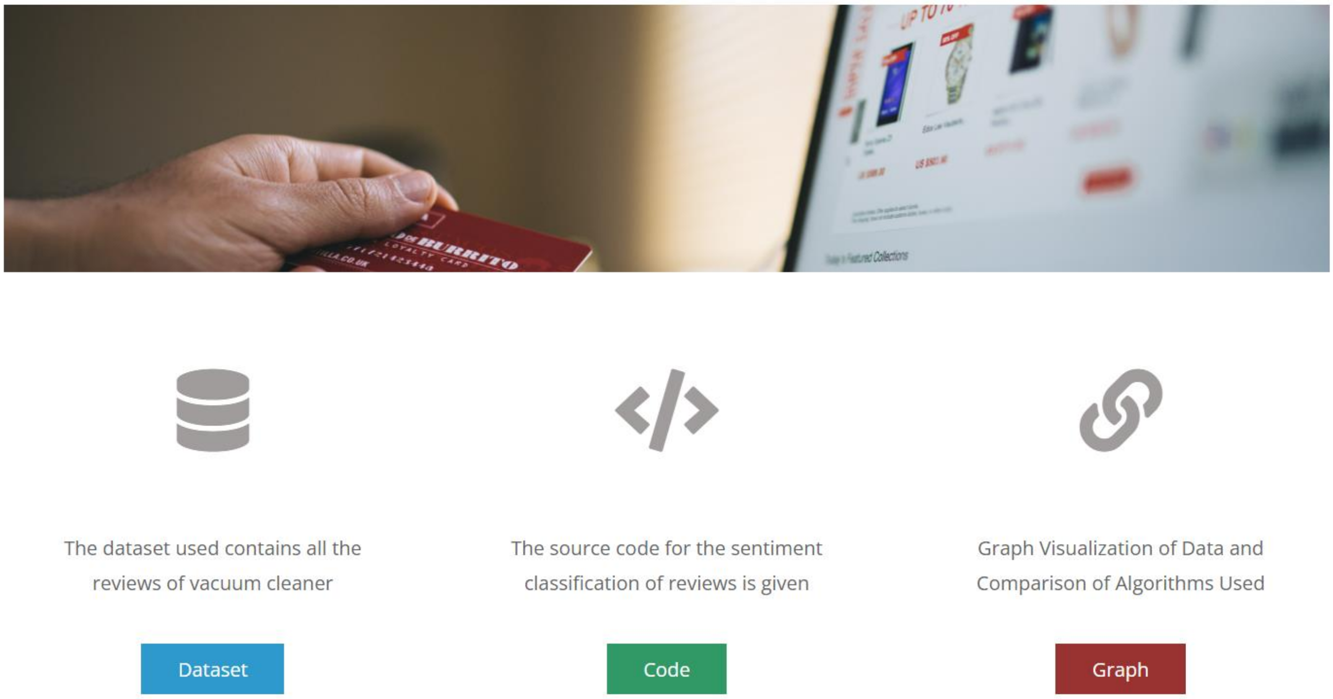

Fig 4.4. Modules Of Sentiment Classification of Reviews

	ReviewText	sentiment
0	Quick delivery. Works great.	Positive
1	Great product works beautifully and the delive...	Positive
2	Love this vacuum. Quick delivery!	Positive
3	Works great for the quick times we need it. T...	Positive
4	Delivered on time, well packed, good condition...	Positive
5	I recently purchased this from Amazon at a gre...	Positive
6	I owned a Mighty Mite vacuum for YEARS! It wa...	Positive
7	10 stars would be better for this little machi...	Positive
8	This vacuum is very easy to push around the ca...	Positive
9	I LOVE this!!! Got it today! Wow, what sucti...	Positive
10	Works very well! Quick delivery!	Positive
11	Very strong. Good price and delivery.	Positive
12	This Dirt Devil Hand Vacuum is excellent and I...	Positive
13	Nice little unit. Item delivered on time, was ...	Positive
14	i think i was paying about $5 for a pack of 3 ...	Positive
15	This isn't just a vacuum cleaner, it is a toy ...	Positive
16	This is the third vacuum of this type I have p...	Positive
17	Delivered in a timely fashion and was as adver...	Positive
18	For some reason I ordered two of these items. ...	Negative
19	This product was delivered folded up in an env...	Negative
20	Inexpensive and quick delivery.	Positive
21	Fast delivery and excellent price.	Positive

Fig 4.5. Classification output of reviews into positive and negative class labels

V. CONCLUSION

There are several machine learning algorithms that can be used to detect and characterize extreme reviews on e-commerce websites. These algorithms include SVM, Multinomial Naive Bayes, Random Forest, Decision Tree Classifier, and Logistic Regression. Each algorithm has its strengths and weaknesses, and the choice of algorithm depends on the specific needs of the e-commerce company. SVM and Multinomial Naive Bayes are efficient algorithms for text classification, while Random Forest and Decision Tree Classifier are better suited for handling noisy and unbalanced data. Logistic Regression is a simple yet effective algorithm for binary classification problems. Efficiency of the algorithms can be increased using some classifiers like (TPOT)Tree-Based Pipeline Optimization Tool which is an automated machine learning package in python used to optimize the series of data transformations that results in high performance of the model. Regardless of the algorithm chosen, detecting and characterizing extreme reviews on ecommerce websites can provide valuable insights into customer preferences and help ecommerce companies make data-driven improvements to their products and services. By analyzing patterns in review text and identifying important features, e-commerce companies can improve their products and services and increase customer satisfaction.

VI. REFERENCES

[1] A. Kim, "That review you wrote on Amazon? Priceless," https://www.usatoday.com/story/tech/news/2017/03/20/ review-you-wrote-amazon-pricess/99332602/, 2017.
[2] Torbet, Georgina. "U.S. Customers Spent over $6 Billion on Black Friday Purchases." Digital Trends, Digital Trends, 25 Nov. 2018, www.digitaltrends.com/web/shopping-totals-black friday/.
[3] Sterling, Greg. "Study Finds 61 Percent of Electronics Reviews on Amazon Are 'Fake'." Marketing Land, 19 Dec. 2018, marketingland.com/study-finds-61-percent-of electronics-reviews-on-amazon-are-fake 254055
[4] Viresh Gupta, Aayush Aggarwal, Tanmoy Chakraborty "Detecting And Characterizing Extremist Reviewer Group In Online Product Review".
[5] Ata-Ur-Rehman, Nazir M. Danish, Sarfraz M. Tanzeel, Aslam Muhammad, "Intelligent Interface For Fake Product Monitoring And Removal".
[6] Q. Ye, Z. Zhang, and R. Law, "Sentiment classification of online reviews to travel destinations by supervised machine learning approaches," Expert Syst. Appl., vol. 36, no. 3, pp. 6527–6535, Apr. 2009.
[7] J. Rout, S. Singh, S. Jena, S. Bakshi " Deceptive Review Detection Using Labelled And Unlabelled Data".
[8] M. Chelliah and S. Sarkar, "Product recommendations enhanced with reviews," in Proc. 11th ACM Conf. Recommender Syst., Aug. 2017, pp. 398–399
[9] S. Xie, G. Wang, S. Lin, and P. S. Yu, "Review spam detection via temporal pattern discovery," p. 823, 2012.
[10] Z. Wang, Y. Zhang, and T. Qian, "Fake Review Detection on Yelp Dataset and features," pp. 1–6.
[11] Sanjay K.S, Dr. Ajit Danti "Detection of Fake Opinions On Online Products Using Decision Tree And Information Gain".
[12] P. Rosso, D. Cabrera, M. Gomez "Detecting Positive And Negative Deceptive Opinions Using PU-Learning".
[13] A. Mukherjee, B. Liu, and N. Glance, "Spotting Fake Reviewer Groups in Consumer Reviews," 2012.
[14] V. K. Madhura N Hegde, Sanjeetha K Shetty, Sheikh Mohammed Anas, "Fake product review monitoring," Int. Res. J. Eng. Technol., vol. 05, no. 06, p. 4, 2018.
[15] Bhavana R Maale, Ayesha Siddiqui "Extremist Reviewer Groups Detection and Characterizing In Online Product Reviews".