Rating Based Sentiment Analysis on Online Mobile Reviews Using VADER Pre-Processing

Developed By

1. **Tirtha Das**
2. **Subhrajit Samanta**
3. **Piya Basak**
4. **Ishita Bhowmick**

Under the Supervision of

Ms. Swarnali Daw
Assistant Professor
Computer Science and Engineering

(May, 2024)

Rating Based Sentiment Analysis on Online Mobile Reviews Using VADER Pre-Processing

A Dissertation Submitted in partial fulfilment for the
Degree of Bachelor of Technology (B.Tech), 8th Semester in
Computer Science & Engineering

Submitted by

Name	University Registration Number	University Roll Number
Tirtha Das	201270100110085	430120010100
Subhrajit Samanta	201270100110041	430120010069
Piya Basak	201270100110132	430120020124
Ishita Bhowmick	201270100110042	430120020070

Under the Supervision of

Ms. Swarnali Daw
Assistant Professor
Computer Science and Engineering

Narula Institute of Technology

MAULANA ABUL KALAM AZAD
UNIVERSITY OF TECHNOLOGY,
WEST BENGAL

Utech

In Pursuit of Knowledge And Excellence

Maulana Abul Kalam Azad University of Technology

(May, 2024)

CERTIFICATE OF ORIGINALITY

The project entitled **“Rating Based Sentiment Analysis on Online Mobile Reviews Using VADER Pre-Processing”** has been carried out by ourselves in partial fulfillment of the degree of Bachelor of Technology in Computer Science & Engineering of Narula Institute of Technology, Agarpara, Kolkata under Maulana Abul Kalam Azad University of Technology during the academic year 2023-2024.

While developing this project no unfair means or illegal copies of software etc. have been used and neither any part of this project nor any documentation have been submitted elsewhere or copied as far in our knowledge.

Signature :

Name : Tirtha Das
University Roll Number : 430120010100
University Registration Number : 201270100110085-(2020-21)

Signature :

Name : Subhrajit Samanta
University Roll Number : 430120010069
University Registration Number : 201270100110041-(2020-21)

Signature :

Name : Piya Basak
University Roll Number : 430120020124
University Registration Number : 201270100110132-(2020-21)

Signature :

Name : Ishita Bhowmick
University Roll Number : 430120020070
University Registration Number : 201270100110042-(2020-21)

CERTIFICATE OF APPROVAL

This is to certify that the project entitled "**Rating Based Sentiment Analysis on Online Mobile Reviews Using VADER Pre-Processing**" has been carried out by Tirtha Das, Subhrajit Samanta, Piya Basak, Ishita Bhowmick, under my supervision in partial fulfilment for the degree of Bachelor of Technology (B.TECH) in Computer Science & Engineering of Narula Institute of Technology, Agarpara, affiliated to Maulana Abul Kalam Azad University of Technology during the academic year 2023-24.

It is understood that by this approval the undersigned do not necessarily endorse any of the statements made or opinion expressed therein but approves it only for the purpose for which it is submitted.

Submitted By:

Name : Tirtha Das
University Roll Number : 430120010100
University Registration Number: 201270100110085

Name : Subhrajit Samanta
University Roll Number : 430120010069
University Registration Number: 201270100110041

Name : Piya Basak
University Roll Number : 430120020124
University Registration Number: 201270100110132

Name : Ishita Bhowmick
University Roll Number : 430120020070
University Registration Number: 201270100110042

Ms. Swarnali Daw

Assistant Professor, Computer Science & Engineering

(External Examiner)

Dr. Subhram Das

HOD, CSE Dept

ACKNOWLEDGEMENT

We seize this moment to extend our heartfelt gratitude to all individuals whose invaluable support played a pivotal role in the successful completion of our final year project, titled **“Rating Based Sentiment Analysis on Online Mobile Reviews Using VADER Pre-Processing”** at NARULA INSTITUTE OF TECHNOLOGY, KOLKATA.

Their unwavering assistance and guidance have been instrumental in achieving a satisfactory outcome. Foremost, we wish to express our profound appreciation to Ms. Swarnali Daw ma’am for being a constant source of inspiration throughout our project journey. Her unwavering support, guidance, and personal involvement in preparing and refining our project work have been immensely beneficial. Her consistent corrections, constructive feedback, and encouragement propelled us forward, fostering our growth and confidence.

We are also deeply grateful to Dr. Subhram Das Sir, our esteemed Head of the Department, for his visionary approach in assigning us this project. His result- oriented perspective provided us with a clear direction, motivating us to excel and deliver our best.

Moreover, our heartfelt gratitude extends to the entire faculty members of the CSE department for their unwavering support, encouragement, and expertise. Their guidance and inputs significantly contributed to the quality and success of our project.

In conclusion, we remain profoundly grateful to each individual who, directly or indirectly, contributed to the completion of this project. Their support has been invaluable, and their dedication has been instrumental in our academic achievement.

CONTENT

LIST OF CONTENTS	PAGE NUMBER

LIST OF TABLES

TABLES	PAGE NUMBER

LIST OF FIGURES

ABSTRACT

Online shopping is rapidly increasing nowadays. As a reason when we are going to purchase any kind of item through the e-commerce site, always we are concerned about the reviews and ratings of the product that we are going to purchase. Naturally, review analysis has become very important in today's era. The reviews are nothing but the opinions which is given by the user who purchased the item. So, opinion classification is very much trending. So, sentiment analysis from the opinion is a very much challenging issue in current days. Sentiment can be classified into different scales that can be good, bad, neutral etc. and if we are also looking forward to the rating of the products, we are also looking forward to thoughts or judgement and likes or dislikes or other feelings and emotions are there. The dataset was collected from the Kaggle website based on a review of the mobile of Amazon. [2] As the Machine Learning (ML) is evolved, here we are going to use ML techniques such as 'Naïve Bayes', 'Decision Tree', 'Random Forest', 'KNN', and 'Logistic Regression' [2] for the rating and feature based sentiment analysis on mobile reviews of amazon website. Here we are going to use NLP and ML based techniques to find out the review. So that users can easily buy the product from the analysis. The study verifies the effectuality of the VADER tool by comparing it with manual tagging. The main contributions of this study are that extracts the sentiment efficiently, achieves 92% accuracy with a decision tree, and gives practical insights to improve and understand public opinions.

Keywords: *Sentiment Analysis, Natural Language Processing, Machine Learning, Mobile Review, VADER tool.*

Chapter I

INTRODUCTION

Sentiment analysis [1] is a study of extracting opinions from the text and determining sentiments expressed on different features or aspects of entities. Some-times many companies give many reviews to increase their sales. It can give any business a short-term boost. Genuine reviewers will often mention how they used the product, what they liked or disliked about it, and how it met their expectations. Fake reviewers are also there for the generic praise. Text analytics can help to read the actual sentiment behind employee feedback and analyses emotional responses to determine bias, and eliminate human errors. Sentiment analysis has gained much attention in recent years. Sentiment analysis is the process of analyzing digital text to determine if the emotional tone of the message is positive, negative, neutral etc. It's a form of text analytics that uses natural language processing (NLP) and machine learning. Overall, social media sentiment analysis is a powerful tool that enables brands to gain a deeper understanding of how they are perceived by their audience feedback. The importance of online reviews in the age of digital commerce cannot be emphasized. The main objective is to under-stand the sentiments of customers. It helps to increase customer experiences and how businesses can hold sentiment analysis. It can be difficult for any organization to deal with their customers when sentiment aspect changes quickly over platforms. As more and more people rely on e-commerce sites to make their purchases, the abundance of insights and firsthand accounts provided by online re-views greatly influence how buyers view products. The growing amount of user-generated material is the reason why sentiment analysis is becoming more and more important in e-commerce and online purchasing. The difficulty is in extracting customer sentiment from large datasets to understand preferences and satisfaction levels. The study intends to evaluate the impact of sentiment analysis on consumer decision-making, improve user experience, establish a relationship between sentiments and purchase behaviour, and develop business strategies to make the most of this analysis in customized online retail marketing. So, sentiment analysis in the e-commerce sector [2,6-9] is giving us the proper idea about the customer demand also. This study delves into the nuances of customer thoughts and opinions expressed in this expansive digital ecosystem by applying sentiment analysis to a sizable dataset of Amazon mobile reviews.

Sentiment analysis can be done using various levels such as Document level, Sentence level, Phrase Level and aspect level which is shown in Fig. 1 [3].

Document Level: With document-level sentiment analysis, the sentiment of complete documents—like books or study guides—is evaluated and predicted using a three-point rating system (positive, negative, or neutral). Machine learning techniques can be used in both supervised and unsupervised settings [4–5], however there are cross-domain and cross-language issues. Sentiment analysis at this higher level is more challenging since document-level processing necessitates particular and constrained document-specific feature words.

Sentence Level: Analyzing each sentence according to matching similarity terms or indexes is known as sentence-level sentiment analysis [10]. Using this method for document-level sentiment analysis is very helpful when working with a wide variety of papers that have different moods. Sentence-by-sentence sentiment analysis computes sentiment using machine learning algorithms akin to document-level analysis. The approach may encounter difficulties in determining subjective polarity, particularly in cases of conditional or ambiguous statements [11]. However, in cases when document-level overall sentiment evaluation be-comes difficult, sentence-level analysis offers a workaround.

Phrase Level: Sentiment analysis at the phrase level extracts opinions from sentence phrases and provides in-depth information. It tackles the difficulties presented by complicated sentences, guaranteeing more accurate sentiment ex-traction, in contrast to document- or sentence-level analysis. This method is especially helpful for product reviews with several lines since it breaks sentences down into their most basic units, words, then analyzes related subjective concepts based on opinion words [12]. Sentiment analysis at the phrase level essentially improves sentiment analysis at the text level.

Aspect Level: This level of sentiment analysis is used in the aspect of the sentences. Each sentence may contain a different aspect. The first concern is finding out the multiple aspects of the sentence and assigning polarity to each aspect individually [13] after that calculate the aggregate polarity for the sentences. From the polarity, we say that the sentence is positive, negative, or neutral.

In this study, we are going to use a new type of opinion-giving system that is rated in online e-commerce sites for product reviews generally. Sentiment analysis from rating is becoming a new trend nowadays. Here we will take product reviews from Amazon of over 4 lakh reviews. Our approach includes two different modules: the first module is concerned with the normal dataset preprocessing techniques followed by the data cleaning and sentiment level assignment manually. Then we will use VADER pre-processing techniques [14] to tag sentiments to the raw dataset. After that, we create a comparison study between two sentiment tagging systems. Focus on the next module where we will use VADER pre-processing [14] techniques to find out the sentiment from the rating. Then we will create a comparison between the manual process and the VADER process on the same dataset. Based on the best sentiment-tagged data we move towards the next module of our paper, where we have used the supervised machine learning techniques to find out the sentiments and will show the comparison study be-tween the algorithms for the rating-based sentiment analysis.

Chapter II

MOTIVATION

Data is crucial in today's world for several reasons, and its importance has been growing rapidly. That’s why we decided to analysis customize data of product review to help business intelligence and economic growth of the company. For example, a business might be interested in fine-grained sentiment analysis to understand customer feedback in more detail, while a social media monitoring tool might use binary sentiment analysis to quickly categorize large volumes of user comments (highly positive, positive, highly negative, negative, and neutral).

Not only in business purpose Sentiment analysis of scientific domain articles is a very trendy and interesting topic nowadays. In political debates for example, we could figure out people’s opinions on a certain election candidates or political parties. The election results can also be predicted from political posts. The social network sites and micro-blogging sites are considered a very good source of information because people share and discuss their opinions about a certain topic freely. They are also used as data sources in the SA process.

The choice of sentiment analysis type depends on the specific goals of the analysis and the nature of the data being analyzed. So here we choose mobile data(rating), which includes data generated from mobile devices like smartphones and tablets, can be valuable for sentiment analysis for several reasons like capture the most recent opinions and reactions, understanding the geographical context of users, identify patterns in user behaviour and encompasses content from various platforms.

In summary, the motivation for sentiment analysis lies in its ability to transform unstructured textual data into actionable insights. Whether for business intelligence, marketing strategies, customer satisfaction, or public opinion analysis, sentiment analysis has become a crucial tool in navigating the information landscape and making informed decisions.

Chapter III

LITERATURE SURVEY

We are going to tag the sentiment in the unlabeled product review dataset followed by some machine learning algorithms used for finding the best machine learning classifier for the taken dataset in case of sentiment analysis. The paper written by Xing Fang and Justin Zhan [1] mainly gives us an idea about the sentiment polarity categorization of the amazon.com product review with a details study of the sentence level and review level categorization. From this, we are going to understand how to take the data from product review and what should be the step-by-step procedures for the preprocessing of the raw dataset.

VADER was used by Elbagir and Yang[16] to classify the emotion of 2,430 political tweets sent out during the 2016 US presidential election. They used the VADER analyzer for sentiment categorization, Python's NLTK for preprocessing, and NodeXL for data gathering. The findings showed that 46.7% of respondents had neutral opinions; for better results, future research is advised to use larger datasets and customized lexicons.

Sentiment analysis (SA) in text mining is explored[17], with lexicon and k-means labeling for automated classification being contrasted. It uses TF-IDF for feature extraction and trains Naïve Bayes and Support Vector Machine (SVM) classifiers on a labeled dataset. To overcome preprocessing issues, a hybrid method that combines SVM and VADER lexicon tagging is presented for the Enron Email dataset. It focuses on both binary and multiclass classification, achieving 58.2% and 82.1% accuracies for Naïve Bayes and SVM, respectively. However, it notes limits in email signature removal and the unresolved negation problem in identifying negative emails.

With an emphasis on developing and approving a Bengali polarity lexicon, Amin et al. [18] adapt VADER to overcome the lack of Bengali sentiment analysis tools. With future machine learning integration planned, their approach comprises preprocessing, boosting, and the production of Bengali valences. Granted the efforts that have already been made, shortcomings include insufficient language complexity capture and errors when booster words are absent.

Sitorus et al. [19] use sentiment analysis on 667 categorized tweets to investigate public opinion over Indonesia's new curriculum, the "Independence Curriculum." For sentiment labeling, TF-IDF and preprocessing procedures are utilized with the VADER library. Sentiment analysis is effectively performed using Naive Bayes and K-Nearest Neighbor classifiers, with negative sentiment predominating at 60.9%.

The HyVADRF and GWO model for Bitcoin sentiment analysis on Twitter is presented by Mardjo and Choksuchat[20]. It achieves 75.29% accuracy, 70.22% precision, 87.70% recall, and a 78% F1-score. The significance of hyperparameter tuning and dataset size are emphasized, and they suggest RF with particular ratios. Subsequent studies could investigate different tuning techniques and expand the model to encompass additional cryptocurrencies.

Tyagi and Sharma[21] do sentiment analysis on product evaluations using Support Vector Machine (SVM) and outperform other algorithms with an accuracy of 89.98%. The study validates SVM's effectiveness for sentiment classification by showcasing how consistently it can identify pertinent phrases connected to the product and both positive and negative sentiments in reviews.

Mubarok et al. [22] use a three-phase approach to assess product reviews: Naïve Bayes sentiment polarity classification, Chi-Square feature selection, and POS tagging. With an astounding F1 measure of 78.12%, the study highlights aspect-based sentiment analysis's efficacy. Naïve Bayes performs better, and a thorough evaluation of every product feature is made easier with the use of a rating chart.

In their study, Fang and Zhan [23] used online product reviews from Amazon.com in a variety of categories to perform sentiment polarity categorization. The study used Naïve Bayesian, Random Forest, and Support Vector Machine models for classification, conducting trials at the sentence and review levels. Based on real customer product reviews, the study offers a thorough method for sentiment analysis.

Amrani et al. [24] present a hybrid algorithm (RFSVM) that combines Random Forest (RF) and Support Vector Machine (SVM) for sentiment analysis of Amazon product ratings. When it comes to classifying reviews as positive or negative, this method performs better than individual classifiers, highlighting the importance of sentiment analysis in decision-making processes. Future research to further improve performance is suggested by the study.

Using the Multinomial Naïve Bayes Classifier, Farisi et al. [25] effectively distinguish between positive and negative reviews through sentiment analysis. The best outcomes, with an average F1-Score of more than 91%, are obtained from preprocessing, feature extraction, and selection comparisons. Specific feature selection and preprocessing methods increase sentiment classification greatly, outperforming the conventional bag-of-words approach.

Huq et al. [26] seek to develop a strong classifier for automatic sentiment analysis of tweets that aren't known to them. Support Vector Machine (SVM) and a Sentiment Classification Algorithm (SCA) based on L-Nearest Neighbor (KNN) are the two approaches they suggest and test. The results show that SCA is more accurate than SVM in identifying whether tweets are good or negative.

In summary, we understand that finding the sentiment from online mobile reviews nowadays becomes very challenging. So, from the above discussion, we are going to find the sentiment on 5 scales of online mobile review using VADER preprocessing [14] and after that here we are going to use supervised machine learning algorithms like Naïve Bayes, Decision Tree, Random Forest, KNN and Logistic Regression for training the data and finding the result.

Chapter IV

BROAD OBSERVATIONS

Sentiment analysis, also known as opinion mining, is a multidisciplinary field that has gained prominence due to the escalating importance of data in contemporary society. The overarching role of data, characterized by its rapid growth in significance, underscores the need for advanced analytical tools to derive actionable insights. One such tool is sentiment analysis, which involves extracting subjective information from textual data to discern the sentiment or emotional tone expressed by the author. While initially applied in business contexts for market intelligence and economic growth, sentiment analysis has evolved to permeate various domains, reflecting its versatility and expanding relevance.

In the realm of business, sentiment analysis is instrumental in leveraging customized data, particularly from product reviews, to enhance business intelligence. By discerning customer sentiments, companies can make informed decisions about their products, marketing strategies, and overall customer satisfaction. This not only contributes to a more competitive market presence but also supports the broader economic growth of the company.

Beyond the corporate sphere, sentiment analysis has found a significant niche in the analysis of scientific domain articles. Researchers and scholars deploy sentiment analysis techniques to gauge the reception of scholarly works, identify emerging trends, and understand the sentiments prevalent in academic discourse. This application highlights the adaptability of sentiment analysis methodologies to diverse forms of textual data.

In the political landscape, sentiment analysis emerges as a potent tool for understanding public opinions. During political debates, sentiment analysis enables the extraction of people's sentiments towards election candidates or political parties. Furthermore, sentiment analysis applied to political posts on social network sites provides a means to predict election results, offering a unique and data-driven perspective on the political landscape.

Social network sites and micro-blogging platforms play a pivotal role in sentiment analysis by serving as rich sources of information. The open and uninhibited nature of discussions on these platforms provides a wealth of data, making them invaluable for sentiment analysis processes. The freely shared opinions and discussions on social media platforms not only reflect public sentiments but also contribute significantly to the data sources used in sentiment analysis.

The motivation for engaging in sentiment analysis lies in its transformative ability to convert unstructured textual data into actionable insights. Whether applied in business intelligence, shaping marketing strategies, measuring customer satisfaction, or analyzing public opinions, sentiment analysis has become an indispensable tool for decision-makers navigating the information landscape. The adoption of advanced technologies, including pre-trained language models and deep learning architectures, has further elevated the accuracy and capabilities of sentiment analysis systems.

However, challenges persist in the form of contextual ambiguity, sarcasm detection, and potential biases in the training data. Navigating these challenges requires a nuanced understanding of language and ongoing efforts to refine and improve sentiment analysis methodologies.

In summary, sentiment analysis stands at the intersection of technology, linguistics, and social sciences, providing a comprehensive lens through which to interpret and respond to the sentiments embedded in textual data. Its broad applicability across industries and its potential to uncover insights from diverse sources position sentiment analysis as a critical tool in the contemporary landscape, driving informed decision-making and offering a unique perspective on the ever-evolving realm of human expression.

Chapter V

OBJECTIVES

The objective of "Rating Based Sentiment Analysis on Online Mobile Reviews Using VADER Pre-Processing" is to employ a combination of machine learning methodologies and natural language processing (NLP) techniques to conduct sentiment analysis on Amazon mobile reviews.

In today's rapidly evolving digital landscape, where online shopping is increasingly prevalent, the significance of review analysis cannot be overstated. Consumer opinions expressed in online reviews play a pivotal role in shaping purchasing decisions, making sentiment analysis a critical tool for both consumers and businesses alike. By categorizing sentiments into positive, negative, or neutral, this study aims to extract valuable insights from the vast pool of unstructured text data available online, particularly in relation to mobile products sold on Amazon.

The study will utilize various machine learning algorithms, including Naïve Bayes, Decision Tree, Random Forest, KNN, and Logistic Regression, to analyze sentiments expressed in Amazon mobile reviews. These algorithms, when combined with NLP techniques, enable the study to effectively classify sentiments and extract actionable insights from the reviews. Furthermore, the study will employ the VADER (Valence Aware Dictionary and sEntiment Reasoner) tool to assess its efficacy in sentiment analysis. By comparing the performance of VADER against manual tagging methods, the study aims to determine the tool's effectiveness in accurately identifying sentiments expressed in the reviews.

The primary contributions of this research lie in its ability to efficiently extract sentiments from online reviews, achieve a high accuracy rate of 92% with a decision tree model, and provide practical insights for improving and understanding public opinions regarding mobile products. Through the application of advanced machine learning techniques and NLP methodologies, the study seeks to empower consumers with comprehensive analyses, enabling them to make informed purchasing decisions.

Simultaneously, businesses stand to benefit from the insights gleaned from sentiment analysis, as they gain a deeper understanding of customer perceptions and preferences, allowing them to enhance customer satisfaction and product quality.

Ultimately, the overarching goal of "Rating Based Sentiment Analysis on Online Mobile Reviews Using VADER Pre-Processing" is to contribute to informed decision-making and strategic planning in the realm of online commerce. By leveraging advanced analytical techniques, the study seeks to bridge the gap between consumer feedback and business intelligence, thereby fostering mutually beneficial outcomes for both consumers and businesses.

Chapter VI

WORKING PROCEDURES

The methodology of this proposed work is illustrated using given figure below. The flow chart states the step-by-step process followed for the sentiment analysis of the online mobile review.

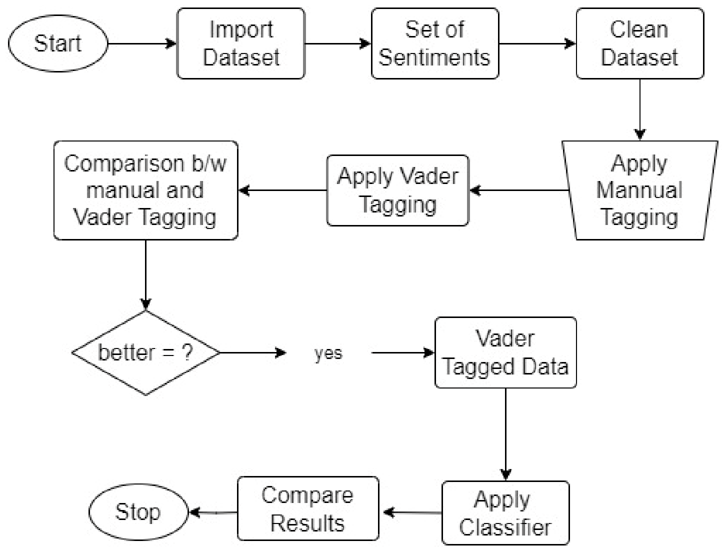

Fig 1: Flow chart of proposed algorithm

6.1 Import Dataset

For this study, Amazon Mobile Review Dataset is collected from the Kaggle Platform. The dataset has more the 4lakh reviews. This dataset has six attributes which are ‘Product Name’, ‘Brand Name’, ‘Price’, ‘Rating’, ‘Reviews’ and ‘Review Votes’.

6.2 Data Cleaning and Pre-Processing

Data Cleaning is one of the major tasks to get accurate and precise results. Here data cleaning is done in the following sequence-wise:

- From this dataset 'Product Name', 'Brand Name', 'Rating', and 'Reviews', columns are used for further calculation. So, 'Price', and 'Review Votes' these two columns are dropped.
- It is noticed that there are more than 65000 data where ‘Brand Name’ is not present. Empty ‘Brand Name’ is tried to be filled from the data present in ‘Product Name’. More than 58000 data are recovered.
- Delete the rows where empty cells are present.
- It is observed there are multiple consecutive similar rows. Delete those rows.
- Remove punctuation, emoji, URL, email, number, and stop words, and fix Unicode from the reviews.

6.3 Apply Manual Tagging

In the dataset, a 5-level rating is provided ranging from 1 to 5 where 1 represents the most negative rating and 5 represents the most positive rating. Here an appropriate tag is provided based on the ratings. It will help us compare the results as well as for clear understanding.

Here rating 1 maps to 'Highly Negative', rating 2 represents 'Negative', rating 3 maps 'Neutral', rating 4 means 'Positive', and rating 5 points to a 'Highly Positive' tag.

6.4 Apply VADER Preprocessing:

VADER (Valence Aware Dictionary and sentiment Reasoner) tool is used to analyze the sentiment of the reviews. VADER, a sentiment analysis tool created especially for text data, is adept at deciphering nuances in social media content. Its lexicon includes sentiment scores for words and modifiers, enabling deeper investigation. Special case rules, such as how punctuation affects sentiment, are included in VADER. VADER's effectiveness and ease of use make it suitable for a wide range of applications. Opinion mining, consumer feedback analysis, and social media analytics all commonly employ it. Because it offers quick and precise sentiment analysis, it is an essential tool for determining the sentiment of text. VADER tool is capable of managing the complexity of natural language and accurately reflects sentiment intensity. Normally to classify the sentiment the most common steps are Lowercasing of a string, removing punctuation, removing stop words, lemmatizing strings, Stemming strings etc. But VADER does not rely on these procedures. It uses the lexicon of sentiment-related words to determine the overall sentiment of a given body of text. By considering components such as degree modifiers, punctuation, and capitalization, it accurately assesses sentiment polarity. Because of this, it is particularly helpful for spotting sarcasm and other linguistic nuances that keyword-based techniques usually miss. Because VADER can recognize sentiment within context, which yields more accurate and reliable sentiment analysis results, it is a suggested alternative for sentiment analysis in a range of textual data. The VADER tool is especially well-suited for the analysis of brief text data from social media and other sources.

6.5 VADER Tagging

VADER tool gives the polarity of the sentences in the range of -1 to 1 where -1 represents the text is negative and 1 represents the text contains a positive sentiment. This range is divided into 5 subparts to give the appropriate tag of the polarity of the sentences. Here -1 to -0.6 (both points inclusive) maps to 'Highly Negative', -0.6 (exclusive) to -0.2 (inclusive) represents 'Negative', -0.2 to 0.2 (both points exclusive) depicts 'Neutral', 0.2 (inclusive) to 0.6 (exclusive) means 'Positive', and finally 0.6 to 1 (both point inclusive) pointing to 'Highly Positive' tag.

6.6 Compare Manual Tag and VADER Tag

Counts of manual tagging and VADER tagging is compared. A significant difference is noticed in the comparison. There is notable decrease from Manual tagging to VADER tagging in ‘Highly Positive’ tag and ‘Highly Negative’ tag and a significant increase from Manual to VADER tagging in ‘Neutral’ tag, ‘Positive’ tag, and ‘Negative’ tag.

6.7 Apply Classifiers

Now various ML classifiers are used to check the accuracy of the task. The classifiers that are used here are ‘Naïve Bayes’, ‘Decision Tree’, ‘Random Forest’, ‘KNN’, and ‘Logistic Regression’. These are well-defined classifiers and are being used to check the accuracy of the work. ‘Review’, ‘Product Name’ and the corresponding Manual Tag or VADER Tag are used as parameters in these Machine Learning classifiers. These classifiers give high accuracy with good precision, and also help to reduce the time complexity. [2] 60% data is used to train the model and the rest of the data is used to test the model. Here independent features are ‘Reviews’ and ‘Product Name’. ‘Manual Tagging’ and ‘VADER Tagging’ are the target features.

6.8 Compare Results

In this step, we find the accuracy of the used supervised classifier for both the manual tagged and VADER tagged dataset using the normal accuracy finding tool. The result contains as follows all classifiers except ‘Naïve Bayes’ classifiers show better accuracy in ‘VADER Tagging’ than ‘Manual Tagging’. Among those ‘Decision Trees’ classifiers give the best accuracy with 92% for ‘VADER Tagging’.

Chapter VII

RESULT EVALUATION AND DISCUSSION

The raw dataset, we are going to apply for the data cleaning procedure is taken from Amazon website mobile reviews. Then on the dataset, we are going to use preprocessing techniques to clean up the dataset. After cleaning that we have seen more than 4 lack sentences have the proper information. After that manual sentiment tagging is used. The result is shown below in fig 2. Along with that also we take the dataset for further processing and feed the dataset into the VADER preprocessing tool, then we get the sentiment-tagged data as shown in Fig 3.

From the below two graphs it is obvious that the VADER-tagged sentiments are highly accurate for the further stage of analysis which is the classification as we have seen that in the case of manual tag, the highly negative is very high com-pared to the VADER-tag and for the positive also the result is opposite. The VADER tag gives us the more highly accurate sentiment level tagging. So, for further process, VADER-tagged is used.

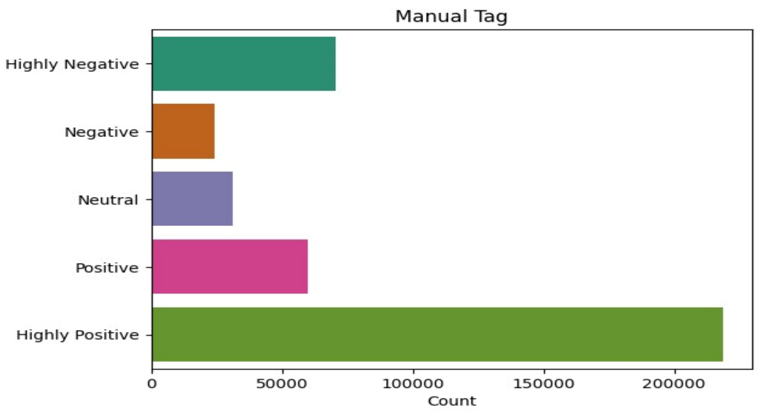

Fig 2: Rating before applying VADER Preprocessing

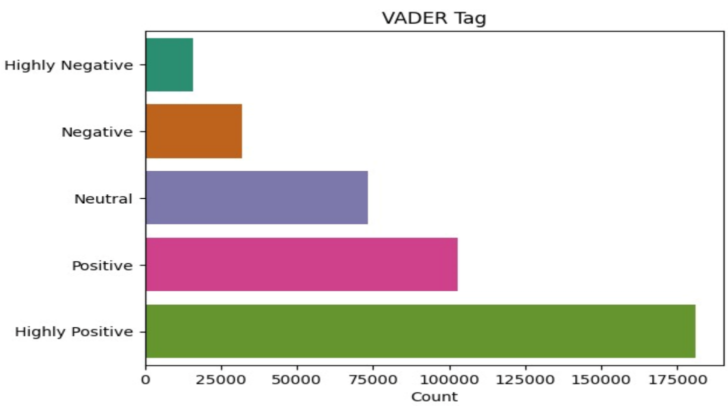

Fig 3: Rating after applying VADER Preprocessing

In the next phase of our proposed system, here we use the supervised machine learning algorithm for the sentiment analysis from the review. Table 1 describes the classifier we have used using the VADER tag. The table gives us an idea about the accuracy achieved by manual tagging and VADER -tagging.

Classifier	Manual Tagging	VADER Tagging
Naïve Bayes	0.72	0.69
Decision Tree	0.83	0.92
Random Forest	0.85	0.91
KNN	0.73	0.79
Logistic Regression	0.73	0.87

Table 1: Accuracy score (F1 Score) of the classifiers

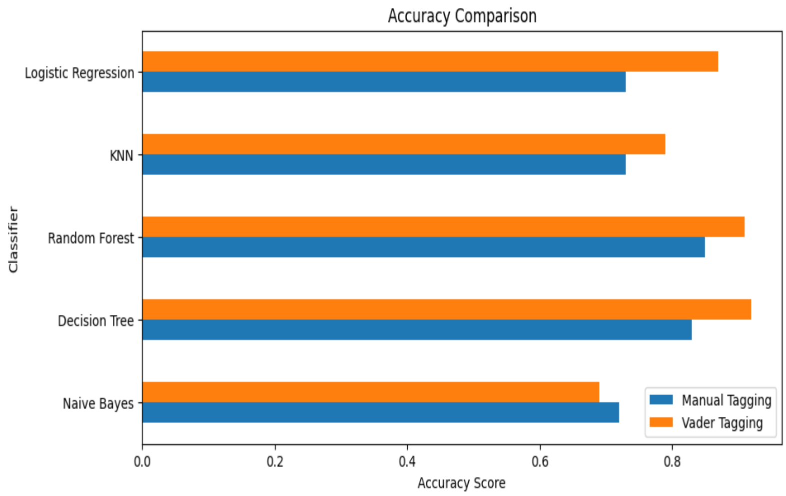

Fig 4: Accuracy score (F1 Score) comparison for classifier

Here we have seen that the 'Naïve Bayes' classifier gives 0.72 as F1 Score in 'Manual Tagging' and 0.69 in 'VADER Tagging'. 'Decision Trees' classifier marks 0.83 as F1 Score in 'Manual Tagging' and 0.92 in 'VADER Tagging'. 'Random Forest' classifier yields 0.85 as F1 Score in 'Manual Tagging' and 0.91 in 'VADER Tagging'. 'Logistic Regression' classifier concedes 0.77 as F1 Score in 'Manual Tagging' and 0.89 in 'VADER Tagging' whereas the 'KNN' classifier shows 0.73 as F1 Score in 'Manual Tagging' and 0.79 in 'VADER Tagging'. These results are shown in the following table (Table 1). All classifiers except 'Naïve Bayes' classifiers show better accuracy in 'VADER Tagging' than 'Manu-al Tagging'. Among those 'Decision Trees' classifiers give the best accuracy with 92% for 'VADER Tagging'.

In Fig 4, here the graph is demonstrated about the accuracy level (F1 Score) comparison (based on the above table) analysis achieved by each machine learning algorithm. From fig 4, the result shows that the decision tree algorithm gives the highest accuracy which is 92% for the VADER-tagged sentiments.

Chapter VIII

SCOPE FOR FUTURE WORK

The future scope of project encompasses a multifaceted approach towards enhancing sentiment analysis in Amazon mobile reviews. Advanced natural language processing (NLP) techniques, machine learning algorithms, and deep learning models offer avenues to improve accuracy.

Refining sentiment analysis models to be more domain-specific, focusing on the unique language and nuances found in Amazon mobile reviews, holds promise for more insightful interpretations. Customizing the model for different mobile categories, such as smartphones and accessories, can further enhance accuracy. Real-time sentiment monitoring, facilitated by streaming data processing and continuous model training, provides up-to-date insights into evolving user opinions.

Aspect-based sentiment analysis allows for a deeper understanding of specific product features beyond overall sentiment. Integrating image and video analysis alongside text reviews offers a comprehensive perspective.

Analysing sentiment trends over time helps identify changing customer preferences and product performance. Developing user profiles based on sentiments and preferences enables targeted product tailoring.

Comparative sentiment analysis across different mobile phone models or brands unveils valuable insights into market dynamics. Providing actionable insights to manufacturers and sellers through common theme identification in negative reviews aids in product improvement. Integrating sentiment analysis with customer support systems streamlines response processes and enhances overall satisfaction. Ethical considerations, including bias mitigation and user privacy, are paramount for fair and unbiased analysis.

Integrating sentiment analysis tools into mobile apps offers users real-time feedback and a more interactive experience. Customizing sentiment analysis for diverse regions and languages accounts for cultural nuances and language variations, bolstering relevance and accuracy. Continuous refinement, ethical adherence, and adaptation to linguistic diversity collectively contribute to a robust and reliable sentiment analysis framework for Amazon mobile reviews.

Chapter IX

CONCLUSION

The study utilizes the VADER tool to conduct sentiment analysis on Amazon smartphone reviews, affirming its effectiveness through robust evaluation against manual ratings. By employing machine learning classifiers such as Random Forest and Decision Tree, the study demonstrates the reliability of VADER-derived ratings, achieving noteworthy accuracy levels of 92% and 91% respectively. This validation underscores VADER's capability in accurately extracting sentiment from textual data, providing a valuable tool for analysing online product reviews.

However, amidst the success, the study acknowledges the inherent challenges in sentiment analysis, particularly in discerning nuanced expressions like sarcasm or irony. Despite VADER's proficiency, these subtle forms of sentiment can pose difficulties, potentially leading to misinterpretations. To mitigate this limitation, the study proposes leveraging emoticons as noisy labels for training data. Emoticons serve as valuable contextual cues, aiding in the accurate classification of sentiment and enhancing the overall performance of sentiment analysis algorithms

Moreover, the study delves into the unique characteristics of product reviews on platforms like Amazon.com. Despite the variability in language and expression, the proposed sentiment polarity categorization process ensures consistency and accuracy in sentiment analysis results. By providing detailed descriptions of each step, the study offers a structured approach to sentiment analysis, facilitating more reliable assessments of sentiment in online discourse.

Furthermore, the research extends beyond mere validation, contributing to the advancement of sentiment analysis methodologies. Through experimentation and analysis, the study sheds light on the intricacies of sentiment classification, paving the way for enhanced techniques and practices in the field. This iterative process of refinement is crucial for ensuring the reliability and applicability of sentiment analysis in various domains, including e-commerce, social media, and customer feedback analysis.

In conclusion, the study highlights the efficacy of the VADER tool in sentiment analysis, while also acknowledging and addressing inherent challenges. By proposing innovative approaches such as emoticon-based training data and sentiment polarity categorization processes, the research not only validates existing methodologies but also drives forward the evolution of sentiment analysis techniques, ultimately enhancing our ability to understand and interpret sentiment in online communication.

REFERENCES

[1] Xing F, Justin Z : Sentiment analysis using product review data. Journal of Big Data 2:5 (2015).

[2] Rambocas M, Gama J: Marketing research: The role of sentiment analysis. Universidade do Porto. Faculdade de Economia do Porto (2013).

[3] Mayur W, Annavarapu C S R, Chaitanya K : A survey on sentiment analysis methods, applications, and challenges. Artificial Intelligence Review: 55:5731–5780 (2022).

[4] Bhatia P, Ji Y, Eisenstein J : Better document-level sentiment analysis from rst discourse parsing. arXiv preprint arXiv:150901599 (2015).

[5] Saunders D: Domain adaptation for neural machine translation. PhD thesis, University of Cambridge (2021).

[6] Shivaprasad, T.K. and Shetty, J.: Sentiment analysis of product reviews: A review. In 2017 International conference on inventive communication and computational technologies (ICICCT) (pp. 298-301). IEEE (2017)

[7] Abirami, A.M. and Gayathri, V : A survey on sentiment analysis methods and approach. 2016 Eighth International Conference on Advanced Computing (ICoAC) (pp. 72-76). IEEE (2017).

[8] Neri, Federico, et al. "Sentiment analysis on social media." 2012 IEEE/ACM international conference on advances in social networks analysis and mining. IEEE, 2012.

[9] Wagh, R. and Punde, P.: Survey on sentiment analysis using twitter dataset. Second International Conference on Electronics, Communication and Aero-space Technology (ICECA) (pp. 208-211). IEEE (2018).

[10] Yang, Bishan, and Claire Cardie. "Context-aware learning for sentence-level sentiment analysis with posterior regularization." Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2014.

[11] Ferrari A, Esuli A: An NLP approach for cross-domain ambiguity detection in requirements engineering. Autom Softw Eng 26(3):559–598 (2019)

[12] Thet TT, Na JC, Khoo CS: Aspect-based sentiment analysis of movie re-views on discussion boards. J Inf Sci 36(6):823–848 (2010).

[13] Lu B, Ott M, Cardie C, Tsou BK: Multi-aspect sentiment analysis with topic models. In:IEEE 11th international conference on data mining workshops. IEEE, pp 81–88 (2011).

[14] C.J. Hutto, Eric G : VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text. Eighth International AAAI Conference on Weblogs and Social Media: Vol. 8 No. 1 (2014).

[15] Swarnali D and Rohini B: Machine Learning Applications Using Waikato Environment for Knowledge Analysis. Fourth International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, pp. 346-351 (2020).

[16] Shihab E, Jing Y: Twitter Sentiment Analysis Using Natural Language Toolkit and VADER Sentiment. Proceedings of the International Multi Conference of Engineers and Computer Scientists, Hong Kong: IMECS, pp. pp: 1-5 (2019).

[17] Ali, Rayan S. H, Neamat El G: Sentiment analysis using unlabelled email data. International Conference on Computational Intelligence and Knowledge Economy (ICCIKE). IEEE, (2019).

[18] A. Amin, I. Hossain, A. Akther and K. M. Alam: Bengali VADER: A Sentiment Analysis Approach Using Modified VADER. International Conference on Electrical, Computer and Communication Engineering (ECCE), pp. pp: 1-6. (2019).

[19] Fernandus P. S., Ema U, Mei P. K.: Public Sentiment Analysis about Inde-pendent Curriculum with VADER Annotations using the Naive Bayes and K-Nearest Neighbor Methods. International Journal of Innovative Science and Research Technology, Vol-8, Issue -8 (2023).

[20] Mardjo, A, Chidchanok C: HyVADRF: Hybrid VADER–Random Forest and GWO for Bitcoin Tweet Sentiment Analysis. IEEE Access 10 : 101889-101897 (2022).

[21] Tyagi, Esha, and Arvind K S: Sentiment analysis of product reviews using support vector machine learning algorithm. Indian Journal of Science and Technology 10.35 : 1-9 (2017).

[22] Mubarok, Mohamad S, Adiwijaya A, and Muhammad D, A: Aspect-based sentiment analysis to review products using Naïve Bayes. In AIP conference proceedings, vol. 1867, no. 1. AIP Publishing (2017).

[23] Fang, Xing, and Justin Z : Sentiment analysis using product review data. In Journal of Big Data 2.1: 1-14 (2015).

[24] Al A, Yassine, Mohamed L, and Kamal E El K : Random forest and support vector machine based hybrid approach to sentiment analysis. In Procedia Computer Science 127: 511-520 (2018).

[25] Farisi, Arif A, Yuliant S, and Said Al F : Sentiment analysis on hotel reviews using Multinomial Naïve Bayes classifier. In Journal of Physics: Conference Series, vol. 1192, no. 1, p. 012024. IOP Publishing, (2019).

[26] Huq, Mohammad R, Ali A, and Anika R : Sentiment analysis on Twitter data using KNN and SVM. In International Journal of Advanced Computer Science and Applications 8.6 (2017).

[27] Dataset - https://www.kaggle.com/datasets/PromptCloudHQ/amazon-reviews-unlocked-mobile-phones.