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

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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.

1. INTRODUCTION

Sentiment analysis [1] is a study of extracting opinions from the text and determining sentiments expressed on different features or aspects of entities. Sometimes 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 understand 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 reviews 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.

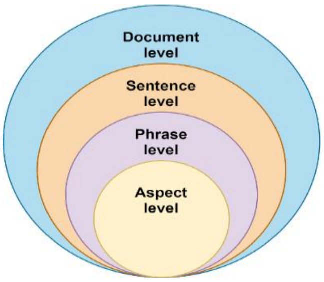

Fig 1: level of sentiment analysis [3]

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 becomes 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 extraction, 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 between the algorithms for the rating-based sentiment analysis.

The rest part of the paper is as follows: the next section “Literature review” discusses the motivation of the problem and what are the solutions available in this topic in recent years. Our proposed methodology to solve the problem of Amazon product reviews is presented in the “Methodology” section. The experimental result and the comparison study-related output are shown in the next section which is called as “Result”. Then the paper will take you towards the “Conclusion” section where we conclude the section with the future scope of the topic.

2. LITERATURE REVIEW

We are going to tag the sentiment in the unlabelled 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.

Zuo [27] introduces a sentiment analysis method employing Naïve Bayes and Decision Tree classifiers for Steam product evaluations. On the Steam Review Dataset, Decision Tree outperforms Gaussian Naïve Bayes by 75% in accuracy, highlighting the value of additional characteristics in enhancing Decision Tree functionality.

A Decision Tree-based method is presented by Yordanova and Kabakchieva [28] to forecast customer sentiment in online hotel reviews. Their work, which builds three models using different datasets and attribute selection techniques, focuses on filtering unusual phrases and achieving the best prediction accuracy with a balanced training set. The suggested model is more accurate and has a lower class recall, which increases how well it can categorize internet hotel reviews.

Yasa et al. (2029) compare Naïve Bayes and Multinomial Naïve Bayes for sentiment categorization in reviews as they investigate consumer opinions around snack food goods. With mean accuracy of 80.5% and 81.3%, respectively, the study highlights the necessity of additional effort to enhance direct product-based grouping for comprehensive evaluation. It should be the goal of future research to improve product-based evaluations.

Using several different algorithms, a study [30] on Amazon mobile phone reviews reveals Random Forest's superior 85% accuracy. Most reviews have four or three stars, which is directly correlated with cost. Longer reviews are more beneficial in terms of utility, and positive sentiments predominate, particularly when it comes to "trust," "anticipation," and "joy." These results help data scientists and researchers select effective sentiment classifiers.

Mehnaz et al. [31] assess sentiment on Twitter with machine learning classifiers, concentrating on product and mobile phone brands. At 93.74% accuracy, Logistic Regression outperforms all other methods, outperforming previous research. The work indicates possible directions for further research into deep learning methods for sentiment analysis and emphasizes the significance of stopword filters and bigger training datasets for increased accuracy.

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.

3. METHODOLOGY

The methodology of this proposed work is illustrated using below given figure 2 below. The flow chart states the step-by-step process followed for the sentiment analysis of the online mobile review.

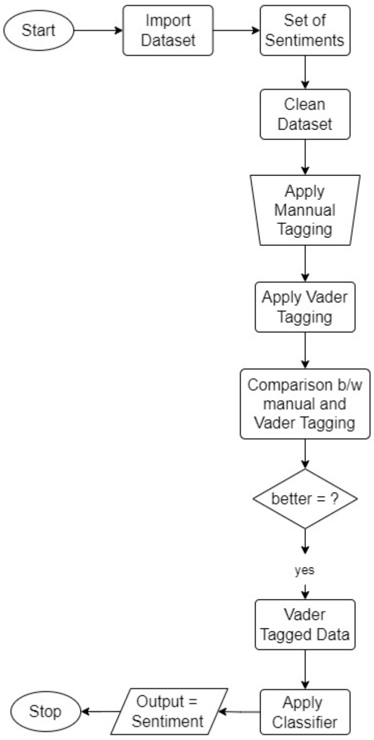

Fig 2: Flow chart of proposed algorithm

3.1. Import Dataset:

For this study, Amazon Mobile Review Dataset is collected from the Kaggle Platform [30]. The dataset has more the 4lakh reviews. This dataset has six attributes which are ‘Product Name’, ‘Brand Name’, ‘Price’, ‘Rating’, ‘Reviews’ and ‘Review Votes’.

3.2. 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.

3.3. 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.

3.4. Apply VADER Preprocessing:

Sentiment analysis in this work is conducted using the VADER (Valence Aware Dictionary and Sentiment Reasoner) program [14], which is adept at identifying subtleties in social media content and was created especially for text data. Sentiment scores for words and modifiers are included in its lexicon to facilitate in-depth analysis. VADER takes into account the effect of punctuation on sentiment while implementing special case rules. Because of its rapid and accurate sentiment analysis capabilities, VADER—which is well-known for its efficacy and user-friendliness—finds applications in opinion mining, consumer feedback analysis, and social media analytics. VADER does not rely on techniques like stop word removal, punctuation removal, or lowercasing, in contrast to standard sentiment categorization stages. Rather, it makes use of sentiment-related word lexicons, precisely determining sentiment polarity while taking context and modifiers into account. VADER's contextual sentiment recognition capability makes it especially helpful for short text data analysis from sources such as social media. All things considered, VADER is a useful tool for sentiment analysis in a variety of textual data, providing improved accuracy and dependability, particularly in identifying linguistic subtleties like sarcasm.

3.5. 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.

3.6. 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.

3.7. Apply Classifiers:

To evaluate accuracy in the task, machine learning classifiers such as "Naïve Bayes," "Decision Tree," "Random Forest," "KNN," and "Logistic Regression" are utilized. 'Review,' 'Product Name,' and the associated Manual or VADER Tags are examples of parameters that are used. These classifiers use a 60% training and 40% testing data split to achieve excellent accuracy, precision, and reduced time complexity. "Product Name" and "Reviews" are independent features, whereas "Manual Tagging" and "VADER Tagging" are target features.

3.8. 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’.

4. RESULT 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:3. Along with that also we take the dataset for further processing and feed the da-taset into the VADER preprocessing [14] tool, then we get the sentiment-tagged data as shown in Fig 4.

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 compared 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.

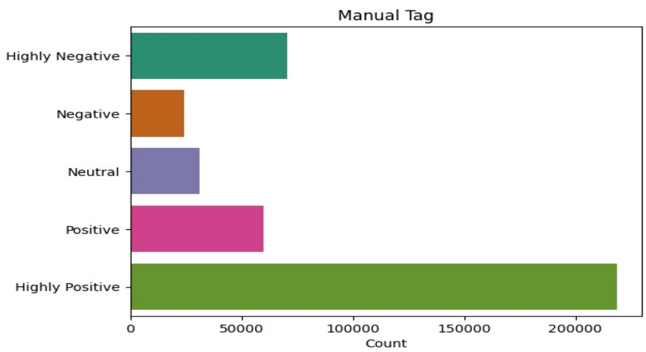

Fig 3: Rating before applying VADER Preprocessing

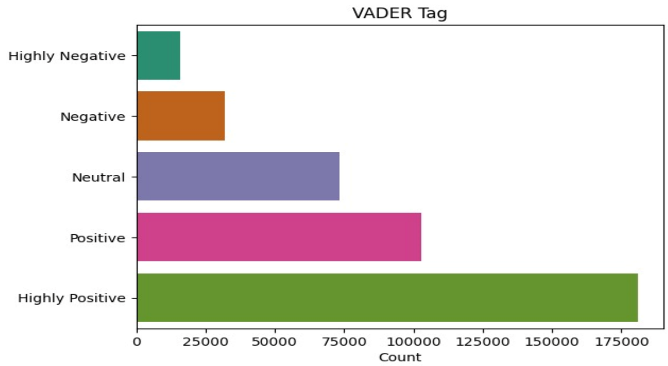

Fig 4: Rating after applying VADER Preprocessing

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

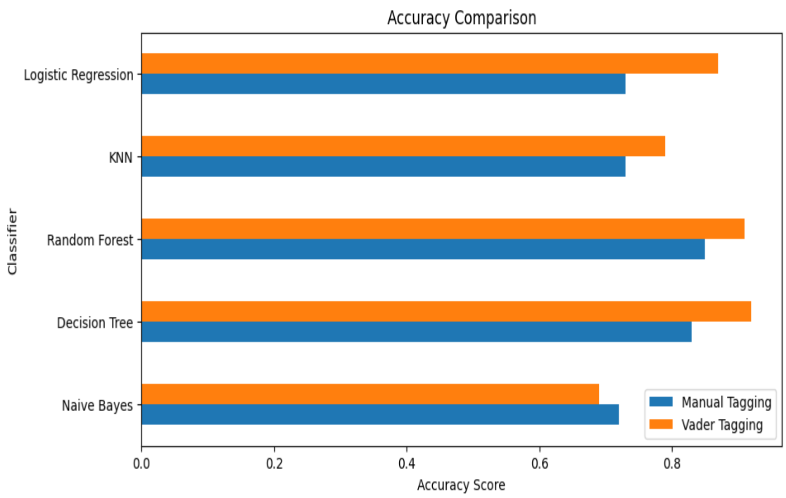

Fig 5: Accuracy score (F1 Score) comparison for classifier

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 ‘Manual Tagging’. Among those ‘Decision Trees’ classifiers give the best accuracy with 92% for ‘VADER Tagging’.

In Fig 5, 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 5, the result shows that the decision tree algorithm gives the highest accuracy which is 92% for the VADER-tagged sentiments.

5. CONCLUSIONS AND FUTURE SCOPE

The VADER tool was utilized in this study to do sentiment analysis on Amazon smartphone reviews. Inspired by earlier studies proving VADER's effectiveness, feelings were taken out of ratings. against evaluate the accuracy of VADER-derived ratings against manual ratings, a variety of machine learning classifiers were used. Significant accuracy values of 92% and 91% were attained by the Random Forest and Decision Tree classifiers, respectively. The study recognizes the possible limitations of sentiment evaluation methods in recognizing sarcasm or irony, even though project aims were met.

The results have practical ramifications for optimizing user interfaces, deploying customized algorithms, and adjusting marketing tactics. Subsequent investigations may delve into more sophisticated sentiment analysis models, tackling matters such as ethical considerations, cross-cultural obstacles, small company effect, and multichannel integration. This strategy seeks to move e-commerce experiences in the direction of customized, moral, and inclusive methods.

As a result, the work advances the field of sentiment analysis research by highlighting VADER's potential for sentiment extraction. In today's changing technological landscape, utilizing such technologies is more important than ever for drawing conclusions from massive amounts of unstructured data, supporting decision-making and improving user experiences.

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