Mobile Review Sentiments: An In-Depth Analysis

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Abstract. Sentiment analysis, a valuable tool in extracting the underlying emotions and opinions conveyed within the textual content, plays a pivotal role in determining the overall sentiment—whether it's positive, neutral, or negative. It is the process of identifying and classifying users' opinions from a piece of text into different sentiments. Its applications are diverse, ranging from evaluating product reviews to assessing brand popularity, as well as gauging public sentiment on a wide array of topics. The primary objective of this paper is to conduct sentiment analysis on a dataset comprising reviews of mobile phones available. This research endeavour is poised to offer invaluable insights to brands and companies by enabling them to gain a deeper understanding of the collective sentiment surrounding their products. The proposed paper is poised to make major contributions in the field of sentiment analysis; since no current papers have taken on both VADER (Valence Aware Dictionary for Sentiment Reasoning) and roBERTa (Robustly Optimized BERT Approach) as means of conjuring a conclusive result on sentiment analysis. It provides insights regarding the tandem in which both the models work and gathers compound scores as well as review analysis. We were able to make sense that the future that it holds includes analysis of multiple languages, understanding nuances and curbing curse words.

KEYWORDS

Sentiment Analysis, VADER, roBERTa, Natural Language Processing, customer feedback

INTRODUCTION

Digital consumerism and e-commerce are on an unprecedented rampage, one needs to get hold of the trends, not only to understand the changing commerce of the game but also how people can put their opinions in front of the product sellers directly. Years ago there were to be many layers/middlemen between the product manufacturers and the consumer. Still, with the advent of social media and e-commerce platforms, the consumer feedback system has become very easy. Platforms like Amazon, Flipkart, eBay, etc have removed these barriers, while it would be a gross overestimation to say that the top people in the management of big manufacturers would be going through all the reviews, a rather sensible estimate would be that they want a mechanism in place that could give them instant and authentic feedback.

Natural language processing (NLP) techniques are usually used in the procedure to recognise and categorise users' ideas into various feelings. Using machine learning algorithms that have been trained on labelled data is one such strategy. These algorithms categorise text data into predetermined sentiment categories, including positive, negative, and neutral, by identifying patterns in the data.

Sentiment analysis, a burgeoning field in NLP(Natural Language Processing), provides the means to decode the emotional underpinnings of text. It is equipped with the tools necessary to determine whether the sentiment expressed within a piece of text is positive, negative, or neutral. In the context of Amazon mobile phone reviews, sentiment analysis serves as a key to the treasure trove of user opinions, enabling to gauge the collective sentiment surrounding these gadgets.

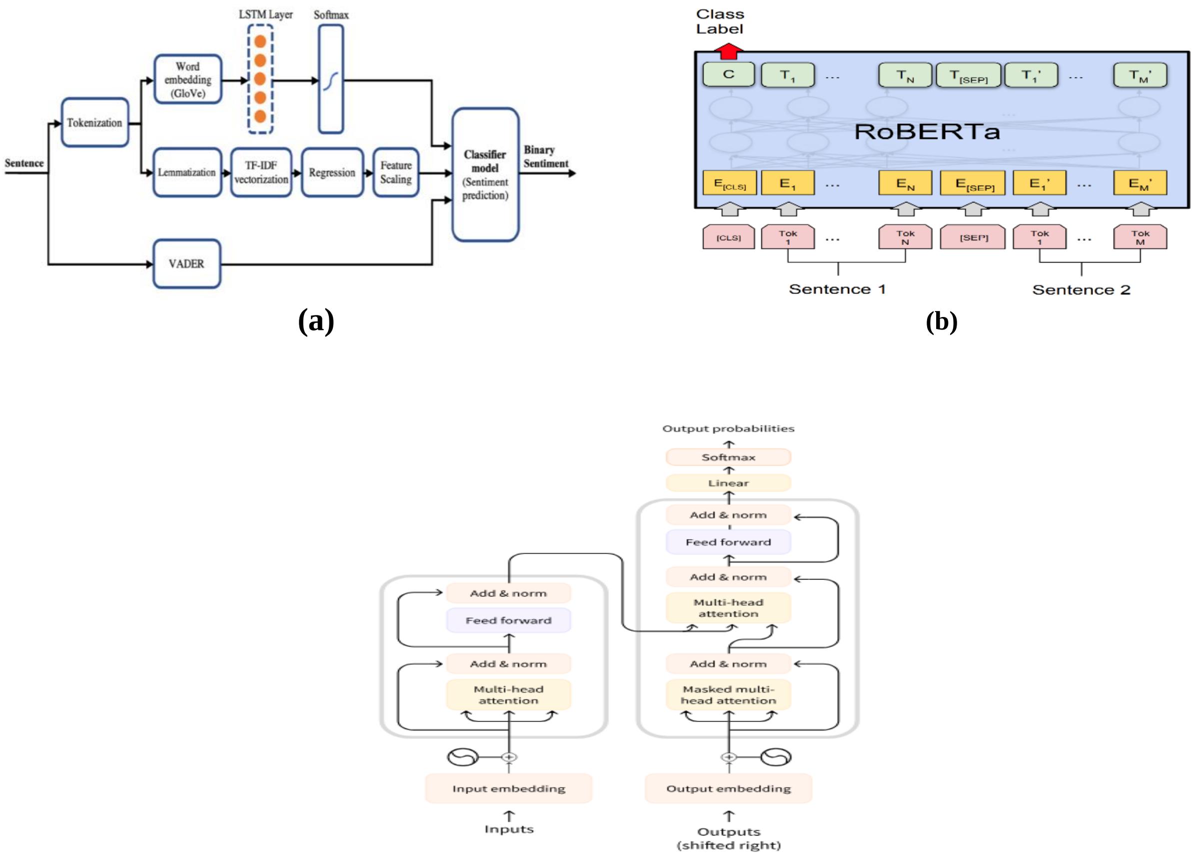
The primary objective of this paper is to study the various NLP techniques that are employed to classify, extract, measure, and comprehend the sentiments expressed within the used dataset. Firstly, preprocessing takes place to get high-quality data, next step is to decide from multiple distinct classification techniques: Logistic, Random Forest, Naive Bayes, VADER, or roBERTa.[12.][13.][14.] The objective is to understand the predictive power of these models and to gauge their effectiveness in identifying sentiment in mobile phone reviews. With comprehensive comparison based on results obtained and accuracy achieved by the classifiers used, shedding light on their strengths and weaknesses in the said context, we gain a more profound understanding of the collective sentiment surrounding the product.

The rich tapestry of the opinions put in by the masses in the Amazon review section will be looked into, by carefully dissecting and by-passing through it. Applications of sentiment analysis in mobile reviews encompass various crucial areas. It serves as a tool for product improvement, allowing businesses to identify areas of concern or satisfaction in order to enhance product quality and features. Sentiment analysis plays a pivotal role in reputation management by enabling brands to monitor and promptly address customer feedback, thereby maintaining a positive online image. Furthermore, it finds application in market research, offering insights into market trends, consumer preferences, and competitive intelligence. In the realm of customer service, it assists in responding to negative reviews and devising solutions to augment customer satisfaction. Finally, sentiment analysis contributes to recommendation systems, enhancing product recommendations based on user sentiment and preferences.

These applications yield several advantages. Sentiment analysis grants access to valuable consumer insights, aiding businesses in understanding what customers appreciate and dislike about their products. Competitive analysis becomes more comprehensive, enabling companies to compare their offerings with those of competitors, fostering improved competitiveness. The focus on quality improvement is enhanced, as companies can address specific concerns raised in evaluations, ultimately elevating overall quality. Moreover, it aids in marketing optimization by highlighting well-received product features. Long-term customer satisfaction is facilitated by monitoring sentiment trends and enhancing brand recognition. Additionally, sentiment analysis improves product development by uncovering unmet customer needs and feature requests, guiding future efforts. It is an invaluable source of market research insights, simplifying the identification of trends and consumer preferences.

However, limitations persist in the realm of sentiment analysis. Understanding context, especially when it involves irony, sarcasm, or subtle wording, can challenge the accuracy of sentiment analysis. Data bias is another critical concern, as biased or unrepresentative data can skew results, particularly when dealing with fake reviews. Handling sentiment analysis for reviews in multiple languages presents multilingual challenges, further complicating the analysis process

The rest of the paper is organized as follows: Literature Survey: which reviews the relevant existing research; Methods: outlining our research approach; Amazon Mobile Review Sentiments: An In-Depth Analysis: is basically a view to the core of our study; Experimental Setup: is the process of detailing our research environment; Result and Inference: presents findings and their interpretations; Conclusion: summarizes key takeaways from the whole process; Abbreviations: helps in explaining acronyms to the layman; Acknowledgments: recognizing contributions of whosoever has been helpful in our endeavor; and References: lists the cited sources.



(a) (b) (c)

FIGURE 1. Models used: (a) Valence Aware Dictionary for Sentiment Reasoning (VADER) (b) Robustly Optimized BERT Pre-training Approach (roBERTa), (c) HuggingFace- Transformers

LITERATURE SURVEY

The rapid increase of mobile devices and the digital age have led to a surge in online mobile reviews. These reviews are valuable resources for both consumers and businesses, shaping purchasing decisions and influencing product development; or even election results [9.]. This literature review provides an overview of the key themes and findings in the field of mobile review sentiments.

In Sentiment Analysis using Improved Vader and Dependency Parsing, the authors explore a research paper that presents innovative strategies for enhancing sentiment analysis. The study targets VADER (Valence Aware Dictionary and Sentiment Reasoner), recognizing its advantages in valence-based sentiment assessment but identifying its lower accuracy compared to other algorithms. To address this, the authors employ various lexicons, both pre-existing and user-created, encompassing emoticons, VADER lexicons, negation, booster words, idioms, and special cases. The methodology involves text standardization, tokenization, and the use of special functions for negation detection and sentiment score normalization. Additionally, the paper integrates the Spacy library for natural language processing, enabling detailed information extraction and sentiment analysis. The presence of verbs in text is examined, and the impact on sentiment is assessed using VADER. This literature survey underscores the significance of these advances in improving sentiment analysis accuracy, thereby contributing to the evolving field's development and application [1.].

The field of Natural Language Processing (NLP) within Artificial Intelligence involves the computerized analysis and comprehension of human language, spanning both written and spoken forms. NLP encompasses a wide array of applications, including language modeling, sentiment analysis, Named Entity Recognition (NER), machine translation, and more. Studies are looking at NLP to detect automation rules and address administrative issues while assisting teachers and helping them teach [2.] [4.]. NER is a specific NLP task involving the extraction of entities such as names of people, organizations, locations, dates, measures, brand names, abbreviations, numbers, and designations from text. The paper discussed in this literature survey focuses on NER for Indian languages, with a particular emphasis on Hindi. Despite Hindi's status as the third most widely spoken language globally, there has been a dearth of NER initiatives for this language. Existing English-based NER systems cannot be directly applied to Hindi due to differences in linguistic features and the lack of comprehensive labelled datasets. To improve the presence of Hindi on the internet and develop an accurate NER system, a thorough understanding of the Hindi language's structure and the exploration of new features is crucial. The paper explores the application of advanced techniques, such as the XLM-Roberta model, to extract entities based on the meaning of a text in Hindi. The NER process is essential for recognizing entities and providing them with corresponding tags. It enables the identification of various types of named entities, including persons, organizations, and more. The methodology discussed in the literature survey showcases the evolution and development of NER methods for Indian languages like Hindi, which hold great potential for enhancing linguistic analysis and information extraction. Overall, this literature survey provides an insightful overview of the evolution and diversity of NER methods and their applications [7.].

The research paper on Sentiment Analysis, which investigates sentiment analysis on TripAdvisor webpages for three prominent monuments in Spain (Alhambra, Mezquita Córdoba, and Sagrada Familia) and compares user ratings to four sentiment analysis methods (SentiStrength, Bing, Syuzhet, and CoreNLP), highlights several significant findings. Initially, the authors of the said paper note that user ratings tend to be overwhelmingly positive, with over 90% of ratings being four or five bubbles. However, the sentiment analysis methods reveal more nuanced results, with Bing and CoreNLP detecting more negativity in the TripAdvisor opinions. Their study also examines the distribution of bubble ratings over the negative sentiment analysis method polarities, highlighting that all methods have varying degrees of misclassification between negative and positive reviews. Ultimately, the research underscores the importance of analyzing sentiments beyond user ratings and recommends a three-step methodology for further analysis: addressing negative opinions identified by sentiment analysis methods through learning models, achieving consensus among sentiment analysis methods, and exploring common aspects to understand the causes of negative comments [5.]. It indicates how different models have influenced the paper.

Many researchers have explored sentiment analysis techniques applied to mobile reviews. The experimental results of the research done on a famous Chinese e-commerce website show that the model can effectively improve the performance of text sentiment analysis [8.]. Researchers at the Grand Valley State University, Allendale and the East Carolina University, Greenville have undertaken a survey that covers the history of text representations from the 1970s and onwards, from regular expressions to the latest vector representations used to encode the raw text data. It demonstrates how the NLP field progressed from where it could comprehend just bits and pieces to all the significant aspects of the text over time [10.].

The literature survey provides valuable insights into sentiment analysis and the influence of mobile reviews, there remain gaps in our understanding of the dynamics between mobile reviews, consumer behaviour, and business strategies. This paper aims to address these gaps by conducting an in-depth analysis of mobile review sentiments, shedding light on their implications for both consumers and businesses in the digital era.

MOBILE REVIEW SENTIMENT ANALYZER

Since Amazon Mobile Review Sentiments, deals with sentiment analysis which delves into Natural Language Processing, and to deal with this realm; the methods that were chosen were VADER (Valence Aware Dictionary for Sentiment Reasoning) and roBERTa (Robustly Optimized BERT Approach). Multiple previous projects mentioned in [6],[8] have been the basis of the majority of our study and experimental setup.

VADER (Valence Aware Dictionary for Sentiment Reasoning)

VADER is a lexicon and rule-based sentiment analysis tool that is specifically designed for social media and short text analysis. It is an NLTK (Natural Language Toolkit) module that provides sentiment scores based on the words used. It is a rule-based sentiment analyzer in which the terms are generally labelled as per their semantic orientation as either positive or negative. It quantifies sentiment by assigning polarity scores (positive, negative, or neutral) to individual words and then calculates an overall sentiment score for a given text. For this research, we utilized the VADER sentiment analysis tool in Python, which has proven to be highly effective for analyzing sentiment in relatively informal text such as online reviews. VADER's findings show that using VADER on microblogging sites where the data sources are an intricate mix of various phrases has the potential to provide huge benefits [3.].

roBERTa (Robustly Optimized BERT Approach)

BERT as in Bidirectional Encoder Representations from Transformers. It is a variant model developed by researchers at Facebook AI. It is a twelve (12) layered model. It is a deep learning model that has demonstrated exceptional performance across a wide range of NLP tasks. It leverages a massive neural network architecture and extensive pretraining on a diverse corpus of text data. The authors of the proposed model have been fine-tuned to extract nine entities from sentences based on the context of sentences to achieve better performance [7] which enhances how efforts are being made to inculcate multilingual input and study it. However, in the study, we employed the Hugging Face Transformers library to fine-tune a RoBERTa model for sentiment analysis; The model helps us with its ability to capture complex contextual information. It is able to provide nuanced sentiment analysis as compared to rule-based approaches.

Transformers form Hugging Face

It has changed the field of NLP by providing powerful and highly customizable tools for text analysis; these models are at the forefront of research and application of natural language processing, offering exceptional performance across a wide range of tasks, including text classification, sentiment analysis and language translation. They have been trained on massive text corpora and learned to encode language in a way that captures rich contextual information which makes it incredibly effective. Two key components of Hugging Face are AutoTokenizer and AutoModel. AutoTokenizer is responsible for tokenizing text and preparing it for input into the deep learning model. It encodes the text into numerical representations, a crucial step in NLP. Its flexibility lies in the fact that it is immensely versatile and can be paired with multiple pre-trained models. This helps in simplifying the process of working with different models. As per Hugging Face AutoModel is a generic model class that will be instantiated as one of the base model classes of the library when created with the AutoModel.from_pretrained(pretrained_model_ name_or_path) or the AutoModel.from_config(config) class methods. It allows users to load various pre-trained models without needing to specify the model architecture explicitly; this adaptability makes it easy to experiment with different models for text classification, sentiment analysis and other NLP tasks.

Popular pre-trained models available for sentiment analysis include BERT, RoBERTa, DistilBERT, and XLNet, among others. These models can be easily accessed and employed with AutoTokenizer and AutoModel, simplifying the process of integrating powerful sentiment analysis capabilities into your NLP projects. Hugging Face with the assistance of AutoTokenizer and AutoModelhave significantly lowered the barrier for using the state-of-art NLP models, making it accessible for users across the spectrum. Availability enhances the utility.

Comparing Vader and roBERTa

VADER and RoBERTa represent two distinct approaches to sentiment analysis. VADER is a lexicon and rule-based tool that provides quick, interpretable results by assigning polarity scores to individual words and calculating an overall sentiment score. It is well-suited for straightforward, high-level sentiment analysis in informal text like social media. On the other hand, RoBERTa is a deep learning model fine-tuned for various NLP tasks, including sentiment analysis. It offers a more nuanced analysis by considering contextual information and can handle complex language nuances like sarcasm and metaphors. It excels at capturing subtleties and delivering in-depth insights, making it a preferred choice for more comprehensive sentiment analysis in diverse text types. The choice between VADER and RoBERTa depends on the specific requirements of the analysis. VADER is a quick and effective tool for a broad understanding of sentiment, while RoBERTa is the method of choice when a deeper, more fine-grained analysis is needed. By utilizing both methodologies, the authors gained a comprehensive view of the sentiment landscape within Amazon mobile phone reviews, providing valuable insights for brands and companies seeking to understand customer opinions and make data-driven decisions for product improvement and marketing strategies. One offers faster reach and the other gives a more nuanced result. By applying both the VADER and roBERTa methods to our dataset of 4,00,000 reviews from the Amazon mobile reviews we were able to extract and evaluate sentiment on a large scale.

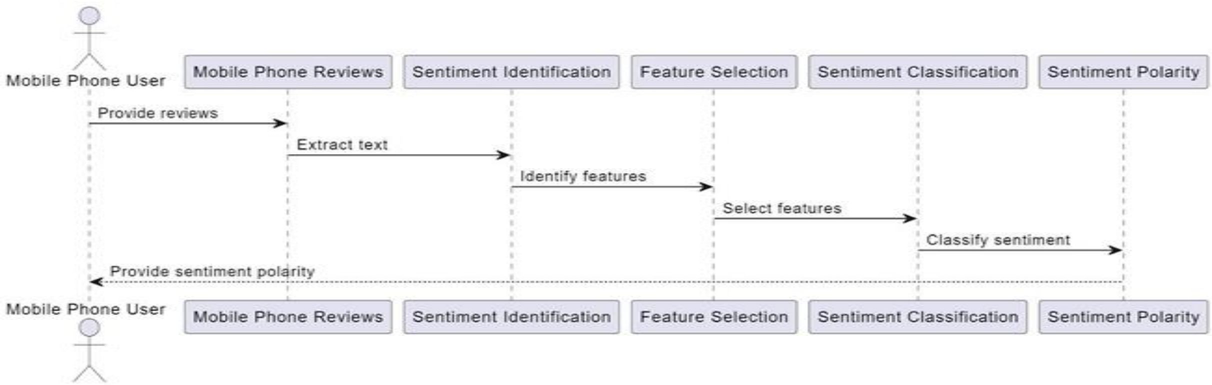


FIGURE 2. Proposed architecture of the Mobile Review Sentiment Analysis showing the working of our model; wherein database provides dataset to the analyzer which in an experimental setup with the help of Vader and roBERTa yields the result.

EXPERIMENTAL SETUP

Sentiment analysis on Amazon mobile reviews is a valuable technique that allows us to extract meaningful insights from the vast amount of feedback provided by mobile phone users on the platform. By applying sentiment analysis, we can categorize these reviews into positive, negative, or neutral sentiments, providing both consumers and manufacturers with a clearer understanding of customer satisfaction, common pain points, and areas of improvement. This analysis is particularly important in the highly competitive and rapidly evolving mobile phone market. It enables potential buyers to make informed decisions by assessing the overall sentiment of reviews and identifying the key features or issues that matter most to them. Sentiment analysis plays a pivotal role in understanding customer feedback and opinions. In this research project, we set out to analyze Amazon reviews and explore the effectiveness of different sentiment analysis models.

Amazon reviews dataset in CSV format, although the dataset comprises nearly half a million reviews, we opt for an initial analysis of the first 500 rows for manageability. The research underscores the potential to scale up the analysis for larger datasets. Key libraries imported for analysis include pandas, numpy, matplotlib, seaborn, and NLTK. Exploratory Data Analysis: The research project commences with exploratory data analysis to gain a deep understanding of the dataset. We employ data visualization to highlight a skew towards positive reviews. This visualization forms the basis for our sentiment analysis approach. The training dataset is made up of a large number of labelled instances, each of which has a text passage and the associated sentiment label (positive, negative, or neutral, for example). The sentiment analysis model is trained using this dataset. Whereas, the test dataset is used to assess how well the trained model performs and is kept apart from the training dataset. In addition, it includes text samples with sentiment labels that the model has never encountered in training.

Sentiment Analysis with NLTK: The research project introduces the VADER approach, a technique that assigns sentiment values to individual words and combines them to determine the overall sentiment of a sentence. We also address the removal of stop words. The nltk library's sentiment intensity analyzer is implemented to evaluate sentiments in text, and we create a sentiment analysis progress bar tracker using the tqdm (progress) notebook library. Polarity Score Calculation: The research project calculates polarity scores across the entire dataset. These scores, ranging from 1 to 5, are used to determine the sentiment of the text. An assumption that higher star ratings correlate with positive sentiment is employed. The resulting scores are stored in a dictionary and transformed into a Pandas DataFrame, facilitating further analysis. The higher the bias, the more positive the review.

Transformer-Based Models: This segment introduces transformer-based models from Hugging Face, focusing on their ability to contextualize language. We employ AutoTokenizer and AutoModel features to encode text and a pre-trained model designed for sentiment analysis on Twitter comments. Roberta Model Application: In this phase, we present a method to apply the Roberta model to the entire dataset, demonstrating its utility. The research project showcases results storage and a combination with VADER model outputs, addressing potential issues like text size constraints and GPU(Graphics Processing Unit) optimization. Data Visualization and Comparison: A results data frame is generated, merging sentiment scores with the original dataset. We employ Seaborn's pair plot to compare sentiment scores between models, unveiling disparities in predictions.

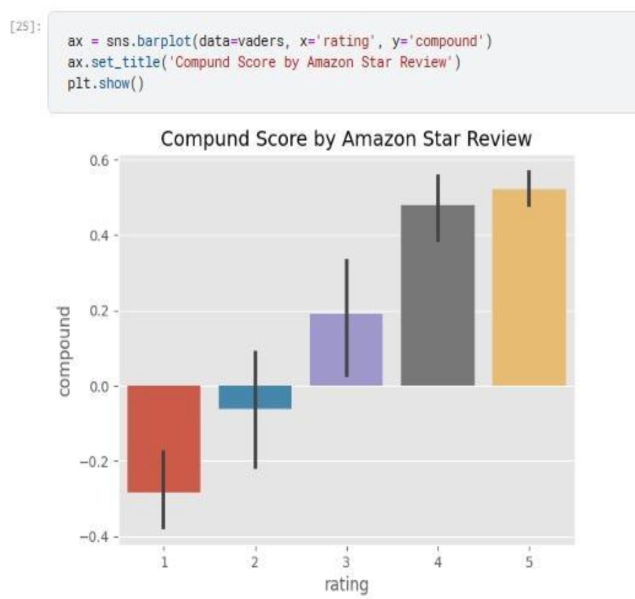
An effective and comprehensive experimental setup is crucial for any data analysis project, especially when conducting sentiment analysis on a large dataset like Amazon reviews. The goal is to gain insights into the sentiments expressed in Amazon reviews, and this objective guides the selection of tools, datasets, and methodologies.

The dataset is a critical component of the experimental setup, thus, herein an Amazon review database in CSV format from kaggle.com is used. To contain the time constraints a subset of about the first 500 rows is chosen. It demonstrates scalability; essential to consider the dataset's size and quality, as it impacts the accuracy and breadth of sentiment analysis. Many Python libraries such as pandas, numpy, matplotlib, seaborn and NLTK have been used. These facilitate data handling, visualization and text analysis. These specific tools reflect their relevance to natural language processing and tasks related to sentiment analysis.

The bar plot is made from the range of the score 1 to 5 revealing a bias towards a positive review, those steps provide insights into the dataset, in deciding how to approach the sentiment analysis. Involves data's distribution and characteristics.

We discuss the VADER approach to sentiment analysis and the removal of stop words. A lot of time is dedicated to how the assumption of a five-star score generally implies a positive sentiment, the polarity score is a major chunk of the project's structure. The creation of a function to apply the Roberta model to the entire dataset is a key part of the experimental setup. It involves handling potential challenges, such as text size issues and highlights the benefits of using a GPU for optimization. The combination of the results with the VADER model showcases the comparative aspect of the analysis, an important element of the setup. The use of seaborn is to give comparative analysis a central part of the setup and reveal insights into the performance of different sentiment analysis methods.

The experimental structure is well-organized and thorough. Clear objectives, carefully chosen tools, and datasets, conducting exploratory data analysis, and incorporating both traditional and cutting-edge new sentiment analysis techniques form the bedrock of our work.



(a)

(b)

FIGURE 3. Data Insights: (a) Compound score by Amazon Star Review to know the ratings of a product, (b) on a scale of 1 to 5 the different measures for positive, neutral and negative remarks

RESULTS AND INFERENCES

The entire process whilst tedious was rather smooth and gave satisfactory results as shown in [Fig. 4 (a), 4(b), 4(c)] wherein we have compared the results of reviews on VADER and roBERTa on three aspects; positive, neutral and negative. There were lot to learn from the entire process and the inferences are: We got to learn a lot about the lexicon-based approach and deep learning model approach, i.e, VADER and roBERTa and how distinctly they work and what outcomes they bring. On the face of it and from the graph obtained by us we can say that VADER is recognized for its simplicity and speed, efficiently identifying overall sentiment polarity in mobile reviews [12.]. Conversely, RoBERTa, a deep learning model, exhibits superior performance in capturing nuanced sentiments and context [13.]. Our findings have practical implications for businesses and researchers. VADER is an efficient tool for quick sentiment assessments and brand monitoring. On the other hand, RoBERTa provides invaluable depth and context for businesses seeking a nuanced understanding of consumer feedback and emotions. As per [Fig. 5(a), 5(b) and 5(c)] it becomes evident that the use of VADER has yielded intricate insights, and gives credible strength to the outcomes of [Fig. 3] which helped us with the compound score for brands such as Apple, Samsung and Blu3.

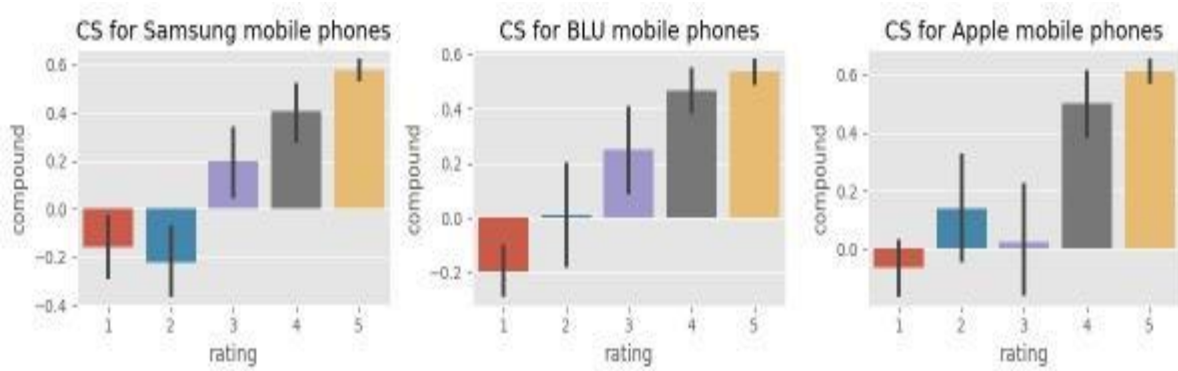
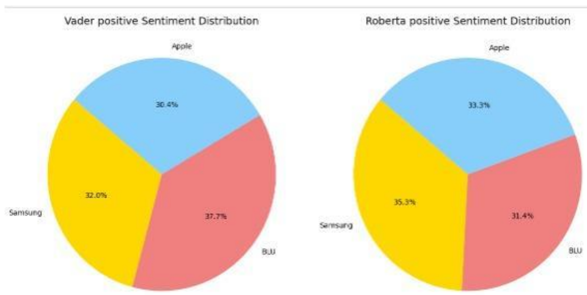


FIGURE 4. Compounded scores for different products (Samsung, BLU, Apple from right to left) on a scale of 1 to 5



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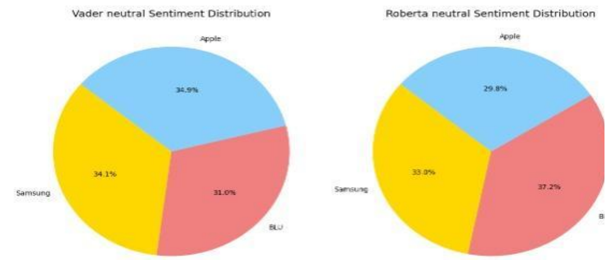

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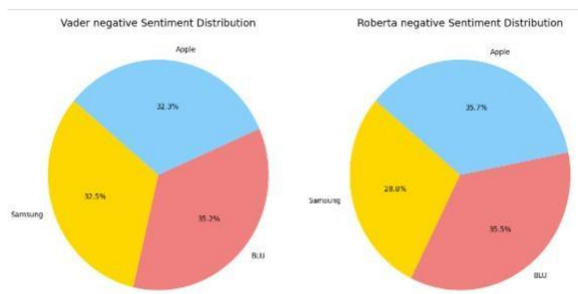
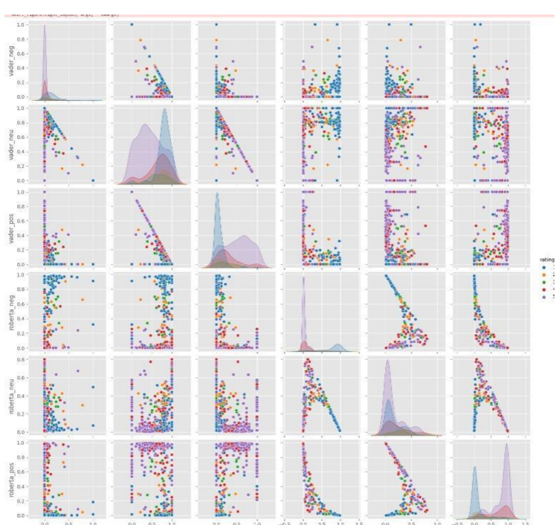


(c)

FIGURE 5. Inference in form of Pie chart: (a) Pie chart representing positive remarks on different brand products, (b) Pie chart representing neutral remarks on different brand products, (c) Pie chart representing negative remarks on different brand products



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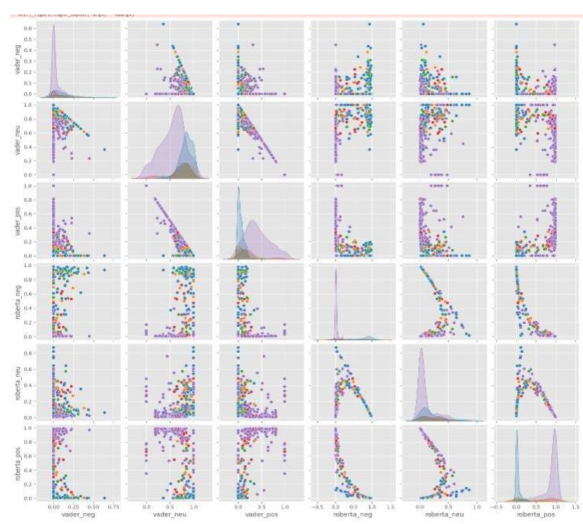

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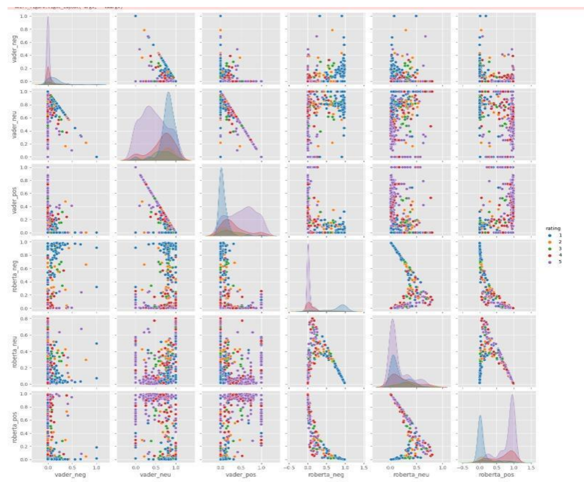

(c)

FIGURE 6. Inference in form of sns pairplot: (a) Multiple graphs for roberta and vader related-actions on Samsung products, (b) Multiple graphs for roberta and vader related-actions on Apple products, (c) Multiple graphs for roberta and vader related-actions on Blu 3 products

CONCLUSION

In conclusion, the research article that has been provided explores the field of sentiment analysis, also known as text sentiment detection. It focuses on Amazon reviews taken from the website Kaggle(a Google subsidiary, wherein one can find AI models, published datasets and other works). The study demonstrates a comprehensive analysis pipeline by using NLTK, Hugging Face's transformer based models (roBERTa). The paper examines a number of sentiment analysis techniques, ranging from Vader's simple polarity score to Roberta's sophisticated contextual nuance detection. The results demonstrate a strong relationship between sentiment scores and review ratings, but they also draw attention to the shortcomings of word-by-word analysis. The study emphasizes how important it is to use deep learning models to get deeper insights. Finally, we compare the two models' performances, highlighting the accuracy and speed of each. For the future, there are intriguing possibilities in sentiment analysis. Exploring various models for cross-linguistic sentiment analysis holds promise. Emotion detection is an emerging area that moves beyond simple positive/negative sentiment categorization to identify specific emotions expressed in reviews. Improved cross-lingual analysis techniques will be vital in a globalized marketplace. Ethical considerations, including addressing bias, impartiality, and privacy concerns, will become increasingly important. Finally, the development of real-time sentiment analysis tools will provide businesses with immediate insights for quick decision-making, allowing them to stay responsive and agile in the face of evolving customer sentiments.In the end, our study promotes the wider use of these models on bigger datasets, offering richer and more complex insights into sentiment analysis.

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