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Feature-Level Rating System using Customer Reviews and Review Votes

CH. Kavya Sri E[1], Kaasi Vishwanath[2], J. Kavya[3], P. Kavya[4], G. Kavya Sri[5], Uppula Nagaiah[6]
[1, 2, 3, 4, 5]B.Tech CSE-AIMLSchool of Engineering Hyderabad, India
[6]Assistant Professor CSE-AIML School of Engineering, Malla Reddy University

Abstract: The rapid growth of online reviews has made customer feedback a critical source of insight for businesses. However, traditional rating systems often offer limited value by providing only an overall score without breaking down individual aspects or features of a product or service. This project proposes a Feature-Level Rating System that uses customer review votes combined with machine learning (ML) and data analysis techniques to deliver more detailed and accurate feature-specific ratings. The proposed system begins by processing large volumes of customer reviews using Natural Language Processing (NLP) techniques to identify key product features mentioned in the feedback. Text classification algorithms, such as Support Vector Machines (SVM) or neural networks, classify the reviews based on feature-specific categories (e.g., battery life, usability, design, etc.). Next, sentiment analysis models, including tools like VADER or Long Short-Term Memory (LSTM) networks, assess the sentiment of each review with respect to specific features. This allows the system to determine whether a customer's opinion is positive, negative, or neutral for each feature. Finally, the system employs machine learning regression models (e.g., Random Forest or Gradient Boosting) to aggregate sentiment scores and calculate individual ratings for each feature, giving a granular view of customer satisfaction. By doing so, businesses gain a deeper understanding of which specific aspects of a product or service are performing well and which require improvement. This feature-level insight provides more actionable data for product development and enhances the customer decision-making process, offering a valuable tool for businesses to better align their offerings with customer expectations.

I. INTRODUCTION

In the modern digital era, online shopping and e-commerce platforms have become an integral part of consumer decision-making. Customers rely heavily on product ratings and reviews to assess the quality and reliability of products before making a purchase. However, the traditional rating systems used by these platforms primarily focus on an overall rating score, which does not provide a clear understanding of how different aspects or features of a product perform individually. This lack of feature-specific insights often leads to misleading evaluations, as a product may receive a high or low rating based on general opinions rather than specific characteristics that matter to different users. For instance, a smartphone may have an excellent battery life but poor camera quality, yet the overall rating might not reflect these contrasting aspects, leading to a biased perception among potential buyers. Furthermore, customer reviews are subjective and vary widely in terms of content, detail, and usefulness. Some reviews provide deep insights into specific product features, while others are vague or irrelevant. To address this, many e-commerce platforms allow users to vote on the usefulness of reviews, which helps highlight the most valuable feedback. However, existing rating systems fail to integrate these review votes into the evaluation process, making it difficult to determine the true impact of customer opinions. As a result, customers often struggle to make informed purchasing decisions, and businesses miss out on crucial insights that could help them improve their products. A more refined and transparent rating system that evaluates customer feedback at a feature level is needed to bridge this gap.

The challenge in developing such a system lies in accurately extracting feature-specific sentiments from textual reviews and integrating review votes to enhance the credibility of ratings. Natural Language Processing (NLP) techniques can be used to identify and classify product features mentioned in reviews, while sentiment analysis can determine whether customers express positive, negative, or neutral opinions about those features. Additionally, by incorporating review votes into the analysis, the system can ensure that highly rated and useful reviews contribute more significantly to the feature-level ratings. This approach not only provides customers with a clearer picture of a product's strengths and weaknesses but also enables businesses to understand customer preferences more effectively.

A major concern in current rating systems is the influence of fake or biased reviews, which can distort product evaluations. Many businesses manipulate ratings by posting artificial reviews to either promote their own products or degrade their competitors.

A feature-level rating system that considers both sentiment polarity and review votes can help mitigate this issue by giving more weight to authentic and highly useful reviews while reducing the impact of misleading or low-quality feedback. This will ultimately lead to a more trustworthy and informative rating system that benefits both consumers and sellers.

Implementing a feature-based rating system will revolutionize how customers interact with online reviews by providing detailed insights into product performance across different attributes. Instead of relying on an overall rating, customers can make informed choices based on the aspects that matter most to them. For businesses, this system will serve as a valuable tool for market analysis, helping them identify product areas that need improvement and enhancing their customer engagement strategies. By leveraging advanced NLP techniques and integrating customer review votes, this project aims to build a robust and intelligent rating mechanism that enhances the credibility, transparency, and effectiveness of online product reviews.

The current review and rating systems on e-commerce platforms and online marketplaces are often insufficient in providing a detailed and reliable assessment of products. Traditional rating systems rely on an overall score, which aggregates customer opinions into a single numerical value without considering the specific features of the product. This approach oversimplifies customer feedback and fails to highlight the varying quality of different product attributes. For example, in the case of a laptop, aspects such as battery life, display quality, performance, and durability may be rated differently by users, but a single overall rating does not provide this level of detail. As a result, potential buyers may make misinformed decisions because they lack access to specific ratings that align with their personal preferences and needs.

Additionally, customer reviews are highly subjective and vary in quality, structure, and usefulness. Some users provide well-detailed insights into specific product features, while others leave vague or one-word reviews that do not contribute meaningfully to the evaluation process. The usefulness of reviews is often determined through review voting mechanisms, where other users can vote on whether a review was helpful or not. However, these votes are typically not integrated into the product's overall rating, leading to an imbalance where influential, well- written reviews do not impact the rating system as much as they should. This results in a scenario where misleading or generic reviews can have the same weight as detailed, informative ones, ultimately reducing the accuracy of product evaluations.

II. RELATED WORK

One of the earliest studies on sentiment analysis for product reviews was conducted by

Pang et al. (2002), who explored machine learning techniques for classifying sentiments in online reviews. Their research demonstrated that Naïve Bayes, Maximum Entropy, and Support Vector Machines (SVM) could effectively categorize customer reviews into positive and negative sentiments. However, their approach considered entire reviews as a single entity rather than analyzing sentiment at the feature level. This limitation sparked further research into aspect-based sentiment analysis (ABSA), where individual product features are identified, and their associated sentiments are extracted.

Hu and Liu (2004) introduced an opinion mining framework that aimed to identify product features in customer reviews and determine whether the sentiment expressed toward each feature was positive or negative. Their work laid the foundation for feature-level sentiment analysis, demonstrating that customers often discuss multiple aspects of a product in a single review. For instance, a customer reviewing a smartphone might praise the camera but criticize the battery life. By extracting and analyzing sentiments for each feature separately, their study enabled a more comprehensive understanding of customer feedback. Further advancements in Natural Language Processing (NLP) and deep learning have significantly improved the accuracy of sentiment analysis.

Liu (2012) expanded on opinion mining techniques by incorporating dependency parsing and semantic analysis to better understand the relationships between words in a sentence. This was particularly useful in handling complex review structures where a feature and its sentiment might not be explicitly stated in a straightforward manner. to sentiment analysis, researchers have explored the credibility and usefulness of customer reviews to enhance rating systems.

Ghosh et al. (2011) analyzed the impact of review helpfulness votes in determining the credibility of reviews. Their findings showed that certain linguistic and structural characteristics, such as detailed explanations, longer reviews, and balanced sentiment, tend to receive more helpful votes.

Schuff (2010) further validated this by analyzing Amazon reviews, where they found that moderate-length reviews with both pros and cons were more likely to be rated as helpful. However, most rating systems still fail to incorporate review helpfulness votes into the final product score. Several studies have proposed methods to integrate helpfulness votes into review aggregation to improve rating accuracy.

Kim et al. (2018) suggested a weighted rating system where reviews marked as "helpful" by a larger number of users contribute more to the final rating than unvoted or low-quality reviews. Their approach aimed to reduce the influence of biased or spam reviews, which have become a significant issue in online marketplaces.

Mukherjee et al. (2013) developed a model to detect fake reviews using machine learning techniques and behavioral analysis. They found that spam reviews often exhibit unnatural posting patterns and extreme sentiments, either overly positive or negative, which distort overall ratings. By filtering out fake reviews and prioritizing credible ones, their model significantly improved the reliability of online ratings. Another important aspect of feature-level rating systems is personalization and user-specific recommendations.

III. METHODOLOGY

The proposed Feature-Level Rating System aims to address the limitations of traditional rating mechanisms by extracting detailed feature-based insights from customer reviews and incorporating review helpfulness votes to enhance rating credibility. This system will leverage Natural Language Processing (NLP), sentiment analysis, and machine learning techniques to analyse customer reviews, identify product features, classify sentiments, and generate feature-specific ratings. Additionally, review helpfulness votes will be used to prioritize high-quality reviews and improve the accuracy of ratings. In the digital age, online reviews play a crucial role in shaping consumer behaviour. Customers rely heavily on reviews when making purchasing decisions. However, traditional rating systems provide only an overall rating, which often does not reflect the strengths and weaknesses of a product's individual features. For instance, a smartphone may have an average rating of 4.2 stars, but this does not tell the buyer whether the battery life, camera, or performance meets their specific expectations. Customers are forced to manually browse through hundreds of reviews to extract meaningful insights about product aspects. To address this issue, we propose a Feature- Level Rating System that analyzes customer reviews at a granular level, extracting opinions on individual product attributes and calculating feature-specific ratings. This system uses Natural Language Processing (NLP), sentiment analysis, and machine learning techniques to analyze customer sentiments, filter out fake reviews, and generate personalized feature-wise ratings. Additionally, it integrates review helpfulness votes, ensuring that more credible and informative reviews contribute more to the final rating.

IV. CONCLUSION

In our work, we investigated the capability of quantum computing systems in recognizing the deep links between words in sentences as opposed to regular computer systems. Through the development and evaluation of several models, we discovered that quantum systems have the potential to excel in capturing complicated linguistic relationships, providing a promising option for furthering natural language processing tasks. One significant finding from our research is that quantum computing models take longer to train than conventional systems. This lengthy training period can be attributed to a variety of variables, including the system's innate ability to discover complicated word relationships and its proclivity to generalize at each step of the algorithm. While this greater computing burden may result in longer training cycles, it also demonstrates the model's ability to capture sophisticated semantic patterns and reach higher levels of accuracy.

However, we discovered that quantum systems are prone to overfitting, especially when trained on restricted datasets. The final model demonstrated the risk of overfitting, emphasizing the significance of carefully analyzing the quantity and diversity of the dataset when developing quantum computing models. Furthermore, while training on actual quantum hardware or cloud-based quantum servers supplied by platforms such as IBM may assist shorten training periods, it is critical to consider the potential restrictions and constraints associated with current quantum computing technology. Finally, our findings highlight the prospective capabilities of quantum computing systems in natural language processing tasks, notably in identifying complicated linguistic links. While quantum models may necessitate lengthier training cycles and careful consideration of dataset size to avoid overfitting, they have enormous potential for furthering the field of natural language understanding. Future research efforts may concentrate on further optimizing quantum algorithms, examining larger and more diversified datasets, and leveraging the full capability of quantum computing to open up new frontiers in language processing and interpretation. The only possible way of reducing the time taken for the models to train would be training them on an actual quantum system (or the could-based quantum server provided by IBM).

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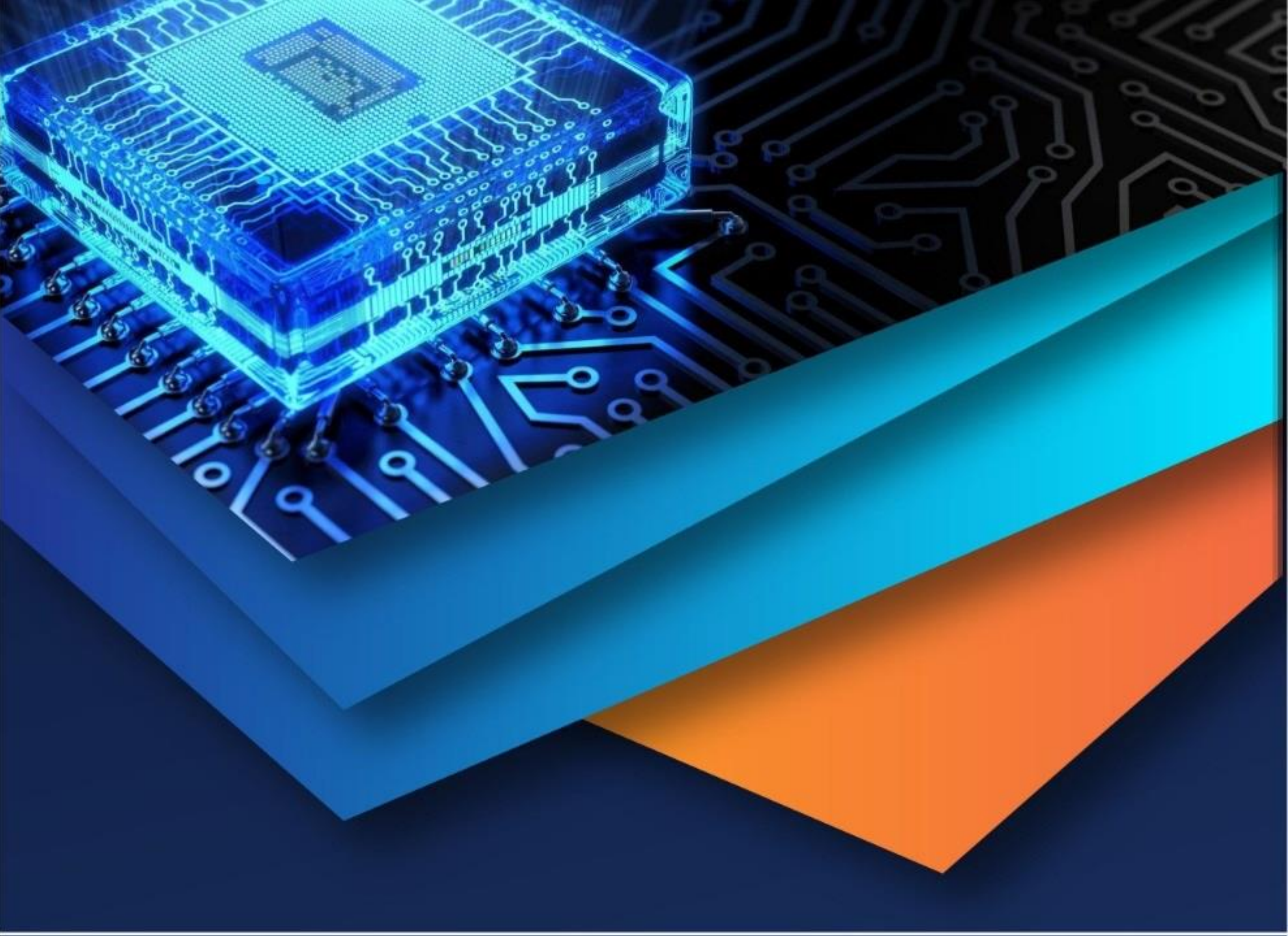

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