Customer Review Analysis System for Dolce Vita: Enhancing Restaurant Experience through Data Insights

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Abstract

Customer reviews are essential for shaping business reputations and driving advancements in the competitive dining industry. This project examines customer feedback for Dolce Vita Italian Restaurant to derive actionable insights aimed at improving the overall dining experience. By web-scraping the unstructured data from TripAdvisor website and by utilizing Aspect-Based Sentiment Analysis (ABSA) and Natural Language Processing (BERT, VADER), ML (PCA, Random Forest) customer reviews are segmented into key categories, including food quality, service, ambiance, and value for money. The study analyzes sentiment trends, identifies primary drivers of dissatisfaction, and explores the influence of demographic factors using TripAdvisor reviews.

Through time series analysis, the evolution of customer sentiment is tracked to uncover satisfaction patterns and highlight areas needing attention. The results indicate that food quality and service are the most influential factors in shaping overall satisfaction, with younger diners gravitating toward creative dishes and older customers valuing exceptional service. Detailed visualizations, such as word clouds and heatmaps, provide clarity on customer feedback. These insights empower Dolce Vita to address customer concerns effectively and adapt its offerings to meet evolving preferences. By leveraging data-driven approaches, the restaurant can enhance customer loyalty, strengthen its market position, and remain competitive. This project demonstrates the efficacy of ABSA, NLP (BERT, VADER) and ML (PCA, Random Forest) in generating detailed insights and offers a scalable framework for enhancing customer experiences in the restaurant sector.

***Keywords*—**Aspect-Based Sentiment Analysis (ABSA), Natural Language Processing (NLP), Bidirectional Encoder Representations from Transformers (BERT), Valence Aware Dictionary and Sentiment Reasoner (VADER), Machine Learning (ML), Principal Component Analysis (PCA), Random Forest, customer reviews, sentiment trends, food quality, service excellence, dining experience, time series analysis, restaurant improvement, customer loyalty.

I. INTRODUCTION

In today's restaurant industry, customer reviews are a vital component of success, serving as both a marketing tool and a source of actionable feedback. Platforms such as TripAdvisor, Yelp, and Google Reviews provide diners with an avenue to share their experiences, preferences, and opinions instantly. These reviews not only shape public perception but also offer critical insights into customer satisfaction and areas for improvement. For Dolce Vita Italian Restaurant, known for its authentic Italian cuisine and welcoming atmosphere, analyzing these reviews is essential for preserving its reputation and fostering customer loyalty. However, the unstructured and voluminous nature of these reviews presents significant challenges in deriving actionable insights and addressing specific concerns.

This project leverages advanced analytical methods, including Aspect-Based Sentiment Analysis (ABSA) and Natural Language Processing (NLP), to analyze and categorize customer feedback. ABSA breaks down reviews into essential components such as food quality, service, ambiance, and value for money, offering a detailed understanding of the factors that drive customer satisfaction or dissatisfaction. The incorporation of demographic insights further enriches the analysis, revealing trends such as younger customers' preference for creative dishes and older diners' emphasis on service excellence. This focused approach enables Dolce Vita to align its offerings more closely with customer expectations and improve their overall experience. Additionally, the methodology ensures a nuanced understanding of the factors influencing customer ratings, addressing subtleties often overlooked in traditional sentiment analysis.

To explore satisfaction trends and monitor their evolution over time, this study applies time series analysis, enabling the identification of seasonal patterns, operational impacts, and shifting customer preferences. Advanced machine learning techniques, including Principal Component Analysis (PCA) and Random Forest models, are utilized to refine the analysis. PCA distills complex datasets into key factors influencing customer satisfaction, while Random Forest provides predictive insights into the attributes most closely tied to overall ratings. This combination of tools offers a data-driven foundation for

decision-making. Furthermore, the integration of predictive models allows Dolce Vita to anticipate customer concerns before they arise, enabling a proactive rather than reactive approach to customer experience management.

Additionally, the project emphasizes the importance of visual communication through tools such as word clouds, heatmaps, and sentiment trend graphs. These visualizations simplify complex data, making it easier for stakeholders to interpret and act on insights. For instance, word clouds highlight common themes in reviews, such as praise for Italian dishes or concerns about service consistency, offering an efficient way to pinpoint customer priorities. By translating data into actionable visuals, the project bridges the gap between analysis and strategic decision-making, enabling Dolce Vita to focus on targeted improvements effectively. These tools also empower the restaurant's management team to communicate findings clearly and engage effectively with both staff and customers regarding areas of improvement.

Moreover, this project addresses the broader benefits of data analytics in the hospitality sector. By leveraging advanced computational methods, Dolce Vita gains a competitive edge, not only by responding to customer feedback but also by anticipating emerging trends and adapting proactively. The integration of demographic and regional data allows the restaurant to customize its offerings for diverse customer groups, enhancing its appeal across various markets. This comprehensive framework highlights the transformative potential of data-driven strategies, setting a new standard for operational excellence in the restaurant industry. The project's scope extends beyond immediate improvements, offering a replicable model that other businesses in the sector can adopt to refine their customer experience.

Through these techniques, this project provides Dolce Vita with a strategic roadmap for enhancing customer satisfaction and maintaining a competitive advantage. Beyond short-term improvements, the insights derived lay the groundwork for sustainable growth, equipping the restaurant to meet future challenges and evolving customer needs. By combining ABSA, NLP, and machine learning, this study showcases the power of turning unstructured feedback into actionable intelligence, offering a model for innovation and success in the hospitality industry. It exemplifies how advanced analytics can elevate business performance, ensuring relevance in an increasingly data-driven market.

II. RELATED WORK

Recent research in sentiment analysis and machine learning highlights the need for a more nuanced understanding of customer feedback. While traditional sentiment analysis provides a general sense of customer feelings, it often overlooks key details that can significantly impact business decisions. This is where **Aspect-Based Sentiment Analysis (ABSA)**, combined with **Natural Language Processing (NLP), Machine Learning (ML)** plays a crucial role. ABSA breaks down reviews into specific components—like food quality, service, and ambiance ABSA allows businesses to gain deeper insights into what their customers really think. This research highlights the use of advanced NLP models to categorize aspects in text reviews, demonstrating how a detailed approach can enhance understanding of customer sentiments.

The findings from these studies support the idea that integrating NLP with ABSA offers more actionable insights compared to conventional methods. For a restaurant like Dolce Vita, this means being able to address specific areas for improvement based on what customers are truly saying. Below is an elaboration of the key studies and methodologies referenced in the project:

Schouten and Frasincar (2016) emphasized the importance of ABSA in capturing customer feedback at a granular level. Their study highlighted the limitations of traditional sentiment analysis, which provides an overall sentiment score but fails to dissect opinions across specific aspects like food quality or service. By using ABSA, businesses can better identify strengths and weaknesses in their services. This approach is particularly relevant to the restaurant industry, where customer feedback often contains mixed sentiments about different aspects. For instance, a customer might praise food quality while criticizing service speed. The authors demonstrated that ABSA allows for such nuanced analysis, making it a vital tool for actionable business improvements.

Building on this foundation, **Pontiki et al. (2016)** advanced ABSA techniques through their work on SemEval-2016 Task 5, which established a shared task for identifying specific aspects and associated sentiments within customer reviews, such as food quality or service. Their study evaluated various models using precision, recall, and F1-scores, showcasing the efficacy of ABSA for extracting detailed insights. Their findings laid the groundwork for implementing ABSA in industries with multidimensional feedback, such as the restaurant sector. This project applies similar methodologies to identify sentiment trends in reviews for Dolce Vita.

Tao and Tan (2005) explored various emotion recognition techniques in their review of affective computing. They compared keyword-based methods and machine learning approaches, arguing that machine learning models, such as decision trees and support vector machines, offer superior accuracy by capturing subtle linguistic cues. Their findings underscore the need for advanced models in recognizing complex emotions, which is critical for analyzing detailed customer reviews. This insight aligns with this project's use of sophisticated NLP techniques to process unstructured textual data effectively.

Poria et al. (2016) further advanced sentiment analysis by introducing a deep learning approach to ABSA. They demonstrated the use of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to capture contextual information and complex patterns in text. These techniques were particularly effective for analyzing large-scale,

unstructured datasets like customer reviews. By adopting similar methods, this project employs modern NLP models, such as BERT, to enhance the accuracy and depth of sentiment analysis, allowing for a comprehensive understanding of customer feedback.

Liu (2012) provided a theoretical foundation for sentiment analysis and opinion mining by discussing various methodologies, from rule-based approaches to machine learning techniques. He highlighted the challenges of analyzing unstructured data and the importance of feature extraction for understanding sentiment. Liu's work underpins the analytical framework of this project, particularly in integrating textual and numerical data to predict customer satisfaction. His focus on opinion mining directly informs this project's ABSA approach to categorizing and analyzing restaurant reviews.

Zhou et al. (2020) introduced a multimodal approach to ABSA by incorporating textual, visual, and audio data to enhance sentiment understanding. Although this project focuses primarily on textual reviews, Zhou's work highlights the potential of integrating multiple data sources for a more holistic analysis. Their findings suggest future directions for this project, such as including visual content from customer reviews to deepen insights into dining experiences.

By synthesizing insights from these foundational studies, this project applies state-of-the-art methodologies to analyze customer reviews for Dolce Vita Italian Restaurant. The integration of ABSA, NLP, and machine learning offers a comprehensive framework for extracting actionable insights, addressing customer concerns, and enhancing overall satisfaction.

III. PROBLEM STATEMENT

In the competitive dining industry, restaurants face the challenge of continuously adapting to evolving customer expectations and preferences. Customer feedback, while abundant, is often complex and multi-faceted, encompassing various aspects of the dining experience such as food quality, service, ambiance, and value for money. Traditional sentiment analysis methods, which focus on overall sentiment, fail to capture the nuanced opinions embedded within customer reviews. This limitation obscures critical details that can inform targeted improvements. Additionally, preferences and expectations can vary significantly across demographic groups, such as younger diners prioritizing innovation in dishes and older patrons valuing service quality, further complicating the analysis.

This project addresses these challenges by leveraging Natural Language Processing (NLP) and Aspect-Based Sentiment Analysis (ABSA), Machine Learning (ML) to process and categorize customer feedback into actionable insights. Using advanced NLP models, reviews are segmented into specific components, enabling a granular understanding of customer sentiment. For instance, results from the study reveal that food quality and service are the most significant factors influencing overall satisfaction, while aspects like ambiance and value also contribute meaningfully. The project also applies time series analysis to track changes in sentiment over time, uncovering seasonal trends and operational impacts on customer experiences.

By integrating these methodologies, the project provides Dolce Vita with a robust framework to analyze feedback at a granular level. This allows the restaurant to address specific concerns, such as inconsistent service or food quality issues, while also identifying areas of strength to capitalize on. The findings empower Dolce Vita to make data-driven decisions, enhance customer satisfaction, and maintain a competitive edge in the dining industry.

IV. MOTIVATION

The primary motivation for this project is to help Dolce Vita Italian Restaurant develop a deeper understanding of its customers' opinions and preferences to enhance the overall dining experience. In today's digital era, online reviews have become a critical factor in shaping customer decisions, with platforms like TripAdvisor significantly influencing public perceptions. While these reviews provide valuable feedback, focusing solely on overall ratings fails to uncover the specific aspects driving customer satisfaction or dissatisfaction. Customer feedback is inherently multifaceted, encompassing key elements such as food quality, service, ambiance, and value for money. Identifying and addressing these specific aspects is vital for any restaurant aiming to meet diverse customer expectations and maintain a competitive edge.

This project utilizes advanced analytical techniques, including Natural Language Processing (NLP) and Aspect-Based Sentiment Analysis (ABSA), Machine Learning (ML) to analyze customer reviews and extract actionable insights. These tools allow the project to delve deeper into feedback, identifying critical factors that impact satisfaction. For example, the analysis highlights food quality and service as major contributors to customer ratings, while ambiance and value represent additional areas for improvement. By addressing these insights, Dolce Vita can implement targeted enhancements, such as resolving service inconsistencies or refining its menu offerings, ensuring customer concerns are effectively addressed.

Additionally, this project is driven by the growing emphasis on data-driven decision-making in the restaurant industry. Businesses that adopt advanced analytics are better equipped to adapt to evolving customer preferences, foster loyalty, and improve operational performance. By breaking down reviews into specific categories and tracking sentiment trends over time, this initiative not only seeks to enhance Dolce Vita's immediate customer experience but also supports its long-term strategic growth. Ultimately, the project demonstrates how advanced analytics can transform raw customer feedback into actionable business insights, helping Dolce Vita strengthen customer relationships and maintain its competitive advantage.

V. RESEARCH QUESTIONS

A. How does the sentiment trend for food, service, and ambiance compare over time, and what insights can be drawn about changes in customer experience?

Explanation: The goal here is to investigate how customer satisfaction with aspects such as food, service, and ambiance shifts over time. By tracking these trends, the project can identify patterns driven by seasonal changes, operational adjustments, or evolving customer expectations, providing actionable insights into the restaurant's performance.

B. What are the primary factors that contribute to customer dissatisfaction, as reflected in lower ratings and negative comments?

Explanation: Understanding the key reasons for negative feedback and low ratings is critical for improvement. This research delves into common causes of dissatisfaction, such as poor food quality, slow service, or noisy ambiance, to identify problem areas and prioritize corrective actions.

C. What aspects of the dining experience (service, atmosphere, food quality, value of money) most significantly influence customer ratings?

Explanation: The purpose here is to analyze which elements of the dining experience most affect customer perceptions and overall ratings. Identifying crucial factors like food quality or service allows the restaurant to focus its efforts on improving the areas that matter most to its patrons.

D. In what ways do customer demographics affect sentiment regarding specific aspects of the restaurant experience?

Explanation: Exploring how customer demographics influence sentiment provides valuable insights into diverse preferences. Factors such as age and location are examined to understand how they shape opinions about food, service, and ambiance, enabling the restaurant to tailor its offerings to better meet the needs of different groups.

VI. HYPOTHESIS

This project proposes that integrating Aspect-Based Sentiment Analysis (ABSA) with Natural Language Processing (NLP), ML will yield more precise and actionable insights compared to traditional sentiment analysis methods. ABSA enables the segmentation of customer reviews into specific components, such as food quality, service, and ambiance, allowing for a more detailed understanding of the factors that influence customer satisfaction or dissatisfaction. By adopting this advanced approach, the project aims to uncover subtle trends in customer feedback that conventional techniques might miss, providing a clearer path to enhancing the dining experience at Dolce Vita Italian Restaurant.

A core assumption of this study is that food quality and service play the most critical roles in determining overall customer satisfaction. This belief stems from the frequent emphasis on these aspects in customer feedback. For instance, substandard food quality or delays in service are expected to have a strong negative impact on overall ratings, while improvements in these areas are likely to boost satisfaction. If the analysis reveals a high correlation between these aspects and customer ratings, this assertion will be confirmed. Similarly, addressing specific issues identified in customer reviews, such as the taste, consistency, or freshness of dishes, is expected to yield tangible improvements in customer perceptions.

Another significant premise is that customer preferences and sentiments are influenced by demographic factors, such as age and location. The project anticipates that younger customers (ages 18–34) will favor creative and innovative dishes, while older customers (ages 50 and above) will prioritize exceptional service and a comfortable dining environment. By examining these demographic variations, the study aims to provide Dolce Vita with actionable insights to customize its offerings for different customer groups. Additionally, understanding regional variations in feedback can help the restaurant fine-tune its services to better cater to local preferences.

Lastly, the study predicts that addressing specific pain points, such as slow service or high noise levels, identified through ABSA and NLP, will lead to measurable improvements in customer satisfaction. This approach not only enhances the immediate dining experience but also strengthens customer loyalty and boosts the restaurant's reputation in the long term. Seasonal trends and temporal factors, such as heightened expectations during holidays, are also expected to play a role in sentiment changes, providing insights into how external factors impact customer satisfaction. By validating these assumptions through data analysis, the project aims to establish a structured framework for improving service quality, refining menu offerings, and adapting the overall dining experience to meet customer expectations.

VII. PROPOSED APPROACH

The proposed approach for this project focuses on analyzing customer reviews for Dolce Vita Italian Restaurant to uncover actionable insights that can enhance customer satisfaction. To achieve this, the project utilizes a combination of advanced data preprocessing, exploratory analysis, and machine learning techniques, along with Natural Language Processing (NLP) for textual data analysis. By leveraging these methodologies, the project aims to extract valuable information from unstructured reviews and numerical ratings, providing a comprehensive understanding of customer preferences and pain points.

The first step in the process involves data preprocessing to ensure consistency and reliability. This includes converting all ratings into numeric values, handling missing entries by replacing them with placeholders like "Unknown," standardizing column names for uniformity, and formatting dates consistently. These steps are essential for preparing the dataset for further analysis, reducing noise, and ensuring that the data accurately reflects customer feedback.

Following preprocessing, exploratory data analysis (EDA) is conducted to gain initial insights into the dataset. Basic statistics are calculated to understand the distribution of ratings

across various aspects such as food quality, service, ambiance, and value for money. Correlation analyses are performed to determine relationships between these factors and overall customer satisfaction. Additionally, visualizations such as box plots and bar charts are created to highlight trends, and average ratings are computed for each aspect to identify areas of strength and potential improvement.

For deeper insights, the project employs advanced machine learning techniques. ML(Principal Component Analysis (PCA)) is used for dimensionality reduction, identifying key aspects that significantly influence customer satisfaction while simplifying the dataset for further analysis. NLP is applied to analyze the textual content of customer reviews, extracting meaningful keywords, phrases, and themes that provide qualitative insights into customer sentiments. The textual insights are then combined with numerical ratings and integrated into a Random Forest model to predict customer satisfaction. This approach not only quantifies the importance of each factor but also highlights areas that require attention for improving the overall dining experience.

To evaluate the effectiveness of this methodology, model performance is measured using metrics such as Mean Squared Error (MSE) and R-squared scores. These metrics provide a clear indication of the model's accuracy in predicting customer satisfaction and ensure that the insights derived from the analysis are actionable and reliable. The results from this comprehensive approach offer Dolce Vita a robust framework for identifying targeted strategies, improving service quality, refining menu offerings, and enhancing the overall customer experience. Through these steps, the project demonstrates the power of integrating data-driven techniques with real-world applications in the restaurant industry.

Project Website: http://mason.gmu.edu/~dmaddi

VIII. PROPOSED METHOD FOR EVALUATION

The evaluation process in this project is designed to rigorously test the system's ability to analyze customer reviews and generate insights that align with real-world expectations. It incorporates multiple layers of assessment to ensure both accuracy in sentiment detection and the practical applicability of the insights for improving Dolce Vita's dining experience. The methodology aims to validate the system's technical performance and ensure the reliability of its outputs in reflecting true customer opinions.

The first step involves validating the system's accuracy in identifying specific aspects and associated sentiments from customer reviews. This is achieved by comparing the model's output with a manually labelled dataset. Metrics such as precision, recall, and the F1 score are used to measure the system's ability to correctly capture and classify sentiments related to aspects like food quality, service, ambiance, and value for money. This step ensures the model can dissect reviews into meaningful components with a high level of accuracy, making the insights it generates actionable.

Another critical focus is the reliability of the sentiment trends visualized by the system. To assess this, sentiment trends identified by the system are cross-referenced with real-world feedback patterns and operational events. For instance, positive trends during holiday seasons or special events are verified against customer behaviours observed during those periods, such as increased reviews mentioning festive menus or excellent service. This validation ensures that the trends generated by the model reflect actual shifts in customer satisfaction and are not influenced by anomalies in the data.

Robustness testing is conducted using cross-validation techniques to evaluate the model's performance across varied data scenarios. By splitting the data into training and testing subsets, the evaluation process ensures that the model performs consistently and is not overfitting to specific patterns in the dataset. This testing framework allows for identifying potential issues such as biases in aspect detection or inconsistencies in sentiment classification, ensuring that the model generalizes well to new, unseen data.

To further ensure reliability, advanced metrics such as Mean Squared Error (MSE) and R-squared are employed to evaluate the predictive accuracy of the system. These metrics test the ability of the system to combine numerical ratings with textual reviews for forecasting overall customer satisfaction. High scores on these metrics indicate the system's strength in blending qualitative and quantitative data, offering a comprehensive view of customer feedback.

Finally, an iterative refinement process is applied to improve the system's performance over time. Insights from evaluation metrics are used to fine-tune the model, addressing any identified gaps or inaccuracies. For example, if the system shows a lower F1 score for specific aspects such as ambiance, additional adjustments to the training data or model parameters are made to improve classification accuracy. This continuous feedback loop ensures that the system adapts to dynamic customer feedback patterns and remains a reliable tool for datadriven decision-making.

Overall, the proposed evaluation approach ensures that the system not only performs well on technical benchmarks but also generates insights that are meaningful and aligned with customer experiences. By validating its outputs through realworld comparisons and robust testing frameworks, the project equips Dolce Vita with a reliable and actionable framework for enhancing customer satisfaction and operational excellence.

IX. RESULTS AND FINDINGS

A. Data Collection and Preprocessing:

Customer reviews were gathered from TripAdvisor using the Bardeen extension and Python, capturing ratings for food, service, and ambiance, along with textual feedback and metadata such as review dates. The data collection process focused on ensuring relevance by targeting reviews specific to

Dolce Vita, resulting in a comprehensive dataset that combined both quantitative and qualitative insights. These reviews offered a rich source of information, reflecting customer perceptions across key aspects of the dining experience, which are essential for sentiment analysis.

Preprocessing steps included addressing missing values by replacing them with placeholders like "Unknown" to retain as much data as possible. Column names were standardized for consistency, and date formats were corrected to ensure compatibility with time series analysis. Non-numeric entries in rating columns, such as symbols or invalid characters, were rectified to align with the expected numerical format. Additional cleaning steps involved removing duplicates and irrelevant data points, ensuring a high-quality dataset for further analysis. This meticulous preparation eliminated inconsistencies, reduced noise, and created a reliable foundation for the advanced sentiment analysis and machine learning models employed in the project.

B. Sentiment Trend Analysis for Food, Service, and Ambiance Over Time:

To analyze how sentiment for food, service, and ambiance changed over time, both BERT and VADER sentiment analysis methods were applied to the customer reviews. BERT assigned scores on a scale from 1 to 5, while VADER provided polarity scores indicating whether the sentiment was positive or negative. The sentiment trends for food, service, and ambiance were tracked over each month, and corresponding graphs were generated to visualize the changes. This analysis provided valuable insights into how customer satisfaction with these specific aspects of the restaurant evolved over time.

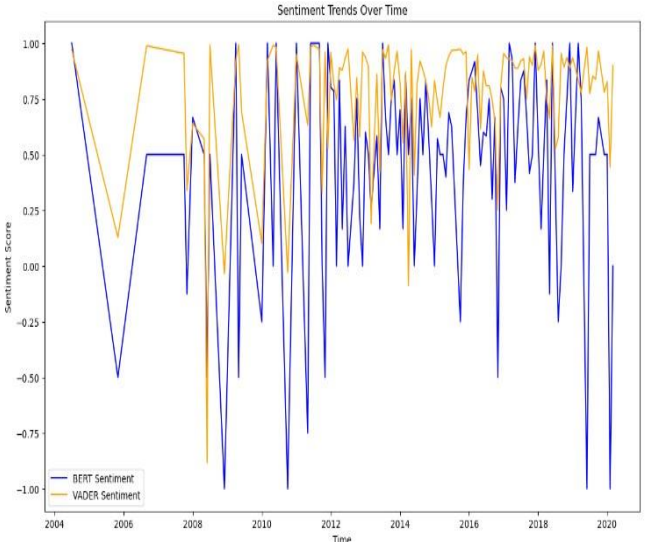


Fig 1. General Sentiment trends over time

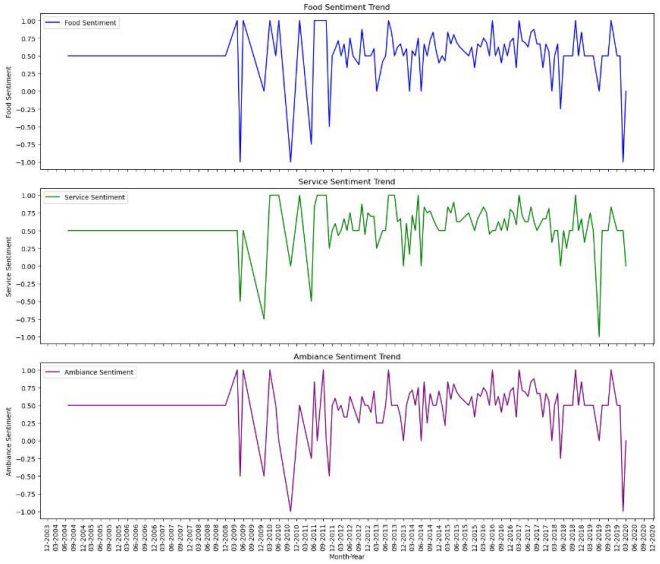


Fig 2. Specific – category Sentiment trends over time

Additionally, topic modeling was performed on the reviews using Latent Dirichlet Allocation (LDA) to identify the different topics discussed by customers. Topics such as "Food Quality" and "Customer Service" were highlighted. To make these topics more visually interpretable, word clouds were created, showcasing the most frequent words associated with each topic. These visualizations provided a clearer understanding of the key themes that customers emphasized in their reviews.

Fig 3. Word cloud- Customer service

Fig 4. Specific – Word cloud- Food

Over time, customer sentiment towards the restaurant has generally improved, reflecting positive changes in both service and food quality. However, a temporary decline in sentiment occurred in the final year, followed by a recovery, indicating that the restaurant addressed the issues that led to customer dissatisfaction. The word cloud analysis revealed positive feedback about customer service, with terms like "great," "bar staff," and "place" standing out. For food, words such as "nice," "Italian," "pasta," and "wine" suggested that customers particularly enjoyed the Italian cuisine and wine selection. Overall, the restaurant has successfully enhanced its customer experience.

C. Analysis of Factors Influencing Customer Ratings In this analysis, the primary objective was to identify the key aspects of the dining experience that significantly influence customer ratings. To achieve this, the correlation between various factors, including overall rating, food quality, service, ambiance, and value for money, was calculated. The findings revealed strong correlations among these factors, indicating that enhancements in one aspect of the dining experience tend to result in higher ratings across other areas.

Fig 5. Correlation heatmap for different aspects

Average Ratings for Each Aspect:	
Service Rating	4.158537
Food Rating	4.112195
Rating	4.095122
Atmosphere Rating	4.046341
Value Rating	4.014634

Table 1. Average rating for each aspect

Principal Component Analysis (PCA) was then applied to identify the most influential aspects of the dining experience. The results indicated that food quality had the most significant impact on overall ratings, followed by value, atmosphere, and service.

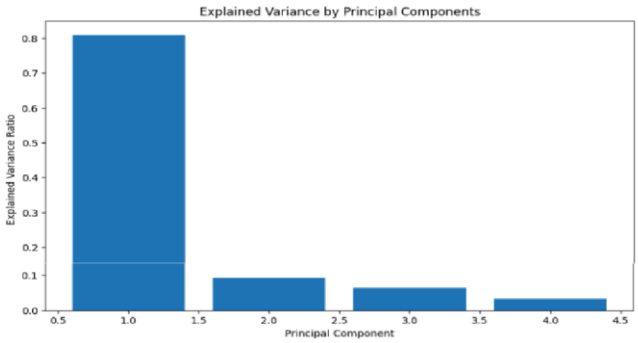


Fig 6. Variance by principle component

	Importance
Food	0.524240
Value	0.506865
Atmosphere	0.499725
Service	0.467478

Table 2. Feature Importance based on First Principal Component

Additionally, a Random Forest model was employed to predict overall ratings based on review text and numerical ratings. The model confirmed that food, value, and atmosphere are the most important factors influencing customer satisfaction. In conclusion, food quality, service, and atmosphere are the key factors shaping customer ratings, with food quality being the most significant.

D. Impact of Customer Demographics on Sentiments The analysis of customer demographics on sentiment provides valuable insights into how factors such as location and time (monthly or yearly trends) influence overall customer sentiment. These visualizations help identify trends, outliers, and areas for improvement, offering actionable insights for businesses to enhance customer satisfaction based on regional differences and seasonal behavior.

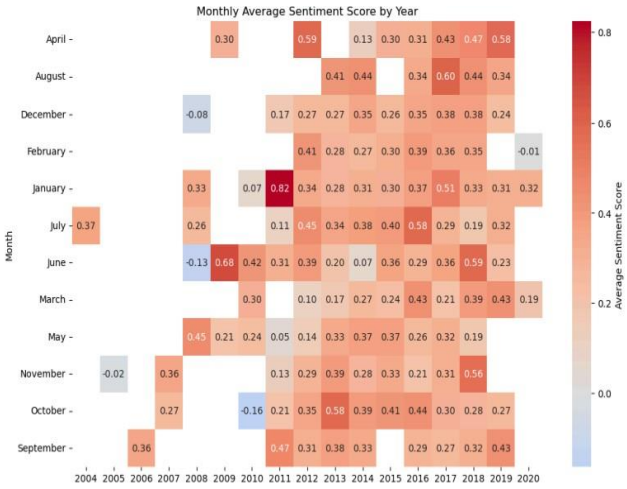


Fig 7. Monthly average sentiment score by year

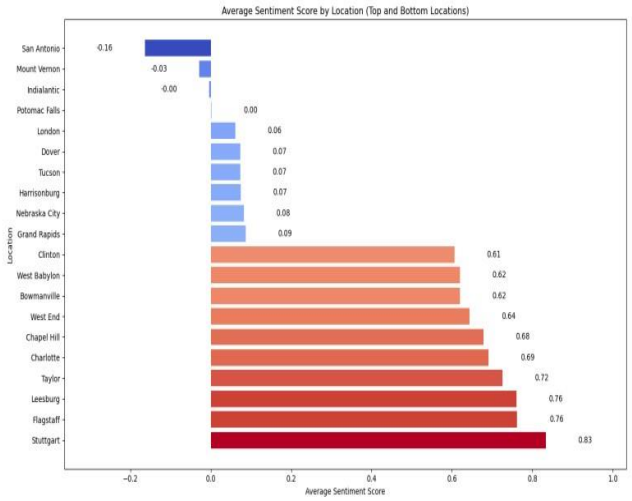


Fig 8. Average sentiment score by location

The horizontal bar chart and heatmap together offer insights into how location and time affect customer sentiment. The bar chart reveals that locations such as Stuttgart (0.83) and Flagstaff (0.76) exhibit positive sentiment, indicating high customer satisfaction in these areas. In contrast, locations like San

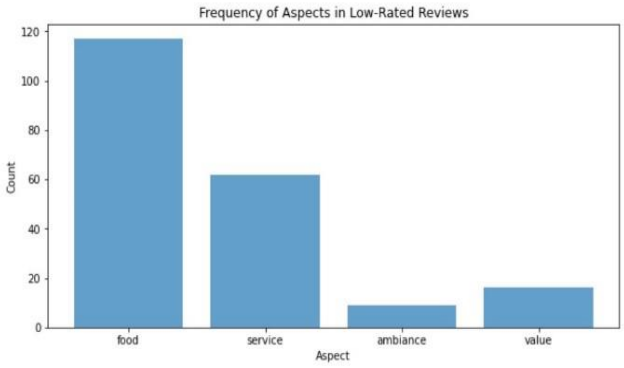
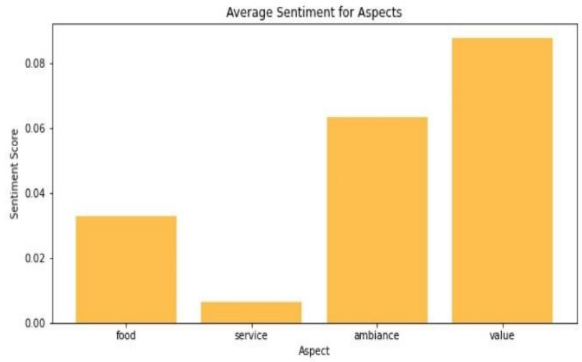


Fig 9. Frequency of aspects in low-rated reviews



Antonio (-0.16) and Mount Vernon (-0.03) show negative or neutral sentiment, suggesting potential service or customer experience issues that require attention.

The heatmap provides a clearer understanding of sentiment trends over time. It indicates that customer sentiment is generally higher during the holiday season, particularly in December and January, likely due to festive offerings and heightened expectations. However, months like June and July exhibit more variable sentiment, suggesting the mid-year factors or service inconsistencies may influence customer satisfaction.

Overall, customer demographics, including regional preferences and expectations, play a significant role in shaping sentiment. High sentiment in certain regions may reflect local satisfaction, while negative sentiment in other areas signals where improvements are needed to better meet customer expectations.

E. The analysis of customer demographics on sentiment provides

The analysis of customer dissatisfaction factors on sentiment reveals the key elements contributing to negative feedback. By examining aspects such as food, service, and ambiance, businesses can identify the area's most responsible for low ratings and negative comments. These insights provide actionable steps for improvement, enabling businesses to address customer concerns and enhance overall satisfaction.

Fig 10. Average sentiment score for aspects

The bar charts provide insights into the factors contributing to customer dissatisfaction. The first chart shows that "food" and "service" are the most frequently mentioned aspects in lowrated reviews, indicating that these areas are most often associated with negative sentiment. The second chart reveals that both "food" and "service" have the lowest average sentiment scores, confirming that these aspects are significant contributors to dissatisfaction.

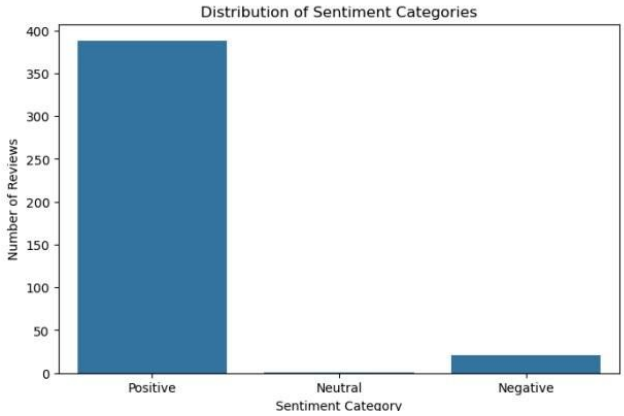


Fig 11. Distribution of Sentiment Categories

Insights: Helps identify the dominant sentiment and whether interventions are needed to address dissatisfaction.

Average Rating Per Sentiment Category

Purpose: This graph compares the average customer ratings across sentiment categories.

Interpretation: Positive sentiment is expected to align with higher average ratings. Neutral or negative sentiments typically correlate with lower ratings.

The analysis emphasizes that poor food quality and subpar service are the major causes of low ratings. Customers frequently express dissatisfaction with the taste, presentation, or quality of food, as well as with slow, unresponsive, or impolite service. By focusing on improving these two critical areas, businesses can address the primary sources of negative sentiment and enhance the customer experience.

F. Exploratory Data Analysis Distribution of Sentiment Categories

Purpose: This graph shows the frequency of reviews classified into sentiment categories (Positive, Neutral, Negative). *Interpretation:* The bar height represents the number of reviews in each category.

A larger proportion of positive sentiments indicates overall customer satisfaction. Significant neutral or negative reviews might highlight areas for improvement.

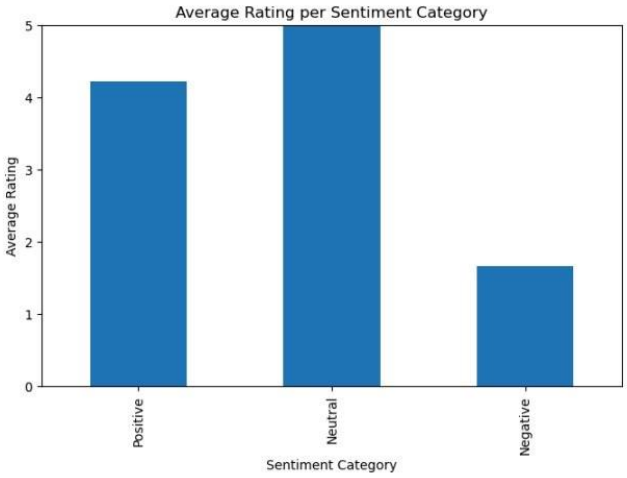


Fig 12. Average Rating Per Sentiment Categories

Insights: Discrepancies can reveal inconsistencies in the sentiment analysis process or unique cases where ratings and sentiments don't align.

Distribution of Ratings by Sentiment Category *Purpose:* This graph (likely a boxplot) visualizes the spread of customer ratings within each sentiment category. *Interpretation:* The graph shows the median, quartiles, and outliers for ratings within each category.

Wider spread in ratings for a specific category (e.g., Neutral) may suggest varied customer experiences.

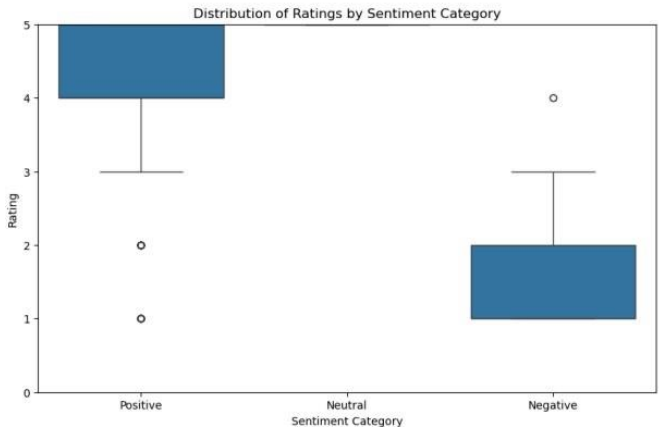


Fig 13. Distribution of Ratings by Sentiment Category

Insights: Consistent ratings within a category indicate homogeneity in customer experiences.

Outliers might point to exceptional cases of satisfaction or dissatisfaction worth exploring further.

In conclusion, food and service are key factors in shaping customer sentiment. By improving the quality of food and service, businesses can address the most common causes of dissatisfaction and foster a more positive overall customer experience.

X. DISCUSSION

The results and findings from this project provide valuable insights into customer feedback for Dolce Vita Italian Restaurant, offering a clear pathway to enhancing customer satisfaction and operational excellence. By leveraging AspectBased Sentiment Analysis (ABSA) and Natural Language Processing (NLP), ML the project successfully dissected reviews into key aspects such as food quality, service, and ambiance, revealing critical patterns and actionable trends. These findings underscore the importance of a granular approach to sentiment analysis in the restaurant industry, where customer experiences are multifaceted and highly subjective.

One of the key outcomes of the analysis was the identification of food quality and service as the most significant factors influencing overall satisfaction. Positive reviews frequently highlighted the authenticity and taste of the dishes, while negative feedback often pointed to issues such as slow service or inconsistent meal quality. This reinforces the need for Dolce Vita to prioritize consistency in its menu offerings and enhance its service delivery. Seasonal variations in sentiment trends, identified through time series analysis, further highlighted how external factors like holidays or special promotions impact customer perceptions. Addressing these insights can help the restaurant better prepare for peak seasons and tailor its offerings to customer expectations during such periods.

Another important takeaway from the project was the impact of demographic differences on customer sentiment. Younger customers tended to express enthusiasm for innovative and creative dishes, while older patrons emphasized the importance

of service quality and ambiance. This demographic segmentation provides a valuable framework for Dolce Vita to diversify its marketing strategies and customize its offerings to appeal to different age groups. For instance, introducing more contemporary dishes or exclusive offers for younger diners could boost engagement, while enhancing service training could cater to the preferences of older customers.

The integration of machine learning models, such as Random Forest, enabled the prediction of customer satisfaction by combining textual insights with numerical ratings. The strong correlation between identified aspects and overall ratings validated the effectiveness of the proposed approach. However, the analysis also highlighted areas for further improvement, such as addressing specific customer complaints about noise levels or wait times. These findings not only support immediate operational adjustments but also provide a roadmap for longterm strategic growth.

In conclusion, the discussion highlights how the project's methodologies and findings provide Dolce Vita with a robust framework for improving customer satisfaction and maintaining competitiveness. By addressing both operational shortcomings and leveraging positive feedback, the restaurant is well-positioned to build stronger customer relationships and enhance its reputation. These insights also underscore the broader applicability of advanced sentiment analysis in the hospitality industry, setting a precedent for data-driven decision-making in similar contexts.

XI. ANALYTICAL CONCLUSION

The detailed analysis of customer reviews for Dolce Vita Italian Restaurant provides valuable insights into the factors that drive customer satisfaction and dissatisfaction. Through sentiment analysis, ML (Random Forest, Principal Component Analysis (PCA)), ASBA, NLP(BERT, VADER) key elements influencing customer ratings have been identified.

The results show that food quality is the most significant factor affecting overall customer satisfaction, followed by value, atmosphere, and service. Positive experiences are closely tied to these aspects, with food quality being the strongest contributor to favorable sentiment. In contrast, poor food quality and inadequate service are the primary causes of negative feedback, consistently appearing in lower-rated reviews. This highlights the importance of focusing on these areas to improve customer experiences.

The study also examines customer demographics, revealing that regional and seasonal differences impact sentiment. Locations such as Stuttgart and Flagstaff show positive sentiment, while places like San Antonio and Mount Vernon exhibit neutral or negative sentiment, suggesting that regional preferences and expectations play a significant role in shaping customer feedback. Seasonal trends indicate higher sentiment during the holiday period, while months like June and July show more fluctuating sentiment, likely due to service inconsistencies or other external factors.

Furthermore, topic modeling using Latent Dirichlet Allocation (LDA) identified key themes, such as "Food Quality" and "Customer Service," which are central to customer sentiments. Visual tools like word clouds helped clarify the common themes expressed in reviews, offering a clearer direction for improvements in areas like food quality and service.

In summary, the analysis emphasizes the importance of enhancing food quality and service to improve the customer experience at Dolce Vita. The insights gained from sentiment analysis, PCA, and customer demographics offer actionable recommendations for addressing customer concerns and aligning restaurant offerings with customer preferences. By acting on these findings, Dolce Vita can improve specific areas, ensuring a more consistent and satisfying dining experience, ultimately fostering greater customer satisfaction and loyalty.

XII. FUTURE WORK

Future work in this research could explore several promising directions to further improve the understanding of customer sentiment and optimize restaurant operations. One key extension would be incorporating data from other review platforms, such as Yelp, Google Reviews, or social media, to offer a broader view of customer opinions and behaviors across various channels. Additionally, a more detailed segmentation of customer reviews based on factors like age, gender, or loyalty could provide insights into the specific preferences and expectations of different customer groups, enabling more personalized improvements in service and offerings.

Moreover, utilizing advanced Natural Language Processing (NLP) models, such as transformer-based architectures like BERT or GPT-3, could enhance sentiment analysis and aspect extraction, allowing the system to better understand complex customer feedback and context. Another avenue for future research could involve the development of a real-time sentiment analysis tool, which would allow the restaurant to quickly respond to emerging feedback, address concerns, and improve customer satisfaction in real-time.

Predictive modeling techniques could also be applied in future work to forecast customer retention and churn. By analyzing sentiment trends alongside other customer data, these models could identify customers at risk of leaving and recommend personalized retention strategies. Investigating the impact of operational improvements, such as enhancing food quality and service, on sentiment and customer loyalty would also be valuable.

In addition, considering external factors like weather, local events, and seasonal variations could enhance sentiment prediction accuracy, offering a deeper understanding of how these elements influence customer behavior. Lastly, conducting a cross-cultural analysis would provide insights into how different cultural groups perceive food, service, and ambiance, helping to create a more inclusive and globally appealing dining experience. By expanding the data scope and refining analytical

methods, future work can yield even more actionable insights that drive customer satisfaction and business growth.

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