WORCESTER POLYTECHNIC INSTITUTE

Pizza Sentiments: Decoding Customer Emotions in YELP Reviews

DS 595 - Natural Language Processing

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Presented To:

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TEAM MEMBERS CONTRIBUTION:

Aayush Shangani has made significant contributions to the development of machine learning models, focusing on both traditional and advanced methods. He applied the TF-IDF (Term Frequency-Inverse Document Frequency) approach to extract features from text data, creating a solid foundation for machine learning tasks. Leveraging this approach, he built models using Decision Trees, Random Forests, Logistic Regression, Support Vector Machines (SVM), K-nearest neighbors (KNN), and Naive Bayes. In addition to traditional machine learning, he also used deep learning models, particularly BERT (Bidirectional Encoder Representations from Transformers).

Darsh Shetty has excelled in constructing machine learning models that utilize the Word2Vec feature extraction technique, which encodes words into a continuous vector space based on their surrounding context. This approach helps capture the semantic relationships between words, enhancing the performance of various machine learning models. He has developed models using Decision Trees, Random Forests, Logistic Regression, SVM, K-nearest neighbors (KNN), and Naive Bayes. He has also fine-tuned deep learning, specifically focusing on BERT, and by fine-tuning BERT, has optimized the model to work effectively with our specific datasets.

Pavan Antala has brought a unique approach to building machine learning models by leveraging Parts of Speech (POS) as a feature extraction method. This technique provides a detailed understanding of grammatical structures in text, allowing for advanced machine-learning applications. He has used POS features to create models with Decision Trees, Random Forests, Logistic Regression, SVM, K-nearest neighbors (KNN), and Naive Bayes. In addition, he has implemented deep learning models with BERT, focusing on fine-tuning with the Low-Rank Adaptation (LoRA) technique. LoRA enables efficient fine-tuning with lower computational resources, providing a significant advantage. He has also designed and trained a Recurrent Neural Network (RNN) from scratch, demonstrating deep learning expertise and a commitment to innovative model development.

Sheroz Shaikh builds deep learning models from scratch. He implemented Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (BI-LSTM) with attention mechanisms. These deep learning architectures are valuable for sequence-based tasks and natural language processing applications. The contributions have focused on creating deep learning models that excel at handling complex data sequences and implementing attention mechanisms, which allowed the model to focus on relevant parts of the input data, leading to improved performance and accuracy. Additionally, he used graph-based embeddings to capture complex relationships, building machine learning models like Decision Trees, Random Forests, Logistic Regression, SVM, K-nearest neighbors (KNN), and Naive Bayes. Furthermore, he applied ensemble techniques, including Voting Classifiers with hard and soft voting, and Stacking Classifiers for improved accuracy and robustness.

THE PROPOSED QUESTION:

Motivation

In today's competitive food industry, understanding customer sentiment is more crucial than ever. For businesses aiming to establish a successful presence, particularly in the pizza market, gaining insights into customer preferences can be the difference between flourishing and faltering. As a leading data science consultancy partnering with prestigious firms like Deloitte and McKinsey, we know that the best business decisions are rooted in solid data analysis. Our project exemplifies this approach, as we embark on a journey to help a client open a new pizza store in the United States. Our client, a budding entrepreneur with a passion for pizza, turned to us for expert guidance in creating a successful pizza establishment. The question at hand was simple yet significant: What makes a pizza place stand out in a saturated market? To answer this, we turned to YELP, a rich source of customer feedback, reviews, and ratings. By examining YELP's pizza-related reviews, we aimed to uncover valuable insights into customer behavior, preferences, and expectations.

It is hypothesized that customer satisfaction is significantly influenced by a combination of quality ingredients, efficient service, and a welcoming atmosphere. This can be further explored by examining the correlation between positive reviews and their presence. Additionally, it is proposed that innovative toppings and unique flavor combinations, while valued, do not overshadow the demand for traditional pizza offerings like classic margaritas and pepperoni. The role of service speed, establishment cleanliness, and staff friendliness may also play a pivotal part in shaping customer sentiment, suggesting that these factors could serve as predictors for positive reviews. Testing these hypotheses through deeper statistical analysis could yield actionable insights for pizza businesses seeking to enhance customer satisfaction and loyalty. Our objective deals with identifying common themes, pinpointing what customers love about their favorite pizza places, and understanding what they find lacking. The diversity of YELP's user base provided us with a broad perspective, encompassing different regions, demographics, and tastes. This variety was crucial for developing recommendations that would resonate with a wide audience. We planned to apply advanced sentiment analysis techniques to extract meaningful insights from the data. By leveraging machine learning and deep learning models, we could discern the underlying sentiments within the reviews, distinguishing between positive, negative, and neutral opinions. This analysis will not only reveal what customers explicitly stated in their reviews but also capture the subtler aspects of their feedback, such as implied preferences and common criticisms. By understanding customer sentiment and behavior, our client can gain an unobstructed vision of what it takes to establish a successful pizza store in the USA. This project underscores the importance of sentiment analysis in business strategy.

Description of the problem

The problem addressed in this project revolves around understanding customer sentiment in YELP pizza reviews. With the vast number of reviews available on the platform, it becomes increasingly challenging to extract meaningful insights from unstructured text data. The objective is to determine the general sentiment of these reviews, identifying patterns and trends that can help pizza establishments improve their products, services, and overall customer experience. Sentiment analysis involves classifying the polarity of reviews- whether they are positive, or negative-based on textual content. This is a complex task due to the variability in language use, individual biases, and contextual nuances. Reviews often contain mixed sentiments, sarcasm, or domain-specific language, which can make it difficult to accurately gauge the underlying sentiment. Furthermore, pizza-related reviews can cover a wide range of topics, from the quality of the pizza and service to the cleanliness of the restaurant and the speed of delivery. This diversity in content requires robust methods for text preprocessing, feature extraction, and machine learning to capture the subtle differences in sentiment. The challenge lies in building models that can effectively analyze this data, providing reliable sentiment classification and uncovering insights that are actionable for businesses. The goal is to create a system that can process large volumes of YELP pizza reviews, identify key themes, and suggest areas for improvement, thus aiding pizza establishments in enhancing customer satisfaction and loyalty.

Description of the dataset

The dataset used in this project is sourced from YELP, a popular platform for customer reviews and business ratings. Specifically, the dataset is filtered for pizza-related reviews, providing a comprehensive view of customer opinions and sentiments regarding various pizza establishments. This dataset serves as the foundation for sentiment analysis, allowing us to explore customer feedback and uncover insights into customer satisfaction and dissatisfaction. The YELP pizza review dataset contains several key attributes that provide context and information for analysis. These attributes include the following:

Review Text:

- This is the primary content of the dataset, consisting of written reviews by customers about their experiences at different pizza establishments. The review text forms the basis for sentiment analysis, capturing customer opinions, descriptions of their experiences, and their overall satisfaction with the service, food, and other aspects of the pizza establishments.

Review Rating:

- Each review is associated with a numerical rating, typically on a scale from 1 to 5 stars, where 1 represents an extremely negative experience and 5 represents a highly positive experience. This attribute is used to gauge the general sentiment of the review and serves as a reference point for model training.

Business Information:

- The dataset includes information about the pizza establishments being reviewed, such as the business name, location, and category. This information is valuable for contextualizing the reviews and understanding where they originated.

Reviewer Information:

- Data related to the reviewers themselves, such as user ID, number of reviews submitted, and their status on the YELP platform, are also included. This information can be useful for identifying frequent reviewers or assessing potential biases in the dataset.

Review Date:

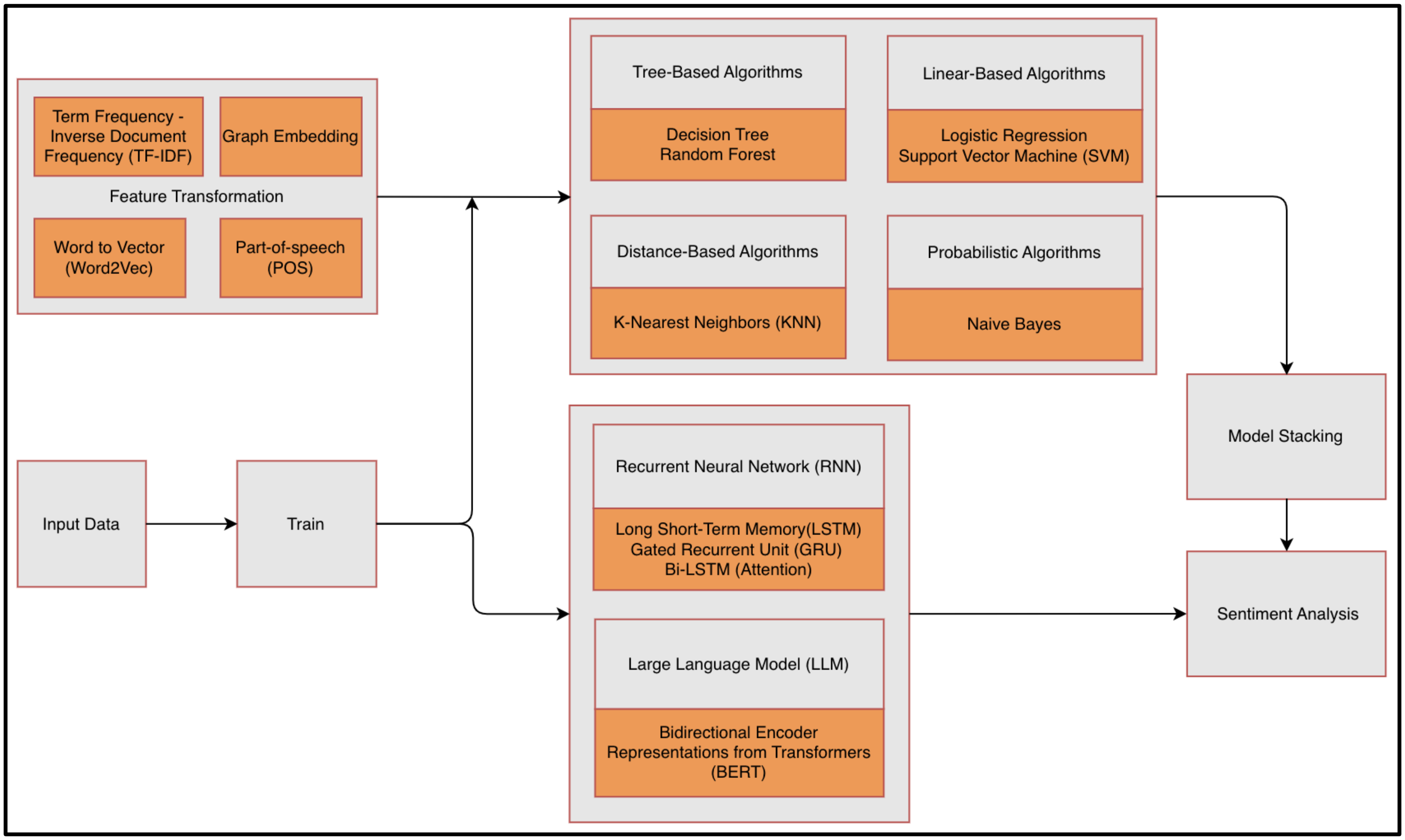
- Each review is timestamped with the date it was submitted. This attribute allows for temporal analysis, enabling the study of trends over time and the correlation of reviews with specific events or seasons.

In data volume, the dataset comprises many reviews, providing a large sample size for analysis. This volume is essential for training machine learning and deep learning models, allowing them to learn from a diverse set of examples and generalize effectively to unseen data. The dataset's diversity in terms of review text, business information, and reviewer demographics provides a rich source of data for sentiment analysis. The inclusion of review ratings offers a reference point for training models, while the business and reviewer information provides context for further analysis. The dataset's structure and attributes allow for a wide range of analyses, from basic sentiment classification to more complex studies of trends and patterns in customer feedback. These characteristics make it an ideal dataset for exploring the factors influencing customer sentiment and gaining actionable insights for businesses in the pizza industry.

THE PROPOSED METHODOLOGY:

The methodology outlined in the flowchart describes the process and machine learning algorithms used for sentiment analysis. The workflow begins with raw input data, which is then transformed into structured features through various techniques. These include Term

Frequency-Inverse Document Frequency (TF-IDF), Word2Vec, Part-of-Speech (POS) tagging, and Graph-based learning, all of which serve to convert raw text into a more structured and analyzable format. Once these features are prepared, the data is used to train diverse types of machine learning algorithms, chosen for their effectiveness in sentiment analysis. The range of algorithms includes tree-based models like Decision Trees and Random Forests, linear-based models such as Logistic Regression and Support Vector Machines (SVM), distance-based models like K-nearest neighbors (KNN), and probabilistic models like Naive Bayes. Each algorithm has its strengths and is selected based on its ability to process the transformed features effectively. Furthermore, the best-performing models are stacked together along with the voting classifier approach to form a robust model that can enhance the overall F1 score. Overall, this methodology emphasizes a structured approach to sentiment analysis, starting with feature transformation and progressing through various machine learning algorithms to identify patterns and determine sentiment within the data. This sequence of processes helps ensure that the resulting analyses are accurate and meaningful.



Additionally, the training data is processed through various deep learning architectures, such as Recurrent Neural Networks (RNNs). This includes Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bi-LSTM with attention mechanisms. These RNN-based models are designed to capture sequential patterns in text, allowing for a deeper understanding of sentiment. Large Language Models (LLMs), like Bidirectional Encoder Representations from Transformers (BERT), are also used in the methodology. BERT, known for its contextual understanding of text, is fine-tuned to improve performance in sentiment analysis. This fine-tuning process involves adjusting the pre-trained model to the specific dataset, allowing it to better recognize the nuances in sentiment, and the model is fine-tuned using the traditional fine-tuning method as well as Low-Rank Adaptation (LoRA). These various pathways-spanning spanning traditional machine learning algorithms, deep learning models, and large language models converge at the sentiment analysis stage. This convergence illustrates the comprehensive range of techniques used to perform sentiment analysis on the input data. The flowchart offers a complete overview of the sentiment analysis process, from feature transformation to the application of diverse algorithms, highlighting the broad array of tools and methodologies employed in this domain.

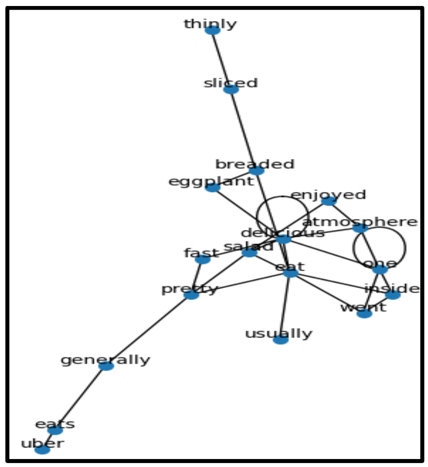
Preprocessing

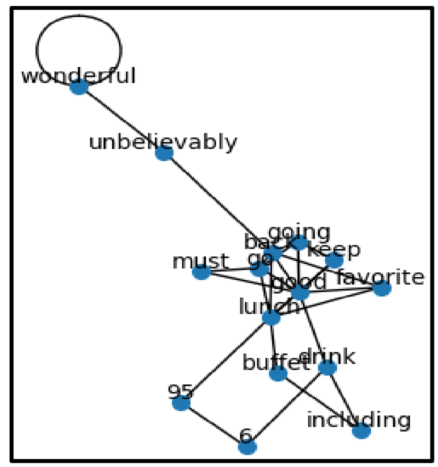
The preprocessing steps for the YELP pizza review data focus on cleaning and preparing the text to be used in machine learning and deep learning models for sentiment analysis. The goal is to ensure the data is consistent, structured, and suitable for various feature extraction techniques. First, the data underwent a thorough cleaning process to remove unwanted elements that could interfere with model training and analysis. This involved eliminating special characters, punctuation marks, and symbols, converting all text to lowercase to maintain uniformity, and removing extra whitespaces that could affect tokenization. Additionally, common stop words such as "the," "is," and "in" were removed to ensure that only significant words were retained for further analysis.

For traditional machine learning models, the subsequent step involved feature extraction, which encompassed various techniques to convert textual data into a numerical format suitable for processing by machine learning algorithms. One such technique employed was TF-IDF (Term Frequency-Inverse Document Frequency), which assigns weights to words based on their frequency in the text and their significance relative to the entire dataset. This method aids in highlighting important terms within the text. Additionally, Part-of-speech (POS) Tagging was utilized to label each token with its grammatical role, providing additional context and facilitating feature extraction. Another technique employed was Word2Vec, which represents words as vectors in a continuous vector space, capturing semantic relationships between words. This approach enables the models to comprehend the context and associations present within the text data, thereby enhancing its suitability for sentiment analysis.

For deep learning models, the cleaned text was tokenized to break it down into individual words or tokens. Tokenization is crucial for facilitating feature extraction and allowing models to understand the structure of the text. The dataset was then split into 80/20 training and test sets to facilitate model training and evaluation. This approach allows models to be trained on one portion of the data while testing their performance on another, ensuring generalization to unseen data. Overall, these preprocessing steps were critical to preparing the YELP pizza review data for sentiment analysis. By ensuring the data was clean, structured, and suitable for feature extraction, the project could effectively use machine learning and deep learning models to gain insights into customer sentiment.

Exploratory Data Analysis (EDA)





EVALUATION METHOD AND THE RESULT:

Methods and Error Metrics

A variety of methods and error metrics were used to evaluate the performance of different machine learning and deep learning models. The chosen metrics included accuracy, precision, recall, and F1-score. These metrics are essential for understanding the strengths and weaknesses of each model, allowing for a comprehensive assessment of their effectiveness in sentiment analysis. Accuracy measures the proportion of correct predictions out of the total predictions made. While this metric helps get an overall sense of a model's performance, it can be misleading when dealing with imbalanced datasets, as it does not account for false positives and false negatives. This is why precision, recall, and F1-score are also crucial metrics in sentiment analysis. Precision measures the proportion of true positive predictions out of all positive predictions. This metric is particularly useful in sentiment analysis because it reflects the model's ability to avoid false positives, which can be critical when determining customer satisfaction or dissatisfaction. Recall, on the other hand, calculates the proportion of true positive predictions out of all actual positive instances. This metric is valuable in sentiment analysis because it indicates how well the model captures all relevant positive cases. A high recall is crucial when the focus is on identifying as many positive sentiments as possible. F1-score is the harmonic mean of precision and recall, providing a balance between these two metrics. It is especially useful in sentiment analysis when there is a need to consider both false positives and false negatives. This score is more informative than accuracy when evaluating models with imbalanced classes, as it accounts for both precision and recall.

The models used in this sentiment analysis project varied in their features and approaches. BERT with LoRA demonstrated high performance due to its transformer-based architecture and fine-tuning capabilities. This model achieved a high F1-score, indicating its ability to capture complex patterns in the text, thanks to BERT's bidirectional context understanding. Logistic Regression with TF-IDF was another successful model, with TF-IDF providing a robust feature extraction technique by focusing on significant terms in the text. This approach worked well for sentiment analysis as it highlighted keywords and phrases that contribute to positive or negative sentiments. Support Vector Machines (SVM) with TF-IDF and Part-of-Speech (POS) Tagging were also effective, with TF-IDF providing a statistical approach to feature extraction and POS Tagging offering grammatical structure insights. These models excelled at finding optimal decision boundaries and had high recall, indicating their effectiveness in capturing positive sentiments. Deep learning models like Bi-LSTM with Attention, LSTM, GRU, and RNN provided a different approach by focusing on sequence-based data and contextual information. The attention mechanism in Bi-LSTM allowed the model to focus on crucial parts of the text, contributing to its effectiveness in sentiment analysis. LSTM, GRU, and RNN were built from scratch and were successful due to their ability to capture long-term dependencies in text data.

Overall, the combination of various error metrics and diverse models provided a comprehensive view of the effectiveness of different approaches in sentiment analysis for YELP pizza reviews. Each metric played a critical role in evaluating model performance, while the various models and features allowed for a thorough exploration of sentiment analysis techniques.

Results

The models were evaluated based on various metrics, including accuracy, precision, recall, and F1 score. This detailed report examines the performance of these models, analyzes the factors contributing to their success or limitations, and offers insights into why certain models worked well while others did not.

The top 7 models from the provided table show strong performance across various metrics such as accuracy, precision, recall, and F1-score, indicating their effectiveness in sentiment analysis. Leading the pack is the BERT model with Lora feature extraction, achieving an impressive accuracy of 88.32 and a high F1-score of 90.57. This strong performance can be attributed to BERT's contextual language processing capabilities combined with the fine-tuning flexibility offered by Lora, resulting in highly accurate and robust models.

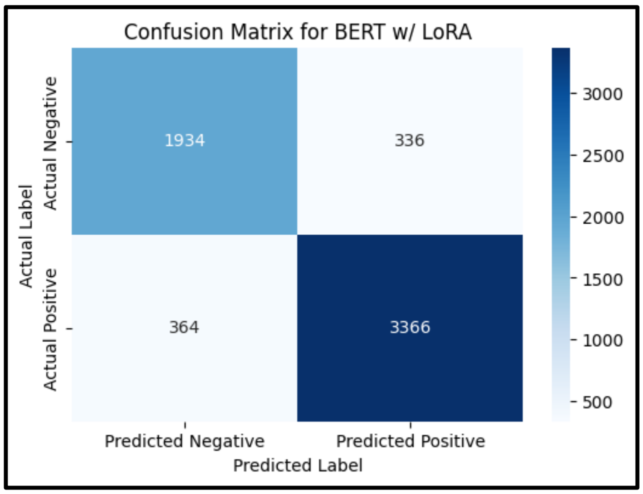
Following closely are logistic regression and various stacking classifiers that use graph-based features. Logistic regression with graph features achieved a notable accuracy of 89.78 and an F1-score of 89.46. This success is likely due to graph-based embeddings' ability to capture complex relationships within the data, enhancing model performance. Similarly, the stacking classifier with Gaussian Naive Bayes (GNB) as the base classifier and logistic regression as the final estimator demonstrated high accuracy and F1-score, indicating the benefits of combining multiple models to boost predictive accuracy.

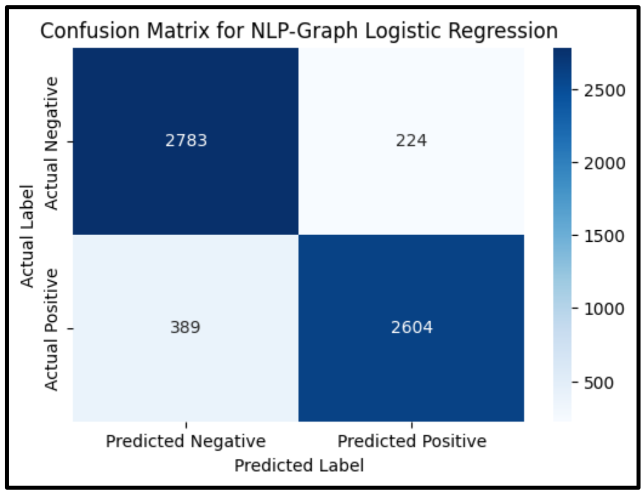
The soft voting classifier, combining logistic regression and SVC, as well as stacking classifiers with various base models, also performed well. These models use ensemble approaches to harness the strengths of multiple algorithms, yielding accuracy and precision that outperform individual models. The soft voting approach allows for a more balanced perspective by considering different model outputs, while stacking classifiers focuses on training a meta-model based on the best-performing base models, resulting in improved generalization.

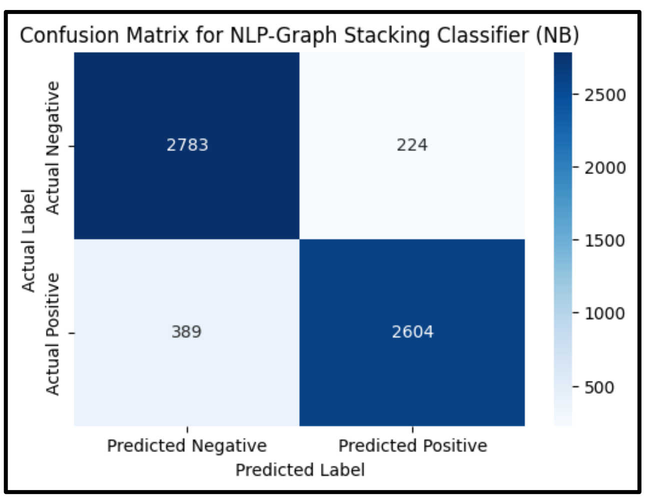
On the other hand, the bottom 5 models demonstrated relatively weaker performance. Naive Bayes with Word2Vec had a low F1-score of 58.06, likely due to the limitations of Naive Bayes in handling complex data structures and the inherent assumptions about feature independence. Support Vector with Word2Vec also struggled, with an F1-score of 76.66, indicating that this combination might not provide the most robust features for sentiment analysis. Similarly, the Decision Tree with Part of Speech Tagging and TF-IDF showed lower accuracy, possibly due to overfitting or insufficient feature representation. Support Vector Machine (SVM) with Word2Vec achieved an F1 score of 76.66. Despite SVM's strong decision-making capabilities, the use of Word2Vec might not have provided the most suitable feature representation for this context. The high recall (100.00) indicates that the model classified all instances as positive, leading to a low precision (62.15), suggesting an imbalance in its decision boundaries. These models' lower performance suggests the need for better feature extraction techniques or ensemble approaches to improve accuracy and generalization.

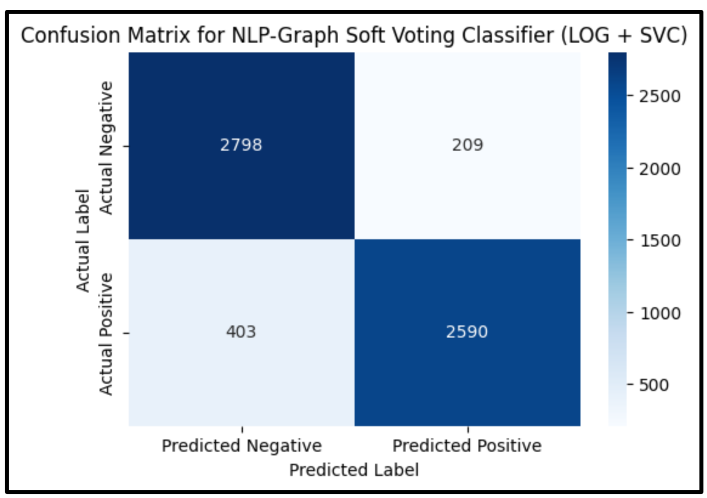
ML Models	Feature	Accuracy	Precision	Recall	F1-Score
Logistic Regression	Graph	89.78	92.06	87	89.46
Stacking Classifier (GNB)	Graph	89.78	92.06	87	89.46
Soft Voting (LogReg + SVC)	Graph	89.78	92.51	86.5	89.41
Stacking Classifier (LogReg)	Graph	89.78	92.51	86.5	89.41
Stacking Classifier (Gradient Boosting)	Graph	89.78	92.97	86	89.35
Logistic Regression	TF-IDF	85.51	82.69	96.99	89.27
Stacking Classifier (SVC)	Graph	89.53	92.47	86	89.12
Hard Voting (LogReg + SVC)	Graph	89.53	92.93	85.5	89.06

DL Models	Feature	Accuracy	Precision	Recall	F1-Score
BERT	Lora	88.32	90.91	90.23	90.57
Bi-LSTM	Attention Mechanism	83.64	87.69	85.71	86.69
RNN	-	82.71	88.10	83.46	85.71
BERT	Fine Tune	83.64	95.37	77.44	85.48
BERT	w/o Fine Tune	82.06	90.33	79.36	84.49
LSTM	-	83.18	89.09	80.33	84.48
GRU	-	74.77	78.33	77.05	77.69









The chart below summarizes top-performing models and their performance metrics. All models along with their performance metrics are available in this table.

ML + DL Models	Feature	Accuracy	Precision	Recall	F1-Score
BERT	Lora	88.32	90.91	90.23	90.57
Logistic Regression	Graph	89.78	92.06	87	89.46
Stacking Classifier (GNB)	Graph	89.78	92.06	87	89.46
Soft Voting (LogReg + SVC)	Graph	89.78	92.51	86.5	89.41
Stacking Classifier (LogReg)	Graph	89.78	92.51	86.5	89.41
Stacking Classifier (Gradient Boosting)	Graph	89.78	92.97	86	89.35
Logistic Regression	TF-IDF	85.51	82.69	96.99	89.27

ANALYSIS AND CONCLUSION:

In analyzing the sentiment from YELP pizza reviews, we employed a range of machine learning and deep learning models, each with different feature extraction techniques. The following key points summarize the analysis and conclusions derived from the study:

Model Performance:

- BERT with LoRA and Logistic Regression with TF-IDF demonstrated high performance, with strong F1 scores and balanced precision and recall. These results indicate that advanced language modeling and robust feature extraction can significantly enhance sentiment analysis accuracy.

Feature Extraction:

- The TF-IDF technique proved effective for several models, highlighting its utility in sentiment analysis. Part of Speech (POS) Tagging also contributed to higher recall, while Word2Vec showed limitations, suggesting that feature selection plays a crucial role in model performance.

Deep Learning Impact:

- Deep learning models like BERT, LSTM, and Bi-LSTM with attention provided additional depth in analysis. These models captured complex patterns and context in text data, leading to a better understanding of sentiment in YELP pizza reviews.

Model Limitations:

- Models with lower performance, such as Naive Bayes with Word2Vec, indicated the importance of feature independence assumptions and the need for careful feature selection. Support Vector Machines with Word2Vec had lower precision, suggesting that not all feature extraction methods are equally effective for sentiment analysis.

Practical Implications:

- The analysis demonstrates that focusing on key aspects of text, along with appropriate feature extraction, can yield reliable sentiment analysis results. These findings can be used to guide business strategies, improve customer satisfaction, and develop targeted marketing approaches based on sentiment trends.

In conclusion, the study reinforces the value of combining various models and techniques to achieve robust sentiment analysis. Future work will continue to explore advanced feature extraction methods and focus on enhancing model stability and generalization to new data.

Future works can include analysis and implementations such as:

✓ Aspect-Based Sentiment Analysis: Develop models that can analyze sentiment specific to various aspects of pizza reviews, such as crust quality, cheese, toppings, delivery service, or dine-in experience, to provide more detailed insights into customer opinions.

✓ Advanced Sentiment Detection: Utilize advanced NLP (Natural Language Processing) techniques to capture subtle nuances in sentiment, such as sarcasm, humor, or cultural references.

✓ Temporal Analysis of Sentiment Trends: Examine how sentiment about pizza reviews changes over time, potentially correlating with events such as promotions, new pizza trends, or changes in customer preferences.

✓ Model Ensemble for Sentiment Analysis: Combine the outputs of multiple machine learning models like Decision Trees, Random Forests, Logistic Regression, SVM, K-nearest neighbors (KNN), and Naive Bayes to create ensemble models. This can improve the robustness and accuracy of sentiment analysis on YELP pizza reviews.

✓ Combine Different Feature Engineering Methods: Combine existing techniques like TF-IDF, POS (Parts of Speech), and Word to Vector as this combination can serve as a better means to capture the underlying distribution and uplift the true prediction.

Concerns and Limitations:

The YELP dataset is a valuable resource for sentiment analysis, but it comes with several significant challenges and limitations that must be addressed to ensure accurate insights.

- ✓ Inconsistencies in Data: The dataset suffers from inconsistencies due to varied user inputs and reviews, such as spelling errors, differing terminology, and mixed-language content. These inconsistencies can lead to inaccuracies in sentiment analysis, causing misinterpretations of customer feedback and generating flawed insights.
- ✓ Subjectivity in Reviews: User reviews are subjective, influenced by individual preferences, emotions, and cultural factors. This inherent subjectivity adds noise to the data, complicating the training and evaluation processes for sentiment analysis models.
- ✓ Model Limitations: Machine learning and deep learning models have inherent limitations. Traditional machine learning models often fail to capture complex relationships, while deep learning models like BERT demand significant computational resources, affecting scalability and accessibility for large-scale analysis.

To address these challenges, it is crucial to approach the YELP dataset with a critical mindset. Ensuring the accuracy of analyses requires careful data preprocessing, including handling inconsistencies, correcting imbalances, and addressing subjectivity. In addition, supplementing the dataset with contextual information and conducting sensitivity analyses can help mitigate some of these limitations. This multi-faceted approach enhances the robustness and validity of sentiment analysis, leading to more reliable insights for businesses and researchers alike.

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