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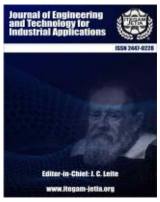

RESEARCH ARTICLE OPEN ACCESS

COMBINING NEURAL AND SEMANTIC FEATURES IN THE ANALYSIS OF BEING SUPPORTIVE IN ONLINE FEEDBACK FROM CUSTOMERS

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ABSTRACT

Over the past ten years, there has been a notable increase in the number of individuals accessing the internet. Positive evaluations serve as social evidence, convincing future purchasers of the product's quality and advantages. They can impact purchase decisions by offering real-world user information. Good reviews increase a product's or brand's trust and reputation. Customers are more inclined to buy from a firm that has received excellent feedback since it demonstrates dependability and contentment. Reviews can be considered user-generated content since they emphasise different applications, features, or advantages associated with a product. This material has the potential to persuade indecisive shoppers. The Yelp website was utilised to scrape feedback data for all Asian restaurants in New York City, which was then trained and assessed using three different models like Navie Bayes, next one is Logistic Regression, and then finally with Support Vector Classifiers. The Logistic Regression classifier outperformed the others by having the lowest proportion of mistakes and the highest Area under the ROC Curve noted as AUC on the receiver operating characteristic curve ROC curve. Commercial insights were gathered by recognising the existence of highly significant phrases while contrasting how they performed to the universal probabilities when the machine learning system was given review data from my restaurant.

I. INTRODUCTION

Customer reviews are extremely important in the current consumer decision-making process. To make educated decisions, prospective purchasers frequently depend on the testimonials of former customers. Here are some crucial elements about product reviews from customers. Consumers often trust the viewpoints of their fellow consumers in addition to marketing communications. Authentic comments from real consumers can reveal insights that product descriptions or ads may not deliver. Influence on purchasing choices denotes that positive evaluations can have a major impact on the choice of a consumer to buy a product. Negative reviews, on the other hand, may dissuade future purchasers. The number as well as the quality of recommendations can influence people's impressions of a product's dependability and efficacy.

Constructive feedback in reviews may provide manufacturers and merchants with important input. It enables them to discover the things consumers like and hate about a product, allowing them to make adjustments. Reviews can help a product's search engine optimisation (SEO) [1]. Products that have additional reviews, especially favourable ratings, are frequently listed more frequently in search results. This might boost a product's visibility and attract additional prospective purchasers. Customers that provide reviews might develop a feeling of community. Reading about other people's encounters with a product might help users connect and share an understanding. Positive evaluations may be repurposed as marketing testimonials. They may be used to promote trust and credibility by including them on product websites, social media, and other promotional materials.

It is critical for potential purchasers to see a variety of viewpoints. A mixture of both favourable and adverse feedback enables customers to get a more balanced opinion about a product. It is also critical to consider how a firm responds to bad evaluations. Responses that are timely and intelligent reflect a commitment to client satisfaction and can help to reduce the effect of negative comments. The significance of reviews varies depending on the platform. Certain websites or platforms may have stricter review rules, resulting in more trust in the legitimacy of the reviews. When reading feedback from consumers, it's critical to assess the overall attitude, the reasons for favourable or negative comments, as well as the reviewers' specific tastes and expectations. This thorough approach enables prospective buyers to make better educated judgements that reflect their own requirements and preferences.

Text mining, additionally referred to as analytics of text, is the process of extracting meaningful knowledge and conclusions from large amounts of unstructured textual data. consumer reviews are a useful source of knowledge that may be mined for insights into consumer attitudes, preferences, and opinions using text mining algorithms. Compile a dataset of consumer reviews from a variety of sources, such as online evaluation sites, social news outlets, and feedback from consumers forms. Remove unnecessary letters, punctuation, and particular symbols from the text data. To guarantee uniformity, convert text to lowercase. Tokenize the text by separating it into distinct words or phrases. To focus on relevant material, remove stop words (a common practise words including "the," "and," and "is").

To depict the frequency of terms, attitudes, or subjects in the reviews, create visualisations such as term clouds, graphs with bars, or heatmaps. To present an easy-to-understand summary of the findings, use infographics or other visual tools. Analyse the data to learn about consumer attitudes, issues, and preferences. Recognise established patterns or patterns that can help you make business decisions. Based on consumer feedback, make ideas for improvement. Implement a method for tracking client feedback in real-time to remain on top of shifting attitudes and new concerns. In accordance with the insights gathered from continuing text mining, revise corporate plans or products/services. Text mining enables organisations to make data-driven choices, improve customer happiness, and improve products by leveraging the large quantity of unstructured written information accessible in user evaluations.

Voice extraction [2], additionally referred to as speech data analysis, is the process of analysing and extracting useful information from spoken words. This procedure may be performed to recordings of sound or conversations including customer evaluations. Compile audio recordings of client feedback from various sources, such as customer care calls, messages on the phone, or interviews conducted over the phone. Transcription is the process of converting spoken speech into written text. This phase is critical for preparing the voice data for text-based analysis [3]. Cleanup and preparatory work the transcription text in the same way as you would in text mining. This involves deleting unnecessary letters, changing the text to smaller letters, representing, and eliminating stop words.

Sentiment Analysis: Using sentiment analysis, you may detect the emotion represented in the transcribed speech data. This can assist in determining whether the tone of the consumer is good, negative, or neutral. Use of voice recognition software to accurately turn spoken words into text. This is especially critical for comprehending the substance of customer reviews. Emotion Detection [4] examines the tone and pitch of the speech to detect emotional indicators such as anger, irritation, or satisfaction. Extraction of Characteristics is used to extract relevant text properties such as keywords, emotion ratings, or identifiable entities from the transcribed text. Visualisation of Data [5] allows to Create visual representations of the outcomes, such as emotion patterns over time or expression concentration in customer evaluations. Make use of visual tools to help decision-makers appreciate the findings.

II. RELATED WORK

Prasad [6] proposed a system that make sure your voice is loud and easily understood. The flow is explained in the Figure 1. Pronounce brand names, characteristics, and specifics correctly. Infuse proper emotions and energy into your speech. Your tone may be cheery, authoritative, calming, or instructive, depending on the product. Maintain a steady pace that is neither too fast nor too sluggish. To emphasise crucial elements or qualities of the product, use intonation. Speak clearly and emphasise crucial parts of the product. Highlight distinct marketing features or major benefits.

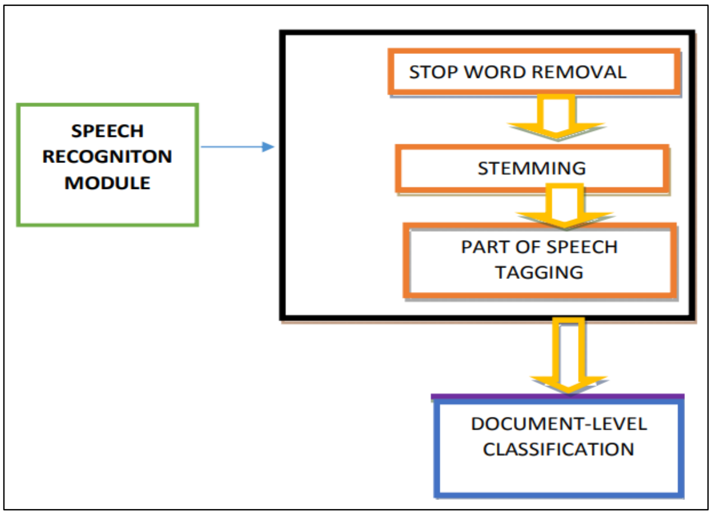

Figure 1: The proposed system of Speech Recognition.
Source: [7].

Maintain a systematic and succinct evaluation. Introduce the product and discuss the product's characteristics, advantages, potential disadvantages, and overall impression. Make eye contact with your audience. Use a voice that is conversational and address any worries or queries your audience may have regarding the product. In this day and age, businesses must work hard not just to obtain new consumers [8], but also to keep present ones pleased. Mohammed [9] discovered in the hotel industry that seven aspects connected to consumer hotel experience are related to customer happiness. The airline industry [10] is likewise concerned with consumer satisfaction studies. Sachin Kumar et al. contrast the aforementioned models in regards to consumer satisfaction forecasting using review data acquired from Twitter as well. For [7] intends to discover the intrinsic link between the customer happiness index and the network interaction by utilising the XGBoost machine learning technique to assist operators in predicting the level of satisfaction in order to improve customer contentment.

For [11] suggests utilising probability's encoder model to analyse and forecast rating from feedback from consumers that were left as open opinion. Opinion mining is a technique that uses classifier models to identify comments as good or negative based on an examination of consumer assessments of a hotel in open comments. According to [12] employs NLP, deep neural networks, and traditional machine learning approaches to obtain the best forecast model. To analyse the outcomes, two experiments are carried out: dichotomous and 3-class loyalty forecasting. The Random Forest and Nave Bayes algorithms beat the other examined classification techniques in the binary situation, with an accuracy of 89%. With a success rate of 67% in the three-class situation, the Random Forest segmentation approach outperformed every other machine learning methods.

According to [13] has developed predictive modelling for subjective assessments using data acquired by various internet sites. We also conducted an explanatory study of the various types of airline services. The research results of this article reveal that the majority of corporate class reviews focus on food as well as staff hospitality, whereas the majority of economy class reviews focus on spaciousness and seat convenience. Hamzah Zureigat [14] offered a research article named HelpPrd that provides an automated evaluation's usefulness prediction approach. To forecast the usefulness of reviews, HelpPrd employs data mining and artificial intelligence algorithms. The described method gathers characteristics from textual reviews and uses them to train 3 kindness classifiers. The experimental findings show that HelpPrd-logistic regression outperformed previous HelpPrd solutions in terms of reliability, accuracy, recollection, and F1-score.

According to [15] suggests a novel paradigm for eliciting consumer demands according to sentimental evaluation of particular product features in online product evaluations. The machines known as support vector machines are employed to create prediction models based on characteristics taken from a set of affective vocabulary lists based on words with English emotional norms and WordNet. For [16] employs the Neuro-Linguistic Programming method to quantify what consumers review, and then employs the neural network to anticipate the psychological tendency of feedback from clients by successfully analysing the nonlinear connection between influencing parameters. Customer reviews may aid in the management of an online shop by predicting emotional tendencies. The results of simulations suggest that our strategy can reach excellent prediction accuracy. The satisfaction forecast accuracy ratings for the three products are 91.95%, next one is 89.93%, and finally 90.96%, respectively.

III. PROPOSED SYSTEM

The objective is to develop a predictive algorithm that can reliably predict a Yelp member's rating of a Asian Based restaurant based on the terms in their published review. We are particularly interested in the terms in these evaluations that are more likely to be in a good (4 or 5) as well as a negative (1, 2 or 3) review.

According to the website Yelp, there are around 531 Asian Based restaurants in New York's five boroughs. This amounts to 83,349 Asian Based restaurant reviews that may be analysed. At a high level, this project aims to design a web scraper to obtain publicly accessible information through the Yelp domain and a model to estimate restaurant rating determined by the phrases in each review. All of the Yelp pages for Asian Based restaurants in New York City have been accessed and analysed. Each restaurant's meta data was utilised for comprehensive analysis of information and visualisation, as seen below in Figure 3. The flow chart of the data for sentimental analysis is shown in Figure 2.

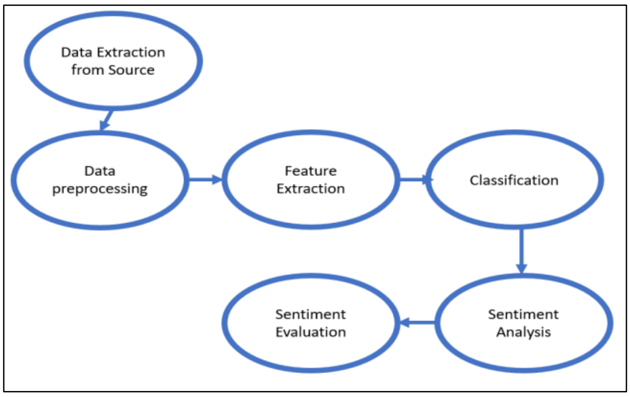

Figure 2: Sentiment analysis System block diagram.
Source: Authors, (2024).

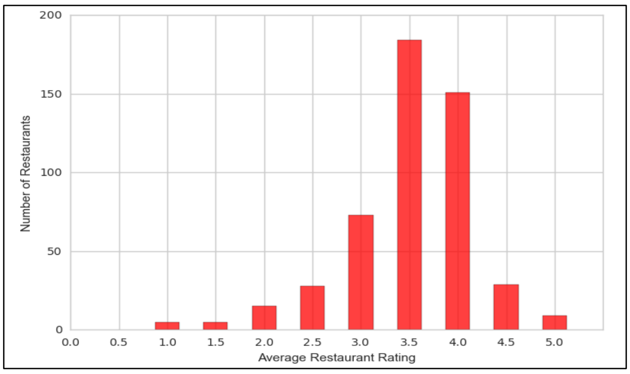

Figure 3: Average grade distribution among Asian Based restaurants in New York City.
Source: Authors, (2024).

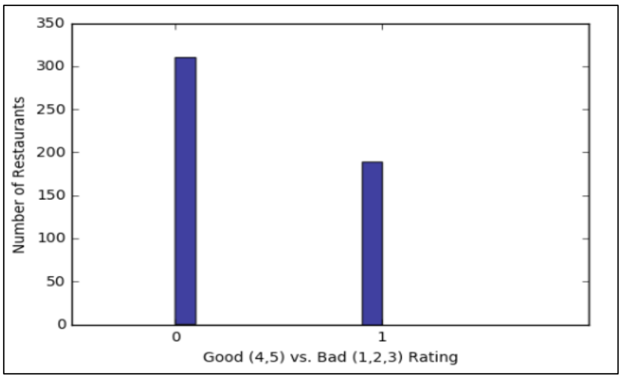

Figure 4: Average grade distribution among Asian Based restaurants in New York City.
Source: Authors, (2024).

The typical Asian Based restaurant in New York City earned a 3.5, as shown in Figure 3 and Figure 4 and the score distribution was fairly evenly distributed with a little left skew. Most Asian Based restaurants ought to be expected to have above-average evaluations (or > 3.0) in order to compete in New York

City. Customers may choose from a wide range of establishments and ethnicities other than Asian Based food.

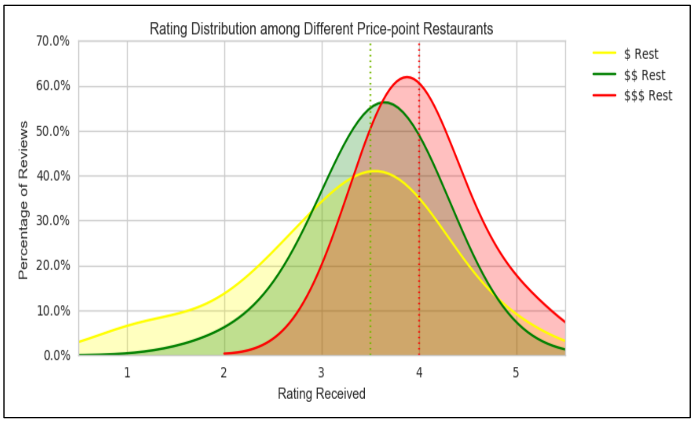

Figure 5: Rating Distribution among different Price-point restaurants.
Source: Authors, (2024).

The vast majority of eateries charge between $11 and $30 per person as shown in Figure 5. Within the $11-$30 price range, the average restaurant received a rating of 3.5 or better. There was clearly more variation in the less than ten dollar sector since the dispersion of evaluations was the biggest. We observe that there are substantially less eateries in the $31-$60 range. However, all restaurants in this category received a rating of 3.5 or above. The median score for both the under $10 and $11-$30 segments was 3.5 stars, whereas the median score for the $31-$60 section was 4.0 stars. Based on the analysis of the three categories, it is feasible to conclude that establishments that cost more are going to typically obtain better and more consistent evaluations.

Several techniques were used to clean and enhance the review data. To begin, each Yelp review was split down into distinct phrases, including spelling and grammar, using a technique known as tokenization. All punctuation was omitted, and every one of the words were rewritten in lower case. Then, an acronym filtering technique was used to eliminate stop phrases (or common terms like "an, or, the, it") and only leave significant descriptive words relevant to a restaurant. This procedure was followed for all 83,349 reviews. The evaluations were then translated into a container of words participation, which implies that any unique words/uni-grams (for example, "delicious") and pair of terms/bi-grams (for example, "simply delicious") that occurred in the 83,349 reviews were shown. The final vocabulary includes around 71,510 distinct characteristics.

Each generated feature was checked for appearance in each unique review. If a certain feature (or term) occurred in a review, it would be expressed as a 1, and 0 if it did not. This criterion was made applicable to all 83,349 evaluations, each of which had 71,510 words that needed to be checked. Furthermore, the frequency with which terms appeared was computed to determine each word's significance to the research. The greater the number of times a term occurred, the more valuable it was in forecasting Asian Based customer mood in general.

To identify and forecast the rating of review data, three Machine Learning Techniques were used: Nave Bayes, Logistic regression, and Support Vector Classification. The Nave Bayes classifier has been selected since it is one among the easiest and most successful text classification techniques. It is computationally cheap, quick to train, and frequently outperforms more difficult and inefficient approaches. Because of its capacity to provide weights to elements for binary classification, Logistic Regression was selected. Along with to being successful, it is also extremely simple to construct, computationally cheap, and the information representation is pretty simple to read.

Table_1: Naïve Bayes.

	Precision	Recall	F1 Score	Support
Bad Review	0.84	0.81	0.83	8761
Good Review	0.90	0.92	0.91	16244
Average/Total	0.88	0.88	0.88	25005

Source: Authors, (2024).

Table 2: Logistic Regression.

	Precision	Recall	F1 Score	Support
Bad Review	0.85	0.80	0.82	8713
Good Review	0.89	0.92	0.91	16292
Average/Total	0.88	0.88	0.88	25005

Source: Authors, (2024).

Table 3: Support Vector Classification.

	Precision	Recall	F1 Score	Support
Bad Review	0.89	0.74	0.81	8660
Good Review	0.88	0.95	0.91	16345
Average/Total	0.88	0.88	0.88	25005

Source: Authors, (2024).

Unexpectedly, with an average rating of 0.88 as shown in the table 1,2 and 3, all three classifiers fared roughly the same on the F1 metric. This meant that the harmonic mean of accuracy and recall should be successfully maximised, as acceptable results in both areas would be preferred than outstanding results on any particular metric.

Unexpectedly all three classifiers obtained a Precision-Recall AUC of 0.96, with just minor variances in ROC AUC. Logistic Regression had the greatest ROC AUC score of 0.94, although Nave Bayes as well as SVC had 0.01 lower at 0.93. This suggested that all classifiers did exceptionally well in terms of properly predicting, minimising mistakes, and recalling a considerable percentage of the dataset.

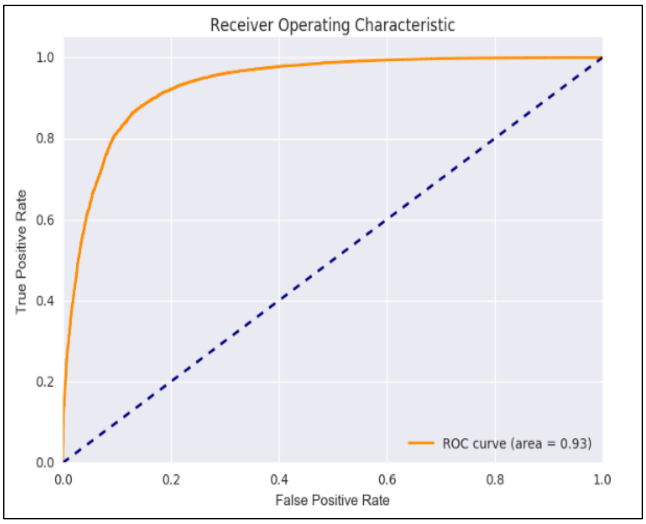

Figure 6: Receiver Operating Characteristic (ROC) curve for Naïve Bayes algorithm.
Source: Authors, (2024).

The ROC curve illustrates the trade-off amongst responsiveness (True Positive Rate) and distinctiveness (True Negative Rate) at various thresholds. A bigger area beneath the curve (AUC) shows that the model is better at differentiating across classes. For varied threshold levels, the Precision-Recall curve depicts the balance that exists between precision and recall. A bigger area under the curve (AUC) implies that the model is doing better when it comes to of precision and recall as shown in Figure 7.

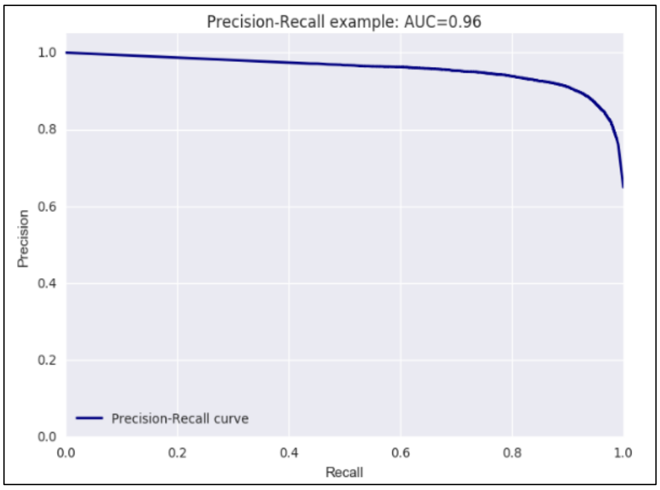

Figure 7: Precision-Recall example curve for Naïve Bayes algorithm.
Source: Authors, (2024).

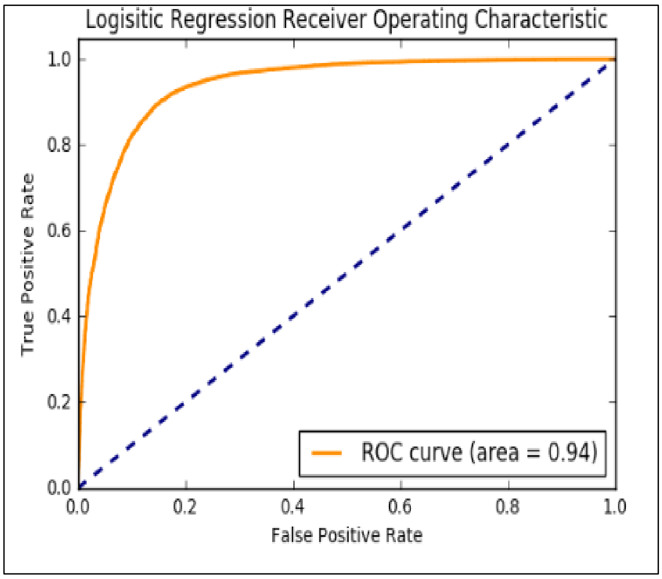

Figure 8: Receiver Operating Characteristic (ROC) curve for Logistic Regression.
Source: Authors, (2024).

The ROC curve illustrates a classification model's performance over multiple thresholds by displaying the compromise amongst True Positive Rate along with False Positive Rate. A bigger area under the curve (AUC) shows that the model is better at differentiating across classes as shown in Figure 8. Precision-Recall charts can be helpful for assessing the effectiveness of a model for classification, for instance Logistic Regression, while dealing with unbalanced datasets shown in Figure 9.

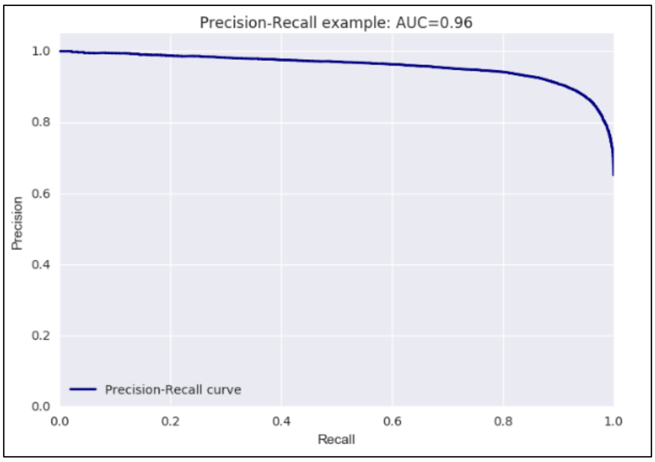

Figure 9: Precision-Recall example curve for Logistic Regression.
Source: Authors, (2024).

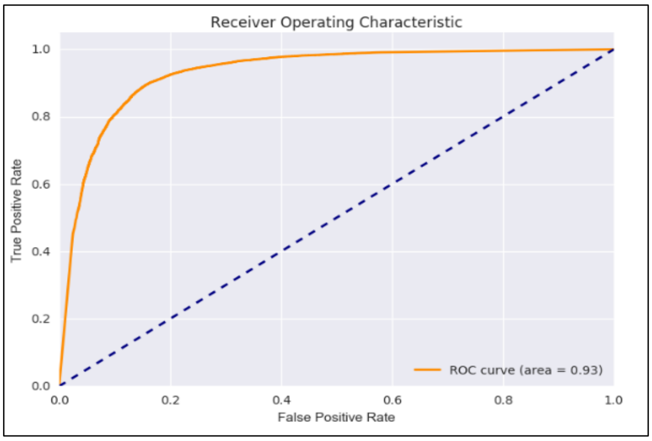

Figure 10: Receiver Operating Characteristic (ROC) curve for Support Vector Classification.
Source: Authors, (2024).

The Receiver Operating Characteristic (ROC) graph is a visual representation of a binary classifier system's diagnostic capabilities as its discrimination threshold is adjusted. While Support Vector Classification (SVC) is an effective technique for classification problems, there are several stages involved in constructing a ROC curve for an SVC model. Begin by running your Support Vector Classification simulation through its paces on your dataset. The FPR False Positive Rate (FPR) and should be plotted on the x-axis, and the TPR True Positive Rate (TPR) should be shown on the y-axis. This will provide the ROC curve as shown in Figure 10.

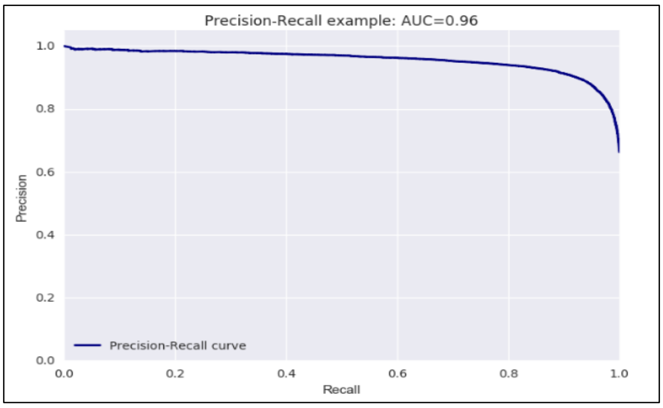

Figure 11: Precision-Recall example curve for Support Vector Classification.
Source: Authors, (2024).

Considering the F1 score along with precision-recall effectiveness of all three classification algorithms as shown in Figure 11 were so identical, the confusion matrix along with ROC curve were the only performance differentiators. When these remaining metrics were considered, the Logistic Regression classifier performed the best. Logistic Regression predicted fewer errors than both Nave Bayes and SVC, as determined by the confusion matrix. Furthermore, Logistic Regression had the greatest ROC AUC with a score of 0.94, compared to 0.93 for the other classifiers. Therefore, the classifier used when assessing our Asian Based restaurant had been the one that was developed using Logistic Regression.

IV. CONCLUSION

The Yelp website was used to scrape the feedback information for all Asian Based restaurants in New York City, which was then trained and evaluated using three distinct models: Nave Bayes, Logistic Regression, and Support Vector Classifiers. According to the lowest percentage of errors and the highest AUC on the ROC curve, the Logistic Regression classifier performed the best. When the machine learning algorithm was given review data from the restaurant, commercial insights were collected by detecting the existence of extremely significant terms and comparing their performance to the universal probability. Extracted business insights assist the company in identifying areas of uniqueness and weaknesses in the form of food, beverages, or services. These insights may be used to help with commercial and investment choices, as well as to improve the overall experience and cuisine of restaurant.

V. AUTHOR'SCONTRIBUTION

Conceptualization: Selvi R, S. Athinarayanan, V Devi, M. Gobinath, M. Robinson Joel, P. Shanthakumar.
Investigation: Selvi R, S. Athinarayanan, V Devi, M. Gobinath, M. Robinson Joel, P. Shanthakumar.
Discussion of results: Selvi R, S. Athinarayanan, V Devi, M. Gobinath, M. Robinson Joel, P. Shanthakumar.
Writing –Original Draft: Selvi R, S. Athinarayanan, V Devi, M. Gobinath, M. Robinson Joel, P. Shanthakumar.
Writing –Review and Editing: Selvi R, S. Athinarayanan, V Devi, M. Gobinath, M. Robinson Joel, P. Shanthakumar.
Resources: Selvi R, S. Athinarayanan, V Devi, M. Gobinath, M. Robinson Joel, P. Shanthakumar.
Supervision: Selvi R, S. Athinarayanan, V Devi, M. Gobinath, M. Robinson Joel, P. Shanthakumar.
Approval of the final text: Selvi R, S. Athinarayanan, V Devi, M. Gobinath, M. Robinson Joel, P. Shanthakumar.

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