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Restaurant Review Sentiment and SWOT Analysis: using AWS and GPT-4 Large Language Models

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Abstract

With the widespread use of the internet today, the emphasis on companies' digital visibility and social media accounts has significantly increased the volume of reviews/feedback from end-users across various platforms. Accurately assessing users' emotional states is of paramount importance for businesses in sustaining competitive advantage. This study conducted a sentiment analysis of Google Maps reviews for restaurants in Gaziantep, a city that stands out in gastronomy tourism, followed by a SWOT analysis based on the collected reviews. Initially, comments collected through web scraping techniques were processed in the preliminary phase. In the second phase, sentiment analysis was performed using machine learning methods frequently employed in the literature for sentiment analysis, such as logistic regression, support vector machine, and Gaussian naive Bayes, along with an ensemble learning method XGBoost and the deep learning method LSTM. Alongside these methods, large language models, such as AWS Comprehend and GPT-4, were integrated into our analysis using their development libraries. For a robust analysis, comments were analyzed in both Turkish and English, achieving success rates above 80% across all performance metrics for machine and deep learning methods and over 90% for AWS and GPT-4. While AWS does not support the Turkish language, GPT-4 has shown similar success rates in both the Turkish and English languages. A SWOT analysis was conducted in the final phase based on the aggregated comments. According to the analysis results, delicious meals, attentive staff, fast service, hygiene and cleanliness, and reasonable prices were identified as strengths, whereas overcrowding, noise, and delays in service were identified as weaknesses.

Keywords Machine Learning · Deep Learning · AWS Comprehend · GPT-4 · Sentiment Analysis · Gaziantep Restaurants

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Introduction

Emotional expressions have a significant impact on the lives of individuals and play a critical role in understanding and interpreting emotions in communication. This understanding allows for a deeper understanding of people's preferences, needs, and motivations, thereby helping to better analyze human behavior and social interactions. In this context, sentiment analysis has become very popular in the research field in recent years (Özel & Çetinkaya Bozkurt, 2024). Sentiment analysis is the study of understanding and classifying the author's thoughts in a text. This analysis aims to identify the emotional content of texts and is performed using methods such as NL processing and machine learning (Demirbilek & Özulukale Demirbilek, 2023). Texts are generally categorized as positive, negative, or neutral, and emotional reactions are measured. When analyzed with these methods, understanding and interpreting emotional expressions in texts are possible (Agarwal et al., 2011).

In the restaurant sector, customer experience is a critical driver of competitive advantage. Favorable customer experiences have been shown to contribute to desirable outcomes such as increased satisfaction, enhanced loyalty, positive attitudes, and stronger brand preference (Ha & Jang, 2010). However, enhancing the customer experience is a significant challenge due to its inherently complex and multidimensional nature (Ponnam & Balaji, 2014). Consequently, restaurant owners and managers must identify the core customer experience attributes and evaluate their impact on customer perceptions (Duarte Alonso et al., 2013).

Google Maps reviews are extremely important for restaurants and greatly influence customer decisions and business success. Approximately 90% of consumers read online reviews before choosing a place to eat, which increases the impact of these reviews on a restaurant's reputation and customer trust (Peters, 2024). First, Google Maps reviews serve as a primary source of information for potential customers when researching new dining options. Customers trust these reviews to evaluate the quality of food, service, and ambiance, trusting them more than personal recommendations. Positive reviews build trust, a vital component in the competitive restaurant industry (Ylimaki, 2024). Google Maps reviews play an important role in increasing a restaurant's search engine optimization, especially on Google Maps. Higher ratings and positive reviews increase a restaurant's visibility in the search results. Google Maps reviews are also an important way for customer engagement. Engaging with customer reviews—regardless of whether they are positive or negative—reflects a restaurant's dedication to customer satisfaction and contributes to customer loyalty development. This interaction helps build a sense of community and encourages customers to communicate. Finally, Google Maps reviews provide a valuable feedback mechanism for continuous improvement. Restaurants can use these reviews to understand customer preferences and identify areas for improvement. This feedback is vital for meeting changing customer expectations and improving the restaurant (Peters, 2024).

Gaziantep has recently become a gastronomy tourism center that attracts a lot of attention from both domestic and international visitors. Gaziantep's inclusion in the "Creative Cities Network" by UNESCO in 2015 in the field of gastronomy may be an important factor in this increased interest. However, an in-depth look at Gaziantep's history reveals that it has been home to many civilizations from ancient times to the present day due to its strategic geographical location and has served as a bridge on trade routes between Anatolia and the Middle East. This has played an important role in the development and diversity of the city's culinary culture (Çekal & Aktürk, 2019). Gaziantep cuisine is one of the leading examples of a fusion cuisine that emerged because of the interaction of Turkiye's rich food tradition with different cultures (Uçuk & Kayran, 2020). This region's rich culinary culture is reflected in the local flavors offered in the menus of the region's restaurants. Local restaurants play a key role in preserving and promoting a region's gastronomic identity. Therefore, assessing how tourists perceive the food and services offered by local restaurants is critical for the sustainable growth of gastronomy tourism (Özen, 2021).

This study aims to analyze customer feedback for selected restaurants in Gaziantep through sentiment and SWOT analysis to derive actionable insights for both academic and practical purposes. By examining user-generated content on digital platforms, this study seeks to uncover customers' emotional evaluations, identify recurring strengths and weaknesses of the service experience, and explore potential opportunities and threats that businesses may face. This approach supports restaurant managers' data-driven decision-making, contributes to the development of customer-centered service strategies, and provides a methodological framework that integrates NLP techniques with strategic planning tools in the context of the hospitality sector. The most important contributions of our study are summarized as follows:

- Our study is one of the first to evaluate the performance of OpenAI GPT-4 in sentiment analysis conducted for both English and Turkish languages, demonstrating the effectiveness of large language models in this domain.
- The performance of GPT-4 is compared with widely used machine learning methods, including AWS Comprehend natural language processing service, LSTM deep learning method, SVM, LR, GNB, and XGBoost under two different languages.
- A comprehensive comparative analysis is conducted based on the performance metrics frequently used in the literature.
- Beyond the primary focus of sentiment analysis studies, i.e., developing high-performance models, a SWOT analysis is performed based on customer reviews. Through SWOT analysis, businesses' strengths and weaknesses, as well as potential opportunities and threats, are evaluated using customer feedback.

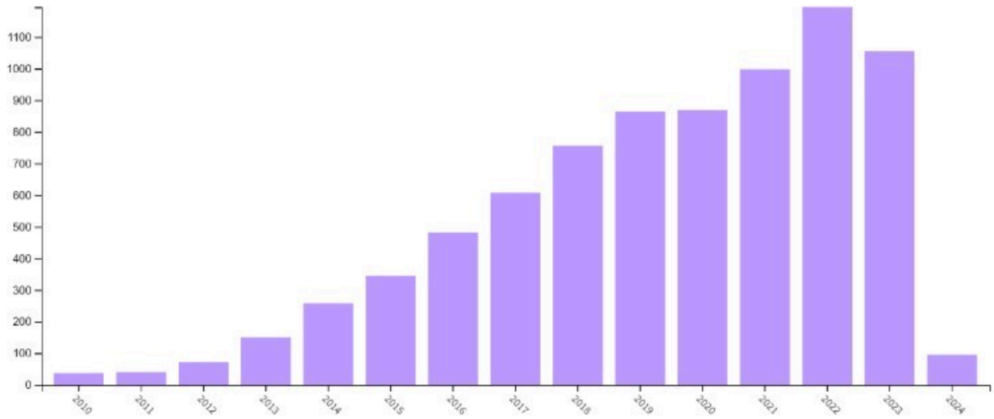
In the second part of our study, we review studies on restaurant sentiment analysis in the literature. In the third section, we explain the data collection and preprocessing phase, the machine and deep learning methods used during sentiment analysis, AWS Comprehend, and ChatGPT/GPT-4 are explained and performance metrics are defined. The fourth section presents the results of the analysis and comparisons, and the fifth section presents the SWOT analysis. The last section presents the study's conclusions.

Related Literature

A search of the Web of Science (WoS) database in March 2024 with the keyword "Sentiment Analysis" only in the titles of the studies yielded 7882 studies, 3974 of which were research articles. The oldest of these studies is "Neural network analysis and the characteristics of market sentiment in the financial markets" by McIntyre-Bhatty (McIntyre-Bhatty, 2000). Figure 1 shows that although the number of studies on sentiment analysis remained low until 2012, it entered a rapid upward trend in 2012 and thereafter, and a total of 1194 studies were published in 2023.

Figure 1

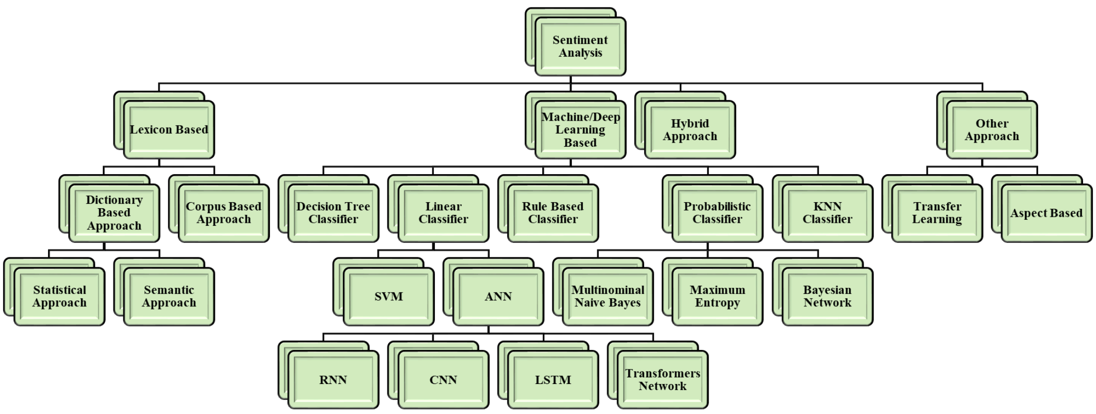
Annual distribution of studies on sentiment analysis (Web of Science, 2024).



The rapid proliferation of social media platforms (Google Maps comments, Facebook, Twitter, Instagram, etc.) has led to the production of large amounts of text every day, especially with digitalization. Sentiment analysis on these texts has been used in different disciplines (Doaa Mohey El-Din Mohamed, 2018; Medhat et al., 2014) such as tourism (Aksu & Karaman, 2022; Yüksel & Tan, 2018; Zeng, 2013), economics (Köksal et al., 2021), management (Uyaroğlu Akdeniz & Cebeci, 2021), psychology (Öztürk, 2022), neurology (Çevik & Kilimci, 2021), computer science (Tuna, 2022), education (Demirbilek & Özulukale Demirbilek, 2023), movie/series reviews (Gündüz, 2023), and solar eclipse (Korkmaz & Bulut, 2023). In addition to different application areas, many methods are used for sentiment classification (Figure 2).

Figure 2

Classification methods used in sentiment analysis (Wankhade et al., 2022).



Given the abundance of studies on sentiment analysis, we will focus on sentiment analysis studies in the restaurant sector within the scope of the literature review. Kang et al. (2012) created a new lexicon for restaurant reviews and proposed an improved naive Bayes algorithm. This study collected approximately 70,000 restaurant reviews from various websites. The data obtained from the restaurant reviews were manually analyzed and a senti-lexicon that includes one-word (unigrams) and two-word (bigrams) statements was developed. Experiments using the improved NB algorithm showed significant improvements in positive and negative classification results compared to SVM and original NB algorithm. Agüero-Torales et al. (2019) analyzed 33,500 English reviews on TripAdvisor about restaurants in Granada, Spain. The authors classified the reviews as positive, negative, or neutral using a lexicon and rule-based sentiment analysis tool called the Valence Aware Dictionary for Sentiment Reasoning (VADER). The results showed that most restaurants reviewed had positive reviews. Asani et al. (2021) developed a recommendation system for extracting food preferences from user reviews. The authors used TripAdvisor reviews from 100 different users in the first nine months of 2018. Using text mining and natural language processing techniques, food names were extracted and clustered based on semantic similarities using the Wu-Palmer method. Sentiment analysis was performed using the SentiWordNet dictionary. The results showed that the proposed system provided personalized restaurant recommendations with 92.8% accuracy. This system recommends nearby open restaurants considering user preferences, location, time, and feedback from other users. Rita et al. (2023) conducted a sentiment analysis of online reviews of Michelin Star restaurants. They collected 8,871 English reviews of 87 restaurants in Europe from TripAdvisor and processed them using Beautiful Soup and Semantria. The findings showed that overall sentiment decreased after restaurants received a Michelin Star, especially in the area of service. On the other hand, emotions related to price increased significantly. The study revealed the impact of the Michelin Star on restaurants' online reputation and identified the factors that were important for positive reviews. Yu et al. (2022) conducted a text mining and sentiment analysis study on 11,140 social media reviews collected from restaurants in Giethoorn, the Netherlands using Lexalytics, an AI-powered data mining application. Reviews were collected from Google Maps, Facebook, and TripAdvisor. The analysis results led to the extraction of themes to guide restaurant management in improving customer satisfaction and encouraging positive social media reviews. This study showed that small business restaurant managers can gain valuable insights by analyzing social media reviews to improve their competitiveness. Hamad et al. (2021) conducted a sentiment analysis of the posts of Twitter users about restaurants using naive Bayes classification algorithms. Real data samples were collected from customer reviews on Twitter, and the proposed method was implemented using Python programming language. The results showed that customers' opinions about restaurants were largely positive and that people generally had a positive attitude toward restaurants. Common metrics, such as accuracy, recall, precision, and error rate, were used to evaluate the performance, reaching 68%, 80%, 73%, and 27%, respectively. Yu et al. (2017) performed a sentiment analysis to identify the characteristics of restaurants based on Yelp reviews. A SVM model was used to analyze the sentiment trend from the word frequency of each review. The word scores from the SVM models were processed into a polarity index that indicates each word's importance for specific types of restaurants. The data were collected from the Yelp Dataset Competition and included 1,363,242 restaurant customer reviews. The study results revealed that customers pay more attention to service quality. Restaurant characteristics by cuisine type were identified, and positive and negative words were determined according to various categories. This analysis helped restaurants and customers better understand their dining experience.

Jonathan et al. (2019) used the random forest method for sentiment analysis of customer reviews about Bangalore restaurants on Zomato. The analysis used 150,000 customer reviews collected from Zomato. The reviews were categorized as positive if they scored four or five points, negative if they scored below three points, and neutral if they scored three points. The model had an accuracy rate of 92% and precision rates of 92%, 93%, and 96% for positive, negative, and neutral sentiments, respectively. The sensitivity rates were 99%, 89%, and 73%, respectively. Renganathan and Upadhya (2021) developed a sentiment analysis model that extracts hidden emotions from tourist reviews of restaurants in Dubai. In the analysis using text mining techniques and the R statistical software package, emotions were categorized under the headings of positive, negative, anger, anticipation, disgust, fear, trust, sadness, and surprise. This study provided insights into visitor preferences by identifying differences in tourist emotion scores across restaurant types. Because of the analysis, there were significant differences in emotion scores according to the type of restaurant. In particular, café-type restaurant customers expressed more positive emotions than other types of restaurant. Shin et al. (2022) examined and analyzed 5,427 restaurant reviews collected from Google Maps. The authors vectorized the importance of words using TF-IDF and calculated the positivity and negativity coefficients of the words in the reviews using the RF algorithm. A dictionary of words for positive and negative sentiment was created using the coefficient of each word. Words were classified into four main evaluation categories, and information about the sentiment in each criterion was obtained. Singgalen (2022) used text mining methods and support vector machine (SVM), naive Bayes, decision tree, and k-nearest neighbor algorithms to analyze 4,130 Tripadvisor user reviews collected for restaurants in the tourist town of Labuan Bajo in Indonesia. The K-Nearest Neighbor algorithm performed the best with 99.27% accuracy, 100% precision, and 98.53% sensitivity. Positive sentiments about restaurants are generally dominant, especially positive opinions about cuisine, services, pricing, restaurant conditions, and business locations. Hossain et al. (2020) used a combined CNN-LSTM architecture for sentiment analysis of restaurant reviews in Bangladesh. The author collected 1,000 reviews from FoodPanda and Shohoz Food web applications and labeled them as positive and negative. After the analysis, the model achieved 94% accuracy. This study presented a new technique for sentiment analysis on Bengali restaurant reviews, which provided high accuracy in the analysis. Table 1 summarizes the studies reviewed in this section according to the data source, number, and classification method used.

Table 1

Classification of the examined studies in terms of database, number of comments, and method of sentiment analysis

Studies	Data Source	#No Comments	Classification Method
Kang et al. (2012)	Vary	70,000	Improved naive Bayes method
Agüero-Torales et al. (2019)	TripAdvisor	33,500	VADER
Asani et al. (2021)	TripAdvisor	100	SentiWordNet
Rita et al. (2023)	TripAdvisor	8,871	Semantria
T. Yu et al. (2022)	Google Maps, Facebook, and TripAdvisor	11,140	Lexalytics
Hamad et al. (2021)	Twitter	1,000	Naive Bayes
B. Yu et al. (2017)	Yelp	1,363,242	SVM
Jonathan et al. (2019)	Zomato	150,000	RF
Renganathan and Upadhya (2021)	TripAdvisor	Unknown	R (Syuzhet Library)
Shin et al. (2022)	Google Maps Reviews	5,427	RF
Singgalen (2022)	TripAdvisor	4,130	SVM, NB, DT, and KNN
Hossain et al. (2020)	FoodPanda and Shohoz	1,000	CNN-LSTM
Our Study	Google Maps Reviews	1,520	LR, SVM, GNB, XGBoost, LSTM, AWS, and GPT-4

A review of the related literature indicates that most studies employ a limited set of analysis methods for sentiment analysis with Naïve Bayes, SVM, and RF being the most commonly used approaches. Although these traditional ML methods have demonstrated their effectiveness in classification tasks, including sentiment analysis, large language models (LLMs), such as AWS Comprehend, ChatGPT, and Google Gemini, exhibit significant potential in enhancing decision-making processes across various domains. This study differentiates itself from existing research by using LLMs for sentiment classification and systematically comparing their performance with established ML and DL methods. Additionally, the inclusion of comparative analyses across Turkish and English languages strengthens the robustness of the findings. Furthermore, to the best of our knowledge, no prior study has combined a comprehensive sentiment analysis with a SWOT analysis based on customer reviews, further highlighting this research's novelty and contribution.

Therefore, this study addresses a notable research gap by (i) evaluating the comparative effectiveness of LLMs in sentiment analysis alongside traditional methods, (ii) applying these methods to a multilingual dataset, and (iii) integrating the sentiment insights into a SWOT analysis for strategic interpretation. This comprehensive contribution responds to recent recommendations in the literature that emphasize the need for integrated, data-driven methods that not only analyze customer reviews but also translate these insights into strategic decision-making tools.

Materials and Methods

In this section, the details of the methodology followed within the scope of the study on sentiment analysis will be explained. Figure 3 shows the flow chart of the methods used in the study.

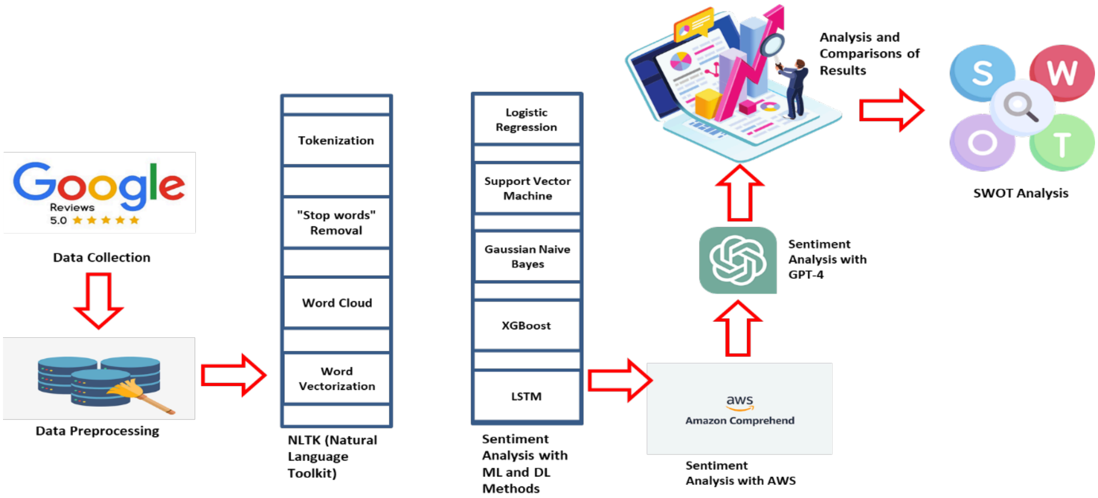
Data Collection and Preprocessing

The reviews for three highly rated and frequently reviewed restaurants in Gaziantep were extracted from Google Maps using the Google Chrome extension "Instant Data Scraper". This tool extracts structured data from websites and exports it into Excel or CSV format. With the support of AI, it effectively filters out irrelevant content and identifies the most relevant data for analysis (Instant Data Scraper, 2024). The restaurants were selected based on their visibility and engagement on Google Maps to ensure a sufficiently large dataset to support reliable sentiment analysis. Data collection was conducted in March/April 2024 and included user reviews posted between 2022 and early 2024. A total of 1,520 comments containing meaningful textual content were randomly selected and manually labeled as either positive or negative for sentiment analysis.

First, emoji and special characters were manually examined and removed/fixed during the labeling process. Comments were normalized by converting all characters to lower case. Then, stopwords, which are common in the Turkish language and considered ineffective in semantic analysis, were removed from the comments using an open-source database. Moreover, all punctuation marks were removed using the "re" library. This process ensured that words such as "what," "how," "and," and "but" were eliminated from the text. This data processing step was performed with a library called the NLTK, which is widely used for natural language processing (NLP) projects in the Python programming language. NLTK offers a wide set of tools for various linguistic tasks, including text classification, language modeling, automatic translation, stemming, tagging, and parsing. NLTK provides a wide range of methods, classes, and resources to facilitate operations on text data and offers user-friendly functions to implement various preprocessing operations, such as tokenization, stop word removal, and stemming (Bird, Klein, & Loper, 2009; NLTK, 2024).

Figure 3

Flowchart illustrating the sentiment analysis process steps in this study



Word clouds are widely used in text analysis and data visualization. This visualization method enables the rapid detection of frequently occurring terms or salient words in a text. Key concepts, themes, or trends of a text are presented in a visual format through this method. Visually depicted words in a larger or more prominent way represent terms that occur with high frequency in the text. This allows readers to easily perceive the outline and highlighted points of the text, thereby helping to gain information about the content of the text quickly and effectively (Büyükeke et al., 2020). Figure 4 shows the word cloud generated by combining the "WordCloud" library with the most frequently repeated words in the analyzed reviews.

Figure 4

Word cloud based on high-frequency terms extracted from customer feedback in Turkish and English

The word "nice" was repeated 300 times, "good" 259 times, and "delicious" 245 times in the reviews, whereas the word "bad" 168 times, "expensive" 110 times, and "crowded" 100 times in the reviews, indicating that the customers were satisfied with the food and/or service. On the other hand, the word "beyran" was mentioned 239 times, "kebab" 208 times, and "lahmacun" 155 times in the comments (Beyran, kebab, and Lahmacun are special dishes that are highly preferred and served in Gaziantep). This indicates that customers prefer these dishes.

Supervised Machine Learning Methods

After the text content in the comments is converted into numerical data, the relevant algorithms can be used for modeling. The "CountVectorizer" module in the frequently used "scikit-learn" library was preferred for this numerical conversion process. To classify the comments, SVM, LR, and GNB methods, which are widely used in the literature, were preferred. All supervised ML methods were implemented using the scikit-learn library with default parameter settings applied for each algorithm (Scikit-learn, 2025).

Support Vector Machine (SVM)

SVM is a type of ML method developed based on a strong theoretical foundation. In its early days, SVM was not widely accepted due to its unsuitability for practical applications. However, the popularity and use of the method increased when satisfactory results were obtained in number recognition, computer vision, and text categorization. Today, SVM gives better or comparable results than other models in solving many problems. SVM is a supervised learning technique used for distribution-independent learning. Unlike classical statistical inference and NNM, SVM differs in terms of assumptions and approaches. While classical statistical inference assumes linear functions and a normal probability distribution, SVM does not make these assumptions (Kecman, 2005).

SVM works by mapping the input data into a higher-dimensional feature space using a kernel function, allowing data points to be nonlinearly separated. The goal of SVM is to maximize the distance between the closest data points from each class of the hyperplane. By maximizing the margin, it aims to improve generalization and reduce overfitting. The SVM uses a subset of training data points consisting of the data points closest to the decision boundary; these points are called support vectors. These support vectors play a critical role in the definition of the hyperplane. Both binary classification and regression problems can be modeled using the SVM. In binary classification tasks, the objective is to identify a hyperplane that maximally separates data points belonging to distinct classes, whereas in regression problems, the goal is to determine a hyperplane that best approximates the functional relationship between input and output variables (Pisner & Schnyer, 2020).

Logistic Regression (LR)

LR is an important statistical technique for classification and prediction tasks. The probability of an event occurring is estimated using the effects of independent variables within the dataset. As an example, we can determine the probability of a sentiment analysis task to classify a comment as positive or negative. As predicted values represent probabilities, the dependent variable is bounded between 0 and 1. The basic principle of LR is to calculate the success rate relative to the failure rate and then apply a logit transformation.

Furthermore, LR can predict the class membership of an observation based on the independent variables' values. This is achieved by establishing a predetermined threshold value that converts the calculated probabilities into classification labels. LR has the flexibility to be extended to cover multi-class scenarios. This enables the development of a single, comprehensive model that can handle various classification tasks rather than training and combining multiple binary classifiers. This generalized model is referred to as softmax regression or multiclass logistic regression (Géron, 2022).

GNB

GNB is a probabilistic classification method that is frequently used in machine learning. GNB works on the basis of the Bayes theorem. The reason why it is called 'naive' comes from the assumption of independence between class labels. This assumption states that each feature or attribute in the dataset is independent of other features. GNB assumes that each attribute's data distribution is normal (Gaussian). Therefore, the distribution of data points for each attribute should follow a normal distribution (Kang et al., 2012). When the features of the dataset are normally distributed and independent of each other, GNB is highly effective. However, real-world datasets can often deviate from these ideal assumptions; thus, the performance of GNB may vary depending on the dataset characteristics and the data distribution complexity.

eXtreme Gradient Boosting (XGBoost)

XGBoost is an optimized and high-performance version of the GB algorithm. In 2016, Tianqi Chen and Carlos Guestrin published a paper titled 'XGBoost: A Scalable Tree Boosting System." The salient features of this algorithm include high prediction accuracy, the ability to prevent overlearning, the ability to deal with missing data, and fast computation. XGBoost can work effectively on large datasets due to its high performance and efficient applicability (Chen & Guestrin, 2016). XGBoost can handle a variety of supervised learning tasks, including classification, regression, and ranking. The basis of the algorithm includes different base classifiers, which are linearly combined to improve the overall performance. During the learning process, an objective function is determined and optimized to provide the smallest error to fit the training data. The trained model is then combined with a prediction function that is used to make predictions to the new data (Duman, 2022). One of the most important features of XGBoost is its ability to effectively adapt to different structural features in datasets, such as density or sparsity. This feature is especially valuable in industrial and scientific applications when large datasets with many variables and large sizes are encountered.

The XGBoost algorithm was implemented using its official Python library with default parameter settings throughout the analysis (XGBoost, 2025).

Long Short Term Memory (LSTM)

LSTM is a recurrent neural network architecture, characterized by its ability to remember values at random intervals. This architecture stores the learned progress, and these stored values are not modified. LSTM includes forward and backward connections between neurons. It is highly suitable for classifying, processing, and predicting time series. It is widely used in many fields, such as sentiment analysis, text generation, and time series. LSTM has important differences from RNN. First, LSTM has a memory mechanism that allows past information to be stored in long-term memory and accessed later when needed. In addition, LSTM includes various 'gate' mechanisms. These gates control the flow of information and determine which information is memorized, which is forgotten, and which is used as output. Finally, LSTM reduces the vanishing gradient problem faced by the RNN more effectively. With these features, LSTM is preferred for solving problems involving long-term dependencies (Zhou et al., 2016). Table 2 shows the parameters used in the LSTM model. The LSTM model was modeled and run on TensorFlow v2.13 Keras Library.

Table 2
LSTM parameters

Parameters	Values/Functions
Batch Size	150
Epoch	15
Number of layers	3
Number of neurons in each layer	16
Activation function of the layers	ReLu

Parameters	Values/Functions
Output layer activation function	Sigmoid
Optimizer/Learning Rate	Adam/0.001
Loss Function	Binary cross-entropy
Embedding Size of Each Word	100

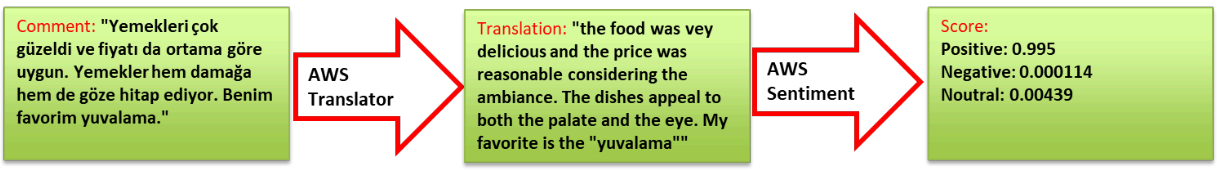
Amazon Comprehend

Amazon Comprehend is a cloud-based service in the field of natural language processing and is designed to analyze, understand, and make inferences from text data. This service can perform various tasks in various NLP. The core capabilities of Amazon Comprehend include functions such as text classification, sentiment analysis, keyword detection, entity recognition, topic modeling, and language detection. It identifies keywords, phrases, and entities in texts. It can also detect emotional tones in texts through sentiment analysis and provide a deeper understanding of text content with topic modeling techniques. The service works quickly and effectively on large-scale text datasets and supports several languages. Amazon Comprehend provides developers and companies with a powerful tool to better understand, summarize, and analyze text data. Owing to its scalability, flexibility, and ease of integration, it can provide solutions suitable for various applications in different industries (AWS, 2024).

To use the Amazon Comprehend service in Python and to perform sentiment analysis for all comments in an iterative manner, the 'Boto3' library was preferred. Boto3 stands out as a Python SDK developed specifically for Amazon Web Services and allows Python developers to integrate services such as Amazon S3 and Amazon EC2. However, since the service does not have Turkish support, we translated Turkish comments into English via Boto3. The results of the sentiment analysis are presented as positive, negative, and neutral scores with 0-1 probability distributions (AWS, 2024; Demirbilek & Özulukale Demirbilek, 2023). Figure 5 shows how a comment's sentiment analysis is performed using the AWS Comprehend service.

Figure 5

Sentiment analysis of a comment via AWS Comprehend



ChatGPT

ChatGPT is an artificial intelligence model developed by OpenAI. Initially, OpenAI developed the first version of GPT (Generative Pre-trained Transformer), a language model by processing large amounts of text data and using deep learning techniques. This model has been trained to have a broad language understanding and is capable of successfully performing various NLP tasks. Following the success of the initial version, OpenAI further developed the GPT architecture to form the basis of ChatGPT. ChatGPT is positioned as an AI model that is specially trained to produce human-like responses and can interact with users. Today, ChatGPT has become a powerful AI model that can interact with humans in a natural way and successfully fulfill general conversation and information provision tasks. ChatGPT can perform various tasks such as text generation, translation, text classification, question-answer matching, language understanding, and sentiment analysis. GPT's flexible and comprehensive architecture allows it to be adapted to different applications and can be used to solve many language processing problems (OpenAI, 2024). In this way, it can be used in many areas and tasks from writing code in a desired programming language to solving mathematical problems, from writing lyrics to photo/video editing, from data analysis to holiday/travel planning.

In our study, the 'Python OpenAI" library was integrated into the written code block to evaluate the emotional state of the comments by ChatGPT. Thanks to this library offered to developers by OpenAI, queries can be made from ChatGPT during the written code execution. In this way, sentiment analysis could be performed very quickly using ChatGPT for the collected comments. GPT-4, the latest version of the GPT series, was used during the analysis.

Performance Evaluation

Accuracy (Acc): It is a performance metric frequently used in machine learning and statistical modeling. The accuracy of a model is defined as the proportion of correctly predicted instances relative to the total number of predictions made. Accuracy is used in classification problems and is calculated using Equation (1):

$$Acc = \frac{\text{Number of Correct Prediction}}{\text{Total Number of Prediction,}} \tag{1}$$

Recall (R): Determines the proportion of the actual positive samples that are correctly identified. Recall is also known as 'True Positive Rate (TPR)." It is calculated using the formula in Equation (2):

$$R = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

In this context, TP (True Positive) refers to the number of instances that the model correctly identified as belonging to the positive class, whereas FN (False Negative) denotes the number of instances that the model incorrectly classified as negative despite actually belonging to the positive class.

Precision (P): Measures the proportion of samples that the model predicts as positive that are actually positive. It is calculated using Equation (3):

$$P = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

FP refers to the number of instances that the model incorrectly classified as belonging to the positive class, despite actually belonging to the negative class.

F-Score: harmonic mean of recall and precision metrics. It provides a point of balance for recall and precision. It simultaneously assesses the accuracy and inclusiveness of the classification model. The F-Score is calculated using the formula in Equation (4):

$$\text{F Score} = 2^* \frac{P^* R}{P + R} \tag{4}$$

AUC and ROC: The ROC curve is a graphical representation of the performance of binary classification models at different thresholds. The true positive rate (Recall) is plotted against the false positive rate (1-Specificity). Specificity is a performance metric that measures a classification model's ability to correctly identify negative examples. This metric is obtained by calculating the ratio of the number of correctly predicted negative examples to the total number of negative examples. The receiver operating characteristic (ROC) curve visualizes the variation between recall and specificity at different thresholds. AUC refers to the area under the ROC curve. This provides a single value summarizing the performance of the binary classification model for all possible threshold values. The area under the curve score ranges between 0 and 1, where higher values reflect superior model performance in distinguishing between classes. An AUC value of 0.5 indicates that the model has the same performance as random prediction, whereas an AUC value of 1 indicates an excellent classifier.

ROC and AUC are metrics commonly used to assess the discriminative power of binary classification models, especially when working with imbalanced datasets or when understanding the balance between sensitivity and specificity is necessary.

Experiments and Discussion

The cross-validation method was applied on 10 randomly selected sets to evaluate the average performance of each method. The model is trained and validated ten times, using a different subset as the validation set each time, while the remaining nine subsets are used for training. The dataset used in the study comprises 1,520 user comments, of which 865 were labeled as positive and 655 as negative, resulting in a class distribution of approximately 57% positive and 43% negative. Given this relatively balanced distribution, we did not anticipate a significant bias in the model training process. In addition to the cross-validation process, the relevant modules in the 'scikit-learn' library were preferred for the application of machine learning techniques. Table 3 shows the results for the English translations of the comments used in the study using AWS, whereas Table 4 shows the results for the Turkish comments. The reason for the bilingual application is the lack of Turkish language support in AWS and the concern that the language factor may affect the results.

Table 3

Performance of used methods in terms of defined metrics for English reviews

	Acc	R	P	F-Score
GNB	0.71	0.83	0.71	0.76
LR	0.84	0.87	0.85	0.86
SVM	0.80	0.85	0.82	0.83
XGBoost	0.82	0.85	0.84	0.84
LSTM	0.83	0.84	0.79	0.82
AWS	0.90	0.94	0.94	0.94
GPT-4	0.93	0.92	0.92	0.92

First, if we look at the results of the analyses performed in the original version of the comments (Table 4), it can be observed that slightly higher results are obtained in all methods compared with the English translation. Table 3 and Table 4 show that when the results are evaluated in both Turkish and English, all the methods used give highly accurate results in terms of each performance metric. With the exception of the GNB method, all machine and deep learning methods classified the comments with a success rate above 80%.

Table 4

Performance of the utilized methods in terms of the defined metrics for the Turkish reviews

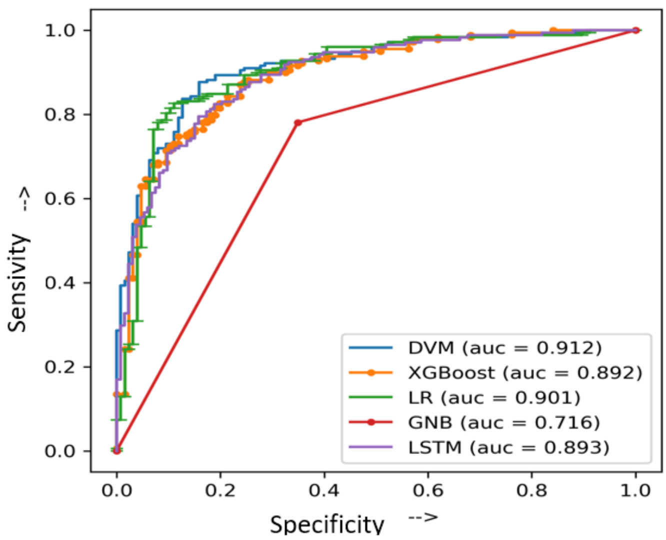
	Acc	R	P	F-Score
GNB	0.75	0.81	0.77	0.79
LR	0.85	0.90	0.85	0.87
SVM	0.82	0.86	0.84	0.84
XGBoost	0.83	0.86	0.84	0.85
LSTM	0.82	0.84	0.86	0.85
s	0.92	0.93	0.93	0.93

Upon examining the outcomes of machine learning techniques and XGBoost, an ensemble learning approach, the LR method achieves the highest model success for both Turkish and English comments, followed by XGBoost. Another advantage of LR is that it gives lower deviation values than other methods. The results of AWS and GPT-4 over the comments translated into English show that these two natural language processing programs can perform more successful classification with a significant difference compared to other methods. It is not surprising that Amazon, which has been conducting sentiment analysis studies on customer comments for a long time, and OpenAI GPT, which has been continuously developed with huge investments in recent years, provided better results. When these two major language models are compared, AWS gives better results in precision, recall, and F-score metrics, albeit by a small margin. The inability of AWS to directly analyze sentiment in Turkish, whereas GPT-4 can classify Turkish comments with a level of precision comparable to English comments, can be considered a distinguishing feature of GPT-4.

Figure 6 shows the ROC and AUC values of the machine and deep learning methods. An AUC value of 1 indicates that positive and negative comments are classified perfectly. An AUC value of 0 indicates that the model classifies all negative comments as positive or all positive comments as negative. The results show that all methods except GNB have high AUC values. We can conclude that the GNB method is more unsuccessful in classifying negative comments than the other methods. The highest AUC value was achieved using the SVM method.

Figure 6

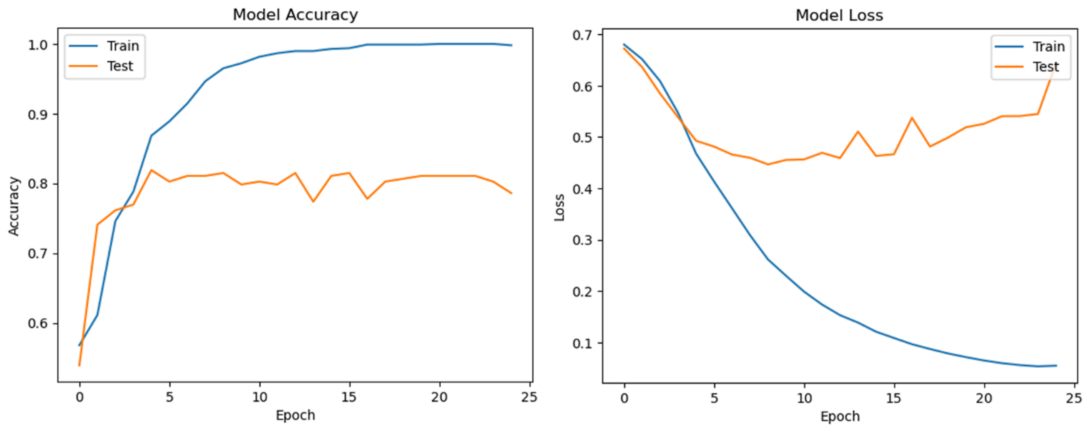
ROC and AUC values of the methods



For deep learning methods, the accuracy and loss function of the model must be monitored according to the number of epochs. Figure 7 shows the accuracy and loss function values of the LSTM over epochs. As the number of epochs increases, the accuracy value of the test data tends to remain constant, while the training data converges rapidly to 1. This indicates that the model tends to overfit the training set. In addition, the loss values for the test data increase when the number of epochs increases. Parameter optimization was performed for different learning rates to overcome these problems, but the overfitting problem persisted. Therefore, the number of epochs for the LSTM model was set to 15.

Figure 7

Model accuracy and loss for the LSTM method in terms of epoch number



Swot Analysis

SWOT analysis—an acronym for Strengths, Weaknesses, Opportunities, and Threats—is a widely recognized strategic planning tool used to evaluate an organization's internal capabilities and external conditions, particularly in times of uncertainty (Rozmi et al., 2018). This framework systematically categorizes factors based on their origin: internal factors include strengths, which enhance the organization's ability to reach its objectives, and weaknesses, which may obstruct performance. Conversely, opportunities and threats are external in nature; opportunities refer to favorable conditions in the external environment that can support goal attainment or inspire new initiatives, while threats denote external challenges that could negatively affect organizational progress (Benzaghta et al., 2021).

The historical development of SWOT analysis remains a topic of academic discussion. Some scholars trace its roots to the early 1950s Harvard Business School, where George Albert Smith Jr. and C. Christensen introduced it as a pedagogical tool to examine case studies within strategic and environmental contexts (Ustabulut, 2021). Others attribute its origin to Albert Humphrey's work at the Stanford Research Institute during the 1960s, where he employed the method in studies of Fortune 500 companies aimed at enhancing organizational change and control systems (Madsen, 2016). SWOT has demonstrated its adaptability and effectiveness across various fields, including education, healthcare, agriculture, and industry. Recent academic developments have focused on integrating SWOT analysis with complementary methodologies, such as the AHP and Porter's Five Forces model. These hybrid approaches have improved analytical rigor and enhanced the strategic decision-making process (Adem et al., 2018; Benzaghta et al., 2021).

As mentioned earlier, social media reviews are the primary source of information for potential customers when researching new dining options. Customers consider these reviews to evaluate the quality of food, service, and ambiance, trusting them more than personal recommendations. On the other hand, based on these reviews, establishments can see their shortcomings and take necessary actions. Within the scope of the study, all comments were evaluated, and the following conclusions were reached:

Strengths: ***Affordable Pricing:*** *Offers good value for money.* ***Clean and Hygienic:*** *The dining areas and restrooms are well-maintained.* ***Quick Service:*** *Delivered meals promptly.* ***Pleasant atmosphere:*** *Customers appreciate the interior and ambiance.* ***Diverse Menu:*** *A wide range of local dishes is included.* ***High-Quality Cuisine:*** *Traditional foods such as byran, küşleme, and lumbar are highly rated.* ***Friendly staff:*** *The staff is attentive and customer-focused.* ***Complimentary Offerings:*** *Free treats before and after meals enhance the dining experience.*	**Weaknesses:** ***Poor complaint handling:*** *Customer feedback is not addressed effectively.* ***Order confusion:*** *Mistakes or mix-ups in food orders occur.* ***Unclean Touchpoints:*** *Items such as tables, menus, and condiments lack proper hygiene.* ***Limited parking:*** *Inadequate parking options near restaurants.* ***Overcrowding and noise:*** *Excessive crowding and noise during busy hours disrupt the dining experience.* ***Small portions:*** *Portion sizes are considered insufficient for certain dishes.* ***Inattentive Service:*** *Some customers feel neglected by the staff.* ***Kitchen noise:*** *Kitchen sounds negatively affect the ambiance.*
Opportunities: ***Customer Feedback:*** *Using suggestions to improve services.* ***Hygiene and sustainability:*** *Building trust through clean and eco-friendly practices.* ***Loyalty Programs:*** *Encouraging repeat visits with rewards.* ***Menu innovation:*** *combining traditional and modern dishes* ***Online services:*** *Expanding reach through delivery and digital platforms.* ***Social Media:*** *Attracting customers through online engagement.* ***Special Events:*** *Drawing interest with themed nights and campaigns.* ***Staff Training:*** *Enhancing service through employee development.*	**Threats:** ***Economic instability:*** *Profit loss due to inflation and cost fluctuations.* ***Rising competition:*** *The number of rival restaurants in the region is growing.* ***External Crises:*** *Business disruptions from pandemics or natural disasters.* ***Negative Online Feedback:*** *Harm to reputation from poor reviews of digital platforms.* ***Technological Adaptation:*** *Keeping pace with digital tools and platforms is necessary.* ***Food Safety Risks:*** *Potential hygiene-related incidents that damage trust.* ***Shifting customer expectations:*** *Difficulty in keeping up with evolving customer preferences.* ***Regulatory Challenges:*** *Compliance burdens related to food, labor, and the environment.*

The SWOT analysis derived from customer reviews offers a comprehensive overview of the selected restaurants' operational and experiential dimensions in Gaziantep. The restaurants' key strengths, such as delicious local cuisine, friendly service, affordability, and rich menu options, align with customer expectations. However, weaknesses, such as crowding, inconsistent order handling, and limited parking, indicate the need for operational adjustments, including improved workflow coordination and infrastructural support. Opportunities identified—such as leveraging social media, enhancing customer loyalty programs, and introducing thematic events—can support long-term strategic positioning. Threats, including intensified competition, changing customer preferences, and potential reputational risks, underscore the importance of maintaining consistent service quality, proactively managing online feedback, and investing in adaptability. Restaurant managers can enhance both customer satisfaction and resilience in a competitive market by translating these findings into actionable strategies.

The SWOT analysis in this study was conducted through a manual and interpretive process based on the user reviews. Rather than applying a fully automated method, the analysis involved identifying recurring themes and contextual cues within the comments and categorizing them into strengths, weaknesses, opportunities, and threats. Given the inherently subjective nature of SWOT analysis, this classification reflects the qualitative interpretation of the data.

Conclusion

This study conducted a sentiment analysis on reviews of restaurants located in Gaziantep via Google Maps, followed by a SWOT analysis. Initially, 1,520 reviews collected from Google Maps were preprocessed and made ready for analysis in the sentiment analysis phase. Machine learning methods commonly used in the literature, such as LR, SVM, and GNB, as well as the ensemble learning method XGBoost and the deep learning method LSTM, were employed for sentiment analysis. Additionally, Amazon's AWS Comprehend service and OpenAI's latest large language model, GPT-4, were used for sentiment analysis. Owing to the lack of Turkish language service in AWS, the reviews were evaluated in both English and Turkish for all methods.

According to the performance metrics used in this study, both AWS and GPT-4 achieved over 90% accuracy, outperforming other methods in both languages. In particular, GPT-4 proved to be as successful in Turkish as in English. Excluding the GNB method, all other ML and DL methods classified the reviews with over 80% success. The results for ML methods and the ensemble method XGBoost showed that LR achieved the highest model success in both Turkish and English reviews, followed by XGBoost. LSTM provided similar results to other ML methods but exhibited overfitting as the number of epochs increased. Overall, the machine and DL methods demonstrated success above 80% across all performance metrics, while commercial software significantly outperformed these methods. Moreover, commercial software can be used for sentiment analysis without the need for coding and machine learning/deep learning training due to user-friendly interfaces. This is a significant advantage, especially for researchers in social sciences, education, and medicine who conduct sentiment analysis studies. On the other hand, AWS Comprehend offers free services up to a certain number of reviews, but once the quota is exceeded, it charges a fee per review. Similarly, the GPT-4 Developer service charges per query, and ChatGPT's GPT-4 version charges a monthly subscription fee of $20.

In addition to sentiment analysis, a SWOT analysis was conducted based on reviews of the restaurants. The strengths of the restaurants included tasty food, friendly staff, quick service, hygiene, and reasonable prices. However, weaknesses such as crowding and noise issues, service delays, and hygiene deficiencies were identified, which could negatively impact customer satisfaction. Restaurants were identified to have opportunities to increase the use of social media to reach broader audiences, improve customer experience, and offer new menu options. Threats included increased competition, negative customer reviews, economic fluctuations, and food safety. Restaurants can create a successful roadmap by maintaining their strengths, minimizing weaknesses and threats, and maximizing opportunities.

The most important contribution of our study to the literature is the use of OpenAI GPT-4, one of the most popular large language models that have recently started to enter our lives in every field, during sentiment analysis. In our study, the performance of GPT-4 is compared with machine learning methods such as AWS Comprehend natural language processing service, LSTM deep learning method used in sentiment analysis studies, SVM, LR, GNB, and XGBoost according to performance metrics frequently used in the literature. In addition to developing high-performance models, which is the focus of sentiment analysis studies, a SWOT analysis was performed based on customer reviews. In this way, the strengths and weaknesses of businesses, potential opportunities, and threats were evaluated by using customer reviews. In addressing a notable gap in the literature, this study contributes by integrating multilingual sentiment analysis—using both conventional machine learning methods and large language models—with SWOT-based strategic interpretation of customer reviews in the context of gastronomy tourism in Gaziantep.

The findings of this study have significant managerial implications for restaurant businesses. Sentiment analysis provides valuable insights into customer satisfaction, enabling managers to identify strengths, address weaknesses, and enhance service quality. The results highlight key operational issues, such as service delays, noise levels, and hygiene concerns, which can improve customer experience and retention if effectively managed. Additionally, the SWOT analysis reveals strategic opportunities, including increased social media engagement and menu diversification, while also identifying potential threats, such as rising competition, negative customer reviews, and economic fluctuations. This study also demonstrates the effectiveness of AI-driven sentiment analysis tools, particularly GPT-4 and AWS Comprehend, which offer high accuracy without requiring extensive technical expertise. Restaurant managers can refine their marketing strategies, improve operational efficiency, and develop proactive risk management approaches by leveraging sentiment analysis for data-driven decision-making, ultimately enhancing their competitive position in the market.

There are also some limitations to this study. First, the study relies solely on Google Maps reviews, which may not provide a comprehensive representation of customer opinions. Other platforms, such as TripAdvisor, Yelp, and Zomato, could offer additional insights. Moreover, while the selected restaurants are among the most popular in Gaziantep and thus provide rich insights into customer experiences, the sample may not fully represent the entire restaurant landscape of the city. The study provides insights into sentiment analysis and SWOT findings but does not evaluate how businesses implement these insights or measure their impact on customer satisfaction and business strategies. Next, the study is based on a snapshot of collected reviews and does not analyze sentiment trends over time. A longitudinal study could provide deeper insights into changing customer perceptions. Finally, SWOT analysis is inherently subjective, as different experts may identify varying strengths, weaknesses, opportunities, and threats based on their interpretation of customer reviews.

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References

Adem, A., Çolak, A., & Dağdeviren, M. (2018). An integrated model using SWOT analysis and Hesitant fuzzy linguistic term set for evaluation occupational safety risks in life cycle of wind turbine. *Safety Science, 106*.

Agarwal, A., Xie, B., Vovsha, I., Rambow, O., & Passonneau, R. (2011). Sentiment Analysis of Twitter Data. *LSM '11 Proceedings of the Workshop on Languages in Social Media*, 30-38.

Agüero-Torales, M. M., Cobo, M. J., Herrera-Viedma, E., & López-Herrera, A. G. (2019). A cloud-based tool for sentiment analysis in reviews about restaurants on TripAdvisor. *Procedia Computer Science, 162*, 392-399.

Aksu, M. Ç., & Karaman, E. (2022). Turistik Mekanlara Yönelik Sosyal Medya Paylaşımlarının Yapay Zekâ Yöntemleriyle Değerlendirilmesi: Artvin İli Örneği. *Journal of Tourism and Gastronomy Studies, 10*(1), 505-524.

Asani, E., Vahdat-Nejad, H., & Sadri, J. (2021). Restaurant recommender system based on sentiment analysis. *Machine Learning with Applications, 6* (100114), 1-10. https://doi.org/10.1016/j.mlwa.2021.100114

AWS. (2024). Available, https://aws.amazon.com/tr/comprehend/, Accessed on, Mar. 01, 2024.

Benzaghta, M. A., Elwalda, A., Mousa, M. M., Erkan, I., & Rahman, M. (2021). SWOT analysis applications: An integrative literature review. Journal of Global Business Insights. *6, 1*, 54-72.

Bird, S., Klein, E., & Loper, E. (2009). *Natural Language Processing with Python*: O'Reilly Media, Inc.

Büyükeke, A., Sökmen, A., & Gencer, C. (2020). Metin Madenciliği ve Duygu Analizi Yöntemleri ile Sosyal Medya Verilerinden Rekabetçi Avantaj Elde Etme: Turizm Sektöründe Bir Araştırma. *Journal of Tourism and Gastronomy Studies, 8*(1), 322-335. doi:10.21325/jotags.2020.550

Chen, T., & Guestrin, C. (2016). *XGBoost: A scalable tree boosting system*. Paper presented at the KDD '16, San Francisco, CA, USA.

Çekal, N., & Aktürk, H. (2019). Gaziantep mutfağına özgü çorbalara ilişkin müşteri değerlendirmelerinin incelenmesi. *Journal of Tourism and Gastronomy Studies, 7*(2), 1488–1498. https://doi.org/10.21325/jotags.2019.431

Çevik, F., & Kilimci, Z. (2021). Derin öğrenme yöntemleri ve kelime yerleştirme modelleri kullanılarak Parkinson hastalığının duygu analiziyle değerlendirilmesi. *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi (PAJES), 27*(2), 151–161.

Demirbilek, M., & Özulukale Demirbilek, S. (2023). Google Yorumları Üzerinden Makine Öğrenme Yöntemleri ve Amazon Comprehend ile Duygu Analizi: İç Anadoluda Bir Üniversite Örneği. *Üniversite Araştırmaları Dergisi, 6*(4), 452-461. https://doi.org/10.32329/uad.1383794

Doaa Mohey El-Din Mohamed, H. (2018). A survey on sentiment analysis challenges. *Journal of King Saud University - Engineering Sciences, 30*(4), 330-338. https://doi.org/10.1016/j.jksues.2016.04.002

Duarte Alonso, A., O'neill, M., Liu, Y., & O'shea, M. (2013). Factors driving consumer restaurant choice: An exploratory study from the Southeastern United States. *Journal of Hospitality Marketing & Management, 22*(5), 547-567.

Duman, E. (2022). Implementation of XGBoost Method for Healthcare Fraud Detection. *Scientific Journal of Mehmet Akif Ersoy University, 5*(2), 69-75.

Géron, A. (2022). *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow* (3rd Edition ed.): O'Reilly Media, Inc.

Gündüz, H. (2023). Derin Transformatörlerden Çift Yönlü Kodlayıcı Temsilleri ve Destek Vektör Makineleri ile Türkçe Film Yorumları Üzerine Duygu Analizi. *KSÜ Mühendislik Bilimleri Dergisi, 26*(2), 542-549.

Ha, J., & Jang, S. S. (2010). Effects of service quality and food quality: The moderating role of atmospherics in an ethnic restaurant segment. *International Journal of Hospitality Management, 29*(3), 520-529.

Hamad, M. M., Salih, M. A., & Jaleel, R. A. (2021). Sentiment analysis of restaurant reviews in social media using Naïve Bayes. *Applications of Modelling and Simulation, 5*, 166-172.

Hossain, N., Bhuiyan, M. R., Tumpa, Z. N., & Hossain, S. A. (2020, 1–3 July 2020). *Sentiment analysis of restaurant reviews using combined CNN-LSTM*. Paper presented at the 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kharagpur, India.

Instant Data Scraper. (2024). Available, https://chrome.google.com/webstore/detail/instant-data-scraper/ofaokhiedipichpaobibbnahnkdoiiah, Accessed on, Feb. 20, 2024.

Jonathan, B., Sihotang, J. I., & Martin, S. (2019, October). *Sentiment analysis of customer reviews in zomato bangalore restaurants using random forest classifier.* Paper presented at the International Scholars Conference.

Kang, H., Yoo, S. J., & Han, D. (2012). Senti-lexicon and improved Naïve Bayes algorithms for sentiment analysis of restaurant reviews. *Expert Systems with Applications, 39*(5), 6000-6010.

Kecman, V. (2005). *Support vector machines: theory and applications*: Springer Berlin Heidelberg.

Korkmaz, A., & Bulut, S. (2023). Social Media Sentiment Analysis for Solar Eclipse with Text Mining. *Acta Infologica, 7*(1). doi:https://doi.org/10.26650/acin.1207100

Köksal, B., Erdem, G., Türkeli, C., & Kamışlı Öztürk, Z. (2021). Twitter'da Duygu Analizi Yöntemi Kullanılarak Bitcoin Değer Tahminlemesi. *Düzce Üniversitesi Bilim ve Teknoloji Dergisi, 9*, 280-297. doi:10.29130/dubited.792909

Madsen, D. Ø. (2016). SWOT analysis: A management fashion perspective. *International Journal of Business Research, 16*(1), 39-56.

McIntyre-Bhatty, Y. T. (2000). Neural network analysis and the characteristics of market sentiment in the financial markets. *Expert Systems, 17*(4), 191-198.

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment Analysis Algorithms and Applications: A Survey. *Ain Shams Engineering Journal, 5*, 1093-1113. doi:http://dx.doi.org/10.1016/j.asej.2014.04.011

NLTK. (2024). Available, https//www.nltk.org/, Accessed on, Feb. 20, 2024.

OpenAI. (2024). ChatGPT (Mar 14 version) [Large language model]. Available, https://chat.openai.com/chat, Accessed on, Apr. 15, 2024.

Özel, M., & Çetinkaya Bozkurt, Ö. (2024). Sentiment Analysis on GPT-4 with Comparative Models Using Twitter Data. *Acta Infologica, 8*(1), 23-33. https://doi.org/10.26650/acin.1418834

Özen, İ. A. (2021). Yerel Restoranların Değerlendirilmesinde Fikir Madenciliği: Gaziantep Örneği (Opinion Mining in the Evaluation of Local Restaurants: The Case of Gaziantep). *Journal of Tourism & Gastronomy Studies, 9*(1), 377-391.

Öztürk, S. (2022). *Bipolar Bozukluk Manik Atak Tanılı Hastaların Atak Şiddetinin Video Tabanlı Duygu Analizi ile Değerlendirilmesi.* (Doktora Tezi), Trakya Üniversitesi Edirne.

Peters, C. M. (2024). The Power of Google Reviews for Restaurant Marketing. Available, https://restaurantsmarketing.com.au/blog/the-power-of-google-reviews-for-restaurant-marketing/#:~:text=Google%20reviews%20are%20extremely%20important,to%20rank%20in%20search%20results, Accessed on, Jan. 31, 2024.

Pisner, D. A., & Schnyer, D. M. (2020). Chapter 6 - Support vector machine. In A. Mechelli & S. Vieira (Eds.), *Machine learning* (pp. 101-121).

Ponnam, A., & Balaji, M. S. (2014). Matching visitation-motives and restaurant attributes in casual dining restaurants. *International journal of hospitality management, 37*, 47-57.

Renganathan, V., & Upadhya, A. (2021). Dubai restaurants: A sentiment analysis of tourist reviews. *Academica Turistica - Tourism and Innovation Journal, 14*(2). doi:https://doi.org/10.26493/2335-4194.14.165-174

Rita, P., Vong, C., Pinheiro, F., & Mimoso, J. (2023). A sentiment analysis of Michelin-starred restaurants. *European Journal of Management and Business Economics, 32*(3), 276-295.

Rozmi, A. N. A., Nordin, A., & Bakar, M. I. A. (2018). The perception of ICT adoption in small medium enterprise: A SWOT analysis. *International Journal of Innovation Business Strategy, 19*(1), 69-79.

Scikit-learn (2025). Available, https://scikit-learn.org/stable/supervised_learning.html, Accessed on, May. 25, 2025

Shin, B., Ryu, S., Kim, Y., & Kim, D. (2022). Analysis on Review Data of Restaurants in Google Maps through Text Mining: Focusing on Sentiment Analysis *Journal of Multimedia Information System, 9*(1), 61-68.

Singgalen, Y. A. (2022). Sentiment Analysis on Customer Perception towards Products and Services of Restaurant in Labuan Bajo *Journal of Information Systems and Informatics, 4*(3), 511-523.

Tuna, M. F. (2022). Mobil Uygulama Müşteri Geri Bildirimindeki Duyguların Makine Öğrenmesi Yöntemleriyle Sınıflandırılması. *Journal of Business and Communication Studies, 1*(1), 83-103. http://dx.doi.org/10.29228/jobacs.63080

Uçuk, C., & Kayran, M. (2020). Gaziantep mutfağının tarihsel gelişimi: Milli mücadele döneminde Gaziantep'te yeme içme faaliyetleri. *Safran Kültür ve Turizm Araştırmaları Dergisi, 3*(2), 258–272.

Ustabulut, M. Y. (2021). SWOT Analysis for the Distance Education Process of Lecturers Teaching Turkish as a Foreign Language. Educational Policy Analysis and Strategic Research, *16*(1), 139-152. https://doi.org/10.29329/epasr.2020.334.8

Uyaroğlu Akdeniz, F. N., & Cebeci, H. İ. (2021). Belediye Hizmetlerin Değerlendirilmesinde Duygu Analizi Yaklaşımı: Sakarya İli Örneği. *Zeki Sistemler Teori ve Uygulamaları Dergisi,* 4(2), 127-135. doi:10.38016/jista.932762

Wankhade, M., Rao, A. C. S., & Kulkarni, C. (2022). A survey on sentiment analysis methods, applications, and challenges. *Artificial Intelligence Review, 55*(7), 5731-5780. doi:https://doi.org/10.1007/s10462-022-10144-1

Web of Science (2024), https://www.webofscience.com/, Accessed on, Feb. 20, 2024.

XGBoost. (2025, May 25). XGBoost Python Package Python Package Introduction. https://xgboost.readthedocs.io/en/stable/python/python_intro.html

Ylimaki, E. (2024). Why Google Restaurant Reviews Are a Must, Available https://trustmary.com/reviews/why-google-restaurant-reviews-are-a-must/, Accessed on, Jan. 31, 2024.

Yu, B., Zhou, J., Zhang, Y., & Cao, Y. (2017). Identifying restaurant features via sentiment analysis on yelp reviews. *arXiv preprint arXiv:1709.08698*, 1-6.

Yu, T., Rita, P., Moro, S., & Oliveira, C. (2022). Insights from sentiment analysis to leverage local tourism business in restaurants. *International Journal of Culture, Tourism and Hospitality Research, 16*(1), 321-336.

Yüksel, A. S., & Tan, F. G. (2018). Metin Madenciliği Teknikleri ile Sosyal Ağlarda Bilgi Keşfi. *Mühendislik Bilimleri ve Tasarım Dergisi, 6*(2), 324-333. https://doi.org/10.21923/jesd.384791

Zeng, B. (2013). Social Media in Tourism. *J Tourism Hospit 2*(1), 1-2. http://dx.doi.org/10.4172/2167-0269.1000e125

Zhou, X., Wan, X., & Xiao, J. (2016, November 1-5, 2016). *Attention-based LSTM network for cross-lingual sentiment classification*, Austin, Texas.