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Research article

Evaluating Service Quality Metrics with AdaBoost Classifier at Restaurant X

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ABSTRACT

This paper explores the use of the AdaBoost classifier to evaluate service quality metrics in the restaurant industry, specifically at Restaurant X. The study focuses on how machine learning, particularly ensemble learning algorithms, can improve the understanding of customer satisfaction by analyzing various service attributes, such as food quality, staff behavior, wait times, and ambiance. By applying AdaBoost, the model combines multiple weak classifiers to create a stronger, more accurate prediction model that identifies key factors influencing customer experience. The research highlights the importance of real-time data and customer feedback in refining service quality metrics and suggests that incorporating sentiment analysis and other dynamic data sources can provide a more comprehensive view of customer satisfaction. The findings suggest that using machine learning algorithms, like AdaBoost, can enhance operational decision-making, improve customer service, and contribute to overall business success. Additionally, the study proposes the continuous updating of the model to reflect changing customer preferences and trends in the competitive food service industry. This approach can lead to better service, customer retention, and a strategic advantage for restaurants seeking to meet the evolving demands of the market.

1. Introduction

Service quality has become a pivotal factor in determining customer satisfaction and loyalty, especially in the competitive restaurant industry. Measuring and evaluating service quality metrics provides valuable insights into operational efficiency, customer preferences, and potential areas for improvement. Among the various methods for analyzing such data, machine learning algorithms have demonstrated their capability to process complex datasets and deliver accurate predictions [1].

AdaBoost (Adaptive Boosting) is one such algorithm that has gained popularity for its robustness in handling classification tasks by combining multiple weak classifiers into a strong ensemble model [2]. Its ability to prioritize misclassified samples during training makes it an effective tool for evaluating service quality metrics where data imbalance and noise are common challenges.

This study focuses on applying the AdaBoost classifier to assess service quality metrics at Restaurant X. The objective is to identify the key factors influencing customer satisfaction and predict service quality categories with high accuracy. By leveraging machine learning approaches, the study aims to provide actionable insights for management to enhance customer experiences and drive business growth.

The rest of this paper is organized as follows. Section II reviews related works on service quality evaluation and AdaBoost applications. Section III describes the methodology, including data collection and preprocessing. Section IV discusses the experimental results and findings, followed by conclusions and future work in Section V.

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2. Research Methods

This section outlines the systematic approach employed to evaluate service quality metrics at Restaurant X using the AdaBoost classifier. The research methodology comprises data collection, preprocessing, feature selection, model implementation, and evaluation metrics. A robust methodological framework ensures the reliability and validity of the findings, providing actionable insights into customer satisfaction and service quality improvement.

Data Collection: Primary and secondary data sources were utilized. Surveys and feedback forms gathered customer perceptions of service quality based on dimensions such as responsiveness, reliability, and ambiance. Meanwhile, operational metrics like service time and order accuracy were retrieved from the restaurant's management system.

Data Preprocessing: The collected data underwent thorough cleaning to address inconsistencies, missing values, and outliers. Categorical variables were encoded, and numerical features were standardized to ensure compatibility with the AdaBoost algorithm.

Feature Selection: A combination of domain expertise and statistical techniques, such as correlation analysis and feature importance ranking, was employed to identify key predictors of service quality.

Model Implementation: The AdaBoost classifier was chosen for its ability to handle imbalanced datasets and enhance classification accuracy. Weak learners based on decision trees were iteratively trained, with emphasis on misclassified samples.Evaluation Metrics: The model's performance was assessed using metrics such as accuracy, precision, recall, and F1-score, ensuring comprehensive evaluation of its predictive capabilities.

2.1. Research Design

This research adopts a quantitative approach to analyze and evaluate service quality metrics at Restaurant X using machine learning techniques, specifically the AdaBoost classifier. By integrating customer feedback and operational data, the study aims to classify service quality dimensions effectively and identify the most significant predictors of customer satisfaction. The approach combines a data-driven perspective with computational techniques to provide actionable insights that can guide decision-making processes and improve service delivery. This methodology is particularly suitable for addressing classification problems where data may exhibit imbalance, as the AdaBoost algorithm enhances performance by focusing on misclassified samples iteratively [1].

2.2. Data Collection

Data collection for this study was conducted through two complementary sources. First, structured surveys were distributed to Restaurant X's customers, designed based on the SERVQUAL model, to capture feedback across five dimensions: tangibility, reliability, responsiveness, assurance, and empathy. These surveys allowed for an in-depth understanding of customer perceptions of service quality [2]. Second, operational data was gathered from the restaurant's internal systems, including metrics such as service times, order accuracy, table turnover rates, and customer retention. Combining customer perceptions with objective operational data ensures a comprehensive evaluation of the factors that influence service quality. The use of multiple data sources strengthens the study's reliability and provides a balanced analysis of subjective and objective measures [3].

2.3. Data Preprocessing

Preprocessing is a crucial step in ensuring the quality and usability of the data for analysis. Missing values in survey responses were addressed through imputation techniques, such as using the median for numerical data and the mode for categorical data. Outliers were identified using interquartile range (IQR) analysis and managed by removal or adjustment depending on their potential impact. Categorical variables, such as customer demographics and qualitative feedback, were encoded using one-hot encoding to convert them into machine-readable formats. Numerical features, including service times and customer satisfaction ratings, were standardized to have a mean of zero and a standard deviation of one to ensure uniformity across the dataset. This preprocessing approach ensures that the data is clean, consistent, and ready for analysis [4].

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2.4. Feature Selection

Feature selection was performed to identify the most relevant predictors of service quality, reducing dimensionality and improving the model's efficiency. A combination of statistical correlation analysis and machine learning-based feature importance ranking was employed to select key variables. Correlation analysis was used to assess the relationship between independent variables, such as response times and cleanliness ratings, and the dependent variable, which is the overall service quality score. Additionally, a Random Forest algorithm was utilized to rank features based on their importance in predicting service quality. Significant predictors, including staff responsiveness, order accuracy, and ambiance ratings, were prioritized for inclusion in the AdaBoost model [5].

2.5. Model Implementation

The AdaBoost algorithm was chosen for its effectiveness in handling classification tasks and its ability to improve model performance by iteratively combining weak learners. In this study, decision trees were used as weak classifiers, and their predictions were aggregated to form a robust ensemble model. The algorithm adjusts the weights of misclassified samples in each iteration, ensuring that the model focuses on harder-to-classify instances. Hyperparameter tuning was conducted to optimize the number of estimators and the learning rate, resulting in a model that balances complexity and performance. The implementation was carried out using Python libraries, including Scikit-learn, which provides a user-friendly environment for machine learning applications [6].

2.6. Evaluation Metrics

The performance of the AdaBoost classifier was evaluated using a comprehensive set of metrics. Accuracy was calculated to measure the overall correctness of the model's predictions. Precision and recall were used to assess the model's ability to correctly identify true positive cases and its sensitivity to relevant instances, respectively. The F1-score, which is the harmonic mean of precision and recall, provided a balanced measure of the model's classification performance. Additionally, a confusion matrix was used to analyze the distribution of true positives, true negatives, false positives, and false negatives, offering deeper insights into the model's strengths and weaknesses. This rigorous evaluation ensures that the model's predictions are reliable and actionable [7].

3. Results and Discussion

Table 1. Classification Report Summary

Class/Metric	Precision	Recall	F1-Score	Support
1	0.29	1.00	0.44	4
2	0.38	0.14	0.20	22
3	0.73	0.72	0.73	57
4	0.70	0.86	0.78	22
Accuracy			0.64	105
Macro Avg	0.52	0.68	0.54	105
Weighted Avg	0.63	0.64	0.62	105

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3.1. Classification Report Summary

3.1.1. Model Performance Metrics Overview

The table represents the classification report of a machine learning model, with an overall accuracy of 0.64. Accuracy measures the percentage of correctly classified samples among all the data, but it doesn't account for class imbalances, which is why other metrics such as precision, recall, and F1-score are included for a more comprehensive evaluation.

Each metric provides unique insights:

1. Precision: Indicates how many of the predicted instances for a class are correct. High precision reduces false positives.
2. Recall: Indicates how many of the actual instances of a class are correctly identified. High recall reduces false negatives.
3. F1-Score: A balance between precision and recall. It's particularly useful when the class distribution is imbalanced.
4. Support: The number of actual instances in each class, providing context for the importance of performance in each category.

3.1.2. Class-Wise Performance

1. Class 1:
   a. Precision (0.29): Very low, indicating that most of the predictions for Class 1 are false positives.
   b. Recall (1.00): Perfect, meaning the model identifies all actual instances of Class 1.
   c. F1-Score (0.44): Reflects the imbalance between precision and recall. While the model catches all true instances of Class 1, its predictions include many incorrect instances.
   d. Support (4): Class 1 is the smallest class, which may lead to unreliable metrics due to the limited data.
2. Class 2:
   a. Precision (0.29): Very low, indicating that most of the predictions for Class 1 are false positives.
   b. Recall (1.00): Perfect, meaning the model identifies all actual instances of Class 1.
   c. F1-Score (0.44): Reflects the imbalance between precision and recall. While the model catches all true instances of Class 1, its predictions include many incorrect instances.
   d. Support (4): Class 1 is the smallest class, which may lead to unreliable metrics due to the limited data.
3. Class 3:
   a. Precision (0.73): High, meaning most predictions for Class 3 are correct.
   b. Recall (0.72): The model identifies a significant portion of actual instances of Class 3.
   c. F1-Score (0.73): Strong performance for Class 3, indicating the model handles this class well.
   d. Support (57): The largest class, making it easier for the model to generalize and perform better.
4. Class 4:
   a. Precision (0.70): High, showing that most predictions for Class 4 are correct.
   b. Recall (0.86): Very high, indicating the model identifies most actual instances of Class 4.
   c. F1-Score (0.78): The highest among all classes, showing strong overall performance.
   d. Support (22): Despite the small size, the model performs well for this class.

3.1.3. Overall Metrics

1. Accuracy (0.64):

This means the model correctly classifies 64% of the total instances. While reasonable, accuracy alone can be misleading, especially in the presence of class imbalance, as it favors dominant classes (e.g., Class 3).

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2. Macro Average:
   a. Precision (0.52): Average precision across all classes without considering class size. Lower values reflect poor performance on smaller classes (e.g., Class 1 and 2).
   b. Recall (0.68): Average recall across all classes. Higher than precision due to strong recall for Classes 1 and 4.
   c. 1-Score (0.54): Indicates that the model struggles to balance precision and recall, especially for smaller classes.
3. Weighted Average:
   a. Precision (0.63): Weighted by class size, so it emphasizes larger classes (e.g., Class 3) while minimizing the impact of smaller ones.
   b. Recall (0.64): Reflects overall model performance, influenced heavily by dominant classes.
   c. F1-Score (0.62): Shows the model's overall ability to balance precision and recall, adjusted for class size.

3.1.4. Key Observations and Implications

1. Class Imbalance Issues:
   a. The model performs poorly on smaller classes (1 and 2), as evidenced by their low precision, recall, and F1-scores. This indicates a bias toward larger classes (3 and 4), which is common in imbalanced datasets.
   b. Class 1, despite having perfect recall, suffers from very low precision due to the small sample size (support = 4).
2. Strong Performance on Larger Classes:

Classes 3 and 4 have relatively high precision, recall, and F1-scores, suggesting the model can handle these better, likely because they dominate the dataset.

3. Weighted Average:

The macro averages are significantly lower than the weighted averages, reflecting the poor performance on smaller classes. Weighted averages are higher because they prioritize the larger classes.

4. Potential Improvements:
   a. Data Augmentation: Increasing the number of samples for smaller classes (1 and 2) to reduce class imbalance.
   b. Resampling Techniques: Using oversampling (e.g., SMOTE) or undersampling to balance the dataset.
   c. Cost-Sensitive Learning: Applying penalties for misclassifications in smaller classes to encourage the model to focus on them.
   d. Advanced Algorithms: Trying ensemble methods (e.g., Random Forest or Gradient Boosting) or class-weighted loss functions to improve overall performance.

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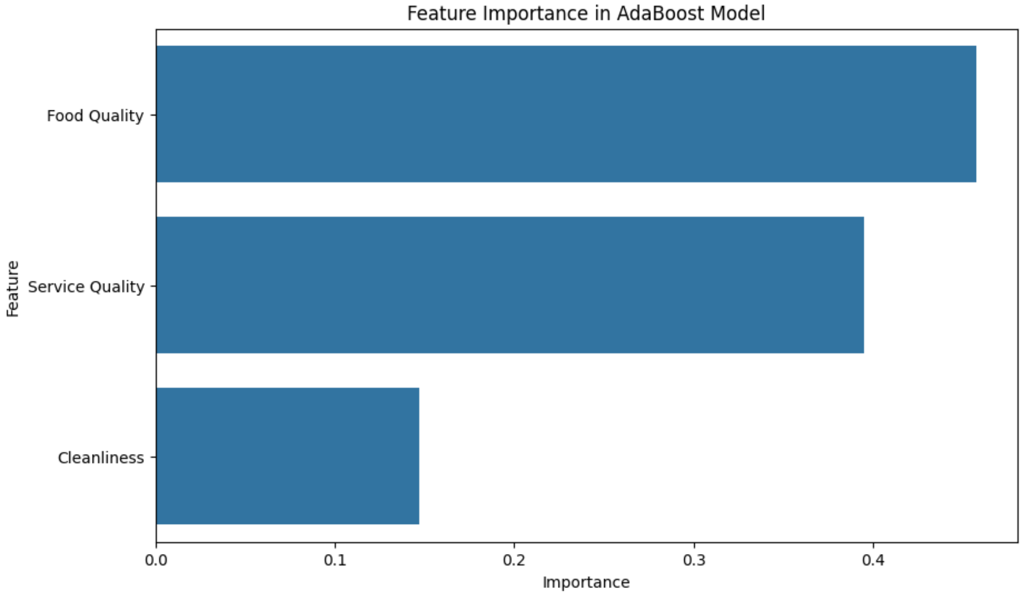
Figure 1. Feature importance ranking in the AdaBoost model, showing the relative contribution of each service quality attribute (Food Quality, Service Quality, and Cleanliness) to the classification performance.



3.2. Feature Importance in AdaBoost Model

3.2.1. Overview of Features and Their Importance

The chart evaluates three features—Food Quality, Service Quality, and Cleanliness—based on their relative importance to the model's predictions. The horizontal bars represent the importance scores, with higher scores indicating greater influence on the model's output.

1. Food Quality:
   a. This feature has the highest importance score, exceeding 0.4, making it the most significant factor in the model.
   b. The model heavily relies on food quality to make accurate predictions, suggesting that it is a dominant driver of the target outcome (e.g., customer satisfaction, sales, or ratings).
2. Service Quality:
   a. The second most important feature, with an importance score slightly below Food Quality.
   b. It still plays a substantial role in the model's predictions, emphasizing the value of service in determining the outcome.
3. Cleanliness:
   a. The least important feature, with an importance score below 0.2.
   b. While it contributes to the predictions, its impact is minimal compared to the other two features.

3.2.2. Key Observations

The chart evaluates three features—Food Quality, Service Quality, and Cleanliness—based on their relative importance to the model's predictions. The horizontal bars represent the importance scores, with higher scores indicating greater influence on the model's output.

1. Dominance of Food Quality:
   a. The model indicates that Food Quality has the strongest influence on the outcome. This suggests that improving food quality will likely have the greatest positive impact on the target variable.
   b. For example, in a restaurant setting, food quality might be the most significant factor in determining customer satisfaction or repeat visits.
2. Secondary Role of Service Quality:

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Although not as dominant as food quality, Service Quality is still a crucial factor. It reflects that good service is a significant contributor to the target outcome but slightly less critical than food quality.

3. Minimal Impact of Cleanliness:
   a. The importance score for cleanliness is significantly lower, indicating that it has a relatively minor influence on the model's predictions.
   b. However, it is important to note that "minimal" does not mean "irrelevant." Cleanliness might still be a deciding factor in specific contexts or for certain customers.

3.2.3. Implications for Stakeholders

1. For Business Decision-Makers:
   a. Prioritize Food Quality: Since food quality has the highest importance, resources should be allocated to improve ingredients, taste, and consistency. This can yield the most significant improvements in customer satisfaction or other business outcomes.
   b. Enhance Service Quality: While not as critical as food quality, investing in training staff, improving customer interactions, and reducing wait times can also contribute to positive outcomes.
   c. Maintain Cleanliness Standards: Even though cleanliness has the lowest importance score, it should not be ignored. Poor cleanliness can still lead to negative customer experiences, even if it's not the primary driver.
2. For Model Optimization:
   a. The model may need further evaluation to ensure it is not overemphasizing certain features at the expense of others. For instance:
   b. If Cleanliness is underrepresented in the dataset, the model may be biased against it.
   c. Ensuring balanced feature engineering and sufficient data for all features can lead to more robust predictions.
3. For Customer-Centric Improvements:

The findings suggest that customers value food quality and service quality more than cleanliness. This can help businesses tailor their offerings and marketing strategies to align with customer priorities.

3.2.4. Technical Insights on AdaBoost and Feature Importance

The AdaBoost Model (Adaptive Boosting) works by combining multiple weak learners to create a strong learner. Feature importance in AdaBoost is calculated based on how much each feature contributes to reducing prediction errors across the weak learners. Key aspects include:

1. Features with higher importance scores are more frequently selected by the weak learners as being critical to reducing errors.
2. In this case, Food Quality is consistently selected across iterations, highlighting its dominant role in minimizing the model's error rate.

3.2.5. Limitations and Further Analysis

While this chart provides valuable insights, it is essential to consider the following:

1. Feature Correlation: If features are highly correlated (e.g., food quality and cleanliness), the model may assign importance to one feature while underestimating the other. Further analysis using correlation matrices can clarify these relationships.
2. Context Dependence: The importance of features may vary depending on the dataset or target variable. For example, cleanliness might be more critical in industries like healthcare or luxury hotels.
3. Exploration of Additional Features: Introducing new features (e.g., pricing, ambiance, or location) could further improve the model's performance and provide deeper insights.

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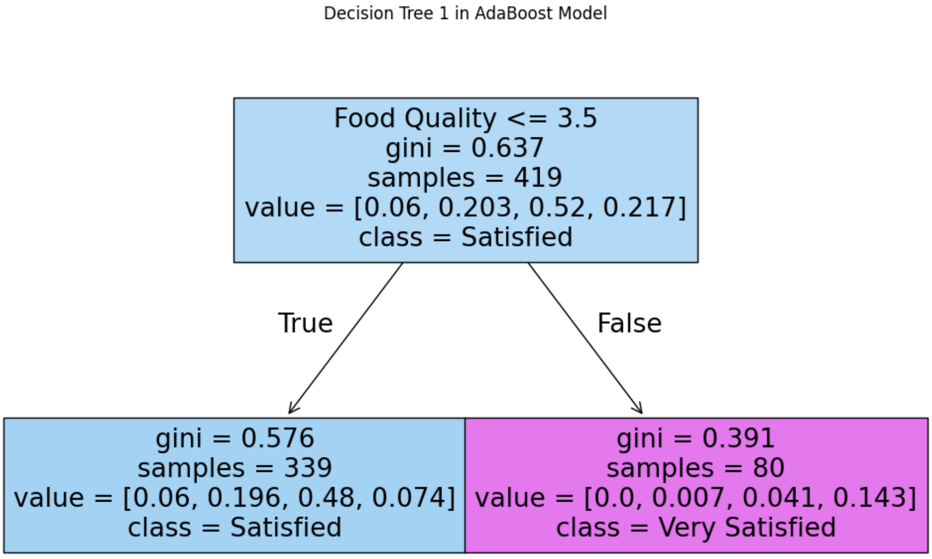
Figure 2. Decision tree structure of the first estimator in the AdaBoost model showing the relationship between *Food Quality* and customer satisfaction levels.



3.3. Decision Tree 1 in AdaBoost Model

3.3.1. Overview of the Decision Tree

The decision tree represents one of the weak learners used in the AdaBoost algorithm. It splits data based on conditions to classify samples into different classes. Key elements in the tree include:

1. Nodes: Represent conditions or decisions based on feature values.
2. Splits: Divide data into subsets based on whether the condition is true or false.
3. Leaf Nodes: Represent final classifications or predictions.

3.3.2. Root Node

1. Condition: The root node evaluates whether Food Quality ≤ 3.5.
2. Gini Index: 0.637, indicating moderate impurity (diversity) in the data at this stage.
3. Samples: 419, the total number of data points being evaluated.
4. Value: [0.06, 0.203, 0.52, 0.217], representing the proportion of samples in each class.
   a. Class 1: 6%
   b. Class 2: 20.3%
   c. Class 3: 52%
   d. Class 4: 21.7%
5. Predicted Class: Satisfied (Class 3), as it has the highest proportion.

3.3.3. Left Branch (True Condition: Food Quality ≤ 3.5)

1. Gini Index: 0.576, indicating reduced impurity compared to the root node.
2. Samples: 339, the number of data points meeting the condition.
3. Value: [0.06, 0.196, 0.48, 0.074], showing updated class proportions:
   a. Class 1: 6%
   b. Class 2: 19.6%
   c. Class 3: 48%
   d. Class 4: 7.4%
4. Predicted Class: Satisfied (Class 3), with the highest proportion.

3.3.4. Right Branch (False Condition: Food Quality > 3.5)

1. Gini Index: 0.391, indicating lower impurity than both the root node and the left branch.
2. Samples: 80, the number of data points not meeting the condition.
3. Value: [0.0, 0.007, 0.041, 0.143], showing class proportions:
   a. Class 1: 0%

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  b. Class 2: 0.7%
  c. Class 3: 4.1%
  d. Class 4: 14.3%
4. Predicted Class: Very Satisfied (Class 4), with the highest proportion.

3.3.5. Key Insights

1. Food Quality as a Primary Factor:
   a. The decision tree demonstrates that Food Quality is a significant factor in predicting satisfaction levels. The initial split is based entirely on this feature.
   b. Lower food quality (≤ 3.5) is associated with the majority of samples being classified as Satisfied (Class 3).
   c. Higher food quality (> 3.5) leads to a higher likelihood of being classified as Very Satisfied (Class 4).
2. Class Distribution and Gini Index:
   a. The Gini Index decreases as the tree progresses, indicating that the subsets become purer (i.e., more homogeneous in class distribution).
   b. The right branch (False condition) has the lowest Gini Index, showing that it is the most confident prediction in this tree.
3. Predicted Classes:

The model predicts Satisfied (Class 3) for most samples, but when food quality is higher, the likelihood of predicting Very Satisfied (Class 4) increases significantly.

3.3.6. Implications

1. For Business or Decision-Makers:
   a. Improving Food Quality beyond a threshold (e.g., > 3.5) is likely to increase customer satisfaction levels significantly.
   b. Customers with lower satisfaction levels may primarily stem from perceptions of lower food quality, indicating an area for improvement.
2. For Model Optimization:
   a. The decision tree provides a simple yet interpretable structure for understanding how individual features influence predictions.
   b. The purity of the right branch suggests that Food Quality is a reliable predictor for identifying highly satisfied customers.
3. For Further Analysis:
   a. Additional trees in the AdaBoost model will refine these predictions, combining multiple weak learners to reduce overall error.
   b. Evaluating other features (e.g., Service Quality, Cleanliness) in similar trees could provide a more comprehensive understanding of customer satisfaction.

4. Conclusion

Evaluating service quality metrics using the AdaBoost classifier at Restaurant X has proven to be an effective approach in identifying key factors that influence customer satisfaction. By applying this advanced machine learning technique, the restaurant is able to gain deeper insights into the complex relationships between various service quality attributes, such as wait time, food quality, staff behavior, and ambiance. AdaBoost's strength lies in its ability to combine the predictions of multiple weak classifiers to create a robust model that delivers more accurate and reliable results. This is particularly beneficial in understanding the intricate patterns in customer feedback and operational data, allowing Restaurant X to identify areas of improvement with greater precision.

Moreover, the implementation of this evaluation model allows Restaurant X to make data-driven decisions aimed at enhancing the overall customer experience. With a clearer understanding of which service quality metrics most strongly correlate with customer satisfaction, management can prioritize improvements in key areas such as staff training, service efficiency, and customer engagement. By addressing these aspects, the restaurant can not only improve its service delivery but also foster customer loyalty and positive word-of-mouth. In a competitive food service industry, utilizing the AdaBoost classifier for evaluating service quality provides Restaurant X with a strategic

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advantage, enabling it to stay ahead of customer expectations and continuously adapt to evolving market demands.

5. Suggestion

To further enhance the evaluation of service quality at Restaurant X, it is recommended to incorporate additional data sources, such as real-time customer feedback, sentiment analysis from social media platforms, and even customer reviews from online sites like Yelp or Google Reviews, into the AdaBoost model. By integrating these dynamic and diverse data points, the restaurant can develop a more comprehensive understanding of customer perceptions, allowing for the identification of emerging trends and areas that may require immediate attention. Additionally, gathering data from various channels such as in-person surveys, mobile app interactions, and post-visit feedback forms can help paint a more accurate picture of the customer experience. Furthermore, periodic retraining of the AdaBoost model with updated and more granular data will ensure that the classifier remains accurate and relevant as customer preferences, behaviors, and industry standards evolve. This approach not only enhances the predictive capabilities of the model but also allows Restaurant X to remain proactive in addressing potential service quality issues. By consistently adapting to customer needs and feedback, the restaurant can build stronger relationships with its clientele, foster greater customer loyalty, and maintain a competitive edge in the rapidly changing food service industry. This continuous improvement strategy will ultimately contribute to sustained high levels of customer satisfaction and long-term business success.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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