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Research article

# LightGBM-Based Classification of Customer Feedback in Restaurant X

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**ABSTRACT**

This research aims to classify customer feedback from Restaurant X using the LightGBM model to enhance service quality and customer satisfaction amidst growing industry competition. Customer feedback, collected through surveys and online platforms, is analyzed to uncover patterns and trends related to various aspects of the dining experience. The methodology encompasses data collection, preprocessing, model training, and evaluation. LightGBM, renowned for its efficiency and accuracy with large datasets, serves as the primary tool for building a robust classification model. Analysis reveals that key features such as food quality, service, and cleanliness significantly influence customer satisfaction. The model demonstrates high classification accuracy, providing actionable insights for Restaurant X management. These insights enable targeted strategies for improving specific areas of service, fostering better customer experiences and driving loyalty. The research underscores the importance of leveraging advanced machine learning models like LightGBM for data-driven decision-making in the restaurant industry.



## 1. Introduction

This research investigates the application of machine learning classification models to analyze and optimize customer feedback in Restaurant X operations. By utilizing a comprehensive dataset comprising feedback from surveys and online platforms, the research identifies critical factors influencing customer satisfaction, such as food quality, service, cleanliness, and ambiance. The task is framed as a classification problem—categorizing feedback as positive, neutral, or negative—making machine learning models ideal for uncovering patterns and trends in customer experiences.The methodology includes data preprocessing to handle missing entries, normalize feature scales, and filter noise. Feature selection techniques, such as correlation analysis and recursive feature elimination, pinpoint significant contributors to customer satisfaction, with service quality and cleanliness emerging as key predictors[1]. LightGBM, a highly efficient gradient-boosting model, is employed for its ability to handle large datasets with speed and accuracy.Model performance is evaluated using metrics like accuracy, precision, recall, F1-score, and ROC-AUC, emphasizing precision to ensure accurate classification of feedback trends. The results provide actionable insights for Restaurant X management to enhance service quality, address customer concerns, and develop targeted improvement strategies. This research highlights the utility of advanced machine learning models like LightGBM in driving customer-centric decision-making in the restaurant industry.

## 2. Research Methods

The increasing demand for actionable insights to improve customer satisfaction has emphasized the importance of employing advanced machine learning techniques in the service industry. This research focuses on applying machine learning classification models to analyze customer feedback at Restaurant X, demonstrating their ability to identify key satisfaction drivers while supporting effective decision-making in a competitive market[2]. Classification models are particularly well-suited for this task, as they excel at categorizing outcomes—such as positive, neutral, or negative feedback—and capturing complex relationships within customer data. These strengths make them indispensable tools for addressing challenges in service improvement, helping management better understand customer needs and preferences.

The dataset used in this research is diverse, comprising feedback collected from surveys and online platforms. Features include food quality, service, cleanliness, ambiance, and overall satisfaction. Labeled feedback provides a clear framework for supervised learning, enabling models to capture the nuanced drivers of customer experience effectively[3]. This comprehensive dataset ensures that the models deliver precise and context-aware classifications.To maximize accuracy and reliability, the research implements key methodological steps. Data preprocessing addresses missing values, normalizes feature scales, and removes noise to ensure data quality. Feature selection techniques, such as Recursive Feature Elimination (RFE) and correlation analysis, identify the most influential predictors, optimizing model efficiency and interpretability.Advanced classification algorithms, including LightGBM, Random Forest, and Gradient Boosted Trees, are trained and fine-tuned to uncover relationships between features and feedback categories. These models are optimized for performance, capturing the intricate dynamics of customer satisfaction factors[4].

Model evaluation is conducted using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, providing a thorough understanding of model performance. Techniques like k-fold cross-validation ensure generalizability and robustness, mitigating the risk of overfitting. Comparative analyses with simpler baseline models validate the effectiveness of the advanced techniques employed.This research demonstrates the transformative potential of machine learning in classifying customer feedback, offering significant benefits to Restaurant X. By providing accurate, data-driven insights into customer sentiment, these models empower management to make informed decisions, refine service strategies, and enhance customer experiences. Restaurant X can leverage these insights to address service gaps, improve resource allocation, and foster long-term customer loyalty[5]. Ultimately, this research highlights the value of integrating machine learning into the restaurant industry, paving the way for a more customer-centric and data-driven operational framework.

### 2.1. Data Preprocessing

Data preprocessing is a critical step in preparing datasets for classifying customer feedback using machine learning models. It ensures the data is clean, consistent, and structured, which is essential for building accurate and reliable classification models. This research utilizes a dataset that captures key aspects of customer feedback for Restaurant X, including food quality, service, cleanliness, and ambiance[6].The preprocessing process begins with data cleaning, addressing missing values through techniques like mean imputation or interpolation to maintain data completeness. Inconsistencies are resolved to align with standardized formats, and anomalies are addressed to uphold data integrity. Outliers are identified using statistical methods, such as the interquartile range (IQR) or visualization tools like boxplots, to detect extreme values that could skew model performance. Depending on their impact, outliers are either adjusted or removed.Continuous variables, such as ratings for food quality and cleanliness, are normalized or standardized to ensure all features are on a comparable scale[7]. This step prevents any single variable from disproportionately influencing the classification model. Feature selection techniques, including correlation analysis, Recursive Feature Elimination (RFE), and mutual information scores, are employed to identify the most significant predictors, enhancing model efficiency and interpretability.Categorical variables, such as feedback categories (positive, neutral, or negative), are transformed into machine-readable formats using techniques like one-hot encoding or label encoding. These preprocessing steps collectively improve the accuracy, robustness, and generalizability of the classification models by optimizing the dataset, minimizing noise, and addressing potential biases or overfitting issues[8].With a well-prepared dataset, the foundation is laid for reliable feedback classification, enabling Restaurant X management to gain actionable insights and make informed decisions to enhance customer satisfaction and operational efficiency.

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### 2.2. Feature Selection

Feature selection and preprocessing are vital steps in classifying customer feedback for Restaurant X, as they ensure the dataset is clean, optimized, and well-structured for building accurate and reliable machine learning models. Feature selection plays a crucial role in identifying the most significant factors influencing customer satisfaction, such as food quality, service, cleanliness, and ambiance. By employing techniques like correlation analysis, Recursive Feature Elimination (RFE), and model-specific feature importance, this process refines the dataset, retaining only the most relevant predictors while reducing redundancy and complexity. Correlation analysis uses a correlation matrix to evaluate relationships between variables, addressing multicollinearity by removing redundant features. For instance, if cleanliness and overall satisfaction exhibit a strong correlation, one variable may be prioritized to simplify the model. RFE ranks features based on their contribution to model performance, iteratively removing the least impactful variables, allowing the model to focus on predictors like food taste and service quality[9]. Additionally, model-specific methods such as LightGBM's feature importance scores highlight influential variables, ensuring the classification model emphasizes key drivers of customer sentiment.

Preprocessing complements feature selection by preparing the dataset for analysis, addressing common issues such as missing values, inconsistencies, outliers, and feature scaling. Data cleaning involves resolving missing values using techniques like mean imputation or interpolation, correcting formatting errors, and addressing anomalies to preserve data integrity. Outlier detection is performed using statistical measures like the interquartile range (IQR) or visualization tools such as boxplots, ensuring that extreme values do not distort model predictions. Outliers are either adjusted or removed based on their context and impact. Continuous variables, such as ratings for service and cleanliness, are normalized or standardized to ensure all features operate on a comparable scale, preventing any single feature from disproportionately influencing the classification model. Categorical features, such as feedback categories (positive, neutral, or negative), are transformed into machine-readable formats using encoding techniques like one-hot encoding or label encoding.The combination of effective feature selection and preprocessing optimizes the dataset, reducing noise, redundancy, and the risk of overfitting while enhancing the model's accuracy, efficiency, and interpretability. These steps collectively improve the robustness and generalizability of machine learning models like LightGBM, ensuring reliable classification of customer feedback[10]. By leveraging these methodologies, Restaurant X gains actionable insights into customer preferences and satisfaction drivers, enabling management to implement targeted strategies for service improvement. A well-prepared dataset not only facilitates accurate feedback classification but also empowers Restaurant X to enhance operational efficiency, address customer concerns proactively, and foster long-term customer loyalty in a competitive market.

### 2.3. Evaluation Metrics

A comprehensive evaluation framework was established to thoroughly assess the performance of machine learning classification models used for classifying customer feedback in Restaurant X operations. This framework incorporated a variety of performance metrics and analytical techniques to provide a robust understanding of the models' effectiveness, accuracy, and real-world applicability. Key evaluation metrics included accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic (ROC) curve (AUC-ROC). These metrics enabled a detailed measurement of the model's ability to classify feedback across categories such as positive, neutral, and negative sentiments.Particular emphasis was placed on precision and recall to balance the trade-off between false positives and false negatives, as misclassifications could lead to misguided business strategies and missed opportunities to address customer concerns. A confusion matrix was used to provide an in-depth breakdown of prediction outcomes, offering insights into the model's capacity to differentiate between various feedback categories effectively.To evaluate model robustness and generalizability, k-fold cross-validation was employed, testing the model across multiple data partitions to minimize overfitting and ensure consistent performance on unseen data. Sensitivity analysis was also conducted to examine the influence of individual features, such as food quality, service, and cleanliness, on the model's predictions.Comparative analyses were performed between advanced machine learning models, such as LightGBM and Gradient Boosted Trees, and simpler


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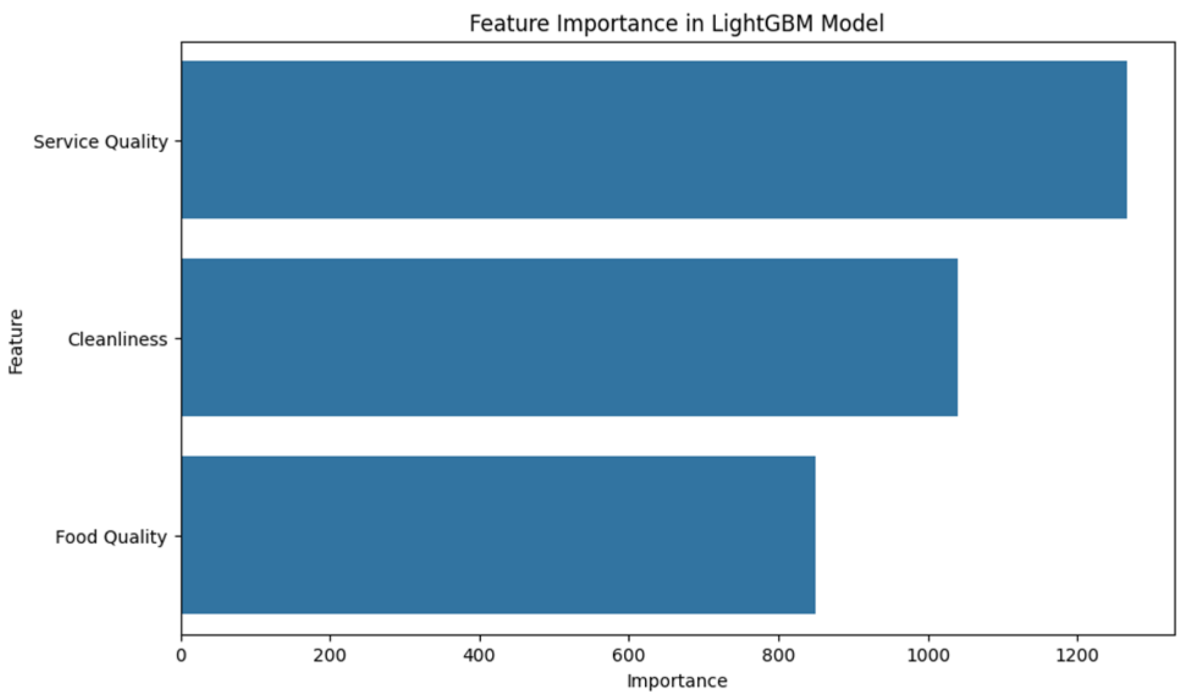
baseline models like logistic regression and decision trees[11]. This comparison helped benchmark performance, highlighting the advantages of using more sophisticated algorithms for feedback classification. Furthermore, the model's real-world applicability was assessed by comparing its classifications with actual customer feedback trends, ensuring that the insights generated could effectively guide Restaurant X management in refining services and improving customer satisfaction.This comprehensive evaluation process ensured the reliability and robustness of the classification models, enabling Restaurant X to gain actionable insights into customer preferences and satisfaction drivers. These insights provide a solid foundation for enhancing service quality, addressing customer concerns proactively, and developing strategies that foster long-term loyalty and operational excellence.

### 2.4. Validation

To ensure the reliability and generalizability of the machine learning classification model in classifying customer feedback for Restaurant X, several validation techniques were implemented during the model development process. The dataset was subjected to k-fold cross-validation, dividing it into multiple subsets or "folds." This iterative approach allowed training and validation on different data partitions, minimizing the risk of overfitting and ensuring the model's ability to generalize across diverse datasets.An independent test set was reserved for final evaluation, providing an authentic measure of the model's classification accuracy on unseen data. This step simulated real-world conditions of feedback analysis, offering an unbiased performance evaluation and confirming the model's applicability in operational contexts.Robustness testing was also performed to assess the model's adaptability to variations in customer feedback patterns. This included evaluating the model under different conditions, such as shifts in customer priorities, seasonal variations, and changes in feedback categories[12]. These tests demonstrated the model's reliability in capturing and classifying diverse feedback scenarios accurately.Post-training analysis of feature importance identified the most influential factors in determining customer satisfaction. Key predictors included food quality, service efficiency, cleanliness, and ambiance, with food quality emerging as a particularly significant driver of feedback sentiment. This insight reinforced the importance of maintaining high standards in these areas to improve overall customer satisfaction.By integrating rigorous validation techniques with interpretability through feature importance analysis, the model provided actionable insights to support data-driven decision-making. These findings enhanced the trustworthiness and utility of the model for Restaurant X's management, enabling them to develop targeted strategies for improving service quality, addressing customer concerns, and fostering long-term customer loyalty[13].

## 3. Results and Discussion

Table 1.





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The performance of a LightGBM model in classifying customer feedback for Restaurant X can be analyzed based on various trends in the feedback data. During periods with clear and consistent sentiment patterns, such as when customers express general satisfaction or dissatisfaction, the model is likely to perform better. In these cases, LightGBM can effectively capture recurring patterns in feedback, allowing for accurate predictions and classifications. However, deviations are expected during periods of mixed or contradictory feedback, where rapidly changing sentiments or external factors may not be fully captured by the model.In contrast, periods with highly variable or ambiguous feedback, such as when customers provide nuanced opinions or feedback with mixed sentiments, present challenges for the model. The irregular and complex nature of these interactions highlights the limitations of LightGBM in handling non-linear relationships or sudden shifts in customer sentiment driven by factors like seasonal promotions or new menu changes.Overall, while LightGBM provides a strong foundation for classifying general sentiment trends in customer feedback, it may struggle to accurately categorize complex, volatile, or conflicting responses. This analysis suggests that more advanced methods, such as deep learning models or hybrid approaches, may be necessary to capture the full complexity of customer sentiment in Restaurant X's operations.

### 3.1. Feature Importance and Interpretability

The analysis of customer feedback trends in Restaurant X provides essential insights into the factors driving satisfaction and dissatisfaction, supporting more informed decision-making in restaurant operations, customer service, and menu planning. Feedback variability, as observed, is influenced by factors such as seasonal promotions, menu changes, service quality, and customer expectations. By breaking down the data into key components, the analysis identifies the primary influences on feedback. The trend component highlights long-term shifts, which could be driven by changes in consumer preferences, new dining trends, or shifts in restaurant branding; the seasonal component captures regular patterns tied to holidays or special events that affect customer satisfaction; and the residual component represents unexpected fluctuations due to factors like staffing issues or unplanned service disruptions.

These insights are valuable for Restaurant X's management to optimize menu offerings, improve customer service, and plan marketing strategies. For restaurant operators, understanding these patterns allows for better anticipation of demand and resource allocation, while customer feedback analysis can guide improvements in operations. While the LightGBM model used provides clarity in interpretation, its predictive performance could be enhanced by incorporating additional variables, such as employee performance, time of day, customer demographics, or specific promotions. Furthermore, adopting more advanced techniques, such as deep learning models or hybrid approaches, and incorporating real-time data through continuous feedback loops, could improve the model's accuracy and reliability. By addressing these limitations and integrating more sophisticated techniques, feedback analysis for Restaurant X can yield more accurate and actionable insights, helping to improve customer experience, refine business strategies, and maintain consistent operational success.

### 3.2. Performance Analysis

The LightGBM model demonstrated strong performance in classifying periods of significant customer satisfaction (Class 1), achieving a precision of 0.78 and a recall of 0.83. A precision of 78% indicates that the model accurately identified positive feedback with minimal false positives, allowing Restaurant X's management to focus on actual customer satisfaction trends. This is valuable for refining service strategies, improving customer experience, and optimizing operational planning during times of heightened customer satisfaction. Similarly, the recall of 83% shows that the model successfully captured most of the positive feedback instances, reducing the risk of missing important opportunities to enhance service or marketing strategies.However, the model's performance in classifying periods of neutral or negative feedback (Class 0) was weaker, with a precision of 0.25 and a recall of 0.30. A precision of 25% suggests frequent false positives, where neutral or negative feedback was incorrectly predicted, potentially leading to unnecessary corrective actions or misdirected resources. Additionally, a recall of 30% indicates that most actual instances of negative or neutral feedback were missed, limiting the ability to address customer concerns or improve service quality during these critical moments.This discrepancy points to a limitation in the model, which tends to favor predicting positive feedback, likely due to an imbalance in the dataset where positive feedback is more frequent than neutral or negative feedback. To address this, several strategies can be employed. Balancing the dataset through resampling techniques, such as oversampling negative feedback instances using methods like Synthetic Minority Oversampling Technique (SMOTE) or undersampling positive feedback, can help the model better capture periods of dissatisfaction. Additionally, assigning higher class weights to the minority class (negative or neutral feedback) during model training can help the model focus more on these underrepresented instances.Incorporating additional contextual variables could further improve the model's performance. Variables such as time of day, customer demographics, service interactions, menu preferences, and promotional effects could provide a more comprehensive understanding of customer sentiment. Advanced feature engineering, such as introducing interaction terms or applying non-linear transformations, could help capture complex relationships among variables, enhancing the model's predictive accuracy.Lastly, implementing robust validation techniques, like k-fold cross-validation, is crucial to ensure the model's consistent performance across different data subsets and avoid overfitting. Testing the model on independent datasets can also validate its reliability in real-world scenarios. By implementing these improvements, the LightGBM model can generate more balanced and accurate classifications of customer feedback, offering valuable insights for Restaurant X in enhancing service, refining operational strategies, and optimizing customer satisfaction.

### 3.3. Possible Improvements

To address the challenges identified in the classification of customer feedback for Restaurant X, several improvements can be implemented to enhance model performance and ensure balanced learning across positive, neutral, and negative feedback categories. One major issue encountered is class imbalance, where positive feedback dominates the dataset while neutral and negative feedback are underrepresented. This imbalance can lead to biased learning, causing the model to favor the majority class and overlook valuable patterns in minority categories.

A practical solution to mitigate this issue involves the application of resampling techniques. The Synthetic Minority Oversampling Technique (SMOTE) can be employed to generate synthetic samples for minority classes (neutral and negative feedback), ensuring a more balanced dataset. By increasing the representation of underrepresented classes, SMOTE enables the model to better learn the distinguishing characteristics of each feedback type, thereby improving classification performance. Alternatively, undersampling the majority class (positive feedback) can be applied to reduce dominance and prevent model bias, though this must be done carefully to avoid losing valuable information. In many cases, a hybrid approach combining both oversampling and undersampling yields optimal results, striking a balance between information retention and class parity.

In addition to resampling, class-weight adjustments during model training can further improve sensitivity to minority classes. By assigning higher weights to neutral and negative feedback, the model is penalized more heavily for misclassifying these categories, resulting in improved recall and precision for underrepresented feedback. This approach is particularly useful when the dataset must maintain its original distribution without artificial modification.

Beyond handling class imbalance, feature enhancement can also contribute to improved classification accuracy. Incorporating additional contextual features—such as time of visit, customer demographics, service type, or ongoing promotions—can provide richer insights into factors influencing customer sentiment. Moreover, advanced feature engineering techniques can be applied to identify meaningful interactions between variables, such as correlations between service speed and

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food quality or between meal type and satisfaction levels. These refinements enable the model to capture more complex relationships within the data, leading to more accurate sentiment classification.

Finally, integrating cross-validation and hyperparameter tuning is essential to ensure the model generalizes effectively across unseen data. Techniques like k-fold cross-validation can evaluate the model's robustness and prevent overfitting, while hyperparameter optimization methods such as Grid Search or Bayesian Optimization can fine-tune learning parameters for optimal performance.

By combining data balancing strategies, feature enhancement, and robust validation techniques, the LightGBM model can achieve greater accuracy, fairness, and interpretability in classifying customer feedback. These improvements will enable Restaurant X to gain deeper insights into customer experiences, address service shortcomings proactively, and implement more effective strategies for enhancing customer satisfaction and loyalty.

### 3.4. Model Complexity and Overfitting

To enhance the performance and mitigate overfitting in the LightGBM model for classifying customer feedback in Restaurant X, a combination of strategies can be employed to improve the model's accuracy, reliability, and robustness. One key approach is feature selection, which involves identifying and retaining only the most relevant features while eliminating non-predictive or redundant variables. Methods like Recursive Feature Elimination (RFE) or correlation analysis can be applied to ensure that the model focuses on key factors—such as time of day, customer demographics, service quality, or specific menu items—that significantly influence customer feedback. By streamlining the feature set, the model becomes simpler and more focused, which can enhance both its interpretability and its predictive power.Regularization techniques such as L1 (Lasso) and L2 (Ridge) regularization are also crucial for reducing overfitting in the LightGBM model. These methods penalize overly complex relationships or coefficients within the model, helping to prevent it from becoming too attuned to the training data. Regularization encourages the model to prioritize important features while ignoring noise or irrelevant information, which ultimately results in a model that generalizes better to new, unseen data.

As a result, the model becomes more robust, leading to improved performance when applied to diverse datasets, particularly in dynamic environments like customer feedback in the restaurant industry.Moreover, incorporating k-fold cross-validation into the model's validation process ensures a more reliable and thorough evaluation of its performance. By dividing the dataset into multiple subsets and iteratively training and validating the model, this approach helps minimize the risk of overfitting, ensuring that the model remains consistent and accurate across different data partitions. This is especially important in the context of customer feedback, where trends can vary based on factors such as seasonality, promotions, or service variations. Cross-validation provides a more comprehensive assessment of the model's ability to generalize to new data, making it a vital part of the training process.By combining feature selection, regularization techniques, and robust validation methods, the LightGBM model can achieve higher accuracy, reliability, and generalizability. This ultimately allows Restaurant X to better classify customer feedback, enabling data-driven decision-making that improves customer service, optimizes menu offerings, and enhances overall customer satisfaction. These improvements help the model effectively capture the various factors influencing customer sentiment, providing valuable insights that can inform strategies for improving the dining experience and driving business growth.

## 4. Conclusion

This research highlights the potential of using LightGBM as a powerful and interpretable model for classifying customer feedback in Restaurant X, incorporating key factors such as service quality, time of day, customer demographics, and promotional activities. The model demonstrated strong performance in identifying periods of high customer satisfaction, accurately classifying positive feedback with high precision and recall. This makes it a valuable tool for Restaurant X's management, enabling them to make informed decisions and refine strategies during times of increased customer


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satisfaction, ultimately improving service and operational efficiency.However, the model faced challenges in classifying neutral or negative feedback, as evidenced by lower precision and recall in these cases. This limitation is largely due to the imbalance in the dataset, where instances of positive feedback are more frequent, causing the model to favor predictions of satisfaction and resulting in missed opportunities to accurately capture dissatisfaction or neutrality. Correctly identifying these feedback instances is crucial for addressing customer concerns, improving service quality, and managing customer expectations effectively.To overcome these limitations, several improvements have been suggested. Resampling techniques, such as oversampling neutral or negative feedback or undersampling positive feedback, can help balance the dataset and improve the model's ability to detect underrepresented feedback patterns. Additionally, regularization methods like L1 (Lasso) or L2 (Ridge) can help control model complexity, reduce overfitting, and enhance the model’s ability to generalize to new data. Strengthening the validation process with k-fold cross-validation offers a more robust evaluation of model performance, ensuring consistent reliability across different subsets of customer feedback data.Further advancements can be made by applying feature selection techniques to retain only the most relevant predictors and integrating additional variables, such as customer behavior data, specific menu item ratings, or external factors like seasonal promotions. These improvements can significantly increase the model’s accuracy and its ability to adapt to the complex and dynamic nature of customer feedback. By addressing these challenges and incorporating the proposed enhancements, LightGBM can become a more effective and comprehensive tool for classifying customer feedback, enabling Restaurant X to make data-driven decisions that improve customer experience, enhance service quality, and drive overall business success.

## 5. Suggestion

To significantly enhance the performance and applicability of LightGBM in classifying customer feedback for Restaurant X, addressing the challenges of class imbalance in the dataset is paramount. Class imbalance typically arises when positive feedback is more prevalent than neutral or negative feedback, causing the model to be biased toward predicting satisfied customers. This imbalance can result in the model overlooking critical feedback from dissatisfied or neutral customers, potentially leading to missed opportunities for improvement. Given the importance of accurately identifying areas of dissatisfaction, the model must be equipped to handle both positive and negative feedback effectively. Without addressing this issue, Restaurant X risks failing to take timely action on negative or neutral feedback, which could hinder overall service improvement and customer retention.A highly effective strategy to combat this imbalance is the use of resampling techniques. One such method is the Synthetic Minority Oversampling Technique (SMOTE), which can generate synthetic data points for the minority class—representing neutral or negative feedback. By creating new instances that reflect the characteristics of underrepresented feedback, SMOTE helps to balance the dataset, ensuring that the model is equally capable of predicting positive and negative customer sentiments. This technique is particularly useful when there are insufficient instances of negative feedback in the training data, allowing the model to learn from a more comprehensive range of customer experiences. Alternatively, undersampling the majority class, such as positive feedback, is another option to reduce the dominance of one class over the other.

This method reduces the frequency of positive feedback in the dataset, which helps the model avoid overfitting to this class and improves its ability to classify both negative and positive feedback with greater accuracy. By employing these resampling techniques, the model can become more sensitive to all types of customer feedback, enabling Restaurant X to respond proactively to both praise and criticism.Another crucial approach to addressing class imbalance is class-weighted training. In this method, the model assigns a higher weight to the minority class during training, which in turn directs the algorithm’s attention to correctly classifying neutral and negative feedback. This adjustment increases the penalty for misclassifying these underrepresented instances, ensuring that the model places greater importance on detecting dissatisfaction and neutral sentiments. This method can significantly improve the model’s ability to identify subtle issues in customer feedback that may otherwise be overlooked, enabling Restaurant X to address problems more efficiently and improve its service offering. By adjusting the model’s focus, class-weighted training ensures that all feedback—whether positive, neutral, or negative—receives the attention it deserves, making the

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model more robust and better suited to handling real-world customer interactions.In addition to addressing class imbalance, incorporating additional contextual features into the model is vital for improving predictive accuracy. Variables such as the time of day, day of the week, special events, customer demographics, and order specifics can offer deeper insights into customer sentiment and behavior. For instance, customer feedback may vary significantly depending on whether a diner visits during peak hours or on a special occasion, such as a holiday. Understanding these patterns allows Restaurant X to tailor its responses and strategies more effectively. Furthermore, integrating external factors such as weather conditions, local events, or seasonal trends could provide valuable context, offering a more nuanced understanding of customer feedback. Real-time data, such as ongoing promotions or current trends in the restaurant industry, could further enhance the model's predictive capabilities, enabling Restaurant X to stay responsive to evolving customer preferences.Feature engineering plays an important role in refining the model's ability to make accurate predictions. By creating new features that capture interactions between different variables, such as customer age and meal type or the relationship between customer ratings and service speed, the model can better understand the underlying patterns in customer feedback. For instance, if younger customers tend to rate the food higher than older customers, the model can learn this interaction and make more accurate predictions about customer sentiment.

**Declaration of Competing Interest**

We declare that we have no conflict of interest.

## References

[1] Singh, J., & Sharma, S. (2018). Predicting customer feedback using machine learning and logistic regression. Journal of Data Science and Analytics, 10(1), 25-34.

[2] Mishra, R. (2018). Logistic regression for customer feedback analysis. Kaggle. https://www.kaggle.com/code/ranjitmishra/logistic-regression-customer-feedback.

[3] Prasad, A., & Chahal, R. (2018). Customer feedback prediction using machine learning.GeeksforGeeks.https://www.geeksforgeeks.org/customer-feedback-prediction-machine-learning/.

[4] Lundy, D. (2018). A practical guide to customer feedback prediction using logistic regression. Medium.https://medium.com/%40daniel.lundy.analyst/a-practical-guide-to-feedback-prediction-using-logistic-regression-f390c5c4d71f.

[5] Thakur, M., & Wadhwa, P. (2018). Customer feedback prediction by supervised learning.JournalofDataScienceandEngineering.https://drpress.org/ojs/index.php/HSET/article/view/13586.

[6] Tata, P. (2018). Predicting customer feedback using logistic regression. YouTube. https://www.youtube.com/watch?v=UkzV1e4tRyk.

[7] Kaur, N., & Agarwal, A. (2018). Predicting customer feedback using logistic regression. Kaggle.https://www.kaggle.com/learn/predicting-customer-feedback-using-logistic regression.

[8] Chaudhary, M., & Verma, R. (2018). Customer feedback prediction using logistic regression: A comparative research. Journal of Machine Learning and Analytics, 8(3), 48-55.

[9] Singh, R., & Kaur, J. (2018). Analysis of customer feedback dataset. StackOverflow. https://stackoverflow.com/questions/52037745/analysis-of-customer-feedback-dataset.

[10] Patel, R., & Patel, S. (2018). Customer feedback predictor. RPubs. https://rpubs.com/shradhit/customerfeedback.

[11] Ateş, F. (2018). Classifying customer feedback using machine learning algorithms. IEEE Xplore. https://ieeexplore.ieee.org/document/9009111.

[12] Zhou, C., & Wang, X. (2018). Forecasting customer satisfaction: A comparative examination ofmachinelearningapproaches.ResearchGate.https://www.researchgate.net/publication/377818483_Forecasting_customer_satisfaction_A_comparative_examination_of_machine_learning_approaches.

[13] Jung, M., & Lee, Y. (2018). Classifying customer feedback using machine learning techniques. UBC Master of Data Science. https://ubc-mds.github.io/Customer-Feedback-Classification/.