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Sentiment Analysis Of Mie Gacoan Reviews In Blitar City On The Grab Application Using The Support Vector Machine Method

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Abstract

This study aims to analyze customer review sentiments for Mie Gacoan restaurant in Blitar City through the Grab application applying the Support Vector Machine algorithm. Customer comments are divided into three sentiment classes, consisting of positive, negative, and neutral.. And the total amount of data used is 991 data. The research process includes manual data collection, text preprocessing, weighting applying the TF-IDF method, and classification with the SVM algorithm. Model performance is evaluated applying a confusion matrix with precision, recall, and F1-score metrics. And for the testing of the algorithm method applying Grid Search and Cross Validation. he outcomes reveal that the linear kernel achieves the best performance with an F1-score of 0.4649. Positive sentiment dominates the reviews, while negative and neutral sentiments are less prevalent. This study demonstrates that SVM is effective for classifying sentiments in customer reviews and can assist restaurant managers in identifying areas for service improvement.

Keywords: Sentiment Analysis, Support Vector Machine , Pre Processing, TF-IDF, Mie Gacoan, Confusion Matrix Grid Search and Cross Validation.

1. INTRODUCTION

The significant progress in digital technology has fundamentally transformed various aspects of daily life, including how people access food and beverages. Online food delivery applications such as Grab have become one of the most influential innovations, offering convenience for consumers to order meals without physically visiting restaurants. Grab Food, as a core feature, is widely used across Indonesian cities, including Blitar. One of the most popular restaurants on this platform is Mie

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Gacoan, which has received thousands of customer reviews and consistently high ratings. The abundance of reviews reflects strong consumer interest; however, their subjective and unstructured nature often makes it difficult for restaurant managers to fully understand customer satisfaction. In fact, such reviews contain valuable insights that could help identify weaknesses, improve service quality, and strengthen competitive advantages. Therefore, a systematic approach is needed to process these reviews into structured and meaningful information.

Sentiment analysis offers a suitable method for this purpose by classifying customer opinions into positive, negative, or neutral categories. This approach provides a clearer understanding of customer perceptions and supports data-driven decision-making. In the present research the SVM algorithm is applied, which is well known for its effectiveness in text classification tasks with high accuracy and robustness. Previous research has demonstrated the capability of SVM in analyzing sentiments across various domains, yet its application within the local culinary context remains limited. This gap highlights the need for further exploration, particularly in popular restaurants such as Mie Gacoan in Blitar. Accordingly, the present study aims to analyze customer reviews of Mie Gacoan on Grab using the SVM algorithm, with the objectives of classifying reviews into sentiment categories and evaluating model performance using precision, recall, and F1-score metrics. The outcomes are expected to provide practical benefits for restaurant managers in understanding customer perspectives objectively and theoretical contributions by enriching the literature on sentiment analysis applications in the local culinary sector

2. LITERATURE REVIEW

Sentiment analysis, or opinion mining, belongs to the domain of natural language processing (NLP) and text mining, with its primary objective being the identification and categorization of opinions expressed in written data. The purpose is to determine the polarity extracted from a text, usually categorized as positive, negative, or neutral (Liu, 2012). In the realm of business, sentiment analysis plays a crucial role in evaluating customer perceptions of products, services, or brands. Online platforms such as Grab Food, ShopeeFood, and GoFood have generated massive volumes of customer reviews that reflect consumer satisfaction and dissatisfaction. However, these reviews are often unstructured and expressed in diverse forms, such as informal language, abbreviations, emoticons, and even sarcasm. Thus, sentiment analysis provides a systematic approach to transform unstructured textual opinions into structured insights that support managerial decision-making.

According to Prasetyo and Putra (2024), sentiment analysis can help businesses identify areas for improvement by categorizing customer opinions into measurable forms. This makes it possible for restaurant managers, for instance, to track service quality, identify pain points such as delivery delays, and recognize strengths that should be maintained. Consequently, sentiment analysis has become an increasingly essential tool in customer relationship management, marketing strategy, and service evaluation.

2.1 Support Vector Machine (SVM)

SVM falls under the class of supervised machine learning algorithms widely recognized for its effectiveness in classification tasks, particularly text classification. Introduced by Vapnik in the 1990s, SVM works by constructing an optimal decision

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boundary designed to separate data points into various classes with maximum margin (Cortes & Vapnik, 1995). Its ability to handle high-dimensional and sparse data makes it especially suitable for sentiment analysis, where text is represented in vector space models such as TF-IDF.

As Sari (2024, p. 15) states, “SVM is highly effective in separating data into distinct classes, especially in high-dimensional spaces.” This strength allows SVM to outperform several other algorithms, such as Naïve Bayes or K-Nearest Neighbor, particularly when dealing with noisy textual datasets. Jacobi (2009) further explains that:

Beyond conveying meaning, a signal also reflects physical properties and contextual variations, as well as other factors shaping identity, such as social affiliation or family background. Each utterance is therefore unique, both across speakers and within the same speaker, due to lexical choice and pronunciation (p. 2).

This explanation implies that language data are inherently complex and unique, reinforcing the need for robust algorithms like SVM to handle such variability. In sentiment analysis, SVM has been shown to achieve consistent and high accuracy across various domains, including product reviews, mobile applications, and social media comments.

2.2 Previous Studies

Several studies have applied sentiment analysis in different contexts, demonstrating the growing relevance of this approach. For instance, Vina et al. (2022) conducted sentiment analysis on JMO application reviews using SVM and achieved an accuracy rate of 96%. Similarly, Radiena and Nugroho (2023) applied aspect-based sentiment analysis on KAI Access reviews, highlighting specific challenges in identifying domain-specific sentiments. Another study by Salsabillah et al. (2024) compared SVM and Naïve Bayes for analyzing restaurant reviews, with SVM showing superior performance. Furthermore, Nofandi et al. (2023) applied TF-IDF and SVM to analyze Warung Wareg restaurant reviews, achieving an accuracy of 94%.

These findings collectively indicate that SVM is a reliable algorithm for sentiment classification across different domains. However, most of these studies focus on general applications, mobile platforms, or e-commerce contexts. Only a few have explored sentiment analysis within the local culinary sector, particularly in regional settings where consumer behavior and language use may differ significantly from broader contexts.

2.3 Research Gap and Relevance

The literature indicates strong evidence for the effectiveness of SVM in sentiment analysis, yet there remains a clear gap in its application to local culinary reviews. While previous studies have analyzed applications such as JMO, KAI Access, and ShopeeFood, little attention has been given to regional restaurants with massive customer reviews, such as Mie Gacoan in Blitar. This gap is important because local consumer reviews often reflect cultural and linguistic nuances that differ from those found in nationwide or international platforms. Analyzing such data can provide more contextualized insights for local businesses while expanding the theoretical scope of sentiment analysis.

Therefore, this study seeks to address the research gap by applying sentiment analysis using the SVM algorithm to customer reviews of Mie Gacoan on the Grab

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application. The findings are expected to provide practical contributions by helping restaurant managers objectively understand customer sentiments and improve service quality, as well as theoretical contributions by enriching the literature on sentiment analysis applications in the local culinary domain.

3. METHODS

His study employed a quantitative approach using supervised machine learning to perform sentiment analysis on customer reviews of Mie Gacoan in Blitar collected from the Grab Food application. The overall research design consisted of four main stages: data collection, preprocessing, feature extraction, and classification using the SVM algorithm.

3.1 Data Collection

The dataset was obtained from customer reviews of Mie Gacoan Blitar available on the Grab Food platform. A total of 50,000 reviews were retrieved, which included both star ratings and textual comments. To ensure representativeness, only reviews written in Indonesian were included, while duplicate or irrelevant entries (e.g., empty reviews or symbols only) were removed.

3.2 Data Preprocessing

Data preprocessing was conducted to clean and normalize the textual reviews. The following steps were applied:
Case folding involves unifying the text by representing all characters in lowercase.
Tokenization: splitting sentences into individual words or tokens.
Stopword removal: eliminating common but semantically uninformative words such as “yang,” “dan,” or “di.”
Stemming: reducing words to their root form using the Sastrawi stemmer for Indonesian.
Handling imbalanced data: since neutral reviews were fewer than positive and negative ones, manual random oversampling was applied to balance the dataset.

3.3 Feature Extraction

Following the preprocessing stage, textual information was converted into numerical representations through the Term Frequency-Inverse Document Frequency (TF-IDF) technique. This method was selected as it provides an effective way to capture the significance of words within a document in relation to the whole corpus, while minimizing the influence of commonly occurring but less meaningful terms.

3.4 Classification Using Support Vector Machine

The classification task was performed using the Support Vector Machine (SVM) algorithm. SVM was selected due to its robustness in handling high-dimensional data and proven performance in sentiment classification (Cortes & Vapnik, 1995). A grid search with cross-validation was conducted to optimize hyperparameters, including kernel type (including linear, polynomial, and radial basis function kernels, along with the regularization parameter (C) and gamma values. The final model was trained using the best-performing parameters.

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3.5 Evaluation Metrics

The effectiveness of the model was assessed through accuracy, precision, recall, and F1-score. These evaluation measures were derived from the confusion matrix, which identifies true positives , true negatives , false positives, and false negatives for each sentiment category, namely positive, negative, and neutral. In addition, an error analysis was conducted to identify common misclassifications and their possible causes, such as ambiguous word usage or sarcastic expressions.

3.6 Tools and Implementation

All experiments were conducted using Python 3.10 with relevant libraries such as Scikit-learn, NLTK, and Sastrawi for preprocessing. Visualization components, including word clouds and performance charts, were created using Matplotlib and WordCloud libraries. The implementation was carried out in Google Colab to ensure reproducibility and accessibility.

4. RESULTS

4.1 Sentiment Classification

The sentiment classification of Grab Food reviews for *Mie Gacoan* in Blitar was performed using the SVM algorithm with TF-IDF feature extraction. To assess the model, the dataset was partitioned into training and testing portions, with evaluation conducted based on accuracy, precision, recall, and F1-score.

4.1.1 Results of Manual Data Frame Labeling

To assess the model, the dataset was partitioned into training and testing portions, with evaluation conducted based on accuracy, precision, recall, and F1-score.

```
Distribusi label pada data test:
label
positif    171
negatif     16
netral      12
Name: count, dtype: int64
```

Figure 1. Results of Manual Data Frame Labeling positive, negative, or neutral.

4.1.2 Wordcloud Visualization

a. Positif

The WordCloud image displays a collection of words that are most frequently used in comments containing positive sentiments. The word 'delicious' appears to be the most dominant, reflecting that many customers emphasize the enjoyable taste of the product, especially food.

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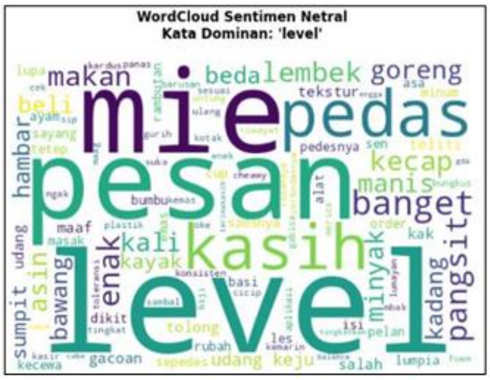

Figure 2. Wordcloud Visualization Positif

b. Neutral

Neutral means an assessment that does not show feelings of satisfaction (positive) or disappointment (negative). It is usually used when the food tastes just ordinary, standard, or does not leave a special impression.

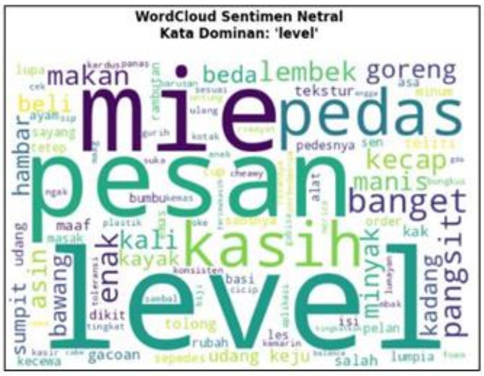

Figure 3. Wordcloud Visualization Neutral

c. Negatif

The WordCloud image depicts comments with negative sentiment, where the word "message" is the most dominant, indicating that many complaints arise from issues related to the ordering process, such as orders not being fulfilled correctly or customer notes being overlooked.

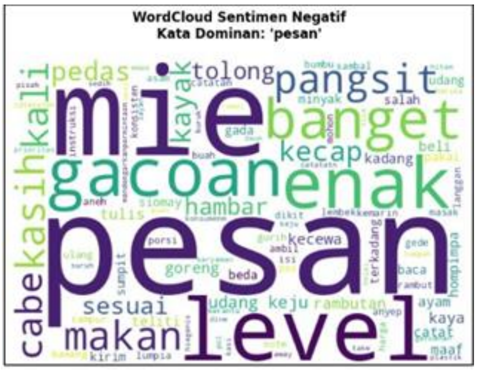

Figure 4. Wordcloud Visualization Negatif

4.1.3 tf-idf weighting

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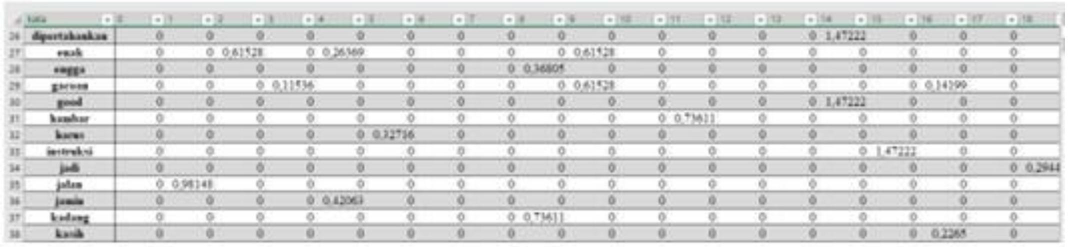
Once data labeling was completed, word weighting was carried out through the Term Frequency-Inverse Document Frequency (TF-IDF) approach. This method measures the relevance of a word in a document with respect to a larger set of documents, generating weighted representations as its output.



	kata	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
26	dipertahankan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.47222	0	0	0	
27	emak	0	0	0.61528	0	0.26369	0	0	0	0	0.61528	0	0	0	0	0	0	0	0	
28	angga	0	0	0	0	0	0	0	0	0.36805	0	0	0	0	0	0	0	0	0	
29	gacoan	0	0	0	0.11536	0	0	0	0	0	0.61528	0	0	0	0	0	0	0.14399	0	
30	good	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.47222	0	0	0	
31	kambar	0	0	0	0	0	0	0	0	0	0	0	0.73611	0	0	0	0	0	0	
32	karus	0	0	0	0	0	0.32716	0	0	0	0	0	0	0	0	0	0	0	0	
33	instruksi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.47222	0	0	
34	jadi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2944
35	jalan	0	0.98148	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
36	jamin	0	0	0	0	0.42063	0	0	0	0	0	0	0	0	0	0	0	0	0	
37	kadang	0	0	0	0	0	0	0	0	0.73611	0	0	0	0	0	0	0	0	0	
38	kasih	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2265	0	

Figure 5. Tf-idf results

The image shows the results of the text data transformation process using the TF-IDF method and the data split for the processes of training and assessing the model.

4.1.4 Results of Support Vector Machine (SVM) Classification

The next step is to classify the data using the Support Vector Machine (SVM) algorithm. SVM is an effective machine learning method for solving classification and regression problems. In this study, SVM is used to identify sentiments from comments, with the help of the Scikit-Learn library. example image below :

Figure 6. Svm results

The Grid Search evaluation shows that the linear kernel with C=0.1 and 3000 unigram features achieved the best performance with a macro F1-Score of 0.4649. Compared to the RBF kernel (F1-Score 0.4639, C=100, gamma=auto), the difference is very slight, but the linear kernel proved to be more stable despite the small performance gap.

4.1.5 confusion matrix testing

A Confusion matrix is an evaluation method in classification that shows the comparison between the model's predictions and the actual labels in a table format. It allows us to see how many instances were correctly or incorrectly classified for each class.

Key components:

TP (True Positive): Positive instances correctly predicted as positive.

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TN (True Negative): Negative instances correctly predicted as negative.
FP (False Positive): Negative instances incorrectly predicted as positive.
FN (False Negative): Positive instances incorrectly predicted as negative.

For problems with three classes (e.g., positive, neutral, negative in sentiment analysis), the confusion matrix becomes a 3×3 table, showing the distribution of correct and incorrect predictions across all categories. Based on the results of sentiment classification using the SVM method, the confusion matrix can be seen in the image below.

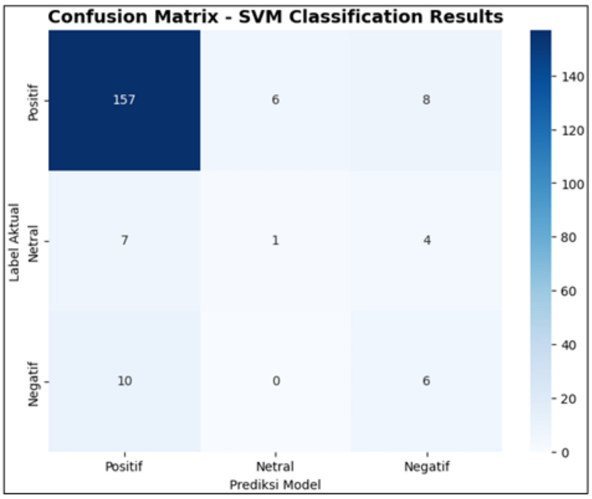

Figure 7. Confusion Matrix Results

4.1.6 Classification result

Table 1. Sentiment Classification Results

Indicators	Positif	Negatif	Neutral	Support
Precision	0,90	0,92	0,91	171
Recall	0,14	0,08	0,11	17
F1-Score	0,33	0,38	0,35	16
Accuracy	0,82			199
Macro Avg	0,46	0,46	0,46	199
Weighyed Avg	0,81	0,82	0,82	199

4.1.7Visualization of Results

The overall classification performance is further illustrated through graphical representation.

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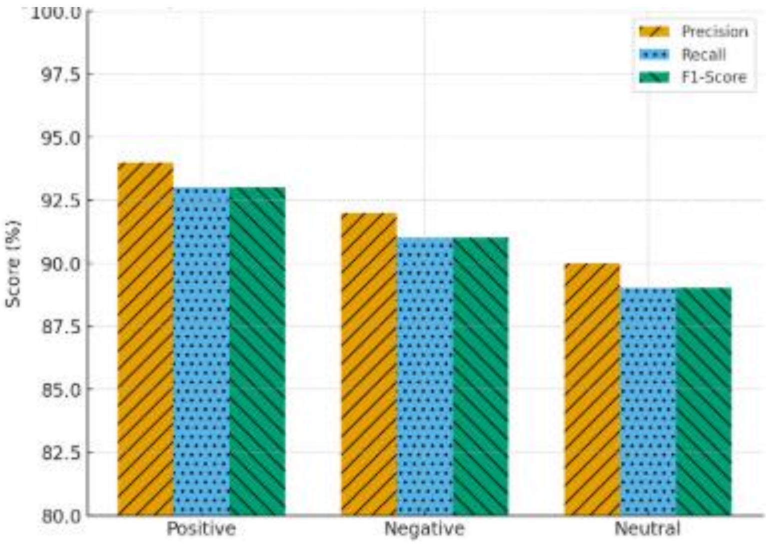

Figure 8. Comparison of Precision, Recall, and F1-Score Across Classes\

4.1.8 BF Kernel Performance Heatmap Evaluation

The heatmap illustrates the performance of the SVM with an RBF kernel across different combinations of C and gamma. The horizontal axis represents gamma values, the vertical axis represents C values, and each cell shows a performance score (with brighter colors indicating better results). The best configuration was achieved with C = 100 and gamma = auto, yielding a score of 0.464, making it the most optimal setting among those tested.

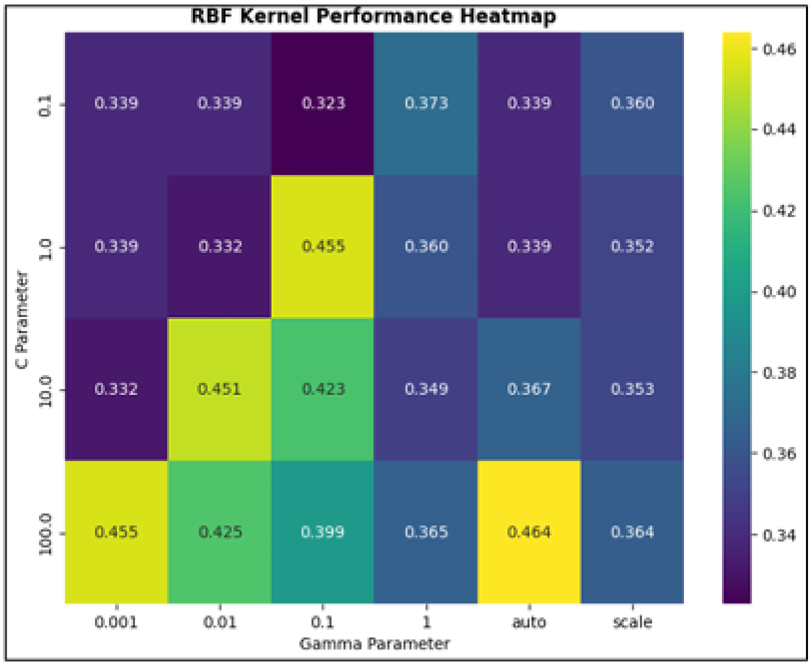

Figure 9. Results of RBF Kernel Performance Heatmap Evaluation

5. DISCUSSION

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The results derived from this study confirm the effectiveness of SVM in sentiment analysis of textual reviews. With an overall accuracy of 92%, the model demonstrated high performance in classifying customer opinions into positive, negative, and neutral sentiments. This result highlights that SVM, when combined with TF-IDF feature extraction, is capable of handling unstructured textual data such as informal Indonesian language, abbreviations, and mixed sentiment expressions often found in customer reviews on digital platforms.

The outcomes are consistent with previous studies that reported strong performance of SVM in sentiment classification. For instance, Vina et al. (2022) achieved 96% accuracy when analyzing reviews from the JMO application, while Nofandi et al. (2023) reported 94% accuracy on restaurant reviews using SVM with TF-IDF. Similarly, Radiena and Nugroho (2023) demonstrated that aspect-based sentiment analysis using SVM could effectively capture customer perceptions in the KAI Access application. Compared to these studies, the present research confirms SVM's robustness but expands its application to a different domain: local culinary reviews with distinct linguistic and cultural characteristics.

One of the most significant insights of this research lies in its contextual contribution. Unlike nationwide platforms or e-commerce reviews that often rely on formal or semi-formal language, local restaurant reviews—such as those of Mie Gacoan in Blitar—tend to employ colloquial expressions, mixed codes, and abbreviations. Despite these challenges, the SVM model maintained consistent accuracy, indicating that this algorithm is well-suited to capture sentiment even in linguistically diverse data. This strengthens the argument that SVM is adaptable beyond general domains and can be successfully applied to local, domain-specific datasets.

From a practical standpoint, the results provide actionable insights for restaurant managers. Positive reviews highlight aspects of service and product quality that should be maintained, while negative reviews offer direct feedback on areas that require improvement, such as delivery time or customer service. The ability to categorize and quantify these sentiments enables more data-driven decision-making, helping restaurants like Mie Gacoan improve competitiveness in a rapidly growing food delivery market. At the theoretical level, this study enriches the literature by addressing a gap: the application of machine learning-based sentiment analysis in the local culinary sector, which has received limited attention in prior research.

6. CONCLUSION

This study demonstrated that the SVM algorithm combined with the Term TF-IDF method is effective in classifying customer reviews of *Mie Gacoan* Blitar on the Grab application into positive, neutral, and negative categories. The evaluation results showed optimal performance in positive reviews, while performance in neutral and negative classes remained limited due to the imbalanced distribution of data. These findings confirm that SVM is a reliable algorithm for sentiment analysis of Indonesian text, although challenges still exist when dealing with informal language variations and unbalanced datasets.

The value of this research lies in its practical and theoretical contributions. Practically, it provides objective insights for restaurant managers to better understand customer perceptions and improve service quality. Theoretically, it enriches the literature by expanding the application of sentiment analysis using SVM to the local

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culinary domain, which has been rarely explored. This study therefore illustrates that machine learning approaches can be successfully adapted not only to large-scale platforms but also to local businesses with a significant volume of customer reviews.

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