



## Sentiment Analysis of Mie Gacoan Pemuda Cirebon Restaurant Reviews Using Support Vector Machine

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### Abstract

The growth of digital platforms has increased the use of sentiment analysis to understand public perceptions of business services. Customer reviews on Google Maps provide valuable insights but are unstructured and linguistically diverse, requiring robust analytical methods. This study conducts sentiment analysis on reviews of Mie Gacoan Pemuda Cirebon using a Support Vector Machine (SVM) classifier. The research focuses on designing an effective text preprocessing pipeline, identifying sentiment distribution, and evaluating SVM performance. The methodology includes web scraping, manual labeling, text preprocessing, TF-IDF feature extraction, dataset splitting, model training, and evaluation using accuracy, precision, recall, and F1-score. The results show that the majority of reviews are positive, and the SVM model achieves strong performance with an accuracy of 0.82. These findings provide an objective overview of customer perceptions and demonstrate the effectiveness of SVM for Indonesian-language sentiment classification. The model can support businesses in improving service quality based on customer feedback.

**Keywords:** *sentiment analysis; Support Vector Machine; Google Maps; customer reviews; text mining.*

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### 1. Introduction

Sentiment analysis has become a crucial approach for understanding public perception through digital reviews, including those available on platforms such as Google Maps. User-generated reviews serve as a valuable data source that reflects real experiences and opinions toward various services. However, the diversity of linguistic expressions, class imbalance, and variations in text quality present significant challenges for extracting information accurately. To address these issues, machine learning methods such as Support Vector Machine (SVM) are widely adopted due to their effectiveness in handling high-dimensional textual data. The integration of feature-weighting techniques like TF-IDF has also been shown to enhance model performance in identifying sentiment patterns. Therefore, this study develops an SVM-based sentiment analysis model for Indonesian-language Google Maps reviews to provide deeper insights into public opinion and support the effective utilization of digital data.

### 2. Methods

This study employs a structured text-processing pipeline consisting of data collection, labeling, text cleaning, dataset splitting, feature extraction, model training, and performance evaluation. Google Maps review data were collected through web scraping, followed by manual labeling into three sentiment categories. Text preprocessing was then applied, including the removal of non-alphabetic characters, case folding, tokenization, stopword removal, stemming, and word normalization to improve data quality.

The dataset was divided using a stratified split to maintain balanced class distribution in both the training and testing subsets. Feature extraction was carried out using TF-IDF, enabling the reviews to be transformed into numerical vectors suitable for machine learning. These vectorized features were subsequently used to train a Support Vector Machine (SVM) model, in which kernel selection and parameter optimization were performed to achieve optimal performance.

Finally, the model's performance was evaluated using accuracy, precision, recall, and F1-score. The evaluation process was supported by a confusion matrix and a classification report to assess the model's ability to correctly predict each sentiment class.

### 3. Results and Discussion

#### 3.1 Results

The dataset used in this study consists of 2,487 Google Maps reviews of Mie Gacoan Pemuda Cirebon. Data were collected using web scraping and manually labeled into three sentiment categories: positive (1,858 reviews), negative (296 reviews), and neutral (333 reviews). Manual labeling ensured that each review accurately represented its sentiment polarity. The dataset exhibits class imbalance, with positive reviews dominating the distribution.

Text preprocessing was applied to clean and normalize the review texts, including lowercasing, removal of non-alphabetic characters, punctuation cleaning, tokenization, stopwords removal, stemming, and word normalization. This process produced standardized tokenized text that improved feature extraction and model interpretability.

The dataset was then divided using an 80:20 stratified split, resulting in 1,989 training samples and 498 test samples. Feature extraction was performed using TF-IDF with a 1–2 n-gram configuration and 10,000 maximum features, enabling the model to recognize both single-word and phrase-level sentiment patterns.

Model training was conducted using LinearSVC with class balancing to address the imbalanced dataset. The evaluation on the test set yielded an overall accuracy of 0.82. A detailed classification report shows that the model performs best on the positive class (precision 0.91, recall 0.90), while the neutral class remains challenging (precision 0.43, recall 0.37). Macro-average metrics indicate moderate performance (precision 0.67, recall 0.71, F1-score 0.69), whereas weighted-average scores remain high (all 0.82), demonstrating robustness to class imbalance. The performance of the sentiment classification model was evaluated using standard metrics, including precision, recall, and F1-score for each sentiment class. Table X presents the detailed classification results of the SVM model on the test dataset, along with the overall accuracy, macro average, and weighted average values.

Table 1: Results

Label	Precision	Recall	F1-Score	Support
Negative	0.68	0.85	0.75	59
Neutral	0.43	0.37	0.40	67
Positive	0.91	0.90	0.91	372
Accuracy	–	–	0.82	498
Macro Average	0.67	0.71	0.69	498
Weighted Average	0.82	0.82	0.82	498

As shown in Table 1, the model demonstrates strong performance in identifying positive reviews, achieving a precision of 0.91 and a recall of 0.90, which reflects the dominance of positive samples in the dataset. The negative class also shows acceptable performance with a recall of 0.85, indicating the model’s ability to correctly detect most negative instances. However, the neutral class exhibits the lowest scores across all metrics, suggesting a higher degree of ambiguity and linguistic overlap with other classes. The overall accuracy of 0.82, supported by a weighted F1-score of 0.82, indicates that the SVM model performs effectively on the dataset, despite class imbalance.

Figure 1 presents the confusion matrix generated from the sentiment classification model. This visualization is used to evaluate the model’s performance in distinguishing between the three sentiment categories negative, neutral, and positive based on the predicted and actual labels. The confusion matrix provides detailed insights into how well the model correctly identifies each class and where misclassifications occur.

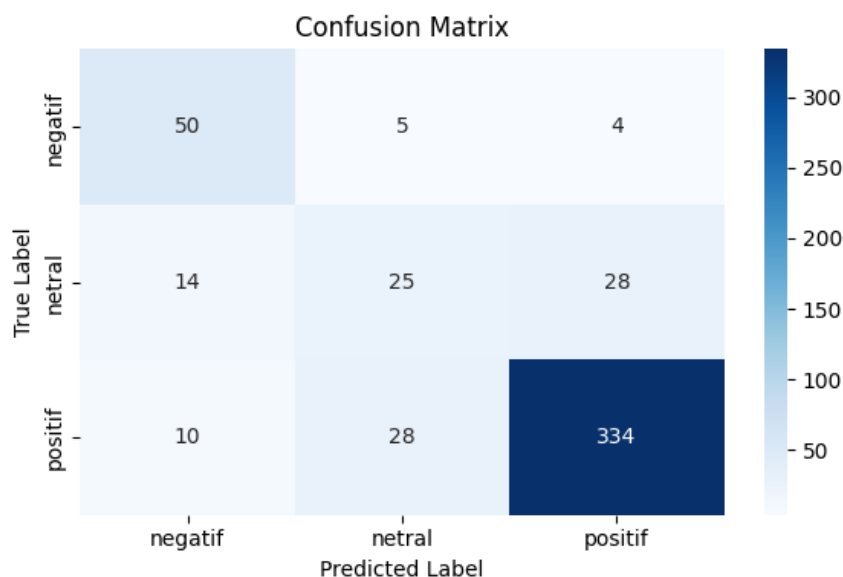


Fig. 1 : Confusion Matrix

The confusion matrix shown above illustrates the distribution of true labels versus predicted labels across the three sentiment classes.

1. **Negative class:** The model correctly classified **50** negative reviews. However, **5** negative reviews were incorrectly predicted as neutral, and **4** were misclassified as positive.
2. **Neutral class:** A total of **25** neutral reviews were correctly identified. Meanwhile, **14** neutral reviews were mistaken for negative, and **28** were predicted as positive.
3. **Positive class:** The model performed most accurately on the positive class, correctly predicting **334** positive reviews. Nevertheless, **10** positive reviews were misclassified as negative and **28** as neutral.

Overall, the matrix indicates that the model achieves strong performance on the positive sentiment category, while misclassification is more common between the negative and neutral classes. This suggests that the model may require further optimization—such as improved feature representation or class balancing—to better distinguish subtle differences between negative and neutral sentiments.

## 3.2 Discussion

### 3.2.1 Text Preprocessing

The preprocessing pipeline effectively reduced noise in the review texts by standardizing linguistic variations, handling informal Indonesian expressions, and ensuring cleaner token-level representations. This aligns with prior research emphasizing the importance of thorough preprocessing for high-quality sentiment classification, particularly in informal user-generated content. The results confirm that proper preprocessing improves TF-IDF feature stability and contributes directly to the classification performance of SVM.

### 3.2.2 Sentiment Analysis Findings

The sentiment distribution indicates that customer perception of Mie Gacoan Pemuda Cirebon is predominantly positive, driven mainly by favorable comments on taste, pricing, and service quality. Negative reviews primarily highlight issues related to cleanliness, long waiting times, and inadequate facilities, while neutral reviews provide factual descriptions without strong emotional tone. These findings are consistent with previous Google Maps sentiment studies and support document-level sentiment theory, confirming that online reviews can serve as a reliable indicator of customer satisfaction. Practically, the restaurant can use these insights to maintain strengths in taste and price while prioritizing improvements in sanitation and service efficiency.

### 3.2.3 SVM Performance

The SVM model demonstrates strong overall performance with 82% accuracy, aligning with existing literature showing SVM's effectiveness for high-dimensional textual classification. The model excels in recognizing positive sentiment due to its large representation in the dataset, but demonstrates weaker performance on the neutral class—a common challenge in sentiment classification where neutral expressions often overlap linguistically with positive or negative tones. While deep learning models such as BERT may achieve higher accuracy, SVM remains an efficient choice for medium-scale datasets and offers reliable performance with lower computational demands.

## 4. Conclusion

This study demonstrates the effectiveness of sentiment analysis using a Support Vector Machine (SVM) model to evaluate customer perceptions of Mie Gacoan Pemuda Cirebon based on Google Maps reviews. The findings highlight three key conclusions. First, the text preprocessing procedures—consisting of cleaning, normalization, and tokenization—successfully produced structured input data, supporting previous studies that emphasize the importance of preprocessing in improving model performance. Second, sentiment distribution analysis shows that the majority of customer reviews (1,858 out of 2,487) are positive, indicating high customer satisfaction and aligning with prior research stating that online reviews reliably reflect user perceptions. Third, the SVM classifier achieved strong performance with an accuracy of 0.82 and consistent precision, recall, and F1-score values, confirming its suitability for high-dimensional text classification tasks using TF-IDF representations. Overall, the study provides empirical evidence that SVM is an effective and efficient method for sentiment analysis of Indonesian-language online reviews.

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