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Customer Review Sentiment Classification of Belikopi Products Using the Support Vector Machine (SVM) Method

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Abstract

The rapid development of information technology and the widespread use of social media have significantly changed the way customers express their opinions and experiences regarding products and services. Platforms such as Instagram, TikTok, and Google Maps have become important sources of customer feedback that can be analyzed to understand public perception and customer satisfaction. Sentiment analysis is one of the text mining techniques that can automatically classify opinions into positive, neutral, and negative sentiments, enabling businesses to make informed decisions based on customer feedback. This study aims to analyze customer sentiment toward Belikopi products using the Support Vector Machine (SVM) classification algorithm. A total of 4,636 customer reviews and comments were collected from Instagram, TikTok, and Google Maps and manually labeled into three sentiment categories: positive, neutral, and negative. Before the classification process, the dataset underwent several preprocessing stages, including case folding, cleaning, tokenizing, stopword removal, and stemming to improve the quality of textual data. Furthermore, the Term Frequency–Inverse Document Frequency (TF-IDF) method was employed to convert text into numerical feature vectors suitable for machine learning classification. The dataset was divided into 80% training data and 20% testing data using a stratified sampling approach to maintain the distribution of sentiment classes. The experimental results showed that the SVM model achieved an accuracy of 93.34%, demonstrating its capability to classify customer sentiment with high performance. The findings indicate that the proposed approach is effective in identifying customer perceptions of Belikopi products and can provide valuable insights for evaluating customer satisfaction, improving product quality, and supporting strategic business decision-making.

Keywords:
Sentiment Analysis; Support Vector Machine; TF-IDF; Belikopi; Social Media.

1. INTRODUCTION

In the era of rapid digital transformation, the way consumers interact with brands has undergone a fundamental and irreversible shift. The emergence of digital platforms such as Google Maps, Instagram, TikTok, and e-commerce has created an ecosystem in which consumers can instantly and openly express their opinions. This phenomenon has generated an enormous volume of online reviews, which are increasingly recognized as one of the most valuable non-financial assets in Accounting Information Systems and Management (Caesar & Prameswara, 2026). These reviews reflect users' real experiences across various dimensions, ranging from expectations regarding product quality to post-purchase satisfaction (Harahap & Putri, 2025). However, organizations face significant challenges due to the unstructured nature and massive volume of textual data, making manual monitoring and evaluation impractical without automated analytical technologies (Utomo et al., 2025).

The Food and Beverage (F&B) industry, particularly the coffee shop sector, represents one of the most dynamic business domains in responding to public opinion on digital platforms. The intense competition between conventional coffee shops and emerging mobile coffee businesses has compelled business owners to better understand continuously evolving customer preferences. Previous studies have demonstrated that despite differences in operational business models, service quality remains the primary determinant influencing both positive and negative customer sentiment (Wulandari et al., 2026). This finding indicates that customers evaluate not only the quality of products but also service interactions, responsiveness, and the overall customer experience provided within the business ecosystem.

The capability to rapidly identify the root causes of customer dissatisfaction plays a crucial role in Customer Relationship Management (CRM) by preventing customer churn and strengthening long-term loyalty. For instance, early detection of customer complaints regarding specific menu items in family restaurants can provide management with actionable insights to implement immediate quality improvements (Nofandi et al., 2023). Furthermore, for companies that have expanded into international markets, such as Kopi Kenangan, monitoring customer sentiment on Instagram has become an essential strategy for assessing brand awareness and product acceptance in overseas markets, including Malaysia and Singapore (Rahmawati & Parmono, 2024).

The importance of sentiment analysis extends beyond the food industry into lifestyle products and digital services, where reputation and user experience significantly influence consumer decisions. In the cosmetics industry, viral products frequently generate polarized public opinions on social media, making automated sentiment classification indispensable for filtering reliable information amid the abundance of skincare products available to consumers (Harnelia, 2024). A similar phenomenon has been observed in the technology sector, where user reviews of applications such as LinkedIn on the Google Play Store serve as valuable indicators for evaluating application usability and technical performance, thereby supporting future software development and feature enhancement (Makhasinul Maarif & Setiyawati, 2024).

From a technical perspective, the effectiveness of text mining heavily depends on selecting an appropriate classification algorithm capable of producing reliable predictive performance. Among conventional machine learning approaches, Support Vector Machine (SVM) has consistently been recognized as one of the most robust algorithms for text classification due to its ability to handle high-dimensional textual data while achieving superior classification accuracy compared to Naïve Bayes (Datau et al., 2025). Nevertheless, challenges such as class imbalance and the widespread use of informal language on social media remain critical issues. Consequently, data balancing techniques, including Synthetic Minority Over-sampling Technique (SMOTE) and undersampling, are often incorporated to improve the model's capability in accurately recognizing minority sentiment classes.

Recent advancements in sentiment analysis have shifted the focus from merely classifying textual opinions toward transforming raw textual data into actionable business intelligence. The integration of Aspect-Based Sentiment Analysis (ABSA) with Business Intelligence (BI) technologies has emerged as a modern analytical approach that enables organizations to monitor customer experiences across specific product or service attributes in near real time (Aulia Siswoyo, 2026). By incorporating sentiment analysis results into interactive strategic dashboards, companies are no longer limited to passively collecting customer feedback. Instead, they can convert thousands of textual reviews into meaningful insights that support evidence-based decision-making, improve service quality, strengthen customer satisfaction, and enhance competitive advantage in increasingly dynamic global markets.

Despite the extensive application of sentiment analysis in various domains, several research gaps remain evident. Most previous studies have focused on a single digital platform, such as Twitter, YouTube, or Google Maps, limiting their ability to capture comprehensive customer perceptions across multiple communication channels. For example, sentiment analysis on GoFood services was conducted using Twitter data to compare the performance of Support Vector Machine (SVM) and Naïve Bayes classifiers, demonstrating the superiority of SVM in classification accuracy. However, the study relied solely on Twitter data, which represents only one source of customer opinion (Melati Indah Petiwi et al. (2022). Likewise, sentiment analysis on public responses to the Ice-Cold documentary utilized YouTube comments and reported that SVM outperformed Random Forest in sentiment classification, yet the analysis was restricted to a single social media platform (Salungweni, Weku, & Ketaren, 2024).

Recent studies in the coffee business have also predominantly relied on reviews collected from Google Maps and GoFood. Although these studies demonstrated that the integration of TF-IDF and SVM effectively classified customer sentiment with satisfactory performance, they were based on relatively small datasets and limited review sources, thereby restricting the generalizability of the findings (Novianto & Suharyadi, 2026).

From a methodological perspective, Support Vector Machine has consistently demonstrated robust performance in text classification tasks due to its capability to construct an optimal hyperplane that effectively separates sentiment classes in high-dimensional feature spaces. Previous comparative studies have repeatedly reported that SVM achieves higher classification accuracy than conventional machine learning algorithms, including Naïve Bayes, across diverse sentiment analysis applications (Yunita & Kamayani, 2023). The effectiveness of SVM becomes even more apparent when combined with TF-IDF feature extraction, which transforms textual documents into weighted numerical representations (Novianto & Suharyadi, 2026).

Despite the extensive application of sentiment analysis in various domains, several research gaps remain evident. Most previous studies have focused on a single digital platform, such as Twitter, YouTube, or Google Maps, limiting their ability to capture comprehensive customer perceptions across multiple communication channels. For example, sentiment analysis of GoFood services was conducted using Twitter data to compare the performance of Support Vector Machine (SVM) and Naïve Bayes classifiers. Although SVM demonstrated superior classification performance, the study relied solely on Twitter data, representing only a single source of customer opinion (Petiwi, Triayudi, & Sholihati, 2022). Likewise, sentiment analysis of public responses to the Ice-Cold documentary utilized YouTube comments and compared SVM with Random Forest, yet the analysis remained restricted to one social media platform.

Recent studies in the coffee business have also predominantly relied on customer reviews collected from Google Maps and GoFood. These studies confirmed that combining TF-IDF with SVM can effectively classify customer sentiment with satisfactory performance. However, the datasets were relatively limited and originated from only one or two review platforms, thereby reducing the comprehensiveness of customer opinion representation.

From a methodological perspective, Support Vector Machine has consistently demonstrated robust performance in text classification because of its capability to construct an optimal hyperplane that separates sentiment classes in high-dimensional feature spaces. Previous comparative studies have reported that SVM generally achieves higher classification accuracy than conventional machine learning algorithms such as Naïve Bayes in various sentiment analysis applications (Gulo & Wibowo, 2026). Furthermore, the effectiveness of SVM can be enhanced through the implementation of the Term Frequency–Inverse Document Frequency (TF-IDF) weighting scheme, which transforms textual documents into numerical feature vectors while emphasizing informative terms and reducing the influence of less significant words.

Belikopi, as one of Indonesia's rapidly growing coffee brands, has accumulated a substantial number of customer reviews across multiple digital platforms, including Google Maps, Instagram, and TikTok. These reviews contain valuable information regarding customer satisfaction, product quality, service performance, pricing, and overall customer experience. Nevertheless, the large volume and heterogeneous characteristics of these textual data make manual analysis inefficient and impractical. To date, studies investigating customer sentiment toward Belikopi by integrating reviews from multiple digital platforms remain very limited. Consequently, a comprehensive sentiment analysis framework capable of processing heterogeneous customer opinions from multiple platforms is still needed (Novianto & Suharyadi, 2026).

Therefore, this study proposes a sentiment analysis framework that integrates customer reviews from Google Maps, Instagram, and TikTok to provide a more comprehensive representation of public opinion toward Belikopi. The collected reviews undergo several Natural Language Processing (NLP) preprocessing stages before being transformed into numerical representations using the TF-IDF feature extraction method and subsequently classified using the Support Vector Machine (SVM) algorithm. The proposed framework is expected to classify customer sentiment into positive, neutral, and negative categories with high accuracy while generating valuable insights that support strategic business decision-making, improve service quality, enhance customer satisfaction, and strengthen Belikopi's competitiveness in Indonesia's increasingly competitive coffee industry.

Table 1. Summary of Previous Studies on Sentiment Analysis Using Support Vector Machine

No.	Author(s)	Research Object	Method	Main Findings	Research Gap
1	Petiwi, Triayudi, & Sholihati (2022)	GoFood customer reviews from Twitter	Naïve Bayes, SVM	SVM achieved higher accuracy than Naïve Bayes in classifying customer sentiment.	Limited to Twitter data, which represents only one social media platform.
2	Salungweni, Weku, & Ketaren (2024)	YouTube comments on the Ice-Cold documentary	Random Forest, SVM	SVM produced better classification performance than Random Forest.	The dataset consisted only of YouTube comments.
3	Novianto & Suharyadi (2026)	Coffee shop reviews from Google Maps and GoFood	TF-IDF, SVM	TF-IDF combined with SVM effectively classified customer sentiment.	Reviews were collected from only two platforms with a relatively limited dataset.
4	Datau et al. (2025)	TikTok reviews of a coffee shop	SVM	SVM successfully analyzed customer sentiment and supported digital marketing strategies.	Only TikTok reviews were analyzed, limiting customer opinion coverage.
5	Wulandari, Setiawan, &	Coffee shop and mobile coffee	Aspect-Based	Service quality was identified as the	Focused on aspect extraction rather

	Perdanakusuma (2026)	business reviews	Sentiment Analysis	dominant factor affecting customer satisfaction.	than overall sentiment classification.
6	Rahmawati & Parmono (2024)	Instagram posts of Kopi Kenangan	Sentiment Analysis	Social media sentiment was useful for measuring brand awareness in international markets.	The study emphasized brand awareness and used only Instagram data.
7	Harnelia (2024)	Skincare product reviews	SVM	SVM effectively classified customer sentiment toward cosmetic products.	The research focused on the cosmetics industry rather than food and beverage services.
8	Gulo & Wibowo (2026)	Indonesian marketplace product reviews	Naïve Bayes, SVM	SVM consistently outperformed Naïve Bayes in sentiment classification.	The object was e-commerce products rather than coffee business reviews.
9	Yunita & Kamayani (2023)	Public policy sentiment	Naïve Bayes, SVM	SVM demonstrated superior classification performance compared with Naïve Bayes.	The dataset was unrelated to customer reviews in the food and beverage industry.
10	Andriyani et al. (2024)	Product reviews	Word2Vec, SVM	Combining Word2Vec and SVM improved sentiment classification performance.	The study did not utilize multiple review platforms or TF-IDF features.
11	This Study	Belikopi customer reviews collected from Google Maps, Instagram, and TikTok (4,636 reviews)	TF-IDF + Support Vector Machine (SVM)	The proposed model achieved an overall accuracy of 93.34% with balanced precision, recall, and F1-score. The integration of three digital platforms provides a more comprehensive representation of customer opinions.	This study addresses the limitations of previous studies by integrating multi-platform customer reviews into a unified sentiment analysis framework using TF-IDF and SVM.

Table 1 summarizes previous studies related to sentiment analysis using machine learning algorithms, particularly Support Vector Machine (SVM). Most existing studies relied on customer reviews collected from a single platform, such as Twitter, YouTube, Instagram, Google Maps, or GoFood, which limited the diversity and representativeness of customer opinions. Although several studies demonstrated that SVM provides robust classification performance, they generally focused on a single review source or a relatively small dataset. In contrast, the present study integrates 4,636 customer reviews collected from Google Maps, Instagram, and TikTok into a unified sentiment analysis framework using TF-IDF feature extraction and the Support Vector Machine (SVM) algorithm. This integration enables a more comprehensive representation of customer perceptions across multiple digital platforms while maintaining reliable classification performance, thereby providing broader insights to support business decision-making.

2. RESEARCH METHOD

2.1. Research Design

This study employed a quantitative approach using text mining techniques to classify customer sentiment toward Belikopi products. The proposed framework consists of five main stages: data collection, text preprocessing, feature extraction, sentiment classification, and model evaluation. The overall research process is illustrated in Figure 1.

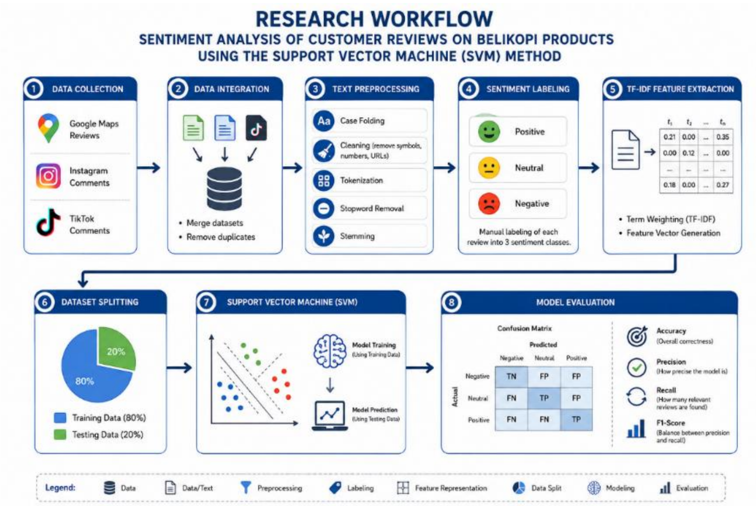

Figure 1. Research Workflow

2.2. Data Collection

The dataset used in this study consisted of customer reviews collected from three digital platforms: Google Maps, Instagram, and TikTok. These platforms were selected because they represent the primary channels through which customers share their experiences and opinions regarding Belikopi products.

The Google Maps reviews were collected using the Apify web scraping platform, while comments from Instagram and TikTok were obtained using publicly available scraping tools. After merging the datasets from the three platforms, duplicate entries, empty reviews, and irrelevant comments were removed. A total of 4,636 valid customer reviews were obtained for further analysis.

Each review was manually labeled into one of three sentiment categories: positive, neutral, and negative. The labeling process was performed based on the semantic meaning and context of each review to ensure reliable sentiment classification.

2.3. Text Preprocessing

Before the classification process, the textual data underwent several preprocessing stages to improve data quality and reduce noise. These preprocessing steps produced a normalized corpus suitable for feature extraction. The preprocessing pipeline consisted of:

a. Case Folding, converting all characters into lowercase.
b. Cleaning, removing URLs, punctuation marks, emojis, numbers, and special characters.
c. Tokenizing, splitting sentences into individual words.
d. Stopword Removal, eliminating common Indonesian words that do not contribute significantly to sentiment classification.
e. Stemming, converting inflected words into their root forms using the Indonesian stemming algorithm.

2.4. Feature Extraction Using TF-IDF

The cleaned text data were transformed into numerical representations using the Term Frequency–Inverse Document Frequency (TF-IDF) weighting method. TF-IDF measures the importance of each word based on its frequency within a document and its rarity across the entire dataset.

The TF-IDF vectorization process was implemented using the Scikit-learn library with the following parameters:

a. max_features = 5000
b. ngram_range = (1,2)
c. min_df = 2
d. max_df = 0.9

The resulting TF-IDF matrix was used as the input feature set for the Support Vector Machine classifier.

2.5. Sentiment Classification Using Support Vector Machine (SVM)

The sentiment classification process was performed using the Support Vector Machine (SVM) algorithm because of its effectiveness in handling high-dimensional text data. SVM classifies textual documents by constructing an optimal hyperplane that maximizes the separation margin between sentiment classes.

The dataset was divided into 80% training data and 20% testing data using the Stratified Train-Test Split method to preserve the distribution of sentiment classes. The SVM classifier was then trained using the training dataset and subsequently tested using unseen testing data.

2.6. Model Evaluation

The performance of the proposed model was evaluated using a confusion matrix. Based on the confusion matrix, four evaluation metrics were calculated:

a. Accuracy: Measures the proportion of correctly classified instances to the total number of testing samples.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{.............} \ (1)$$

b. Precision: Measures the proportion of correctly predicted positive instances among all instances predicted as positive by the classification model.

$$\text{Precision} = \frac{TP}{TP+FP} \quad \text{.............} \ (2)$$

c. Recall (Sensitivity): Measures the model's ability to correctly identify all actual positive instances in the testing dataset.

$$\text{Recall} = \frac{TP}{TP+FN} \quad \text{.............} \ (3)$$

d. F1-Score: Represents the harmonic mean of precision and recall, providing a balanced evaluation of the model's classification performance, particularly when the class distribution is imbalanced.

$$\text{F1-Score} = 2\ x\ \frac{Precision\ x\ Recall}{Precision\ +\ Recall} \quad \text{.............} \ (4)$$

where:
TP (True Positive) = Positive instances correctly classified as positive.
TN (True Negative) = Negative instances correctly classified as negative.
FP (False Positive) = Negative instances incorrectly classified as positive.
FN (False Negative) = Positive instances incorrectly classified as negative.

The evaluation results were used to measure the effectiveness of the proposed Support Vector Machine model in classifying customer sentiment toward Belikopi products.

3. RESULTS AND DISCUSSION

3.1. Results

This section presents the results of the sentiment classification of Belikopi customer reviews using the Support Vector Machine (SVM) algorithm. The discussion begins with the characteristics of the collected dataset, followed by the text preprocessing process, sentiment labeling, TF-IDF feature extraction, sentiment classification, and model performance evaluation. The evaluation was conducted using a confusion matrix and classification metrics, including Accuracy, Precision, Recall, and F1-Score. Furthermore, the experimental results are discussed to demonstrate the effectiveness of the proposed approach in classifying customer sentiment and to compare the findings with those reported in previous studies.

3.1.1. Dataset Characteristics

A total of 4,636 customer reviews were collected from Google Maps, Instagram, and TikTok. After removing duplicate, empty, and irrelevant reviews, the dataset was prepared for manual sentiment labeling. The collected reviews represent customers' opinions regarding Belikopi products and services across multiple digital platforms.

3.1.2. Text Preprocessing

The collected customer reviews were preprocessed to improve text quality before the sentiment labeling and classification processes. Text preprocessing aims to eliminate irrelevant information and standardize textual data, thereby improving the effectiveness of the classification model.

The preprocessing stage consisted of five steps: case folding, cleaning, tokenization, stopword removal, and stemming. Case folding converted all characters into lowercase letters. The cleaning process removed URLs, punctuation marks, numbers, emojis, and other special characters. Tokenization split each review into individual words, while stopword removal eliminated common Indonesian words that carried little semantic meaning. Finally, stemming transformed each word into its root form using an Indonesian stemming algorithm.

Table 2. Example of Text Preprocessing

Original Review	Case Folding	Cleaning	Tokenizing	Stopword Removal	Stemming
The coffee is really good!!	The coffee is very good	The coffee is very good	The coffee is very good, very good.	The coffee is very good.	The coffee is very good.

The preprocessing stage successfully removed textual noise and standardized customer reviews, making them suitable for feature extraction.

3.1.3. Data Labeling

After the preprocessing stage, each review was manually labeled into one of three sentiment categories: positive, neutral, and negative. The labeling process was performed by considering the semantic meaning and overall context of each review.

Reviews expressing customer satisfaction regarding product quality, taste, service, price, or facilities were labeled as positive. Reviews containing objective statements or opinions without a clear emotional tendency were categorized as neutral. Meanwhile, reviews describing complaints, dissatisfaction, or negative experiences related to Belikopi products or services were labeled as negative.

Table 3. Example of Sentiment Labels

No.	Customer Review	Sentiment Label
1	The coffee is good; the price is also still affordable	Positive
2	The place is comfortable and the service is very friendly	Positive
3	The coffee is ordinary, nothing special	Neutral
4	The place is pretty clean, but it's often crowded during lunch time	Neutral
5	The order came very long and the drinks were not suitable	Negative
6	The waiter was not friendly and the taste of the coffee was disappointing	Negative

The labeled dataset was subsequently used as the input for the TF-IDF feature extraction process and the Support Vector Machine (SVM) classification model.

3.1.4. WordCloud Analysis

WordCloud is a text visualization technique used to display the most frequently occurring words in a collection of textual data. In this study, WordCloud is employed to provide a visual representation of customer reviews after the text preprocessing and sentiment labeling stages. The size of each word reflects its frequency of occurrence, where larger words indicate higher frequencies. This visualization helps identify dominant terms within each sentiment category and provides an initial understanding of customer opinions before the TF-IDF feature extraction and SVM classification processes.

Figure 2 illustrates the WordCloud generated from customer reviews labeled as positive. The visualization is dominated by words such as "enak" (delicious), "nyaman" (comfortable), "ramah" (friendly), "murah" (affordable), and "recommend", indicating that customers generally express satisfaction with the taste of Belikopi products, service quality, and the overall dining experience. The dominance of these positive terms suggests that the majority of customers have favorable perceptions of Belikopi products and services.

Figure 2. Positive Sentiment WordCloud

Figure 3 presents the WordCloud of reviews classified as neutral. Frequently occurring words include "kopi" (coffee), "menu", "tempat" (place), "minum" (drink), and "beli" (buy). These words mainly describe products, locations, or customer activities without expressing strong positive or negative emotions. This indicates that neutral reviews generally contain descriptive information rather than subjective opinions.

Figure 3. Neutral Sentiment WordCloud

Figure 4 shows the WordCloud of reviews labeled as negative. Dominant words such as "lama" (slow), "kecewa" (disappointed), "kurang" (poor), "dingin" (cold), and "mahal" (expensive) indicate that customer complaints are primarily related to service speed, product quality, and pricing. The presence of these terms provides valuable insights into aspects that require improvement to enhance customer satisfaction.

Figure 4. Negative Sentiment WordCloud

Overall, the WordCloud visualizations reveal the dominant vocabulary associated with each sentiment category. Positive reviews are characterized by words reflecting satisfaction with product quality and service, neutral reviews mainly contain descriptive terms, while negative reviews highlight customer complaints regarding service and product experience. These findings complement the quantitative analysis by providing an intuitive overview of customer perceptions before the feature extraction and classification stages.

3.1.5. TF-IDF Feature Extraction

After labelling, the cleaned reviews were transformed into numerical feature vectors using the Term Frequency–Inverse Document Frequency (TF-IDF) method. TF-IDF assigns higher weights to words that frequently appear in a particular review but occur less frequently across the entire dataset. The TF-IDF vectorization was implemented using the following parameters:

a. Maximum features = 5000
b. N-gram range = (1,2)
c. Minimum document frequency = 2
d. Maximum document frequency = 0.9

The resulting TF-IDF matrix consists of weighted numerical features that represent the importance of each term in the dataset. These feature vectors were then used as input for the Support Vector Machine classifier.

```
Jumlah Data : 4636

Kolom Dataset
['No', 'Platform', 'Sumber ', 'Tanggal', 'Teks', 'case_folding', 'cleaning', 'tokenizing', 'stopword', 'stemming', 'hasil_preprocessing', 'label']

Jumlah Data Setelah Cleaning : 4205

Distribusi Label
netral     : 2422
positif    : 1509
negatif    : 274

Jumlah Fitur : 4837
Shape Matrix : (4205, 4837)

5 Data Pertama
    aa  abis  abis beli  abis minum   ac  ac dingin  ac enak  ac nyaman  \
0  0.0   0.0        0.0         0.0  0.0        0.0      0.0        0.0
1  0.0   0.0        0.0         0.0  0.0        0.0      0.0        0.0
2  0.0   0.0        0.0         0.0  0.0        0.0      0.0        0.0
3  0.0   0.0        0.0         0.0  0.0        0.0      0.0        0.0
4  0.0   0.0        0.0         0.0  0.0        0.0      0.0        0.0

   ac wifi  acnya  ...  yuh  yuk  yuk gass  yuk ikut  yukk  yukk ikut  yummy  \
0      0.0    0.0  ...  0.0  0.0       0.0       0.0   0.0        0.0    0.0
1      0.0    0.0  ...  0.0  0.0       0.0       0.0   0.0        0.0    0.0
2      0.0    0.0  ...  0.0  0.0       0.0       0.0   0.0        0.0    0.0
3      0.0    0.0  ...  0.0  0.0       0.0       0.0   0.0        0.0    0.0
4      0.0    0.0  ...  0.0  0.0       0.0       0.0   0.0        0.0    0.0

   yuu   za  zonk
0  0.0  0.0   0.0
1  0.0  0.0   0.0
2  0.0  0.0   0.0
3  0.0  0.0   0.0
4  0.0  0.0   0.0

[5 rows x 4837 columns]
```

Figure 5. Example of TF-IDF Features

The TF-IDF representation effectively converts textual data into high-dimensional numerical vectors, enabling the Support Vector Machine algorithm to identify the most discriminative terms for sentiment classification.

3.1.6. Sentiment Classification

The TF-IDF feature vectors were divided into 80% training data and 20% testing data using the Stratified Train-Test Split method. The Support Vector Machine (SVM) classifier was then trained using the training dataset and evaluated using the testing dataset.

```
============================================================
HASIL PEMBAGIAN DATA
============================================================
Jumlah seluruh data   : 4205
Jumlah data training  : 3364
Jumlah data testing   : 841

Persentase training : 80.00%
Persentase testing  : 20.00%

Ukuran Matriks TF-IDF
Training : (3364, 4837)
Testing  : (841, 4837)

Distribusi Label Training
label
netral     1938
positif    1207
negatif     219

Distribusi Label Testing
label
netral     484
positif    302
negatif     55
         Keseluruhan (%)  Training (%)  Testing (%)
label
netral             57.60         57.61        57.55
positif            35.89         35.88        35.91
negatif             6.52          6.51         6.54
```

Figure 6. Sentiment Distribution in the Training and Testing Datasets

3.1.7. Classification Report

After the training process, the performance of the Support Vector Machine (SVM) model was evaluated using the testing dataset. The evaluation was conducted by generating a classification report that measures the model performance using four metrics: Precision, Recall, F1-Score, and Accuracy. These metrics provide a comprehensive assessment of the model's capability to classify customer reviews into positive, neutral, and negative sentiment classes.

a. Accuracy $= \frac{TP+TN}{TP+TN+FP+FN} = \frac{785}{841} = 0{,}9334 = 93.34\%$

b. Precision $= \frac{TP}{TP+FP} = \frac{785}{785+56} = \frac{785}{841} = 0{,}9334 = 93.34\%$

c. Recall = $\frac{TP}{TP+FN} = \frac{785}{785+56} = \frac{785}{841} = 0{,}9334 = 93.34\%$

d. F1-Score = $2\ x\ \frac{Precision\ x\ Recall}{Precision\ +\ Recall} = 2\ x\ \frac{0{,}9334\ x\ 0{,}9334}{0{,}9334\ +\ 0{,}9334} = 0{,}9334 = 93.34\%$

```
==================================================
CLASSIFICATION REPORT
==================================================
              precision    recall  f1-score   support

     negatif       0.80      0.67      0.73        55
      netral       0.93      0.96      0.95       484
     positif       0.96      0.94      0.95       302

    accuracy                           0.93       841
   macro avg       0.90      0.86      0.88       841
weighted avg       0.93      0.93      0.93       841


Confusion Matrix:
[[ 37  16   2]
 [  9 464  11]
 [  0  18 284]]

Akurasi: 0.9334126040428062
```

Figure 7. Classification Report of the SVM Model

The proposed SVM model achieved an overall accuracy of 93.34%, indicating that it successfully classified most customer reviews into their respective sentiment categories. Furthermore, the weighted average values of 93.34% for Precision, 93.34% for Recall, and 93.34% for F1-Score demonstrate that the model produced consistent classification performance across the three sentiment classes.

3.1.8. Confusion Matrix Analysis

The confusion matrix was employed to analyze the detailed classification performance of the proposed model by comparing the predicted sentiment labels with the actual labels.

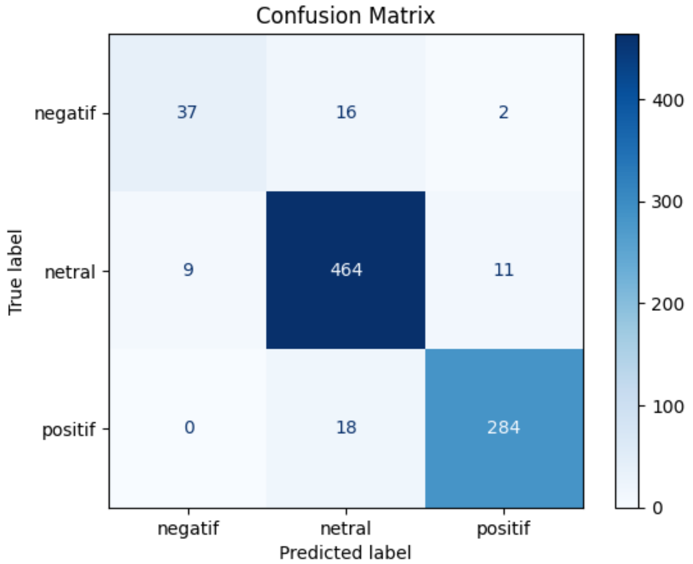

Figure 8. Confusion Matrix of the SVM Model

Confusion Matrix Explanation

a. Negative reviews correctly predicted as Negative: 37
b. Negative reviews incorrectly predicted as Neutral: 16
c. Negative reviews incorrectly predicted as Positive: 2
d. Neutral reviews incorrectly predicted as Negative: 9
e. Neutral reviews correctly predicted as Neutral: 464
f. Neutral reviews incorrectly predicted as Positive: 11
g. Positive reviews incorrectly predicted as Negative: 0
h. Positive reviews incorrectly predicted as Neutral: 18

i. Positive reviews correctly predicted as Positive: 284

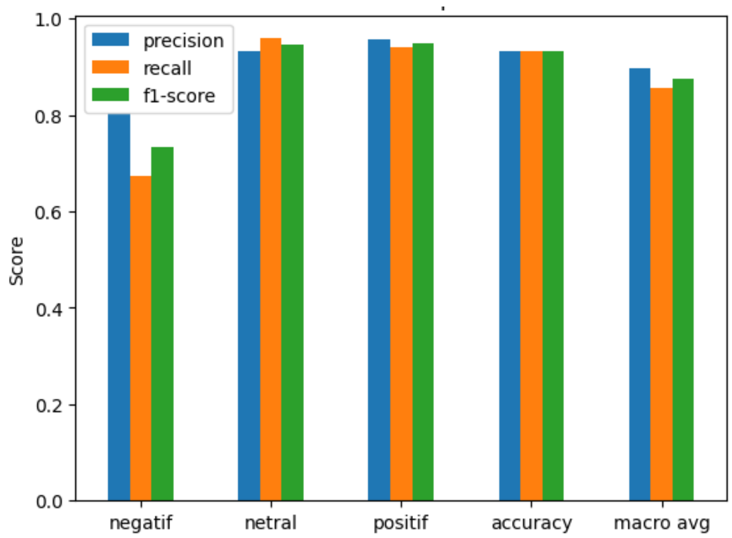

Figure 9. Per-Class Model Performance

The confusion matrix indicates that the majority of customer reviews were correctly classified into the corresponding sentiment categories. Most prediction errors occurred between the positive and neutral classes, as several reviews contained similar expressions with relatively weak sentiment polarity. Conversely, negative reviews were generally classified correctly because they contained more explicit complaint-related vocabulary, making them easier for the model to distinguish.

Overall, the confusion matrix confirms that the Support Vector Machine classifier demonstrates good discriminative capability in multiclass sentiment classification, with relatively few misclassifications among the three sentiment classes.

3.2. Discussion

The experimental results demonstrate that the proposed sentiment classification framework effectively analyzes customer reviews collected from Google Maps, Instagram, and TikTok. By combining text preprocessing, TF-IDF feature extraction, and the Support Vector Machine algorithm, the model achieved an accuracy of 93.34%, indicating excellent classification performance.

The high Precision, Recall, and F1-Score values further indicate that the proposed model can accurately identify positive, neutral, and negative customer sentiments while maintaining balanced performance across all classes. The implementation of TF-IDF successfully transformed textual reviews into informative numerical feature vectors, enabling the SVM classifier to identify discriminative patterns within the customer opinions.

Compared with previous studies that utilized reviews from a single platform, this study integrates customer reviews from three different digital platforms, namely Google Maps, Instagram, and TikTok. This integration provides a more comprehensive representation of customer perceptions toward Belikopi products and services because each platform reflects different customer behaviors and communication styles. Consequently, the proposed approach offers broader sentiment coverage than studies relying on a single source of customer reviews.

The findings of this study are consistent with previous research reporting that Support Vector Machine is one of the most effective machine learning algorithms for text classification because of its ability to handle high-dimensional data efficiently. The results also confirm that integrating TF-IDF with SVM produces reliable sentiment classification performance, making this approach suitable for customer opinion analysis in the food and beverage industry.

From a practical perspective, the proposed sentiment classification model can support Belikopi management in monitoring customer satisfaction, identifying service and product issues, evaluating business performance, and formulating data-driven improvement strategies. By automatically analyzing customer reviews from multiple digital platforms, business owners can obtain valuable insights into consumer preferences and respond more quickly to customer feedback, thereby enhancing service quality and maintaining competitiveness in the increasingly dynamic coffee industry.

Although the Support Vector Machine (SVM) model achieved a high classification accuracy of 93.34%, recent studies have shown that deep learning approaches such as Long Short-Term Memory (LSTM) and Bidirectional Encoder Representations from Transformers (BERT) can provide better contextual understanding for sentiment classification, particularly when dealing with large-scale datasets and complex linguistic structures. However, these methods generally require substantially greater computational resources and larger annotated datasets. Considering the size of the dataset and the objective of developing a practical web-based sentiment analysis system, SVM remains an efficient and reliable choice for this study. Future research may compare the proposed SVM model with deep learning approaches such as LSTM and BERT to evaluate potential improvements in classification performance.

The proposed sentiment analysis system was implemented as a web-based application to facilitate the analysis and visualization of customer reviews for Belikopi products. The application was developed using PHP, MySQL, Bootstrap, and Chart.js, while the sentiment classification model was built using the Support Vector Machine (SVM) algorithm with TF-IDF feature extraction.

The implementation process began with collecting customer review data from various online platforms. The collected reviews were preprocessed through several stages, including case folding, tokenization, stopword removal, and stemming. After preprocessing, the text data were transformed into numerical vectors using the TF-IDF method before being classified by the SVM model.

The developed system provides several main features to support sentiment analysis activities. Users can upload review data, manage the dataset, visualize sentiment distribution, and evaluate the classification performance. The dashboard displays statistical information regarding the total number of reviews and the distribution of positive, negative, and neutral sentiments. Furthermore, visualization is presented using pie charts, bar charts, doughnut charts, line charts, and progress indicators to provide a clearer understanding of customer sentiment patterns.

To evaluate the classification model, the system displays several performance metrics, including Accuracy, Precision, Recall, and F1-Score, along with a Confusion Matrix and Classification Report. These evaluation results allow users to measure the effectiveness of the SVM model in classifying customer reviews into the predefined sentiment categories.

Overall, the developed web application successfully integrates data management, sentiment classification, visualization, and performance evaluation into a single platform. This implementation enables users to analyze customer opinions efficiently and provides valuable insights for supporting business decision-making related to product quality and customer satisfaction.

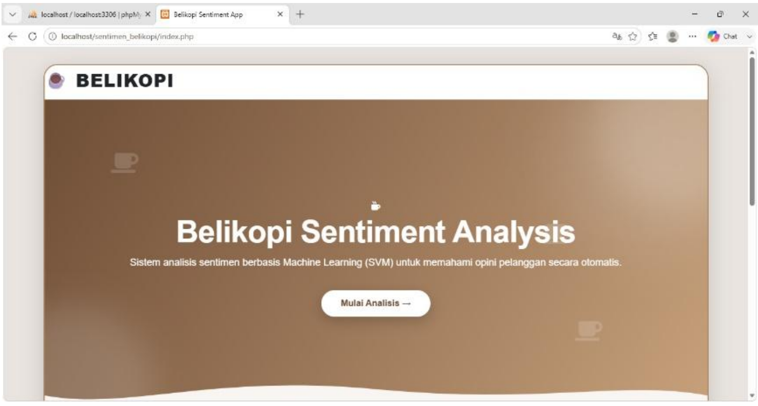

Figure 10. Landing Page of the Proposed Sentiment Analysis System

The landing page serves as the main interface of the proposed web-based sentiment analysis system. It provides a brief description of the application and allows users to access the sentiment analysis dashboard through the "Start Analysis" button.

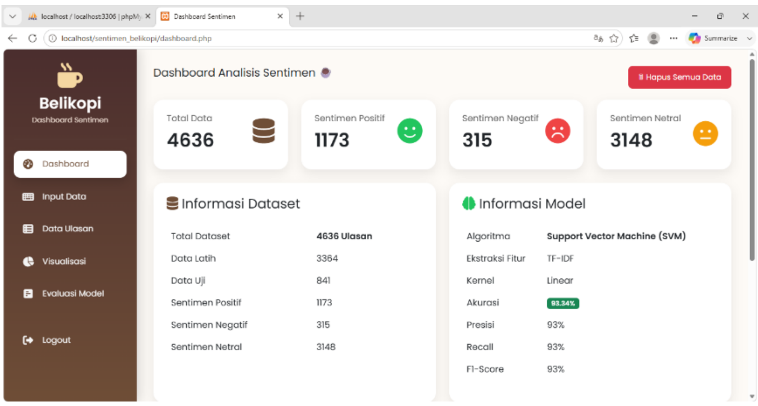

Figure 11. Dashboard Interface

The dashboard displays a summary of the sentiment analysis results, including the total number of customer reviews, the distribution of positive, negative, and neutral sentiments, dataset information, and the machine learning model configuration. This interface provides users with an overview of the analysis results before exploring the detailed pages.

4. CONCLUSION

This study successfully implemented a sentiment analysis model to classify customer reviews of Belikopi products using the Support Vector Machine (SVM) algorithm. The research applied a text mining framework consisting of data collection, text preprocessing, manual sentiment labeling, TF-IDF feature extraction, and sentiment classification using SVM. A total of 4,205 customer reviews collected from Google Maps, Instagram, and TikTok were utilized as the dataset, representing customer opinions from multiple social media platforms.

The experimental results demonstrate that the proposed model achieved excellent classification performance, obtaining an accuracy of 93.34%, precision of 93.34%, recall of 93.34%, and an F1-score of 93.34%. These results indicate that the Support Vector Machine algorithm is highly effective in classifying customer reviews into positive, neutral, and negative sentiment categories. In addition, the application of TF-IDF feature extraction successfully transformed textual data into meaningful numerical representations, allowing the classifier to identify sentiment patterns accurately and consistently.

The sentiment distribution further reveals that the majority of customer reviews are categorized as neutral and positive, while negative reviews constitute only a small portion of the dataset. This finding suggests that customers generally have favorable perceptions of Belikopi products and services. At the same time, the existence of negative reviews provides valuable feedback that can help business owners identify weaknesses, improve service quality, enhance customer satisfaction, and support strategic decision-making based on customer opinions.

Furthermore, the implementation of the proposed web-based sentiment analysis system demonstrates that machine learning techniques can be effectively integrated into an interactive application for managing customer review data. The system enables users to upload datasets, classify sentiments automatically, visualize sentiment distributions, and evaluate classification performance through various metrics and graphical representations. These features make the application practical for both academic research and business analysis.

Overall, this study confirms that the integration of text preprocessing, TF-IDF feature extraction, and the Support Vector Machine algorithm provides a robust and reliable approach for sentiment classification of customer reviews. The proposed system can serve as a useful decision-support tool for monitoring customer perceptions and evaluating product quality. Future research may improve the model by utilizing larger and more balanced datasets, incorporating additional review sources, applying automatic sentiment labeling techniques, and exploring advanced deep learning methods such as Long Short-Term Memory (LSTM), Bidirectional Encoder Representations from Transformers (BERT), or hybrid machine learning models to further enhance classification performance and generalization capability.

Future research is recommended to compare the proposed SVM model with advanced deep learning methods, such as LSTM and BERT, to evaluate potential improvements in sentiment classification accuracy and contextual understanding.

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The primary contribution of this study lies in integrating customer reviews from three digital platforms into a unified sentiment analysis framework using TF-IDF and SVM. The proposed framework demonstrates that combining heterogeneous review sources can produce reliable sentiment classification and provide more comprehensive insights for business decision-making.

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