SENTIMENT ANALYSIS OF JIWA+ APPLICATION USERS BASED ON MACHINE LEARNING FOR DIGITAL SERVICE EVALUATION

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Abstract

The rapid growth of Indonesia's coffee industry has increased competition and encouraged coffee businesses to adopt digital technologies to improve service quality. Janji Jiwa utilizes the Jiwa+ mobile application to support digital services; however, user reviews on the Google Play Store show mixed sentiments toward the application. This study aims to analyze user sentiment toward the Jiwa+ application using machine learning based sentiment analysis as a tool for evaluating digital service quality in the coffee business sector. User review data were collected from the Google Play Store through web scraping and processed using text preprocessing techniques, including cleaning, case folding, tokenization, normalization, stopword removal, and stemming. The reviews were manually labeled into positive and negative sentiments and classified using Support Vector Machine (SVM) and Naive Bayes algorithms with TF-IDF feature extraction. Model performance was evaluated using accuracy, precision, recall, and F1-score metrics. The results indicate that SVM outperforms Naive Bayes, achieving an accuracy of 92% compared to 89% for Naive Bayes. Feature analysis shows that positive sentiment is associated with ease of use and promotional benefits, while negative sentiment highlights issues related to payment processes, application reliability, and stock availability. These findings demonstrate that sentiment analysis can provide valuable insights for improving digital services in the coffee industry.

Keywords: Sentiment Analysis, Jiwa+ Application, Machine Learning, Support Vector Machine, Naive Bayes, Digital Services

1. INTRODUCTION

Indonesia has experienced significant growth in its coffee industry, with PoiData.io reporting over 461,000 coffee shops nationwide—the highest globally as of late 2025 (PoiData.io, 2025). This growth reflects Indonesia's strong coffee culture and underscores the sector's strategic role in the creative economy. However, the rapid expansion has intensified competition, driving businesses to innovate and differentiate. In line with national development strategies, the government prioritizes downstreaming coffee production to increase value added and enhance competitiveness in domestic and global markets (Badan Riset dan Inovasi Nasional, 2025). Amid this competitive landscape, coffee businesses increasingly adopt digital technologies, particularly mobile applications, to improve service efficiency and

customer satisfaction, highlighting the role of technological innovation in adapting to changing consumer behavior.

Janji Jiwa is a well-known coffee brand in Indonesia that actively adopts digital innovation to support its business operations (Riyantie et al., 2021). Through the Jiwa+ mobile application, the company offers digital services such as online ordering, promotions, and customer loyalty programs to enhance customer experience and meet the growing demand for digital-based services in the coffee industry (Jiwa Group, n.d.). The Jiwa+ application has generated numerous user reviews on the Google Play Store, reflecting diverse positive and negative sentiments. However, manually analyzing large-scale textual reviews is inefficient and subjective, while numerical ratings alone are insufficient to capture detailed user perceptions of digital service quality.

Sentiment analysis has been widely applied as an effective approach for automatically analyzing user opinions expressed in textual data (Aftab et al., 2023). Previous studies have demonstrated that machine learning methods such as Naive Bayes and Support Vector Machine (SVM) achieve reliable performance in classifying user reviews into positive and negative sentiments (Jannah & Kusnawi, 2024). These methods have been successfully used to evaluate user satisfaction and identify service-related issues across various digital platforms, providing actionable insights for business decision-making (Umezurike et al., 2025). By comparing the performance of Naive Bayes and SVM, sentiment analysis can support digital service evaluation by revealing strengths and weaknesses in service quality. Therefore, this study aims to analyze user sentiment toward the Jiwa+ application using machine learning methods as a basis for evaluating digital services in the coffee business sector.

2. METHODOLOGY

Figure 1. Research Stages

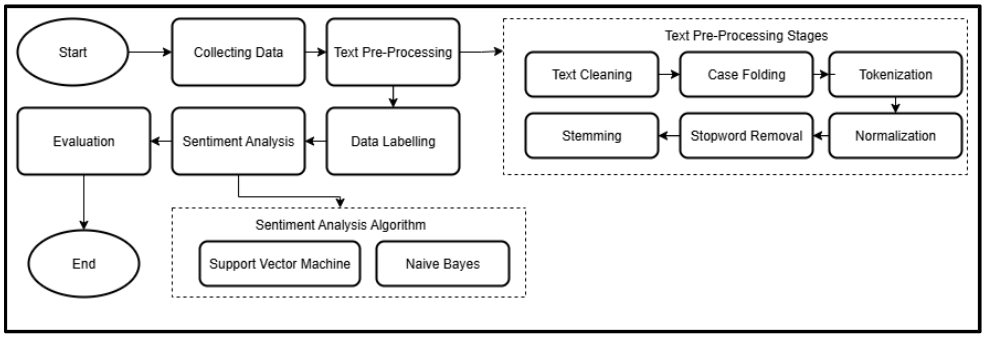
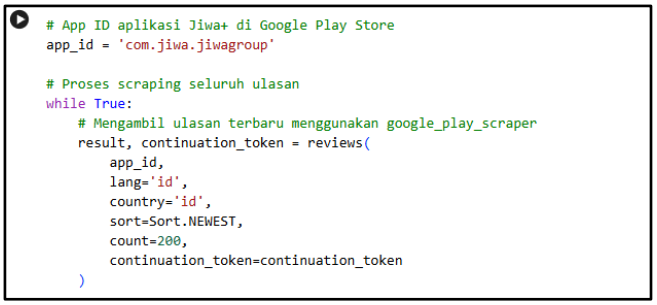


Figure 1 presents the research stages of machine learning–based sentiment analysis on the Jiwa+ application, starting from data collection and text preprocessing. The data are then labeled and classified using SVM and Naive Bayes algorithms, followed by performance evaluation using appropriate metrics.

2.1 Collecting Data

This study collects data in the form of user reviews of the Jiwa+ application obtained from the Google Play Store.

Figure 2. Data Collection Process



```
# App ID aplikasi Jiwa+ di Google Play Store
app_id = 'com.jiwa.jiwagroup'

# Proses scraping seluruh ulasan
while True:
    # Mengambil ulasan terbaru menggunakan google_play_scraper
    result, continuation_token = reviews(
        app_id,
        lang='id',
        country='id',
        sort=Sort.NEWEST,
        count=200,
        continuation_token=continuation_token
    )
```

Figure 2 illustrates the data collection process using web scraping with the google_play_scraper library. Reviews were collected iteratively until no additional data were available, with each review providing essential information such as review text and user rating for sentiment analysis.

2.2 Text Pre-Processing

Text preprocessing is an essential stage in sentiment analysis to clean and structure raw text data for machine learning. In this study, preprocessing includes text cleaning, case folding, tokenization, normalization, stopword removal, and stemming, which are applied sequentially to prepare user reviews for effective sentiment classification (Aprilia et al., 2025).

2.3 Data Labeling

Data labeling is performed manually with two sentiment classes: positive and negative. Positive reviews that reflect satisfaction with the Jiwa+ application are labeled as 1, while negative reviews indicating dissatisfaction are labeled as 2. This labeling serves as ground truth data for training and evaluating the machine learning models.

2.4 Sentiment Analysis

2.4.1 Support Vector Machine Algorithm

Support Vector Machine (SVM) is a supervised learning algorithm commonly used for text classification, including sentiment analysis. SVM identifies an optimal hyperplane that separates sentiment classes with maximum margin (Rahmawati et al., 2025). In this study, a linear SVM is applied due to its effectiveness in handling high-dimensional TF-IDF features and its robustness in classifying positive and negative sentiments in Jiwa+ application reviews.

2.4.2 Naive Bayes Algorithm

Naive Bayes is a probabilistic classification algorithm based on Bayes' theorem with an assumption of conditional independence among features. Despite its simplicity, it is effective and efficient for text classification, including sentiment analysis. In this study, Naive Bayes calculates the probability of each sentiment class from word

occurrences in user reviews and assigns the class with the highest probability, making it suitable as a comparative model for large-scale textual data.

2.5 Evaluation

Model performance is evaluated using a confusion matrix and several standard classification metrics. The confusion matrix summarizes prediction results into four components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which represent correct and incorrect classifications for positive and negative sentiments. Table 1 shows the confusion matrix components.

Table 1. Confusion Matrix Components

Actual	Prediction	
	Positive	Negative
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

Source: Rahmawati et al., 2025

Based on these components, accuracy measures the overall proportion of correctly classified data, precision indicates the reliability of positive predictions, recall reflects the model's ability to correctly identify actual positive sentiments, and the F1-score provides a balanced measure by combining precision and recall. These metrics are used to comprehensively assess the effectiveness of the sentiment analysis models.

3. FINDINGS AND DISCUSSION

3.1 Collecting Data

Figure 3. Jiwa+ App Review Data Collection Results

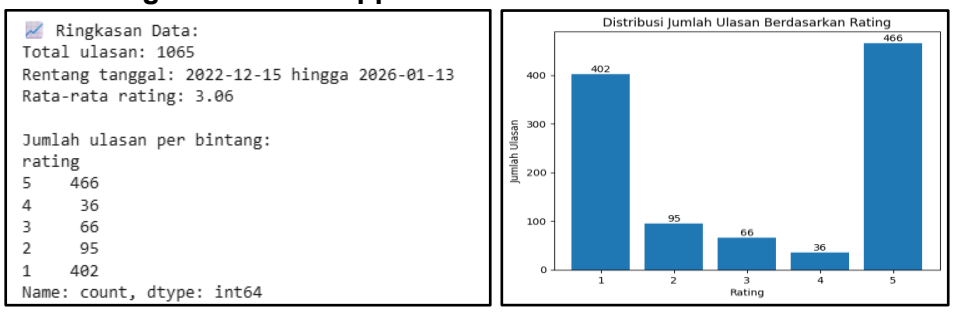


Figure 3 shows the result of data collection. At this stage, 1,065 user reviews of the Jiwa+ application were collected from the Google Play Store, covering the period from December 15, 2022, to January 13, 2026. The dataset has an average rating of 3.06, indicating moderate overall user sentiment. This distribution suggests contrasting user experiences and provides a relevant basis for conducting sentiment analysis on the Jiwa+ application.

3.2 Text Pre-Processing

3.2.1 Text Cleaning

Text cleaning aims to remove noise and irrelevant elements from the raw text. In this stage, punctuation and unnecessary symbols are eliminated while preserving the original meaning of the review, resulting in cleaner and more structured text for further processing. **Table 2** shows the result of the text cleaning process.

Table 2. Text Cleaning Result

Before Text Cleaning	After Text Cleaning
Kok tidak bisa pembayaran? Ketika saya klik pembayaran menggunakan shoppee tidak muncul pin untuk pembayaran dan ke cancel	Kok tidak bisa pembayaran Ketika saya klik pembayaran menggunakan shoppee tidak muncul pin untuk pembayaran dan ke cancel

3.2.2 Case Folding

Case folding converts all characters in the text into lowercase form. This step ensures text uniformity and prevents words with different letter cases from being treated as separate tokens. **Table 3** shows the result of the case folding process.

Table 3. Case Folding Result

Before Case Folding	After Case Folding
Kok tidak bisa pembayaran Ketika saya klik pembayaran menggunakan shoppee tidak muncul pin untuk pembayaran dan ke cance	kok tidak bisa pembayaran ketika saya klik pembayaran menggunakan shoppee tidak muncul pin untuk pembayaran dan ke cance

3.2.3 Tokenization

Tokenization breaks the cleaned and case-folded text into individual tokens or words. This process transforms a sentence into a list of meaningful units that can be further analyzed in subsequent preprocessing steps. Table 4 shows the result of tokenization process.

Table 4. Tokenization Result

Before Tokenization	After Tokenization
kok tidak bisa pembayaran ketika saya klik pembayaran menggunakan shoppee tidak muncul pin untuk pembayaran dan ke cance	['kok', 'tidak', 'bisa', 'pembayaran', 'ketika', 'saya', 'klik', 'pembayaran', 'menggunakan', 'shoppee', 'tidak', 'muncul', 'pin', 'untuk', 'pembayaran', 'dan', 'ke', 'cance']

3.2.4 Normalization

Normalization replaces non-standard, misspelled, or informal words with their standard forms. This step helps reduce vocabulary variation caused by slang or typographical differences, ensuring more consistent textual representation. Table 5 shows the result of normalization process.

Table 5. Normalization Result

Before Normalization	After Normalization
['kok', 'tidak', 'bisa', 'pembayaran', 'ketika', 'saya', 'klik', 'pembayaran', 'menggunakan', 'shoppee', 'tidak', 'muncul', 'pin', 'untuk', 'pembayaran', 'dan', 'ke', 'cance']	['kok', 'tidak', 'bisa', 'pembayaran', 'ketika', 'saya', 'klik', 'pembayaran', 'menggunakan', 'shopee', 'tidak', 'muncul', 'pin', 'untuk', 'pembayaran', 'dan', 'ke', 'cancel']

3.2.5 Stopword Removal

Stopword removal eliminates common words that do not carry significant semantic meaning for sentiment classification. By removing these words, the text focuses more on terms that contribute to expressing user sentiment. Table 6 shows the stopword removal result.

Table 6. Stopword Removal Result

Before Stopword Removal	After Stopword Removal
['kok', 'tidak', 'bisa', 'pembayaran', 'ketika', 'saya', 'klik', 'pembayaran', 'menggunakan', 'shopee', 'tidak', 'muncul', 'pin', 'untuk', 'pembayaran', 'dan', 'ke', 'cancel']	['bisa', 'pembayaran', 'klik', 'pembayaran', 'menggunakan', 'shopee', 'muncul', 'pin', 'pembayaran', 'cancel']

3.2.6 Stemming

Stemming reduces words to their root or base forms by removing prefixes and suffixes. This process groups words with similar meanings into a single form, thereby reducing dimensionality and improving model efficiency. Table 7 shows the stemming result.

Table 7. Stemming Result

Before Stemming	After Stemming
['bisa', 'pembayaran', 'klik', 'pembayaran', 'menggunakan', 'shopee', 'muncul', 'pin', 'pembayaran', 'cancel']	['bisa', 'bayar', 'klik', 'bayar', 'guna', 'shopee', 'muncul', 'pin', 'bayar', 'cancel']

3.3 Data Labeling

Data labeling was performed by classifying user reviews into positive and negative sentiment categories, as shown in Table 8. Data that has positive sentiment will be labeled 1, while negative reviews will be labeled 2.

Table 8. Data Labeling Result

Review	Label
kerenn bangett sii sekarangg apknyaa, makin menarik tampilannyaa trusa sekarangg banyakk promo tiap harii	1 (Positive)

tidak bisa melihat menu dan memesan karena selalu keluar dari aplikasi sendiri	2 (Negative)

Figure 4. Jiwa+ App Distribution of Sentiment Labels

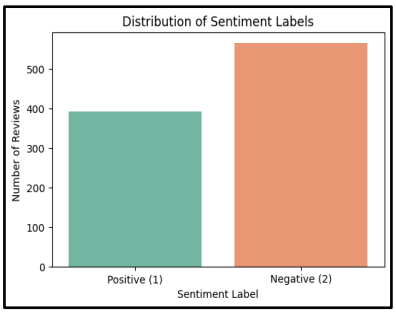


Figure 4 shows the distribution of sentiment labels, where negative reviews slightly dominate positive reviews. This indicates that a significant number of users experienced issues when using the Jiwa+ application.

3.4 Sentiment Analysis

3.4.1 Support Vector Machine Algorithm

Figure 5. Splitting Data & Training SVM Model

```
# Persiapan Data untuk SVM
X = df['final_text']
y = df['label']          # 1 = positif, 2 = negatif

# Split Data Training dan Testing
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.2,
    random_state=42,
    stratify=y
)
```

```
# Inisialisasi model Support Vector Machine (SVM)
svm_model = SVC(
    kernel='linear',
    C=1,
    random_state=42
)

# Melatih model SVM menggunakan data latih
svm_model.fit(X_train_tfidf, y_train)
```

Figure 5 shows the process of splitting data and training SVM model. At this stage, the preprocessed review text (final_text) is used as input data, while sentiment labels serve as the target variable. The dataset is split into training and testing sets using an 80:20 ratio. The Support Vector Machine model with a linear kernel is trained using the TF-IDF features from the training dataset. This model learns an optimal hyperplane that separates positive and negative sentiment classes with maximum margin. The trained model is then ready to classify unseen review data.

3.4.2 Naive Bayes Algorithm

Figure 6. Splitting & Training NB Model

```
X = df['final_text']
y = df['label']

X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.2,
    random_state=42)

print(f"Data Training: {len(X_train)}")
print(f"Data Testing : {len(X_test)}")
```

```
# Inisialisasi TF-IDF
tfidf = TfidfVectorizer()

# Transformasi teks menjadi angka
X_train_tfidf = tfidf.fit_transform(X_train)
X_test_tfidf = tfidf.transform(X_test)

# Training Model
nb_model = MultinomialNB()
nb_model.fit(X_train_tfidf, y_train)

# Melakukan Prediksi
y_pred = nb_model.predict(X_test_tfidf)
```

Figure 6 illustrates the model development process, where the preprocessed dataset is partitioned into training and testing sets using an 80:20 ratio. Textual features from the 'final_text' column are transformed into numerical vectors via TF-IDF before being fed into the Naive Bayes algorithm for sentiment classification and subsequent performance evaluation.

3.5 Evaluation

Table 9. Evaluation Result

Algorithm	Accuracy	Precision	Recall	F1-Score
SVM	0.92	0.92	0.92	0.92
Naive Bayes	0.89	0.90	0.88	0.89

The experimental results show that the Support Vector Machine (SVM) algorithm outperforms Naive Bayes in classifying user sentiment toward the Jiwa+ application. SVM achieved an accuracy of 92%, with balanced precision, recall, and F1-score for both positive and negative classes, indicating strong and consistent classification performance. The confusion matrix further demonstrates that SVM produces relatively few misclassifications, reflecting its ability to separate sentiment classes effectively in high-dimensional TF-IDF feature space. In comparison, Naive Bayes obtained a lower accuracy of 89%, with higher recall for the negative class but noticeably lower recall for the positive class, suggesting a tendency to misclassify positive reviews as negative. Overall, these results indicate that SVM provides more reliable and stable performance than Naive Bayes for sentiment analysis of Jiwa+ user reviews.

Figure 7. Top Positive and Negative Features SVM

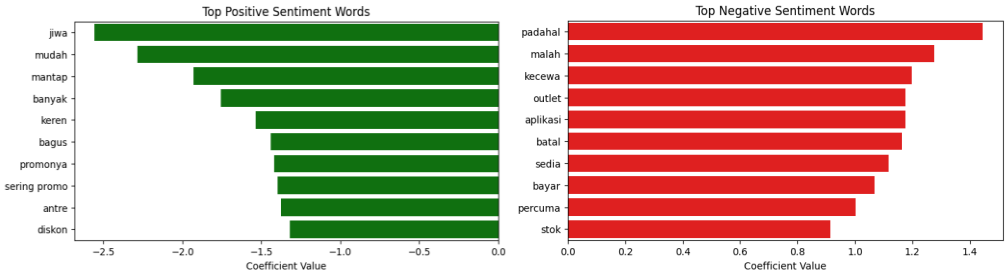


Figure 7 presents the top positive and negative sentiment features identified using the SVM algorithm. Positive sentiment is mainly associated with words such as “mudah,” “mantap,” “keren,” “bagus,” “promonya,” and “diskon,” indicating that users appreciate ease of use, attractive promotions, and perceived value offered by the Jiwa+ application. These results suggest that usability and promotional strategies play an important role in shaping positive user perceptions and supporting customer retention in digital service platforms. From a business perspective, maintaining a user-friendly interface and consistent promotional programs can enhance Jiwa+’s competitiveness in the coffee retail market.

In contrast, negative sentiment is dominated by words such as “batal,” “kecewa,” “outlet,” “aplikasi,” “batal,” “bayar,” and “stok,” which point to operational and service-related issues. These terms indicate customer dissatisfaction related to order cancellations, stock availability, outlet performance, and technical problems within the application. Such issues can directly affect customer trust and brand loyalty if not addressed promptly (Meidina et al., 2022). From a managerial standpoint, these insights highlight the importance of improving inventory management, ensuring system reliability, and strengthening coordination between the application and physical outlets. Previous studies have shown that negative experiences in mobile applications significantly influence customer switching behavior and brand perception (Patel, 2024).

4. CONCLUSION

This study successfully applied machine learning–based sentiment analysis to evaluate user perceptions of the Jiwa+ application using Google Play Store reviews. Through systematic text preprocessing, data labeling, and TF-IDF feature extraction, both Support Vector Machine (SVM) and Naive Bayes algorithms were implemented and evaluated. The results show that SVM outperformed Naive Bayes with accuracy, precision, recall, and F1-score all reaching 0.92, indicating reliable sentiment classification capability.and demonstrating its effectiveness in handling high dimensional textual data. Further feature analysis indicates that positive sentiment is driven by usability and promotional features, which should be consistently maintained to strengthen customer satisfaction and loyalty. Meanwhile, negative sentiment highlights operational and technical issues such as payment failures, stock availability, and application performance, which can serve as critical evaluation points for Jiwa+ management to improve service quality. Overall, these findings emphasize that sentiment analysis provides valuable business insights, enabling Jiwa+ to preserve its strengths while strategically addressing weaknesses to enhance competitiveness in the coffee retail industry.

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