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Comparison of Sentiment for Midi Kriing and Alfagift Apps Using SVM with TF-IDF Weighting

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Abstract

The advancement of information and communication technology has impacted various aspects of life, including shopping. With increasing internet access, online shopping apps have become a primary tool for consumers. Alfa Group, a major player in the retail industry, has launched two online shopping apps, Midi Kriing and Alfagift. This study aims to compare user sentiment for these two apps based on data from Google Play Store.Using the Support Vector Machine method with TF-IDF weighting, this research analyzes 2,000 reviews from each app. The data, collected from Google Play Store, was divided into 80% for training the model and 20% for testing it. The results indicate that Midi Kriing has an overall accuracy of 87%, while Alfagift has an overall accuracy of 85%. Both apps demonstrate strong performance in sentiment detection, but Midi Kriing is slightly superior in overall accuracy. These findings provide insights into user satisfaction with the apps and can help consumers determine the best online shopping app from Alfa Group. Additionally, the results can be used by Alfa Group to enhance the services of both apps in the future.

Keywords: *sentiment analysis, support vector machine, google play store, midi kriing, alfagift*

1. Introduction

The development of information and communication technology has significantly influenced various aspects of life, including shopping. The growing accessibility of the internet has positioned online shopping applications as a primary tool for consumers. In Indonesia, the number of online shopping application users reached 196.47 million in 2023 and is expected to continue increasing[1]. Alfa Group, as a key player in the retail industry, has launched two online shopping applications, Midi Kriing and Alfagift, which offer a wide range of products such as food, beverages, and daily necessities. This initiative aims to expand services and enhance the consumer shopping experience.

Online shopping applications, such as Midi Kriing and Alfagift, offer convenience in shopping through features that allow users to browse and purchase products without visiting physical stores. Midi Kriing, managed by PT Midi Utama Indonesia Tbk, provides a variety of products for daily needs[2], while Alfagift, operated by PT Sumber Alfaria Trijaya Tbk, stands out with special offers and surprises[3]. These two applications are part of Alfa Group's efforts to deliver a comfortable and innovative shopping experience.

This study will analyze user sentiment in reviews of Midi Kriing and Alfagift on the Google Play Store using the Support Vector Machine (SVM) method with TF-IDF weighting. Sentiment analysis aims to identify positive, negative, or neutral opinions about the two applications. This research is expected to provide insights into user satisfaction and offer valuable feedback for developers to improve service quality. Based on various prior studies, SVM has proven to be effective in text classification, making it a suitable method for accurately measuring user sentiment in reviews[4].

Research on the application of classification algorithms in sentiment analysis has yielded diverse and intriguing results. Siddik, in the Journal of Information Technology and Computer Science, implemented the Naive Bayes algorithm to classify student satisfaction with university services, achieving an accuracy of 96.24% from 213 student data points. This study demonstrates that Naive Bayes can deliver excellent results in satisfaction classification, highlighting its potential for similar future applications[5]. Conversely, Nitami et al., in the Jurnal Manajemen Informatika dan Sistem Informasi, applied Naive Bayes for sentiment analysis of J&T Express

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reviews on the Google Play Store. Using 500 review data points, the study achieved an accuracy of 87%, indicating the method's effectiveness in understanding user sentiment, albeit with lower accuracy compared to Siddik's study. This suggests that while Naive Bayes is effective, there is room for improvement through alternative methods or further optimization[6].

Another study by Hermanto, published in the Jurnal Ilmu Pengetahuan dan Teknologi Komputer, compared the accuracy of Naive Bayes and Support Vector Machine (SVM) in handling student complaint services. After data cleaning, involving 5,954 data points, SVM achieved an accuracy of 84.45%, while Naive Bayes only reached 69.75%. These findings indicate that SVM tends to be more accurate in handling complaint data, while Naive Bayes might be better suited for other applications[7]. Faesal et al., in another journal, employed the K-Means method for sentiment analysis of tweets about online store products. With 1,130 tweets, the study achieved an accuracy of 92.86%. This demonstrates the strength of K-Means in clustering text-based data, yielding excellent results and indicating its potential for social media sentiment analysis[8]. Meanwhile, Rasyida, in the Jurnal Informatika Kaputama, applied Naive Bayes to determine poverty status, achieving an accuracy of 70% from 100 data points. This outcome suggests that although Naive Bayes is useful, its lower accuracy indicates the need for further exploration to enhance its performance[9].

Similar research was conducted by Fakhriza Firdaus and Ali Mukhlis in the Jurnal Riset Komputer, which demonstrated the application of Naive Bayes in bankruptcy prediction, achieving an exceptionally high accuracy of 99.2% from 250 data points[10]. Rahma's research, published in the Jurnal AUTOMATA, showed that Naive Bayes is effective in detecting Indonesian language spam emails, reaching an accuracy of 94% from 617 data points[11]. Meanwhile, Azhar, in his study published in Penelitian Ilmu Komputer Sistem Embedded And Logic, compared Naive Bayes with SVM for sentiment analysis in a marketplace, with SVM achieving an accuracy of 81.21% and Naive Bayes 69.74% without feature optimization. Ayumi, in the Journal of Scientific and Applied Informatics, also found that SVM outperformed Naive Bayes in sentiment analysis related to fuel price increases, with an accuracy of 90% compared to Naive Bayes' 78%[12]. Finally, Ananda et al., in the Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer, demonstrated that the performance of SVM with linear and radial basis function kernels varied, with the linear kernel providing the highest accuracy of 90% in certain scenarios. This study highlights the importance of selecting the right method and parameters to achieve the best results in sentiment analysis[13].

Previous studies have shown that while many studies have explored sentiment analysis using various methods, this research offers a new approach. By comparing two applications within a single company group, Midi Kriing and Alfagift, using the SVM method with TF-IDF weighting, this study provides insights into user preferences, helping determine which of the two applications Midi Kriing or Alfagift is more trustworthy for use, based on the accuracy of sentiment analysis results from their reviews.

2. Research Methods

The workflow in this study involves several stages, starting with data collection through scraping, labeling, preprocessing, TF-IDF weighting, and sentiment classification using SVM. Evaluation is carried out using a confusion matrix. A detailed explanation can be seen in Figure 1.

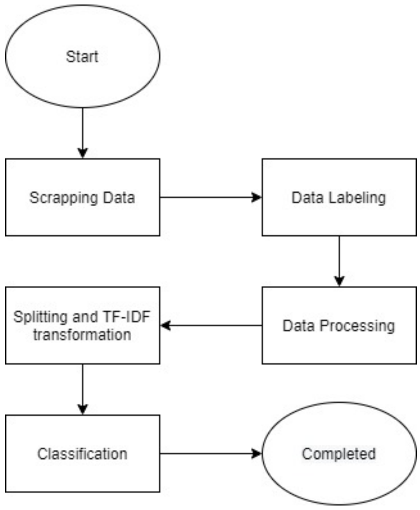

Figure 1. Research Flow

2.1 Data Collection

Data collection is an important initial step for analysis. The data is directly gathered from user reviews on the Google Play Store using a web scraping technique with a Python library called Google-Play-Scraper, focusing on the 2,000 most relevant reviews. This technique allows the researcher to automatically extract reviews from the Alfagift and Midi Kriing application pages. After the data is collected, it is stored in CSV format and filtered to include only the review and score columns. The data is also sorted by date to ensure that the sentiment analysis process can be conducted more effectively. An example of the data obtained from scraping can be seen in the Figure 2.

content	score
Yang bener aja ni, minta masukin OTP, dimasuki...	1
Belanja lebih mudah praktis cepatdan mudah	5
Belanja lebih mudah Cepat dan praktis	5
Bagaimana sih punya app, ada pilihan waktu tap...	1
Pesan dari jam 1 siang, estimasi dtg jam 5 sor...	1

Figure 2. Sample data obtained.

2.2 Labeling

The sentiment labeling process involves evaluating application reviews based on the scores given. Each review from the Google Play Store application is identified and labeled according to its score[14]. Reviews with a score below 3 are labeled as negative, scores above 3 are labeled as positive, and a score of exactly 3 is labeled as neutral. The purpose of this labeling is to facilitate analysis using the Support Vector Machine algorithm and TF-IDF weighting to evaluate and compare user sentiments between the Midi Kriing and Alfagift applications. A visualization of the labeled review data, which includes both the Midi Kriing and Alfagift applications, can be seen in the table 1 showing the labeling results below.

Table 1. Labeling

Labeling Midi Kriing

content	score	Label
Yang bener aja ni, minta masukin OTP, dimasuki...	1	Negatif
Belanja lebih mudah praktis cepatdan mudah	5	Positif
Belanja lebih mudah Cepat dan praktis	5	Positif
Bagaimana sih punya app, ada pilihan waktu tap...	1	Negatif
Pesan dari jam 1 siang, estimasi dtg jam 5 sor...	1	Negatif
Bagus banget belanja disini promonya menarik	5	Positif
Ribet banget nih aplikasi mau daftar aja susah...	2	Negatif

Labeling Alfagift

content	score	Label
Tiap belanja dibilang struknya masuk alfagift,...	5	Positif
Sangat membantu 🤩Tidak perlu cape-cape harus d...	5	Positif
Aplikasi berat, struk ga langsung masuk. Payah...	1	Negatif
Mudah,Tdk ribet Tdk buang waktu banyak...promo...	5	Positif
Pengiriman cepat, promo lengkap, produk lengka...	5	Positif
Pengiriman cepat,promo lengkap,produk lengkap,...	5	Positif
Pengiriman cepat,promo2 juga lengkap,produk ju...	5	Positif

2.3 Preprocessing Data

The preprocessing stage in this study begins with data cleaning to remove noise or irrelevant information. Next, case folding is performed, which involves converting all uppercase letters to lowercase for consistency[15]. After that, stopword removal is applied to eliminate unimportant connecting words such as "and," "or," etc. The cleaned data is then split into smaller units through the tokenization process. Finally, stemming is performed to convert words to their root forms, making the analysis more accurate.

a. Cleaning

In the data cleaning stage, steps will be taken to remove unnecessary components from the text. This includes the removal of punctuation marks such as periods, commas, question marks, and exclamation marks. Additionally, elements like HTML tags, URLs, hashtags, and mentions will also be removed from the text[16]. An example of the cleaning process can be seen in the table 2 and table 3.

Table 2. Cleaning dataset Midi Kriing

Before Cleaning	After Cleaning
Yang bener aja ni, minta masukin OTP, dimasukin tpi salah.	Yang bener aja ni minta masukin OTP dimasukin tpi salah

Table 3. Cleaning dataset Alfagift

Before Cleaning	After Cleaning
Pengiriman cepat, promo lengkap, dan produk lengkap	Pengiriman cepat promo lengkap produk lengkap

b. Case Folding

Case folding is the process of converting uppercase letters to lowercase in text. In sentiment analysis, case folding helps reduce word variations that have the same meaning but are written in different cases[17]. For example, the words "wajah" and "WAJAH" have the same meaning, but without case folding, these two words would be treated as different and analyzed separately in the sentiment analysis process. An example of the case folding process can be seen in the table 4 and table 5.

Table 4. Case Folding Dataset Midi Kriing

Before Case Folding	After Case Folding
Yang bener aja ni minta masukin OTP dimasukin tpi salah	yang bener aja ni minta masukin otp dimasukin tpi salah

Table 5. Case Folding Dataset Alfagift

Before Case Folding	After Case Folding
Pengiriman cepat promo lengkap dan produk lengkap	pengiriman cepat promo lengkap produk lengkap

c. Stopword Removal

Stopword removal is the process of removing common words that frequently appear in text, such as prepositions, affixes, pronouns, conjunctions, and other words that do not contribute significantly to understanding the meaning of the text[18]. These words are typically connecting words like "yang," "dan," "di," "dari," and other words that are not particularly important in text analysis. In sentiment analysis, removing stopwords can help improve accuracy because stopwords do not provide useful information in determining the sentiment or meaning of a sentence. An example of the stopword removal process can be seen in the table 6 and table 7.

Table 6. Stopword Removal Dataset Midi Kriing

Before Stopword	After Stopword
yang bener aja ni minta masukin otp dimasukin tpi salah	bener aja ni masukin otp dimasukin otp tpi salah

Table 7. Stopword Removal Dataset Alfagift

Before Stopword	After Stopword
pengiriman cepat promo lengkap dan produk lengkap	pengiriman cepat promo lengkap produk lengkap

d. Tokenizing

Tokenizing is a stage in text preprocessing that aims to divide text into smaller units called tokens, which can then be analyzed. Tokens can be words, phrases, or specific characters, with each token representing a unit of meaning in the text[7]. An example of the tokenizing process can be seen in the table 8 and table 9.

Table 8. Tokenizing Dataset Midi Kriing

Before Tokenizing	After Tokenizing
bener aja ni masukin otp dimasukin otp tpi salah	bener, aja, ni, masukin, otp, dimasukin, otp, tpi, salah

Table 9. Tokenizing Dataset Alfagift

Before Tokenizing	After Tokenizing
pengiriman cepat promo lengkap produk lengkap	pengiriman, cepat, promo, lengkap, produk, lengkap

e. Stemming

The goal of stemming is to reduce word variations that appear in the text while preserving the meaning of the word, even when it appears in different forms[4]. For example, the words "membaca," "membacaan," and "membacakan" all have the same root word, "baca." By using a stemming algorithm, all three words will be transformed into "baca." An example of the stemming process can be seen in the table 10 dan 11.

Table 10. Stemming Dataset Midi Kriing

Before Stemming	After Stemming
bener, aja, ni, masukin, otp, dimasukin, otp, tpi, salah	benar, aja, ini, masuk, otp, masuk, otp, tapi, salah

Table 11. Stemming Removal Dataset Alfagift

Before Stemming	After Stemming
pengiriman, cepat, promo, lengkap, produk, lengkap	kirim, cepat, promo, lengkap, produk, lengkap

2.4 Splitting Data dan Pembobotan TF-IDF

The data splitting process involves dividing the application review dataset into two parts training data and testing data. The training data is used to train the model, while the testing data measures how well the model predicts sentiment on new data. This process is performed using the train_test_split() function from the Python scikit-learn library[14].

Next, TF-IDF (Term Frequency-Inverse Document Frequency) weighting is applied to convert the review text into a numerical format suitable for classification models. The TF-IDF method evaluates each word based on its frequency in the document and how unique the word is across all documents, thereby improving the accuracy of sentiment classification using the SVM algorithm. Here is the script used for weighting in this study.

```
from sklearn.feature_extraction.text import TfidfVectorizer

tfidf_vectorizer = TfidfVectorizer()
tfidf_train = tfidf_vectorizer.fit_transform(X_train)
tfidf_test = tfidf_vectorizer.transform(X_test)
```

```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

Figure 3. TF-IDF Weighting Script

2.5 Classification

Sentiment classification using the SVM (Support Vector Machine) method aims to identify the sentiment of reviews as positive, negative, or neutral. SVM works by finding the optimal hyperplane that separates sentiment categories in the data[13]. The features generated from the TF-IDF weighting are used as input to the SVM model, which then projects the data into a higherdimensional space to find the separating boundary with the largest margin. With this approach, the model not only classifies the sentiment of reviews but also measures the sentiment value for each application, namely Midi Kriing and Alfagift, allowing for the comparison of accuracy and user perception between the two applications. The SVM's goal is to find the best hyperplane that separates the data from two classes, with the maximum margin. The equation for the hyperplane is expressed as:

$$f(x)=w{\cdot}x+b$$

w : weight vector.

x : feature vector (input data).

b : bias or intercept.

If the text has features "positive," "negative," and "neutral" with TF-IDF scores, SVM uses these values to determine whether the text falls into a positive or negative sentiment based on the hyperplane learned during training.

3. Results and Discussion

The data collection process was carried out using web scraping techniques with a Python library called Google-Play-Scraper. The data collected consists of 2000 user reviews for the Midi Kriing app and 2000 user reviews for the Alfagift app. This data was then saved in CSV format and underwent a preprocessing stage, where it was cleaned of symbols, common words (stopwords), and irrelevant elements. Afterward, the review data was weighted using the TF-IDF method before being classified with the Support Vector Machine algorithm, with an 80% split for training data and 20% for testing data.

The sentiment classification results for the Midi Kriing app using the SVM method with TF-IDF weighting show promising performance. The positive sentiment category performed the best, with a precision of 0.94, recall of 0.93, and an F1-score of 0.93, indicating that the model effectively identifies positive sentiment with high accuracy. Negative sentiment also performed well, with a precision of 0.81, recall of 0.84, and an F1-score of 0.82. However, the model's performance significantly declined in the neutral sentiment category, with a precision of 0.17, recall of 0.15, and an F1-score of 0.16, suggesting that the model struggles to identify neutral sentiment. Overall, the model achieved an accuracy of 0.87, with a weighted average for precision, recall, and F1-score also at 0.87. However, the low results for neutral sentiment indicate that the model may be more effective for binary classification (positive vs negative) and less effective at identifying more ambiguous or neutral sentiments. These results can be seen in the Figure 4.

	precision	recall	f1-score	support
Positif	0.94	0.93	0.93	258
Negatif	0.81	0.84	0.82	129
Netral	0.17	0.15	0.16	13
accuracy			0.87	400
macro avg	0.64	0.64	0.64	400
weighted avg	0.87	0.87	0.87	400

Figure 4. Midi Kriing Classification Results

The sentiment classification results for the Alfagift app show that the positive sentiment category performed the best, with a precision of 0.89, recall of 0.95, and an F1-score of 0.92, indicating that the model effectively identifies positive sentiment with high accuracy. Negative sentiment also performed well, with a precision of 0.76, recall of 0.79, and an F1-score of 0.77. However, the model's performance significantly decreased in the neutral sentiment category, with a precision of 0.40, recall of 0.08, and an F1-score of 0.13, suggesting that the model struggles to identify neutral sentiment. Overall, the model achieved an accuracy of 0.85, with a weighted average for precision of 0.83, recall of 0.85, and F1-score also at 0.83. However, when compared to the Midi Kriing app, Alfagift has a slightly lower accuracy score, with a difference of 0.02. These classification results can be seen in the Figure 5.

	precision	recall	f1-score	support
Positif	0.89	0.95	0.92	267
Negatif	0.76	0.79	0.77	107
Netral	0.40	0.08	0.13	26
accuracy			0.85	400
macro avg	0.68	0.60	0.61	400
weighted avg	0.83	0.85	0.83	400

Figure 5. Alfagift Classification Results

4. Conclusion

The results of the preprocessing stage show that the dataset used consists of 2000 reviews for each application, Midi Kriing and Alfagift. Next, the testing process involves data splitting, with 80% used for training data and 20% for testing data. The sentiment analysis results indicate that Midi Kriing performs very well in detecting positive sentiment, with a precision of 0.94, recall of 0.93, and an F1-score of 0.93. However, the model struggles to identify neutral sentiment, with much lower results (precision 0.17, recall 0.15, F1-score 0.16). Overall, the accuracy of this application is 0.87.

Alfagift is also effective in detecting positive sentiment, with a precision of 0.89, recall of 0.95, and an F1-score of 0.92. Negative sentiment is also well recognized (precision 0.76, recall 0.79, F1-score 0.77). However, this application also struggles to identify neutral sentiment (precision 0.40, recall 0.08, F1-score 0.13). The overall accuracy of Alfagift is 0.85, slightly lower than that of Midi Kriing. Both applications excel in identifying positive sentiment, but both face similar challenges in classifying neutral sentiment. Midi Kriing slightly outperforms Alfagift in terms of overall accuracy, with 0.87 compared to 0.85. Thus, based on this analysis, Midi Kriing can be considered slightly better than Alfagift based on user review sentiment on Google Play Store.

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