

Sentiment Analysis of Indrive App Usage Reviews on Google Playstore Using Support Vector Machine (SVM) and Naïve Bayes Algorithm

Afifani Aulida Romadholi¹, Andry Rachmadany², Bayu Hari Prasojo³

^{1,2,3}Muhammadiyah University of Sidoarjo, Indonesia



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ABSTRACT

Objective: This study aims to analyze user sentiment toward the InDrive application on Google Play Store by employing Support Vector Machine (SVM) and Naïve Bayes algorithms, motivated by the increasing number of user reviews that are difficult to evaluate manually, thus requiring a text mining approach to efficiently classify opinions into positive and negative categories. **Method:** A dataset of 30,000 reviews was collected through web scraping, and the analysis involved several stages, including preprocessing (cleaning, case folding, normalization, tokenizing, stopword removal, and stemming), term weighting using TF-IDF, and classification using SVM and Naïve Bayes. **Results:** The results revealed that SVM outperformed Naïve Bayes with an accuracy of 78%, precision of 0.80, and recall of 0.74, whereas Naïve Bayes achieved 76% accuracy, 0.79 precision, and 0.70 recall, indicating that SVM is more effective in handling complex user review data compared to Naïve Bayes. **Novelty:** The novelty of this research lies in applying a comparative study of the two algorithms to InDrive application reviews, which has not been extensively explored, and is expected to provide insights for developers to better understand user perceptions and improve the quality of application services.

INTRODUCTION

The advancement of smartphone application technology on the Android platform continues to increase, directly changing people's patterns and habits in carrying out daily activities [1]. Along with the growing mobility needs of society, this sector has undergone many adjustments. Conventional motorcycle taxis, for instance, still play an important role in Indonesia as an efficient transportation alternative, especially in urban areas often plagued by traffic congestion. This service is a mainstay for workers with busy schedules who require fast and easily accessible transportation [2].

Online transportation innovations are now increasingly popular because they can meet the public's demand for fast and practical services. Technological developments, the increasing number of smartphone users, and high mobility are the main factors driving the rapid growth of digital transportation applications [3]. This phenomenon not only demonstrates a change in how people use transportation but also impacts public behavior, creating both challenges and new opportunities in the environmental sector [4].

Online motorcycle taxis are one form of application-based transportation designed to facilitate people's daily activities. Today, there are many online motorcycle taxi services competing in the market, such as Gojek, Grab, Maxim, and InDrive. Each application offers its own advantages, whether in terms of driver services, application features, or prices offered to users [5]. One of the transportation applications gaining popularity in various countries, including Indonesia, is InDrive. This application offers

various services, from motorcycle taxis, passenger cars, courier services, intercity deliveries using cars, to large-item shipments with special vehicles. Interestingly, InDrive allows users to bid their own price and freely choose the driver whose service they want to use [6].

The Google Play Store provides a review feature that allows users to give feedback after using an application. This feature is an effective source of information to assess the quality and user experience of a particular application. Reviews can be positive suggestions or complaints. However, reviewing all comments manually is certainly not easy. Although the InDrive application is already available on the Google Play Store, some users remain dissatisfied with their experiences when using the application [7]. Therefore, a method is needed to filter and analyze these reviews. One such method is sentiment analysis, a technique used to identify, extract [8], and classify user opinions or feelings from a set of text data [9]. Sentiment analysis goes beyond simple text classification, encompassing complex linguistic phenomena such as irony, negation, and sentiment shifts [10].

However, with the large volume of incoming reviews, it remains difficult to identify the aspects that need immediate improvement. Currently, there is no systematic and accurate method for classifying reviews into positive or negative categories. By classifying reviews based on sentiment, developers will find it easier to obtain insights into user sentiment toward the application [11]. Reading user reviews one by one is impossible when dealing with large datasets. This process would take a very long time and be inefficient [12]. The more review data there is, the longer it will take application managers to analyze and draw conclusions about the prevailing sentiment. Sentiment analysis, as a text mining process, classifies unstructured data to generate sentiment information efficiently using data mining algorithms [13].

Sentiment analysis is a method for collecting data from various platforms available on the internet. This process focuses on analyzing and understanding emotions in textual reviews to capture public perceptions [14], make predictions, assess public mood, and automatically represent netizens' feelings in a particular situation [15]. Concentration on a specific topic refers to the use of words related to that topic, which may differ from those used in other topics [16]. Sentiment analysis has developed into one of the most active fields of natural language research in understanding public opinion [17], supported by increasingly diverse and accurate machine learning techniques [18]. Sentiment analysis has now evolved beyond text, extending to multimodal data such as images and videos, thus broadening its application scope [19].

Sentiment analysis is an effective way to understand customer satisfaction levels, identify the problems they face, and determine which parts of a service or product need improvement [20]. Sentiment analysis identifies patterns in text and then classifies them into positive or negative categories. The sentiment analysis process consists of three main stages: preprocessing, weighting, and classification [21], where the choice of method significantly affects model performance [22]. This is important for various applications,

such as analyzing customer sentiment from Google Play Store reviews, thereby helping to improve application services [23].

In previous research [24], it was still limited to the naïve Bayes algorithm and K-nearest neighbor analysis in the sentiment of the InDrive application, so the scope of the study still did not touch on the use of other algorithms that have the potential to be more optimal. Therefore, this study is present to fill this gap by testing the Support Vector Machine (SVM) algorithm which is known to be superior in text processing, so it is expected to be able to provide more comprehensive results. The InDrive application was chosen in this study because so far there has been no research that examines the application of the SVM and Naïve Bayes algorithms in this application.

In this research, a number of reviews were taken from the InDrive application on the Play Store website through data scraping. The review data were then analyzed using the Support Vector Machine (SVM) algorithm implemented in the Python programming language with Google Colab tools. This research is expected to serve as material to further improve service quality and help provide a clearer picture of user assessments of the InDrive application.

The literature review aims to discuss two important aspects that influence the continuation of the indrive application, namely sentiment analysis and classification, which aims to distinguish between positive and negative sentiments.

1. Sentiment analysis

The process of processing text data to determine the meaning of the sentiment contained in a sentence [25].

2. Classification

Classification is the process of predicting the category of data based on sentiment. The two classification algorithms used in this study are Support Vector Machine and Naïve Bayes.

a. Support Vector Machine

Support Vector Machine (SVM) is a powerful sentiment analysis technique [26] that is a supervised learning method in machine learning used for data classification. SVM works by determining the optimal hyperplane as a separator between classes and the largest margin, which is the distance between the outermost samples known as Support Vectors [27]. SVM generally provides high accuracy, especially for data that is linear or nearly linearly separable. However, this algorithm has limitations in handling small differences in sentiment expressions or paraphrases [28].

b. Naïve Bayes

Many studies in the field of machine learning utilize sentiment analysis or opinion extraction. Some algorithms that are often used for sentiment analysis include Naïve Bayes, maximum entropy, and support vector machine. The Naïve Bayes classifier is very efficient and requires a number of parameters that are proportional to the number of variables (features/predictors) in the learning problem. Training with the maximum likelihood method can be done by evaluating closed-form expressions, which requires linear time, unlike the more expensive iterative approach in other classifiers [29].

RESEARCH METHOD

This study uses a quantitative descriptive approach, which aims to describe and understand phenomena in depth based on data collected from the field. Data was obtained through the latest reviews of the Shopee app on Google Playstore using web scraping.

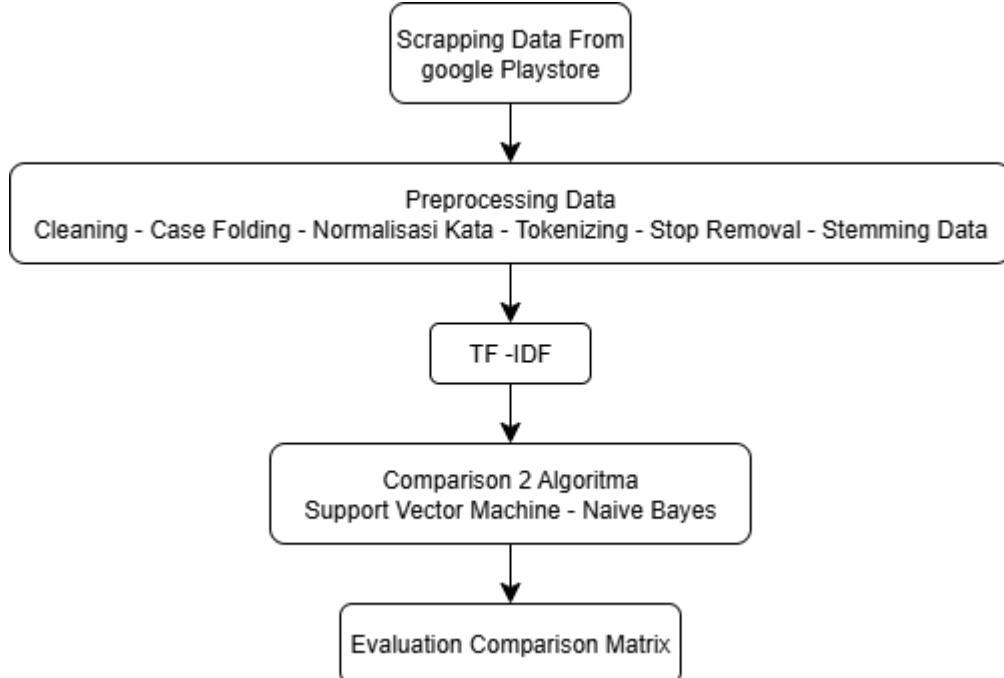


Figure 1. Research Flow Stages.

1. Population and sampling

This data sampling involves all Indrive user reviews found on Google Play Store. The population involves 30,000 Indrive app review datasets from the Google Play Store website, which were obtained through a web scraping process using Google Colab tools.

2. Data collection

Text mining is a part of data mining that focuses on processing unstructured text data with the aim of obtaining valuable information and knowledge from the data source [30]. In this study, the review dataset will be grouped into two classes: positive and negative reviews.

3. Data Preprocessing

The data preprocessing stage is a data processing stage that serves to improve imperfect datasets, such as removing unused symbols, incomplete sentences, and spelling errors [31]. This stage is carried out to facilitate the data processing process with accurate results. The following are the steps taken during data preprocessing:

a. Cleaning

The cleaning stage is the stage of correcting and deleting irrelevant data. The purpose of this stage is to facilitate sentiment analysis [32].

b. Case Folding

The case folding stage is the stage of changing the letters in a word, such as changing capital letters to lowercase letters.

c. Word Normalization

The word normalization stage involves normalizing non-standard words into standard forms.

d. Tokenizing

The tokenization stage is an important stage in lexical analysis that divides text or sentences into small units called tokens. Tokens can be words, phrases, or characters, depending on the level of detail required [33].

e. Stopword Removal

The stopword removal stage is the stage where unimportant words that do not have a significant influence on the sentiment analysis process are removed.

f. Data Stemming

This stage is the stage of obtaining root words by removing affixes in order to improve classification accuracy [34].

4. TF-IDF Word Weighting

TF-IDF (Term frequency-inverse document frequency) is a common method of weighting each word. Term frequency (TF) measures how often a word appears in a document, while Inverse Document Frequency (IDF) indicates the importance of a word based on how rarely it appears in all documents [35].

RESULTS AND DISCUSSION

Results

A. Data Collection

There are 30,000 review data obtained through data scraping. The following are the results of the data processed using Google Colab.

Table 1. Scraping Results.

	Content	Score	At
0	kembalikan sistem driver sebelum update. siste...	1	2025-07-02 22:54:43
1	kenapa di upgrade malah makin jelek aplikasiny...	2	2025-07-01 23:02:08
2	update masih membingungkan tujuan nya mungkin ...	4	2025-07-01 05:46:52
3	Tolong adakan sistem GPS tracking untuk penump...	5	2025-07-01 23:57:56
4	Untuk Driver sistem nya yg adil donk,jgn slalu...	2	2025-07-02 23:54:47
5	untuk penumpang, tolong jgn berikan fitur Bisa...	4	2025-06-29 01:03:00
6	kenapa saat saya daftar untuk driver mobil ada...	2	2025-06-28 05:07:21

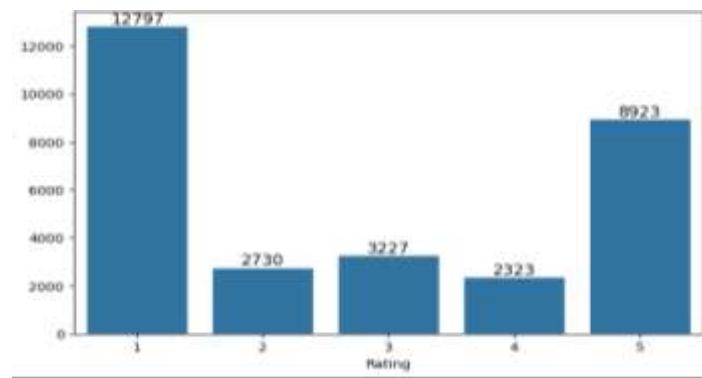


Figure 2. Review Rating Chart.

Based on the data collected, there are ratings given by users where the number of 1-star reviews is the highest at 12,797, compared to 5-star reviews at 8,923 and 4-star reviews as the lowest with 2,323 reviews.

B. Data Pre-processing

At this stage, data cleaning, case folding, word normalization, tokenizing, stopword removal, and data stemming are performed. The following is the data after the preprocessing stage:

Table 2. Data After the Pre-Processing Stage.

	Content	Clean_Content
0	UI/UX & System aplikasi masih jelek dan ada bu...	ui ux system jelek ada bug diperbaiki mengalam...
1	Tolong buat sistem ongkosnya sesuai rekomendas...	buat ongkosnya sesuai rekomendasi jangan seena...
2	assalamualaikum , Saya termasuk driver hampir ...	termasuk hampir sebulan pendapatan penumpang s...
3	udah cukup bagus sekarang, cuman saran sih wak...	udah cukup bagus cuman saran waktu ekstinas t...
4	Gilak ,masa otomatif klik.penumpang nya belum ...	otomatif klik penumpang belum muncul system bu...
5	sistem prioritas kagak jelas, yg perjalanan ud...	prioritas kagak jelas perjalanan banyak mulu u...
6	sekarang ketika autobid orderan masuk tolong d...	orderan masuk tambahkan tombol konfirmasi terl...
7	sangat kecewa sistem apk indriver sekarang, su...	sangat kecewa indriver menjalankan orderan wak...
8	terlihat sepele tapi sangat penting. tolong su...	terlihat sepele sangat penting suara ringtone ...
9	semakin lama saya sebagai driver indriver kok ...	semakin lama indriver aneh rating naik turun g...
10	Kepada Direktur In Drive, harap perbaiki siste...	kepada direktur in drive harap perbaiki kerja ...

C. Data Labeling

Data labeling aims to classify text in a sentence or document as positive or negative. This stage is the initial stage in machine learning. The following are the results of sentiment data analysis after data labeling.

Table 3. Sentiment Analysis Results.

No	Content	Score	Sentiment
0	ui ux system jelek ada bug diperbaiki mengalam...	1	Negatif
1	buat ongkosnya sesuai rekomendasi jangan seena...	4	Positif
2	termasuk hampir sebulan pendapatan penumpang s...	1	Negatif
3	udah cukup bagus cuman saran waktu ekstinas t...	5	Positif
4	otomatif klik penumpang belum muncul system bu...	1	Negatif
...
29995	sangat buruk system sangat merugikan rubah harga	1	Negatif
29996	perjalanan nyaman tepat waktu	5	Positif
29997	daritadi jam sampai gk ada satupun nyangkut su...	2	Negatif
29998	dicari murah gmpng cri milih pula tentuin ntaps	5	Positif
29999	cepat sediain stok atributnya cepat draiver pe...	5	Positif

After web scraping, data pre-processing, and data labeling, a visualization of the analysis results was produced in the form of a Word Cloud displaying words in sentiment.



Figure 3. Sentiment Word Cloud.

A Support Vector Machine (SVM) classification model with RBF kernel was created and trained using training data whose features had been extracted using TF-IDF.

Discussion

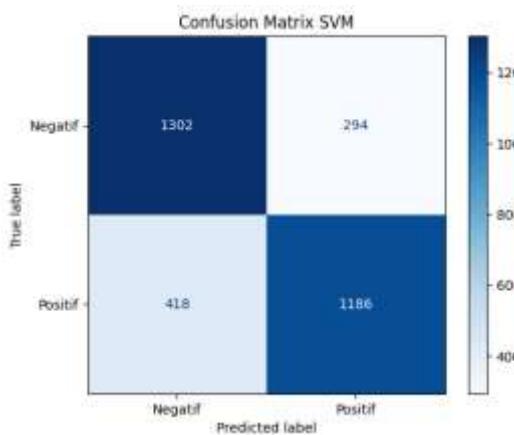


Figure 4. Confusion Matrix.

Based on the confusion matrix above, it can be seen that:

1. True negative ($TN = 1302$) is data that is actually negative and successfully predicted as negative.
2. False positive ($FP = 294$) is data that is actually negative and successfully predicted as positive.
3. False negative ($FN = 418$) refers to data that is actually positive and was correctly predicted as negative.
4. True positive ($TP = 1186$) refers to data that is actually positive and was correctly predicted as positive.

From the values in the confusion matrix above, evaluation metrics for each class (Negative and Positive) such as precision, recall, and F1-score are obtained.

Table 4. SVM Performance Evaluation Results.

	Precision	Recall	F1-Score	Support
Negative	0.76	0.82	0.79	1596
Positive	0.80	0.74	0.77	1604
Accuracy			0.78	3200
Macro avg	0.78	0.78	0.78	3200
Weighted avg	0.78	0.78	0.78	3200

Table 5. Naïve Bayes Performance Evaluation Results.

	Precision	Recall	F1-Score	Support
Negative	0.73	0.81	0.77	1596
Positive	0.79	0.70	0.74	1604
Accuracy			0.76	3200
Macro avg	0.76	0.76	0.76	3200
Weighted avg	0.76	0.76	0.76	3200

CONCLUSION

Fundamental Finding : This study finds that the Support Vector Machine (SVM) algorithm demonstrates superior performance compared to the Naïve Bayes algorithm in classifying user sentiment toward the InDrive application on Google Play Store

reviews. The SVM model achieved an accuracy rate of 78%, outperforming Naïve Bayes, which reached 76%, indicating that SVM is more effective in capturing patterns within user-generated textual data. These results emphasize the critical role of algorithm selection in sentiment analysis tasks, particularly when the objective is to accurately interpret user opinions. By producing more reliable classification outcomes, SVM provides a stronger analytical basis for understanding user satisfaction and dissatisfaction. Overall, the findings highlight SVM as a more robust method for sentiment classification in app review analysis. **Implication :** The implications of these findings suggest that developers and service providers can benefit from adopting more accurate machine learning algorithms, such as SVM, to analyze user sentiment effectively. Improved sentiment classification enables developers to better identify recurring complaints, user expectations, and areas requiring service enhancement. From a managerial perspective, reliable sentiment analysis supports data-driven decision-making aimed at improving application quality and user experience. Additionally, these results provide practical guidance for researchers and practitioners in selecting appropriate analytical techniques for sentiment analysis studies. Consequently, the study contributes to improving the strategic use of sentiment analysis in digital service development. **Limitation :** Despite its contributions, this study has several limitations that should be acknowledged. The analysis is confined to user review data obtained solely from the Google Play Store, which may not fully represent user sentiment across other platforms or social media channels. Furthermore, the study employs binary sentiment classification, which limits the depth of insight into more nuanced user emotions. Another limitation is the comparison of only two machine learning algorithms, which does not capture the full range of available or emerging sentiment analysis methods. These constraints restrict the generalizability and comprehensiveness of the findings. **Future Research :** Future research is recommended to address these limitations by expanding data sources to include multiple platforms, such as social media and other app marketplaces, to enhance external validity. Subsequent studies should also consider implementing multi-class sentiment classification to capture more detailed emotional categories. In addition, integrating advanced approaches, particularly deep learning-based models, may yield higher accuracy and richer insights into user sentiment. Comparative studies involving a broader range of algorithms would further strengthen understanding of optimal methods for sentiment analysis. Through these extensions, future research can provide a more comprehensive and accurate picture of user perceptions in digital applications.

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Afifani Aulida Romadholi

Muhammadiyah University of Sidoarjo, Indonesia

Email: aulidar35@gmail.com

***Andry Rachmadany (Corresponding Author)**

Muhammadiyah University of Sidoarjo, Indonesia

Email: rachmadany@umsida.ac.id

Bayu Hari Prasojo

Muhammadiyah University of Sidoarjo, Indonesia

Email: bayuhari1@umsida.ac.id
