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Sentiment Analysis of User Reviews of TikTok App on Google Play Store Using Naïve Bayes Algorithm

Rokyatul Hasanah [1], Sahrul Sani SR [2], Misbahul Munzir [3], Asno Azzawagama Firdaus [4,*], Chaerus Sulton [5], Muhajir Yunus [6]
[1,2,3,4] Department of Computer Science, Universitas Qamarul Huda Badaruddin, Indonesia
[5] Department of Management, Universitas Terbuka, Indonesia
[6] Universitas Muhammadiyah Gorontalo, Indonesia

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ABSTRACT

In recent years, user interaction through mobile applications has grown rapidly, making user reviews an important source of feedback for improving service quality. This study explores sentiment analysis on 5,000 user reviews of the TikTok application, collected from the Google Play Store using the google-play-scraper library. The data underwent several preprocessing steps, such as case folding, text cleaning, and selecting relevant columns like review content and rating score. Sentiment labeling was based on rating values: scores of 4 and 5 were treated as positive, while scores of 1 and 2 were considered negative. From the results, it was observed that negative reviews appeared more frequently, indicating an imbalance in the dataset. Despite this, the Naïve Bayes classification algorithm still achieved a reasonably good performance in categorizing the sentiments. These findings suggest that even with simple models, valuable insights can be gained from user-generated content. Moreover, the results provide meaningful input for TikTok developers to better understand user concerns and emphasize the potential need for applying balancing techniques in future analysis. Further studies are encouraged to explore other algorithms that may improve sentiment classification accuracy on more complex datasets.

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Corresponding Author:

Asno Azzawagama Firdaus, Department of Computer Science, Universitas Qamarul Huda Badaruddin, Indonesia
Email: asnofirdaus@gmail.com

1. INTRODUCTION

The development of digital technology today continues to experience significant acceleration, encouraging people to be more responsive in dealing with various innovations that are present. One tangible form of this change is the increasing use of mobile devices and digital applications in various daily activities, such as communication, information search, and online economic activities. Social media has become one of the most dominant and widely used digital platforms by the public, not only for socializing, but also as a means of entertainment, education, and marketing [1].

TikTok is a short video-based social media application that is experiencing rapid growth and gaining high popularity globally, including in Indonesia. Not only providing creative entertainment content, TikTok also provides a TikTok Shop feature that allows users to conduct buying and selling activities directly within the

application [2]. This innovative move makes TikTok a social media that not only focuses on entertainment, but also supports e-commerce activities directly. However, with the increase in users and features offered, there are also various opinions from users regarding their experience using this application [3].

User reviews of the TikTok app can be found in large numbers on the Google Play Store platform. These comments reflect a variety of views, both positive and negative, and can be an important source of information in evaluating user satisfaction[4]. However, since the reviews are free text, an analysis method is needed to systematically understand and categorize these opinions. One effective approach in this regard is sentiment analysis, which is a text data processing technique to identify and categorize opinions based on the sentiments contained in them [5].

To obtain accurate results in sentiment analysis, a text classification algorithm that is able to process data effectively is required. One algorithm that is often used is Naïve Bayes, which is based on the principle of probability and is considered suitable for the classification of documents or short texts due to its simple nature and has a fairly good accuracy rate in various studies [6].

This research uses the Naïve Bayes algorithm to analyse the sentiment of user reviews of the TikTok application on the Google Play Store. The stages in this research are carried out systematically, starting with the retrieval of review data through the web scraping process, the next step is the data preprocessing stage, which includes case folding (changing all letters to lowercase), data cleaning by removing unnecessary characters or symbols, and further cleaning of the text (text cleaning) to ensure the data is in a condition ready for analysis [7][8].

The main objective of this research is to build a sentiment classification model that is able to classify user opinions into two categories, namely positive sentiment and negative sentiment[9]. The results of this analysis are expected to provide a deeper understanding of public perception of the TikTok application. In addition, this research is also a scientific contribution in showing the application of the Naïve Bayes method to text data analysis, as well as its relevance in processing user opinions in the era of digital technology [10].

2. METHODS

The research stages are visualized through the following flowchart.

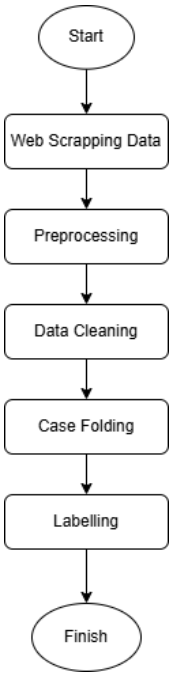

Figure 1. Research flow

2.1. Web Scrapping

Through the web scraping method, this research obtains data from websites automatically without the involvement of manual copying. In this stage, the google-play-scraper library is used to retrieve user reviews of the TikTok Shop Seller Center app on the Google Play Store. This approach enables large-scale data collection from various users, which then becomes the main source for sentiment analysis using the Naïve Bayes algorithm [11].

2.2. Preprocessing

Preprocessing is the initial stage in data processing for sentiment analysis, with the aim of filtering out irrelevant words or sentences and normalizing word forms so that the vocabulary becomes more concise [12][13].

2.3. Data Cleaning

In sentiment analysis, data cleaning is one of the decisive steps. Scraping results from the Google Play Store often contain noise such as special characters, emojis, links, or irrelevant words. Therefore, this process aims to remove unnecessary elements so that the data becomes cleaner and ready to use. With cleaned data, analysis can focus on important information and help improve the overall accuracy of sentiment prediction [14].

2.4. Case Folding

Case folding is the stage where all letters in the text are converted into a uniform format, e.g. all lowercase, so that variations in writing such as “Application” and “app” are not considered different by the algorithm. Without case folding, the same word with different casing can be treated as separate entities, which can affect the analysis results [15].

2.5. Labelling

Labelling is a crucial stage in sentiment analysis, where each review is assigned a certain category to indicate the sentiment contained in it. In the sentiment analysis research of TikTok Shop Seller Center app reviews on the Google Play Store, this process is carried out by grouping each user review into positive or negative sentiment categories [16].

3. RESULTS AND DISCUSSION

3.1. Web Scrapping

The data retrieval process is carried out by applying web scraping techniques through the Google Collaboratory platform. In this stage, the google-play-scraper library was used to extract user reviews from the Google Play Store. A total of 5,000 review data was collected and used as material in this study. Figure 2 shows the initial results of the scraping process which shows the data in raw form. Next, the data is organized into four main columns userName, score, at, and content to facilitate the next stage of analysis [17].

	userName	score	at	content
0	Pengguna Google	1	2025-06-15 21:48:38	updatean nya gak bagus, tiktok jadi ngelag, ng...
1	Pengguna Google	1	2025-06-12 05:25:05	setelah di update saya kira sudah selesai masa...
2	Pengguna Google	1	2025-06-15 22:18:23	padahal buka tiktok cuma niat belanja. gabisa ...
3	Pengguna Google	1	2025-06-15 15:14:38	tiba tiba tanda suka,coment sama panah bagikan...
4	Pengguna Google	5	2025-06-16 15:32:28	Saya sangat suka tiktok, tapi...Kanapa akhir2 ...

Figure 2. Web Scrapping Results

Since this research only requires the content and score columns, data filtering is done so that only these two columns are used to analyze reviews into positive and negative sentiment categories, as shown in Figure 3 [18].

	content	score
1794	Mohon maaf kepada tim tiktok tolong banget dip...	1
4	Saya sangat suka tiktok, tapi...Kanapa akhir2 ...	5
4757	Baik tapi kenapa suda di update baru berapa ha...	5
138	tolong dong tiktok, awalnya setelah upload vid...	1
4758	app nya eror terus 3 hari sekali download lagi...	5

Figure 3. Filter Data from Web Scrapping

3.2. Data Cleaning

```
<class 'pandas.core.frame.DataFrame'>
Index: 5000 entries, 4757 to 3132
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   content  5000 non-null   object
 1   score    5000 non-null   int64
 2   Label    4164 non-null   object
dtypes: int64(1), object(2)
memory usage: 156.2+ KB
```

Figure 4. Data Information

Figure 4 shows the data structure consisting of two main columns: content and score. The content column has an object type because it contains text or a combination of text and other characters, while the score column has an int64 data type, which indicates that it contains an integer number. Both columns have no missing values in the DataFrame. Next, a text preprocessing stage is performed to remove noise, such as unnecessary characters, links, and irrelevant words. Through this process, the data becomes more organized and structured, so it is ready to be used in the next analysis process, which is shown in Figure 5 [19].

	content	score	Label	text_clean
0	Mohon maaf kepada tim tiktok tolong banget dip...	1	Negatif	mohon maaf kepada tim tiktok tolong banget dip...
1	Saya sangat suka tiktok, tapi...Kanapa akhir2 ...	5	Positif	saya sangat suka tiktok tapikanapa akhir ini a...
2	Baik tapi kenapa suda di update baru berapa ha...	5	Positif	baik tapi kenapa suda di update baru berapa ha...
3	tolong dong tiktok, awalnya setelah upload vid...	1	Negatif	tolong dong tiktok awalnya setelah upload vid ...
4	app nya eror terus 3 hari sekali download lagi...	5	Positif	app nya eror terus hari sekali download lagi ...
5	setelah pembaruan malah ngebug parah,padahal s...	1	Negatif	setelah pembaruan malah ngebug parahpadahal si...
6	kirain cuma tiktok ku doang yang tiba tiba nge...	2	Negatif	kirain cuma tiktok ku doang yang tiba tiba nge...
7	chat olshop nya sampah kali 😪 bug nya banya...	1	Negatif	chat olshop nya sampah kali bug nya banya kal...
8	taik apasih tiktok sekarang aneh bgt dikit" ja...	1	Negatif	taik apasih tiktok sekarang aneh bgt dikit jar...
9	tiktok sekarang aneh pas pengen buka aplikasi ...	2	Negatif	tiktok sekarang aneh pas pengen buka aplikasi ...
10	min, ini tiktok ku kenapa ngelek padahal jarin...	5	Positif	min ini tiktok ku kenapa ngelek padahal jaring...
11	seler di tiktok banyak penipu. jual barang pic...	1	Negatif	seler di tiktok banyak penipu jual barang picn...
12	padahal buka tiktok cuma niat belanja. gabisa ...	1	Negatif	padahal buka tiktok cuma niat belanja gabisa p...

Figure 5. Results of Data Cleaning Process

Figure 5 shows the difference in the review data before and after going through the cleaning stage. After going through this stage, the data becomes tidier by removing unnecessary elements, such as punctuation marks and

special characters. This cleaning process aims to ensure that the data being analyzed is clean, consistent, and free from errors or noise that could affect the overall sentiment analysis results [20].

3.3. Case Folding

	content	score	Label	text_clean
1794	Mohon maaf kepada tim tiktok tolong banget dip...	1	Negatif	mohon maaf kepada tim tiktok tolong banget dip...
4	Saya sangat suka tiktok, tapi...Kanapa akhir2 ...	5	Positif	saya sangat suka tiktok tapikanapa akhir ini a...
4757	Baik tapi kenapa suda di update baru berapa ha...	5	Positif	baik tapi kenapa suda di update baru berapa ha...
138	tolong dong tiktok, awalnya setelah upload vid...	1	Negatif	tolong dong tiktok awalnya setelah upload vid ...
4758	app nya eror terus 3 hari sekali download lagi...	5	Positif	app nya eror terus hari sekali download lagi ...
3500	setelah pembaruan malah ngebug parah,padahal s...	1	Negatif	setelah pembaruan malah ngebug parahpadahal si...
831	kirain cuma tiktok ku doang yang tiba tiba nge...	2	Negatif	kirain cuma tiktok ku doang yang tiba tiba nge...

Figure 6. Results of Case Folding Process

Figure 6 shows the comparison of data before and after case folding. Before this process, the text still contains capital letters, while after case folding all characters are converted to lowercase. By equalizing capital and lowercase letters, this process helps maintain consistency in text data processing [21].

3.4. Labelling

Labelling review data is done to show the type of sentiment contained in each review, by grouping user comments into certain sentiment categories. This stage makes it easier for the system to understand user opinions or assessments of a product or service. After the data has gone through the preprocessing process, the next step is labelling as shown in Figure 7 [22].

4708	Udah bener di jalan entertain aja. pake meramb...	1	Negatif
708	Tiktok tuh skrng knpa ya udh updte versi terba...	1	Negatif
1955	semakin kesini semakin susah di buka tiap Ming...	2	Negatif
546	ini tiktok gw kenapa gk bisa masuk ya? selalu ...	1	Negatif
4793	kenapa tidak bisa di buka tik tok nya gara-gar...	1	Negatif
4727	saya bisa dapat uang dari tiktok, tapi tolong ...	2	Negatif
4751	ya apknya bagus, cuma nih ya gw ngetik kata' y...	2	Negatif
4262	Apknya banya bugnya sering bgt kalo mau masuk ...	3	None
4465	baik untuk creator tapi masak setiap mau tembu...	1	Negatif
360	kadang kadang kalau mau nonton tiktok susah di...	3	None
726	tiktok nya eror bug sama kalo mau liat aktivit...	4	Positif
3039	sangat buruk, pembagian reward hadiah banyak s...	1	Negatif
2035	kenapa setelah update malah sering ngelag dan ...	1	Negatif
4125	Bagus tapi susah update terbaru plus kalau udh...	1	Negatif
707	kinerja app tiktok sekarang kurang bagus, seri...	1	Negatif
4776	kenapa tiktok saya ga keluar like,komen,sharen...	3	None

Figure 7. Results of the Labelling Process

The determination of the sentiment label is based on the score given by the user, where the score reflects the value or assessment of a review. In this study, sentiment is classified into two categories, namely positive sentiment and negative sentiment. Reviews with a rating value of 4 and 5 are categorized as positive sentiment, while reviews with a rating of less than 3 are included in the negative sentiment [23].

Here are the results of the comparison of reviews based on negative and positive sentiment labels for the TikTok app. There are more reviews labeled negative than positive. This imbalance indicates an unbalanced data distribution between the two labels [24].

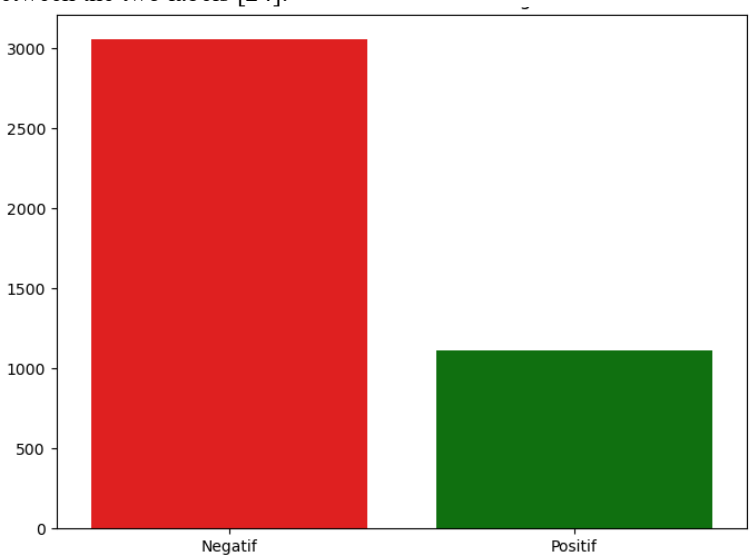

Figure 8. Positive and Negative Label Results

The diagram shows a comparison of the number of reviews labeled as negative and positive. The horizontal axis (Labels) shows the Negative and Positive sentiment categories, while the vertical axis (Number of Reviews) depicts the number of reviews in each category. Negative reviews are much more numerous at around 3,000 while positive reviews are only around 1,100. This illustrates the unbalanced distribution of data, with the dominance of negative sentiment [25].

4. CONCLUSION

This study revealed that TikTok user reviews on the Google Play Store showed a predominance of negative sentiment over positive, signaling an unbalanced distribution of data. Nevertheless, the Naïve Bayes model built after the preprocessing stages (case folding, text cleaning, and score-based labeling) managed to classify sentiments with sufficient performance, proving that this simple approach is still relevant for large-scale text analysis. The review imbalance condition emphasizes the need to apply strategies such as oversampling or under sampling so that the model can learn patterns from both classes equally. Practically, the results of this analysis provide valuable insights for TikTok developers and TikTok Shop actors in recognizing the features or services that receive the most criticism and appreciation based on further improvement and development. Methodologically, Naïve Bayes proved to be fast and easy to implement, but this research also opens opportunities to explore other methods (e.g. SVM, Random Forest, or deep learning-based models) and more sophisticated data balancing techniques to achieve better performance in the future.

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