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Research article

Sentiment Analysis of User Reviews of the CapCut Application on Google Play Store Using the Naive Bayes Algorithm

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ABSTRACT

The rapid growth of digital technology has increased the use of video editing applications, including CapCut, which is highly popular among Android users. However, a high number of downloads does not necessarily reflect user satisfaction. This study aims to analyze user sentiment toward CapCut based on reviews from the Google Play Store. A total of 500 reviews were collected using the google-play-scraper Python library and automatically labeled based on rating values. The data were processed through text preprocessing, TF-IDF weighting, and sentiment classification using the Multinomial Naive Bayes algorithm. Sentiments were categorized into positive, neutral, and negative classes. The results show that positive sentiment dominates with 54.2%, followed by negative sentiment at 38.8% and neutral sentiment at 7%. The model achieved an accuracy of 81.72% with balanced precision and recall values. Overall, most users express positive perceptions of CapCut, although complaints regarding advertisements and paid features remain notable.

1. Introduction

The development of mobile technology has driven the increasing need for video editing applications to support the activities of content creators and general users. CapCut is one of the most widely used apps on Android because it offers complete features and an easy-to-understand interface. However, despite having a high number of downloads, it does not fully reflect user satisfaction levels as there are still complaints related to performance, ads, and premium features in user reviews [1].

This situation shows the importance of a systematic approach to understanding user opinions objectively. Text-based sentiment analysis on user reviews on platforms such as the Google Play Store is one of the effective methods to help developers understand user perceptions and needs more accurately [2].

Several previous studies have shown that machine learning methods such as Multinomial Naive Bayes are able to perform well in text-based sentiment classification because they are simple, fast, and stable against large datasets. One study applied this algorithm in the analysis of digital application reviews and obtained a high enough accuracy that it was recommended in the classification of texts based on user opinions [3].

However, research that specifically focuses on analyzing user sentiment towards the CapCut application on the Google Play Store is still limited, so further research is needed. Based on this, this study aims to (1) analyze the distribution of sentiment of CapCut application users in Google Play Store reviews and (2) evaluate the performance of Multinomial Naive Bayes in sentiment classification using text preprocessing, TF-IDF, and machine learning modeling [4].

2. Researcher Methodology

A. Research Design

This study uses a quantitative approach with an experimental method based on text mining to classify the sentiment of CapCut application users. The research process was carried out through the stages of data collection, text preprocessing, feature weighting using TF-IDF, Naive Bayes classification model training, and model performance evaluation. This approach has been used in digital application sentiment analysis research because it is able to provide a systematic flow in the processing of text data up to the model evaluation stage [5].

This research stage includes review data collection, text preprocessing, feature extraction using TF-IDF, Naive Bayes classification model training, and model performance evaluation. The combination of

preprocessing, TF-IDF, and machine learning-based algorithms has been shown to improve classification accuracy in mobile app review sentiment analysis research [6].

B. Data Collection

Data is collected from the Google Play Store using *the google-play-scraper* Python library. The CapCut application (ID: com.lemon.lvoverseas) was chosen as the object of the research because it has a high level of use and receives many reviews from Indonesian users. Data collection is limited to 500 recent reviews to be efficient but still representative. The scraped data structure includes attributes such as the username, review date, rating, and review body, and then saved in CSV format for the next process. This data collection approach has been used in Play Store-based digital application review analysis research and has been proven to be effective in obtaining relevant datasets [7].

C. Sentiment Data Labeling

Labeling is done automatically based on the rating value on the review, namely: a 1–2 star rating is categorized as a negative sentiment, a 3-star rating is a neutral sentiment, and a 4–5 star rating is a positive sentiment. The labeling results show that the majority of users give positive reviews of the performance and features of the CapCut app [8].

D. Pre-Processing

The text preprocessing stage is carried out to convert raw text into clean and ready-to-process data. The steps include case folding, cleansing, tokenizing, stopword removal, and stemming using the Sastrawi library. This preprocessing process is important because it can reduce noise in the text, thereby improving the efficiency and accuracy of the sentiment classification model [9].

E. Feature Extraction Using TF-IDF

Feature extraction is performed using *the Term Frequency – Inverse Document Frequency (TF-IDF)* method to convert text into numerical representations. The parameters used are *ngram_range = (1,2)* and *max_features = 10,000*, thus considering unigrams and bigrams. TF-IDF is a commonly used method in text modeling because it is able to assess the importance of words in a document relative to the entire corpus [10].

F. Classification of Sentiment with Naive Bayes

The sentiment classification model used is Multinomial Naive Bayes because this algorithm is efficient and corresponds to TF-IDF-based text representations. The training process was carried out using 80% training data and 20% test data. The model was developed using the Naive Bayes probability formula to determine sentiment classes based on the distribution of words in the data [11].

The model is built with the basic formula:

$$P(c \mid d) = \frac{P(c) \prod_{i=1}^{n} \quad P(w_i \mid c)}{P(d)}$$

where is the probability that a document belongs to the class, and is the probability that the word appears in that class.$P(c \mid d)dcP(w_i \mid c)w_i$

G. Model Evaluation

Model evaluation was carried out using accuracy, precision, recall, F1-Score, and confusion matrix metrics to see the prediction distribution of each class. In addition, visualizations such as sentiment distribution graphs and wordcloud are created to aid in the interpretation of model results. Evaluations like this are commonly used in machine learning-based sentiment analysis research to ensure stable and measurable model performance [12].

H. Research Tools

The experiment was carried out using:

Table 1. Research Tools

Data components	Description
Programming languages	Python 3.10
Work environment	Google Colab
Main library	pandas, google-play-scraper, scikit-learn, Literature, tqdm, matplotlib, seaborn, wordcloud

3. Results and Discussion

A. Data Collection and Labeling Results

The research data was obtained from 500 user reviews of the CapCut application on the Google Play Store using

google-play-scraper Python library.

Each data contains userName information, review date (at), rating (score), and review content (content). Labeling

Done based on the rating value:

- 1–2 stars → Negative
- 3 stars → Neutral
- 4–5 stars → Positive

The distribution of labeling results is presented in Table 2 below.

Table 2. Data labeling

Categories	Number of reviews	Introduce yourself
Positive	271	54,2%
Neutral	194	38,8%
Negatives	35	7,0%

B. Text Preprocessing Results

The preprocessing stage successfully converts raw text into clean, structured text. The *process of case folding*, *cleansing*, *stopword removal*, and *stemming* produces a new column named clean_text that is ready to be processed using the TF-IDF method.

Examples of pre-processing results:

Previous: "The application is baguzzz easy to learn 👍👍👍"

After: "good app easy to teach"

This stage is important because it reduces noise in the text data, thereby improving the accuracy of classification.

C. Naive Baye Model Training Results

The Multinomial Naive Bayes model was trained using data that had been extracted into TF-IDF vectors with a division of 80% of the training data and 20% of the test data.

The results of the model evaluation are shown in Table 3.

Table 3. Evaluation results

Metrics	Value (%)
Accuracy	81.72
Precision	82.0
Recall	80.0
F1 Score	81.0

The model shows good performance with an accuracy of 81.72%. The relatively balanced precision and recall values indicate that the model is able to classify positive and negative reviews with fairly stable proportions.

D. Confusion Matrix

The prediction distribution of each class can be seen in Figure 2.

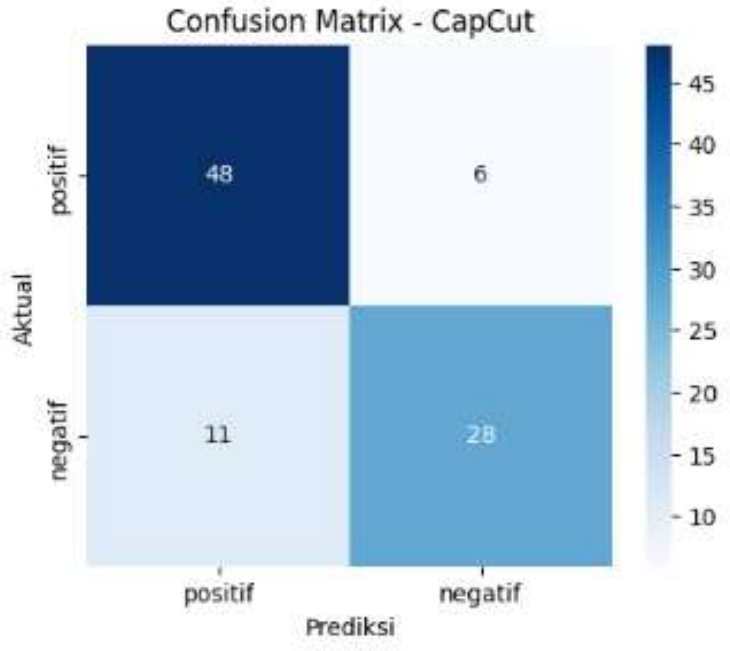

Figure 1. Confusion Matrix

From the confusion matrix, it can be seen that the model is most correct in classifying positive (48 reviews true) and negative (28 reviews true) classes. The misclassification is relatively small, showing the model is quite accurate in recognizing the difference between positive and negative comments on CapCut.

E. Sentiment Distribution Analysis

The results show that positive sentiment dominates with 271 reviews, followed by negative as many as 194, and neutral as many as 35.

This condition indicates that the majority of users have a good view of the application, especially on the ease of use and quality editing results.

F. WordCloud Positive and Negative Sentiment

To see which words appear most often in each category, a *WordCloud visualization* is created as shown in Figure 3 and Figure 4

Figure 2. WordCloud Positive

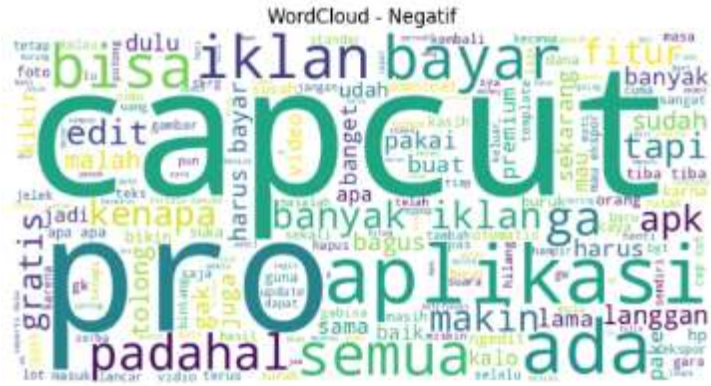

Figure 3. WordCloud Negative

WordCloud positive reviews feature dominant words such as *good*, *can*, *app*, *edit*, and *very*. This shows user satisfaction with CapCut's key features such as easy video editing and good finishes.

Meanwhile, WordCloud's negative reviews show words like *ads*, *pay*, *pro*, *why*, and *all*, which describe user complaints against over-advertising and paid (*premium*) features.

G. Results Discussion

Based on the results of the analysis, the Multinomial Naive Bayes model managed to classify the sentiment of CapCut user reviews with an accuracy of 81.72%. An average F1-score of 81% indicates a balance between precision and the ability to recognize true sentiment. The dominance of positive sentiment indicates that users are generally satisfied with CapCut's performance and ease. However, negative reviews remain an important input — especially when it comes to excessive advertising and premium features that are considered to be detrimental to convenience [13].

These results are consistent with a study on public service application reviews in Indonesia, where the combination of TF-IDF and Naive Bayes showed adequate performance in the classification of user sentiment [14]. Meanwhile, research on Telegram app reviews and other mobile services shows that similar methods provide reliable results for Indonesian texts, supporting the validity of this approach in local contexts. Thus, the method used in this study proved to be effective in measuring the perception of Indonesian-language application users, while strengthening the support that text-mining based on TF-IDF + Naive Bayes is relevant and practical for application review analysis [15].

4. Conclusions and Suggestions

This study successfully conducted a sentiment analysis of 500 user reviews of the CapCut application on the Google Play Store using the Multinomial Naive Bayes algorithm with a representation of TF-IDF features, resulting in an accuracy of 81.72% with balanced precision and recall values. These findings show

that the Naive Bayes method is effective in classifying user opinions towards Indonesian text-based applications. The results of the analysis show that the majority of users give positive sentiment (54.2%), which reflects satisfaction with the ease of use, completeness of features, and video editing results. However, negative reviews (38.8%) are still found and generally focus on complaints related to paid premium ads and features. Overall, the results of this study can be an input for developers to improve the user experience and prove that sentiment analysis based on *text mining* is effectively used as an evaluation tool for the quality of digital applications.

Further research is recommended to use a larger amount of data to make the classification results more accurate and representative, as well as test other algorithms such as Support Vector Machine (SVM) or Random Forest as a performance comparison with Naive Bayes. In addition, temporal analysis needs to be done to see changes in user sentiment over time. For the developers of CapCut, the results of this study show that the advertising aspects and premium features need to be reviewed because they are the main source of user complaints. The analysis model used in this study also has the potential to be applied to other digital applications as an automatic evaluation tool for user satisfaction levels.

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