

Application of Support Vector Machine Algorithm for Sentiment Analysis of Deepseek App User Reviews on Google Play Store

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Abstract

The rapid advancement of artificial intelligence (AI) technologies has led to the emergence of various intelligent applications, including DeepSeek. With over 10 million downloads and thousands of user reviews on the Google Play Store, DeepSeek has garnered significant public attention. These user reviews provide valuable insights into perceptions of the app's performance, highlighting the need for systematic analysis to support service improvement. Furthermore, controversies and restrictions surrounding DeepSeek in certain countries due to data security and privacy concerns underscore the importance of understanding public sentiment more deeply. This study employs the Support Vector Machine (SVM) algorithm to classify the sentiment of 1,000 user reviews obtained via web scraping. The dataset was processed through text preprocessing stages, including case folding, cleaning, normalization, tokenization, stopword removal, and stemming. Feature extraction was performed using TF-IDF, and classification utilized the One-vs-All approach. Evaluation results demonstrate that the SVM model successfully categorized sentiments into positive, neutral, and negative classes with an accuracy of 80%. The highest F1-scores were achieved in the positive (0.84), negative (0.77), and neutral (0.75) categories. The analysis revealed 38.73% positive, 36.98% neutral, and 24.29% negative reviews. These findings confirm the effectiveness of SVM for sentiment analysis of Indonesian texts and its potential in informing AI-based product development strategies.

Keywords: Sentiment Analysis, Support Vector Machine, DeepSeek, Google Play Store, Machine Learning.

1. Introduction

The development of information technology, especially artificial intelligence (AI), has led to the creation of intelligent applications such as DeepSeek. This app utilizes natural language processing to assist with information retrieval, and has been downloaded more than 10 million times on the Google Play Store, making it one of the most popular AI apps globally [1].

However, DeepSeek's adoption is not free from challenges. Some countries such as the United States, Italy, and India have restricted the use of the app due to concerns over data security and user privacy [2]. This situation shows the importance of understanding public perception. Therefore, a solution is needed to analyze user sentiment in an efficient way. Sentiment analysis is the process of extracting opinions, sentiments, and emotions contained in text with the aim of understanding users' perceptions of a particular subject [3]. Sentiment analysis aims to extract emotions, opinions, or feelings in text-based data to understand user attitudes towards an entity [4].

In this case, the Support Vector Machine (SVM) algorithm can be used to analyze DeepSeek user sentiment. Support Vector Machine is a classification method that works by finding the optimal hyperplane in high-dimensional space, to maximally separate classes [5]. SVM is better to be used as a classification method in the sentiment analysis process of Indonesian textual reviews, this is evidenced by the accuracy results obtained by the SVM method which is greater than the Naïve Bayes classifier method, which is 81.46%, while the Naïve Bayes classifier method gets an accuracy of 75.41%. [6]. In 2017, Hartmann-Boyce and her colleagues evaluated various apps available on the Google Play Store to analyze user preferences and feedback regarding apps used in weight monitoring and loss. Their results showed that user reviews and ratings influence the success of an application [7].

The results of this research are expected to provide insight for developers to improve the quality of applications and address user concerns. This research aims to apply the SVM algorithm in sentiment analysis of user reviews of the DeepSeek application. Using this method, this research will categorize user reviews based on positive, neutral and negative sentiments. Given that DeepSeek has faced restrictions in several countries due to concerns regarding data security and user privacy, this analysis becomes even more important.

2. Research Methods

The stages of research that will be carried out in this study are depicted in the chart below :

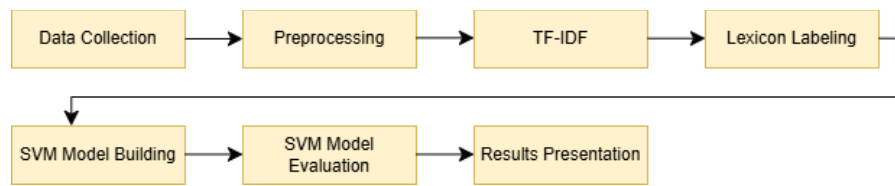


Fig. 1: Research flow

2.1. Data Collection

The data collection process was done by web scraping using Google Colab and converted into CSV format. The data collected includes usernames, and reviews. Data collected as much as 1000 data.

2.2 Preprocessing

The Preprocessing is the initial stage in data processing, especially in data science, machine learning, and (NLP). Its main goal is to prepare the raw data into a clean, structured form, ready to be analyzed or trained into a model.

The following are the stages of preprocessing:

2.3 Case Folding

Case folding is the process of converting all letter characters into lowercase form. This is important because in text analysis, words like "AI" and "ai" should be treated as the same word.

2.4 Cleaning

Cleaning is the process of cleaning the text by removing irrelevant elements, such as punctuation, numbers, special characters, URLs, mentions, hashtags, and excess spaces, so that the text becomes cleaner and ready for analysis.

2.5 Normalize

Normalization is the process of converting words or phrases that use English, slang, or non-standard forms into more standard forms. The purpose of normalization is to facilitate text processing and analysis, as slang words are often not found in standard dictionaries or have confusing writing variations.

2.6 Tokenize

Tokenize is the process of breaking down text into the smallest meaningful units, called tokens. Tokens can be words, numbers, or symbols present in the text. Tokenization separates the text to facilitate further processing such as word frequency analysis, classification, and others.

2.7 Stopword Removal

Stopword Removal is a step to remove words that appear frequently in language but do not carry significant meaning for analysis. Words such as "yang

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Andriyani, T. (2025, February 13). DeepSeek Ramai Diblokir Banyak Negara, Pakar UGM Nilai Setiap Punya Kedaulatan Digital. Universitas Gadjah <https://ugm.ac.id/id/berita/deepseek-ramai-diblokir-banyak-negara-pakar-ugm-nilai-setiap-negara-punya-kedaulatan-digital/>

Alsaedi, A., & Khan, Z. (2019). A study on sentiment analysis techniques of Twitter data. *International Journal of Advanced Computer Science and Applications*, 10(2), 361–374.

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Ardiansyah, A., Suleman, Pratama, E. A., & Fadlilah, N. I. (2024). Analisis sentimen pengguna terhadap aplikasi ChatGPT di Google Play Store: Penerapan algoritma Support Vector Machine. *Jurnal Teknik Informatika dan Sistem Informasi*, 11(2), 247–254.

", "yang", "adalah", "di", and "dengan" are generally considered unimportant in the context of text analysis.

2.8 Stemming

Stemming is the process of converting words into their root form, removing affixes such as prefixes, suffixes, or inserts. For example, the word "membantu" will be stemmed to "bantu". It aims to reduce word variation and treat words that have the same basic meaning as the same entity.

2.9 TF-IDF

TF-IDF aims to convert text to numeric and measure the extent to which a word is important to a document, by considering how often the word appears in the document (local frequency) and how rarely the word appears across documents (global frequency).

Description :

t : term (word)

d : document

N : total number of documents

df (t) : number of documents containing word t

2.10 TF (Term Frequency)

Measures how often a word appears in a document.

$$TF(t,d) = \frac{\text{Number of occurrences of word } t \text{ in the document}}{\text{Total number of words in the document } d} \quad (1)$$

2.11 IDF (Inverse Document Frequency)

IDF (Inverse Document Frequency) is used to measure how important a word is in the entire document collection. The less often a word appears in all documents, the higher the IDF value.

$$IDF(t) = \log_{10} \left(\frac{N}{df(t)} \right) \quad (2)$$

2.12 TF-IDF

Here is the TF-IDF formula, which is a combination of Term Frequency (TF) and Inverse Document Frequency (IDF).

$$TF-IDF(t,d) = TF(t,d) \times IDF(t) \quad (3)$$

2.13. Lexicon Labeling

Lexicon labeling is a sentiment analysis method that uses a list of words/dictionaries that have been labeled with sentiments such as positive, negative, or neutral to determine the sentiment of a document, sentence, or phrase.

2.14. SVM Model Building

SVM works by finding the best hyperplane that separates two classes of data. The general formula of the hyperplane.

$$f(x) = w \cdot x + b \quad (4)$$

Description:

w: weight vector

x: input feature vector

b: bias

2.15. SVM Model Evaluation

The evaluation stage is a process to measure the performance of the classification model by comparing the model's prediction results to the actual label. Evaluation is done using metrics such as accuracy, precision, recall, and F1-score obtained from the confusion matrix. The goal is to find out how well the model classifies data correctly and consistently.

Here is the formula used:

$$\text{Accuracy} : \frac{TP + TN}{TP + FP + FN + TN} \quad (5)$$

$$\text{Precision} : \frac{TP}{TP + FP} \quad (6)$$

$$\text{Recall} : \frac{TP}{TP+FN} \quad (7)$$

$$\text{F1-Score} : \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

2.16. Results Presentation

At this stage, the results of the sentiment classification process that has been carried out will be presented in the form of visualizations, such as bar charts and evaluation tables. Presentation in visual form aims to make it easier to understand the performance of the model.

3. Result and Discussion

3.1 Data Collection

Data collection is done by web scraping method using Google Colab. In this study, the google-play-scraper library was used to retrieve DeepSeek application user review data on the Google Play Store. The amount of data used as a dataset is 1000 reviews. Wordcloud can be seen in figure 2 :



Fig. 2: Wordcloud Before Processing

After the dataset is collected, a duplicate data removal process is carried out to ensure that the review dataset used is unique and has no repetition of data.

```
<class 'pandas.core.frame.DataFrame'>
Index: 928 entries, 0 to 999
Data columns (total 1 columns):
# Column Non-Null Count Dtype
---
0 ulasan 928 non-null object
dtypes: object(1)
memory usage: 14.5+ KB
```

Fig. 3: Duplicate Data Deletion

Based on the execution results, it is known that the amount of data before is 1000 reviews and the amount of data after duplicate removal is 928 reviews. This means that there are 72 duplicate reviews that have been successfully removed, so that the data used in the preprocessing and model training stages is cleaner and avoids bias due to data repetition.

3.2. Preprocessing

Preprocessing results can be seen in figure 4 :



Fig. 4: Wordcloud After Preprocessing

3.3 TF-IDF

With the TF-IDF calculation, the review data that was originally in text form has now been converted into a numerical representation, where each word has a weight according to its importance in the document. The data is ready to be used for the next stage which is lexicon labeling and sentiment classification using Support Vector Machine (SVM).

	Term	TF-IDF
0	simpan	0.534680
1	mantap	0.550098
2	loh	0.412089
3	guna	0.598530
4	suka	1.000000
...
295	lambat	0.318804
296	chatgpt	1.000000
297	salah	0.468391
298	aplikasi	0.765941
299	minggu	0.541052

300 rows × 2 columns

Fig. 5: TF-IDF Result

3.4 Lexicon Labeling

Lexicon labeling is a technique that uses a dictionary of sentiment-labeled words (positive, neutral and negative) to identify and classify emotions or opinions in a review. The Indonesian lexicon dictionary is downloaded from GitHub, which contains a list of positive, neutral and negative words.

Result Labeling lexicon based on 3 categories (positive, neutral, negative)

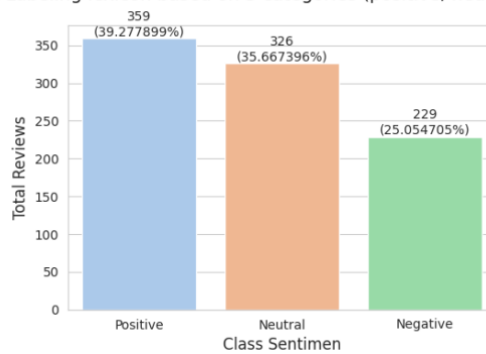


Fig. 6: Lexicon Labeling Result

Figure 6 shows the results of lexicon-based sentiment labeling of 928 DeepSeek app user reviews, classified into three main categories: positive, neutral, and negative. From these results, 354 reviews or about 38.73% fall into the positive category. This shows that most users gave favorable responses or expressed satisfaction with the application. Meanwhile, there are 338 reviews or around 36.98% that are neutral, which generally contain comments that do not show a firm opinion, either in a positive or negative direction. The negative category includes 222 reviews or 24.29%, indicating complaints, criticism or dissatisfaction from some users with the app's performance or features. Overall, this distribution reflects that users' perceptions of the DeepSeek app tend to be predominantly positive, but there is still room for improvement based on the negative feedback provided.

3.5 SVM Model Building

Before the model is created, a process of dividing the data into training data and testing data must be carried out. The division is done where the text data is divided with a ratio of 80% for training and 20% for testing.

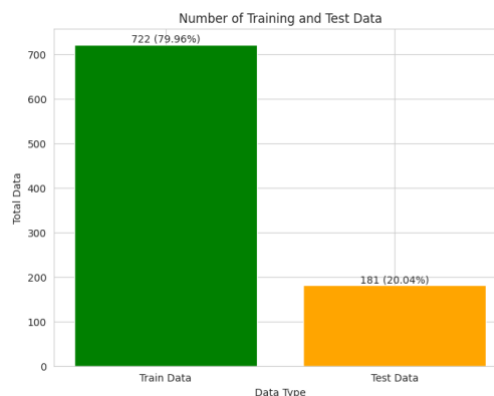


Fig. 7: Division of Training Data and Test Data

After dividing the data, the SVM model will be created. At this stage, the classification model is trained with a multi-class classification model using the OneVsRestClassifier approach with an SVC (Support Vector Classifier) estimator in it. The training process is carried out using training data that has gone through the vectorization process.

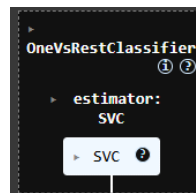


Fig. 8: OneVsRestClassifier

3.6 SVM Model Evaluation

After completing the model training process, an evaluation was conducted to assess the performance of the Support Vector Machine (SVM) in classifying user review data. First, the model's accuracy was calculated as the ratio of correct predictions to the total number of test data. Additionally, a classification report was generated, presenting key performance metrics such as precision, recall, and F1-score for each sentiment class (positive, neutral, and negative). The evaluation results, as previously described, demonstrate the model's effectiveness in classifying the test data. These results, including the accuracy and other performance metrics, are summarized and illustrated in Figure 9.

SVM Classification Report:				
	precision	recall	f1-score	support
Negatif	0.82	0.73	0.77	51
Netral	0.73	0.78	0.75	55
Positif	0.83	0.85	0.84	75
accuracy			0.80	181
macro avg	0.79	0.79	0.79	181
weighted avg	0.80	0.80	0.80	181

Fig. 9: SVM Model Evaluation Result

The SVM model achieved 80% accuracy on 181 test data, indicating good classification performance. The evaluation results show that the model is most accurate in recognizing the Positive class with the highest f1-score of 0.84, followed by the Negative (0.77) and Neutral (0.75) classes. The precision and recall values for each class are also relatively balanced, with a macro average and weighted average f1-score of 0.79 and 0.80, respectively. Overall, the model shows good and consistent performance, although it can still be improved especially in distinguishing data with neutral sentiment.

3.7 Results Presentation

Presentation of results is the final stage in the sentiment analysis process which aims to present the classification results of the SVM model in graphical form to make it easier to understand and analyze. In this research, visualization is used to describe the distribution of sentiment data (positive, neutral, negative), as well as model performance through evaluation metrics such as precision, recall, and f1-score.

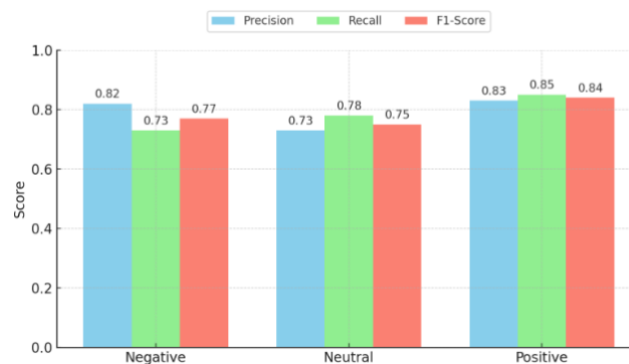


Fig. 10: Bar Diagram

4. Conclusion And Suggestions

This research shows that the SVM algorithm is effective in classifying the sentiment of DeepSeek app user reviews into positive, neutral and negative categories, with an accuracy of 80% from 181 test data. The model was most accurate in detecting positive sentiment (f1-score 0.84), followed by negative (0.77) and neutral (0.75). The majority of reviews were positive (38.73%), which reflects users' favorable perception of the app. The preprocessing process and TF-IDF feature extraction were instrumental in the success of the model, although the limitation of the lexicon dictionary is still an obstacle, especially in recognizing non-formal vocabulary.

For future research, it is suggested that the lexicon dictionary be expanded by adding slang vocabulary and current terms to improve the labeling quality. In addition, the use of hybrid methods that combine lexicon and deep learning approaches can help overcome ambiguity in neutral sentiments. Expansion of data sources from various platforms is also recommended to make the model more adaptive to various user language styles.

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