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SIGNAL App Review Sentiment Analysis using Support Vector Machine (SVM) on Google Play Store Comments

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Abstract

The SIGNAL (National Digital Samsat) application is a digital innovation that makes it easier to pay motor vehicle taxes in Indonesia. This study aims to analyze user sentiment towards the SIGNAL application through reviews on the Google Play Store, using Support Vector Machine (SVM) as a classification method. The analysis process includes the stages of review data collection, pre-processing (text cleaning, tokenization, stopword removal, and stemming), text transformation to numeric features using Term Frequency-Inverse Document Frequency (TF-IDF), and SVM model training. The dataset is taken from 10,000 of the latest reviews consisting of reviews classified into three sentiment categories: positive, negative, and neutral. The evaluation results show that the SVM model has a high accuracy of 91%, with consistent precision, recall, and F1-score values in each sentiment category. Positive sentiment dominates reviews (59%), followed by negative sentiment (33.8%) and neutral (7.2%). This analysis provides valuable insights for developers to improve the quality of applications, especially in understanding user needs and expectations.

Keywords: Sentiment analysis, signal app, support vector machine (SVM), google play store, text classification.

1. Introduction

In the digital era like today, technology has changed various aspects of human life, including in terms of managing administration and paying taxes (Apriani et al., 2023). One of the most significant forms of digital transformation is the emergence of applications that simplify administrative processes, including paying motor vehicle taxes (Ihdini and Sari, 2023). In the past, vehicle owners had to come directly to the Samsat office to make annual tax payments, which often required a lot of time and energy. However, with the development of technology, various mobile applications are now available to provide more practical and efficient solutions (Mudjiyanti et al., 2022).

One application that introduces the convenience of paying motor vehicle taxes is SIGNAL (National Digital Samsat). The SIGNAL application was launched as a faster, more efficient, and more accessible tax payment solution for people in various regions of Indonesia (Martha and Jayadi, 2025). Unlike previous applications such as Sambara, which was only available for the West Java region, the SIGNAL application has a wider coverage, namely it can be used in 29 provinces in Indonesia (Saputri and Mutiarini, 2024). This is certainly a major breakthrough, because it provides convenience for users from various regions that were previously limited to manual systems or applications that could only be used locally.

The SIGNAL application allows its users to make motor vehicle tax payments directly via their smartphones without having to visit the Samsat office (Devaranti et al., 2023). Although the SIGNAL application offers various conveniences, like other digital applications, user reviews are very important to evaluate the performance and quality of the application. Therefore, analyzing comments and reviews of SIGNAL application users is very important (Fauzy and Abdullah, 2024). By analyzing sentiment from reviews given by users, we can gain a better understanding of public perception of this application, both related to user satisfaction, problems faced, and suggestions given.

In this study, sentiment analysis of SIGNAL application user reviews will be carried out using Support Vector Machine (SVM), one of the popular machine learning methods in the field of text classification. SVM is well suited to handle classification problems involving high-dimensional data, such as text analysis in app reviews. SVM works by mapping data into a higher feature space and then finding the best hyperplane that separates the classes of data.

Through this approach, this study aims to identify the sentiment contained in the reviews, namely whether user comments are positive, negative, or neutral. In addition, this analysis also aims to provide useful insights for SIGNAL app developers in improving the quality of the application and services provided. With the information obtained from sentiment analysis, developers can better understand user needs and expectations, and overcome existing problems.

2. Methodology

In this study, the methodology used to analyze sentiment from SIGNAL app reviews on the Google Play Store involves several clearly structured stages. This process includes data collection, data preprocessing, sentiment classification modeling using Support Vector Machine (SVM), model evaluation, and visualization of results. The following is a detailed explanation of each stage of the methodology:

2.1. Data Collection

In this study, the data used were taken from SIGNAL application reviews available on the Google Play Store. The data includes two main components, namely review text and rating score. The review text is a description or comment written by the user about the SIGNAL application, while the rating score refers to the star rating given by the user, which is used to assess the sentiment of the review, whether it is positive, neutral, or negative. The data collection process is carried out automatically using web scraping techniques or the Google Play Store API, which allows for sufficient data collection for further analysis purposes.

2.2. Data Preprocessing

The preprocessing process is very important to prepare the data before being applied to the SVM model. The preprocessing stages carried out include:

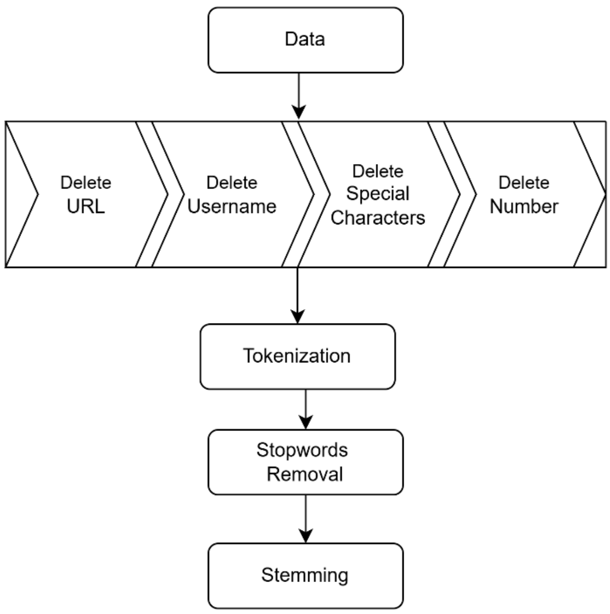


Figure 1: Flowchart of preprocessing stages

2.2.1. Text Cleaning

The first step in preprocessing is text cleaning, which aims to remove irrelevant elements from the review (Husada and Paramita, 2021). This includes removing URLs contained in the text, as URLs do not provide useful information for sentiment analysis (Jianqiang and Xiaolin, 2017). In addition, user mentions such as @username, special characters such as punctuation and symbols, and numbers that are not related to the review content are also removed, as they can interfere with the analysis process (Tan et al., 2023). Finally, words that do not contribute significant semantic meaning, or known as stopwords, are also removed. Stopwords are common words such as "and," "or," or "that" that do not have a major impact on sentiment analysis (Ladani and Desai, 2020).

2.2.2. Tokenization

Tokenization is the process of separating text into smaller units, namely tokens, which are usually words. In this stage, the review text will be divided into word tokens that are easier to analyze (Vijayarani and Janani, 2016). This process is carried out using a tokenization method that is in accordance with the Indonesian language, to ensure proper word separation.

2.2.3. Stopwords Removal

Stopwords in languages that are not Indonesian are removed from the review data using the Sastrawi library. Stopwords are words that appear very often in the text but do not carry important information, such as prepositions, conjunctions, or conjunctions (Bhirud et al., 2019).

2.2.4. Stemming

Stemming aims to change words into their basic form or root words, so that word variations can be reduced. Stemming helps reduce data complexity and improves consistency, which in turn improves the model's performance in classifying sentiment (Singh and Gupta, 2016).

2.3. Sentiment Classification

The processed data is then categorized into three sentiment classes based on the rating score given by the user, Positive Label with reviews with a rating score of 1, Neutral label with reviews with a rating score of 0 and Negative label with reviews with a rating score of -1. Sentiment classification is carried out using a Support Vector Machine (SVM) based classification model. This classification process involves several steps:

1) Each processed review is converted into a feature vector using a text representation method such as Bag-of-Words (BoW) or Term Frequency-Inverse Document Frequency (TF-IDF). This method converts text into a matrix of numeric features that can be used by the classification algorithm.
2) Data Split (Train-Test Split): The review data is divided into two sets: training data (80%) and testing data (20%). This split is used to train the model and test its performance after training.
3) The SVM model is trained using the processed training data. This process involves finding optimal hyperparameters through grid search or cross-validation techniques to avoid overfitting.
4) Once the model is trained, it is tested on test data to measure its performance in classifying review sentiment. The model's prediction results are compared with the original labels to calculate evaluation metrics.

2.4. Model Evaluation

To evaluate the performance of the model in classifying review sentiment, several classification metrics are used to assess the effectiveness of the model. The first metric used is accuracy, which measures the percentage of reviews correctly classified by the model (Saeik, 2021). Next, precision is used to calculate the proportion of correct positive predictions among all positive predictions, providing an idea of how accurate the model is in identifying positive sentiment (Kustyana et al., 2024). Recall measures the proportion of truly positive reviews that are successfully detected by the model, providing an idea of the model's ability to find truly positive reviews (Husain and Kadir, 2024). F1-Score, which is the harmonic mean between precision and recall, provides a balanced picture of the model's performance in terms of precision and ability to detect positive sentiment (Powers, 2020). To further explore the errors made by the model, a confusion matrix is used that displays the distribution of model predictions, so that the types of errors that occur can be detected, such as when the model incorrectly classifies negative reviews as positive or vice versa (Saeik et al., 2021). The following formulas are used to calculate Accuracy, Precision, Recall and F1-Score:

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \times 100\% \tag{1}$$

$$Precision = \frac{TP + TN}{TP + TN + FN + FP} \times 100\% \tag{2}$$

$$Recall = \frac{TP}{TP + FP} \times 100\% \tag{3}$$

$$F1 - score = \frac{TP}{TP + FN} \times 100\% \tag{4}$$

where:

TP: True Positive
TN: True Negative
FP: False Positive
FN: False Negative

3. Results and Discussion

3.1. Review Score Distribution

The numbers 1, 2, 3, 4, and 5 in the reviews usually refer to the star rating system used to assess the quality of the SAMSAT application. The distribution of review scores in this study is visualized in the form of a bar chart.

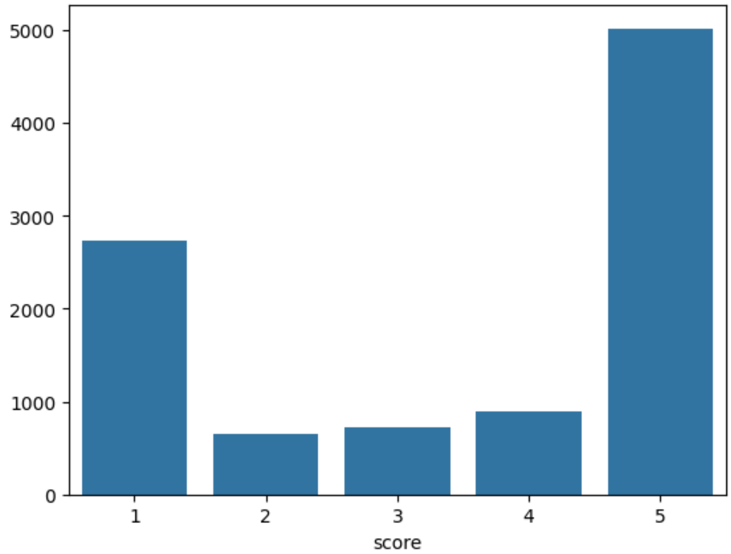


Figure 2: Review star score distribution

Figure 2 shows the distribution of review scores visualized in the form of a bar chart. This distribution shows an interesting pattern where score 5 has the highest frequency with around 5000 reviews, followed by score 1 with around 2800 reviews. Meanwhile, scores 2, 3, and 4 have relatively lower and balanced frequencies, each ranging from 700-900 reviews. This distribution pattern shows a tendency for polarization in giving reviews, where users are more likely to give extreme values (very positive or very negative) compared to medium values.

3.2. Sentiment Distribution

Figure 2 visualizes the distribution of sentiment in the form of a pie chart divided into three categories positive, negative, and neutral.

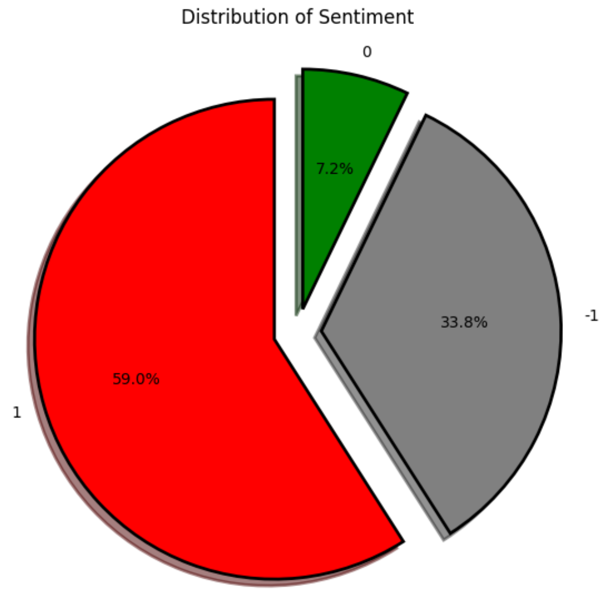


Figure 3: Proportion of positive, neutral, and negative sentiment reviews

The analysis results show that positive sentiment dominates with a proportion of 59.0% of the total data, followed by negative sentiment at 33.8%, and neutral sentiment at only 7.2%. This distribution reinforces the findings from the previous bar chart, where the majority of reviews tend to have clear sentiment (positive or negative) with very few neutral reviews. The dominance of positive sentiment indicates that in general, users respond well to the subject being reviewed.

3.3. Word Frequency

Word frequency analysis visualized in the form of a word cloud shows an interesting pattern of user reviews of the Samsat application service.

Figure 4: Word cloud frequency

The word frequency results of the word "application" appear as the most dominant word in the visualization, followed by keywords such as "pay", "tax", and "samsat" which also have a high frequency of occurrence. This indicates that most reviews focus on the use of the application for tax payment services at Samsat.

In the context of user experience, several positive words often appear, such as "easy", "steady", "fast", and "smooth". The high frequency of these words illustrates the level of user satisfaction with the services provided. The words "thank you" and "alhamdullilah" which also appear with significant size indicate positive appreciation from users for the services received.

The technical and operational aspects of the service are reflected in the emergence of words such as "process", "signal", "online", and "stnk". These words indicate the focus of the review on the user experience in accessing digital services for vehicle administration matters. The word "vehicle" itself appears with a fairly high frequency, confirming the specific context of the service being reviewed, namely related to motor vehicle administration.

Overall, this word cloud provides an illustration that the majority of user reviews are positive, with a focus on the ease and efficiency of vehicle tax payment services through the Samsat application. The high frequency of words related to ease and satisfaction indicates that this application has succeeded in providing a good experience for its users in making vehicle tax payment transactions online.

3.4. SVM Classification Report

The report of classification results of accuracy, precision, recall and F1-score will be displayed in Figure 5.

SVM Classification Report:

	precision	recall	f1-score	support
Negative	0.85	0.93	0.89	1782
Neutral	0.98	0.89	0.93	1784
Positive	0.92	0.92	0.92	1748
accuracy			0.91	5314
macro avg	0.92	0.91	0.91	5314
weighted avg	0.92	0.91	0.91	5314

Figure 5: Evaluation metrics between models

The performance evaluation of the SVM model in sentiment classification showed very satisfactory results with an overall accuracy level reaching 91%. This indicates that from a total of 5314 data tested, the model successfully classified 91% of the data correctly according to the actual sentiment label. Model performance can be seen in more detail through various evaluation metrics for each sentiment class.

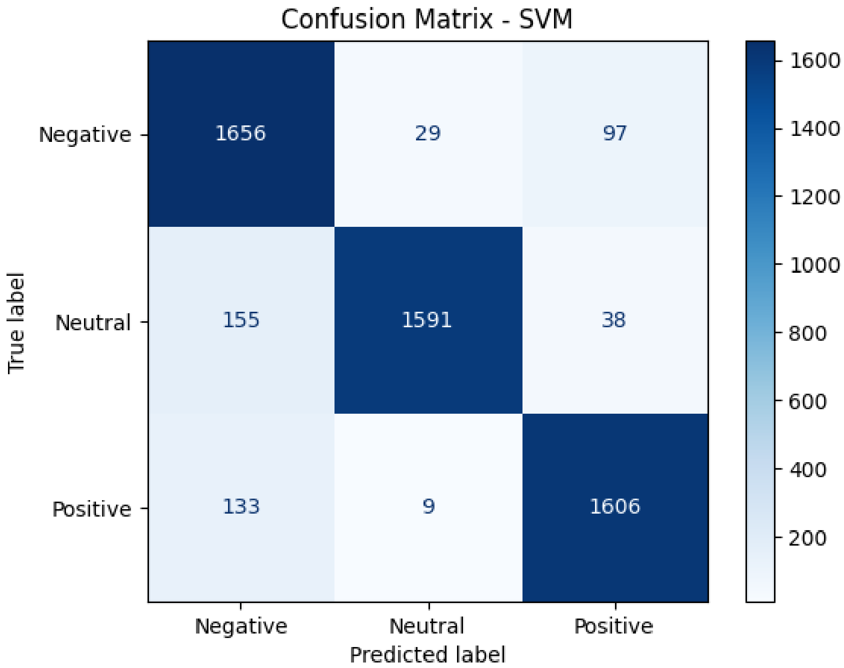
In terms of precision, the model shows excellent ability in predicting each sentiment class. For neutral sentiment, the model achieved the highest precision of 98%, meaning that almost all predictions for the neutral class are correct. Meanwhile, for positive sentiment, the model achieved a precision of 92%, and for negative sentiment it was 85%. The overall average precision reached 92%, indicating the model's consistency in providing accurate predictions for all classes.

In terms of recall, the model showed good ability in identifying actual data from each class. The highest recall was achieved in the negative sentiment classification of 93%, followed by positive sentiment of 92%, and neutral sentiment of 89%. The average recall reached 91%, indicating that the model has a balanced ability in recognizing data from each sentiment class.

The F1-score, which is the harmonic mean between precision and recall, shows consistent performance across all classes. Neutral sentiment achieves the highest F1-score of 93%, followed by positive sentiment at 92%, and negative sentiment at 89%. The average F1-score reaches 91%, confirming that the model has a good balance between precision and recall in its classification. The dataset used in the evaluation has a fairly balanced distribution with 1782 samples for negative sentiment, 1784 samples for neutral sentiment, and 1748 samples for positive sentiment. This balanced distribution contributes to the consistent performance of the model across all sentiment classes. Overall, the evaluation results show that the SVM model is very effective in the sentiment classification task, with balanced and accurate performance across all evaluation metrics.

3.5. Confusion Matrix

The confusion matrix and classification report of the SVM model used for sentiment classification will be visualized in Figure 5.



Gambar 6: Confusion matrix sentiment classification results

The model shows excellent performance with an overall accuracy of 91%. In the analysis per class, the model shows balanced performance with high F1-score values for all categories: negative sentiment (0.89), neutral (0.93), and positive (0.92). The neutral class achieves the highest precision of 0.98, although its recall is lower at 0.89. Positive sentiment shows the most balanced performance with the same precision and recall of 0.92. The confusion matrix also reveals that the most misclassifications occur between the negative and neutral classes, where 155 negative reviews are predicted as neutral and 133 negative reviews are predicted as positive. However, the number of misclassifications is relatively small compared to the total amount of data, indicating that the SVM model is very effective in distinguishing review sentiments.

4. Conclussion

This study successfully analyzed the sentiment of SIGNAL application user reviews using the SVM method. The process starts from collecting review data on the Google Play Store, followed by pre-processing stages such as text cleaning, tokenization, stopword removal, and stemming. The SVM model showed high performance with 91% accuracy, providing consistent results in classifying positive, negative, and neutral sentiments. Positive sentiment dominates the review data, reflecting a high level of user satisfaction. These results can be used by developers to understand user needs and improve the quality of the SIGNAL application.

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