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Sentiment Analysis of SPayLater and SPinjam Features in the Shopee Application Using the Support Vector Machine (SVM) Algorithm

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Abstract

The rapid development of information technology and the increasing use of e-commerce applications have generated a large number of user reviews that can be used to measure user satisfaction. SPayLater and SPinjam, as features in the Shopee application, receive various responses in the form of positive, negative, and neutral sentiments, making automatic sentiment analysis necessary. This study aims to analyze user sentiment and implement the Support Vector Machine (SVM) algorithm to classify reviews. The data used consist of 500 user reviews obtained from the Google Play Store. The method includes preprocessing, labeling, and classification using SVM. The results show that there are 231 positive, 230 negative, and 39 neutral sentiments. Model evaluation yields an accuracy of 74%, precision of 0.78, and recall of 0.84, indicating that the model performs fairly well. The developed system is also capable of processing data automatically and displaying classification results effectively. Therefore, the SVM algorithm is effective for sentiment analysis of SPayLater and SPinjam services in the Shopee application.

Keywords: *Sentiment Analysis, Support Vector Machine, SPayLater, SPinjam*

1. Introduction

In the era of the Industrial Revolution 4.0, rapid development is taking place. Fierce competition in the Indonesian industry forces businesses to continuously innovate to conquer the market. Shopee is one of the largest marketplace platforms in Indonesia, offering various payment features, such as Shopee Paylater, SPinjam, and Affiliate [1]. SPayLater and SPinjam services are experiencing rapid growth in popularity among the public, due to their ease of use and direct integration within the e-commerce ecosystem. Users are required to exercise discretion in utilizing these features, as the ease of access offered has the potential to encourage excessive spending in the future [2].
The proliferation of paylater and loan services circulating in the community has caused confusion in choosing the right service, especially because some are not registered with the Financial Services Authority (OJK) and have high interest rates. This condition then triggers public doubts about using paylater and loan services [3]. SPaylater and Spinjam receive various reviews from users, especially on the Play Store platform, which not only provide feedback for developers but also help other users in making decisions. Therefore, a machine learning-based sentiment analysis system with a Natural Language Processing (NLP) approach is needed to automatically process and classify user reviews so that they can provide more objective information to support decision-making.
Machine learning is a subset of artificial intelligence (AI) used to develop computer systems that can learn from data, recognize patterns, and solve problems without the need for explicit programming at each step [4]. This technique has demonstrated potential in sentiment analysis by predicting and improving the accuracy of user opinions about the Shopee app by analyzing various forms of feedback or reviews. The user review data was then classified to identify and separate reviews into positive and negative categories [5]. In this sentiment analysis research, the classification method used was machine learning-based, applying the Support Vector Machine (SVM) algorithm as the primary approach.
The Support Vector Machine (SVM) algorithm is a computational method for high-dimensional data, resulting in improved accuracy [6]. SVM has the ability to process high-dimensional data with high accuracy and faster predictions [7]. SVM can be applied to data with regular or unknown distributions. This method is also capable of solving classification and regression problems, both linearly and nonlinearly [8]. In this method, a hyperplane is formed to separate different classes [9].
Several previous studies have shown that the Support Vector Machine (SVM) algorithm is quite effective in sentiment analysis. Research conducted by [3] analyzed sentiment toward Shopee PayLater and GoPayLater services using Twitter data using a lexicon-based SVM approach, and produced good classification performance. Another study by [10] also applied the SVM algorithm to analyze Shopee app user sentiment based on Play Store reviews and demonstrated optimal classification results in identifying user opinions. However, these

studies focused on specific services or data sources and did not specifically address user sentiment analysis toward the SPayLater and SPinjam features on the Shopee app.
Therefore, this study will examine sentiment analysis toward the SPayLater and SPinjam services on the Shopee app using the Support Vector Machine (SVM) algorithm to obtain an objective and accurate picture of user sentiment. Therefore, this research is presented under the title "Sentiment Analysis of SPayLater and SPinjam on the Shopee App Using the Support Vector Machine (SVM) Algorithm."

2. Research Methods

2.1. Research Method Flow

The research method in this study was designed to conduct sentiment analysis on user reviews of the SPayLater and SPinjam features on the Shopee application by applying the Support Vector Machine (SVM) algorithm and feature weighting using TF-IDF. The research process consists of several main stages, namely review data collection, sentiment labeling, preprocessing, feature extraction using TF-IDF, building a classification model with the SVM algorithm, and evaluating model performance. The design of the research method flow used in this study is shown in Figure 1.

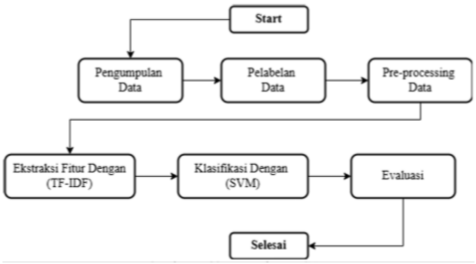


Fig. 1: Research Method Flow

2.2. Data Collection

The data used in this study is secondary data in the form of user reviews of the SPayLater and SPinjam features on the Shopee application. The data was obtained from the Google Play Store platform, which contains user opinions and responses regarding the use of these services. The data collection process was carried out automatically using web scraping techniques with the help of the Python programming language through the Google Colab platform. In this process, several supporting libraries were used, such as google-play-scraper to retrieve review data and pandas for data processing. The number of data collected was 500 user reviews with a data collection period from October 2025 to March 2026. The obtained data was then saved in CSV format to facilitate processing in the next stage. The design of the data collection flow can be seen in Figure 2.

Fig. 2: Data Collection Flow

2.3. Data Labeling

The data labeling stage was carried out to assign sentiment categories to each collected review: positive, negative, and neutral. The labeling process in this study refers to user ratings on the Google Play Store, where reviews with ratings of 4 and 5 are classified as positive, reviews with ratings of 3 as neutral, and reviews with ratings of 1 and 2 as negative. This approach was used to simplify the classification process and generate structured training data that can be used in modeling using the Support Vector Machine (SVM) algorithm.

2.4. Pre-processing Data

In the pre-processing stage, the raw data is processed and adjusted into CSV format to suit the analysis requirements. Irrelevant attributes are then removed to improve data processing efficiency. In general, the main stages in the pre-processing process can be seen in Figure 3.

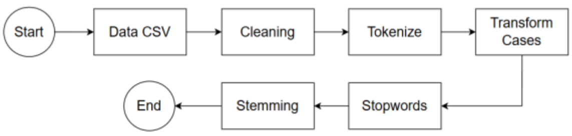


Fig. 3: Preprocessing Flow

a. Data: Importing a CSV file containing raw user reviews of the SpayLater and SPinjam services on the Shopee app into the Google Colab programming environment.
b. Cleaning: Cleaning the review text of special characters, numbers, punctuation, and emojis that have no impact on the sentiment analysis process.
c. Tokenization: Breaking down the review text into word units (tokens) to facilitate further text processing.
d. Transform Case: Converting all letters in the review text to lowercase to standardize word forms and avoid differences in meaning caused by capitalization.
e. Stopword Removal: Removing common words that do not contribute significant information to sentiment analysis using an Indonesian stopword dictionary.

f. Stemming: Converting words to their base form to reduce variations in words with similar meanings, thereby helping to improve the accuracy of sentiment classification using the Support Vector Machine (SVM) algorithm.

2.5. Feature Extraction With TF-IDF

The feature extraction stage is carried out to convert preprocessed text data into a numeric representation that can be processed by a classification algorithm. In this study, the method used is Term Frequency–Inverse Document Frequency (TF-IDF), which functions to assign weights to each word based on its level of occurrence in the document and its level of importance to the overall data. Through this approach, words that appear frequently in one document but rarely in others will have a higher weight, thus being able to represent more relevant information. The result of this process is a numeric feature matrix that is then used as input in the classification process using the Support Vector Machine (SVM) algorithm.

2.6. Classification With SVM

Support Vector Machine (SVM) is a method for making predictions in both classification and regression cases [11]. The classification stage is carried out by applying the Support Vector Machine (SVM) algorithm to group user review sentiments into positive, negative, and neutral categories. The SVM algorithm works by forming an optimal hyperplane that is able to separate data between classes based on features that have been extracted using TF-IDF. In this study, the SVM model was trained using training data to recognize sentiment patterns, then tested using test data to evaluate its ability to classify data that has never been seen before. This approach was chosen because SVM has good capabilities in handling high-dimensional text data and produces quite optimal classification performance.

2.7. Evaluation

In this study, model performance evaluation was conducted using a confusion matrix to determine the level of classification performance produced. The confusion matrix was chosen because it can provide detailed information about the model's prediction results, including the number and types of errors that occurred. In this matrix, each column represents the predicted class, while each row shows the actual class [12]. The confusion matrix creation process was carried out using the scikit-learn library. In addition, evaluation metrics such as accuracy, precision, recall, and F1-score were used to measure model performance, which are explained in Table 1.

Table 1: Confusion Matrix

Actual	Predicted	
Positive	True Positive (TP)	False Negative
Negative	False Positive (FP)	True Negative

True Positive (TP) is the number of positive labeled data that is correctly classified by the system, while True Negative (TN) is the number of negative labeled data that is also correctly classified. Meanwhile, False Positive (FP) shows the number of negative data that is incorrectly predicted as positive, and False Negative (FN) is the number of positive data that is incorrectly classified as negative [13].

1) Accuracy is the degree of closeness between the predicted value and the actual value. The formula for calculating accuracy is:

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

2) Precision is the level of accuracy between the requested information and the answer provided by the system. The formula for calculating precision is:

$$Presicion = \frac{TP}{TP + FP} \tag{2}$$

3) Recall is the system's success rate in recognizing relevant data from all positive data. The formula for calculating recall is:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

4) F1-Measure (F1 Score) is a measure of the equivalence of precision and recall values, as these two values typically differ significantly. The formula for calculating F1-Measure (F1 Score) is:

$$F1 - Measure = 2 \times \frac{(recall\ \times precission)}{(recall + precission)} \tag{4}$$

3. Results and Discussion

3.1. Data Collection Results

At this stage, the research was conducted by collecting data in the form of user reviews of the Shopee application obtained from the Google Play Store platform. Data collection was carried out using web scraping techniques with the help of the Google Play Scraper library. From this process, 500 user reviews were obtained for the period October 2025 to March 2026. All collected review data was then saved in comma-separated values (CSV) format to facilitate processing in the next stage. The results of the data scraping process are shown by displaying the top three data points in Table 2.

Table 2: The results of scraping the review data above

No	Date	Rating	Review
1	3/22/2026	5	Sangat bermanfaat dan berguna sekali kami sangat terbantu dengan adanya aplikasi ini tapi setiap bulan sekali aplikasi nya gak digunakan karena pengguna nya harus pakaiðŸ˜
2	3/22/2026	3	Sudah berapa bulan spaylater di bekukan, sudah mengajukan tapi tidak ada respon dari pihak spaylater, aneh aja baru sekali telat bayar langsung kena bekukan
3	3/22/2026	1	Sediain pembayaran pake saldo shopeepay pas flash sale Jangan cuman spaylater saya yg belum punya KTP susah dan saya sudah mencoba pake KTP ortu verivikasi nya susah!

Based on the data obtained, it appears that user reviews have varying sentiments, ranging from positive, neutral, to negative. The data will then undergo a preprocessing stage to prepare for sentiment analysis using the Support Vector Machine (SVM) algorithm.

3.2. Data Labelling Results

Data labeling was performed to group each user review into specific sentiment categories: positive, negative, and neutral. The labeling process in this study refers to the ratings given by users on the Google Play Store, where ratings of 4 and 5 are classified as positive sentiment, ratings of 3 as neutral sentiment, and ratings of 1 and 2 as negative sentiment. This approach was used because ratings are considered capable of representing the tendency of user opinions towards the services provided. With this labeling, the data is structured and ready to be used as training data in the classification process using the Support Vector Machine (SVM) algorithm.

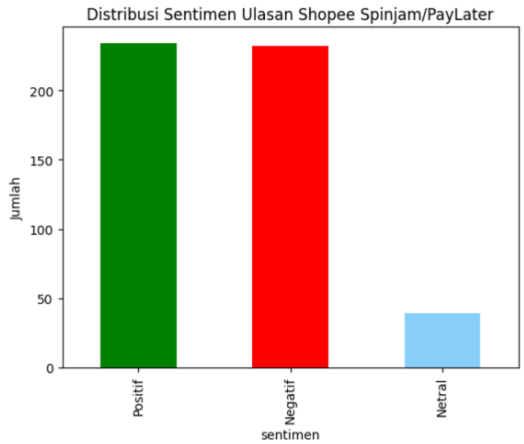


Fig. 4: Data Labeling Visualization Results

Based on the visualization in the image above, it is known that the number of data points with positive sentiment is 231, negative sentiment points with 230, and neutral sentiment points with 39. This distribution shows that the number of data points in the positive and negative sentiment categories is relatively balanced, with neutral sentiment points being smaller than the other two categories.

3.3. Data Pre-processing Results

The preprocessing stage is carried out to clean and prepare text data to be more structured before being used in the classification process. At this stage, several main steps are carried out, namely cleaning to remove special characters, numbers, punctuation, and other irrelevant elements; case folding to convert all text to lowercase; tokenizing to break sentences into word units; stopword removal to remove common words that have no significant meaning; and stemming to convert words to their basic form. Through this preprocessing stage, the originally unstructured text data can be reduced to a simpler and more informative representation, thereby improving the quality of the features used in the sentiment classification process using the Support Vector Machine (SVM) algorithm. The results of data changes before and after processing are shown in Table 3.

Table 3: Pre-Processing Results

Riview	Pre-Processing	Results
Sangat bermanfaat dan berguna sekali kami sangat terbantu dengan adanya aplikasi ini tapi setiap bulan sekali aplikasi nya gak digunakan karena pengguna nya harus pakaiðŸ˜	Cleaning	Sangat bermanfaat dan berguna sekali kami sangat terbantu dengan adanya aplikasi ini tapi setiap bulan sekali aplikasinya tidak digunakan karena penggunanya harus pakai
	Transform Cases	sangat bermanfaat dan berguna sekali kami sangat terbantu dengan adanya aplikasi ini tapi setiap bulan sekali aplikasinya tidak digunakan karena penggunanya harus pakai
	Tokenize	['sangat', 'bermanfaat', 'dan', 'berguna', 'sekali', 'kami', 'sangat', 'terbantu', 'dengan', 'adanya', 'aplikasi', 'ini', 'tapi', 'setiap', 'bulan', 'sekali', 'aplikasi', 'nya', 'gak', 'digunakan', 'karena', 'pengguna', 'nya', 'harus', 'pakai']
	Stopwords	['sangat', 'bermanfaat', 'berguna', 'sekali', 'sangat', 'terbantu', 'aplikasi', 'bulan', 'sekali', 'aplikasi', 'digunakan', 'pengguna', 'harus', 'pakai']
	Stemming	['sangat', 'manfaat', 'guna', 'sekali', 'bantu', 'aplikasi', 'bulan', 'sekali', 'aplikasi', 'guna', 'guna', 'harus', 'pakai']

Additionally, to see the distribution of frequently occurring words in the review data, a word cloud visualization was performed. Word clouds display words with high frequency in visual form, where the size of the word indicates its occurrence in the dataset.

Fig. 5: Word Cloud Sentiment

Based on the word cloud visualization results, it is known that in positive sentiment, words that frequently appear include “pay,” “limit,” “shopping,” and “easy,” which indicate that users feel helped and satisfied with the services used. Meanwhile, in negative sentiment, words such as “no,” “but,” “limit,” “bill,” “disappointed,” “long,” and “frozen” were found, which indicate various obstacles and user dissatisfaction with SPayLater and SPinjam services. Meanwhile, in neutral sentiment, the dominant words that appear include “no,” “can,” “already,” “application,” “pay,” “limit,” and “bill,” which indicate that reviews in this category tend to be informative and do not show a strong opinion tendency towards the services used.

3.4. Feature Extraction (TF-IDF)

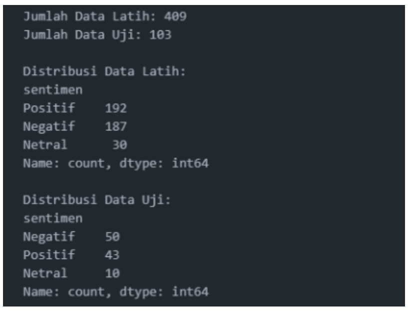
Review data that has gone through the preprocessing stage is still in text form (words), while in the classification analysis process, the data needs to be converted into numeric or numerical form. The data must first be converted to numeric form by weighting the words using TF-IDF. The word weighting process using TF-IDF displays the terms with the highest weight. The following is the script used in the TF-IDF weighting stage, along with the weighting results, which can be seen in Table 4.

Table 4: TF-IDF Word Weighting Results

Term	Weigh
shopee	28.507004420866117
bayar	25.794234691998085
belanja	19.51455036676913
spaylater	18.465245039830684
aplikasi	17.0356120042234
paylater	16.846161545198875
pakai	15.506196997957902
limit	15.224117922594779
spinjam	13.830539573056639
lambat	13.70624208101318

3.5. Training Data

The next step is to divide the data into training data and testing data. This division aims to train the model using a portion of the data and test the model's ability to classify previously unseen data. Data division is performed using the train_test_split method, with 80% training data and 20% testing data. The results of the data division are then stored in the training and testing data variables for use in the modeling phase.



```
Jumlah Data Latih: 409
Jumlah Data Uji: 103

Distribusi Data Latih:
sentimen
Positif    192
Negatif    187
Netral      30
Name: count, dtype: int64

Distribusi Data Uji:
sentimen
Negatif    50
Positif    43
Netral     10
Name: count, dtype: int64
```

Fig. 6: TF-IDF Feature Extraction Results

Based on the results of data division using the train_test_split method, 409 data were obtained as training data and 103 data as test data. In the training data, the sentiment distribution consisted of 192 positive data, 187 negative data, and 30 neutral data. Meanwhile, in the test data, there were 43 positive data, 50 negative data, and 10 neutral data. These results indicate that the distribution of data in the positive and negative categories is relatively balanced, while the number of data in the neutral category is smaller than the other two categories. This data division aims to ensure the model can be properly trained using the training data and its performance is tested using previously unknown test data.

3.6. Implementation Of The Support Vector Machine (SVM) Algorithm

At this stage, the Support Vector Machine (SVM) algorithm was applied to classify user review sentiment into three categories: positive, negative, and neutral. The SVM algorithm was chosen because of its excellent ability to handle high-dimensional data, such as text data that has undergone a TF-IDF weighting process. In this study, two types of kernels were used: Radial Basis Function (RBF) and linear, to compare the performance of each model.

3.6.1. Model Evaluation

Model evaluation was conducted to assess the performance of the Support Vector Machine (SVM) algorithm in classifying sentiments of user reviews. The testing process used a cross-validation method with evaluation parameters including accuracy, precision, recall, and F1-score. The evaluation was conducted by testing the model using two kernels: Radial Basis Function (RBF) and Linear. Each model was tested using cross-validation to obtain the average value of each evaluation metric.

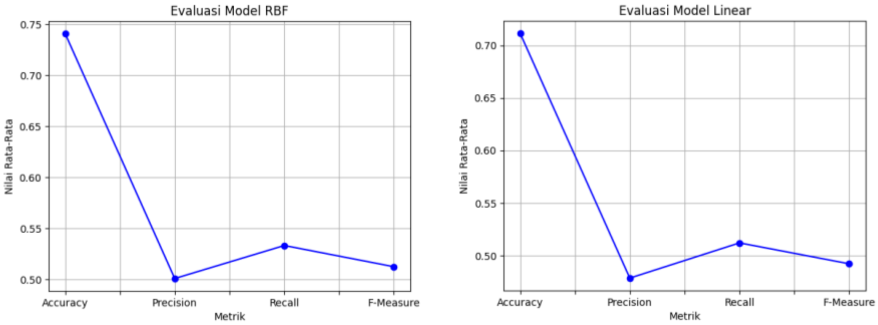


Fig. 7: Model Evaluation Results

Based on the evaluation results, the SVM model with the RBF kernel produced an accuracy of 0.741, a precision of 0.501, a recall of 0.533, and an F1-score of 0.513. Meanwhile, the model with the Linear kernel obtained an accuracy of 0.712, a precision of 0.479, a recall of 0.512, and an F1-score of 0.492. These results indicate that the SVM model with the RBF kernel has better performance than the Linear kernel. This is because the RBF kernel is able to capture more complex data patterns than the Linear kernel.

3.6.2. Confusion Matrix & Classification Report

A confusion matrix is used to evaluate model performance in more detail by displaying the number of correct and incorrect predictions for each sentiment category. Furthermore, a classification report is used to determine the precision, recall, and F1-score values for each class. The SVM model is trained using a linear kernel, then predictions are made on the test data. The prediction results are then compared with the actual data to generate a confusion matrix and classification report.

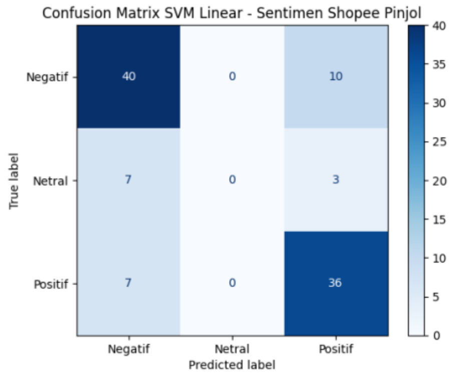


Fig. 8: Confusion Matrix Results

Based on the results of the confusion matrix in Figure 8, it is known that:
1) A total of 40 data points with negative sentiment were correctly classified, while 10 were incorrectly predicted as positive sentiment.
2) In the neutral class, the model was unable to correctly classify the data, with most neutral data points being incorrectly classified into both the negative and positive classes.
3) A total of 36 positive data points were correctly classified, while 7 positive data points were incorrectly classified as negative.

```
Classification Report:
               precision    recall  f1-score   support

     Negatif       0.74      0.80      0.77        50
      Netral       0.00      0.00      0.00        10
     Positif       0.73      0.84      0.78        43

    accuracy                           0.74       103
   macro avg       0.49      0.55      0.52       103
weighted avg       0.67      0.74      0.70       103
```

Fig. 9: Classification Report Results

Based on the classification report, it was found that:
1) The negative class has a precision of 0.74, a recall of 0.80, and an F1-score of 0.77.
2) The positive class has a precision of 0.73, a recall of 0.84, and an F1-score of 0.78.
3) The neutral class has a precision, recall, and F1-score of 0.00. Based on the confusion matrix results, manual calculations were performed to obtain accuracy, precision, and recall values. These calculations aimed to validate the previously obtained model evaluation results.

1. Calculation of accuracy value

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Based on the prediction results, the number of correctly classified data was 40 negative data and 36 positive data, so the total correct predictions were 76 out of 103 test data.

$$Accuracy = \frac{76}{103} = 0.7388 = 0.74$$

2. Calculation of precision value

$$Precision = \frac{TP}{TP + FP}$$

$$Precision = \frac{36}{36 + 10} = 0.7826$$

3. Calculation of recall value

$$Recall = \frac{TP}{TP + FN}$$

$$Recall = \frac{36}{36 + 7} = 0.8372$$

Based on the calculation results, an accuracy value of 0.74, a precision value of 0.78, and a recall value of 0.84 were obtained. These results indicate that the model performs quite well in classifying data, especially in the positive class.

3.7. System Implementation

Implementation is the final stage in the design process for a sentiment analysis system for the SPayLater and SPinjam features in the Shopee app, using the Support Vector Machine (SVM) method. At this stage, the designed system is realized in the form of a web-based application that can be used to analyze user review data. The following is an explanation of the user interface of the developed system:

1. Home Page

The Home Page is the main page that appears when users first access the system. This page provides general information regarding the website's purpose and function as a sentiment analysis system for user reviews of the SPayLater and SPinjam features. The home page can be seen in Figure 10.

Fig. 10: Classification Report Results

2. Single Text Sentiment Analysis Page

The Single Text Sentiment Analysis page is part of the system that allows users to enter review text directly through the provided input field. During the implementation phase, the entered text will undergo pre-processing stages, such as cleaning, tokenizing, filtering, and stemming. Next, the data will be classified using the Support Vector Machine (SVM) algorithm to determine the sentiment category, namely positive or negative. The classification results are then displayed directly to the user as the output of the analysis process. The single text sentiment analysis page can be seen in Figure 11.

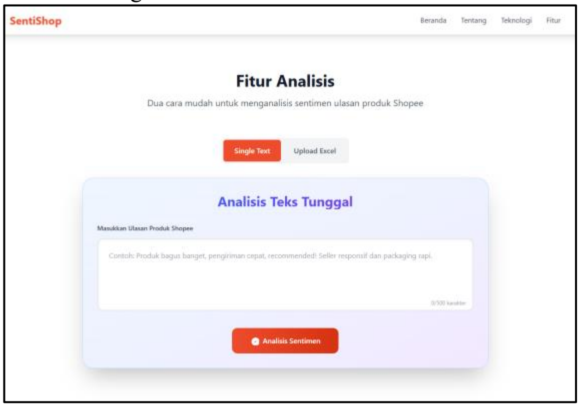


Fig. 11: Classification Report Results

3. File-Based Sentiment Analysis Page

The File-Based Sentiment Analysis (CSV/Excel) page is implemented to support sentiment analysis with larger data sets. On this page, users can upload CSV or Excel files containing user review data sets. The system automatically processes all data in the file through pre-processing and classification stages using the SVM method. The analysis results are then presented as a summary of the overall sentiment classification, allowing users to more efficiently understand the distribution of sentiment toward the SPayLater and SPinjam services on the Shopee app. The file-based sentiment analysis page can be seen in Figure 14.

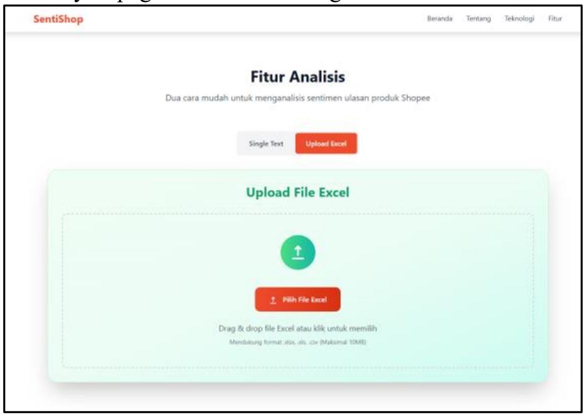


Fig. 12: Classification Report Results

4. Conlusion

Based on the results of research conducted on sentiment analysis of user reviews of the SPayLater and SPinjam services on the Shopee app using the Support Vector Machine (SVM) algorithm, it can be concluded that the method used is capable of classifying sentiment quite well. This study used 500 user review data obtained from the Google Play Store, which then underwent preprocessing, data labeling, feature extraction using TF-IDF, and classification using the SVM algorithm. The analysis results showed that the sentiment distribution consisted of 231 positive data, 230 negative data, and 39 neutral data. This indicates that user responses to the SPayLater and SPinjam services tended to be balanced between positive and negative sentiment.

Based on the model evaluation results, the Support Vector Machine (SVM) algorithm with a Radial Basis Function (RBF) kernel achieved an accuracy of 74%, a precision of 0.78, a recall of 0.84, and an F1-score of 0.81. These results indicate that the model performs quite well in classifying sentiment in user reviews. Furthermore, the use of the TF-IDF method facilitates the representation of text data into numerical form, allowing for more effective classification. Overall, the combination of the TF-IDF method and the SVM algorithm is quite effective in analyzing user review sentiment for the SPayLater and SPinjam services on the Shopee app.

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