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SENTIMENT ANALYSIS OF THE HALODOC APPLICATION USING THE SUPPORT VECTOR MACHINE (SVM) ALGORITHM

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Abstract: The Halodoc application, as a digital healthcare service platform, has been widely used for various medical purposes, such as doctor consultations, medication purchases, and laboratory services. User interactions and reviews play a crucial role in enhancing service quality. Sentiment analysis was conducted using the Support Vector Machine (SVM) method to assess user perceptions and satisfaction based on reviews obtained from the Google Play Store platform. The analysis process included data collection, text preprocessing, data transformation using TF-IDF, and training an SVM model to predict sentiment. The model achieved its highest accuracy of 88.32% in the first scenario. However, accuracy slightly decreased in the second and third scenarios, reaching 86.25% and 86.94%, respectively. The analysis results indicated that the model performed best in the first scenario, with the lowest number of prediction errors. Additionally, the model was more accurate in classifying negative and positive sentiments than neutral ones.

Keywords: halodoc application; sentiment analysis; support vector machine algorithm

Abstrak: Aplikasi Halodoc, sebagai platform layanan kesehatan digital, telah banyak digunakan untuk berbagai keperluan medis seperti konsultasi dokter, pembelian obat, dan layanan laboratorium. Interaksi pengguna dan ulasan mereka memiliki peran krusial dalam meningkatkan mutu layanan. Analisis sentimen dilakukan dengan menggunakan metode Support Vector Machine (SVM) untuk mengetahui persepsi dan kepuasan pengguna berdasarkan ulasan yang diperoleh dari Platform Google Play Store. Proses analisis mencakup pengumpulan data, pra-pemrosesan teks, transformasi data menggunakan TF-IDF, dan pelatihan model SVM untuk memprediksi sentimen. Hasil pelatihan model dengan akurasi tertinggi sebesar 88,32% pada skenario pertama. Akurasi sedikit menurun pada skenario kedua dan ketiga, masing-masing sebesar 86,25% dan 86,94%, Hasil analisa menunjukkan bahwa model memiliki performa terbaik pada skenario pertama dengan jumlah kesalahan prediksi terkecil. Selain itu, model cenderung lebih akurat dalam mengklasifikasikan sentimen negatif dan positif dibandingkan netral..

Kata kunci: algoritma support vector machine; analisis sentimen; aplikasi halodoc

INTRODUCTION

With the increasing demand for easily accessible healthcare services, various digital health platforms have emerged, providing practical solutions for the public, one of which is the Halodoc application [1]. The Halodoc application emerged in response to the public's need for easier and faster access to healthcare services in the digital era. This application offers various services, such as online doctor consultations, medication purchases, and medical appointment scheduling, allowing users to access healthcare services without having to visit a healthcare facility in person. [2]. Halodoc is a startup in the telemedicine industry established in April 2016 by Jonathan Sudharta. In 2020, Halo-doc was recognized as one of the 150 most promising digital health companies in the world. Halodoc collaborates with thousands of doctors who have completed their medical degree, registration certificate (STR), and practice license (SIP). Additionally, Halodoc partners with the Indonesian Medical Association (IDI) and the Indonesian Medical Council (KKI) to ensure that the certifications held by these doctors are legitimate. [3].

As the number of Halodoc application users continues to grow, there is still a lack of understanding regarding their experience and satisfaction with the service. Additionally, user reviews, which are scattered and subjective, make it difficult to gain a clear understanding of service quality. [4] The sentiment analysis approach is used to understand user experiences on the Google Play Store platform by analyzing the sentiment of user reviews or comments. [5] This process extracts subjective information from text data to identify and categorize user opinions based on patterns of positive, negative, or neutral sentiment found in the text. [6]

The research conducted [7] The research conducted on the implementation of the SVM algorithm for sentiment analysis of the OLX application used 2,500 review data from the Play Store. The model training achieved an accuracy of 85%, with a negative precision of 86% and a positive precision of 82%; a negative recall of 91% and a positive recall of 73%; and an F1 score of 85% using an 80:20 ratio for training and test data. Previous research conducted by [8] regarding sentiment analysis, this study analyzes user reviews of the Korlantas digital application on Google Play Store using the Support Vector Machine (SVM) method. Based on the training results, the SVM model demonstrated good performance in a 90:10 data ratio scenario, achieving an accuracy of 0.82. However, the model performed poorly in the 80:20 and 60:40 data ratio scenarios, with an accuracy of 0.74.

SVM is widely used in various text processing applications, including sentiment analysis, due to its ability to achieve high accuracy. This study applies the SVM algorithm to classify user reviews of the Halodoc application into positive, negative, or neutral sentiment categories. [9] Additionally, the use of three comparison scenarios 90:10, 80:20, and 70:30 is implemented to evaluate and compare how parameter changes affect accuracy, precision, recall, and F1 scores, as well as to ensure that the model has good generalization capability [10].

METHOD

This study analyzes user opinions on the Halodoc application available on the Google Play Store by applying the Support Vector Machine algorithm, with the research stages illustrated in Figure 1.

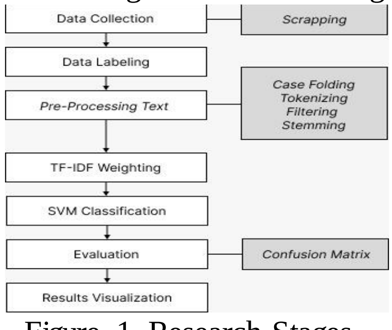

Figure 1. Research Stages

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Data collection was conducted using a scraping technique by utilizing the Python library Google Play Scraper. The collected data consists of 10,000 review entries, which were then filtered within the time range of 2022 to 2025. After filtering, a total of 2,907 reviews were obtained and subsequently sorted based on relevance.

The scraped data was then assigned sentiment labels based on scores. The score is derived from user ratings on a 1-5 scale. The sentiment labeling criteria are as follows: Scores 1–2 are classified as negative sentiment with a code of -1, a score of 3 is categorized as neutral sentiment with a code of 0, and scores 4–5 are considered positive sentiment with a code of 1.

Text pre-processing is performed to simplify the analysis process by converting unstructured data into structured data. This stage includes converting all words to lowercase (case folding), splitting text into tokens (tokenizing), extracting important words from the tokens (filtering), and finding the root form of words (stemming). [11]

After undergoing the text pre-processing stage, the dataset is divided into two parts: the training dataset and the testing dataset. The classifier model is built using word weighting (TF-IDF) with the training dataset. The next step is to train the SVM model using the training dataset that has been transformed into TF-IDF vectors. The training data is used to train the model, while the test data is used to evaluate the trained model in terms of accuracy, precision, and recall for sentiment classification. [12]

Next, the accuracy level is calculated based on the classification results obtained from applying the model to the test dataset. Accuracy is measured using a confusion matrix, which provides values for accuracy, precision, and recall. Precision indicates how accurately the model predicts positive and negative sentiments, while recall shows how well the model captures all relevant reviews.

The visualization stage is carried out using charts and word clouds for all reviews. The word cloud generates a visual representation of the written text, which can be used as a tool for text analysis. A visualization displays the words, with their size depending on how frequently they appear in the text. In short, the most frequently occurring words in the data will appear the largest. [13]

RESULTS AND DISCUSSION

Data Collection

According to the results of scraping 10,000 review data, which were then filtered within the time range from 2022 to 2025, a total of 2,907 review data were used in this study. The data graph in Figure 2 represents the scraping results, showing ratings as evaluations when using the Halodoc application.

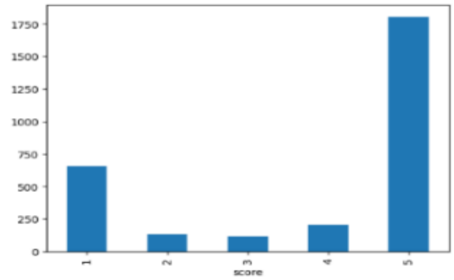

Figure 2. Scraping Results with User Scores/Ratings from Halodoc

Data Labeling

The scraped data is then labeled with sentiment based on the score. The score comes from user ratings on a scale of 1–5. Sentiment labels are assigned based on the following criteria: scores of 1–2 are classified as negative sentiment

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with a code of -1, a score of 3 is classified as neutral sentiment with a code of 0, and scores of 4–5 are classified as positive sentiment with a code of 1. The results of sentiment labeling per year are shown in Figure 3.

Year	sentiment	sentiment
2022	-1	325
	0	39
	1	438
2023	-1	175
	0	24
	1	265
2024	-1	256
	0	41
	1	1011
2025	-1	30
	0	11
	1	292

Figure 3. Sentiment Labeling Results Each Year

Text Pre processing

After the labeling process was completed, there were 2,006 positive sentiments, 786 negative sentiments, and 115 neutral sentiments. This sentiment dataset falls under unstructured text data and requires text pre-processing, which includes steps such as case folding, tokenizing, filtering, and stemming. These steps are carried out to improve data quality, reduce noise, and ensure a more accurate and meaningful analysis.

An example of text that will undergo text preprocessing is: "Sangat membantu, cukup dengan jari sdh dapat konsultasi dgn dokter dan dapat resep obatnya, ini hebatnya teknologi, terima kasih Halodoc." The results of this process implementation can be seen in Table 1, ensuring a more accurate and meaningful analysis.

Table 1. *Text Pre Processing* Results

Pre processing	Result
Case folding	very helpful, just with your finger you can consult a doctor and get a prescription for medicine, this is great technology, thank you halodoc
Tokenizing	'very', 'helpful', 'enough', 'with', 'finger', 'already', 'can', 'consultation', 'with', 'doctor', 'and', 'can', 'prescription', 'medicine', 'this', 'amazing', 'technology', 'thank you', 'halodoc'
Filtering	'help', 'enough', 'finger', 'already', 'consultation', 'doctor', 'prescription', 'medicine', 'amazing', 'technology', 'thank you', 'halodoc'
Stemming	'help', 'finger', 'already', 'consultation', 'with', 'doctor', 'prescription', 'medicine', 'herbal', 'technology', 'thank you'

TF-IDF Weighting

The data that has undergone text pre-processing is then cleaned of missing values and assigned word weighting using TF-IDF, with results as shown in Figure 4.

```
Fitur (kata-kata) yang ada: ['0922' '100rb' '10hari' ... 'zaman' 'zonk' 'zzzz']

Matriks TF-IDF:
   0922  100rb  10hari  10menit  10meter  10mnt  10ribu  11rb  12000  12siang  \
0   0.0    0.0     0.0      0.0      0.0    0.0     0.0   0.0    0.0      0.0
1   0.0    0.0     0.0      0.0      0.0    0.0     0.0   0.0    0.0      0.0
2   0.0    0.0     0.0      0.0      0.0    0.0     0.0   0.0    0.0      0.0
3   0.0    0.0     0.0      0.0      0.0    0.0     0.0   0.0    0.0      0.0
4   0.0    0.0     0.0      0.0      0.0    0.0     0.0   0.0    0.0      0.0

   ...  yaelah  yagimana  yakali  ynag  yosa  youtube  yuuuu  zaman  zonk  \
0  ...     0.0       0.0     0.0   0.0   0.0      0.0    0.0    0.0   0.0
1  ...     0.0       0.0     0.0   0.0   0.0      0.0    0.0    0.0   0.0
2  ...     0.0       0.0     0.0   0.0   0.0      0.0    0.0    0.0   0.0
3  ...     0.0       0.0     0.0   0.0   0.0      0.0    0.0    0.0   0.0
4  ...     0.0       0.0     0.0   0.0   0.0      0.0    0.0    0.0   0.0

   zzzz
0   0.0
1   0.0
2   0.0
3   0.0
4   0.0

[5 rows x 3815 columns]
```

Figure 4. TF-IDF Weighting Results

SVM Classification Process

The primary goal of the initial classification process is to divide

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documents into two parts: training data and test data. The training data is used as the data learned by the machine in a specific manner. The classification analysis of the Support Vector Machine algorithm applies a ratio comparison between training data and test data.

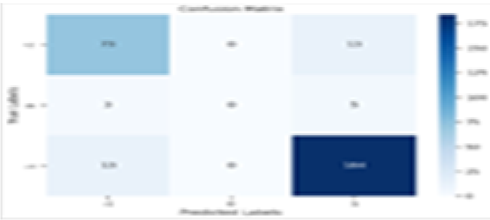

Figure 5. Confusion Matrix Scenario 1

To perform accuracy testing, the data is divided into training and testing data using various ratios.

Table 2. Accuracy Results of Dataset Comparison

Training Data	Testing Data	Accuracy Results
90	10	88,32%
80	20	86,25%
70	30	86,94%

The results of the testing in Table 2 above show varying accuracy values, influenced by differences between the training and testing data. In the first test, an accuracy of 88.32% was obtained with a 9:1 ratio, using 2,616 training data and 291 testing data. The second test resulted in an accuracy of 86.33% with an 8:2 ratio, using 2,325 training data and 582 testing data. Meanwhile, in the final test, an accuracy of 86.95% was achieved with a 7:3 ratio, using 2,034 training data and 873 testing data. The SVM classification results are presented in Table 3.

Table 3. Classification Results of SVM

Data Comparison		Data Quantity		Accuracy	Sentiment Label	Precision	Recall	F1-Score
Training Data	Test Data	Training Data	Test Data					
90	10	2616	291	88,32 %	Positive	0.82	0.85	0.83
					Neutral	0.00	0.00	0.00
					Negative	0.91	0.93	0.92
					Average	86%	88%	87%
80	20	2325	582	86,25 %	Positive	0.79	0.82	0.81
					Neutral	0.00	0.00	0.00
					Negative	0.89	0.94	0.91
					Average	83%	86%	84%
70	30	2034	873	86,94 %	Positive	0.81	0.81	0.81
					Neutral	0.00	0.00	0.00
					Negative	0.90	0.94	0.92
					Average	84%	87%	85%

Evaluation

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Scenario 1

Figure 5 presents the evaluation results of Scenario 1, as shown in Figure 5, with a confusion matrix indicating that the model achieved an accuracy rate of 88.32%, with a precision of 86%, a recall of 88%, and an F1 score of 87%. The model attained an accuracy of 88.32% based on the ratio of correct predictions to the total test data (257/291). The sentiment distribution in the data consists of 86 negative, 8 neutral, and 197 positive samples. According to the confusion matrix, the model successfully identified 73 true negatives, 184 true positives, and no true neutral samples. Based on the evaluation, it was found that the total number of misclassified data points was 34 out of 291 test samples.

Scenario 2

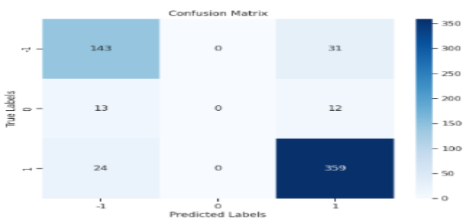

Figure 6. Confusion Matrix Scenario 2

Figure 6 presents the evaluation results of Scenario 2 using a confusion matrix, showing that the model achieved an accuracy of 86.25%, with a precision of 83%, a recall of 86%, and an F1-score of 84%. The model's accuracy of 86.25% is based on the ratio of correct predictions to the total test data (502/582). The sentiment data is divided into 174 negative, 25 neutral, and 383 positive instances. According to the confusion matrix, the model successfully identified 143 true negatives, 359 true positives, and no true neutrals. Based on the evaluation conducted, it is observed that the total number of misclassified data points is 80 out of 582 test data samples.

Scenario 3

Figure 7. Confusion Matrix Scenario 3

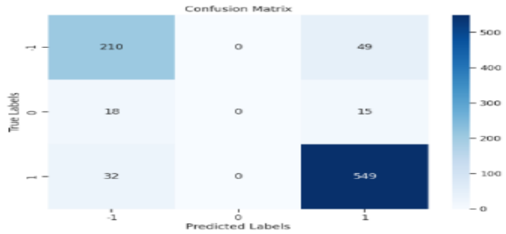

Figure 7 presents the evaluation results of Scenario 3 using a confusion matrix, showing that the model achieved an accuracy of 86.94%, with a precision of 84%, recall of 87%, and an F1-score of 85%. The model attained 86.94% accuracy based on the ratio of correct predictions to the total test data (759/873). The sentiment distribution in the data consists of 259 negative, 33 neutral, and 581 positive instances. According to the confusion matrix, the model successfully identified 210 true negatives, 549 true positives, and no true neutrals. Based on the evaluation conducted, the total number of incorrectly predicted data points is 114 out of 873 test data samples.

Result Visualization

The result visualization in this study uses a word cloud to represent textual data, where words that appear more frequently in the dataset are displayed in a larger size compared to those that appear less frequently. Figures 8, 9, and 10 illustrate the word cloud representations for positive, negative, and neutral sentiments.

Figure 8. Wordcloud of positive

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Figure 9. Wordcloud of negative

Figure 10. Wordcloud of neutral

CONCLUSION

The sentiment analysis of the Halodoc application using the SVM algorithm demonstrates fairly good performance, achieving the highest accuracy of 88.32% in the first scenario (with a 9:1 train-test data ratio). However, accuracy slightly decreased in the second and third scenarios, reaching 86.25% and 86.94%, respectively, indicating that increasing the proportion of test data does not al-ways improve accuracy. Performance evaluation using precision, recall, and F1-score suggests a well-balanced ability to predict sentiment, with average precision values ranging from 84% to 86%, recall from 86% to 88%, and F1-score from 84% to 87%.

The model performs better in identifying negative and positive sen-timents compared to neutral sentiment, as no true neutral cases were identified in the confusion matrix. Additionally, pre-diction errors increased as the test data ratio increased, suggesting that the model performs optimally with a larger amount of training data. While SVM offers stable performance, but future research could explore deep learning models like RNNs and Transformers for capturing complex linguistic patterns. Ensemble methods such as bagging and boosting may also improve robustness and accuracy, enhancing sentiment analysis beyond traditional machine learning approaches.

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