

How Positive Sentiment of Telemedicine Applications using Naïve Bayes and Support Vector Machine?

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ABSTRACT

The telemedicine software lets users schedule appointments with physicians or hospitals, purchase medications online, read health-related news and publications, and have online consultations with doctors. Public opinion is necessary for this application to meet societal needs. The public's perception of contemporary health applications can be ascertained by looking to public opinion. Fine-grained sentiment analysis is used in public opinion taking to extract information from evaluations posted by the public and categorize it into positive and negative groups. Using RapidMiner as a supporting tool, sentiment analysis uses the Naïve Bayes Classification algorithm and Support Vector Machine to determine an accuracy value. After analyzing data from two different sources—Twitter and Playstore—it can be said that the Support Vector Machine algorithm performs 90.99% more accurately in predicting public opinion than the Naïve Bayes algorithm, which achieves 88.55% accuracy.

ABSTRAK

Perangkat lunak telemedis memungkinkan pengguna menjadwalkan janji temu dengan dokter atau rumah sakit, membeli obat secara online, membaca berita dan publikasi terkait kesehatan, dan melakukan konsultasi online dengan dokter. Opini publik diperlukan agar aplikasi ini dapat memenuhi kebutuhan masyarakat. Persepsi masyarakat terhadap aplikasi kesehatan masa kini dapat diketahui dengan melihat opini masyarakat. Analisis sentimen terperinci digunakan dalam pengambilan opini publik untuk mengekstrak informasi dari evaluasi yang diposting oleh publik dan mengkategorikannya ke dalam kelompok positif dan negatif. Menggunakan RapidMiner sebagai alat pendukung, analisis sentimen menggunakan algoritma Naïve Bayes Classification dan Support Vector Machine untuk menentukan nilai akurasi. Setelah menganalisis data dari dua sumber berbeda—Twitter dan Playstore—dapat dikatakan bahwa algoritma Support Vector Machine memiliki kinerja 90,99% lebih akurat dalam memprediksi opini publik dibandingkan algoritma Naïve Bayes yang mencapai akurasi 88,55%.

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INTRODUCTION

In today's era, technology plays an important role in human life. this is evidenced by the drastic increase of 4 million smartphone users compared to January 2020 and an increase of 27 million internet users compared to January 2020 (Brem et al., 2021). Technology also plays an important role in the world of health (He et al., 2020). To meet the needs of the community in the health sector, the telemedicine application helps distribute health facilities to people who have geographical constraints, especially people who live in areas that lack health facilities and medical personnel (Laili, 2016; Widiyanto, 2017). The most medical personnel are on the island of Java, namely 62.7% (23,044 people), while the areas with the fewest medical personnel are in North Kalimantan (343 people), West Sulawesi (358 people) and Maluku (308 people). While the distribution of 49.5% hospitals are in Java (Kemp, 2021). Based on research data from APJII (Association of Indonesian Internet Service Providers) people who use the internet in the health sector, 51.06% use the internet to search for articles and journals about health, while 14.05% are used to conduct online consultations with doctors (Imarotunnisa Oktavia et al., 2020). This data proves that people are still reluctant to use telemedicine applications in meeting their health needs. In the era of the Covid-19 Pandemic, where physical interaction becomes risky, people prefer telemedicine (Haleem et al., 2021). People still doubt how telemedicine works, which requires doctors to examine patients remotely, this can lead to inaccurate or missed diagnoses (Lee et al., 2021). Telemedicine eliminates physical interaction between doctors or medical personnel and patients, which can affect the quality of service and the relationship between patients and doctors. This limitation can also affect the doctor's ability to directly observe the patient's physical condition (Andreadis et al., 2023). Apart from that, common problems related to digitalization are related to security and privacy. Telemedicine requires sending medical data electronically, which can be vulnerable to cyberattacks and data privacy breaches (Wenhua et al., 2024; Yuninda et al., 2022).

Therefore, it is necessary to carry out a sentiment analysis to realize a telemedicine application that suits the needs of the community (Sari, 2019). This sentiment analysis is useful for taking public opinion about health applications on Twitter and Playstore and then it will be processed using the Naïve Bayes algorithm and Support Vector Machine to get a confusion matrix (Ferdiansyah & Wella, 2022; Kornelius & Wella, 2021). Public opinion that has been processed will become useful information for the company as a telemedicine application developer to determine the next development step in order to provide what is needed by the community (Bau & Tee, 2023).

RESEARCH METHODS

Sentiment Analysis

Sentiment analysis or opinion mining is one of the NLP (Natural Language Processing) techniques that aims to track and process data automatically to see someone's opinions and opinions about a product or a topic (Deviyanto & Wahyudi, 2018). Sentiment analysis is widely used to classify polarities in sentences to find out whether the opinion contains a positive or negative category (Rofiqoh et al., 2017). In looking at the polarity and public opinion, there are 4 types of sentiment analysis that can be used: (1) Fine-Grained Sentiment Analysis is a classification method that makes sentiment polarity an aspect / object. The polarity of the sentiment in question is the value of positive or negative opinions contained in the sentence directly or indirectly (K. Y. Setiawan et al., 2014). (2) Emotion Detection is a classification method that makes a person's emotions an object / aspect, but because people's expressions differ from one another, sometimes classification will be difficult (Bau & Tee, 2023). (3) Aspect-Based Sentiment Analysis (ABSA) is an opinion mining technique that is useful for getting positive, neutral or negative sentiments related to an aspect in a customer review or review (G. Setiawan et al., 2019). (4) Multilingual Sentiment Analysis is a method commonly used to classify opinions in various languages. However, this method has the disadvantage of having to create vocabulary from scratch (Shinde & Takalikar, 2016).

Naive Bayes Classification

Naïve Bayes Classification (NBC) is a statistical classification method using probability methods that have classification capabilities such as decision trees and neural networks (Annur, 2018). The Naïve Bayes method was created by a British scientist named Thomas Bayes. This Naïve Bayes Classifier is also known as Bayes theorem because it predicts future opportunities based on past experiences. One of the main characteristics of the Naïve Bayes Classification is that this theorem has strong assumptions (Ferdiansyah & Wella, 2022; Syarli & Muin, 2016). One of the advantages of Nave Bayes is that this method only requires a small amount of data to determine the parameters in the classification process, Nave Bayes can also be used using quantitative and qualitative data (Saleh, 2015).

$$P(H|X) = \frac{P(X|H)P(H)}{P(X)} \quad (1)$$

Support Vector Machine

The Support Vector Machine was developed by Boser, Guyon and Vapnik in 1992 which was published during the Annual Workshop on Computational Learning Theory. Support Vector Machine (SVM) is one of the machine learning algorithms which is a combination of previous computational theories that were developed to classify linear data and non-linear data with the aim of finding the best margin hyperplane to separate a dataset (Octaviani et al., 2014). Making a hyperplane line by drawing a straight line cannot be done directly if the data structure used is non-linear data where the data is still mixed. Therefore we need a kernel trick method, which is a way to create a new dimension (Kornelius & Wella, 2021; Octaviani et al., 2014). Kernel trick is a way to convert non-linear data sets into linear data in order to draw hyperplane lines according to support vectors (Li, 2024).

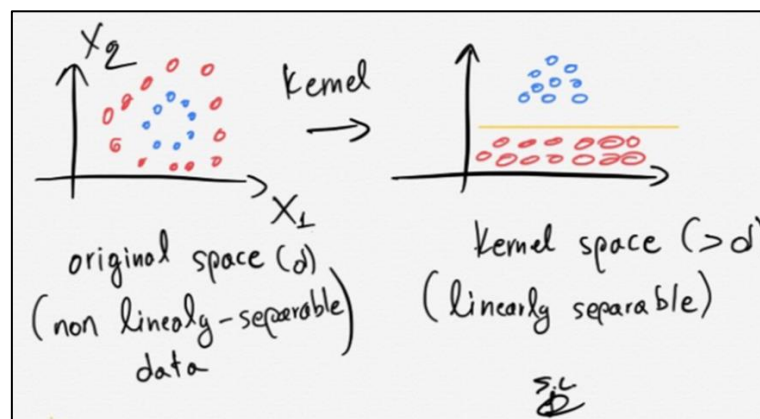


Figure 1. Kernel trick

Confusion Matrix

Confusion matrix is one method to calculate accuracy and recall by comparing the model classification with the actual classification. There are 4 classification results generated by the confusion matrix, namely True Positive, True Negative, False Positive and False Negative. There are 3 values that can be used to measure how well an algorithm predicts a model using the four classification results (TP, FN, FP, TN), namely accuracy, recall, and precision (Rahman et al., 2017).

$$Accuracy = \left(\frac{TP+TN}{TP+FN+FP+TN} \right) \times 100\% \quad (2)$$

$$Precision = \left(\frac{TP}{TP+FN} \right) \times 100\% \quad (3)$$

$$Recall = \left(\frac{TP}{TP+FN} \right) \times 100\% \quad (4)$$

Information:

- True Positive (TP): the truth is positive, and the test predicts a positive.

- True Negative (TN): the truth is negative, and the test predicts a negative.
- False Negative (FN): the truth is positive, but the test predicts a negative.
- False Positive (FP): the truth is negative, but the test predicts a positive.

Data Collection

The data collection technique in this study is a Twitter crawler on tweets collected using python. This data collection is carried out for 50 days, from February 15, 2021 to April 6, 2021. The criteria for data collected are that tweets must be in Indonesian, tweets taken only in 2021 to maintain data validation and the Twitter API only allows data retrieval for 7 days. to the back. The number of tweets collected initially had 6000 tweets but due to the large amount of data that did not match the opinion criteria, only 1000 tweets were left. Tweets that were deleted were tweets that had neither negative nor positive opinions, retweets and tweets from the official accounts @Halodoc, @Alodokter_id and @Klikdokter.com. The data collection technique carried out in the Playstore is to use a software called Octoparse web scraper. The criteria for the data taken are opinions that use Indonesian and all opinions taken are sorted by "Most Relevant", the data taken is random data that has reviews of 1 star, 2 star, 3 star, 4 star and 5 star. So the probability of getting data with positive and negative opinions is 1 in 1. This data collection was carried out on March 21, 2021 to March 22, 2021 and succeeded in collecting 4000 total data.

Manual Labelling

The data labeling process was carried out manually by 3 sources. The selected resource persons are students who have grades in Indonesian language courses with a minimum grade of A. Each resource person will receive a dataset containing 4184 data in excel form that must be labeled. The three labeling results will be compared and the majority label will be taken.

Preprocessing

Data Cleansing: the stage of cleaning data from 'noise' or garbage that can interfere with the accuracy of the resulting sentiment.

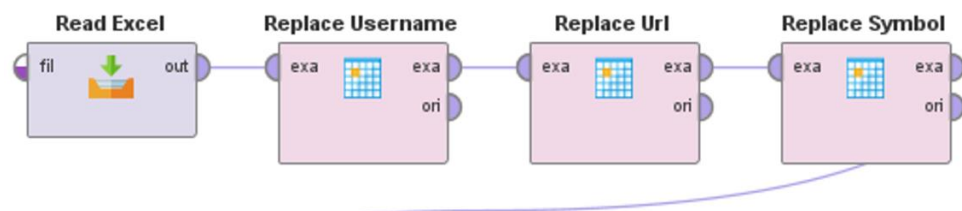


Figure 2. Step by step cleansing

Case Folding and Remove Duplicates: make all sentences/words lowercase and remove all duplication data.

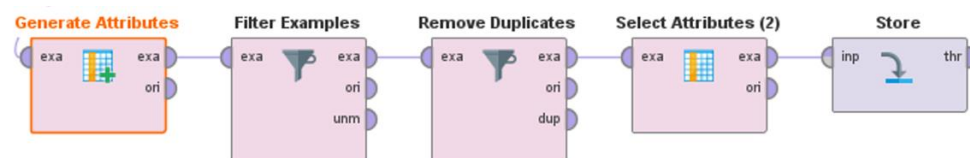


Figure 3. Step by step case folding and remove duplicates

Tokenizing: cutting sentences into word pieces (tokens). This stage is carried out because it can facilitate the model for weighting positive and negative words. Eliminate Stopwords: stages of removing words that often appear but have no effect on sentiment. Usually these discarded words are conjunctions, nouns, and pronouns. Normalization: the stage of changing a non-standard word into a standard, such as slang words, typing errors, and repeated words using numbers.



Figure 4. Step by step tokenizing, eliminate stopwords and normalization Model Training

At this stage, data modelling is carried out to classify sentiment using RapidMiner. The following are the stages of data modelling:

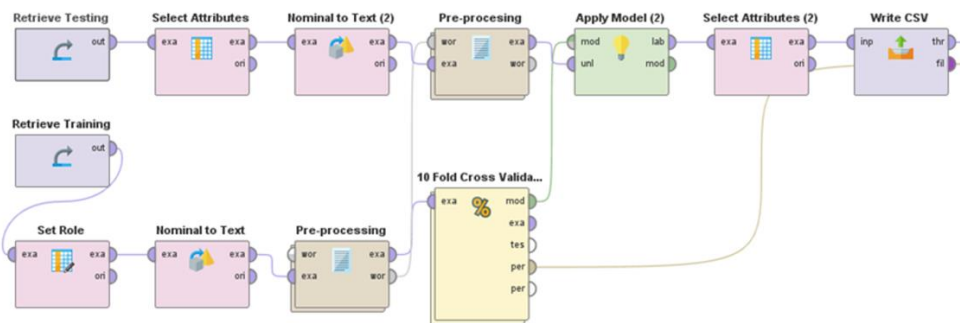


Figure 5. RapidMiner process

This RapidMiner stage is divided into 2 parts where the lower part is the stage of model training using training data while the upper part is the stage of taking the model that has been carried out (below) to predict sentiment data testing. This model training uses K-fold Cross Validation, which is a validation method that is useful for predicting the prediction accuracy of a model, especially on data that has a limited amount of data. In this study, the number of k that will be used is 10, which means that there will be 10 stages of model evaluation in turn. In this operator, two algorithms will be used to perform the comparison, namely Naïve Bayes and Support Vector Machine.

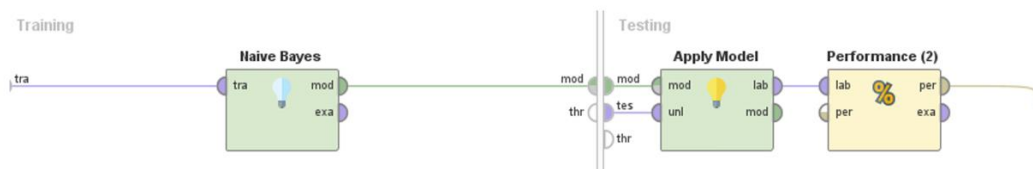


Figure 6. Modelling step with Naive Bayes

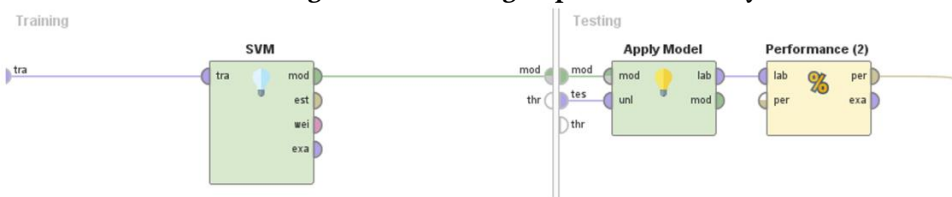


Figure 7. Modelling step with support vector machine

After the k-fold cross validation model training stage has been completed, the output of the k-fold cross validation will be taken to be used as a model in predicting positive negative opinions on data testing.

prediction(s...	confidence(positif)	confidence(negatif)	text
positif	0.793	0.207	sdh pakai aplikasi memsudahkan membeli obat keluar rumah pesan obat obat re...
negatif	0.463	0.537	tes swab pcr cibis tanggal desember hasil keluar tanggal keluar hasil bayar mahal...
positif	0.868	0.132	terimakasih seneng halodoc kesehatan tetjawan terimakasih dokter konsultasi teri...
positif	0.825	0.175	bagus sangat aplikasi sgt dari kontrol mertua jd ga hrs nunggu obat nya adikala p...
positif	0.581	0.419	terimakasih aplikasi halodoc kedepannya mohon upgrade pembayaran cash kala...
positif	0.865	0.135	konsultasi dengan dokter menggunakan aplikasi terima kasih
positif	0.867	0.133	terima kasih dari mohammad adam eldi sudah kasih saran resep semoga keluh...
positif	0.708	0.292	chatnya alhamdulillah bls benar terimakasih halodoc dokter via chat
positif	0.863	0.137	terimakasih halodoc aplikasi konsultasi kesehatan klinik rumah sakit konsultasi d...
positif	0.916	0.084	pengalaman aplikasi pandemijadi petlu repot rs keluhan ringan alergi flusemoga ...
positif	0.765	0.235	puji tuhan dokternya chat free biaya respon okay maju halodoc tetep bantu kalanga...
positif	0.682	0.318	aplikasi nya pas kebenar dapat dokter focus jd agak dijawab nya terima kasih hall...
positif	0.745	0.255	puas pelayanan docter nya lambat membalas chattapi puasssssssss hhhhhhhh
negatif	0.190	0.810	aja chat ama dokter udh selesai chat nya cpt sangatin aplikasi cpt sangat bertany...
positif	0.833	0.167	terimakasih halodoc si silu terbantu dokternya ramah konsul respon cepat resep o...
positif	0.876	0.124	aplikasi aplagi disaat pandemi ga bs bebas rs utk memeriksakan sakit dengan ge...

Figure 8. Example of labeled testing data

Above is the result of data classification testing where there are predictions (negative-positive sentiment), confidence (positive), confidence (negative), and text. Confidence here means how confident the model is in making predictions where if it is close to 1, it means the model is very confident that the predictions that have been made are correct.

RESULTS AND DISCUSSION

Confusion Matrix Naïve Bayes and Support Vector Machine

Tabel 1. Algorithm Comparison Table

	Naïve Bayes	Support Vector Machine
Accuracy	88.55%	90.99%
Precision	64.51%	82.15%
Recall	86.04%	66.15%

Based on the comparison table above, it can be concluded that the Support Vector Machine has slightly better accuracy in predicting sentiment with 90.99% compared to Naïve Bayes 88.55%. The Support Vector Machine algorithm is also far superior in terms of precision with 82.15% compared to Naïve Bayes' 64.51%. However, for recall, the Naïve Bayes algorithm is much better at finding repetitive words in doing sentiment analysis with 86.04% compared to Support Vector Machine with 66.15%.

The Number of Positive and Negative Data Testing

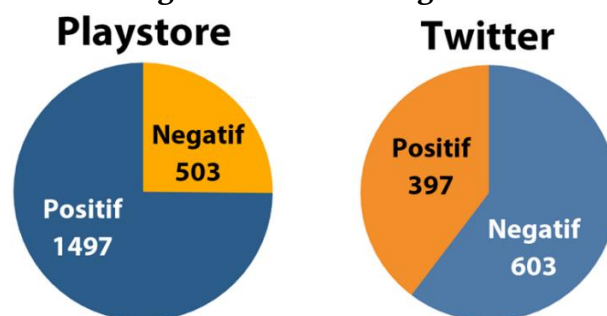


Figure 9. The number of positive and negative data testing with Naive Bayes

Above are the final result of the negative-positive classification for Twitter and Playstore data using the Naïve Bayes algorithm where from 2000 Playstore data that has been classified there are 1497 positive sentiments and 503 negative sentiments which means the telemedicine application is considered quite good, while from 1000 testing data Twitter that has been tested, there are 397 positive sentiments and 603 positive sentiments, which means that the telemedicine application has a bad image among Twitter users.

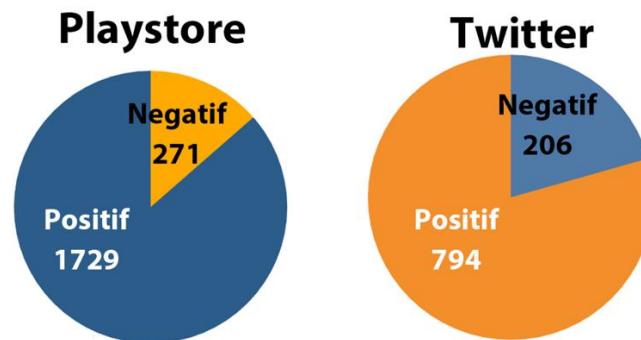


Figure 10. The number of positive and negative data testing with SVM

Above are the final result of the negative-positive classification for Twitter and Playstore data using the Support Vector Machine algorithm where from 2000 Playstore data that has been classified there are 1729 positive sentiments and 271 negative sentiments which means that telemedicine applications are also considered quite good, while from 1000 Twitter testing data that has been tested, there are 794 positive sentiments and 206 positive sentiments, which means that the telemedicine application has a good image among Twitter users. Both algorithms are able to predict the Playstore dataset with more or less similar results, but for the Twitter dataset, the Support Vector Machine algorithm gets 794 positive results and 206 negative results while Naïve Bayes gets 397 positive results and 603 negative results, both of these algorithms have Twitter dataset predictions. which is the opposite where Naïve Bayes is more dominantly negative while Support Vector Machine is more dominantly positive, therefore a comparison is needed to determine which algorithm is more appropriate by manual labeling of Twitter testing data. After labeling the Twitter testing data, it was found that 729 data were positive while 271 data were negative. Therefore, it can be concluded that the Support Vector Machine algorithm is better at classifying sentiments.

Tabel 2. Positive-Negatif Data Comparison

	Naïve Bayes		SVM	
	Positive	Negative	Positive	Negative
<i>Twitter</i>	397	603	794	206
<i>Playstore</i>	1497	503	1729	271
TOTAL	1894	1106	2523	477

The Most Frequent Positive and Negative Words



Figure 11. Playstore most frequent positive words



Figure 12. Playstore most frequent negative words

Figure 11 and Figure 12 are the words that appear most often in Playstore reviews. Figure 4.34 shows the 50 positive words that appear most often, there are words such as pelayanan, ramah, pandemi, bermanfaat, memudahkan which means that people are satisfied with the services provided by health applications that are able to meet health needs, especially during the COVID-19 pandemic like this. Apart from the positive side of the telemedicine application on the Playstore, there are also negative impressions given by users as shown in Figure 4.35 such as bayar, saldo, berlangganan, kecewa, kepotong, dan respon. This is because some telemedicine applications have insurance that is auto-debited to the user's account, so users often feel cheated for not subscribing and protesting. In addition, there are also cases where users often pay for consultations but there is no response from the doctor due to busy doctors or application errors.

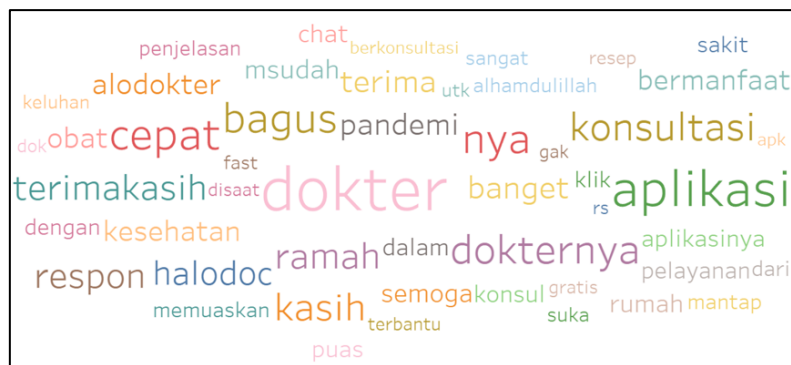


Figure 13. Twitter most frequent positive words



Figure 14. Twitter most frequent negative words

These are the positive and negative words that most often appear on Twitter social media. Figure 13 shows the positive words given by its users such as bagus, cepat, ramah, mantap, bermanfaat, memuaskan which means that the telemedicine application is quite good among twitter users. While in Figure 14 which shows negative words there are bayar, kepotong, cs, telpon, ganggu, database because one of the telemedicine application service providers experienced a data leak which caused many users to be called by fraudsters besides that there was anxiety directed at customer service who often call to offer insurance on a regular basis.

CONCLUSION

Based on the classification results that have been obtained using the Naïve Bayes algorithm and Support Vector Machine, which produces far more positive data than negative data, it can be concluded that the community is quite satisfied with the telemedicine application. Based on the confusion matrix that has been generated, the Support Vector Machine algorithm gets a slightly greater accuracy of 90.99% compared to Naïve Bayes (88.55%). In terms of precision, the Support Vector Machine algorithm gets a much higher percentage of 82.15% compared to Naïve Bayes' 64.51% precision. However, for recall, the Naïve Bayes algorithm is much better at finding repeated words with 86.04% compared to the Support Vector Machine's 66.15%. It can be concluded that the Support Vector Machine algorithm is more suitable for use in this study. At the end of the sentiment analysis there is a visualization of the most common positive and negative words. Some of the negative words that most often appear are telpon, saldo, berlangganan, bocor dan respon that can be taken into consideration for further updates such as increasing application and database security, changing marketing methods, and conducting application quality control.

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