Sentiment Analysis toward the Use of MySAPK BKN Application in Google Play Store

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***Abstract*—In realizing the Electronic-based Government System (*Sistem Pemerintahan Berbasis Elektronik* - SPBE) policy, the National Civil Service Agency (Badan Kepegawaian Nasional - BKN), as the fostering government agency for the State Civil Aparatus (*Aparatur Sipil Negara* - ASN), needs to carry out an accurate, up-to-date, and integrated data management through an Android-based application named MySAPK. Over time, users encounter various troubles operating this application and writing down their reviews on the Rating & Review feature in Google Play Store. From May 9, 2017, until October 18, 2021, reviews written by users amounted to 4,778. This paper conducted a sentiment analysis on MySAPK users' reviews. Stages carried out included data collection, data labeling (annotation), data preprocessing, word feature extraction, classification modeling, modeling evaluation, sentiment analysis, and recommendation result preparation. The classification modeling of the sentiment using the naïve Bayes and support vector machine (SVM) resulted in an accuracy level of 92.47% and 94.14%, respectively. The sentiment measurement results showed that users who wrote reviews with positive sentiments amounted to 2,118 (44.3%), and negative sentiments amounted to 2,660 (55.7%). Factors that prompted users to leave positive sentiment reviews are the excellent application quality, providing benefits, making it easier to fill out and store ASN data, and gratitude comments for BKN. On the other hand, factors causing users to leave negative sentiments reviews include requesting to fix the application, having difficulty accessing the application, failing to fill out and update data, and encountering an error server. To address these issues, this paper suggests that BKN could increase supporting server capacity and update the most recent version to fix the bugs. The research result is expected to serve as a reference for BKN in evaluating and improving the quality of ASN services via the MySAPK app.**

***Keywords*—ASN, PNS, Sentiment Analysis, MySAPK, BKN, Google Play Store, Naïve Bayes, Support Vector Machine (SVM).**

I. INTRODUCTION

The rapid proliferation of information and communication technology (ICT) can increase the effectiveness and efficiency of various sectors' performances [1]. Among the sectors utilizing ICT proliferation is the government. The Indonesian government has issued a policy on implementing ICT to the central and regional agencies through the Electronic-based Government System (*Sistem Pemerintahan Berbasis Elektronik* - SPBE) regulation to realize a clean, effective, transparent, and accountable governance [2]. Accurate, up-to-date, integrated, accessible, and accountable data is required to strengthen the governance objectives. As a result, the government has issued a policy called One Data Initiative (*Satu Data Indonesia* - SDI) [3].

Until June 30, 2021, the number of State Civil Apparatus (*Aparatur Sipil Negara* - ASN), comprising Civil Servants (*Pegawai Negeri Sipil* - PNS) and Contract-based Government Employees (*Pegawai Pemerintah dengan Perjanjian Kerja* - PPPK) in central and regional agencies, amounted to 4,131,705 [4]. These million ASN data require proper data management to improve service quality in personnel management, such as promotion, transfer, and retirement [5].

To achieve the quality and integrated One Data ASN in civil service management, the National Civil Service Agency (Badan Kepegawaian Nasional - BKN), as the fostering government agency for ASN, must conduct an accurate, up-to-date, and integrated ASN data management in implementing the government policy on SPBE and SDI. BKN has developed a mobile and web-based application called MySAPK by leveraging information technology advancement. MySAPK is an application used by ASN to independently update data, including personal data, position history, educational history, employee performance target (*sasaran kerja pegawai* – SKP) history, award history, rank and class history, family history, tenure review history, agency transfer history, CLTN history, CPNS/PNS history, and organizational history [6].

MySAPK application can be accessed via web browser and Android-based smartphone application. The users, especially ASN, can download this application for free in Google Play Store. Those who have used MySAPK can give ratings (1-5 star rating) and leave reviews or comments related to the user experience via the Ratings & Reviews feature. Until mid-October 2021, this application received a rating of 2.6. Star 1 ratings dominated the rating values, followed by star ratings with a score of 5 [7]. The small rating values indicate that the application's performance when used by users is not optimal.

This paper focuses on MySAPK users' reviews in Google Play Store. BKN has provided a web portal containing guidance and help tickets for ASN when they encounter problems filling out data through the MySAPK app. Unfortunately, the help ticket feature on the web portal cannot be accessed [8]. As a result, users who experience various troubles while using MySAPK leave negative reviews on the Google Play Store. As a government agency that manages the MySAPK app, BKN, needs to evaluate services, one of which is by analyzing the sentiment towards user reviews.

Sentiment analysis on a particular issue or topic in social media, product reviews, and application services can be applied using a machine learning algorithm approach, such as the naïve Bayes and support vector machine (SVM). The naïve Bayes

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and SVM are the most common modeling algorithms used to classify text with various performances, depending on the number of variants, features, and collected data. This algorithm works very well in classifying texts with a small amount of data and pieces of documents. Meanwhile, SVM is very good at categorizing text with a relatively large amount of data or complete documents [9].

This study aims to analyze the sentiments of MySAPK application users through reviews on the Google Play Store. The analysis results were reprocessed to obtain the factors experienced by users. The best classification model can be generated as a result of this study and used as an evaluation material for BKN. Hence, the service quality for ASN remains consistent and even increasing in realizing One ASN Data in Indonesia.

II. Sentiment Analysis

A. Related Research

Sentiment analysis research on reviews and social media topics has been frequently conducted. The research was carried out to determine the sentiment of Jabodetabek KAI commuter passengers toward COVID-19 spread on Twitter [10]. The analysis was done using the naïve Bayes and decision tree. The result showed 135 positive sentiments, 152 negative sentiments, and 53 neutral sentiments. The naïve Bayes algorithm, with an accuracy level of 73.59%, outperformed the decision tree with an accuracy level of 56.83%.

Another research examined the public's sentiment of two influencers, namely Fiersa Besari (@fiersabesari) and Keanu (@aglkeanu), on Twitter [11]. As many as 3,243 tweet data were collected using the Twitter API feature prior being labeled manually. There were 1,282 positive and 1,312 negative sentiments on the tweet data of Fiersa Besari; at the same time, there were 321 positive sentiments and 328 negative sentiments on the tweet data of Keanu. In this research, the naïve Bayes algorithm, SVM, logistic regression, and decision tree algorithm were used to compare sentiment accuracy levels. The results revealed that the naïve Bayes algorithm achieved the highest F1-Score with 81.56% for Fiersa Besari and 70.78% for Keanu. This research is beneficial to identify which influencers have a positive image in the digital marketing of a particular product.

Sentiment analysis was also used to identify a movie's quality on Twitter. This research employed supervised learning SVM with 10-fold cross-validation and obtained an accuracy level of 71.87%. Next, the parameter was increased using particle swarm optimization (PSO), resulting in a better accuracy level of 77% [12].

In addition, research on sentiment analysis was conducted to determine the customer satisfaction of by.U telecommunications service providers through user reviews on the Google Play Store. This study obtained 8,925 review data. Manually, rated 4 and 5 reviews were labeled positive sentiment, rated 1 and 2 reviews were labeled negative sentiment, and rated 3 reviews were labeled neutral. Review data comprising 4,874 positive sentiments and 4,051 negative sentiments labels were obtained. The SVM algorithm with 5-fold validation was used and the highest accuracy of 86.1% at the validation value of fold 2 was obtained [13].

B. Sentiment Analysis

Sentiment analysis is the field of study which analysis opinions, ratings, attitudes, and emotions towards an entity such as a service, product, issue, or occurrence. It is applied in numerous business and social fields since opinions influence many aspects, from individual behavior to organizational decision-making. The importance of sentiment analysis is associated with the rapid development of opinion in social media like product or service reviews and various discussions on blog forums, Twitter, or social networks [14].

C. Text Mining

Text mining has been widely used to identify and extract information from unstructured texts. It is used to extract facts and relationships in a structured form that can be used to annotate custom databases, transfer knowledge between domains, and, generally, in business intelligence, support an organization's operational and strategic decision-making [15].

D. Naïve Bayes Classifier

The naïve Bayes classifier works based on the Bayes theorem proposed by an English statistician, Thomas Bayes, in 1763 [16]. One advantage of the naïve Bayes' classification is its classification ability using a small amount of training data. This classification uses rating and review texts to train classifications that can help understand positive or negative reviews. The naïve Bayes is arithmetic correlating the input data in the form of vectors to the output in the form of class labels [17].

E. Support Vector Machine (SVM)

SVM is a supervised learning model whose implementation requires a training stage using an SVM sequential training followed by a testing process. The SVM classification attempts to separate the data space using nonlinear or linear classifications between different classes. The SVM classification concept is a hyperplane that serves as a separator between two class data (positive and negative things) [18]. In Fig. 1 [19], there are two classes x, o and hyperplanes A, B, C. Hyperplane A is the best separator between classes since it has the most significant distance from each data point that represents the maximum margin of separation [19].

III. Methodology

This research, generally, consists of several stages, starting from data collection, data labeling (annotation), data preprocessing, word feature extraction, classification modeling, classification modeling evaluation, sentiment analysis, and recommendation result preparation. These stages are illustrated in Fig. 2.

A. Data Collection

In this stage, data were collected from user reviews of the MySAPK application in Google Play Store with scraping

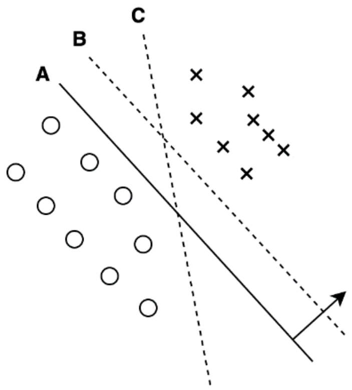

Fig. 1 SVM in classification breakdown.

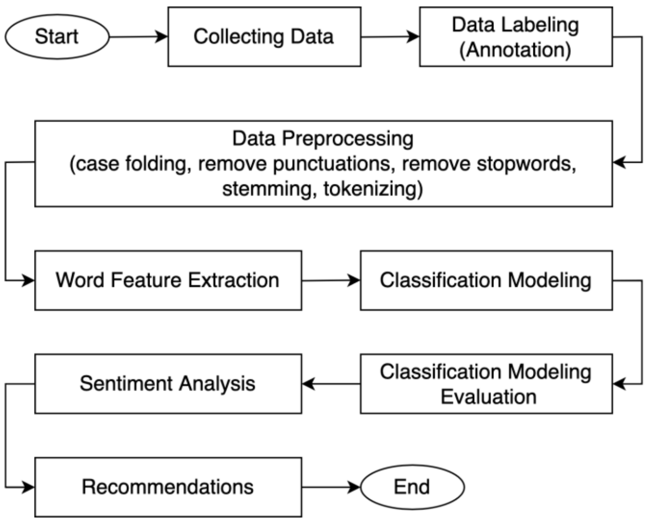

Fig. 2 Research stages.

method using the Python programming library called Google-Play-Scraper [20]. The Rating & Review feature in Google Play can indicate the performance level of a specific application. A star rating with a score of 1 means very poor, 2 means poor, 3 means fair, 4 means good, 5 means very good [21]. The review category selected for this research was most relevant, with a star rating of 1, 2, 4, and 5. The collected review data were then saved in comma-separated values (CSV) document format.

B. Data Labeling (Annotation)

In this stage, data labeling (annotation) was done manually. Two annotators, namely the writers whose study background was information technology, carried out the annotation. User reviews were labeled positive and negative, then saved in CSV documents.

C. Data Preprocessing

Data preprocessing was the first stage in classifying a text. It consisted of several stages as follows [22].

1) Case Folding: This process converts all text characters to lowercase.

2) Remove Punctuations: This process removes all text characters consisting of punctuation, number, URL, ASCII code, and emoji.

3) Remove Stopwords: This process eliminates meaningless words that often appeared in the text by using 759 Indonesian stopword databases [23].

4) Stemming: The stemming process seeks to find base words by eliminating prefixes and suffixes of a word. It was conducted using a Python programming library called Sastrawi [24] based on the Adriani algorithm [25].

5) Tokenizing: This process divides the text into structured word parts to count the number of words that appear [26].

D. Word Feature Extraction

The subsequent step was the word feature extraction using the term frequency–inverse document frequency (TF–IDF). TF–IDF is an algorithm generally used to calculate the word weight in a particular document. The term frequency (TF) represents the number of words that often appear in a document. Often, frequently appearing words will interfere with unique words' searching process. The inverse document frequency (IDF) reduces the word's weight that repeatedly occurs and can measure the importance of the word's meaning in a document. Equation (1) shows the TF calculation. $TF(t,d)$ denotes the word frequency of t words in document d, $N(t,d)$ is the number of t words appearing in document d, and T is the total of words in the document. Equation (2) is used to calculate the IDF, where $IDF(t)$ represents how rare the word frequency in the document, N represents the number of documents, and $N(t)$ represents the number of documents with t words. Hence, (3), which was the product of TF and IDF, was used to calculate TF–IDF [27].

$$TF(t,d) = \frac{N(t,d)}{T} \tag{1}$$

$$IDF(t) = logN/(N(t)) \tag{2}$$

$$TF - IDF = TF * IDF \tag{3}$$

E. Classification Modeling

This stage applied classification modeling using two machine learning algorithms, namely the naïve Bayes and SVM, with the Python programming library called the scikit-learn [28]. These classification modeling were performed separately to obtain the best accuracy result between the two-classification modeling employed. The classification modeling requires the training data from the dataset [29]. In this study, 90% of the total dataset was used for training data.

F. Classification Modeling Evaluation

The final stage in this research was to measure the evaluation of the performance of the machine learning classification modeling performed in the previous step. This evaluation measurement aimed to compare the performance and effectivity of the two-machine learning classification modeling used. Among the techniques used to evaluate and summarize the performance of machine learning classification modeling was the confusion matrix. As shown in Table I, the confusion matrix is a 2 × 2 matrix summarizing the total correct and incorrect classification results. The value combination of true

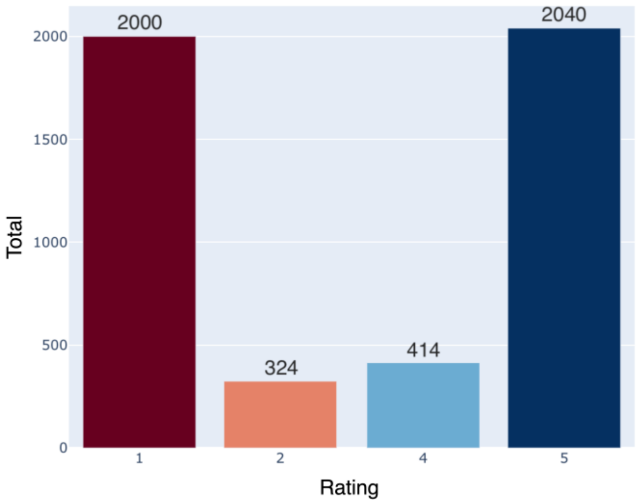

Fig. 3 Distribution of MySAPK application rating score data

TABLE I
CONFUSION MATRIX

<table>
<tr><td colspan="2"></td><td colspan="2">Actual Classification</td></tr>
<tr><td colspan="2"></td><td>Positive</td><td>Negative</td></tr>
<tr><td rowspan="2">Prediction Classification</td><td>Positive</td><td>True positive (TP)</td><td>False positive (FP)</td></tr>
<tr><td>Negative</td><td>False negative (FN)</td><td>True negative (TN)</td></tr>
</table>

positive (TP), false positive (FP), false negative (FN), and true negative (TN) resulted in four measurement variables [30]. The accuracy value, precision, recall, and F1-Score were obtained using (4), (5), (6), (7), respectively.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{4}$$

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F1 - Score = \frac{2 \, . \, recall \, . \, precision}{recall + precision} \tag{7}$$

G. Sentiment Analysis

The word cloud was then used to do sentiment analysis. Word cloud is a picture representing words used in a particular dataset. Words with bigger font sizes indicate more frequent appearances than those in smaller sizes [31].

IV. RESULT AND DISCUSSION

A. Annotation Result

The scraping method with Google-Play-Scraper was employed to acquire as many as 4,778 review data of the MySAPK application in the Google Play Store collected from May 9, 2017, until October 18, 2021. The reviews data selected were reviews with the star rating of 1, 2, 4, and 5, which details are in Fig. 3. The annotation was done manually by two annotators with study backgrounds in information technology. After that, sentiments were categorized into two, namely positive and negative sentiment. The annotation results of the

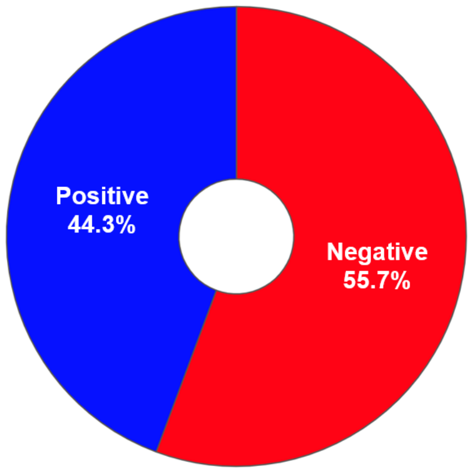

Fig. 4 Annotation result of the sentiment of MySAPK application users.

TABLE II
DATA PROCESSING RESULTS

Stages	Result
User reviews	Kepada admin BKN!!!, tolong perbaiki server MySapk, kalian yg sebagai lembaga kepegawaian tolong jangan mempersulit ASN 😣😣😣, deadline pengisian tinggal beberapa hari lagi dan berkas sudah hampir selesai server malah error. Gimana sih ???.
Case folding	kepada admin bkn!!!, tolong perbaiki server mysapk, kalian yg sebagai lembaga kepegawaian tolong jangan mempersulit asn 😣😣😣, deadline pengisian tinggal beberapa hari lagi dan berkas sudah hampir selesai server malah error. gimana sih ???.
Remove punctuations	kepada admin bkn tolong perbaiki server mysapk kalian yg sebagai lembaga kepegawaian tolong jangan mempersulit asn deadline pengisian tinggal beberapa hari lagi dan berkas sudah hampir selesai server malah error gimana sih
Remove stopwords	admin bkn tolong perbaiki server mysapk lembaga kepegawaian tolong mempersulit asn deadline pengisian tinggal berkas selesai server error
Stemming	admin bkn tolong baik server mysapk lembaga pegawai tolong sulit asn deadline isi tinggal berkas selesai server error
Tokenizing	admin | bkn | tolong | baik | server | mysapk | lembaga | pegawai | tolong | sulit | asn | deadline | isi | tinggal | berkas | selesai | server | error

4,778 review data showed that 2,118 users left positive sentiment reviews (44.3%), while 2,660 users left negative sentiment reviews (55.7%). Fig. 4 shows that the percentage of sentiment annotation with negative sentiment reviews outnumber positive ones. These annotation data were then saved in the CSV document as a dataset processed in the next stage.

When compared, the application rating does not correspond to the sentiment elicited by the annotation. The application rating suggests that more users give ratings with a score of 4 (good) and 5 (very good) than ratings with a score of 1 (very poor) and 2 (poor). A total of 2,454 users gave a score of 4 and 5, with a division of 414 and 2,040, respectively; meanwhile, a

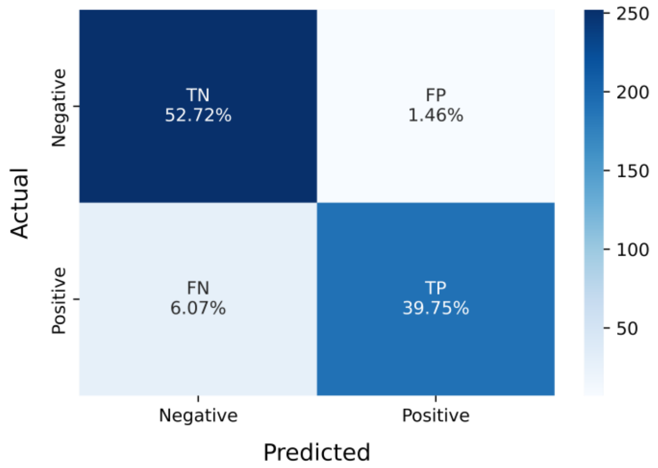

Fig. 5 Confusion matrix of the naïve Bayes.

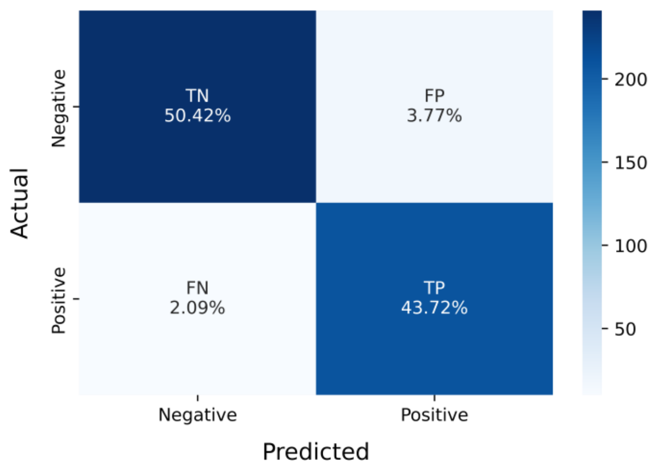

Fig. 6 Confusion matrix of the SVM.

TABLE III
DIVISION OF TRAINING DATA AND TEST DATA

Sentiment Label	Training Data	Test Data
Negative	2,401	259
Positive	1,899	219
Total	4,300	478

total of 2,324 users gave a score of 1 and 2, with a division of 2,000 and 324, respectively. This discrepancy arose as a result of users providing sentiments that contradicted the score. It was found that some users gave a score of 4 or 5, but the reviews were negative.

B. Data Preprocessing Results

After the review dataset of MySAPK application users was annotated, the data preprocessing was carried out five times. The result of each data preprocessing is shown in Table II.

C. Dataset Division for Classification Modeling

The classification modeling of naïve Bayes and SVM was done using training data to obtain the sentiment prediction model. Test data taken from the dataset were used to evaluate the prediction results generated by the classification models. In this research, the comparison of training and test data was 90:10, which division was obtained through the scikit-learn. Table III shows the distribution of training and test data from 4,778 MySAPK review datasets.

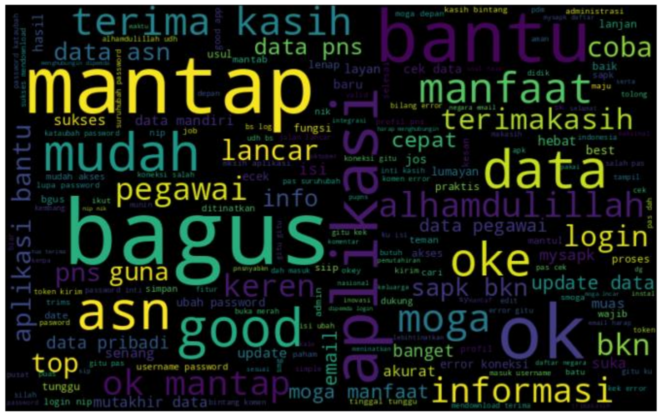

Fig. 7 Word cloud of positive sentiments.

TABLE IV
RESULTS OF PRECISION, RECALL, AND F1-SCORE

Classification Modeling	Sentiment Label	Precision	Recall	F1-Score
Naïve Bayes	Negative	0.90	0.97	0.93
	Positive	0.96	0.87	0.91
SVM	Negative	0.96	0.93	0.95
	Positive	0.92	0.95	0.94

D. Results of Classification Modeling Evaluation

The conducted naïve Bayes and SVM classification modeling must be evaluated using the confusion matrix to obtain the best accuracy value, precision, recall, and F1-Score among the two modeling algorithms. Fig. 5 is the confusion matrix of the naïve Bayes. The actual values are actual data reviews, while predicted values are prediction data of reviews. Four combination values were obtained from the 478 data tested from the two sentiments.

- True positive resulted in 39.75%, meaning that 190 review test data with positive labels could be correctly predicted as positive labels by the naïve Bayes.
- False positive resulted in 1.46%, meaning that seven review test data with negative labels were incorrectly predicted as positive labels by the naïve Bayes.
- False negative resulted in 6.07%, meaning that 29 review test data with positive labels were incorrectly predicted as negative labels by the naïve Bayes.
- True negative resulted in 52.72%, meaning that 252 review test data with negative labels could be correctly predicted as negative labels by the naïve Bayes.

Fig. 6 shows the confusion matrix from 509 review data using the SVM, resulting in the following four value combinations.

- True positive resulted in 43.72%, meaning that 209 review test data with positive labels could be correctly predicted as positive labels by the SVM.

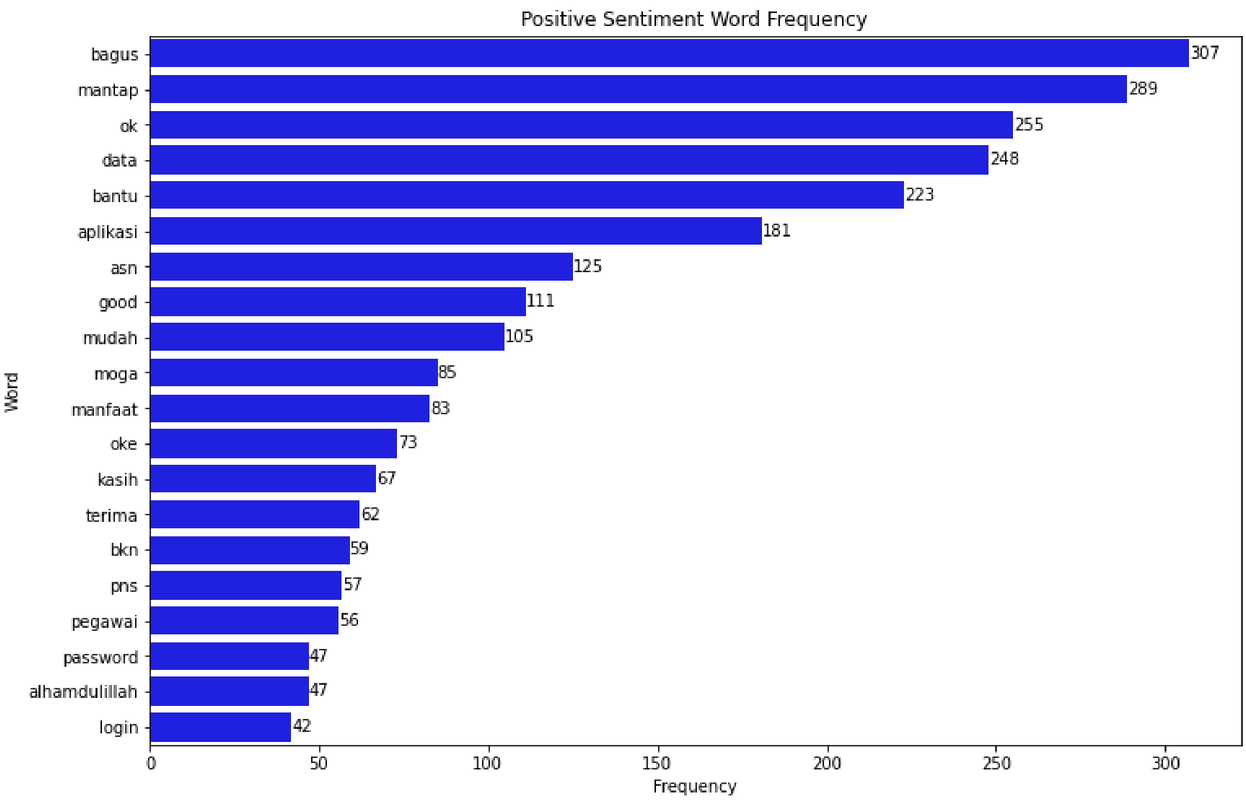

Fig. 8 Frequency of positive sentiment words.

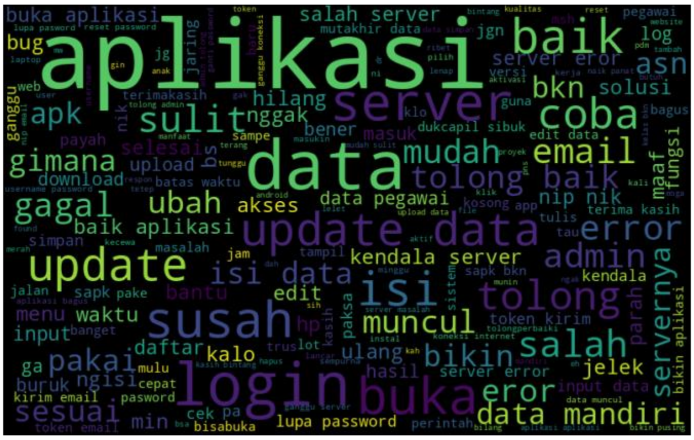

Fig. 9 Word cloud of negative sentiments.

- False positive resulted in 3.77%, meaning that eighteen review test data with negative labels were incorrectly predicted as positive labels by the SVM.
- False negative resulted in 2.09%, meaning that ten review test data with positive labels were incorrectly predicted as negative labels by the SVM.
- True negative resulted in 50.42%, meaning that 241 review test data with negative labels could be correctly predicted as negative labels by the SVM.

Using the confusion matrix, the modeling evaluation measurement showed that the naïve Bayes classification model could correctly predict 442 review data consisting of 190 positive sentiment review data and 252 negative sentiment review data. On the contrary, 36 review data were incorrectly predicted by the naïve Bayes, including seven negative sentiment review data and 29 positive sentiment review data. In the SVM classification modeling, 450 review data could be correctly predicted. These data consisted of 209 positive sentiment review data and 241 negative sentiment review data. On the other hand, 28 review data were incorrectly predicted by the SVM, including eight negative sentiment review data and ten positive sentiment review data.

The precision, recall, and F1-Score values of each classification modeling were obtained from the measurement of the modeling classification, as shown in Table IV. Referring to (4), the accuracy value generated through the naïve Bayes

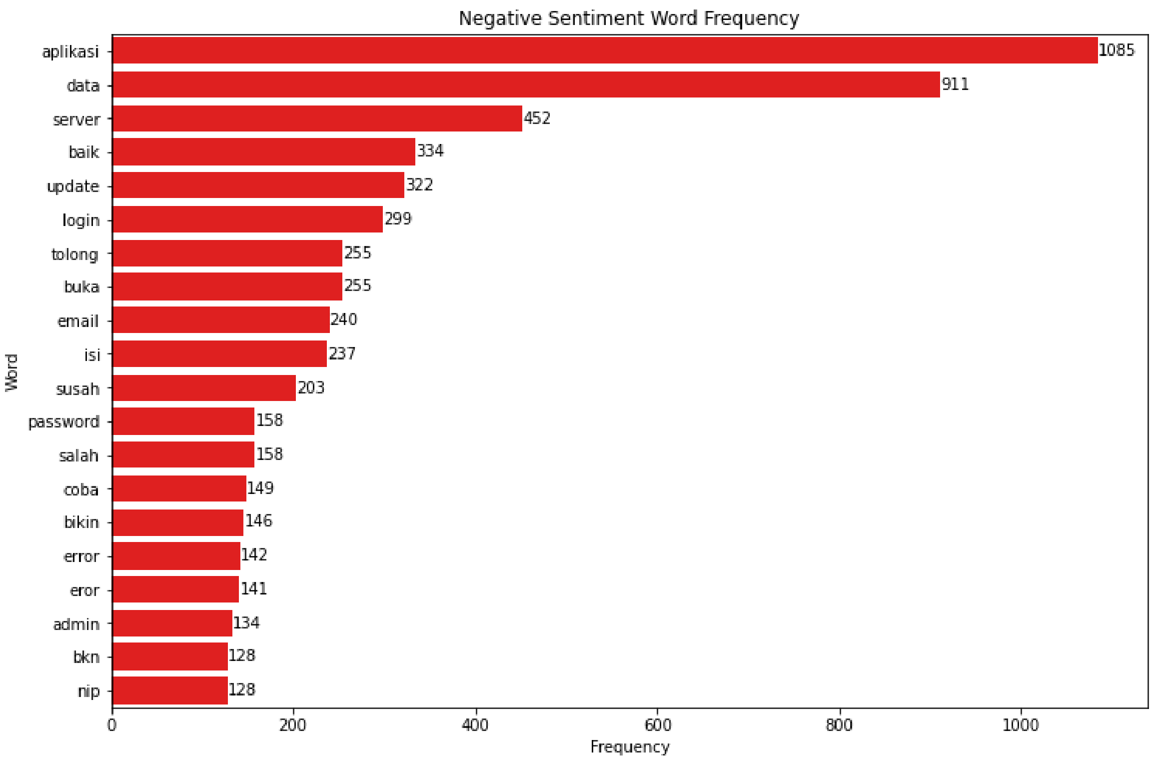

Fig. 10 Frequency of negative sentiment words.

(NB) classification modeling was 0.9247 or 92.47%, while the SVM was 0.9414 or 94.14%. Thus, the SVM algorithm had the highest accuracy value in the classification modeling of user reviews of the MySAPK application, with 94.14%.

$$NB\ Accuracy = \frac{0.3975 + 0.5272}{0.3975 + 0.0146 + 0.0607 + 0.5272} = 0.9247 \approx 92.47\%$$

$$SVM\ Accuracy = \frac{0.4372 + 0.5042}{0.4372 + 0.0377 + 0.0209 + 0.5042} = 0.9414 \approx 94.14\%.$$

E. Analysis of Sentiment Results

MySAPK application sentiment results revealed that more users left negative sentiment reviews than positive ones, with each percentage being 55.7% and 44.3%, respectively. The sentiment analysis of positive and negative reviews was then carried out using a word cloud. The word cloud presentation can illustrate the intent of the reviews written by the MySAPK application users.

Fig. 7 and Fig. 8 illustrate the word cloud and the word frequency of the positive sentiment. There are many words with positive sentiments, such as “bagus”, “ok”, “mantap”, “bantu”, “good”, “mudah”, “moga”, “manfaat”, “terima”, and “kasih”. The top four frequently appearing words in positive sentiment reviews are “data”, “aplikasi”, “asn”, and “bkn”. These words are the object that gained users’ positive sentiment. Some reviews that contain words with positive sentiments include: “aplikasi sangat bagus (good)”, “aplikasi ok dan mantap”, “membantu dalam menyimpan data-data ASN”, “mempermudah dalam mengisi data”, “semoga memberi manfaat untuk ASN”, and “ucapan terima kasih kepada BKN”. It indicates that users experience positive impacts when using the MySAPK app.

On the contrary, Fig. 9 and Fig. 10 demonstrate the word cloud and the word frequency of the negative sentiment. The three most frequently appeared words in the negative sentiments are “aplikasi”, “data”, and “server”. Those three words that appeared in the negative sentiment are accompanied by additional words, such as “baik”, “update”, “login”, “tolong”, “buka”, “email”, “isi”, “susah”, “password”, “salah”, “coba”, and “error”. Some reviews that contain words with negative sentiments include: asking for assistance to fix the application, being unable to update data, having difficulty logging in even though the email and password are correct, having difficulty opening the application, failing to fill in data due to an error, and receiving notifications about server error and please try again later. It conveys the complaints and issues that users encounter when using the MySAPK app.

The issues that appeared in the negative sentiments indicate that the performance of the supporting server and MySAPK application is less than optimal. To address issues and improve service for ASN, BKN should increase the capacity of the supporting server so that many users can access it simultaneously. BKN also needs to improve the Android-based MySAPK application by launching the latest version update to address any errors or bugs encountered by users.

In Fig. 10, the word “baik” is a basic word with positive sentiment. However, in the classification, this word was classified as having a negative sentiment. It happens because the word "baik" was derived from the word "memperbaiki" or "diperbaiki", which in the classification were found in many reviews with negative sentiments. The basic words appearing in the sentiment classification were the results of the stemming process at the preprocessing stage of the data, so the word "memperbaiki" or "diperbaiki" became "baik" after going through the stemming process.

V. Conclusion and Suggestion

From May 9, 2017, until October 18, 2021, the reviews of MySAPK applicationusers in the Google Play Store amounted to 4,778. The sentiment calculation results showed that more users left negative sentiment reviews with 2,660 (55.7%) than positive ones with 2,118 (44.3%). In the sentiment classification modeling, the naïve Bayes achieved an accuracy of 92.47 percent, and the SVM attained an accuracy of 94.14 percent.

This research also uncovers causative factors influencing users to give positive or negative reviews. Among the factors that cause users to give positive sentiments is the excellent application quality, providing benefits, making it easier to fill out and store ASN data and gratitude comments for BKN. On the other hand, among the factors that prompted users to write negative sentiments reviews are requesting to fix the application, having trouble accessing the application, failing to fill out and update data, and encountering an error server. To improve service quality, BKN needs to overcome these issues by increasing the capacity of the supporting server and releasing an updated version of the application to address errors or bugs.

It is hoped that future research will improve the performance of the stemming algorithm during the data preprocessing stage. As a result, meaningfully positive words with positive sentiments are not converted into words with negative sentiments when sentiment classification is carried out, and vice versa.

Conflict of Interest

The authors declare no conflict of interest in this research.

Author Contribution

Conceptualization, Raksaka Indra Alhaqq and I Made Kurniawan Putra; methodology, Raksaka Indra Alhaqq; writing—original draft preparation, Raksaka Indra Alhaqq; review and editing, Raksaka Indra Alhaqq, Yova Ruldeviyani, and I Made Kurniawan Putra.

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