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Performance Comparison of *Naïve Bayes* and SVM Algorithms in Sentiment Analysis on JKN Application Data

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A B S T R A C T

In 2022, 67.88% of Indonesia's population owned mobile devices. BPJS Kesehatan responded to this trend by launching the Mobile JKN application to provide modern, accessible healthcare services. To drive continuous innovation, BPJS Kesehatan needs insights into user feedback regarding the Mobile JKN application. Given the large volume of reviews, sentiment analysis is employed to classify reviews into positive or negative categories. This study compares the performance of Naïve Bayes and SVM (Support Vector Machine) algorithms in sentiment classification using a dataset from the Mobile JKN application. The dataset consists of 200 reviews labeled by two different raters, yielding 110 positive and 90 negative reviews for the first set and 114 positive and 86 negative reviews for the second set. Testing was conducted using three data split scenarios for training and testing: 70:30, 80:20, and 90:10. Model performance was evaluated using a confusion matrix, with metrics including accuracy, precision, recall, and F1-score. The results show that the Naïve Bayes algorithm achieved its best performance with a 90:10 data split, yielding an accuracy of 85%, precision of 77%, recall of 100%, and F1-score of 87%. Conversely, the SVM algorithm performed best with an 80:20 data split, achieving 93% accuracy, 100% precision, 84% recall, and an F1-score of 91% for the first rater's dataset. For the second rater's dataset, SVM reached optimal performance with a 90:10 data split, yielding 90% accuracy, 100% precision, 80% recall, and an F1-score of 89%. Overall, the comparison highlights that SVM outperforms Naïve Bayes in terms of accuracy and precision, making it more effective for predicting positive sentiment in Mobile JKN application reviews.

1. Introduction

In this digital era, the use of mobile devices has become an integral part of daily life across various aspects of society. This is evidenced by a report from Indonesia's Central Statistics Agency, which indicates that 67.88% of the Indonesian population owned mobile devices in 2022 [1]. As the number of Indonesians using mobile devices continues to rise, government institutions and legal entities have begun to adapt to the prevailing trends in mobile device usage. One such entity is BPJS Kesehatan, which has embraced this trend in its operations. BPJS Kesehatan is a national health insurance program aimed at ensuring that the public receives healthcare services and protection to meet their fundamental health needs [2]. As stipulated in Article 28H paragraphs (1), (2), and (3) and Article 34 paragraphs (1) and (2) of the 1945 Constitution of the Republic of Indonesia, As stipulated in Article 28H paragraphs (1), (2), and (3) and Article 34 paragraphs (1) and (2) of the 1945 Constitution of the Republic of Indonesia [3]., BPJS Kesehatan has developed the Mobile JKN application. This mobile service application transforms the conventional service system into an electronic-based system, enabling broader accessibility and usability for the general public [4].

As a healthcare service provider, BPJS Kesehatan must continuously innovate to enhance the quality of its services [5]. Therefore, it is crucial to understand users' perspectives or reviews of the application, as the quality of the application directly impacts user satisfaction [6]. By understanding users' perspectives, the developers of the Mobile JKN application are expected to more easily gain insights into user reviews, assist in comprehending the evaluations provided, and effectively enhance the quality of the application [7].

Reviews related to the Mobile JKN application are often shared through social media, with Twitter being one of the most commonly used platforms for expressing opinions [8] . Twitter (X) is a social media platform that allows users to post short messages known as tweets. According to Katadata, the number of Twitter users in Indonesia reached 27.05 million, making it the fourth largest globally in 2023. With such a large user base and rapid interaction, Twitter has become one of the primary sources for collecting user reviews on various services, including the Mobile JKN application [9].

However, due to the large volume of reviews, a systematic and accurate method is needed to classify these reviews into positive and negative sentiment categories. Sentiment analysis is a field of study that analyzes people's opinions or sentiments toward various entities, such as products or services. In sentiment analysis, the main focus is on identifying opinions that express either positive or negative sentiment [10].

Sentiment analysis employs various machine learning algorithms, including Naïve Bayes and Support Vector Machine (SVM). The Naïve Bayes algorithm is a method that uses probability to classify data whose class is unknown, based on previous data sets [11]. Although it does not fully satisfy the independence assumption between features, Naïve Bayes can still classify effectively and accurately. For this reason, Naïve Bayes is frequently used to support decision-making, prediction, and classification of emotions and sentiment opinions [12]. On the other hand, the Support Vector Machine (SVM) algorithm is a supervised learning model that is capable of analyzing data, identifying patterns, and classifying with high accuracy [13]. SVM uses a hyperplane to separate positive and negative classes by determining the margin or separator between them [14]. Support Vector Machine (SVM) utilizes a hyperplane to distinguish between positive and negative classes by determining the margin or boundary that separates them [15].

This study aims to conduct sentiment analysis on reviews of the Mobile JKN application using two algorithms, namely Naïve Bayes and Support Vector Machine (SVM), to classify the review data. The results of both methods will be compared to determine the most effective sentiment analysis outcome.

2. Method

2.1. Data Collection

The dataset was collected through user reviews or opinions from the Twitter platform, totaling 200 data points, with the keyword "Mobile JKN," and the posting period ranging from July 1, 2023, to December 31, 2023.

The dataset crawling process utilized the tweet-harvest package. Tweet-harvest is a package used to collect tweets from Twitter search results based on specific keywords, language, and time range. The collected tweets were then saved in CSV file format. The steps of this process are depicted in Figure 1 below.

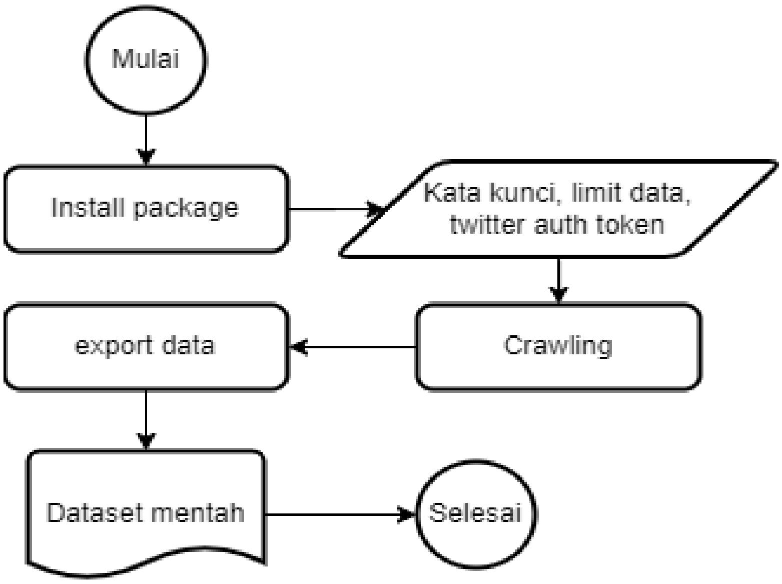

Figure 1. Data Collection Method

The first step in performing data crawling using the tweet-harvest package is to install the necessary packages, including tweet-harvest. Next, run tweet-harvest by including the search keyword, the number of data points to be collected, and the Twitter authentication token. In this study, the researcher used the search keyword "Mobile JKN since:2023-07-01 until:2023-12-31 lang:id," which is intended to search for tweets containing the keyword "Mobile JKN" within the time frame from July 1, 2023, to December 31, 2023, and only retrieve tweets in the Indonesian language. Afterward, the data crawling process is executed, and once the crawling is completed, the data is exported into an Excel file.

As for secondary variables, the researcher obtained secondary data through literature review and literature studies. In the data collection process through literature review, the researcher sought references relevant to the research object and topic. This search was conducted in libraries, bookstores, and online via the internet. The information gathered was used to construct the theoretical foundation, research methodology, algorithm implementation, and system development. In the data collection process through literature studies, the researcher collected and studied various information related to the problem and methods from multiple sources, including books, research journals, and online media.

After collecting the data, the next step was to manually label the tweets into positive or negative classes. Manual labeling was conducted by two individuals to obtain two sets of manual labeling results for the same dataset. This approach allows for a comparison of sentiment analysis results based on the same dataset but labeled by different individuals.

2.2. Text Preprocessing

Text preprocessing is the initial step in sentiment analysis aimed at cleaning the dataset from unnecessary elements or noise. In a dataset already labeled as positive or negative, there are often irrelevant characters such as symbols, uppercase letters, and others. Therefore, preprocessing is essential to cleanse the dataset effectively [12]. The stages in the text preprocessing process include:

1. Cleansing, the process of eliminating non-alphabetic characters such as punctuation, symbols, emoticons, and website addresses aims to reduce noise in the data set.
2. Case Folding, at this stage words that still use capital letters (uppercase) are changed to lowercase.
3. Normalization, changing abbreviated or extended words into standard words according to the Big Indonesian Dictionary (KBBI).
4. Tokenizing, the process of breaking sentences into tokens or terms, useful for further analysis.

5. Stopword Removal, eliminating words that are considered unimportant or meaningless, such as common words (stopwords).
6. Stemming, the process of changing affixed words into basic words.
7. Division of test data and training data

To achieve optimal performance and determine the most suitable test-to-train data ratio, this study divides the test and training data using three different ratios: 70:30, 80:20, and 90:10. The distribution of test and training data for each ratio is presented in the following table.

Table 1. Distribution of Training Data and Test Data

percentage of training data	percentage of test data	amount of training data	amount of test data
70%	30%	140	60
80%	20%	160	40
90%	10%	180	20
total data		200	

2.3. TF-IDF

TF-IDF (Term Frequency-Inverse Document Frequency) is a computational method used to measure the weight of words within a document or text, commonly employed in sentiment analysis in the context of text mining. This algorithm assigns a weight to each word (term) based on its frequency within a specific document or tweet [9]. This weighting aims to assign a unique value to each word, enhancing the capability for sentiment analysis and making it suitable for classifying multiple classes [16].

TF-IDF combines Term Frequency (TF) and Inverse Document Frequency (IDF). In computing weights using TF-IDF, the Term Frequency (TF) for each word is calculated with each word's weight assigned as 1, while the Inverse Document Frequency (IDF) is computed to reflect the importance of a word within the dataset or document [17]. The TF-IDF algorithm equation is in equation 1 below.

$$W_{t,d} = \frac{f_{t,d}}{n_d} \times \log\left(\frac{N}{n_t}\right) \quad (1)$$

2.4. *Naïve Bayes Classifier*

The Naïve Bayes Classifier, introduced by British scientist Thomas Bayes, is a widely applied classification method in sentiment analysis. This method classifies words and documents based on probability and operates under the assumption of independence between classes [9]. In the context of sentiment analysis, the Naïve Bayes classifier can effectively predict the polarity of tweets, determining whether they are positive or negative, even when applied to relatively small datasets. Despite the assumption that features in the data are independent, Naïve Bayes consistently demonstrates strong and accurate performance. This reliability makes it a popular choice for supporting decision-making and for the classification of opinions and emotions 1. The Naive Bayes calculation is in equation 2.

$$P(C|X) = \frac{P(X|C).\,P(C)}{P(X)} \quad (2)$$

2.5. *Support Vector Machine*

Support Vector Machine (SVM) is an effective classification algorithm widely applied in sentiment analysis [18]. SVM, a non-probabilistic algorithm, is capable of separating data both linearly and non-linearly and can handle both discrete and continuous variables [19]. The primary objective of SVM is to identify the optimal hyperplane that separates classes with the maximum margin. In the context of sentiment analysis, SVM can generate an optimal decision boundary to distinguish between positive and negative sentiments in review data.

The strength of SVM lies in its ability to maximize the margin between classes, which significantly contributes to its high accuracy. This method is particularly effective in text classification tasks, such as sentiment analysis, due to its robustness in handling complex data structures [20]. The Support Vector Machine algorithm formula is in equation 3 below.

$$(w \cdot x_i) + b = 0 \tag{3}$$

2.6. Confusion Matrix

The Confusion Matrix is a valuable method for analyzing the quality of classifiers in the process of testing machine learning classification models. Through this testing, values such as accuracy, recall, precision, and F1-score are calculated to evaluate the model's performance. This method provides a comprehensive overview of how well the model can classify data [21]. The confusion matrix table can be seen in table 2 below.

Table 2. Data Confusion Matrix

Actual Value	Prediction Value	
	Positive	Negative
Positive	True Positive	False Negative
Negative	False Positive	True Negative

Some metrics that are commonly calculated from the confusion matrix are accuracy, precision and recall as well as F1-score. The equation of each metric can be seen in the following equation.

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

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

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

$$F1-score = 2 \times \left(\frac{recall \, . \, precission}{recall+precission}\right) \tag{7}$$

3. Results and Discussion

3.1 Results and Discussion of Sentiment Analysis

The sentiment analysis results for the dataset labeled by rater one, with a breakdown of 110 positive sentiment data and 90 negative sentiment data, can be seen in Table 3 below.

Table 3. Results of Sentiment Analysis of One Labeler Dataset

Ratio	Manual		Naïve Bayes		SVM	
	P	N	P	N	P	N
70:30	31	29	41	19	30	30
80:20	19	21	25	15	16	24
90:10	10	10	13	7	8	12

The following is an explanation of the results of the sentiment analysis based on the table above.

1. With a training data ratio of 70% and test data ratio of 30% (140 training data and 60 test data), the Naïve Bayes algorithm produced more positive results compared to both the manual method and SVM, classifying 41 data as positive sentiment and 19 data as negative sentiment. In contrast, the SVM algorithm classified 30 data as positive and 30 data as negative, showing a more balanced result, while the manual method classified 31 data as positive and 29 data as negative.

2. With a training data ratio of 80% and test data ratio of 20% (160 training data and 40 test data), the Naïve Bayes algorithm classified 25 data as positive sentiment and 15 data as negative sentiment, showing a tendency to detect more positive sentiment compared to the manual method, which classified 19 data as positive and 21 data as negative. The SVM algorithm classified 16 data as positive sentiment and 24 data as negative sentiment, showing a more balanced but slightly more negative tendency compared to Naïve Bayes and the manual results.
3. With a training data ratio of 90% and test data ratio of 10% (180 training data and 20 test data), the Naïve Bayes algorithm classified 13 data as positive sentiment and 7 data as negative sentiment, showing a tendency to detect more positive sentiment compared to the manual method, which classified 10 data as positive and 10 data as negative. The SVM algorithm classified 8 data as positive sentiment and 12 data as negative sentiment, which is more similar to the manual results but with a stronger negative tendency.

Overall, it can be concluded that the Naïve Bayes algorithm tends to produce more positive sentiment compared to the manual results and SVM across all test and training data ratios. Meanwhile, the SVM algorithm shows a more balanced performance, but it tends to generate more negative sentiment compared to the manual results.

Next are the results of sentiment analysis on the dataset labeled by the second labeler, with a breakdown of 114 positive sentiment data and 86 negative sentiment data. The results of the sentiment analysis can be seen in Table 4 below.

Table 4. Results of Sentiment Analysis of One Labeler Dataset

Ratio	Manual		Naïve Bayes		SVM	
	P	N	P	N	P	N
70:30	32	28	41	19	34	36
80:20	19	21	26	14	19	21
90:10	10	10	13	7	8	12

The following is an explanation of the results of the sentiment analysis based on the table above..

a) **At a training-to-test data ratio of 70% to 30% (140 training data and 60 test data):**
The Naïve Bayes algorithm shows a tendency to detect more positive sentiment compared to the manual results and SVM, classifying 41 data as positive sentiment and 19 as negative sentiment. Meanwhile, the SVM algorithm classifies 34 data as positive sentiment and 36 as negative sentiment, indicating a more balanced performance but with more negative sentiment predictions compared to the manual results.

b) **At a training-to-test data ratio of 80% to 20% (160 training data and 40 test data):**
The Naïve Bayes algorithm classifies 26 data as positive sentiment and 14 data as negative sentiment, showing a tendency to detect more positive sentiment compared to the manual results. On the other hand, the SVM algorithm classifies 19 data as positive sentiment and 21 as negative sentiment, indicating sentiment analysis results identical to the manual results.

c) **At a training-to-test data ratio of 90% to 10% (180 training data and 20 test data):**
The Naïve Bayes algorithm classifies 13 data as positive sentiment and 7 data as negative sentiment, showing a tendency to detect more positive sentiment compared to the manual results. Meanwhile, the SVM algorithm classifies 8 data as positive sentiment and 12 as negative sentiment, which closely resembles the manual results but still shows a greater tendency for negative sentiment.

Overall, it can be concluded that the Naïve Bayes algorithm tends to produce more positive sentiment compared to both the manual results and the SVM algorithm across all training-to-test data ratios.

Meanwhile, the SVM algorithm demonstrates more balanced performance, but it tends to generate more negative sentiment compared to the manual results.

3.2 Results and Discussion of Comparative Algorithm Performance

The following table shows a performance comparison on datasets that have been labeled by one labeler.

Table 5. Performance Comparison of Single Labeler Dataset Algorithms

Algorithm	Ratio	Accuracy	Precision	Recall	F1-Score
NB	70:30	83%	76%	100%	86%
NB	80:20	85%	76%	100%	86%
NB	90:10	85%	77%	100%	87%
SVM	70:30	92%	93%	90%	92%
SVM	80:20	93%	100%	84%	91%
SVM	90:10	90%	100%	80%	89%

In the comparison of the 70:30 training-to-test data ratio, the Naïve Bayes algorithm achieved a performance with accuracy of 83%, precision of 76%, recall of 100%, and F1-score of 86%. In contrast, the SVM algorithm achieved accuracy of 92%, precision of 93%, recall of 90%, and F1-score of 92%. These results indicate that at the 70:30 ratio, the SVM algorithm outperforms Naïve Bayes in sentiment classification. The SVM algorithm excels in producing higher accuracy and precision, while Naïve Bayes shows perfect recall but with lower precision. This suggests that SVM is better at accurately and consistently identifying sentiment at this ratio.

At the 80:20 training-to-test data ratio, the Naïve Bayes algorithm achieved performance with an accuracy of 85%, precision of 76%, recall of 100%, and F1-score of 86%. In comparison, the SVM algorithm achieved an accuracy of 93%, precision of 100%, recall of 84%, and F1-score of 91%. These results indicate that at the 80:20 ratio, the SVM algorithm performs better in sentiment classification. The SVM algorithm demonstrates superior accuracy and precision, suggesting that it is more effective in minimizing classification errors compared to Naïve Bayes at this ratio.

At the 90:10 training-to-test data ratio, the Naïve Bayes algorithm achieved performance with an accuracy of 85%, precision of 77%, recall of 100%, and F1-score of 87%. In comparison, the SVM algorithm achieved an accuracy of 90%, precision of 100%, recall of 80%, and F1-score of 89%. These results indicate that at the 90:10 ratio, the SVM algorithm also performs better in sentiment classification compared to Naïve Bayes. At this ratio, SVM continues to show higher accuracy and precision, while Naïve Bayes maintains a higher recall but with lower precision.

The following discussion focuses on the dataset that has been labeled by the second labeler. The table below presents a comparison of the performance of the Naïve Bayes algorithm with the SVM algorithm on the dataset labeled by the second labeler.

Table 1. Comparison of Performance of Two Labeling Dataset Algorithms

Algorithm	Ratio	Accuracy	Precision	Recall	F1-Score
NB	70:30	82%	76%	97%	85%
NB	80:20	82%	73%	100%	84%
NB	90:10	85%	77%	100%	87%
SVM	70:30	87%	85%	91%	88%
SVM	80:20	85%	84%	84%	84%
SVM	90:10	90%	100%	80%	89%

At a 70:30 training-to-testing data ratio, the Naïve Bayes algorithm demonstrates performance with an accuracy of 82%, precision of 76%, recall of 97%, and F1-score of 85%. On the other hand, the SVM algorithm produces an accuracy of 87%, precision of 85%, recall of 91%, and F1-score of 88%. These results indicate that

SVM performs better in sentiment classification compared to Naïve Bayes, with advantages in accuracy, precision, and F1-score. While Naïve Bayes has a higher recall, meaning it detects positive sentiments more frequently, SVM is more consistent in producing accurate classifications.

At an 80:20 training-to-testing data ratio, the Naïve Bayes algorithm achieves an accuracy of 82%, precision of 73%, recall of 100%, and F1-score of 84%. Meanwhile, the SVM algorithm obtains an accuracy of 85%, precision of 84%, recall of 84%, and F1-score of 84%. This indicates that at this ratio, SVM still excels in precision and accuracy. Although Naïve Bayes has a perfect recall, its lower precision suggests that there are more errors in predicting positive sentiments compared to SVM.

At a 90:10 training-to-testing data ratio, the Naïve Bayes algorithm achieves an accuracy of 85%, precision of 77%, recall of 100%, and F1-score of 87%, while the SVM algorithm obtains an accuracy of 90%, precision of 100%, recall of 80%, and F1-score of 89%. These results show that at this ratio, SVM excels again in accuracy and precision, while Naïve Bayes maintains a higher recall. SVM is more effective in accurately separating classes, even though its recall is slightly lower compared to Naïve Bayes.

Based on the comparison results, both the dataset labeled by rater one and the dataset labeled by rater two show that the Naïve Bayes algorithm tends to have a very high recall across all data ratios, indicating that this algorithm consistently detects positive sentiment. However, its lower precision suggests that there are many false positive predictions. This could be attributed to the inherent nature of Naïve Bayes, which assumes feature independence. As a result, when certain features (words) appear more frequently in positive data, the algorithm tends to make more positive predictions, even if they are incorrect.

Meanwhile, the SVM algorithm consistently demonstrates better performance in terms of accuracy and precision, indicating a superior ability to separate positive and negative classes. The very high precision across all data ratios suggests that SVM's positive predictions are more accurate. This can be attributed to the advantages of SVM in handling high-dimensional and complex data, as well as its ability to find the optimal hyperplane that separates the data classes effectively.

Overall, the results of this comparison indicate that the SVM algorithm outperforms Naïve Bayes in terms of accuracy and precision across various data train-test ratios, while Naïve Bayes demonstrates a higher recall but with lower precision. Additionally, the comparison highlights that SVM is more consistent in overall performance, whereas Naïve Bayes may be a suitable choice when the primary goal is to ensure that all positive sentiments are correctly identified, even at the cost of a higher false positive rate.

4. Conclusion

The results of the study show that the confusion matrix testing of the Naïve Bayes algorithm on the dataset labeled by both validator one and validator two indicates that this algorithm performs best at the 90:10 train-test ratio with an accuracy of 85%, precision of 77%, recall of 100%, and F1-score of 87%. Although Naïve Bayes almost always achieves perfect recall, it has lower precision compared to SVM, suggesting that Naïve Bayes tends to produce more false positives.

The confusion matrix testing on the SVM algorithm shows that its best performance on the dataset labeled by validator one occurred at the 80:20 train-test ratio, with an accuracy of 93%, precision of 100%, recall of 84%, and F1-score of 91%. Meanwhile, the best performance of the SVM algorithm on the dataset labeled by validator two was at the 90:10 train-test ratio, with an accuracy of 90%, precision of 100%, recall of 80%, and F1-score of 89%. The higher precision across all data ratios indicates that the positive predictions made by SVM are more accurate compared to Naïve Bayes.

The comparison between the Naïve Bayes and SVM algorithms shows that SVM consistently outperforms Naïve Bayes in classifying sentiment in the Mobile JKN app review dataset. SVM not only achieves higher accuracy in all data split scenarios but also demonstrates higher precision. This makes SVM more accurate in predicting positive sentiment. Therefore, SVM is better suited for sentiment analysis on this dataset compared to Naïve Bayes.

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