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Sentiment analysis of mobile jkn application reviews using the multinomial naïve bayes algorithm

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ABSTRACT

Digital transformation in healthcare services has significantly improved public access to information. The Mobile JKN (National Health Insurance) application was developed to facilitate easier access to healthcare services. However, its effectiveness needs to be evaluated through sentiment analysis of user reviews on the Google Play Store. This study aims to determine user sentiment toward the Mobile JKN application using the Multinomial Naïve Bayes method, a commonly used classification technique in machine learning. The data was collected through web scraping and processed through several stages, including tokenization, stopword removal, and text normalization. Sentiment labels were then assigned using a lexicon-based approach, specifically the INSET lexicon, before classification. The analysis revealed that the majority of reviews expressed negative sentiment, particularly concerning application performance, technical issues, and healthcare service quality. The results also showed that the Multinomial Naïve Bayes model was able to classify the data with an accuracy of 81%. Therefore, the Mobile JKN application still requires technical improvements and service enhancements to provide a better user experience. This study offers valuable insights for developers and can serve as a foundation for policy-making to improve the quality of digital healthcare services.

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1. INTRODUCTION

Health is a fundamental need for every individual. With good health, people can carry out their daily activities more productively. In Indonesia, there is a high and growing demand for healthcare services each year(Mauludin Rohman & Adinugroho, 2021). To address this, the Social Security Administering Body for Health (BPJS Kesehatan) officially launched the Mobile JKN application in 2017. The app was designed to improve accessibility and practically support various healthcare services directly from users' mobile devices. Every registered participant has access to the online services provided through the application (Roiqoh et al., 2023). The Mobile JKN application simplifies the administration of healthcare services, but still faces various technical challenges. Approximately 28% of user complaints are related to authentication issues, such as errors in entering the national identity number (NIK) and limitations on using the app on only one device (Narmansyah et al., 2022). Additionally, 31% of users reported encountering server errors during transactions, while 42% experienced difficulties receiving OTP codes due to network problems or incorrect input(Mantiri et al., 2023). Moreover, 14% of users stated that features such as healthcare facility registration and doctor consultations often do not function properly. Although some users find the application adequate, 72% still complain about server errors and frequent updates. The frequent technical issues in the Mobile JKN application not only reduce user satisfaction with the app itself but may also undermine public trust in the overall quality of healthcare services provided by BPJS Kesehatan Therefore, sentiment analysis is needed to better understand user complaints and improve overall user satisfaction(Khalid et al., 2023).

Sentiment analysis is an automated process used to interpret and manage textual data by determining whether the expressed sentiment is positive or negative. This task is typically carried out using techniques such as natural language processing (NLP), text analysis, and computational linguistics(Samudera et al., 2024). Among the available methods, Multinomial Naïve Bayes is considered the most suitable for this type of analysis. It is chosen for its simplicity, efficiency, and strong performance in text classification tasks. The algorithm relies on word frequency as its main feature, making it effective for handling large datasets while still performing well with smaller ones. Compared to other methods like Support Vector Machines (SVM) or Neural Networks, Multinomial Naïve Bayes is faster, requires less training data, and is more resistant to overfitting(Zhang et al., 2023).

Sentiment analysis was conducted on user reviews of the Mobile JKN application on the Google Play Store to understand user satisfaction better better. These reviews are valuable for both new users and developers in evaluating the app's performance(Saad & Saberi, 2017). However, inconsistencies between star ratings and written reviews often occur due to the unstructured nature of user comments. Therefore, it is essential to use techniques that go beyond just analyzing ratings and also take the content of the reviews into account to accurately interpret user opinions (Dan & Saufa Yardha, 2024). Sentiment analysis helps evaluate various aspects such as opinions, attitudes, emotions, and user judgments regarding the application’s services.

This study conducts aspect-based sentiment analysis on the Mobile JKN application using user reviews from the Google Play Store, collected through web scraping with Python (Nurzaman et al., 2024). The data were cleaned and preprocessed before being analyzed using the Multinomial Naïve Bayes method. The results are expected to provide insights into public opinion and support the future development of the application.

The significance of this research lies in its ability to provide valuable information for the Mobile JKN application developers in identifying areas that need improvement, both in terms of features, application stability, and user satisfaction. By understanding the sentiments and issues faced by users, developers can be more focused in designing application updates that not only enhance functionality but also improve the overall user experience. Additionally, the findings can assist policymakers and development teams in formulating more precise and responsive solutions to user complaints, which in turn can increase public trust in the healthcare services provided by BPJS Kesehatan.

2. RESEARCH METHOD

This study collects user review data of the Mobile JKN application from the Google Play Store using web scraping techniques(Jeffson Sagala & Samuel, 2024). Once the data is gathered, the analysis is conducted using the Multinomial Naïve Bayes method to measure the model's accuracy and sensitivity(Mantik, Saputri, et al., 2022). The research steps include data collection and cleaning, text preprocessing, sentiment labeling using the INSET lexicon, dataset splitting, TF-IDF transformation, implementation of the Multinomial Naïve Bayes algorithm, and evaluation of classification accuracy.

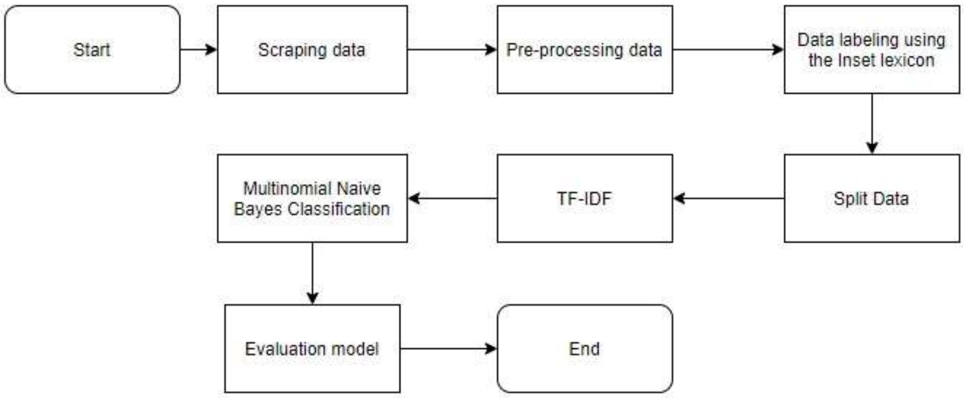

Figure 1. Stages of the Research Process

2.1 Data Collection

Scraping is a technique used to collect data from websites, including text, links, and media. In this study, scraping was used to automatically extract user reviews of the Mobile JKN application from the Google Play Store(Kusumo, 2022). This approach speeds up the data collection process and provides a more accurate representation of user experiences(Priyanto & Ma'arif, 2018). During the process, the sentiment distribution (positive and negative reviews) was analyzed to identify class imbalance, which could impact the model's performance in classifying sentiments accurately.

Table 1. Data Scraping Results

ID	*Comment*	*Score*
1	good, and the service was quite satisfactory	4
2	this is ridiculous! I was in a hurry, and the request still couldn't be processed—what's going on?!	1
3	very helpful and useful.	5
4	the app is ineffective and fails to provide any value	1
5	there's no need to visit the BPJS office; everything is easier with the JKN app.	4

2.2 Data Processing

At this stage, the data is cleaned by removing attributes that are not relevant to the study(Raffi et al., 2023). This process involves eliminating duplicate entries, assessing data quality, and correcting any errors present in the dataset(Mantik, Wanti Wulan Sari, et al., 2022). Additionally, steps were taken to address class imbalance, either by using [oversampling/undersampling] techniques or by employing evaluation metrics such as precision, recall, and F1-score

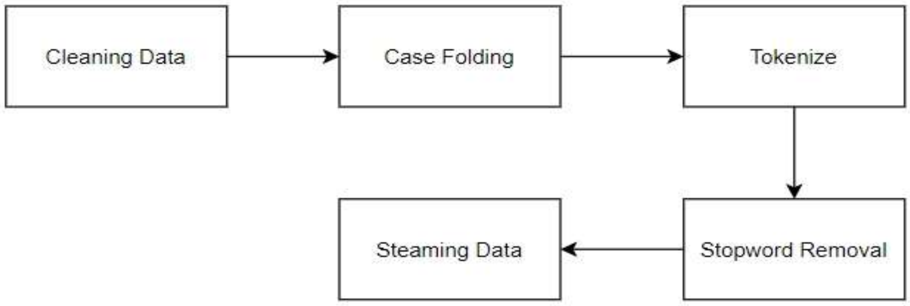

Figure 2. Data Processing Flow

2.3 INSET Lexicon labeling

Labeling with the INSET lexicon automatically identifies opinionated sentences by using a predefined list of opinion words as a reference(Ariyatma & Priambodo, 2025). This process calculates the total weight of words in the text, where a score greater than 0 is categorized as a positive opinion and a score less than 0 as a negative opinion(Muhammad Fernanda Naufal Fathoni et al., 2024). Although the sentiment labels are based on the INSET lexicon, class imbalance still influences model performance

Table 2. INSET Lexicon labeling without neutral data

Positive	*Negative*
7478	1719
Total data	
9197	

2.4 TF-IDF

TF-IDF converts text into numerical form by combining Term Frequency (TF), which measures word frequency in a document, and Inverse Document Frequency (IDF), which assesses word rarity across documents(Rifaldi et al., 2024). This method highlights the importance of words in context(Herwijayanti et al., 2018). TF-IDF was applied to convert text data into numerical features, recognizing that term frequency may be influenced by class distribution in the dataset.

2.5 Multinomial Naïve Bayes

The Multinomial Naïve Bayes algorithm is a probability-based method used in NLP that classifies text by analyzing word frequency(Yuyun et al., 2021). It ignores word order, treats text as a bag of words, and uses a multinomial distribution(Zulfikar et al., 2023). Efficient for text classification, it is fast and effective for tasks like sentiment analysis and spam detection(Bunga et al., 2018).

$$P(C) = \frac{count\ (c)+K}{N+K.|classes|} \quad (1)$$

Explanation:
P : Probability
Count (c) : Number of occurrences of class c
K : Smoothing parameter (usually 1)
N : Total number of occurrences across all samples
|classes| : Total number of exiting classes

$$P(W|C) = \frac{count+K}{count\ (C)+|V|.1} \quad (2)$$

Explanation:

Count	: Number of occurrences of attribute in a specific class
K	: Parameter value
Count (c)	: Number of occurrences of class c in the sample
N	: Total number of occurrences
|v|	: Number of attributes in the sample

2.6 Confusion Matrix

A confusion matrix is a method used to evaluate how well a classification model predicts data(Fahmy Amin, 2023). This technique presents results such as accuracy, precision, recall, and F1 score in the form of a table(Evans, 2022). The table compares the model's predictions with the actual conditions, making it easier to analyze the model's performance(Fibriyanti Arminda et al., 2023).

Aktual Values

Predictid Values		Positive	Negatif
	Positive	**TP** (*True Positive*)	**FP** (*False Positive*)
	Negative	**FN** (*False Negative*)	**TN** (*True Negative*)

Figure 3. Confusion Matrix Table

Explanation: (a) True Positive (TP): The number of data points correctly classified as the positive class. (b) True Negative (TN): The number of data points correctly classified as the negative class. (c) False Positive (FP): The number of data points that actually belong to the negative class but were incorrectly classified as positive. (d) False Negative (FN): The number of data points belonging to the positive class but incorrectly classified as negative.

Accuracy, precision, recall, and F1-score are metrics derived from the confusion matrix. Accuracy reflects overall model performance, precision shows the correctness of positive predictions, recall measures how many actual positives are detected, and F1-score balances both for a complete evaluation.

3. RESULTS AND DISCUSSIONS

3.1 Processed data

The data scraped from the Google Play Store is cleaned and selected to make it more organized and easier to analyze. The process includes cleaning, case folding, tokenization, word normalization, stopword removal, and stemming to eliminate irrelevant elements and structure the text more organized.

```
while count < target_count:
    try:
        new_reviews, _ = reviews(
            app_id,
            lang='id',
```

```
            country='id',
            sort='newest',
            count=batch_size,
            continuation_token=None if count == 0 else continuation_token
        )
        all_reviews.extend(new_reviews)
        count = len(all_reviews)
        if len(new_reviews) < batch_size:
            break
        time.sleep(2)

    except Exception as e:
        print("Error:", e)
        break
```

Figure 4. The looping process continues until the target count is reached.

This process involves collecting reviews of the Mobile JKN application from the Google Play Store using a scraping technique with a looping mechanism to ensure the desired amount of data is gathered. In this case, a total of 15,000 review data points were collected.

Table 3. Clean text and case-folding result

ID	*Results of Cleaning and Case Folding*
10	the app is unreliable, failing to register at higher-level healthcare facilities. Despite recent updates, it has become even more problematic, and it seems the developers are not addressing these issues
16	the app is fairly good, user-friendly, and easy to comprehend.
25	Why does the app keep having issues when entering the phone number, despite having sufficient credit, signal, and a stable network? Even after the update, it still doesn't function properly
27	the app is increasingly making tasks easier when its services are needed

In this process, the text will be cleaned by removing unnecessary symbols or characters, such as punctuation marks, symbols, and emoticons. Case folding is then used to convert uppercase letters to lowercase.

Table 4. Tokenization Results

ID	Tokenization Results
19	[‘always’, ‘ask’, ‘verification’, ‘transfer’, ‘when’, ‘give’, ‘assessment’, ‘lacking’, ‘same’, ‘doctor’, ‘from’, ‘healthcare facility’, ‘app’, ‘error’]
20	[‘updated’, ‘but’, ‘error’, ‘cannot’, ‘log’, ‘in’, ‘app’, ‘what’, ‘is’, ‘this’, ‘it’, ‘intern’, ‘didn’t’, ‘check’, ‘your’, ‘work’, ‘results’]
50	[‘always’, ‘fail’, ‘to’, ‘perform’, ‘verification’, ‘please’, ‘make’, ‘it’, ‘easier’]
52	[‘cannot’, ‘verify’, ‘face’, ‘keeps’, ‘failing’]

The tokenization process is used to break the text into smaller units called tokens. Tokens can be words, phrases, characters, or other units.

Table 5. Stopword Removal result

ID	*Stopword Removal Result*
100	[‘face’, ‘verification’, ‘system’, ‘please’, ‘don’t’, ‘make’, ‘it’, ‘difficult’, ‘how’, ‘can’, ‘it’, ‘take’, ‘an’, ‘hour’, ‘to’, ‘verify’, ‘and’, ‘fail’, ‘please’, ‘help’]
114	[‘treatment’, ‘jkn, ‘app’, ‘makes’, ‘it’, ‘convenient’, ‘practical’, ‘helps’, ‘patients’]
116	[‘helps’, ‘smoothness’, ‘health’, ‘control’]
129	[‘please’, ‘help’, ‘sir’, ‘madam’, ‘open’, ‘jkn, ‘forgot’, ‘gmail’, ‘password’, ‘using’, ‘gmail’, ‘how’, ‘is’, ‘the’, ‘solution’, ‘to’, ‘open’, ‘active’]

The stopword removal process is used to eliminate words that do not carry significant meaning in the text.

Table 6. Stemming result

ID	*Stemming Result*
251	[‘register’, ‘app’, ‘is’, ‘difficult’, ‘even’, ‘though’, ‘already’, ‘registered’, ‘with’, ‘bpjs, ‘mandiri, ‘there’, ‘are’, ‘too’, ‘many’, ‘requirements’, ‘illogical’, ‘to’, ‘register’, ‘the’, ‘app’]
252	[‘history’, ‘payment’, ‘contribution’, ‘can’t’, ‘know’, ‘yes’, ‘if’, ‘program’, ‘instructions’, ‘employees’, ‘private’, ‘sector’, ‘yes’]
263	[‘app, ‘is’, ‘bad’, ‘difficult’, ‘to’, ‘access’, ‘makes’, ‘the’, ‘app’, ‘collect’, ‘it’, ‘foolish’]
271	[‘App’, ‘is’, ‘easy’, ‘simple’, ‘user’, ‘friendly’]

In this process, the data will be converted to its root form by removing affixes (prefixes, suffixes, and infixes) without considering grammatical structure.

3.2 Labeling with the INSET Lexicon

After the data is processed, sentiment labeling is performed using the INSET Lexicon. Each word in the review is compared with entries in the dictionary to determine whether the sentiment is positive or negative, allowing the system to automatically classify the sentiment.

Table 7. Labeling result

ID	*Comment*	*Sentiment*
10	it always asks for pin verification, and when giving feedback, it's lacking compared to the doctor from the healthcare facility, and the app keeps erroring	Negative
11	after the update, it still errors and I can't log in. what is this app? Is it the intern's work in it? wasn't your work checked?	Negative
19	the app is great, very helpful	Positive
22	very easy and informative	Positive

From the labeling results above, only positive and negative sentiments were selected. Neutral data was not used because it is less relevant for decision-making.

3.3 Split data

The data is divided into two parts with an 80:20 ratio, where 80% is used for training data and 20% for testing data. This approach allows for an objective evaluation of the model's performance in classifying sentiment.

Table 8. Results of the 80:20 data split

Training Data	*Testing Data*
7357	1840

3.4 Classification with Multinomial Naive Bayes

The data, split into 80% training and 20% testing, is classified using MultinomialNB. Model performance is evaluated with metrics like the confusion matrix, accuracy, precision, recall, F1-score, and classification report. Accuracy shows overall correctness, precision, and recall assess prediction quality, and the F1-score reflects balance.

```
accuracy = accuracy_score(y_test, y_pred)
print(f"🎯 Accuracy after tuning: {accuracy:.4f}")

print("\n📊 Classification report:\n")
print(classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(6,4))
sns.heatmap(cm,        annot=True,        fmt="d",        cmap="Blues",
xticklabels=["Negative",      "Positive"],      yticklabels=["Negative",
```

```
"Positive"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix Multinomial Naïve Bayes")
plt.show()
```

Figure 5. Evaluation process of classification results using the MultinomialNB model

```
🎯 Accuracy after tunning: 0.8128

📊 Classification report:

              precision    recall  f1-score   support

     negatif       0.00      0.00      0.00       342
     positif       0.81      1.00      0.90      1485

    accuracy                           0.81      1827
   macro avg       0.41      0.50      0.45      1827
weighted avg       0.66      0.81      0.73      1827
```

Figure 6. Evaluation of MultinomialNB Classification Results with Tuning

Accuracy Calculation Result:

$$\text{Accuracy} = \frac{TP+TN}{Total\ Samples} = \frac{1485+0}{1827} = \frac{1485}{1827} \times 100\%$$

$$= 81.3\% \text{ (rounded to 81\%)}$$

An accuracy of 81% was achieved because the model successfully classified all positive data correctly (true positive = 1,485) with no instances misclassified as negative (false negative = 0). However, the model failed to recognize negative data, as all negative reviews were classified as positive (false positive = 342), and none were correctly identified as negative (true negative = 0). Although the accuracy appears high, it does not reflect the overall performance of the model since it only recognized the positive class while ignoring the negative class. This is evident from the precision, recall, and F1-score for the negative class, which are all zero.

4. CONCLUSION

The results of this study show a sentiment analysis of user reviews toward the Mobile JKN application using the Multinomial Naïve Bayes method and the INSET lexicon approach for labeling. The findings indicate that the majority of reviews are negative, primarily due to technical issues and suboptimal user experiences, although there are also positive comments related to access to healthcare services. The sentiment classification using the Multinomial Naïve Bayes model achieved an accuracy rate of 81%. Despite the high accuracy, the model was not effective in classifying sentiment accurately, as it was only able to identify positive sentiment and failed to classify negative sentiment, based on the confusion matrix results. Therefore, future research is recommended to explore alternative models that are more capable of accurately classifying sentiment, such as deep learning approaches, and to collect data from various sources to gain a broader understanding of user experiences with the Mobile JKN application. The insights from this analysis can provide valuable input for the development team and policymakers in enhancing their response to public complaints. By identifying the main issues and sentiments expressed by users, they can more easily prioritize the necessary improvements and solutions. This approach will help ensure quicker, more targeted responses, as well as increase user satisfaction and maintain trust in the application and the healthcare services it provides.

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