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Sentiment Analysis of "Cek Bansos" Application Reviews on Google Play Store Using the Naïve Bayes Algorithm

Novi Firda Aini[1]*, Odi Nurdiawan[2], Tati Suprapti[3], Arif Rinaldi Dikananda[4], Fathurrohman[5]

[1,2]*Informatics Engineering, STMIK IKMI CIREBON*
[3]*Informatics Management, STMIK IKMI CIREBON*
[4,5]*Software Engineering, STMIK IKMI CIREBON*
novifirda75@gmail.com[1], odinurdiawan2020@gmail.com[2], tatisuprapti1120004@gmail.com[3], rinaldi21crb@gmail.com[4], fathurrahman.ikmi@gmail.com[5]*

Abstract

The rapid development of digital public services requires a deeper understanding of user perceptions and experiences regarding government applications, including Cek Bansos. This study aims to identify the polarity of user reviews by applying the Multinomial Naïve Bayes algorithm to review data collected from the Google Play Store. The methodology includes text preprocessing, sentiment labeling, feature extraction using TF–IDF, and model training and evaluation based on accuracy, precision, recall, and F1-score. The results show that the model achieves an accuracy of 79.5%, with very high performance in the negative class (recall 0.97) but poor performance in the neutral class due to data imbalance. The dominance of negative sentiment in the dataset indicates that users face significant technical difficulties, particularly in registration, verification, and service access. These findings demonstrate that Multinomial Naïve Bayes is effective as a baseline model for sentiment analysis; however, improving data balance and quality is necessary to produce a more stable, accurate, and representative model for evaluating digital public services.

Keywords: *sentiment analysis, Multinomial Naïve Bayes, TF–IDF, user reviews, Cek Bansos.*

1. Introduction

The development of information technology has encouraged governments in various countries to adopt digital-based public services as part of the implementation of e-government. In Indonesia, government mobile applications serve as the main medium for disseminating information, distributing social assistance, and providing fast and standardised public services. The increasingly intensive use of these applications requires data-based evaluation to understand public perceptions and satisfaction levels regarding the quality of available digital services. In this context, sentiment analysis is a relevant approach because it can automatically extract and interpret public opinion through user reviews using machine learning methods.

Previous studies have shown the importance of sentiment analysis in assessing the effectiveness of public service applications. [1] identified issues such as security, performance, and reliability of features in the Sapawarga and JAKI applications through sentiment classification based on machine learning algorithms. [2] showed similar findings in the Mobile JKN health application, particularly regarding usability and user registration processes. More broadly, [3] emphasises that sentiment analysis supports data-driven policy making. Other studies show improved analysis capabilities through Artificial Intelligence-based models such as BERT [4] and deep learning approaches such as BiLSTM [5], which are able to capture emotional context and represent public opinion more accurately. These findings reinforce the position of sentiment analysis as a strategic component in the development and evaluation of digital public services.

However, studies on the Cek Bansos application are still relatively limited, even though this application plays an important role in providing online social assistance information. The lack of empirical research based on user reviews indicates a knowledge gap, particularly in understanding how public perceptions can be accurately identified and classified, and how the results of such analysis can be used to improve the quality of the application's services.

This study attempts to address this gap by applying the Naïve Bayes algorithm to classify user reviews of the Cek Bansos application on Google Play Store into positive, negative, and neutral categories. The Naïve Bayes algorithm was chosen because of its simplicity, efficiency, and ability to work optimally on large text data sets. In addition, this study examines technical challenges that commonly arise in sentiment analysis, such as class imbalance, label noise, and code-switching in user reviews. Efforts to improve the reliability and transparency of classification results are also a focus to ensure that sentiment analysis can be used effectively in the evaluation of digital public services.

The scope of the research is limited to user reviews taken from the Google Play Store within a certain period so that the analysis results remain relevant to current social dynamics and policies. Preprocessing procedures are carried out thoroughly to improve text quality before analysis, while model performance evaluation is conducted using accuracy, precision, recall, and F1-score metrics. This approach enables objective assessment of the effectiveness of the classification model applied.

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1. Research Metodology

2.1. Research Design

This study utilises an experimental quantitative approach designed to evaluate the effectiveness of the Naïve Bayes algorithm in classifying sentiment in user reviews of the Cek Bansos application. This design was chosen based on the need to produce measurable tests that can be analysed using objective statistical metrics. The experimental quantitative approach is in line with the principle of reproducibility as described by [6], which emphasises that machine learning-based research must be structured with a clear, standardised, and repeatable workflow.

The methodological flow includes the stage of automatic data collection through web scraping, followed by text data pre-processing, sentiment labelling, feature extraction based on numerical representation, training and testing of the Naïve Bayes algorithm, and model performance evaluation. To clarify the research workflow, a methodology diagram needs to be included in this section. Therefore, the appropriate position to place the research flow diagram is after this paragraph as Figure 1 Research Design.

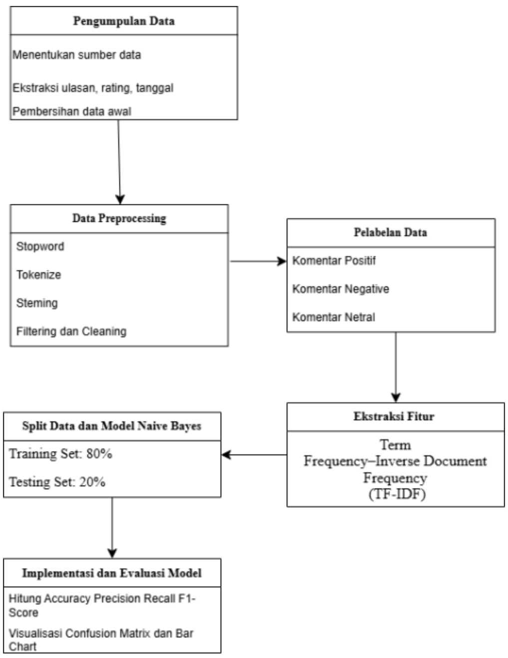


Fig. 1: Research Design

2.2. Data Sources and Dataset Structure

The research data was obtained from user reviews of the Cek Bansos application, which were collected through web scraping on the Google Play Store platform. Each review entry consisted of user comments, a rating in the form of a star scale, and the time of upload. The collected data was then exported into CSV format so that it could be processed using Python-based software.

The reviews obtained describe the authentic opinions of the public regarding government digital services, making them highly relevant for use as objects of sentiment analysis. The dataset structure used in this study reflects three key attributes that serve as the basis for analysis. Details of the dataset structure are shown in Table 1, which shows the important components that form the basis of the pre-processing and sentiment labelling processes.

Table 1: User Review Dataset Structure

Atribut	Tipe Data	Deskripsi
content	String	Teks ulasan asli pengguna
score	Integer	Rating bintang 1–5
at	Datetime	Tanggal unggahan ulasan
sentiment_label	Categorical	Label sentimen (positif, negatif, netral)

2.3. Data Pre-processing

The pre-processing stage is carried out to ensure that the review text can be analysed efficiently by the machine learning algorithm. This process begins with standardising the letter format through case folding so that all characters are converted to lowercase. The next step is to clean the text of non-alphabetic characters such as numbers, punctuation marks, symbols, emojis, and links. The cleaning process is carried out to reduce semantic interference and maintain data homogeneity.

After the text is cleaned, tokenisation is performed to break down the review sentences into word units. The next stage involves the removal of stopwords, which are common words that do not provide significant meaning in the analysis, such as conjunctions and demonstratives. This stage is followed by a stemming process using the Sastrawi library, which converts inflected words into their basic form. [7] states that a rigorous pre-processing process has a direct influence on classification performance because it reduces irrelevant linguistic variation. Examples of text transformation results from the initial stage to the end of pre-processing are shown in Table 2.

Table 2: Examples of Pre-Processing Results

Tahap	Contoh Kalimat
Teks Asli	“Aplikasinya susah login!! Tolong diperbaiki… 😭🙏”
Case Folding	“aplikasinya susah login!! tolong diperbaiki… 😭🙏”
Cleaning	“aplikasinya susah login tolong diperbaiki”
Tokenizing	aplikasi, susah, login, tolong, diperbaiki
Stopword Removal	aplikasi, susah, login, perbaiki
Stemming	aplikasi, susah, login, baik

2.4. Sentiment Labelling

Sentiment labelling is carried out so that each review can be grouped into positive, negative, or neutral categories. The labelling process uses a semi-automatic approach, which is a combination of lexicon-based methods with manual validation by researchers. This approach was chosen to maintain label consistency, especially given the nature of the language used in public application user reviews, which is often informal and mixed with foreign terms [8]emphasises that manual validation is essential in mixed language data to avoid label noise and ensure basic accuracy for model learning. This labelling produces a structured dataset that is ready to be used as ground truth in the model training and evaluation process.

2.5. Feature Extraction

After the data is labelled, all review texts are converted into numerical representations using the Bag-of-Words and Term Frequency–Inverse Document Frequency (TF-IDF) techniques. The BoW representation converts documents into vectors that describe word frequency, while TF-IDF assigns weights based on the level of importance of words in the corpus. TF-IDF is used as the main feature because it is able to suppress the weight of words that appear very frequently but are not informative, and strengthen the weight of words that appear infrequently but have important semantic contributions. The mathematical concept of TF-IDF can be explained by the following formula:

$$TF - IDF(t,d) = TF(t,d) * log\left(\frac{N}{DF(t)}\right) \quad (3)$$

This formula combines local frequency values and global word distribution information to produce weights that reflect the importance of words for each document.

2.6. Algorithm Modelling and Training

The classification model used in this study consists of two variants of the Naïve Bayes algorithm, namely Multinomial Naïve Bayes (MNB) and Bernoulli Naïve Bayes (BNB). MNB is used for word frequency-based data, while BNB assumes binary feature values based on the presence of words in a document. The dataset was divided into training and test data with a ratio of 80:20 so that the model could learn word distribution patterns optimally and be tested objectively.

The basic model parameters are described in Table 3, which shows the alpha value for Laplace smoothing, as well as the normalisation configuration and the use of prior probabilities. The use of both Naïve Bayes variants aims to obtain a performance comparison so that it can be determined which model is more effective in processing public service application review texts.

Table 3: Naïve Bayes Model Parameters

Model	Parameter	Nilai	Deskripsi
Multinomial NB	alpha	1.0	Mengurangi kemungkinan *zero-frequency*
Bernoulli NB	alpha	1.0	Menstabilkan probabilitas kelas
Semua Model	fit_prior	True	Menggunakan probabilitas awal kelas
Semua Model	norm	L2	Normalisasi vektor fitur

2.7 Model Evaluation

The trained model was evaluated using four quantitative metrics, namely accuracy, precision, recall, and F1-score. These four metrics provide a comprehensive overview of the model's performance in an unbalanced dataset. Accuracy measures the proportion of correct predictions, precision assesses the accuracy of predictions per class, recall measures the model's ability to capture all relevant data, while F1-score balances precision and recall. The mathematical formulas for these four metrics are as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, Precision = \frac{TP}{TP+FP}, \tag{1}$$

$$Recall = \frac{TP}{TP+FN}, F1 = \frac{2*Precision*Recall}{Precision+Recall} \tag{2}$$

The evaluation also includes confusion matrix analysis to see the distribution of prediction errors in each class, in order to provide a deeper understanding of the performance characteristics of each Naïve Bayes variant.

2. Results And Discussion

3.1. Dataset Description and Review Profile

This study utilises 1,000 public reviews of the Cek Bansos application downloaded from the Google Play Store through a structured data collection process. This dataset reflects authentic interactions between the public and digital public service applications, thus having strategic value in directly assessing user perceptions of the quality of government services. An example of the raw data structure can be seen in Table 1, which shows a variety of reviews ranging from technical complaints to descriptions of user experiences.

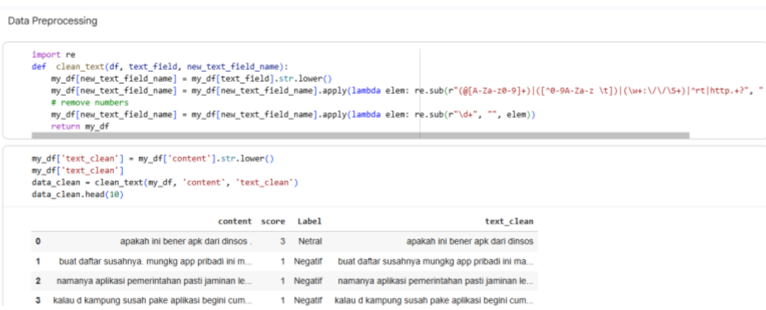
Table 4: Raw Cek Bansos Application Dataset

No	Username	Score	Tanggal	Content
1	Hadi Santoso	1	11/06/2025	*"halo aku kasih bintang 1 dulu… ribet dan ga fungsi…"*
2	Adi Wijaya	3	11/06/2025	*"…istri saya terdaftar PKH tapi tidak pernah dapat bantuan…"*
3	Ayu Diana	1	09/06/2025	*"…aplikasi gak bisa dipencet, error banget…"*
4	Bang Bross	1	09/06/2025	*"…buat akun selalu keluar sendiri…"*
5	Rahmatullah	1	20/08/2021	*"…username kepanjangan tidak bisa dipakai…"*

The variety of reviews shows a range of user experiences, but the distribution of scores reveals a strong tendency towards dissatisfaction. In general, users complain about three main issues: difficulty logging in, account registration failures, and data synchronisation problems. The social impact of these technical issues is quite significant, as the application is used to access government social assistance services, so application failures directly affect beneficiaries' access to their rights.
The negative trend that emerges in the dataset is consistent with the patterns found by [2] and [1], where digital public service applications tend to receive more complaints than appreciation because users usually only write comments when they encounter problems.

3.2. Text Pre-processing Results

Pre-processing is an important stage to ensure that the review text has a consistent linguistic structure. The initial raw data contains informal language variations, emoticon usage, spelling errors, and everyday conversational words. A series of pre-processing stages were carried out, which are visualised in the following series of images.


Data Preprocessing

```
import re
def  clean_text(df, text_field, new_text_field_name):
    my_df[new_text_field_name] = my_df[text_field].str.lower()
    my_df[new_text_field_name] = my_df[new_text_field_name].apply(lambda elem: re.sub(r"(@[A-Za-z0-9]+)|([^0-9A-Za-z \t])|(\w+:\/\/\S+)|^rt|http.+?", "
    # remove numbers
    my_df[new_text_field_name] = my_df[new_text_field_name].apply(lambda elem: re.sub(r"\d+", "", elem))
    return my_df
```

```
my_df['text_clean'] = my_df['content'].str.lower()
my_df['text_clean']
data_clean = clean_text(my_df, 'content', 'text_clean')
data_clean.head(10)
```

	content	score	Label	text_clean
0	apakah ini bener apk dari dinsos .	3	Netral	apakah ini bener apk dari dinsos
1	buat daftar susahnya. mungkg app pribadi ini m...	1	Negatif	buat daftar susahnya mungkg app pribadi ini ma...
2	namanya aplikasi pemerintahan pasti jaminan le...	1	Negatif	namanya aplikasi pemerintahan pasti jaminan le...
3	kalau d kampung susah pake aplikasi begini cum...	1	Negatif	kalau d kampung susah pake aplikasi begini cum...

Fig. 2: Data Preprocessing

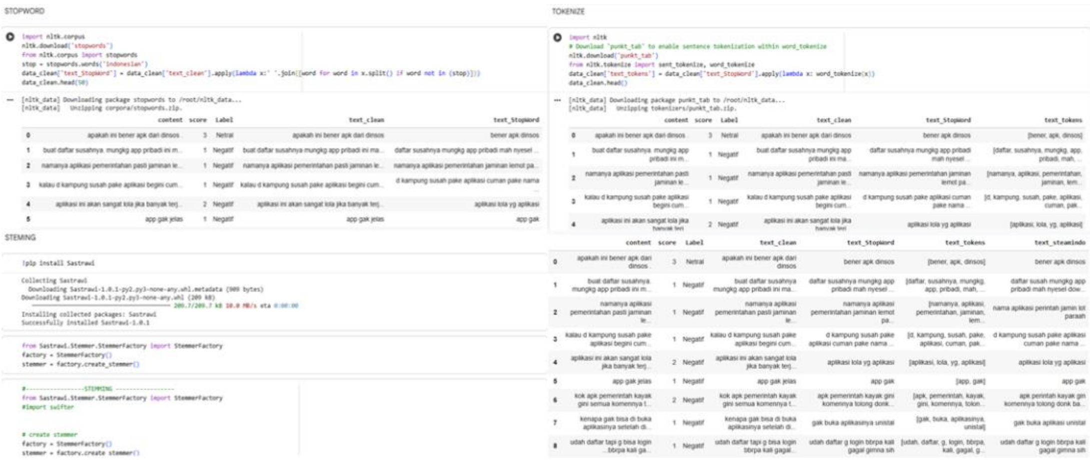


Fig. 3: Preprocessing Results

During the cleaning stage, the text is converted to lowercase and characters that do not support analysis, such as numbers, symbols, HTML entities, and links, are removed. The next stage is stopword removal, which involves removing common words that have no semantic power, such as ‘that’, ‘and’, “in”, ‘this’. By removing stopwords, the text becomes more focused on meaningful words that have the potential to influence sentiment.

The tokenisation process breaks sentences down into word units (tokens), while stemming uses the Sastrawi algorithm to return words to their base form. This transformation produces a more uniform linguistic representation, which is very important for the Naïve Bayes algorithm because the model is sensitive to word frequency.

After undergoing a series of transformations, the dataset produces the columns text_clean, text_StopWord, text_tokens, and text_steamindo, each representing a different cleaning stage. Initial validation through cross-validation showed an accuracy of 86.05%, indicating that the linguistic transformations successfully improved the consistency of the data structure. These findings are in line with research [7], which confirms that preprocessing significantly improves the performance of informal text-based models.

3.3 Sentiment Labelling

Review labelling was carried out using a semi-automatic approach, beginning with mapping scores to sentiment categories and reinforced by manual verification. The labelling rules applied were scores of 1–2 as Negative, scores of 3 as Neutral, and scores of 4–5 as Positive. This process is visualised in Figure 4. Examples of labelling results are shown in Table 5, and the final sentiment distribution can be seen in Table 6.

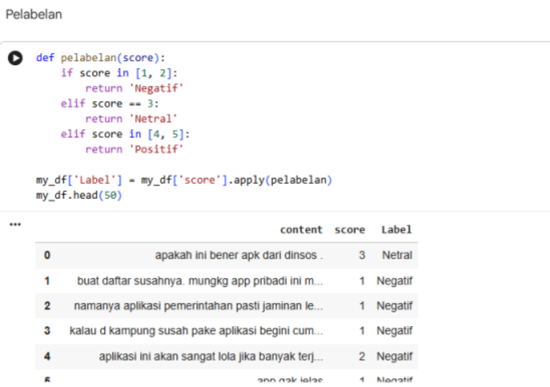


Fig. 4: Data Labelling

Table 5: labelling results

Username	Content	Sentiment
Hadi Santoso	“error… ribet… tidak fungsi”	Negative
Adi Wijaya	“berharap lebih mudah…”	Neutral
Ayu Diana	“aplikasi tidak bisa login”	Negative
Putri Rahmawati	“terima kasih, proses cepat”	Positive

Table 6: Sentiment Distribution

Sentimen	Jumlah	Persentase
Negative	815	81.5%
Positive	117	11.7%
Neutral	68	6.8%

The dominance of negative groups is a common phenomenon in government application reviews. The high percentage of complaints indicates serious problems that need to be followed up by application developers. In addition, label imbalance also affects the performance of classification models, especially in recognising minority classes such as positive and neutral.

3.4 Feature Extraction and Word Pattern Analysis

The study used two feature extraction techniques: Bag-of-Words (BoW) and Term Frequency–Inverse Document Frequency (TF–IDF). A comparison of the two can be seen in Table 4.

Table 7: Comparison of BoW and TF–IDF

Metode	Jumlah Fitur	Sparsity	Informasi Relevan	Kelebihan
BoW	5.870	93.5%	Rendah	Sederhana dan cepat
TF–IDF	2.450	88.2%	Tinggi	Lebih diskriminatif

TF–IDF has been proven to provide more representative weights because it reduces overly general words such as ‘application’, ‘social assistance’, and ‘data’. Conversely, negative keywords such as ‘error,’ ‘failed,’ and ‘cannot’ are given higher weights, making them easier for the model to recognise. These findings support the theory that TF–IDF is effective for short, repetitive texts, such as application reviews[9].

3.5 Model Training and Evaluation

The classification model used in this study is Multinomial Naïve Bayes with TF–IDF feature representation. The complete model training and testing process flow can be seen in Figure 5, which shows the stages from data processing to performance evaluation.

```
MultinomialNB Accuracy: 0.795
MultinomialNB Precision: 0.7411827560795874
MultinomialNB Recall: 0.795
MultinomialNB f1_score: 0.7531655092592593
confusion_matrix:
 [[142   0   5]
 [ 11   0   1]
 [ 24   0  17]]
====================================================

              precision    recall  f1-score   support

     Negatif       0.80      0.97      0.88       147
      Netral       0.00      0.00      0.00        12
     Positif       0.74      0.41      0.53        41

    accuracy                           0.80       200
   macro avg       0.51      0.46      0.47       200
weighted avg       0.74      0.80      0.75       200
```

Fig. 5: Model Evaluation

After the model was trained, 20% of the data was allocated as a testing set to measure its generalisation ability. The evaluation results show that the model achieved an accuracy of 79.5%, with a precision (macro) value of 0.7411, recall of 0.795, and an F1-score of 0.7531. In general, these values indicate that the model is capable of performing classification quite well on the available review data.

The performance details per class are shown through the confusion matrix in Figure Confusion Matrix. From this visualisation, it can be seen that the model has a very high performance in the negative class, with a recall of 0.97. This means that the model is very sensitive in detecting complaints or negative reviews, and is able to recognise almost all examples in that class. Conversely, the neutral class is not identified at all (recall 0.00). This condition is caused by the very small number of neutral samples and the similarity of the meaning of neutral text to both the positive and negative classes. The positive class shows moderate performance with a recall of 0.41, reflecting that the model still has difficulty recognising expressions of satisfaction amid the dominance of negative reviews.

This uneven performance pattern between classes is a strong indication of a class imbalance problem. This phenomenon is consistent with the findings in [1] and [10]which state that probabilistic models, including Naïve Bayes, tend to be biased towards the class with the dominant amount of data. As a result, minority classes such as neutral and positive become much more difficult for the model to recognise accurately.

3.6 Sentiment Visualisation

The word cloud visualisation in Figure 6 provides a semantic overview of the most dominant words in each sentiment category. This visual representation clarifies the linguistic patterns that emerge in user reviews and helps identify emotional tendencies in each sentiment group.

Fig. 6: Negative, Positive and Neutral WordCloud

In negative sentiment, words such as ‘error’, ‘no’, “failed” and ‘difficult’ dominate. The appearance of these words indicates that most users experience technical problems or obstacles when using the application. Conversely, positive sentiment brings up words such as ‘good’, ‘helpful’, “fast”, and ‘thank you’, reflecting successful experiences and satisfaction in a number of cases. For neutral sentiment, the words that appear tend to be informative, such as ‘account’, “email”, and ‘register’. This pattern indicates that the reviews provided are descriptive without emotional expression, either positive or negative.

Furthermore, Figure 7 displays a graphical composition of the number of reviews based on sentiment category. This visualisation emphasises the dominance of negative sentiment in the dataset, followed by positive and neutral sentiment in smaller numbers, thus supporting the previous findings regarding the imbalance in data distribution.

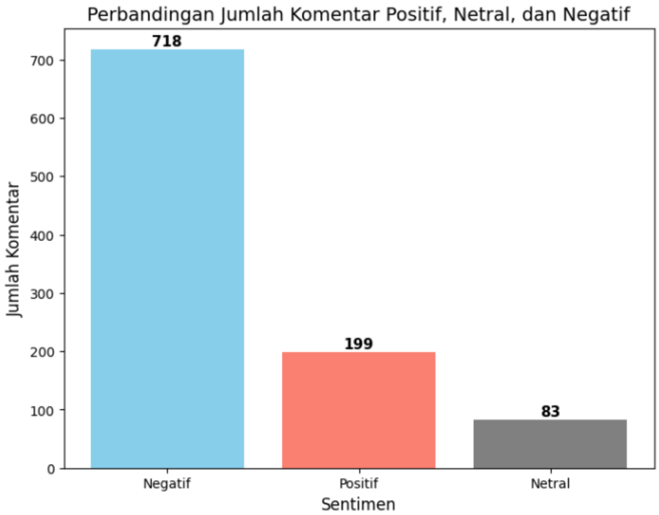


Fig. 6: Visualisation of the Number of Reviews

3.7. Discussion of Results

The dominance of negative reviews indicates a high level of public dissatisfaction with the Cek Bansos application. Most complaints focus on login issues, registration failures, and data discrepancies, all of which directly impact the user experience. Given that this application is used as a means of accessing government assistance, these technical disruptions have significant social consequences for the people who need these services.

From a modelling perspective, the high performance of the model on negative sentiment shows that the Naïve Bayes algorithm is able to capture the linguistic patterns of user complaints well. However, the model's inability to recognise the neutral class further emphasises the heavy class imbalance in the dataset. This condition indicates the need for improvements, such as adding data to the neutral and positive classes, applying resampling techniques, or using alternative algorithms such as SVM and BiLSTM, which are more sensitive to linguistic context variations.

The effectiveness of TF–IDF representation, which helps improve model performance, is also in line with previous research findings. Overall, these findings provide practical direction for application development, particularly in relation to improving login system stability, refining data verification processes, and improving the interface to make it easier to use. These results form an important basis for the formulation of data-driven policies in the digital transformation of government services.

4. Conclusion

This study presents a sentiment analysis of user reviews of the Cek Bansos application using the Multinomial Naïve Bayes algorithm with TF–IDF feature representation support. Through preprocessing stages including cleaning, stopword removal, tokenisation, and stemming, the review data was successfully standardised, thereby improving the quality of text representation for the modelling process. The labelling results show a strong dominance of negative sentiment, reflecting a high level of user dissatisfaction with the application's performance, particularly regarding login difficulties, registration failures, and data inconsistencies. This imbalance in sentiment distribution has a significant impact on model performance, especially in distinguishing minority sentiments.

The constructed Multinomial Naïve Bayes model achieved an overall accuracy of 79.5%, with excellent performance in detecting negative sentiment (recall 0.97). However, the model failed to recognise neutral sentiment and only showed moderate performance on positive sentiment. These findings indicate that although the Naïve Bayes algorithm can be an effective baseline for identifying dominant complaints, the unbalanced data distribution and linguistic variation of minority classes limit the model's ability to achieve consistent performance. Overall, this study shows that a machine learning-based sentiment analysis approach can provide significant insights into public perception and can serve as a basis for evaluating improvements in the quality of digital public service applications.

Based on the results of this study, several recommendations can be made for further development. Data balancing efforts are highly recommended to improve the model's ability to recognise minority classes, particularly positive and neutral sentiments. Techniques such as oversampling, undersampling, or synthetic approaches such as SMOTE have the potential to improve the representation of disproportionate classes. In addition, exploring other algorithms such as SVM, Random Forest, or deep learning-based models such as BiLSTM and transformers has the potential to produce more stable performance, especially in more complex language patterns.

From an application development perspective, the research results indicate the need for special attention to system stability, ease of registration, and reliability of key features. The dominant negative sentiment findings indicate that technical improvements in these areas will have the greatest impact on increasing user satisfaction. With targeted and data-driven updates, the Cek Bansos application can provide better services, enhance user experience, and strengthen public trust in government digital services.

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