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Research article

Sentiment Analysis of User Reviews of GoPay Services on the Gojek Application Using the Naïve Bayes Method

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ABSTRAK

The development of digital technology has driven the emergence of various application-based financial services, including GoPay within the Gojek platform. GoPay facilitates cashless transactions such as payments for transportation, food, and bills. As the number of users increases, various reviews reflecting satisfaction and complaints about the service have emerged. This study aims to analyze user sentiment toward the GoPay service in the Gojek application using the Naïve Bayes method. User review data were obtained through a web scraping process totaling 1,000 entries, followed by data cleaning, text normalization, tokenizing, and sentiment labeling into positive, negative, and neutral categories. The TF-IDF method was used for word weighting to convert text into numerical form before classification with the Multinomial Naïve Bayes algorithm. The results show that the Naïve Bayes model is capable of classifying user reviews with an accuracy rate of 90%. Based on the confusion matrix and classification report, the neutral sentiment category dominates with the highest recall value of 1.00, while positive and negative sentiments have lower proportions. This indicates that most users provide neutral feedback regarding the GoPay service in the Gojek application. Overall, the Naïve Bayes method has proven effective in analyzing user sentiment toward digital services such as GoPay, making the results of this study a useful reference for Gojek developers in improving service quality and user satisfaction.

1. Pendahuluan

The development of digital technology has transformed the way people conduct financial transactions, particularly through application-based services. In Indonesia, digital payment systems have become one of the major innovations in the financial technology (fintech) sector, offering convenience, speed, and security in cashless transactions [1]. GoPay, as one of the leading digital wallets, is integrated into the Gojek platform and facilitates various transactions ranging from transportation payments and food purchases to bill payments [2]. The rapid growth of GoPay users has been accompanied by an increasing number of user reviews on the Gojek application on the Google Play Store, which contain opinions and perceptions regarding service quality [3]. Analyzing these reviews is important to understand user satisfaction and to provide feedback for developers in improving service quality.

Sentiment analysis is an approach widely used to extract user opinions from review texts by classifying them into positive, neutral, and negative categories [4]. The Naïve Bayes algorithm, particularly the Multinomial Naïve Bayes variant, has proven effective in text classification because it can efficiently handle large datasets while delivering competitive performance [5]. Previous studies, such as that conducted by Rahman et al. [6], indicate that Naïve Bayes can achieve high accuracy in classifying online transportation application reviews. In addition, the Term Frequency–Inverse Document Frequency (TF-IDF) technique is used for feature weighting, transforming textual data into numerical representations prior to classification, thereby improving model accuracy [7].

Despite the effectiveness demonstrated by previous studies, several limitations remain. Some studies employ limited datasets that do not adequately represent the diversity of user opinions, while neutral sentiment reviews are often neglected, even though they can provide valuable insights into user perceptions that are neither entirely positive nor negative [8]. Furthermore, several studies have not utilized web scraping techniques to automatically collect data from application platforms, resulting in datasets that may not be up to date.

Consequently, it remains unclear how well the Naïve Bayes method performs in classifying the full spectrum of user opinions regarding GoPay services on Gojek.

Based on these gaps, this study aims to analyze user sentiment toward GoPay services on the Gojek application using the Naïve Bayes method, supported by text preprocessing steps including data cleaning, tokenization, text normalization, sentiment labeling, and word weighting using TF-IDF. The main objective of this research is to evaluate the performance of Naïve Bayes in classifying reviews into positive, neutral, and negative categories, as well as to provide insights that can be utilized by Gojek developers to improve service quality and user satisfaction.

2. Research Methods

This research uses a quantitative approach with text mining methods to analyze user review sentiment regarding the GoPay service within the Gojek app. The entire process is automated using coding, from data collection to classification model evaluation. The research flow consists of six main stages:

A. Data collection

Review data was obtained from the Google Play Store through web scraping using the Python programming language. The focus of data collection was reviews discussing GoPay services. The collected data included review text, date, and star rating, and was immediately saved in CSV format for further analysis.

B. Data Preprocessing

The review text is processed automatically through a preprocessing stage, which includes:

1. Text cleaning (data cleaning): removing irrelevant punctuation, numbers, and special characters.
2. Stopword removal: removing common words that don't provide significant meaning.
3.Tokenization: separating text into meaningful words as part of automated preprocessing.

C. Data Labeling

Each review is automatically assigned a sentiment label (positive, negative, or neutral) using a custom Python script, so all training and testing data is consistent and standardized.

D. Feature Extraction

The processed text is automatically converted into a numerical representation using the Term Frequency–Inverse Document Frequency (TF-IDF) method. TF-IDF weights words based on their frequency of occurrence in documents and their relevance across the corpus, ensuring optimal features for classification.

E. Classification with Naïve Bayes

A Multinomial Naïve Bayes model was trained using automatically processed data to predict review sentiment on the test data. The data was divided into a training set (80%) and a test set (20%), with all splitting performed via a Python script.

F. Model Evaluation

Classification results were automatically evaluated using accuracy, precision, and recall. Additionally, a confusion matrix was generated through the code to visualize model performance and determine the distribution of the most dominant sentiments toward GoPay services.

3. Results and Discussion

This chapter presents the results of a sentiment analysis of user reviews of the GoPay service on the Gojek app. The research results are presented systematically following the analysis process, from data processing to model performance evaluation. This presentation includes visualization, model performance measurements, and result interpretation to provide a comprehensive overview of the review characteristics and the effectiveness of the methods used.

3.1 Data Collection Stage

Data collection was the initial stage of this research, aimed at obtaining user reviews regarding the GoPay service within the Gojek app. Data was collected automatically using web scraping from the Google Play Store, allowing for efficient and large-scale collection of reviews.

This scraping process resulted in 1,000 user reviews, which were then stored in CSV format for further analysis. The data collected included review text and additional information such as star ratings and review dates. However, the focus of this research analysis was on review text discussing the GoPay service. The raw data from GoPay user reviews is visualized in Figure 1.

1	userName	content	score
2	RozaLutfian Nisa	baik dan ramah sekali	5
3	Dewanti dhede	terima kasih telah membuat saya dalam perjalanan lebih cepat sampai tujuan dan terima kasi	5
4	Deny Setiawati	bagus	5
5	Reyner	Halo Gojek kenapa ini kok chat gojek nya gak bisa dipakai saya gak tau informasi gojek nya dir	1
6	Sumpena Pena	bagus sangat mudah	5
7	Juni Siauce	semoga makin sukses	5
8	fitria aulia bintang	bagos	5
9	Herdiana Natsir	best	5
10	Anita Christin	pelayanan gojek transport selalu yg terbaik i like gojek😊	5
11	Welly G	Disaat jam sibuk, disaat hujan mulai turun, pengambilan pun bisa sampai 4 km lebih. dan Apli	1
12	Cory Rogers Cory Rogers	langanan plus sama engak sama aja diskon cuman 1.000 di motor ijo sebelah gak pake langgar	3
13	Akhsan	Pakai gojek plus g sampai yang 3 bulanan gk ada bedanya dengan gk pakai. Tarifnya sama aja,	1
14	Agoes Narto	Maaf, hari ini saya uninstall aplikasinya. Itu dikarenakan saya sudah tidak bisa melakukan top	1
15	Yulianus Sijabat	josttttt	5
16	Abdur rahman Sadis	Saya kasih masukan, saya telpon ke gojek habis pulsa banyak, karena kelamaan prosedurnya,	1
17	Spi rit	bikin opsi chat sama penjual	1
18	Dewek Bae	sangat membantu buat saya yg gak tau jalan	5
19	jhomboy LTMPT	gofood ny GK jelas!!!!!!!!!	1
20	Mas Rifan	lebih bagus	5
21	Aulia Ranum	susah login. nomor hp ilang	5
22	Rasyid Nur Azis	layanan gofoodnya diperbaiki dah, jangan nyiksa orang dengan menunggu pesannya dateng,	1
23	Searasyanan	apk gjls, tiap order aja alesannya ditungguin mlah minta kortingan jam... perbaiki lgi pak... ny	1
24	smsl Junior	sangat cocok	5
25	Jasson Matthew	sangat puas.	5

Figure 1. Raw Data Display of GoPay Service User Reviews

3.1 Data Preprocessing Stage

After obtaining the raw data, a data quality check was performed to ensure all reviews were ready for further processing. At this stage, the data was checked for missing text, duplicates, and irrelevant characters that could impact the analysis results. This step laid the foundation for the data cleaning process to ensure the reviews used in the research were of good and consistent quality, as seen in Figure 3.

1	userName	content	score	cleaned_review
2	RozaLutfian Nisa	baik dan ramah sekali	5	ramah
3	Dewanti dhede	terima kasih telah membuat saya dala	5	terima kasih perjalanan cepat tujuan terima kasih promonya yg membantu hemat
4	Deny Setiawati	bagus	5	bagus
5	Reyner	Halo Gojek kenapa ini kok chat gojek n	1	halo gojek chat gojek nya gak dipakai gak tau informasi gojek nya dimana nunggu lamaudh gitu pakai teleponteleponnya aneh
6	Sumpena Pena	bagus sangat mudah	5	bagus mudah
7	Juni Siauce	semoga makin sukses	5	semoga sukses
8	fitria aulia bintang	bagos	5	bagos
9	Herdiana Natsir	best	5	best
10	Anita Christin	pelayanan gojek transport selalu yg ter	5	pelayanan gojek transport yg terbaik i like gojek
11	Welly G	Disaat jam sibuk, disaat hujan mulai tu	1	disaat jam sibuk disaat hujan turun pengambilan km aplikator order tercover sayang aplikator lupa pengambilan butuh biaya kerja ekstra sa
12	Cory Rogers Cory Rogers	langanan plus sama engak sama aja dis	3	langanan plus engak aja diskon cuman motor ijo sebelah gak pake langganan tetep harga murah harga doh doh mengecewakan
13	Akhsan	Pakai gojek plus g sampai yang 3 bulan	1	pakai gojek plus g bulanan gk bedanya gk pakai tarifnya aja vouchernya kemana dah katanyaa murah aja harganya
14	Agoes Narto	Maaf, hari ini saya uninstall aplikasinya	1	maaf uninstall aplikasinya top up saldo gopay alasan kartu diblokir bank bank bank periksaan kartu pemblokiran bank gojek ya uninstall sa
15	Yulianus Sijabat	josttttt	5	josttttt
16	Abdur rahman Sadis	Saya kasih masukan, saya telpon ke go	1	kasih masukan telpon gojek habis pulsa prosedurnya sayasangat rugikan harga appilasi layanan gomart fiskon contoh hidrococo applikasi g
17	Spi rit	bikin opsi chat sama penjual	1	bikin opsi chat penjual
18	Dewek Bae	sangat membantu buat saya yg gak tau	5	membantu yg gak tau jalan
19	jhomboy LTMPT	gofood ny GK jelas!!!!!!!!!	1	gofood ny gk
20	Mas Rifan	lebih bagus	5	bagus
21	Aulia Ranum	susah login. nomor hp ilang	5	susah login nomor hp ilang
22	Rasyid Nur Azis	layanan gofoodnya diperbaiki dah, jan	1	layanan gofoodnya diperbaiki dah nyiksa orang menunggu pesannya dateng pikir aja restoran jarak ga km ditambah makanan cepat saji kay
23	Searasyanan	apk gjls, tiap order aja alesannya ditun	1	apk gjls order aja alesannya ditungguin mlah kortingan jam perbaiki lgi nyesel bngt
24	smsl Junior	sangat cocok	5	cocok
25	Jasson Matthew	sangat puas.	5	puas

Figure 2. GoPay Review Data Display After Cleaning

3.2 Data Labeling

The next step is data labeling to determine the sentiment of each review. Each review is automatically labeled as positive, negative, or neutral using a Python script, readying the data for feature extraction and classification. A visualization of the labeling results can be seen in Figure 3.

1	userName	content	score	cleaned_review	label
2	RozaLutfian Nisa	baik dan ramah sekali	5	ramah	netral
3	Dewanti dhede	terima kasih telah membuat saya dalam perjalanan lebih cepat	5	terima kasih perjalanan cepat tujuan terima kasih promonya yg membantu hemat	positif
4	Deny Setiawati	bagus	5	bagus	positif
5	Reyner	Halo Gojek kenapa ini kok chat gojek nya gak bisa dipakai saya g	1	halo gojek chat gojek nya gak dipakai gak tau informasi gojek nya dimana nunggu lamaudh gitu pakai telep	negatif
6	Sumpena Pena	bagus sangat mudah	5	bagus mudah	positif
7	Juni Siauce	semoga makin sukses	5	semoga sukses	netral
8	fitria aulia bintang	bagos	5	bagos	netral
9	Herdiana Natsir	best	5	best	netral
10	Anita Christin	pelayanan gojek transport selalu yg terbaik i like gojek😊	5	pelayanan gojek transport yg terbaik i like gojek	positif
11	Welly G	Disaat jam sibuk, disaat hujan mulai turun, pengambilan pun bi	1	disaat jam sibuk disaat hujan turun pengambilan km aplikator order tercover sayang aplikator lupa pengar	netral
12	Cory Rogers Cory Roger	langanan plus sama engak sama aja diskon cuman 1.000 di motc	3	langanan plus engak aja diskon cuman motor ijo sebelah gak pake langganan tetep harga murah harga doh	netral
13	Akhsan	Pakai gojek plus g sampai yang 3 bulanan gk ada bedanya deng	1	pakai gojek plus g bulanan gk bedanya gk pakai tarifnya aja vouchernya kemana dah katanyaa murah aja hi	netral
14	Agoes Narto	Maaf, hari ini saya uninstall aplikasinya. Itu dikarenakan saya s	1	maaf uninstall aplikasinya top up saldo gopay alasan kartu diblokir bank bank bank periksaan kartu pemb	netral
15	Yulianus Sijabat	josttttt	5	josttttt	netral
16	Abdur rahman Sadis	Saya kasih masukan, saya telpon ke gojek habis pulsa banyak, k	1	kasih masukan telpon gojek habis pulsa prosedurnya sayasangat rugikan harga appilasi layanan gomart fo	netral
17	Spi rit	bikin opsi chat sama penjual	1	bikin opsi chat penjual	netral
18	Dewek Bae	sangat membantu buat saya yg gak tau jalan	5	membantu yg gak tau jalan	netral
19	jhomboy LTMPT	gofood ny GK jelas!!!!!!!!!	1	gofood ny gk	netral
20	Mas Rifan	lebih bagus	5	bagus	positif
21	Aulia Ranum	susah login. nomor hp ilang	5	susah login nomor hp ilang	netral
22	Rasyid Nur Azis	layanan gofoodnya diperbaiki dah, jangan nyiksa orang dengan	1	layanan gofoodnya diperbaiki dah nyiksa orang menunggu pesannya dateng pikir aja restoran jarak ga km	positif
23	Searasyanan	apk gjls, tiap order aja alesannya ditungguin mlah minta kortin	1	apk gjls order aja alesannya ditungguin mlah kortingan jam perbaiki lgi nyesel bngt	positif
24	smsl Junior	sangat cocok	5	cocok	netral
25	Jasson Matthew	sangat puas.	5	puas	positif

Figure 3. GoPay Review Data Display After Labeling

3.3 Feature Extraction

The feature extraction stage aims to transform preprocessed text data into a numerical representation for processing by a classification algorithm. The method used is Term Frequency–Inverse Document Frequency (TF-IDF), which assigns weights to each word based on its frequency of occurrence in a document and the entire corpus. Prior to the feature extraction process, a word analysis was performed to identify the most frequently occurring words in user reviews of GoPay services.

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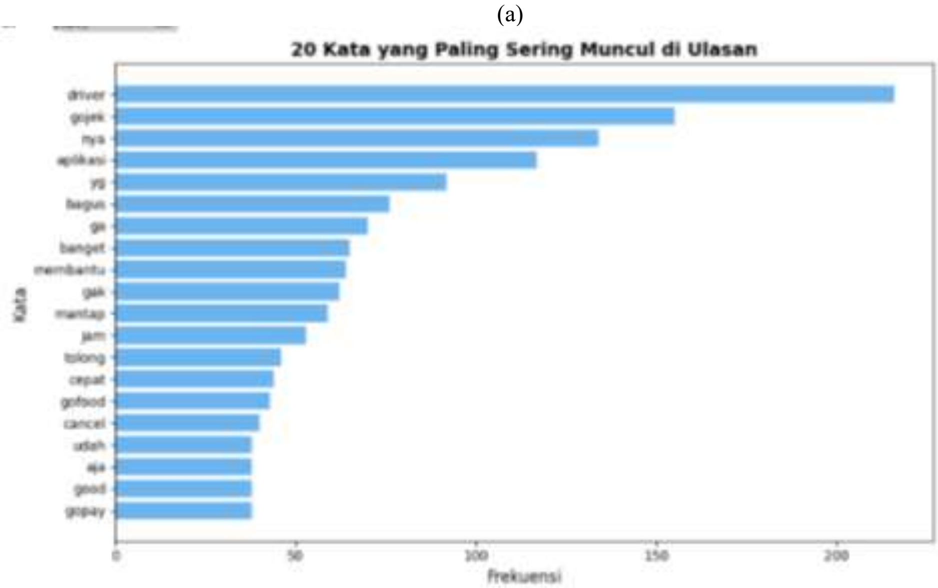
(a)



(b)

Figure 4 (a) and (b). Wordcloud view and graph of the 20 most frequently appearing words.

WordCloud visualizations and a top-20-word chart were used to display the most frequently occurring words in user reviews related to GoPay services. In WordCloud, word size reflects their frequency of occurrence, so larger words appear more frequently in the review corpus. Meanwhile, a bar chart of the top 20 words presents quantitative frequency of occurrence, making it easier for readers to directly compare dominant words. These two visualizations provide an initial overview of the topics and opinions frequently appearing in reviews and serve as the basis for the feature extraction phase using the TF-IDF method.

After word analysis, the text data is converted into numerical form using the TF-IDF method. The resulting transformation is a large-dimensional matrix, where each row represents one review and each column represents one word feature. The TF-IDF transformation yields:

```
Bentuk data TF-IDF training : (784, 1000)
Bentuk data TF-IDF testing  : (196, 1000)
```

A snapshot of the TF – IDF transformation results can be seen in Figure 5.

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```
    fitur_0  fitur_1  fitur_2  fitur_3  fitur_4  fitur_5  fitur_6  fitur_7  \
0       0.0      0.0      0.0      0.0      0.0      0.0      0.0      0.0
1       0.0      0.0      0.0      0.0      0.0      0.0      0.0      0.0
2       0.0      0.0      0.0      0.0      0.0      0.0      0.0      0.0
3       0.0      0.0      0.0      0.0      0.0      0.0      0.0      0.0
4       0.0      0.0      0.0      0.0      0.0      0.0      0.0      0.0

   fitur_8  fitur_9  ...  fitur_990  fitur_991  fitur_992  fitur_993  \
0      0.0      0.0  ...        0.0        0.0        0.0        0.0
1      0.0      0.0  ...        0.0        0.0        0.0        0.0
2      0.0      0.0  ...        0.0        0.0        0.0        0.0
3      0.0      0.0  ...        0.0        0.0        0.0        0.0
4      0.0      0.0  ...        0.0        0.0        0.0        0.0

   fitur_994  fitur_995  fitur_996  fitur_997  fitur_998  fitur_999
0        0.0        0.0        0.0        0.0        0.0        0.0
1        0.0        0.0        0.0        0.0        0.0        0.0
2        0.0        0.0        0.0        0.0        0.0        0.0
3        0.0        0.0        0.0        0.0        0.0        0.0
4        0.0        0.0        0.0        0.0        0.0        0.0

[5 rows x 1000 columns]
   fitur_35  fitur_43  fitur_44  fitur_45  fitur_67  fitur_85  fitur_100  \
0  0.430726  0.000000       0.0  0.000000  0.000000  0.000000   0.000000
1  0.000000  0.201568       0.0  0.000000  0.352752  0.352752   0.321315
2  0.000000  0.000000       1.0  0.000000  0.000000  0.000000   0.000000
3  0.000000  0.000000       0.0  0.000000  0.000000  0.000000   0.000000
4  0.000000  0.000000       0.0  0.691099  0.000000  0.000000   0.000000

   fitur_268  fitur_298  fitur_469  fitur_509  fitur_541  fitur_581  \
0   0.000000   0.000000   0.000000   0.000000    0.00000   0.000000
1   0.223401   0.249804   0.307107   0.313813    0.39169   0.321315
2   0.000000   0.000000   0.000000   0.000000    0.00000   0.000000
3   0.000000   0.000000   0.000000   0.000000    0.00000   0.000000
4   0.000000   0.000000   0.000000   0.000000    0.00000   0.000000

   fitur_673  fitur_869  fitur_888  fitur_908
0   0.507095    0.00000        0.0   0.746545
1   0.213159    0.00000        0.0   0.000000
2   0.000000    0.00000        0.0   0.000000
3   0.000000    0.00000        1.0   0.000000
4   0.000000    0.72276        0.0   0.000000
```

Figure 5. Display of TF-IDF Transformation Results

Figure 5 shows the results of a numerical representation using the TF-IDF method, where the weight of each word reflects its frequency in a single review relative to the entire corpus. The data snippet shows that most of the initial features have a value of 0.0, indicating that the words do not appear in a particular review, while several columns have numeric values, representing the weight of the words in the review. This TF-IDF matrix serves as the input feature for the Naïve Bayes algorithm, allowing the model to learn word patterns associated with positive, neutral, or negative sentiment for accurate classification.

3.4 Klasifikasi Dengan Naïve Bayes

After successfully extracting the data using TF-IDF, the next step was the classification process using the Multinomial Naïve Bayes algorithm.

The data was divided into two parts: 784 training data sets and 196 test data sets. The model was trained using the training data to learn the relationship patterns between features and sentiment labels (negative, neutral, positive).

The training data showed that the Naïve Bayes model had an accuracy of 0.9 (90%) on the test data. This value indicates that the model is quite good at classifying user reviews into the appropriate sentiment categories.

```
Akurasi Model: 0.9
```

3.5 Evaluasi Model

Model evaluation was conducted to assess classification performance based on the model's prediction results on the test data. Measurements were performed using a Confusion Matrix and Classification Report, which includes Precision, Recall, and F1-Score metrics for each sentiment class. The resulting confusion matrix can be seen in Figure 6.

```
Confusion Matrix:
[[  1   5   0]
 [  0 163   0]
 [  0  15  16]]
```

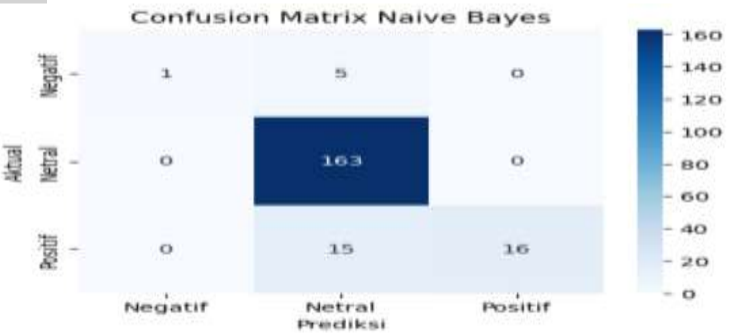

Figure 6. Confusion Matrix Display

Figure 6 displays the Naïve Bayes classification confusion matrix in heatmap form, ranging from white to dark blue, with darker colors indicating a higher number of predictions. This matrix visually demonstrates how well the model recognizes each sentiment class. The heatmap shows that the neutral class has the highest number

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of correct predictions, indicated by the dark blue color on the diagonal, while the negative and positive classes have smaller diagonal values, indicating several prediction errors. This visualization provides an intuitive overview of the model's error distribution and classification performance for each class.

```
Classification Report:
precision    recall  f1-score   support

negatif       1.00      0.17      0.29         6
netral        0.89      1.00      0.94       163
positif       1.00      0.52      0.68        31

accuracy                          0.90       200
macro avg     0.96      0.56      0.64       200
weighted avg  0.91      0.90      0.88       200
```

Based on the Data Classification Report, the Naïve Bayes model performed differently for each sentiment class. The neutral class performed best with a recall of 1.00 and an f1-score of 0.94, indicating that all neutral reviews were correctly recognized. The positive class had a recall of 0.52 and an f1-score of 0.68, indicating that only about half of the positive reviews were correctly classified. Meanwhile, the negative class performed the lowest, with a recall of 0.17 and an f1-score of 0.29, indicating that the model still struggled to detect negative reviews. Overall, the model achieved an accuracy of 0.9 (90%), with a weighted average f1-score of 0.88, indicating that Naïve Bayes was effective in classifying user review sentiment, especially for the neutral class.

To provide a clearer picture of the performance comparison between sentiment classes, a comparison graph of Precision, Recall, and F1-Score values is shown in the following graph.

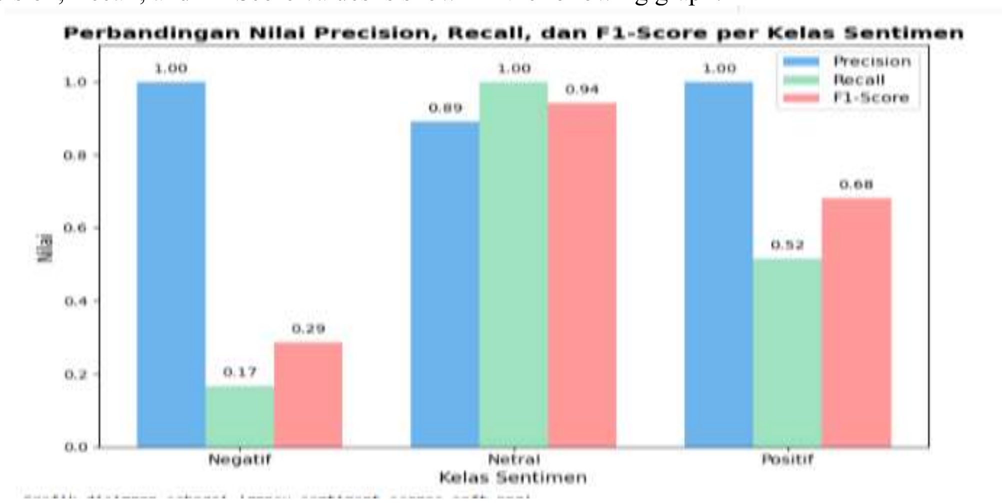

Figure 7. Comparison Graph of Precision, Recall, and F1-Score Values

Graph 7 displays a comparison of Precision, Recall, and F1-Score values for each sentiment class: negative, neutral, and positive. The graph shows that the negative class has the highest Precision value of 1.00, but its Recall value is very low at 0.27, resulting in an F1-Score of 0.29. This indicates that the model is very accurate in recognizing truly negative data, but there are still many negative data that are not detected properly. In the neutral class, the Precision value is 0.68 and Recall reaches 1.00 with an F1-Score of 0.80, indicating that the model is able to recognize all neutral sentiment data well although there are still some misclassifications from other classes. Meanwhile, the positive class obtained a Precision value of 0.92, Recall 0.52, and F1-Score 0.68. These results indicate that the model is quite good at identifying positive data, although there are still some positive data that are not perfectly detected. Overall, this graph illustrates that the best model performance is in the neutral class, followed by the positive class, while the negative class has the lowest performance in terms of the balance between prediction accuracy and completeness.

4. Conclusion

This study analyzes user review sentiments towards GoPay services on the Gojek application using the TF-IDF-based Naïve Bayes method. Data of 1,000 reviews were obtained through web scraping and processed through the stages of cleaning, labeling, feature extraction, classification, and model evaluation. The feature extraction results show that the TF-IDF numerical representation is able to capture word weights effectively to distinguish user sentiments. The classification process using Multinomial Naïve Bayes divided the data into 784 training data and 196 test data, resulting in an accuracy of 0.9 (90%), indicating the model is quite reliable in classifying reviews. Based on the evaluation using the Confusion Matrix and Classification Report, the best performance was obtained in the neutral class with a recall of 1.00 and an f1-score of 0.94, while the positive class had a recall of 0.52 and an f1-score of 0.68, and the negative class was the most challenging class with a recall of 0.17 and an f1-score of 0.29. These findings indicate that the majority of user reviews are neutral, and the Naïve Bayes model is quite effective in supporting sentiment analysis in digital services like GoPay.

Overall, this study demonstrates that Naïve Bayes with TF-IDF can be a reliable tool for automatically understanding user opinions. The analysis results can then be used as input for Gojek developers to improve service quality and user satisfaction.

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