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CLASSIFICATION OF USER REVIEW SENTIMENT TOWARD PAYLATER SERVICES ON THE KREDIVO AND AKULAKU APPS USING NAÏVE BAYES

KLASIFIKASI SENTIMEN ULASAN PENGGUNA TERHADAP LAYANAN PAYLATER PADA APLIKASI KREDIVO DAN AKULAKU MENGGUNAKAN NAÏVE BAYES

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Abstract

PayLater services are one of the rapidly growing digital financial innovations widely utilised in fintech apps in Indonesia, including Kredivo and Akulaku. User reviews on the Google Play Store reflect a range of experiences, from satisfaction with the ease of use of the service to complaints regarding bills, interest rates, late payment fees, credit limits, and app performance. This study aims to classify the sentiment of user reviews regarding PayLater services on the Kredivo and Akulaku apps using the Multinomial Naïve Bayes algorithm. Data was collected via web scraping from the Google Play Store and automatically labelled based on user ratings, with ratings of 1-2 classified as negative sentiment and ratings of 4-5 as positive sentiment, whilst a rating of 3 was excluded as it was considered ambiguous. Following a preprocessing stage comprising cleaning, case folding, tokenisation, stopword removal, and stemming, as well as feature extraction using TF-IDF, 3,652 reviews were obtained with a training-to-test data split ratio of 80:20. The results indicate that positive sentiment dominates the dataset at 56.49%, whilst negative sentiment accounts for 43.51%. Analysis by application revealed that Kredivo was dominated by positive sentiment (68.20%), whilst Akulaku was dominated by negative sentiment (51.70%). The Naïve Bayes multinomial model achieved an accuracy of 84.13%, with average precision, recall, and F1-score values of 0.84, demonstrating good and balanced classification performance across both sentiment classes.

Keywords : Sentiment analysis, PayLater, Kredivo, Akulaku, Multinomial Naïve Bayes.

Abstrak

Layanan PayLater merupakan salah satu inovasi keuangan digital yang berkembang pesat dan banyak dimanfaatkan pada aplikasi fintech di Indonesia, termasuk Kredivo dan Akulaku. Ulasan pengguna di Google Play Store mencerminkan beragam pengalaman, mulai dari kepuasan terhadap kemudahan layanan hingga keluhan terkait tagihan, bunga, denda, limit, dan kinerja aplikasi. Penelitian ini bertujuan mengklasifikasikan sentimen ulasan pengguna terhadap layanan PayLater pada aplikasi Kredivo dan Akulaku menggunakan algoritma Multinomial Naïve Bayes. Data dikumpulkan melalui teknik web scraping dari Google Play Store dan dilabeli secara otomatis berdasarkan rating pengguna, dengan rating 1-2 sebagai sentimen negatif dan rating 4-5 sebagai sentimen positif, sedangkan rating 3 dikecualikan karena dianggap ambigu. Setelah melalui tahap preprocessing yang meliputi cleaning, case folding, tokenisasi, stopword removal, dan stemming, serta ekstraksi fitur menggunakan TF-IDF, diperoleh 3.652 ulasan dengan rasio pembagian data latih dan data uji sebesar 80:20. Hasil penelitian menunjukkan bahwa sentimen positif mendominasi dataset sebesar 56,49%, sedangkan sentimen negatif sebesar 43,51%. Analisis per aplikasi menunjukkan bahwa Kredivo didominasi sentimen positif (68,20%), sementara Akulaku didominasi sentimen negatif (51,70%). Model Multinomial Naïve Bayes memperoleh akurasi sebesar 84,13% dengan nilai rata-rata precision, recall, dan F1-score sebesar 0,84, menunjukkan kinerja klasifikasi yang baik dan seimbang pada kedua kelas sentimen.

Kata Kunci : Analisis sentimen, PayLater, Kredivo, Akulaku, Multinomial Naïve Bayes.

1. INTRODUCTION

Advances in information and communication technology have driven transformation in the digital finance sector. One form of innovation within the financial technology ecosystem is the PayLater service, a payment facility that allows users to make purchases now and pay later (Ryando et al., 2025) (Indriani & Wibowo, 2022). This service is growing in popularity as it offers ease of access, payment flexibility, and supports the public's digital transactions (Wahyuta Kusuma et al., 2024). In Indonesia, the use of PayLater has increased, particularly following the COVID-19 pandemic. This increase is linked to the rise in online shopping activity and the public's need for more practical digital payment methods (Aghnia et al., 2021). However, behind the convenience it offers, PayLater also raises a number of issues, such as the risk of consumer debt, difficulties in managing finances, reliance on digital credit facilities, and complaints regarding bills, interest, penalties, limits, and the collection process. Kredivo and Akulaku are fintech apps that provide digital credit and PayLater services in Indonesia. Both apps have a wide range of user reviews on the Google Play Store, ranging from positive reviews regarding ease of use to negative reviews concerning service and app issues (Fahrezi Putra Ichsansyah & Korespondensi, 2026). User reviews on the Google Play Store can be utilized as a data source to understand user experiences, complaints, and opinion trends regarding PayLater services (Parameswari et al., 2025).

The large volume of user reviews makes manual analysis less effective. Therefore, a machine-learning-based sentiment analysis approach is required to classify user opinions as positive or negative In sentiment analysis, the common stages include data collection, preprocessing, feature extraction, data splitting, modelling, and model evaluation (Aji & Fatma Wati, 2020). The preprocessing stage is used to clean the text data of irrelevant elements, whilst the TF-IDF method can be used to convert text into a numerical form so that it can be processed by classification algorithms (Penelitian et al., 2023).

Naïve Bayes is one of the classification methods frequently used in text processing because it has a relatively simple and efficient computational mechanism and is capable of handling word-based data quite well (Amrie et al., 2022). Several previous studies have also utilized the Naïve Bayes algorithm in sentiment analysis, including studies on PayLater services and fintech app reviews (Ryando et al., 2025). Additionally, other studies indicate that user reviews of the Kredivo and Akulaku apps on the Google Play Store can serve as a data source for identifying user sentiment trends toward digital credit services.

A number of previous studies have examined sentiment analysis in PayLater services, online lending apps, and reviews of digital applications, using different subjects and methods. (Safira et al., 2023) investigated public sentiment towards PayLater using a Naïve Bayes Classifier, (Indriani &

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Wibowo, 2022) analyses the opinions of ShopeePayLater users on Twitter using the same algorithm. On a more specific subject, (Iqbal et al., 2024) discussed sentiment regarding online lending apps, including Akulaku and Kredivo, using Support Vector Machines. Furthermore, (Wijaya & Panjaitan, 2024)demonstrated that user reviews on the Google Play Store can be utilized as a data source for sentiment analysis using both the Naïve Bayes approach and a lexicon.

Based on this research, sentiment analysis has been widely used to understand user opinions regarding PayLater, online loans, and digital applications. However, this study has a more specific focus, classifying the sentiment of user reviews of PayLater services on the Kredivo and Akulaku applications using the Naïve Bayes algorithm. Sentiment in this study is divided into two categories, namely positive and negative, so that the analysis results are expected to reveal user opinion trends more clearly.

2. RESEARCH METHOD

The purpose of this research is to classify the sentiment of user reviews of the PayLater service on Kredivo and Akulaku applications using the Naïve Bayes algorithm. The review data was obtained from the Google Play Store platform through web scraping and then processed through a series of systematic steps to generate a sentiment classification model. Sentiment classification in this study consists of two classes, namely positive and negative, based on the rating scores given by the users. The research workflow applied comprises seven main stages, namely data collection, data labelling, pre-processing, feature extraction, data splitting, modelling, and model evaluation, as shown in Figure 1.

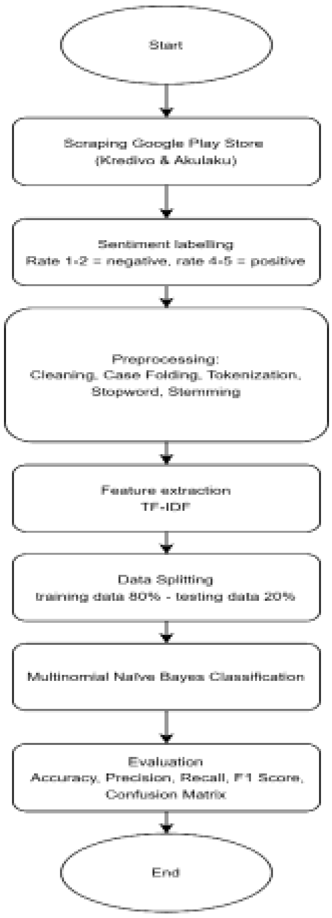

Figure 1. Research Methodology Flowchart

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Data Collection

For data collection, web scraping techniques were used with the help of google-play-scraper library in python in the Google Colab environment. The data collected was user reviews of Kredivo and Akulaku apps from the Google Play Store platform. The attributes used in this research were review content and rating scores. All the review data from both apps were then combined into a single dataset for the purpose of sentiment classification. The amount of data that was successfully collected during the scraping stage was over 2,000 reviews in Indonesian before any further filtering and data processing.

Data Labelling

Sentiment labelling is performed automatically based on user ratings on the Google Play Store. Reviews with a rating of 4 or 5 are categorised as positive sentiment, whilst ratings of 1 or 2 are categorised as negative sentiment (Afif & Nugroho, 2025). Reviews with a 3-star rating are not included in the dataset, as these are considered neutral or ambiguous and do not indicate a clear bias of sentiment. An approach based on ratings is used since ratings are a direct assessment by users and allow for consistent labelling without manual annotation (Rahmi Anissa et al., 2025).

Data Prepocessing

The preprocessing stage aims to clean and prepare raw text data so that it can be processed optimally by classification algorithms. All preprocessing steps are carried out using the NLTK and PySastrawi libraries in Python, including cleaning to remove irrelevant elements such as URLs, punctuation marks and symbols; case folding to convert all text to lowercase; tokenisation to break sentences down into individual words; stopword removal to eliminate common words that do not contribute to sentiment meaning; and stemming using PySastrawi to convert inflected words to their base forms (Ariany et al., 2026).

Feature Extraction

Feature extraction was performed to transform the preprocessed review text into a numerical representation suitable for Naïve Bayes processing. The TF-IDF (Term Frequency-Inverse Document Frequency) method was adopted as the feature weighting approach, computing the importance of each term by accounting for its occurrence frequency within a review and its distribution across the entire corpus (Rahman et al., 2024). The use of TF-IDF allowed user reviews to be expressed in a structured numerical format. In this study, features were constructed from unigrams and bigrams, with a total of 5,000 features. The resulting feature vectors were subsequently used as input for sentiment classification using the Multinomial Naïve Bayes algorithm (Helmayanti et al., 2023)(Mubarokah, 2025).

Data Splitting

The dataset that had passed the feature extraction stage was divided into training and testing data using the train_test_split function from the scikit-learn library. In this study, an 80:20 split was used, with 80% of the data used to train the model and 20% to evaluate model performance. This ratio was selected to provide sufficient data for the learning process while still allocating representative data for testing (Kurniawan et al., 2025).

Multinomial Naïve Bayes Classification

The classification stage in this study was carried out using the Multinomial Naïve Bayes algorithm. This algorithm is widely used in text classification as it operates on the basis of the probability of a word appearing in a document. In sentiment analysis, Multinomial Naïve Bayes classifies each review into a specific sentiment class by calculating the probability of that review falling into the positive or negative category (Ryando et al., 2025; Ichsansyah & Subektiningsih, 2026). The model is trained using training data that has been represented numerically via TF-IDF. Once the training process is complete, the model is used to predict sentiment labels on the test data. The prediction results are then compared with the actual labels to measure the performance of the classification model (Sidik et al., 2022) (Hamad et al., 2021).

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Evaluation

Model evaluation was conducted to assess the performance of the Multinomial Naïve Bayes algorithm in classifying user reviews into positive and negative sentiment classes. The evaluation process involved comparing the model's predicted labels with the actual sentiment labels in the test data (Susanti et al., 2026).

Model performance in this study was measured using five evaluation metrics: accuracy, precision, recall, F1-score, and confusion matrix. Accuracy was used to measure the overall correctness of the classification results. Precision measures how accurately the model predicts each sentiment class, whilst recall measures the model's ability to identify all reviews belonging to a specific class. The F1-score is used to represent the balance between precision and recall. Furthermore, the confusion matrix is used to provide a more detailed picture of correct and incorrect predictions for each sentiment class (Fahrezi Putra Ichsansyah & Korespondensi, 2026).

3. RESULT AND DISCCUSSION

Data Collection and Distribution

User review data was obtained through web scraping from the Google Play Store for the Kredivo and Akulaku apps. Following an automated labelling process based on user rating scores where reviews with ratings of 1-2 were labelled negative and those with ratings of 4-5 were labelled positive, whilst excluding reviews with a rating of 3, a final dataset of 3,652 reviews was obtained. The dataset was then split using an 80:20 ratio, resulting in 2,921 training data points and 731 test data points. The distribution of sentiment labels in the dataset shows that positive reviews dominate, with 2,063 reviews (56.49%), whilst negative reviews number 1,589 (43.51%). This distribution indicates that, overall, users of the PayLater service on the Kredivo and Akulaku apps tend to give positive ratings, although the proportion of negative sentiment, which stands at 43.51%, still warrants serious attention from the app developers. The sentiment label distribution is presented in Table 1.

Table 1. Sentiment Label Distribution

Sentiment Label	Number	Percentage
Positive	2.063	56.49%
Negative	1.589	43.51%
Total	**3.652**	**100%**

Preprocessing Results

Following the preprocessing stage which included cleaning, case folding, tokenization, stop word removal, stemming, removal of empty data, and removal of duplicate data the review data was successfully cleansed of irrelevant elements, such as symbols, punctuation marks, URLs, numbers, and common words that contribute little to sentiment analysis. The stemming stage was carried out to convert inflected words to their base forms, thereby minimizing word-form variation. Once the preprocessing was complete, 3,652 reviews were obtained, which were then ready for use in the feature extraction and modelling stages.

Sentiment Distribution by Application

An analysis of sentiment distribution by app was conducted to identify trends in user opinions regarding each app separately. The results of the analysis reveal quite significant differences between the Kredivo and Akulaku apps, as shown in Table 2.

Table 2. Sentiment Distribution by Application

Application	Negative	Positive
Akulaku	51,70%	48,30%
Kredivo	31,80%	68,20%

Table 2 shows the distribution of user sentiment which shows different trends between Akulaku and Kredivo apps. The Akulaku app experienced a higher percentage of negative sentiment at 51.70% compared to positive sentiment at 48.30%. This shows the reviews of the PayLater service by Akulaku users tend to reflect a less satisfactory experience. This could be related to the technical issues of the

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app, the verification process, credit limits, bills, interest rates, late payment fees, or collection process. Conversely, the Kredivo app shows a dominance of positive sentiment at 68.20%, whilst negative sentiment stands at 31.80%. These results indicate that the majority of Kredivo users give more positive feedback for the PayLater service. The positive sentiment could be due to users feeling helped by the ease of transactions, payment flexibility, or the digital credit services provided. Therefore, it can be concluded that Kredivo has a more positive user perception than Akulaku based on the sentiment distribution in the analyzed review data.

Naïve Bayes Classification Results

Sentiment classification in this study was carried out using the Multinomial Naïve Bayes algorithm. The dataset used was divided into 2,921 training data points and 731 test data points. Based on the evaluation results, the Naïve Bayes model was able to classify the sentiment of user reviews with an accuracy rate of 84.13%. The complete classification results are presented in Figure 2.

```
••• Akurasi: 84.13 %
              precision    recall  f1-score   support

     negatif       0.79      0.87      0.83       318
     positif       0.89      0.82      0.85       413

    accuracy                           0.84       731
   macro avg       0.84      0.84      0.84       731
weighted avg       0.85      0.84      0.84       731
```

Figure 2. Naïve Bayes Classification Results

Based on Figure 2, the evaluation results show that the Multinomial Naïve Bayes model is able to classify positive and negative sentiment fairly well. In the negative class, the model achieved a precision of 0.79, a recall of 0.87, and an F1-score of 0.83. The higher recall value indicates that the model successfully identified the majority of negative reviews, although there were still some positive reviews that were incorrectly classified as negative. In the positive class, the model achieved a precision of 0.89, a recall of 0.82, and an F1-score of 0.85. The high precision value indicates that the reviews predicted as positive by the model were, for the most part, correctly classified as positive. Overall, the macro average and weighted average scores were in the range of 0.84. These results indicate that the model performs consistently in distinguishing between the two sentiment classes.

Confusion Matrix Analysis

The confusion matrix results from the classification process are shown in Figure 3 below.

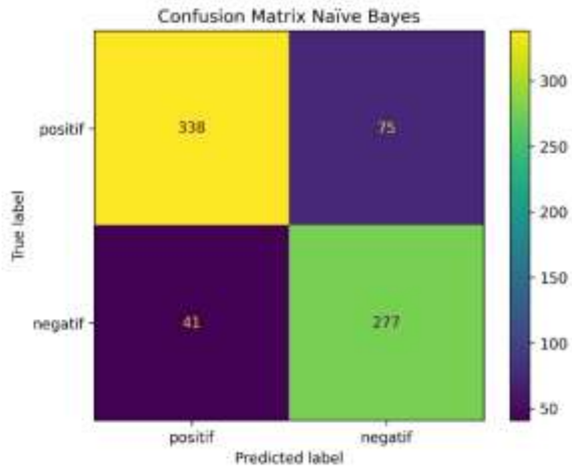

Figure 3. Confusion Matrix

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According to Figure 3, the model successfully classified 338 out of 413 positive reviews correctly as positive sentiment. Meanwhile, 75 positive reviews were still incorrectly predicted as negative sentiment. In the negative class, the model was able to correctly predict 277 out of 318 reviews as negative sentiment, whilst 41 negative reviews were misclassified as positive sentiment. The number of errors in positive reviews predicted as negative is greater than that of negative reviews predicted as positive. This is also evident from the positive class recall value of 0.82, which is lower than the negative class recall of 0.87. This means that the model performs slightly better at identifying negative reviews than positive ones. These errors may occur because some positive reviews still contain words that appear negative or critical, even though the user has given a high rating.

Discussion

The results of the study show that the Multinomial Naïve Bayes algorithm is capable of classifying the sentiment of user reviews regarding the PayLater service on the Kredivo and Akulaku apps with an accuracy of 84.13%. This figure indicates that the model performs reasonably well in distinguishing between positive and negative reviews. These results are consistent with previous research showing that Naïve Bayes can be used for sentiment classification of digital app reviews. (Fahrezi Putra Ichsansyah & Korespondensi, 2026) achieved an accuracy of 82% on Kredivo reviews, whilst (Susanti et al., 2026) achieved an accuracy of 92.01% on the same dataset. Meanwhile, (Ryando et al., 2025) achieved an F1-score of 0.432 in sentiment analysis of PayLater on Twitter. These differences in results may be influenced by the data source, the volume of data, text characteristics, and the preprocessing steps employed. The sentiment distribution per application shows that Kredivo has a higher proportion of positive sentiment, at 68.20%, whilst Akulaku stands at 48.30%. Conversely, negative sentiment is more dominant for Akulaku, at 51.70%, compared to 31.80% for Kredivo. These findings suggest that user reviews of the PayLater service on Kredivo tend to be more positive than those for Akulaku based on the analysed data.

Overall, the results of this study indicate that sentiment analysis using the Multinomial Naïve Bayes classifier can provide insight into users' perceptions of the PayLater service. These findings can also serve as a basis for evaluation by app developers in understanding which aspects of the service are viewed positively and which still require improvement.

4. CONCLUSION

This study was conducted to classify user sentiment towards the PayLater service on the Kredivo and Akulaku apps in the Google Play Store using the Multinomial Naïve Bayes algorithm. Based on the results obtained, it can be concluded that the review data used in this study comprised 3,652 reviews following the filtering, labelling, and pre-processing stages. The data was then processed through feature extraction using TF-IDF and classified into two sentiment classes, namely positive and negative. The sentiment distribution shows that positive reviews are more prevalent, totaling 2,063 reviews or 56.49%, whilst negative reviews number 1,589 or 43.51%. When viewed by app, Kredivo has a higher percentage of positive sentiment, at 68.20%, whilst Akulaku has a higher percentage of negative sentiment, at 51.70%. These results indicate that user reviews of the PayLater service on Kredivo tend to be more positive compared to Akulaku, based on the analysed data.

It is hoped that the findings of this study will provide insights for the developers of the Kredivo and Akulaku apps in understanding user perceptions of PayLater services. The information derived from this sentiment classification can be used as a basis for evaluation to improve service quality, particularly in areas that continue to receive a high volume of negative feedback from users. For future research, the scope of the data could be expanded by including other PayLater applications, applying word normalization during the preprocessing stage, and comparing the performance of Naïve Bayes with other algorithms such as Support Vector Machines or Random Forests.

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