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Sentiment Analysis of Kredivo App Users Using the K-Nearest Neighbor Algorithm

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Abstract: In today's technological era, the internet has played an important role in all aspects of human life. This is also what drives various mobile applications to develop very rapidly. Kredivo is an instant credit solution that provides convenience to buy now pay later in a 1-month tenor or 3-month installment tenor with 0% interest. In addition, Kredivo is not only used for shopping purposes, but borrowers can also make withdrawals in the form of cash. However, not all users are satisfied with the service of the application. and the many comments submitted through the Kredivo application review feature on the Google Play Store. Therefore, in this study, researchers tried to conduct a sentiment analysis of Kredivo application users using the K-Nearest Neighbor algorithm. The purpose of this study was to determine the accuracy value produced by the K-Nearest Neighbor algorithm. From testing 1880 data using the cross-validation model, it was found that reviews containing positive sentiment were 62.55% and containing negative sentiment were 37.45%. Evaluation of the classification results using the Confusion Matrix test obtained an accuracy value of 79.36%, with a recall value of 83.08%, precision of 72.15%, and recall (Specificity) of 73.15%, so it can be concluded that the K-Nearest Neighbor algorithm can classify sentiments well using review data on Kredivo application users.

Keywords: Analysis; Sentiment; Kredivo; CRISP-DM; K-Nearest Neighbors.

1. Introduction

The internet plays a very important role in almost all aspects of human life in the era of rapidly developing digital technology today. The internet is an incorporeal that serves as communication media as well as the means of obtaining mediums, transactions, and even to become various innovations. The use of the internet is closely associated with mobile devices, which enable access to information at the press of a button, anytime and anywhere. So, this phenomenon gives rise to the development of mobile applications that are developing at a fast pace and spreading into different sectors like the e-commerce sector, financial services, and other consumer services. This mobile application has been a game changer in the interaction of individuals with the world of web as it enables to perform daily activities in an effective and efficient manner [1]. One of the applications that has developed rapidly is digital financial application. From banking applications to online loan applications, these applications offer users convenience for financial management. In Indonesia Kredivo is one of the applications that are quite popular. Kredivo is an application for online loans that makes it easy for its users to buy goods in installments with low interest even without interest for installment terms of 1 month or 3 months. Moreover, Kredivo offers cash disbursement with interest which is relatively cheap, beginning from 1.99%/month. Users of this application are referred to digital credit cards, and they can make online and offline transactions with more than 4000 merchants partnering with Kredivo [2]. With an average of 4.8, Kredivo has also been downloaded over 10 million times on the Google Play Store, with over 3 million reviews or comments from users. These numbers reflect how popular this application is among smartphones users in Indonesia. But even though this application is one of the most used applications it does not mean that Kredivo is free from problems. Service quality complaints were mentioned in several user reviews. For instance, some users complained their transactions could not be processed despite the credit limit still being available (they've previously received credit), or they finally could not use Kredivo features after years of using the service. This indicates that despite many users have this application, the quality of service provided needs to be improved to meet the expectations of broader users [3].

A good approach to find user issues is to perform sentiment analysis on user reviews from places like the Google Play Store. The main idea of this sentiment analysis is to detect the feelings or opinions of users about the application whether they are positive, negative or neutral. By conducting sentiment analysis, application developers can better understand what makes users satisfied and which areas of the application still need improvement. The K-Nearest Neighbor (K-NN) algorithm is a commonly used machine learning algorithm for sentiment analysis. K-NN is a classification algorithm that can classify user reviews into categories such as positive, negative, or neutral based on the features contained in the review text 4. The K-NN algorithm has been used in several previous studies for sentiment analysis in mobile applications. PREVIOUS RESEARCH For example, a study conducted by Saifurridho, Martanto, and Hayati (2024) tested the implementation of the K-NN algorithm to read the sentiment of Shopee application users. The results of the study showed that the K-NN algorithm successfully produced good accuracy with accuracy, precision, recall and f1-score values of 70%, 50.5%, 44.8%, and 48.3%, respectively [3]. Syafrizal, Afdal, and Novita (2024) conducted a similar study to analyze sentiment towards reviews on the PLN Mobile application and applied the same algorithm, they obtained a higher accuracy of 90.23% with a recall value of 72.38% [4]. However, although the K-NN algorithm has been proven successful in sentiment analysis, different applications have unique characteristics, meaning that results from other applications cannot be automatically or immediately transferred to Kredivo. Therefore, this study will conduct a sentiment analysis of Kredivo application user reviews using the K-Nearest Neighbor algorithm with the aim of determining user satisfaction and things that still need to be improved. This research is expected to provide a significant contribution to the development of the Kredivo application in improving service quality and user satisfaction. The questions to be answered from this study include, first, how is the sentiment of Kredivo application users as seen from their reviews on the Google Play Store? Second, what is the importance of implementing the K-Nearest Neighbor algorithm to analyze these sentiments and determine areas that may need to be improved? By answering these questions, it is hoped that information can be obtained that can be used to improve the quality of Kredivo services and provide a better experience for its users.

2. Research Method

2.1 Research Data

In this study, the data used were obtained from user reviews of the Kredivo application on the Google Play Store. The data collection process was carried out using scraping techniques to automatically access and download review data. To simplify the process, tools were used based on Google Colab, a cloud-based computing platform that allows Python programming without requiring complicated hardware configuration. By using scraping, the review data obtained was quite large and diverse, consisting of various types of sentiments and comments from Kredivo users. Overall, 2000 user reviews were successfully downloaded and analyzed in this study. Each review contains text that describes the user's experience with the Kredivo application, which is then categorized based on positive, negative, or neutral sentiment. The scraping process was carried out by paying attention to the ethics and data usage policies of the Google Play Store to ensure that the data collected does not violate privacy rights or the terms of the platform. In addition, data collection was carried out within a certain time period, namely throughout the last 6 months, to obtain relevant and current reviews.

2.2 Test Design

The method used in this study is the K-Nearest Neighbor (K-NN) algorithm, which is known as one of the effective classification algorithms in sentiment analysis. The K-NN algorithm works by classifying data based on its proximity to other data points in the feature space. In the context of this study, the K-NN algorithm will be used to classify the sentiment of Kredivo user reviews that have been collected into three categories, namely positive, negative, or neutral. The testing process begins with data preprocessing, which includes cleaning the text from irrelevant elements, such as punctuation, numbers, and unimportant words (stopwords). After that, the tokenization stage is carried out to break the review text into smaller words or tokens, which will become features in the sentiment analysis process. Furthermore, the vectorization stage is carried out to convert the text into a numeric representation using the TF-IDF (Term Frequency-Inverse Document Frequency) method, which will measure how important a word is in a document compared to the entire document collection. After the data preparation stages are complete, the data is then entered into the K-NN algorithm model for training and testing. In the training process, the K-NN model will learn patterns in the data to be able to classify reviews based on the sentiment contained in it. To measure the performance of the model, an evaluation is carried out using metrics such as accuracy, precision, recall, and f1-score. All tests are carried out using the RapidMiner tool, a data mining platform that provides various algorithms and analysis techniques to process and analyze data.

2.3 CRISP-DM Methodology

In this study, the methodology used to guide the analysis process is the Cross Industry Standard for Data Mining (CRISP-DM), which is one of the most widely used methodologies in data mining projects. This methodology consists of six main stages that need to be passed, namely:

1) Business Understanding
   At this stage, the research objectives and problems to be solved are clearly identified. This study aims to analyze Kredivo user review sentiments to determine the factors that influence user satisfaction or dissatisfaction with the application.
2) Data Understanding
   At this stage, the data that has been collected is explored and understood. The review data obtained will be evaluated and analyzed to identify the quality, accuracy, and relevance of the data in achieving the research objectives.
3) Data Preparation
   This stage includes the process of cleaning, transforming, and selecting data. Review data that has been downloaded through scraping will be cleaned, processed, and prepared for use in the modeling stage. This includes the process of removing duplication, removing incomplete data, and selecting relevant features.
4) Modeling
   At this stage, the K-Nearest Neighbor model is applied to analyze user review sentiments. This model will be trained using the prepared data, and testing is carried out to measure the model's performance in classifying user review sentiments.
5) Evaluation
   After the model is built, an evaluation phase is carried out to ensure that the model has successfully met the desired objectives. Model performance measurements using metrics such as accuracy, precision, recall, and f1-score will be carried out to assess the quality of the model.

6) Deployment
In the final stage, the research results will be disseminated for use by interested parties, such as Kredivo application developers, to improve service quality based on the results of the sentiment analysis that has been carried out.

These stages will be followed systematically and structured to produce an effective model in analyzing the sentiment of Kredivo application users. The following figure shows the stages of implementing the CRISP-DM methodology used in this study.

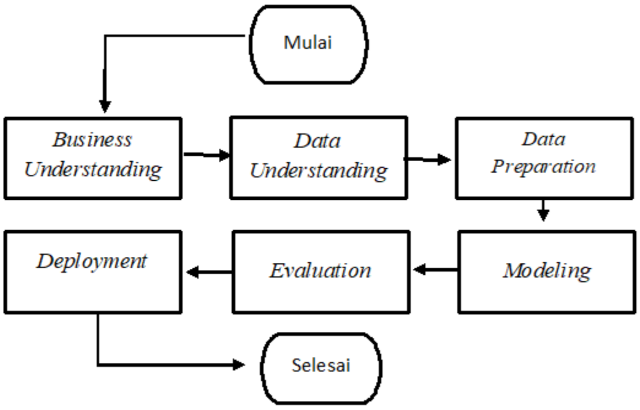

Figure 1. Stages of Implementing the CRISP-DM Methodology

3. Result and Discussion

3.1 Results

3.1.1 Research Tools

The tools and materials used in this research are:

Table 1. Software Specifications

No	Software	Version	Function
1	Operating System	Windows 11	Used as the operating system
2	Microsoft Office Excel	2021	For data cleaning and labeling
3	Microsoft Office Word	2021	For writing the thesis proposal/thesis
4	RapidMiner	AI Studio 2024.01	Used to apply algorithm methods
5	Google Colaboratory	-	Used for data scraping

Table 2. Hardware Specifications

No	Hardware	Specifications
1	Device Name	ASUS DESKTOP-TO87CUL
2	Processor	Intel(R) Celeron(R) N4020 CPU @ 1.10GHz 1.10 GHz
3	Installed RAM	8.00 GB (7.83 GB usable)
4	System Type	64-bit operating system, x64-based processor

3.1.2 Implementation and testing

In this section, the steps involved in the implementation and testing of the research are described. The research focuses on understanding customer satisfaction with the Kredivo application based on ratings and reviews on Google Play Store using the K-Nearest Neighbor (KNN) algorithm. The research will utilize data collected from Google Play Store.

1) Business Understanding
At this stage, the researcher aims to understand the object or problem being addressed throughout the study. The problem being raised is to determine the level of customer satisfaction with the Kredivo app based on the ratings and reviews available on the Google Play Store, using the K-Nearest Neighbor algorithm. Data for this study will be obtained from Google Play Store.

2) Data Understanding
This phase involves understanding the data that will be used for research purposes before proceeding to the next stage, which is preprocessing [2]. The data collection steps undertaken are as follows:
   a) Data Collection
   The research begins by collecting user reviews of the Kredivo app from Google Play Store using scraping techniques with the help of Google Colab tools. A total of 2,000 reviews were collected from Google Play Store. The scraped data was then saved in a CSV format.
   b) Data Selection
   Data selection involves removing unnecessary data [11]. The initial dataset consisted of 2,000 entries, with attributes such as review ID, username, user image, content, score, etc. Not all of these attributes are used for the research; only the content and score attributes were retained. A new attribute was also added for sentiment labeling.
   c) Data Labeling
   In this step, the reviews data is processed for classification. A new attribute, sentiment, is assigned to each review [5]. The sentiment is determined based on the rating provided by the user. For example, ratings of 4 or 5 are considered positive sentiment, while ratings of 1 or 2 are negative, and a rating of 3 is considered neutral. The labeling process uses an IF formula: if the score column is <3, the label is negative; if the score is 3, the label is neutral; otherwise, the label is positive.

After the labeling process is complete, only the reviews with negative and positive sentiments are kept for classification. Reviews with neutral sentiment are removed. After removing the neutral reviews, the remaining dataset consists of 1,884 entries, with 705 labeled as negative and 1,179 as positive.

3.1.3 Data Preparation

The next process in this study is Preprocessing. In this stage, the labeled sentiment data undergoes a cleaning process to make it easier for classification. Below are the results of the text preprocessing steps conducted in this research:

1) Cleansing
The purpose of the cleansing process is to remove characters that do not contribute to the classification results. This includes removing punctuation, numbers, emoticons, spaces, and duplicates. After cleaning, the data is saved in CSV format. Below are Figures (2) and (3), showing the cleaning process and results of the dataset used in this research [6].

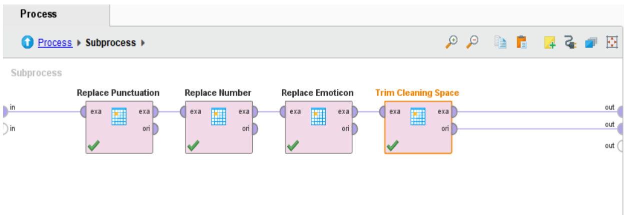

Figure 2. Cleansing Process

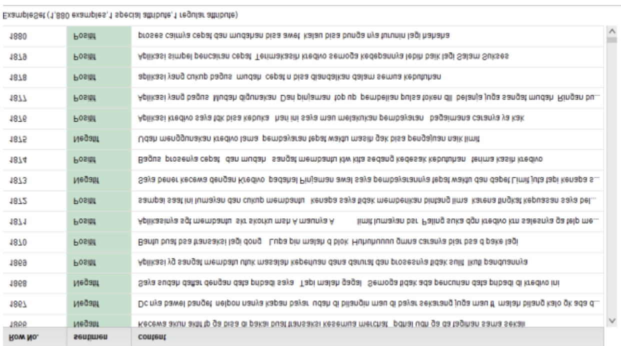

Figure 3. Cleansing Process Results

2) Case Folding
The case folding step involves converting all uppercase letters in the dataset to lowercase. This process utilizes the "transform cases" operator, converting all text to lowercase. Below are figure (4) and table (3), showing the process and results of this step:

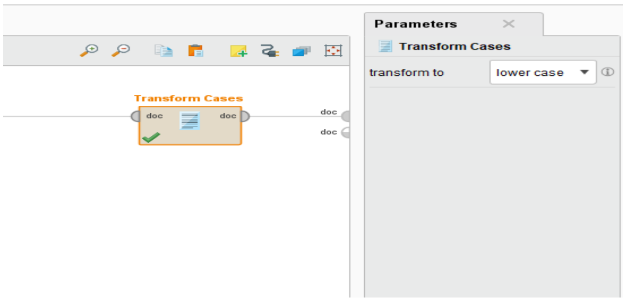

Figure 4. Case Folding Process

Table 3. Case Folding Results

Before	After
Cicilan dengan suku bunga rendah mudah membuat akun dan pasti langsung di ACC simpel dan sangat mudah ketika menggunakan nya ditambah dengan fitur fitur nya yang sangat lengkap banget membuat kita semakin gampang saat menggunakan aplikasi ini Aplikasi i	cicilan dengan suku bunga rendah mudah membuat akun dan pasti langsung di acc simpel dan sangat mudah ketika menggunakan nya ditambah dengan fitur fitur nya yang sangat lengkap banget membuat kita semakin gampang saat menggunakan aplikasi ini aplikasi i

3) Tokenizing
Tokenizing is the process of splitting a sentence into individual words. This step uses the "tokenize" operator with the "non letters" mode. Below are Figure (5) and table (4), showing the process and results:

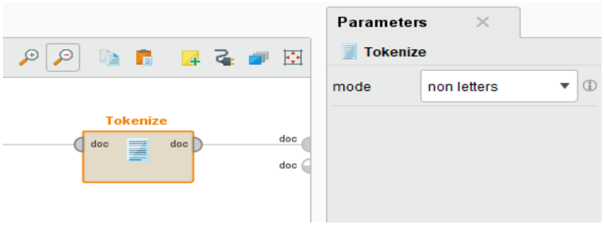

Figure 5. Tokenizing Process

Table 4. Tokenizing Results

Before	After
simpel ga ribet daftar cepet cairnya juga sangat kilat tetep yang terbaik kredivo	'simpel', 'ga', 'ribet', 'daftar', 'cepet', 'cairnya', 'juga', 'sangat', 'kilat', 'tetep', 'yang', 'terbaik', 'kredivo'

4) Stopword Removal
In this stage, frequently used words that do not add meaningful value to the classification are removed using the Stopwords Removal operator. Examples of stop words in Indonesian include "yang", "dari", "di", "dan", "adalah", etc. In this study, a stopword list available at Kaggle was used. Below are the images and table showing the results of this step:

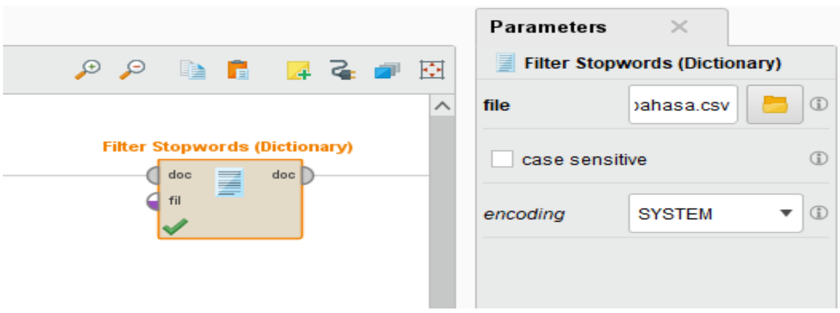

Figure 6. Stopword Removal Process

Table 5. Stopword Removal Results

Before	After
awal bukanlah akhir yah friend makin bagus terutama setelah di update berulang ulang yang awal nya terlalu banyak bugs sistem yang error lama kelamaan sudah mulai berkurang dan hilang tidak dia dia membuang data internet untuk mendownload aplikasi pinj	yah friend bagus update berulang ulang nya bugs sistem error berkurang hilang membuang data internet mendownload aplikasi pinj

5) Filter Tokens
This step involves removing tokens (or words) based on length using the Filter Tokens (by Length) operator, with parameters for a minimum of 4 characters and a maximum of 25 characters. Below are figure (7) and table (6), showing the process and results of filtering:

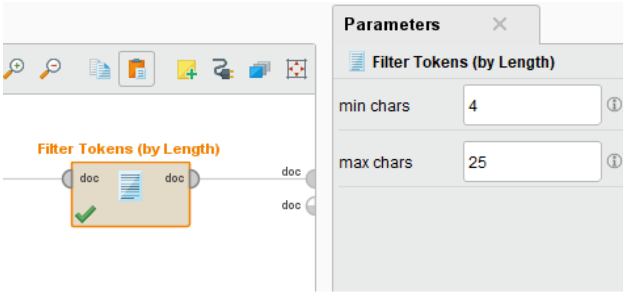

Figure 7. Token Filter Process

Table 6. Filter Tokens Results

Before	After
yah friend bagus update berulang ulang nya bugs sistem error berkurang hilang membuang data internet mendownload aplikasi pinj	friend bagus update berulang ulang bugs sistem error berkurang hilang membuang data internet mendownload aplikasi pinj

3.1.4 Modelling

At this stage, modeling is done by applying the K-Nearest Neighbor algorithm. Data division is done using cross validation with a k-fold value = 2 to 10, which is dividing the overall data into 10 parts. The following modeling process can be seen in Figure 8.

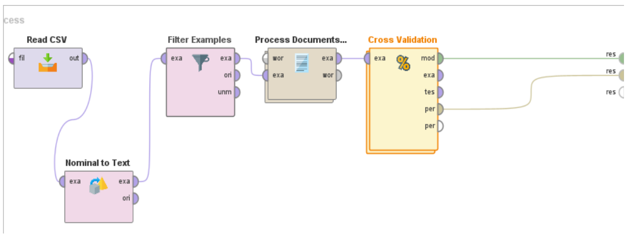

Figure 8. Cross Validation Process

In the validation subprocess there is a division of training data and testing data as in Figure 9.

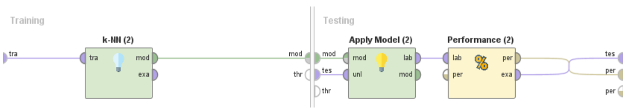

Figure 9. Subprocess Cross Validation

The results of the modeling stage using k-fold validation, the resulting accuracy values can be seen in Table 7.

Table 7. Cross Validation Results

No	K-Nearest Neighbor (Accuracy)
2	78,35 %
3	77,55 %

4	78,09 %
5	78,24 %
6	78,46 %
7	79,36 %
8	78,19 %
9	79,20 %
10	78.09 %

Based on the results of the k-fold validation experiment, it was found that K-NN had the highest accuracy value, namely 79.36% at the k-fold value number = 7 in each experiment, the positive percentage was 62.55% and the percentage was 37.45%.

3.1.5 Evaluation

The evaluation is carried out by testing using a confusion matrix to see the results of testing data obtained from the modeling stage with the K-Nearest Neighbor algorithm. The confusion matrix presented in table 4.13 is the result of the evaluation of cross validation measurements with the highest accuracy value, namely k-fold number = 7. The following results of the confusion matrix can be seen in table 8.

Table 8. Results of K-Nearest Neighbor Confusion Matrix

	True Positive	True Negative	Class Precision
pred. Positive	977(TP)	189(FP)	83,79%
pred. Negative	199(FN)	515(TN)	72,13%
Class Recall	83,08%	73,15%	

$$a. Accurary = \frac{\mathrm{TP + TN}}{\mathrm{TP + TN + FP + FN}}\ X\ 100\%$$

$$= \frac{977 + 515}{977 + 515 + 189 + 199}\ X\ 100\%$$

$$= 79{,}36\ \%$$

$$b. Recall \quad = \frac{\mathrm{TP}}{\mathrm{TP + FN}}\ X\ 100\%$$

$$= \frac{977}{977 + 199}\ X\ 100\%$$

$$= 83{,}08\ \%$$

$$c. Precision = \frac{\mathrm{TP}}{\mathrm{TP + FP}}\ X\ 100\%$$

$$= \frac{977 + 515}{977 + 515 + 189 + 199}\ X\ 100\%$$

$$= 79{,}36\ \%$$

$$d. Specificity = \frac{\mathrm{TN}}{\mathrm{TN + FP}}\ X\ 100\%$$

$$= \frac{515}{515 + 189}\ X\ 100\%$$

$$= 73{,}15\ \%$$

Based on the table calculation, it can be concluded that precision shows the level of accuracy of data predicted to be positive against the amount of data that is correctly predicted to be positive, resulting in a percentage of accuracy of 83.79% and for negative sentiment data, it has a precision of 72.15%. For positive sentiment, it has a recall of 83.08%, so it can be concluded that the model can find back information or data that is truly positive well, and for negative sentiment, it has a recall (Specificity) of 73.15%, this is also quite good that the model can find back information data that is truly negative. The accuracy value produced using the K-Nearset Neighbor algorithm with a k-fold validation model, k-fold number = 7 and k = 10 is 79.36%, so it can be concluded that the K-Nearest Neighbor algorithm can classify sentiment well using review data on users of the credit application.

3.1.6 Deployment

At this stage, a better model is run based on the previous evaluation stage to determine the results of the sentiment analysis in the form of the number of positive sentiments and negative sentiments [2].

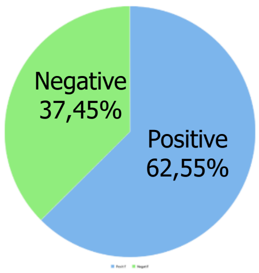

Figure 10. Visualization with Pie Chart

The results of modeling with cross validation of user sentiment of the Kredivo application with a total of 1880 data used. The diagram in the form of a pie chart visualization in the image shows that 62.55% of users gave positive reviews and 37.45% gave negative reviews of the Kredivo application. The following is a wordcloud visualization for the appearance of words in the positive and negative sentiment classes in Figure 11.

Figure 11. Positive Class WordCloud

Referring to Figure 11, 10 words can be produced that frequently appear in positive sentiment, namely the word "kredivo", "membantu", "aplikasi", "limit", "mudah", "cepat","bayar", "bagus", "pinjaman", dan "bunga".

Figure 12. Negative Class WordCloud

Referring to Figure 12, 10 words were found that frequently appeared in negative sentiment, namely the word "kredivo", "bayar", "limit", "transaksi", "aplikasi", "telat", "pembayaran", "akun", "tagihan", "udah". Based on the results of Figures 11 and 12, it can be concluded that the word "Kredivo" appears frequently and is the word most used by users to provide reviews of the Kredivo application on the Google Play Store.

3.1.7 Final Test Results

This study uses the CRISP-DM (Cross-Industry Standard Process for Data Mining) model, and the algorithm used in this study is K-Nearest Neighbor. From the evaluation of the performance of the confusion matrix with 1880 review data and divided into training data and testing data using the cross-validation model, the results obtained were an accuracy value of 79.36%, with a recall value of 83.08%, precision 72.15%, and recall (Specificity) 73.15%. so, it can be concluded that the K-Nearest Neighbor algorithm can classify sentiment well using review data on users of the Kredivo application.

3.2 Discussion

From the test results using cross-validation with k-fold values 2 to 10, the highest accuracy was obtained in k-fold number 7 with an accuracy value of 79.36%. This value shows that the K-NN algorithm has succeeded in classifying the sentiment of Kredivo application users with a high level of accuracy. These results are in line with previous studies showing that the K-NN algorithm can be used effectively in sentiment analysis on mobile applications, as found in research by Syafrizal *et al*. (2024), who used the K-NN algorithm for sentiment analysis on the PLN Mobile application, which also showed good accuracy [4]. However, although the accuracy obtained is quite high, there is a difference between precision and recall for positive and negative sentiments. Precision for positive sentiment reached 83.79%, while for negative sentiment it was only 72.13%. This shows that the model is better at classifying positive reviews accurately than negative reviews. However, recall for positive sentiment (83.08%) shows that the model can identify most of the positive reviews well. On the other hand, the recall for negative sentiment is 73.15%, which also shows that this model is quite effective in detecting negative reviews, although there are still some negative reviews that are not detected. This result is consistent with the findings of a study by Ahmad (2023), which also showed that although the K-NN algorithm is effective for sentiment analysis, there are challenges in classifying reviews with negative sentiment with high precision [7]. This difference in performance between positive and negative sentiments could be due to the imbalance in the number of positive and negative reviews, which is more on the positive side.

Model evaluation was performed using a confusion matrix that shows the test results of the K-NN model. Based on the confusion matrix results table, the model successfully classified 977 positive reviews correctly (True Positive/TP) and 515 negative reviews correctly (True Negative/TN). However, there were also 189 positive reviews that were misclassified as negative (False Positive/FP) and 199 negative reviews that were misclassified as positive (False Negative/FN). The precision value for positive sentiment of 83.79% indicates that 83.79% of all reviews predicted as positive are truly positive. While the precision for negative sentiment of 72.13% indicates that 72.13% of all reviews predicted as negative are truly negative. Despite errors in classification, the high precision value for positive sentiment indicates that the model is reliable in identifying truly positive reviews. Recall for positive sentiment (83.08%) indicates that the model successfully found most of the positive reviews, but there were some positive reviews that were not detected. On the other hand, the recall for negative sentiment is lower (73.15%) indicating that this model has limitations in detecting negative reviews perfectly. Therefore, to improve recall for negative sentiment, further research may need to consider other techniques or model parameter adjustments.

The results of sentiment visualization using a pie chart show that 62.55% of users gave positive reviews of the Kredivo application, while 37.45% gave negative reviews. These results provide an overview of the level of satisfaction of Kredivo application users, the majority of whom gave positive reviews. However, even though many reviews are positive, negative reviews reaching almost 40% are still something that application developers need to pay attention to in improving service quality. In addition, word cloud visualization provides further insight into words that often appear in positive and negative reviews. In positive reviews, words such as "kredivo", "membantu", "mudah", and "cepat" frequently appear, indicating that users appreciate the ease and speed of the application's service. On the other hand, in negative reviews, words like "bayar", "transaksi", "telat", and "tagihan" frequently appears, indicating a problem in the payment and transaction aspects that are of concern to users. The results of this sentiment analysis provide a useful picture for Kredivo application developers. Although many user reviews are positive, the issues expressed by users in negative reviews need more attention. Reviews that mention "telat", "tagihan", and "transaksi" show that there are still obstacles in the payment process and transaction management that need to be fixed. Kredivo application developers can use this information to improve features related to payments and transactions and ensure that the application can function properly in various conditions. By paying attention to negative reviews and improving the user experience in terms of transactions and payments, Kredivo can increase user satisfaction levels and reduce the number of negative reviews in the future.

Although the results of this study indicate that the K-NN algorithm is effective in classifying review sentiments, there are several limitations that need to be considered. One is the imbalance between the number of positive and negative reviews, which may affect the model's performance in classifying negative sentiment. Therefore, further research can consider using oversampling or under sampling techniques to deal with data imbalance. In addition, although K-NN produces good results, further research can try other algorithms, such as Support Vector Machine (SVM) or Naïve Bayes, to compare their performance in classifying review sentiment. By using various algorithms, it is hoped that a more accurate model can be found in classifying the sentiment of Kredivo application users.

4. Related Work

Several studies have used the K-Nearest Neighbor (K-NN) algorithm to analyze user review sentiments for various digital applications and services. For example, research by Syafrizal *et al.* (2024) on sentiment analysis of PLN Mobile application reviews using the K-NN algorithm showed very good results, with an accuracy of 90.23% [4]. This study used a dataset consisting of 90% training data and 10% test data. The evaluation results using K-NN showed high accuracy, precision, and recall, indicating that K-NN is a very effective method for analyzing sentiment in mobile application reviews [6]. In addition, Lestari and Mahdiana (2021) also conducted a similar study by applying K-NN to sentiment analysis of public reviews on Twitter regarding the ban on homecoming in 2021. In this study, K-NN produced quite good results with an accuracy of 85.6%, indicating that K-NN can be used in the context of sentiment analysis of various types of text data, including social media [6]. These results demonstrate the flexibility of K-NN in analyzing sentiment on diverse datasets, both from application platforms and social media. The K-Nearest Neighbor (K-NN) algorithm is widely used in sentiment analysis to classify user reviews on mobile applications. One relevant study is Rahayu *et al.* (2022), which applied the K-NN method to analyze sentiment towards the FLIP financial technology application. This study shows that K-NN can be used well to analyze user sentiment towards financial applications, with sufficient accuracy, demonstrating the ability of K-NN in the financial application domain [12]. In addition, Kusuma and Cahyono (2023) also used the K-NN algorithm to analyze public sentiment towards the use of e-commerce. This study indicates that K-NN can classify sentiment effectively, despite the challenges of dealing with very large and varied data [13]. Onantya and Adikara (2019) applied K-NN for sentiment analysis on BCA Mobile application reviews by combining the BM25 technique to improve the quality of text features. They found that K-NN combined with BM25 can improve performance in terms of accuracy and precision in sentiment classification [17].

Several studies also compare the performance of K-NN with other algorithms in sentiment analysis. Ramadhina and Sofian (2024) conducted a comparison between K-NN and Decision Tree in sentiment analysis of online loan application review data registered with the OJK. The results of this study indicate that K-NN has advantages in terms of accuracy and precision compared to Decision Tree, although both algorithms have good performance in classifying review sentiment. This suggests that K-NN may be a better choice in situations where accuracy and precision are important factors in sentiment analysis [2]. Research by Muhammadin and Sobari (2021) also compared various algorithms, including K-Nearest Neighbor, for sentiment analysis on the Kredivo application. This study tested the comparison between K-NN, Support Vector Machine (SVM), and Naïve Bayes Classifier (NBC), and the results showed that K-NN provided good accuracy but not as good as SVM in the context of sentiment analysis on Kredivo application reviews. This study provides a useful perspective in understanding the advantages and disadvantages of each algorithm in application sentiment analysis [1]. Muttaqin and Kharisudin (2021) compared K-NN with SVM in sentiment analysis of Gojek application reviews. They showed that although SVM gave slightly better results, K-NN was still a good choice due to its simplicity and ease of implementation [14]. Research by Indrayuni *et al.* (2021) also compared several algorithms including K-NN, Naïve Bayes, and SVM for sentiment analysis of the Halodoc application. The results showed that although K-NN gave good results, SVM was slightly superior in terms of precision and recall [15]. Firdaus (2022) used K-NN to analyze sentiment on the topic of Omicron COVID-19 on social media. The results of this study indicate that K-NN can be used to analyze sentiment related to social and health issues with a very good level of accuracy [16].

The K-NN algorithm has also been applied to other different applications to understand user sentiment. More specific research on digital financial applications has also been conducted, with results relevant to this study. Ahmad (2023) analyzed user sentiment towards online loan applications such as Kredivo and Akulaku using the Support Vector Machine (SVM) method. This study shows that although SVM has good performance in classifying sentiment, K-NN can provide competitive results, especially in terms of speed and simplicity of implementation. Thus, this study supports the selection of K-NN as a feasible algorithm for sentiment analysis on the Kredivo application, which is a digital financial application that has many users [7]. Giovani *et al.* (2020) conducted a sentiment analysis of the Ruang Guru application on Twitter using K-NN. They found that K-NN was able to produce stable and effective sentiment analysis, even on unstructured data such as tweets on Twitter [10]. Rohmansa *et al.* (2024) applied K-NN for sentiment analysis on the Discord application. This study uses the K-NN method to classify Discord application user reviews into positive and negative categories, with satisfactory results. The results of this study indicate that K-NN is very effective in processing large review data and providing accurate results in a relatively short time [18]. Salsabila *et al.* (2023) study also used K-NN for Discord application review classification. They used the Information Gain and Naïve Bayes methods together with K-NN to improve sentiment classification performance. The results of this study confirm that K-

NN can provide better results compared to several other methods, depending on the quality of the data used [11].

In addition to the K-NN algorithm, other studies also show the development of the use of other methods such as Naïve Bayes and Support Vector Machine (SVM) in sentiment analysis. Agustin *et al.* (2024) used the SVM algorithm to analyze sentiment towards the Kredivo application. The results of this study showed that SVM performed better than K-NN in terms of accuracy and recall, but K-NN remains a popular choice due to its ease of implementation and simpler tuning parameters [5]. Research by Giovani *et al.* (2020) also compared K-NN with other methods in sentiment analysis of the Ruang Guru application using Twitter. They found that K-NN provided stable results and was easy to implement on various types of platforms, while other methods such as Naïve Bayes and SVM required more adjustments in terms of parameters [10]. Several studies have also focused on sentiment analysis of digital financial applications using the K-NN algorithm. Ramadhan (2020) examined the sentiment analysis of user reviews of applications on the Google Play Store using K-NN. This study proves that K-NN is a good method for analyzing sentiment towards applications with many reviews, although there are challenges in dealing with ambiguous reviews [20].

Although K-NN has proven to be effective in sentiment analysis, several studies have shown that other techniques, such as deep learning and ensemble methods, can provide better results, especially in dealing with large and complex data. Therefore, further research can explore techniques such as Random Forest, XGBoost, or even LSTM (Long Short-Term Memory) for further sentiment analysis. Future research can also explore combining K-NN with other methods, such as transfer learning-based learning algorithms, to improve the model's understanding of more complex sentiments and finer nuances in user reviews. From existing research, it can be concluded that K-NN is one of the most effective algorithms for sentiment analysis, both in e-commerce applications, financial applications, and social applications. Although there are comparisons with other methods, K-NN remains a good choice due to its ease of implementation and adequate results. This study opens opportunities for further development, including the application of new techniques that can improve the accuracy and capabilities of the model.

5. Conclusion and Recommendations

Based on the results of the study on the analysis of Kredivo application user sentiment, it can be concluded that the K-Nearest Neighbor (K-NN) algorithm is effective for classifying sentiment in user reviews. The K-NN model produces adequate accuracy with a value of 79.36%, and its performance in classifying positive and negative sentiments can be said to be quite good. The evaluation results show that the recall reaches 83.08%, which means that this model has succeeded in identifying most of the positive reviews, but the precision for negative sentiment still needs to be improved, with a precision value of 72.15% and a specificity of 73.15%. Data visualization using a pie chart shows that most users, namely 62.55%, gave positive reviews of the Kredivo application, while 37.45% gave negative reviews, indicating that this application received a positive response from its users. In addition, visualization using Word Cloud reveals that the most frequently used word in reviews is "kredivo," which confirms that this brand is very dominant in user conversations, both in positive and negative contexts. For further development and research, there are several suggestions that can be considered. First, adding slang dictionary data in the stop word removal process is highly recommended, considering that many comments use non-standard language or informal terms, which are often unrecognizable by the model without such updates. Second, automation in sentiment labeling can improve efficiency and consistency in the data classification process. The use of more sophisticated machine learning models or deep learning techniques can be considered to achieve more accurate results. Third, for further research, it is recommended to compare the K-NN algorithm with other algorithms such as Support Vector Machine (SVM) or Naïve Bayes to evaluate which one gives the best results in sentiment analysis on Kredivo application reviews.

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