Sentiment Analysis of Indonesian Digital Payment Customer Satisfaction Towards GOPAY, DANA, and ShopeePay Using Naïve Bayes and K-Nearest Neighbour Methods

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Abstract—The utilization of different results from the pace of technological development provides a lot of convenience, benefits, and time efficiency. Now, many related companies or organizations are engaged in technology, offering various services that they have developed to meet the needs of a highly consumptive society, with different terms and conditions. There are many descriptions related to the experience of using the platform that it developed on social media, where everyone can express their feelings and opinions about something since people commonly use Twitter. This study used sentiment analysis and opinion mining to see public satisfaction with digital payment services available in Indonesia by focusing on several available services such as GOPAY, DANA, and ShopeePay. The dataset that became the source of this research was taken from Twitter data through several preparation stages, including data crawling, data cleaning, feature selection, and classification with two machine learning approaches (K-Nearest Neighbour and Naïve Bayes). The raw data held is pre-processed until making the clean data. According to the classification algorithm, a feature search is implemented in this study so that the classification process and data modeling validation provide significant results.

Keywords: Sentiment Analysis; Naïve Bayes; K-Nearest Neighbour; Machine Learning; Twitter

1. INTRODUCTION

Rapid advances in technological developments also affect all essential factors in human life [1]. Various human jobs now become easier with the help of technology. In addition, the implementation of technology into human needs makes all activities run practically and quickly, one of which is in the financial sector, where currently there are payment methods that utilize digital services [2]-[3]. In this digital economy era, the Central Bank of Indonesia involves various services that can adequately change the business model to contribute to a significant increase in inefficiency. Until 2021, several private digital payment services are commonly used in Indonesia, where this research focuses on digital financial services on GOPAY (established in mid-2016), DANA (established in 2018), and ShopeePay (established in 2018).

Moreover, along with technological developments that not only affect the financial sector but also provide a forum for the community to express themselves in a social network without limitation of place and time, currently, many social media are also being developed that facilitate this need [4]-[5]. One of them is Twitter, which allows its users to send and read messages and connect with people worldwide as one of the platforms that establishes communication with customers, the services of the three digital payments that focus in this research indeed have official Twitter accounts, including GOPAY (@gopayindonesia), DANA (@danawallet), and ShopeePay (@ShopeePay_ID). It collected the number of tweets from all Twitter accounts of the digital payment service provider with a minimum limit of 4,000 tweets and a maximum limit of 40,000 tweets. The growth of textual data sources is then broadly defined as text-based mining because we can extract information and explore interesting patterns [6]. Text mining regarding social media requires a lot of effort because the data collected often needs to be checked. After all, it is not following the appropriate vocabulary or linguistic rules [7].

Since Twitter has become a gold mine for organizations to monitor their reputations and brands, researchers have used text mining for social media sentiment analysis via Twitter. Previous research has conducted sentiment analysis through Twitter tweets to determine the level of customer satisfaction from cellular data services and adopted the Naïve Bayes classification algorithm [8]. Other researchers used sentiment analysis to classify customer reviews and implemented several machine learning-based classification algorithms such as Naïve Bayes [9]. This study found that the Naïve Bayes technique gave better results than the other two classification algorithms. Similar to the first research on social media sentiment analysis, there is an attempt to measure brand reputation based on people's responses to their service quality through customer sentiment analysis from Twitter data [10-11].

Research using this text mining technique will certainly produce sentiment analysis with good results to find out customer opinions about a brand through their tweets or other textual data sources since the research that used the algorithm classifier will show the performance of which digital payment has the best performance for the needs of customers [12-13]. However, it found some limitations because previous research used the Naïve Bayes classification algorithm to perform sentiment analysis based on Twitter data. Meanwhile, concerning digital payments in Indonesia, more attention is paid to customers' needs to use an application system in their daily lives, evaluate the performance of public services, find the relationship between characteristics and interest in using digital payments. The trend of digital payment services in Indonesia does this research to find their reputation.
among the public based on customer satisfaction with public services, where datasets are collected from Twitter and processed based on sentiment analysis [14].

2. RESEARCH METHOD

2.1 Research Model

Research-based on experimental studies to analyze customer satisfaction sentiment towards digital payment services, where the dataset taken and sourced from Twitter data, provides a lot of good responses from the community. Because it can generate wants and needs for a product, it affects the interest of an individual or group to buy the outcome [15]-[16]. We know that the K-Nearest Neighbor algorithm has a good level of precision. Meanwhile, the K-Nearest Neighbor algorithm is also implemented on the dataset to measure whether the proposed K-Nearest Neighbor method can reduce complexity when applied to big data. Based on these experiments, it can conclude that the K-Nearest Neighbor and Naïve Bayes algorithms have a reasonably high precision value.

The subject that is the focus of this research is customer satisfaction with digital payment services in Indonesia, with an emphasis on an approach known as disconfirmation of expectations [17]. This approach defines the phenomenon of customers comparing the performance of available products and services with their previous expectations or expectations. In addition, there are two other approaches, such as an approach that plays a role in investigating the confirmation and disconfirmation of expectations, concluding the direct method. The system is commonly used to provide a concise rating scale to measure the value of warranty and disconfirmation. The research model proposed in this study can be seen in Figure 1 below.

Figure 1. The proposed research model.

To provide an overview of this research at the modeling stage, the raw data is taken from Twitter. A sentiment analysis process is carried out with classification based on the K-Nearest Neighbor and Naïve Bayes algorithms before finally cross-validating to obtain the final results related to customer satisfaction data. However, in the K-Nearest Neighbor algorithm, there is no process about the feature selection stage for marking on training and testing data, as has been done by the Naïve Bayes algorithm. So that in the end, the research carried out to represent customer satisfaction with digital payment services in Indonesia is categorized as Positive, Neutral, or Negative.

2.2 Research Method

This study focuses on textual information derived from social media messages using a step-by-step methodology to filter text information to make efforts to find sentiment analysis related to the level of customer satisfaction with digital payment services in Indonesia. This research also applies a hybrid technique that combines the two main methods, K-Nearest Neighbor and Naïve Bayes, to improve the performance and accuracy of the classification results.

2.2.1 Crawling Data Twitter

Twitter data crawling is carried out to collect datasets containing tweets, retweets, quote retweets, replies, which include the keywords “gopay”, “bayar”, and “shopeepay” during the period August-October 2021. Then, the data cleaning process is carried out for the sake of facilitating the analysis process by eliminating some characters or text that are distracting and irrelevant to the information related to the keywords being searched for.

2.2.2 Naïve Bayes and K-Nearest Neighbour Methods

This research implements data classification and modeling based on the K-Nearest Neighbor and Naïve Bayes algorithms. Both algorithms have excellent performance and reliability compared to other data mining algorithms. The use of these two algorithms referred to the cross-validation technique. It is usually carried out after manual classification assessments to collect training data.

2.2.3 Testing and Evaluation

After the modeling has been developed to test the data in the previous step, further testing of the data will be carried out by applying the cross-validation technique according to the method implemented in this study.
In addition, evaluation is also carried out to prove the magnitude of the sentiment value of each digital payment, where at this evaluation stage, the accuracy value of the implemented algorithm model is also generated. In this study, the evaluation criteria considered were accuracy, recall, and precision. In addition, a confusion matrix is also generated from the results of the tests that have been carried out.

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Accuracy is the proportion of the total correct predictions for all data. Represented through the following equation.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$  \hfill (1)

Precision is a measure of the accuracy of a data modeling result. Represented through the following equation.

$$\text{Precision} = \frac{TP}{TP + FP}$$  \hfill (2)

A recall is a measure of the completeness of a data modeling result. Represented through the following equation.

$$\text{Recall} = \frac{TP}{TP + FN}$$  \hfill (3)

3. RESULT AND DISCUSSION

The research process is carried out by taking the necessary data, namely using the Twitter Data Crawling method through Twitter social media by implementing the Twint library on Python, which then collects data related to customer satisfaction statements for several digital payment services in Indonesia based on the keywords “Gopay”, “Dana”, and “Shopeepay”, during the period August-October 2021. The results of the collected tweet data are then presented in Table 1 below.

| Digital Payment | Total Data    |
|-----------------|--------------|
| Gopay           | 3167 tweets  |
| Dana            | 2202 tweets  |
| Shopeepay       | 2541 tweets  |

Based on Table 1 above, it can state that the Twitter data crawl carried out contains data related to Gopay as many as 3167 tweets, Dana as many as 2202 tweets, and Shopeepay as many as 2541 tweets, where the data taken is based on available tweets during the data collection period. After getting the data needed from the crawling process, then proceed with several processes to get the results of sentiment analysis.

3.1 Data Cleaning

The data cleaning process is carried out to delete or eliminate irrelevant and noisy tweets on the research object. Of the 3167 tweets obtained based on the results of crawling with the keyword “Gopay”, the remaining 328 tweets are relevant to research needs. Based on 2202 tweets crawled with the keyword “Dana”, the remaining 267 tweets are relevant to research needs. Meanwhile, from 2541 tweets crawled with the keyword “Shopeepay”, the remaining 327 tweets are relevant to research needs. Deleting tweets that are not relevant to the research needs will be very helpful in increasing the accuracy of the sentiment analysis carried out because the tweets that have
been cleaned, of course, only talk about the performance of the digital analyzed in this paper so that the remaining
tweets are believed to have been according to the needs of research analysis.

3.2 Data Labelling

The following process is Data Labeling, where labeling is done to clean data before implementing it in the classifier
model. Data labeling is done manually, where the author reads the data and determines whether the data is neutral,
positive, or negative. Data labeling serves to train machine learning.

Based on the keyword “Gopay”, from 328 tweets, 100% of the tweets (328 tweets) were labeled as neutral,
positive, or negative. Then, based on the keyword “Dana”, from 238 tweets, 100% of the tweets (238 tweets) were
labeled as neutral, positive, or negative. Meanwhile, based on the keyword “Shopeepay”, from 327 tweets, 99.69% (326 tweets) were labeled as neutral, positive, or negative. Then, as much as 10% of the overall data will be used
as testing data, where the data is used to measure the extent to which the accuracy of the implemented classifier
can provide accurate classification results.

3.2.3 Sentiment Analysis Process

The sentiment analysis process in this study uses the RapidMiner application, where the stages of the process are
presented in Figure 2 below.

![Figure 2. Sentiment Analysis Process](image)

Labeling of available datasets is done manually with the categories “Neutral”, “Positive”, and “Negative”. Data related to the number of tweets containing the sentiment category are presented in Table 2 and Figure 3 below.

| Digital Payment | Sentiment |          |          |          |
|-----------------|-----------|----------|----------|----------|
| GOPAY           | Positive  | Neutral  | Negative |
|                 | 181       | 91       | 56       |
| DANA            | 85        | 84       | 69       |
| ShopeePay       | 113       | 146      | 67       |

![Table 2. Sentiment Towards 3 Digital Payment Dataset.](image)

![Figure 3. Sentiment Towards 3 Digital Payments.](image)
Based on searches containing the keywords "Gopay", "Dana", and "ShopeePay", there are several dominant words that often appear, shown in Figure 3. The larger the word size, the more these words appear and are discussed. Of all the datasets collected regarding this study’s needs, ten words with a high occurrence rate are presented in Table 3.

Table 3. Dominant Words from Word Cloud Related to All Digital Payments (in Bahasa).

| Words | Total |
|-------|-------|
| bayar | 252   |
| dana  | 231   |
| pake  | 80    |
| kalo  | 26    |
| beli  | 15    |
| spay  | 15    |
| pakai | 14    |
| butuh | 12    |
| udah  | 12    |
| gitu  | 10    |

Figure 4. Dominant Words from Word Cloud Related to All Digital Payments (in Bahasa).

3.2.4 Testing Methods

Based on the sentiment analysis that has been done, the datasets are implemented in the Naïve Bayes and K-Nearest Neighbor methods. This test is carried out through cross-validation, where each dataset is tested independently and gradually into the technique applied in this study.

By implementing the Naïve Bayes and K-Nearest Neighbor algorithms on the dataset that is the subject of this research, it is then possible to know the evaluation results of each method tested in this study. Each analyzed dataset contains the values of Accuracy, Precision, and Recall to state how much the value of each sentiment category is, which is processed through machine learning.

Figure 5. Sentiment Analysis Testing.

3.2.4.1 Naïve Bayes

In connection with testing by implementing machine learning, we later discovered that the accuracy of testing with the Naïve Bayes method on the GOPAY dataset was 27.15%. Each value of Precision and Recall related to testing with the dataset is presented in Table 4 and represented in Figure 3.

Table 4. Testing Accuracy with the Naïve Bayes Method on the GOPAY Dataset.

|         | true Negative | true Positive | true Neutral | Class Precision |
|---------|---------------|---------------|--------------|-----------------|
| pred. Negative | 55            | 157           | 73           | 19.30%          |
| pred. Positive  | 1             | 20            | 4            | 80.00%          |
The accuracy of testing using the Naïve Bayes method on the DANA dataset is 29.86%. Each value of Precision and Recall related to testing with the dataset is presented in Table 5 and represented in Figure 4.

**Table 5.** Testing Accuracy with the Naïve Bayes Method on the DANA Dataset.

|                | true Negative | true Positive | true Neutral | Class Precision |
|----------------|---------------|---------------|--------------|-----------------|
| pred. Negative | 2             | 0             | 1            | 66.67%          |
| pred. Positive | 82            | 69            | 84           | 29.36%          |
| pred. Neutral  | 0             | 0             | 0            | 0.00%           |
| class recall   | 2.38%         | 100.00%       | 0.00%        |

The accuracy of testing using the Naïve Bayes method on the ShopeePay dataset is 30.40%. Each value of Precision and Recall related to testing with that dataset is presented in Table 6 and represented in Figure 5.

**Table 6.** Testing Accuracy with the Naïve Bayes Method on the ShopeePay Dataset.

|                | true Negative | true Positive | true Neutral | Class Precision |
|----------------|---------------|---------------|--------------|-----------------|
| pred. Negative | 65            | 124           | 89           | 23.38%          |
| pred. Positive | 2             | 16            | 6            | 66.67%          |
| pred. Neutral  | 0             | 6             | 18           | 75.00%          |
| class recall   | 97.01%        | 10.96%        | 15.93%       |

Figure 3. Accuracy Testing with Naïve Bayes Method on the GOPAY Dataset.

Figure 4. Testing Accuracy with the Naïve Bayes Method on the DANA Dataset.

Figure 5. Testing Accuracy with the Naïve Bayes Method on the ShopeePay Dataset.
3.2.4.1 K-Nearest Neighbour

In connection with testing by implementing machine learning, we later discovered that the accuracy of testing with the Naïve Bayes method on the GOPAY dataset was 27.15%. Each value of Precision and Recall related to testing with the dataset is presented in Table 4 and represented in Figure 3.

Testing with similar stages to the Naïve Bayes method were also carried out by applying the K-Nearest Neighbor algorithm, where we also found that the test using the K-Nearest Neighbor method on the ShopeePay dataset had a value of 32.68%, where each value of Precision and Recalls related to testing with the dataset are presented in Table 7 and represented in Figure 6.

Table 7. Testing Accuracy with the K-Nearest Neighbour Method on the GOPAY Dataset.

| Class      | pred. Negative | true Positive | true Neutral | Class Precision |
|------------|----------------|---------------|--------------|-----------------|
| pred. Negative | 44             | 128           | 58           | 19.13%          |
| pred. Positive  | 12             | 49            | 19           | 61.25%          |
| pred. Neutral   | 0              | 4             | 14           | 77.78%          |
| class recall    | 78.57%         | 27.07%        | 15.38%       |

Figure 6. Testing Accuracy with the K-Nearest Neighbour Method on the GOPAY Dataset.

Testing with similar stages to the Naïve Bayes method were also carried out by applying the K-Nearest Neighbor algorithm, where we also found that the test using the K-Nearest Neighbor method on the ShopeePay dataset had a value of 32.68%, where each value of Precision and Recalls related to testing with the dataset are presented in Table 8 and represented in Figure 7.

Table 8. Testing Accuracy with the K-Nearest Neighbour Method on the DANA Dataset.

| Class      | pred. Negative | true Positive | true Neutral | Class Precision |
|------------|----------------|---------------|--------------|-----------------|
| pred. Negative | 84             | 69            | 85           | 35.29%          |
| pred. Positive  | 0              | 0             | 0            | 0.00%           |
| pred. Neutral   | 0              | 0             | 0            | 0.00%           |
| class recall    | 100.00%        | 0.00%         | 0.00%        |

Figure 7. Testing Accuracy with the K-Nearest Neighbour Method on the DANA Dataset.

Testing with similar stages to the Naïve Bayes method were also carried out by applying the K-Nearest Neighbor algorithm, where we also found that the test using the K-Nearest Neighbor method on the ShopeePay dataset had a value of 32.68%, where each value of Precision and Recalls related to testing with the dataset are presented in Table 9 and represented in Figure 8.
Table 9. Testing Accuracy with the K-Nearest Neighbour Method on the ShopeePay Dataset.

| true Negative | true Positive | true Neutral | Class Precision |
|---------------|---------------|--------------|-----------------|
| pred. Negative | 51            | 101          | 70              | 22.97% |
| pred. Positive | 16            | 39           | 25              | 48.75% |
| pred. Neutral  | 0             | 6            | 18              | 75.00% |
| class recall   | 76.12%        | 26.71%       | 15.93%          |

Figure 8. Testing Accuracy with the K-Nearest Neighbour Method on the ShopeePay Dataset.

Table 10. Comparison of the Accuracy of Sentiment Analysis Results from Naïve Bayes and K-Nearest Neighbor Methods.

| Methods                | Digital Payment |             |
|------------------------|-----------------|-------------|
|                        | GOPAY | DANA | ShopeePay |
| Naïve Bayes            | 27.15% | 29.86% | 30.40% |
| K-Nearest Neighbour    | 32.68% | 35.31% | 33.12% |

Based on the description of the testing of the two methods for each digital payment that is the focus of this research, the following is the Accuracy value of each of the tests carried out. It can be seen in Table 10, that overall, the implementation of the K-Nearest Neighbor method in sentiment analysis related to digital payments in Indonesia provides better accuracy results than the Naïve Bayes method. In the test using the K-Nearest Neighbor method, the accuracy value on GOPAY is 32.68%, DANA is 35.31%, and ShopeePay is 33.12%.

4. CONCLUSIONS.

Technology implementation has moved quite widely in human life, especially in Indonesia. We can carry out various activities with the help of technology, one of them is about payments, which can now be done by applying for technological advances. In Indonesia, many digital payments are commonly used, such as GOPAY, DANA, and ShopeePay, which are the main focus of this study. Expressions of satisfaction with the use of each platform are widely contained through the Twitter dataset, which later becomes a medium for data collection. Based on the testing method implemented in this study, we found that the K-Nearest Neighbor algorithm can provide better accuracy values than the Naïve Bayes algorithm. Based on the implementation of the K-Nearest Neighbor method, we later discovered that in Indonesia, the public generally gives a better rating in terms of user satisfaction with features and ease of application, which GOPAY, ShopeePay, and DANA own, respectively.

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