

Sentiment Analysis Of Public Comments On Quick Response Code Indonesian Standard (Qris) On Twitter Social Media Using The Naïve Bayes Classifier Method

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Abstract

Nowadays, technological developments have an inevitable impact on various aspects of human life. One real example of the development of E-Wallet which is very easy to access on a smartphone. However, the large variety of e-wallets available can be confusing for users because they need to download and manage many applications on their cellphones, therefore Bank Indonesia has found a solution for faster retail transactions, namely with a QR code or known as a Quick Response Code Indonesian Standard (QRIS). The use of QRIS has become a positive trend in the business and consumer world, this is due to the benefits of more efficient non-cash transaction processing. Even though QRIS is considered easy to use and brings benefits to many parties, not everyone responds positively. Some people also have negative comments regarding the QRIS payment system. To see their various views and opinions regarding the implementation of QRIS, researchers took one of the social media platforms, namely Twitter. Therefore, a public sentiment analysis was carried out to understand how the public responded to QRIS, whether it included positive or negative sentiment? In order to achieve this goal, researchers use the Naïve Bayes Classifier method, where this method analyzes a problem with a good level of accuracy and can help in evaluating concerns that need to be corrected, in order to obtain appropriate and accurate comparison results of negative and positive sentiment in analyzing sentiment. public comments on QRIS on Twitter social media using the Naïve Bayes Classifier method.

Keywords: Naïve Bayes Classifier, Comments, QRIS

1. Introduction

Technological advances have provided great opportunities in various fields, such as transportation, information, education and shopping. One real example of technological developments that have had a big impact is the existence of e-wallets which can now be accessed and used easily via smartphone.

In the field of transportation, technology has brought innovations such as ridesharing applications which allow us to quickly and easily get transportation. This technology also allows us to monitor traffic in real-time, find the best route, and avoid traffic jams

In the information sector, the internet and the development of social media have provided unlimited access to information and communication. We can easily access news, articles and other resources from all over the world [1].

In education, technology has opened the door to online learning, allowing access to a variety of courses and learning resources from anywhere. It also gives flexibility to students to study according to their own schedule [2]. Meanwhile, the development of e-wallets is a very concrete example of how technology has made daily activities easier. E-wallets allow us to make payments, transfer money, and even shop easily and quickly using smartphones. This has reduced dependence on cash and accelerated the transaction process, making the shopping and transaction experience more efficient and convenient.

However, one challenge that arises is the large variety of e-wallets available in Indonesia. This can be confusing for users as they need to download and manage multiple

apps on their phones. In overcoming this problem, Bank Indonesia has sought a solution by proposing a new strategy to process retail transactions more quickly and reduce dependence on cash. One of the approaches introduced is the use of QR codes, known as Quick Response Code Indonesian Standard (QRIS).

QRIS, or Quick Response Code Indonesian Standard, is a QR code standard developed by Bank Indonesia and the Indonesian Payment System Association (ASPI) to facilitate digital transactions via server-based electronic money applications or mobile banks. With the adoption of QRIS, Bank Indonesia is trying to create a more integrated and efficient digital transaction ecosystem in Indonesia. It also helps improve financial accessibility, reduce the need for cash, and promote financial inclusion across the country. In future developments, the use of QRIS is expected to make a positive contribution to economic growth and transformation of the way Indonesian people transact.

Research conducted by Setiawan and Mahyuni [3] showed that the use of QRIS allows providers of goods and services (merchants) to accept payments without the need to have different types of QR codes for each existing e-wallet [4]. The use of QRIS helps MSMEs (Micro, Small and Medium Enterprises) improve their businesses, as it helps in accepting digital payments easily and expands customer reach.

Even though QRIS is considered easy to use and brings benefits to many parties, not everyone responds positively to it. Some people have negative comments regarding the QRIS payment system. Some of them may have doubts or concerns about the security of transactions, while others may feel less comfortable with technological changes in their daily lives.

Twitter is a social media platform that is currently very popular in Indonesia. The presence of Twitter as a broad communication channel allows people to share their views and opinions on various topics, including the implementation of QRIS [5]. Therefore, analyzing public sentiment is an important step. It is important to understand how people respond to QRIS, whether with positive or negative sentiment. The method involves counting the number of positive and negative words contained in each opinion piece. If the opinion has more positive words, then the sentiment is considered positive, but if the number of negative words is more dominant, then the sentiment is considered negative.

By conducting sentiment analysis of public opinion on Twitter [6]. Regarding QRIS, we can measure public responses in more detail. This helps in evaluating the effectiveness and acceptability of QRIS implementation as well as identifying issues or concerns that need to be addressed. This research aims to analyze public opinion sentiment regarding the implementation of QRIS as a payment method in Indonesia, especially via the social media platform Twitter. Which will be applied with the help of the Naïve Bayes method in analyzing public comments on QRIS and can produce accuracy values in this sentiment analysis.

Thus, the use of the Naïve Bayes method [7] In this research provides a solid foundation for analyzing public sentiment regarding QRIS on the Twitter platform. It is hoped that the results of this analysis will provide valuable insight into how society responds to the implementation of QRIS as a payment method, and in doing so, can help stakeholders make more informed decisions and policies. In addition, this method also shows great potential in processing large and diverse data for sentiment analysis purposes.

2. Research Methodology

2.1. Research Stages

In this research, there are several sequences or stages of the process that will be carried out in this research. This stage is an illustration of researchers to solve the problems discussed previously

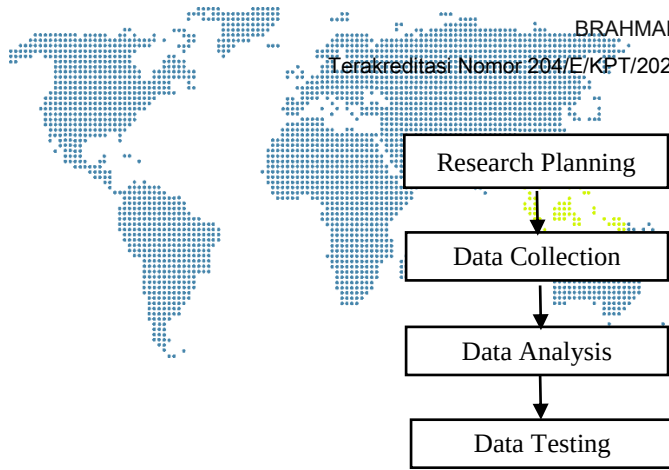


Figure 1. Research Framework

Based on the framework above, several stages can be described as follows:

The first step in the work process is collecting literature, identifying problems and collecting comments from Twitter social media accounts. by using data crawling techniques. Then labeling will be carried out to get the sentiment of the comments obtained.

Next, the preprocessing stage is carried out, the next step is to carry out feature extraction to simplify the process of leaning naïve Bayes classifier. The next step is a very important step, namely carrying out the naïve Bayes classifier process. Then the next stage is model testing, namely the stage to measure the performance value of the classification that has been carried out. After the model test has been completed, the model is then evaluated by looking at the level of accuracy of the method through the confusion matrix and accuracy table for each model.

2.2. Discussion Plan

This stage is a process for grouping tweet data into previously defined categories. The classification process in this research uses the Naive Bayes algorithm. The data that will be classified is tweet data or positive or negative opinions that have passed the data processing stages. The process that will be followed is determining features, extracting features, and classifying them according to the model that has been created. This process will provide classification results, namely positive or negative according to the data model that has been created.

To classify sentiment, using data from preprocessing to word weighting with Tf-Idf. After the training data has been successfully processed, the test data is used to test the accuracy of the classification carried out. The final result of the process obtained from the classification will be a prediction of positive and negative sentiment in the form of a confusion matrix and classification report whose contents are precision accuracy, recall, and f1 score [8] as a result of the classification process.

2.3. Naïve Bayes Classifier

Naïve Bayes is an algorithm from machine learning. In database development, Naïve Bayes includes supervised learning, namely a type of machine learning that requires samples as training data that have labels. Supervised learning is grouped into two, namely classification and regression. [9] Classification at the time of variables into categories such as red or yellow, disease or no disease, and so on. Regression when the variables are real values such as weight, money value, and so on. Naïve Bayes includes supervised learning classification like other examples, namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Artificial Neural Network (ANN), Trees Gradient Boosted (TGB), and Random Trees (RT) while regression is like Decision Tree , Logistic Regression, and Kernel Regression.

Bayes' theorem is pattern recognition through a fundamental statistical approach. Bayes' theorem can be described as the probability of relationship A occurring provided relationship B has occurred, and vice versa. In the field of modern medicine, Bayes' theorem is often used. Bayes' theorem plays a role in improving probability calculations by utilizing additional information data. The following is the Bayes theory equation [10]:

$$P(X|Y)(Y) = \frac{P(X|Y)(Y)}{P(X)} \quad (1)$$

Where:

- X = unknown data class
- Y = as a hypothesis for a specific class
- P (Y|X) = probability of hypothesis Y based on condition X
- P(Y) = probability corresponding to hypothesis X
- P (X|Y) = probability of X condition based on hypothesis Y
- P(X) = probability Y

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3. Results And Discussion

3.1. Discussion

A. Data Retrieval

The data retrieval process will apply data crawling techniques, which is an automatic method of retrieving data from certain websites or applications using certain keywords. In this research, the data crawling process will be carried out using the Python and Node.js programming languages, with the addition of the tweet-harvest package.

In collecting sentiment data in this research, several keywords related to the QRIS payment method were used, such as "QRIS technology", "QRIS security", "QRIS payment", and other keywords. The tweet data taken is the result of user activity from June 2023 to January 2024. In total, there are 636 user tweet data which will be used as material for analyzing public sentiment towards the QRIS payment method. The crawl results consist of 6 columns. The following is some data has been obtained from the data crawling process:

Table 1. Data Crawling Result

Created_At	Full_Text	Username
Wed Jan 17	@flip_id Tahun baru saatnya membuat resolusi baru yang lebih baik dari tahun sebelumnya. Hidup sehat jadi prioritas di tahun ini, rutin jogging pagi semoga bisa terlaksana. Tahun baru tentu teknologi semakin canggih, dimana2 ada QRIS,bayar pakai QRIS @flip_id lebih praktis & banyak untung	D17_jogja
Tue Jan 16	@Pai_C1 The real sampah masyarakat dam benalu. Udik sih udik aja, tapi jangan ganggu kemajuan teknologi. Lu menolak QRIS karena ga bs lagi korupsi kan ðŸ—¿	SoniJPKus uma
Mon Jan 15	@Pai_C1 Engga usah tanggepin teruskan untuk pake qris untuk metode pembayaran, lagaian kok engga mau berubah ke arah yg lebih baik masih betah aja engga mau ikutin perkembangan teknologi	najaejae14 1402
Mon Jan 15	Kemajuan teknologi perlahan kerjaan jukir hilang, Pemerintah tidak bisa	Hamdie19

Created At	Full Text	Username
	mencarikan pekerjaan pengganti. Bukan suudzon tapi kalo apa2 susah ya mungkin impact nya kriminalitas meningkat. Lebih setuju ada jukir atau tanpa jukir bayar via qris?	

B. Data Preprocessing

In text mining, there are several preprocessing steps that must be carried out, including cleaning, tokenization, case folding, and stopwords removal.

1. Cleaning

The tweet data contained in table 1 is still not organized and is difficult for the system to understand when conducting sentiment analysis. Therefore, a cleaning stage was carried out to remove hashtags, mentions, retweets, extra spaces, symbols, unicode, URLs and other elements.

2. Tokenize

After carrying out the cleaning stage, the next step is to carry out the tokenization or tokenization process. This process is carried out to break sentences into chunks of words or tokens. The tokenize process is carried out using operators in the rapid miner by adding a text processing extension. This operator will be very helpful and make the tokenization process easier.

3. Case Folding

The next step is to carry out the process of changing uppercase letters to lowercase (lowercase) for each word that has been tokenized. With the case folding process, there will be no data redundancy that only differs in the letters. The case folding process is carried out using the transform case operator on the rapid miner.

4. Stopword Removal

Stopword removal is a process carried out to delete words that do not have value such as 'and', 'which', 'in', 'for', and others. These words were deleted because their use was deemed not to affect the sentiment of a sentence. The list of stopwords that will be deleted will be taken from the existing dataset on the Kaggle site. Next, the stopwords removal process will be used using the stopwords filter operator in the rapid miner.

C. Data Labeling

After successfully collecting and processing the data, the next step is to label each dataset. The labeling process is carried out manually by dividing it into two classes, namely positive and negative sentiment. With the data labeling process, the existing dataset can then be applied to a sentiment classification model using the Naive Bayes method. The following are several examples of labeling existing datasets:

Table 2. Dataset Labeling

Dataset	Kelas
tahun baru saatnya membuat resolusi baru yang lebih baik dari tahun sebelumnya hidup sehat jadi prioritas di tahun ini rutin jogging pagi semoga bisa terlaksana tahun baru tentu teknologi semakin canggih dimana2 ada qris bayar pakai qris lebih praktis amp banyak untung	Positif
the real sampah masyarakat dam benalu udik sih udik aja tapi jangan ganggu kemajuan teknologi lu menolak qris karena ga bs lagi korupsi kan	Positif
engga usah tanggepin teruskan untuk pake qris untuk metode pembayaran lagaian kok engga mau berubah ke arah yg lebih baik masih betah aja engga mau ikutin perkembangan teknologi	Positif
perlahan kerjaan jukir hilang pemerintah tidak bisa mencari pekerjaan pengganti bukan suudzon tapi kalo apa2 susah ya mungkin impact nya kriminalitas meningkat mending gausah pakai qris	Negatif
kira bisa bayar pake cash padahal sekarang naik bus di bandung udah gabisa bayar cash mana ga ngerti qris mungkin butuh waktu lebih lama kali yaaa supaya masyarakat terbiasa tapi kalo masyarakat kecil atau orang tua yang ga ngerti teknologi susah juga tapcash juga	Negatif

There are 636 rows of data in this research's sentiment dataset. Where the sentiment labeling results obtained were 330 data which was negative sentiment and 306 data which were positive sentiment. Furthermore, this dataset, which totals 636 data, will be divided into two parts, namely training and testing data which will be used in implementing the sentiment analysis model with Naive Bayes.

D. Manual Naive Bayes calculations

The process of weighting words for each document obtained from comment data will later be able to help in the classification process with the Naive Bayes algorithm. In the process of giving weight to existing words, the TF-IDF (Term Frequency – Inverse Document Frequency) method is used. The following is an example of TF-IDF calculation on some existing comment data.

Table 3. Comment Data

Doc 1 (positif)	canggih bayar praktis untung
Doc 2 (positif)	metode pembayaran berubah baik perkembangan
Doc 3 (negatif)	bayar cash ngerti butuh waktu lama masyarakat terbiasa susah
Doc 4 (negatif)	kebijakan minimal susah pengguna teknologi terkini

The next step is to carry out TF-IDF calculations to assign a weight value to each word in the document. The Tf value is obtained by calculating the frequency of words in a document. Meanwhile, the IDF value is obtained using the equation below:

$$IDF = \log\left(\frac{N}{dft}\right) \quad (2)$$

The resulting weight value for each document is obtained by multiplying the TF and IDF values obtained.

Table 4. TF and IDF Calculating Results

Term	TF				Doc Freq (dft)	IDF
	Doc 1	Doc 2	Doc 3	Doc 4		
canggih	1	0	0	0	1	0,602
Bayar	1	0	1	0	2	0,301
praktis	1	0	0	0	1	0,602
untung	1	0	0	0	1	0,602
metode	0	1	0	0	1	0,602
pembayaran	0	1	0	0	1	0,602
berubah	0	1	0	0	1	0,602
Baik	0	1	0	0	1	0,602
perkembangan	0	1	0	0	1	0,602
Cash	0	0	1	0	1	0,602
Ngerti	0	0	1	0	1	0,602
Butuh	0	0	1	0	1	0,602
Waktu	0	0	1	0	1	0,602
Lama	0	0	1	0	1	0,602
masyarakat	0	0	1	0	1	0,602
terbiasa	0	0	1	0	1	0,602
Susah	0	0	1	1	2	0,301
kebijakan	0	0	0	1	1	0,602
minimal	0	0	0	1	1	0,602
pengguna	0	0	0	1	1	0,602
terkini	0	0	0	1	1	0,602
Total Doc (N)	4					
Total Kata (V)	21					

The IDF value is obtained using the equation below.

$$IDF_{canggih} = \log\left(\frac{N}{dft}\right) = \log\left(\frac{4}{1}\right) = 0,602$$

Next, manual calculations are carried out using the Naive Bayes algorithm, namely calculating the prior probability values on the existing sample data. The following equation is used:

$$p(x) = \frac{\text{Jumlah Dokumen dengan kelas } x}{\text{Total Jumlah Dokumen}} \quad (3)$$

The following are the results of probability calculations for each class in the sample data. Where from the sample data used there are 2 documents with positive sentiment and 2 documents with negative sentiment.

$$p(\text{Positif}) = 2/4 = 0,5$$

$$p(\text{Negatif}) = 2/4 = 0,5$$

The following is an example of a calculation to calculate the likelihood probability value for each word in document 1. Where the words in document 1 are "sophisticated", "pay", "practical", "profit".

Positive Probability of Each Word

Total weight of positive sentiment documents = WD1 + WD2 = 2.107 + 3.01 = 5.117

$$p(\text{canggih}|\text{positif}) = \frac{0,602+1}{5,117+12} = 0,0613$$

$$p(\text{bayar}|\text{positif}) = \frac{0,301+1}{5,117+12} = 0,0498$$

$$p(\text{praktis}|\text{positif}) = \frac{0,602+1}{5,117+12} = 0,0613$$

$$p(\text{untung}|\text{positif}) = \frac{0,602+1}{5,117+12} = 0,0613$$

Negative Probability of Each Word

Total weight of negative sentiment documents = WD3 + WD4 = 4,816 + 2,709 = 7,526

$$p(\text{canggih}|\text{negatif}) = \frac{0+1}{7,526+12} = 0,0351$$

$$p(\text{bayar}|\text{negatif}) = \frac{0,301+1}{7,526+12} = 0,0456$$

$$p(\text{praktis}|\text{negatif}) = \frac{0+1}{7,526+12} = 0,0351$$

$$p(\text{untung}|\text{negatif}) = \frac{0+1}{7,526+12} = 0,0351$$

Class Probability in Document 1 Positive class

$P(\text{"canggih bayar praktis untung"} | \text{positif}) = P(\text{canggih} | \text{positif}) \times P(\text{bayar} | \text{positif}) \times P(\text{praktis} | \text{positif}) \times P(\text{untung} | \text{positif}) \times P(\text{positif})$

$$P(\text{Dok1} | \text{positif}) = 0,0613 \times 0,0498 \times 0,0613 \times 0,0613 \times 0,5 = 0,0000057$$

Negative class

$P(\text{"canggih bayar praktis untung"} | \text{negatif}) = P(\text{canggih} | \text{negatif}) \times P(\text{bayar} | \text{negatif}) \times P(\text{praktis} | \text{negatif}) \times P(\text{untung} | \text{negatif}) \times P(\text{negatif})$

$$P(\text{Dok1} | \text{positif}) = 0,0351 \times 0,0456 \times 0,0351 \times 0,0351 \times 0,5 = 0,00000098$$

Based on the calculation results above, it was found that the positive class probability value in document 1 was greater than the negative class probability value. Therefore document 1 is classified into the positive sentiment class category.

3.2. Application of the Naive Bayes Model

The first step that will be taken is to import the crawling data that has been collected previously

Index	Label	Text
1	Positif	Takut baru adalah masalah yang dihadapi oleh banyak orang. Hal ini disebabkan oleh banyak faktor, salah satunya adalah ketakutan yang berlebihan. Takut baru...
2	Negatif	Hal ini disebabkan oleh banyak faktor, salah satunya adalah ketakutan yang berlebihan. Takut baru adalah masalah yang dihadapi oleh banyak orang...
3	Positif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
4	Negatif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
5	Positif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
6	Negatif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
7	Positif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
8	Negatif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
9	Positif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
10	Negatif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
11	Positif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
12	Negatif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
13	Positif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
14	Negatif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
15	Positif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
16	Negatif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...
17	Positif	Salah satu penyebab dari ketakutan baru adalah kurangnya pengetahuan tentang hal-hal yang baru. Oleh karena itu, penting untuk meningkatkan pengetahuan...

Figure 2. Dataset Import Results

The next stage is to change the full_text attribute into text form using the nominal to text operator.

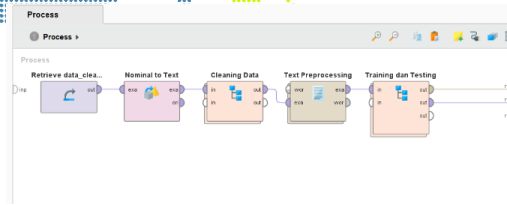


Figure 3. Analysis model design

The next step is to connect the prediction results into a performance operator to measure the classification performance of the model that has been built.

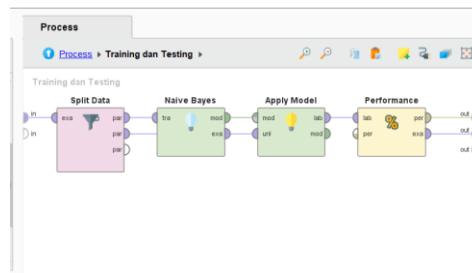


Figure 4. Process Training and Testing

A. Model Performance

The next step is to calculate accuracy by applying test data to the model. Accuracy calculations are carried out using a confusion matrix which will compare the model prediction results with the actual classes in the test data.

Row No.	Label	prediction	test	confidence	confidence	amin	akutal	shang	sham
1	MFATP	POSTP	peraturan kecapan pada tiling persendirian mencirikan perangka	1	0	0	0	0	0
2	POSTP	POSTP	pipa colok berkarat penyalangannya adalah gila carian alqur'annya	1	0	0	0	0	0
3	POSTP	POSTP	peristiwa bencana gila pacha kelonggangan	1	0	0	0	0	0
4	POSTP	POSTP	kehidupan maya maya maya maya maya maya maya maya	1	0	0	0	0	0
5	NGATP	POSTP	kehidupan maya maya maya maya maya maya maya maya	1	0	0	0	0	0
6	POSTP	POSTP	kehidupan maya maya maya maya maya maya maya maya	1	0	0	0	0	0
7	NGATP	POSTP	kehidupan maya maya maya maya maya maya maya maya	1	0	0	0	0	0
8	POSTP	POSTP	kehidupan maya maya maya maya maya maya maya maya	1	0	0	0	0	0
9	POSTP	POSTP	kehidupan maya maya maya maya maya maya maya maya	1	0	0	0	0	0
10	NGATP	NGATP	kehidupan maya maya maya maya maya maya maya maya	0	1	0	0	0	0
11	POSTP	POSTP	kehidupan maya maya maya maya maya maya maya maya	1	0	0	0	0	0
12	POSTP	POSTP	kehidupan maya maya maya maya maya maya maya maya	1	0	0	0	0	0
13	MFATP	MFATP	kehidupan maya maya maya maya maya maya maya maya	0	1	0	0	0	0
14	NGATP	NGATP	kehidupan maya maya maya maya maya maya maya maya	0	1	0	0	0	0
15	POSTP	POSTP	kehidupan maya maya maya maya maya maya maya maya	1	0	0	0	0	0
16	POSTP	POSTP	kehidupan maya maya maya maya maya maya maya maya	1	0	0	0	0	0
17	POSTP	POSTP	kehidupan maya maya maya maya maya maya maya maya	1	0	0	0	0	0

Figure 5 Test Data Prediction Results

accuracy	acc POSTP	acc NGATP	akutal
0.834%	0.834%	0.834%	0.834%
0.834%	0.834%	0.834%	0.834%
0.834%	0.834%	0.834%	0.834%

Figure 6. Measurement of model accuracy

Table 5. Confusion Matrix Results

		Kelas Sebenarnya	
		Kelas Positif	Kelas Negatif
Nilai Prediksi	Prediksi Positif	56	16
	Prediksi Negatif	5	50

The results of the confusion matrix calculations that have been carried out:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \times 100\% = \frac{88+40}{56+16+50+5} \times 100\% = 83,46\%$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\% = \frac{56}{56+16} \times 100\% = \frac{56}{72} \times 100\% = 77,78\%$$

$$\text{Recall} = \frac{TP}{TP+FN} \times 100\% = \frac{56}{56+5} \times 100\% = \frac{56}{61} \times 100\% = 91,8\%$$

From the 127 data tested, an accuracy value of 83.46% was obtained.

3.3. Results

The results obtained from the application of the Naive Bayes model in sentiment analysis of the QRIS payment method are divided into 2 classes, namely positive and negative sentiment. From the 636 tweet data that had been processed, positive sentiment was obtained with a percentage of (48%) or 306 data and negative sentiment with a percentage of (52%) or 330 data. The results of sentiment analysis can be illustrated in the Figure below:

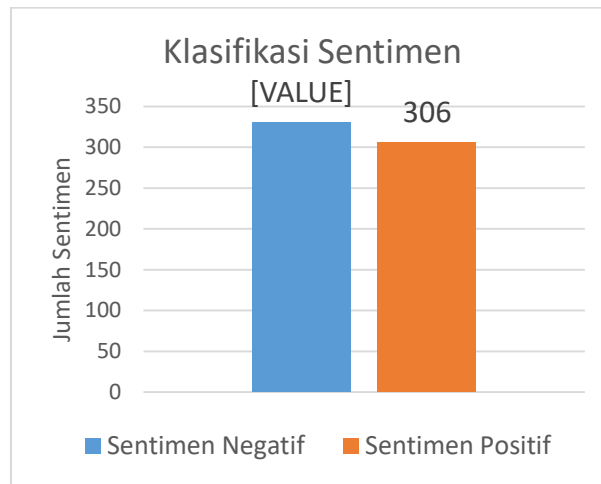


Figure 7. Sentiment Count Graph

Next, we will visualize word data contained in positive or negative sentiment classes by mapping the word cloud. The following are the results of the existing wordcloud visualization:



Figure 8. Wordcloud Negative Sentiment



Figure 9. Wordcloud Positive Sentiment

4. Conclusion

Based on all the research discussions that have been carried out, the Naive Bayes method has been proven to be able to be used to analyze sentiment about a problem with a good level of accuracy. In this research, a comparison of training data and test data was used with a ratio of 80:20%, chosen randomly. Where the resulting model can predict or classify sentiment with an accuracy level of 83.46%. In this research, a total of 636 tweet data were obtained which had been pre-processed and ready to be used in implementing the model. In its application, 509 training data and 127 test data were used. The 636 existing tweet data, we obtained (48%) or 306 positive sentiment data and (52%) or 330 negative sentiment data. In this research, it is proven that the Naive Bayes method can be used to design a sentiment analysis model for the QRIS payment method on the Twitter application. Next, different classification methods can be used, such as Support Vector Machine (SVM), K-NN, Decision Tree, or other classification methods

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