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Sentiment Analysis on Twitter Social Media Regarding Covid-19 Vaccination with Naive Bayes Classifier (NBC) and Bidirectional Encoder Representations from Transformers (BERT)

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Abstract. The Covid-19 vaccine is an important tool to stop the Covid-19 pandemic, however, there are pros and cons from the public regarding this Covid-19 vaccine.
Purpose: These responses were conveyed by the public in many ways, one of which is through social media such as Twitter. Responses given by the public regarding the Covid-19 vaccination can be analyzed and categorized into responses with positive, neutral or negative sentiments.
Methods: In this study, sentiment analysis was carried out regarding Covid-19 vaccination originating from Twitter using the Naïve Bayes Classifier (NBC) and Bidirectional Encoder Representations from Transformers (BERT) algorithms. The data used in this study is public tweet data regarding the Covid-19 vaccination with a total of 29,447 tweet data in English.
Result: Sentiment analysis begins with data preprocessing on the dataset used for data normalization and data cleaning before classification. Then word vectorization was performed with TF-IDF and data classification was performed using the Naïve Bayes Classifier (NBC) and Bidirectional Encoder Representations from Transformers (BERT) algorithms. From the classification results, an accuracy value of 73% was obtained for the Naïve Bayes Classifier (NBC) algorithm and 83% for the Bidirectional Encoder Representations from Transformers (BERT) algorithm.
Novelty: A direct comparison between classical models such as NBC and modern deep learning models such as BERT offers new insights into the advantages and disadvantages of both approaches in processing Twitter data. Additionally, this study proposes temporal sentiment analysis, which allows evaluating changes in public sentiment regarding vaccination over time. Another innovation is the implementation of a hybrid approach to data cleansing that combines traditional methods with the natural language processing capabilities of BERT, which more effectively addresses typical Twitter data issues such as slang and spelling errors. Finally, this research also expands sentiment classification to be multi-label, identifying more specific sentiment categories such as trust, fear, or doubt, which provides a deeper understanding of public opinion.

Keywords: Sentiment Analysis, Naïve Bayes Classifier (NBC), Bidirectional Encoder Representations from Transformers (BERT)
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INTRODUCTION

On December 31, 2019, the first case of the Covid-19 outbreak was reported in Wuhan, China. Meanwhile, the first case outside of China was reported in Thailand on January 13, 2020. Since then, the virus that is currently endemic has spread to more than 50 other countries [1]. Because the spread of the Covid-19 virus is so fast and the dangers that can arise if it is not treated immediately, the most appropriate treatment to stop the spread of this virus is to develop a vaccine [2]. Since it was first launched, there have been pros and cons from the public regarding the halalness of the vaccine, the side effects that have arisen, the suitability of the type of vaccine chosen and so on. These responses were conveyed by the public in many ways, one of which is through social media such as Twitter. Twitter has an average of around 206 million daily active users worldwide in the second quarter of 2021. The country with the most Twitter users is the United States with 73 million users in July 2021 Therefore, Twitter is a place to conduct sentiment analysis research to understand and process data to reveal sentimental information contained in an opinion phrase [3].

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Sentiment analysis is a process that aims to determine the content of datasets in the form of text (documents, sentences, paragraphs) that are positive, negative or neutral [4]. So that sentiment on social media such as Twitter is important to observe to determine the right strategy by the government and related health institutions in dealing with Covid-19, especially in terms of public communication [5]. One way that can be done for sentiment analysis is by text mining. Text mining is a science that aims to process text so that it becomes useful information and mines data in the form of text that is sourced from that data. The use of text mining is carried out for clustering, classification, information retrieval, and information extraction [6].

There are many algorithms that can be used in text mining, especially for sentiment analysis, one of which is the Naïve Bayes Classifier (NBC) algorithm. Naïve Bayes is very simple, effective and very popular for text classification and has good performance in many domains. The Naïve Bayes Classifier uses prior probabilities (probability values that are believed to be correct before conducting experiments) based on each label which is the frequency of each label in the training set and the contribution of each feature. So, the Naïve Bayes Classifier will assume that in each category, each word is independent of one another or independent [7].

Besides the Naïve Bayes Classifier algorithm, there is also the Bidirectional Encoder Representations from Transformers (BERT) algorithm. The BERT algorithm was just created in 2018, where this algorithm is a pre-trained model algorithm and produces a high level of accuracy in sentiment analysis [8]. Although there are many methods for classifying text with good performance, but most methods do not consider the order of words in sentences, and there are several words that are the same but have different meanings depending on the context of the sentence, this can be overcome by using the BERT algorithm. BERT is designed to train a deep two-way representation of text, namely by understanding the text before and after it [9].
In this study, sentiment analysis will be carried out using the Naïve Bayes Classifier (NBC) and Bidirectional Encoder Representations from Transformers (BERT) algorithms with sentiment data sourced from Twitter data. So that later it can be known which algorithm has better performance between the two.

METHODS
Will be done in this research is to implement the features of the selected algorithm so that it can run normally. The framework in this study is to compare the accuracy of a classification algorithm, namely the Naïve Bayes classifier (NBC) and the Bidirectional Encoder Representations from Transformer (BERT) in conducting sentiment analysis with Twitter data. The model framework that will be carried out can be seen in Figure 1.

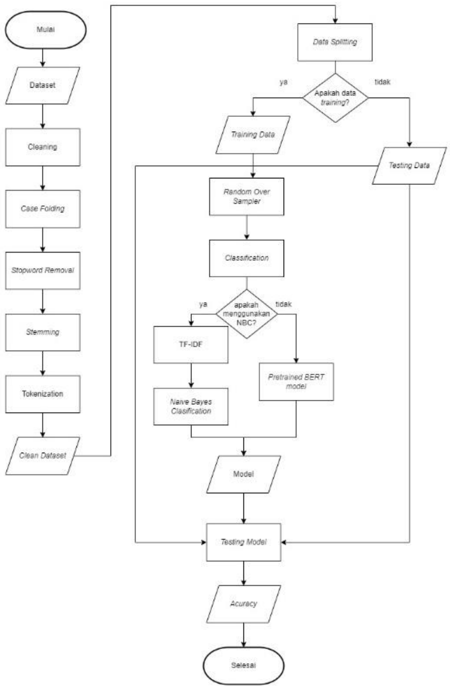

Figure 1. Flowchart Research Design

RESULT AND DISCUSSION

In this study the method used is the Naïve Bayes Classifier (NBC) algorithm and the Bidirectional Encoder Representations from Transformers (BERT) for sentiment analysis on Twitter data regarding the Covid-19 vaccination. The research was carried out in several stages, namely the data preprocessing stage, the data vectorization stage, and the classification stage. The following is a more complete explanation regarding the results of the study.

Wordcloud

Based on the preprocessing data that has been done before, a word cloud can be created to find out popular words in the data used. Figure 2 shows the wordcloud results for all data.

Figure 2. Wordcloud results for all data

Then in Figure 3 displays wordcloud results on data with neutral sentiment.

Figure 3. Wordcloud results on data with neutral sentiment

Then in Figure 4 displays wordcloud results on data with positive sentiment.

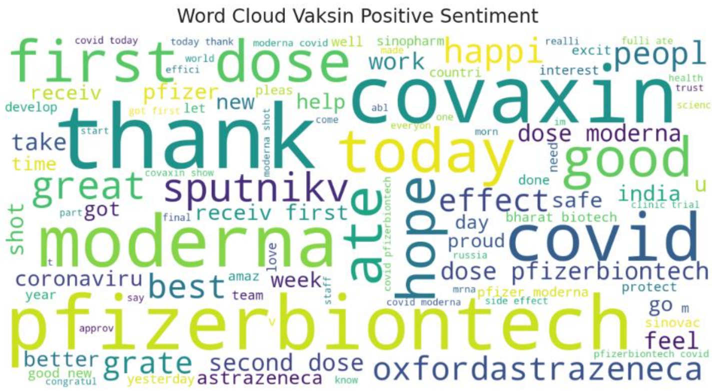

Figure 4. Wordcloud results on data with positive sentiment

Then in Figure 5 displays wordcloud results on data with negative sentiment.

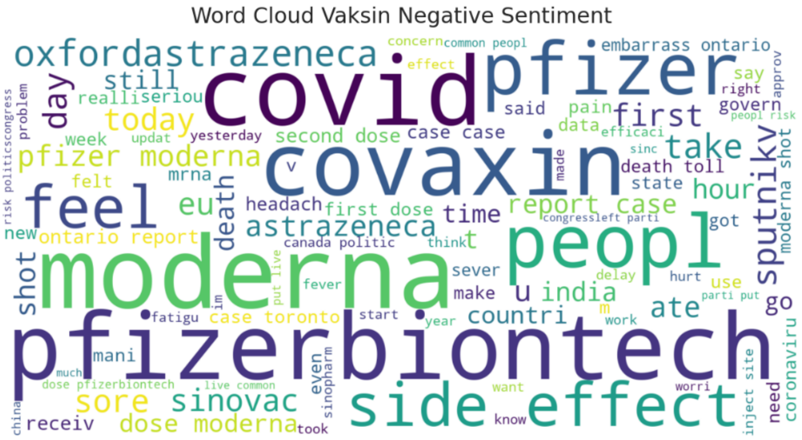

Figure 5. Wordcloud results on data with negative sentiment

Resampling Data

In this study, resampling was carried out using an oversampling technique, by duplicating data for the minority class in the training data. To do over sampling, we use a random over sampler from Imbalanced-learn. This random over sampler will select random data in the minority class of training data to be duplicated so that the training data will increase in number. Figure 6 is a comparison of the data before and after resampling data.

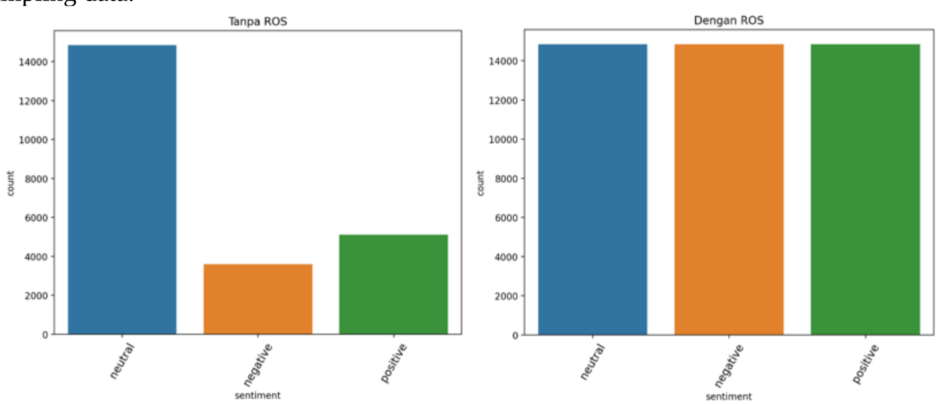

Figure 6. Comparison of the data before and after resampling data

TF-IDF Weighting

The data used in this study for the TF-IDF value after being calculated by the system is as shown in Figure 7.

```
(0, 55210)    0.22637879719066417
(0, 245648)   0.22637879719066417
(0, 46228)    0.22637879719066417
(0, 172924)   0.22637879719066417
(0, 55412)    0.22637879719066417
(0, 205402)   0.22637879719066417
(0, 88646)    0.22637879719066417
(0, 229131)   0.22637879719066417
(0, 55208)    0.2180423284287802
(0, 245647)   0.22637879719066417
(0, 46227)    0.22637879719066417
(0, 172923)   0.22637879719066417
(0, 55411)    0.22637879719066417
(0, 205401)   0.22637879719066417
(0, 88645)    0.22637879719066417
(0, 177125)   0.06304525082514838
(0, 229120)   0.18362493475534641
(0, 55207)    0.2180423284287802
(0, 245641)   0.17444915510009423
(0, 45892)    0.110821884131163
(0, 172917)   0.15079309302578064
(0, 55410)    0.22637879719066417
(0, 205305)   0.10787721035273132
(0, 88596)    0.14636195309415548
(1, 73473)    0.20740639139839678
:     :
(44516, 277604)     0.20942293995801384
(44516, 100774)     0.20942293995801384
(44516, 112785)     0.20942293995801384
(44516, 105628)     0.20942293995801384
(44516, 252693)     0.20942293995801384
(44516, 125880)     0.18398485102833695
(44516, 249293)     0.20942293995801384
(44516, 96600)      0.20942293995801384
(44516, 14638)      0.20942293995801384
(44516, 100773)     0.20942293995801384
(44516, 112783)     0.1850685992487605
(44516, 249292)     0.20942293995801384
(44516, 96585)      0.17405439904880268
(44516, 105589)     0.1431747818462127
(44516, 105495)     0.2061659737807659
(44516, 277603)     0.2061659737807659
(44516, 125720)     0.13322520043297395
(44516, 105490)     0.1517416343871313
(44516, 100668)     0.10844742955872118
(44516, 112684)     0.11746288617216079
(44516, 277578)     0.12285714369850213
(44516, 14583)      0.1278516740872032
(44516, 105409)     0.1364185266281218
(44516, 252373)     0.09880373465071172
(44516, 204650)     0.10991782850738183
```

Figure 7. TF-IDF value

If it is assumed to write the TF-IDF value in Figure 7 is (A, B) C then:
A : is the index of data that is calculated
B : is the word index in the data
C : is the result of the TF-IDF value

Naïve Bayes Classifier

In this study, a classification comparison was made using several types of Naïve Bayes Classifier methods. The methods implemented in this study are Bernoulli Naïve Bayes and Multinomial Naïve Bayes with the classification results of these methods as shown in Table 1.

Table 1. Comparison several types of Naïve Bayes Classifier

Method	Accuracy results
Bernoulli Naïve Bayes	0.7246770904146839
Multinomial Naïve Bayes	0.6742012236573759

Based on the results in Table 1, it is found that the Bernoulli Naïve Bayes method produces a better accuracy value than the Multinomial Naïve Bayes method, so the Bernoulli Naïve Bayes method will then be used for classification. In this study, five experiments were carried out in classifying to get the best model performance. Based on the experiments that have been carried out, the results are as shown in Table 2.

Table 2. Results of the Naïve Bayes Classifier experiment

Trials	Accuracy results
1	0.7289259007477906
2	0.7268864717878993
3	0.728585995921142
4	0.7217878993881713
5	0.7243371855880354

Based on the results of the experiments that have been carried out as shown in Table 4.22, the best results were obtained in the first experiment. Measurement of accuracy in data classification here is carried out by forming a confusion matrix based on the prediction results of the model that has been made and the resulting confusion matrix is as shown in the Figure 8.

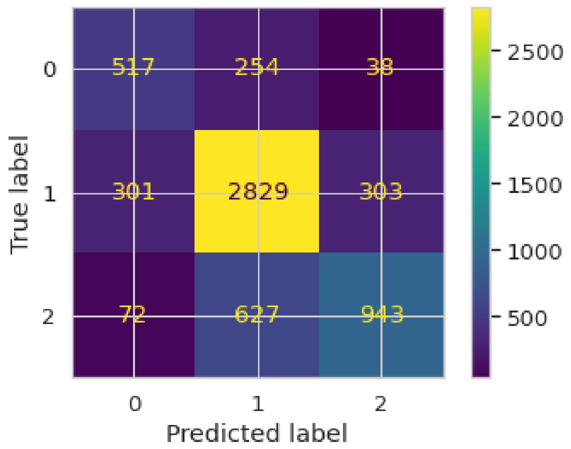

Figure 8. Confusion Matrix Naïve Bayes Classifier

From the results of evaluating the performance of the Naïve Bayes Classifier model in conducting sentiment analysis with Twitter data, the results obtained are an accuracy value of 73%, a precision value of 68%, a recall value of 69%, and an f1-score value of 68%.

Bidirectional Encoder Representations from Transformer (BERT)

After tokenizing the data with BertTokenizer, the data will be entered in the training process with the Bert model that has been created. For training data, a learning rate of 2e-5 was used and five experiments with the BERT algorithm were carried out to get the best performance. Based on the experiments that have been carried out, the results are as shown in Table 3.

Table 3. Results of the BERT algorithm

Trials	Accuracy results
1	0.8269884432358939
2	0.8490822569680488
3	0.8344663494221617
4	0.8334466349422162
5	0.8334466349422162

Based on the experimental results as shown in Table 3, the best performance was obtained in the second experiment. Each BERT model training process is carried out for five epochs with the results shown in Table 4.

Table 4. Training BERT model

Epoch	Accuracy
1	0.8402447314751869
2	0.8490822569680488
3	0.8405846363018354
4	0.8405846363018354
5	0.8405846363018354

From the classification results that have been carried out by the BERT model, a confusion matrix is obtained as shown in Figure 2

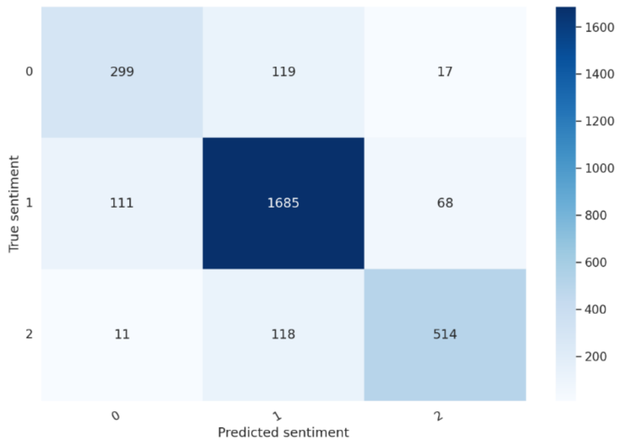

Figure 9. Confusion matrix BERT

From the results of evaluating the performance of the Bidirectional Encoder Representations from Transformer (BERT) model in conducting sentiment analysis with Twitter data, the results obtained were 85% accuracy, 80% precision, 80% recall, and 80% f1-score.

Comparison of the Naïve Bayes Classifier Method with the Bidirectional Encoder Representations from Transformer (BERT)

The results of the classification of the two methods are as shown in Table 5.

Table 5. Comparison of Naïve Bayes Classifier Algorithm with Bidirectional Encoder Representations from Transformer (BERT)

Algorithm	Precision	Recall	F1-score	Accuracy
Naïve Bayes Classifier	68%	69%	68%	73%
Bidirectional Encoder Representations from Transformer (BERT)	80%	80%	80%	85%

Based on Table 5 is known that the Bidirectional Encoder Representations from Transformer (BERT) obtains higher accuracy results compared to the Naïve Bayes Classifier. Therefore, it can be concluded that in this study the Bidirectional Encoder Representations from Transformer (BERT) algorithm has better performance compared to the Naïve Bayes Classifier.

CONCLUSION

Based on the results of research that has been done regarding sentiment analysis with the Naïve Bayes Classifier (NBC) and Bidirectional Encoder Representations from Transformers (BERT), the results obtained in this study are the Naïve Bayes Classifier (NBC) and Bidirectional Encoder Representations from Transformers (BERT) algorithms in analyzing sentiment with tweet data regarding covid-19 vaccination, with a training data ratio of 80% and 20% testing data, the highest accuracy results were 73% for the Naïve Bayes Classifier (NBC) algorithm and 85% for the Bidirectional Encoder Representations from Transformers (BERT) algorithm. Based on these results, it can be concluded that the performance of the Bidirectional Encoder Representations from Transformers (BERT) algorithm is better at performing sentiment analysis with Twitter data regarding the Covid-19 vaccination.

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