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Predicting Handling Covid-19 Opinion using Naive Bayes and TF-IDF for Polarity Detection

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ABSTRACT

There are many public responses about implementing government policies related to Covid-19. Some have positive and negative opinions, especially on the official social media portal of the government. Twitter is one social media where people are free to express their opinions. This study aims to find out the opinion of sentiment analysis on Twitter in implementing government policies related to Covid-19 to classify public opinion. Several stages in analyzing public sentiment are taken from the tweet data. The first step is data mining to get the tweets that will be analyzed later. Furthermore, cleaning tweet data and equalizing tweet data into lowercase. After that, perform the tweet's basic word search process and calculate its appearance frequency. Then calculate using the Nave Bayes method and determine the sentiment classification of the tweet. The results showed that Indonesia's public sentiment about covid-19 prevention is neutral. The performance of the application shows an Accuracy value of 76.7%. In conclusion this means that the Indonesian government needs to evaluate the policies taken to deal with Covid-19 to create positive opinions to create solid cooperation between the government and the government. Residents in tackling the Covid-19 outbreak.

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1. INTRODUCTION

A sickness outbreak rocked the world at the start of the year 2020. This epidemic spread rapidly, infecting nearly every country on the planet. This is a coronavirus infection, also known as Coronavirus illness (COVID-19). WHO has classified the world in a global emergency about this virus since January 2020, according to the World Health Organization [1]. The COVID '19 outbreak was widespread over the world in 2019. Within ten months, 38,085,762 infected people were found, with 28,628,813 (96 percent) recovering and 1,086,055 dying (4 percent). Even the transfer pace was lightning quick, affecting the entire world in seconds. The mortality rate was quite low. In response to the COVID-19 epidemic, practically all countries have enacted preventive policies such as social distance and remaining at home [2].

In Indonesia, the Indonesian government has declared a catastrophe emergency in response to the virus epidemic, which will last until February 2020. It continues and is being followed by the spread of countermeasures in different regions of Indonesia. The virus has spread to several areas until it occurred in May 2020. Other countermeasures implemented by the Indonesian government include the use of Physical Distancing, a concept states that to reduce and even break the chain of Covid-19 infection, one must maintain a safe distance of at least 2 meters from other humans, avoid direct contact with other people, and avoid mass gatherings [3]. Sentiment analysis examines people's attitudes, views, feelings, judgments, and assessments regarding various goods, services, issues, subjects, people, and organizations [4]. The primary goal of sentiment analysis is to categorize polarity or textual elements found in sentences or documents and identify the viewpoint being expressed [4].

A previous study by [5] used Naive Bayes to map the keywords and sentiment of Twitter users toward a product's halalness. It divided the polarity into three categories: positive, neutral, and negative. Out of a total of 967 tweets, there were 682 (70%) tweets with positive responses, 135 (14%) tweets with negative responses, and 150 (16%) tweets with neutral responses. Furthermore, the employment of multinomial discriminative methods of Naive Bayes and TF-IDF enhanced accuracy by 0.3%, according to the data [6]. Using the Nave Bayes technique, we observed a high categorization accuracy of 91 percent for short Tweets. We also discovered that the logistic regression categorization algorithm provides 74% decent accuracy with shorter Tweets [7]. We classify Twitter's sentiment data by displaying machine learning results using the Naive Bayes technique. Even though it takes longer than the listing technique, this algorithm can generate reasonably accurate estimations [8]. The Nave Bayes and decision tree approaches were compared in this study. With 73.59% accuracy, Nave Bayes outperformed Decision Tree [9].

The Naive Bayes, Support Vector Machine, and Maximum Entropy methods were compared in this study. Max Entropy possessed an accuracy value of 82.6% and a precision value of 84.05%, whereas Naive Bayes possessed an accuracy value of 86% and a precision value of 88.69 percent., SVM had an accuracy value of 74.6 percent and a precision value of 75.88 percent, and SVM had an accuracy value of 74.6 percent and a precision value of 75.88 percent. According to the study, the most accurate machine learning methods are Naive Bayes. They are considered fundamental learning approaches, although the Maximum Entropy method is useful in some situations [10]. Based on statistical data, the goal of this work was to identify a machine learning strategy that was relatively better than SVM and Naive Bayes classifiers. The system achieves 82.85 percent precision, 82.88 percent recall, and 82.66 percent f1 score for SVM classifiers.

Since 1950, Nave Bayes has been widely employed for document classification [10]. However, Naive Bayes classifiers are built on too simplistic assumptions of conditional probability and data distribution shape [11, 12]. Data from has also been utilized extensively for crisis analysis and tracking, including pandemic analysis [13]. The application is built utilizing the Python and PHP programming languages. This investigation yielded an accuracy rating of 91.67 percent [14]. Previous research [15] compared the selection of features using BOW and TF-IDF. TF-IDF is one of the selection features that includes information other than the frequency of word occurrences, unlike BOW. However, TF-IDF also analyzes the document's most and least significant terms. The conclusion is that TF-IDF is superior to BOW, hence TF-IDF is utilized to choose features in this study.

According to [16], in his research, the hybrid method (stacking ensemble) using the naive Bayes algorithm, decision tree, and support vector machine does not guarantee better results than other classification models. This is because there are several considerations, such as dataset imbalances, differences in data types, differences in features, and so on. To perform a more in-depth sentiment analysis, it is necessary to analyze using a more heterogeneous base classifier and feature selection, one of which is TF-IDF. The number of datasets affects a sentiment analysis system's accuracy and classification ability. Research conducted [17] shows the use of datasets below 1000, namely as many as 200 datasets, and produces an accuracy value of 65%. Based on this research, this study tries to increase the number of datasets and see its effect on the accuracy of results. Previous research conducted by [18], showed that the amount of training and test data affected the sentiment analysis results. This study [18] divided training data and test data into a ratio of 60%: 40%, 70%: 30%, and 80%: 20%. The results of each test showed low accuracy values, namely 54.69%, 57.45%, and 62.50%. According to research [19], Naive Bayes shows a lower accuracy value of 53.27% compared to SVM, which has an accuracy value of 54.21%. Based on this research, this study seeks to test the best comparison of training data and test data for sentiment analysis using different datasets and increasing the accuracy of the Naive Bayes algorithm.

The results of the sentiment analysis classification are assessed based on three values, precision, recall, and F-Measure. Research conducted [20] shows that the values of precision, recall, and F-Measure obtained are below 60%, namely 59.11%, 56.80%, and 57.96%. Two polarities are used, namely positive and negative. This research examines the use of polarity with three polarities, namely, negative, neutral, and positive. With the implementation of government policies related to Covid-19, there are many polarities of public responses, some have positive opinions, and some have negative opinions, especially on Twitter, where people are free to express their opinions. Based on the previous discussion, the author tries to research opinion sentiment analysis on Twitter in implementing government policies related to Covid-19 using Naive Bayes. The Naive Bayes algorithm performs better than competing algorithms in several studies. Feature weighting using TF-IDF increases accuracy and performs heterogeneous classifications to produce accurate analysis results. It can be used as a reference for the government in making and evaluating covid-19 prevention policies. In Indonesia. To support the application of Naive Bayes in improving the classification of public opinion on Twitter social media, which was built using the python language. The purpose of this research is to find out the opinions of Indonesian people on Twitter regarding the policies taken by the government in tackling Covid-19 in Indonesia using natural language processing techniques, namely sentiment analysis by combining the Naive Bayes algorithm and TF-IDF feature selection.

2. RESEARCH METHOD

The stages of the research process carried out in this study are described in a research methodology flow as shown in Figure 1.

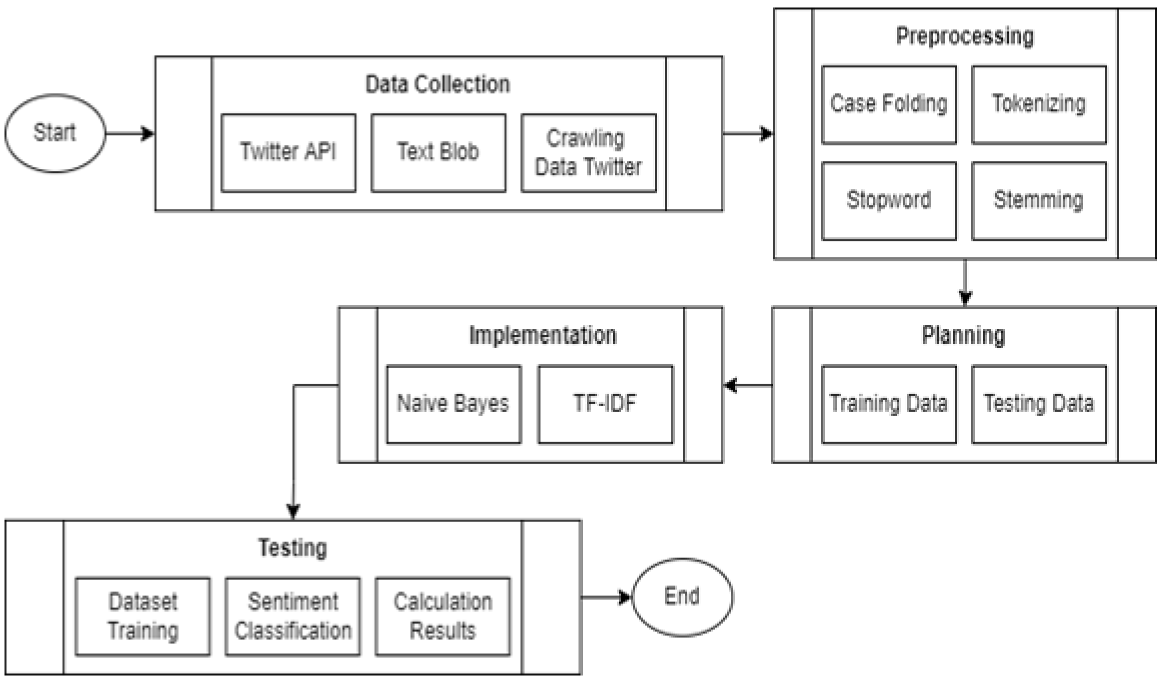

Figure 1. Research framework

The stages of the framework of thought have the following explanation:

2.1. Data Collection

Data collection is carried out at this stage to support how the system will be built. Before collecting Twitter data, it is necessary to prepare the Twitter API. Twitter data collection is done by the Twitter data scraping method. In collecting data, this study uses several keywords as presented in the Table 1.

Table 1. Data Collection

Keyword	Date	Total	Sample
Penanggulangan Covid	From: 01-10-2020 To: 25-12-2020	771	- Ada satu circle di prodi gue. pas ppmb mereka bikin video lomba temanya upaya penanggulangan covid. bah ngejelasinnya, praktek di videonya mah apik bener. padahal mereka sering ngumpul di cafe dempet dempetan ga pake masker - Dalam penanggulangan covid-19, Bhabinkamtibmas Desa Sukaresmi BRIPKA Ricky AN, SH melaksanakan giat kontrol satgas kang kabur/tukang jaga lembur dan memberikan himbauan kepada masyarakat Desa Sukaresmi dalam mematuhi protokol kesehatan saat beraktifitas serta tetap bersama Polri - Ekonominya udh meroket blm cuk? Penanggulangan covid ape koped cuk? Menkesnya aje yg dokter ga bs ngelarin ape lagi si ET cuk
Vaksin	From: 11-10-2020 To: 18-10-2020	143	- Dana penanggulangan covid 19 berapa ya? Kenapa vaksin harus bayar? Ibarat perang masa pemerintah gak nyediaan senjata dan amunisi secara gratis...ini loh rakyat pengen bantu ikut perang masa harus beli amunisi Yg bener aje lah bos.... - udah sah jadi perda penanggulangan covid.. nolak test rapid, test swab, vaksin, denda 5 juta.. padahal reaksi tubuh orang sama vaksin beda2.. virusnya katanya mutasi terus.. di filipina ratusan anak mati karna vaksin DBD.. di korea puluhan orang mati karna vaksin Flu.. - Penanggulangan Covid-19 hendaknya tdk se-mata2 mengandalkan Vaksin. Baik jika diterapkan berbagai upaya spt: Protokol Kesehatan; Puasa Bergunjing & Mengudap di luar rumah 14 hr; penggunaan Bahan Herbal utk imunitas; Sembur Ruang2 Tertutup dgn Bayklin + Air; Asapi dgn Tembakau dll
PSBB	From: 22-11-2020 To: 22-11-2020	2	- PSBB Jakarta apa mungkin untuk supaya tidak ada demo ya? Bukan semata penanggulangan covid Liar juga nih pemikiran - KEGAGALAN PEMBANGUNAN EKONOMI Krn KEGAGALAN MENJALANKAN TEGAKNYA HUKUM, GAGALNYA : 1. PEMBERANTASAN KORUPSI. 2. SUPREMASI HUKUM 3. MELINDUNGI RAKYAT KALANGAN BAWAH 4. PENANGGULANGAN VIRUS CORONA COVID 19. Bkn PSBB di DKI tlh diberlakukan perpanjangan
Masker	From: 03-01-2021 To: 10-01-2021	84	- Rutan Balige terima bantuan Alat Pelindung Diri berupa Masker Non-Medis dari Badan Penanggulangan Bencana. Terimakasih atas Bantuannya. Mudah mudahan dapat kami pergunakan untuk pencegahan penyebaran Covid-19 di Rutan Balige. - Iya kan ga jelas tuh utang nambah bnyak tp ga tau bwt apa alokasinya, ktnya bwt penanggulangan covid tp faktanya segalanya mesti bayar masker aja beli sendiri.. Trus?? - Mari teman-teman tetap ingat 3M !!! Menjaga jarak, Memakai Masker dan Mencuci Tangan.

To perform textual data processing at the next stage, a TextBlob library is needed. Before entering the pre-processing stage, the data that has been collected will be labeled according to the sentiment polarity by the author and divided in three polarity, namely positive, neutral, and negative, which will later be used as a reference by the system in classifying sentiments. In labeling sentiments on datasets, this study uses machine learning tools that have previously been trained and tested using datasets that already have sentiments to assess a sentiment as having a positive, negative, or neutral polarity.

2.2. Preprocessing

Case folding, tokenizing, stopword, and stemming are some of the preprocessing phases that are performed on tweet data before processing [21]. Case folding is generalizing capital letters by changing all letters to lowercase. Tokenizing is the process of breaking these sentences into words or tokens, which are used to distinguish between word separators. Tokenizing also includes removing numbers, removing punctuation such as symbols and punctuation that are not important, and removing whitespace. Stopwords are removing words that are ignored in processing and are usually stored in stop lists. The stemming stage is the stage for reducing the number of different indices by returning words that have suffixes and prefixes to their primary form.

2.3. Planning

At this stage, a design for the distribution of training data and test data will be made based on the dataset that has been obtained. Because the dataset obtained was 1000 tweets in this study, this study will try to compare three datasets, namely 70%-30%, 80%-20%, and 90%-10%, based on references in previous studies.

2.4. Implementation

At this stage, according to the collected data, it is made into a web-based application using the Nave Bayes algorithm with the TF-IDF weighting feature using the python language.

a. Term Weighting

In news classification, word weighting is used to get a category. One of the weighting methods is TF-IDF (Term Frequency Inverse Document Frequency). The weight value of a word (term) states the importance of the weight in representing the title. In the TF-IDF weighting, the weight will be greater if the frequency of occurrence of the word is higher, but the weight will decrease if the word appears more often in other news.

The following is the equation (1) used for TF-IDF calculations:

$$idf = log(\frac{N}{df}) \tag{1}$$

N is News and Df is Number of word where a word (term) appears

b. Naïve Bayes Classifier

The Naive Bayes algorithm in this study is used to classify public sentiment into three polarities: negative, neutral, and positive. The naive Bayes classification method utilizes probability calculations and statistics. These calculations are used to predict future probabilities based on experience. The following is the equation (2) used for probability calculations in programming:

$$P(a_i|V_j) = \frac{n_k}{n + |vocabulary|} \tag{2}$$

While the equation (3) is the naive Bayes equation which is used to carry out the classification

$$V_{map} = argmax_{vj \in V} P(V_j)\phi_i P(a_i|V_j) \tag{3}$$

Based on equation (3), it can be seen that the dependence of each document on a collection of documents is represented by the symbol $P(V_j)$, while $P(a_i|V_j)$ represents the suitability of the appearance of the word W_k in the document with the class category V_j, then the frequency of the k-word in each category defined by the symbol n_k, and | vocabulary | means the number of words in the test document.

2.5. Testing

In the last stage, the training dataset was tested by looking at the level of accuracy generated by the training from each experiment. Then perform sentiment analysis based on available data and calculate the level of precision, recall, and accuracy using a confusion matrix. In this study, the analysis was carried out by dividing the training data and testing data into three categories to test a good level of accuracy for sentiment classification with 1000 datasets, namely 70%-30%, 80%-20%, 90%-10%.Then it will use the formula and look for precision, recall, accuracy and f-1 measure values to determine the classification results with the following formula (4), (5), (6), and (7) [6].

$$Precission = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + TN} \times 100 \tag{6}$$

$$F1 - Measure = 2 \times \frac{precission + recall}{precission + recall} \tag{7}$$

The accuracy formula determines the ratio of correct predictions (positive and negative) to the entire data. Then the precision formula is used to measure the ratio of true positive predictions compared to the overall positive predicted results. Then, the recall formula is used to calculate the ratio of true positive predictions compared to all true positive data. Furthermore, the F1-Score is used to compare the weighted average precision and recall.

3. RESULT AND ANALYSIS

3.1. Data Collection

Data collection that was carried out using the Twitter API shows that there are 1000 data collected as a dataset. Of the 1000 datasets, labeling was carried out, which were classified into three sentiments: negative, neutral, and positive. The data that has been collected is labeled according to the sentiment polarity by the author uses machine learning tools that have previously been trained and tested using datasets that already have sentiments to assess a sentiment as having a positive, negative, or neutral polarity. Table 2 shows the number of dataset divisions based on sentiment after labeling.

Table 2. Object Research

Class	Total Data	Resources
Positive	314	Twitter
Negative	321	Twitter
Neutral	365	Twitter

In Table 2, it is explained that the dataset to be used in this study does not have a balanced number of classifications. The highest number was dominated by negative sentiment, followed by neutral and positive sentiment. This will likely affect the results and the level of accuracy resulting from sentiment analysis.

3.2. Pre-Processing

a. Case Folding
The use of capital letters is not uniform across all text sources. As a result, case folding is required to convert the document's complete text into a standard format (uppercase or lowercase). For example, users who type "Berita," "BERITA," or "Berita" to acquire information about "BERITA" get the same retrieval result, namely "Berita." Case folding is the process of transforming all uppercase letters in a document to lowercase. The letters 'a' to 'Z' are the only acceptable ones. Other than letters, all characters will be eliminated. An example of the tokenizing stage can be seen in Table 3.

Table 3. Case Folding

Input Text	Output Text
@ZaskiaWulanda13 : Khofifah menjdi pembicara Sharing Session Penanggulangan Covid - 19 yang digelar oleh GATRA Media Group bersama Satgas Penanganan Covid - 19 [Gubernur Jatim]	@ZaskiaWulanda13: khofifah menjadi pembicara sharing session penanggulangan covid - 19 yang digelar oleh gatra media group bersama satgas penanganan covid 19 [gubernur jatim]
@MaheraSandra : Diketahui bahwa Gubernur Khofifah menjadi pembicara Sharing Session Penanggulangan Covid-19. >> Gubernur Jatim	@MaheraSandra: diketahui bahwa gubernur khofifah menjadi pembicara sharing session penanggulangan covid19. >> gubernur jatim
@AlmiraAra10 : Sharing Session Penanggulangan Covid-19 akan dibicarakan oleh Gubernur	@AlmiraAra10sharing session penanggulangan covid19 akan dibicarakan oleh gubernur

b. Tokenizing The tokenizing stage is then utilized to break down the sentences in the string into single-word chunks. An example of the tokenizing stage can be seen in Table 4.

Table 4. Tokenizing

Input Text	Output Text
khofifah menjadi pembicara sharing session penanggulangan covid yang digelar oleh gatra media group bersama satgas penanganan covid gubernur jatim	khofifah | menjadi | pembicara | sharing | session | penanggulangan | covid | yang | digelar | oleh | gatra | media | group | bersama | satgas | penanganan | covid | gubernur | jatim
diketahui bahwa gubernur khofifah menjadi pembicara sharing session penanggulangan covid gubernur jatim	diketahui | bahwa | gubernur | khofifah | menjadi | pembicara | sharing | session | penanggulangan | covid | gubernur | jatim
sharing session penanggulangan covid akan dibicarakan oleh gubernur	sharing | session | penanggulangan | covid | akan | dibicarakan | oleh | gubernur

c. Stopword At this stage, the disposal of words that are less important or words that often appear (Stopwords), such as connecting words and adverbs that are not unique words, such as ”sebuah”, ”oleh”, ”pada”, and so on. The stop words in this investigation were generated using a modified Sastrawi library [20]. Table 5 provides an illustration of the stopword stage.

Table 5. Stopword

Input Text	Output Text
khofifah| menjadi | pembicara | sharing | session | penanggulangan | covid | yang | digelar | oleh | gatra | media | group | bersama | satgas | penanganan | covid | gubernur | jatim	khofifah | pembicara | sharing | session | penanggulangan | covid | digelar | oleh | gatra | media | group | satgas | penanganan | covid | gubernur | jatim
diketahui | bahwa | gubernur | khofifah | menjadi | pembicara | sharing | session | penanggulangan | covid | gubernur | jatim	diketahui | gubernur | khofifah | pembicara | sharing | session | penanggulangan | covid | gubernur | jatim
khofifah | menjadi | pembicara | sharing | session | penanggulangan | covid | yang | digelar | oleh | gatra | media | group | bersama | satgas | penanganan | covid | gubernur | jatim	khofifah | pembicara | sharing | session | penanggulangan | covid | digelar | oleh | gatra | media | group | satgas | penanganan | covid | gubernur | jatim

d. Stemming The stemming stage removes affixes, prefixes, and suffixes to change the words back to their original form. Table 5 provides an illustration of the stemmer stage.

Table 6. Stemmer

Input Text	Output Text
khofifah | pembicara | sharing | session | penanggulangan | covid | digelar | oleh | gatra | media | group | satgas | penanganan | covid | gubernur | jatim	khofifah | bicara | sharing | session | tanggulang | covid | gelar | oleh | gatra | media | group | satgas | tangan | covid | gubernur | jatim
diketahui | gubernur | khofifah | pembicara | sharing | session | penanggulangan | covid | gubernur | jatim	tahu | gubernur | khofifah | bicara | sharing | session | tanggulang | covid | gubernur | jatim
sharing | session | penanggulangan | covid | dibicarakan | oleh | gubernur	sharing | session | tanggulang | covid | bicara | oleh | gubernur

Word weighting is used in news classification to determine a category. TF-IDF (Term FrequencyInverse Document Frequency) is one of the weighting methods. Its weight value expresses the importance of a word (term) in representing the title. The weight will be more significant in the TF-IDF weighting if the frequency of occurrence of the term is higher. However, it will be lower if the word appears more frequently in other news.

3.3. Planning

After the preprocessing stage, the dataset will be separated into training and testing data before being analyzed using the Naive Bayes and TF-IDF algorithms. Based on research [18], the dataset is divided by a ratio of 70%:30% and 80%:20% and utilizing the confusion matrix to calculate the accuracy. In this study, try adding a 90%:10% ratio. Table 7 shows the number of divisions of training data and training data based on the comparison above.

Table 7. Training Data and Testing Data

Data Comparison		Amount of Data	
Training Data	Testing Data	Training Data	Testing Data
70%	30%	700	300
80%	20%	800	200
90%	10%	900	100

3.4. Implementation and Testing

At this stage, implementation, testing and evaluation of the performance of the proposed model will be carried out using the confusion matrix and calculating the values of precision, recall, f-score, and accuracy. Table 8. describes the results of data acquisition and then, through preprocessing 1000 existing data, divided into three sentiments, namely category one is positive, category 2 is neutral, and category 3 is negative. The data that has been normalized before being entered into the classification engine is separated into training data and test data.

Table 8. Confusion Matrix Sentiment Analysis

Actual Class	Predicted Class		
	Negative	*Neutral*	*Positive*
Negative	229	63	29
Neutral	24	317	24
Positive	34	59	221

Based on calculations using a confusion matrix, this study resulted in Sentiment Analysis using DMNB and TF-IDF on Twitter regarding the Covid-19 response into three categories, namely positive, neutral, and negative with positive sentiment as much as 28.7%, neutral as much as 43.9%, and negative as much as 27.4%. Then, from the results obtained in Table 8, an evaluation will be carried out using a formula to determine the results of precision, recall, and F-Score calculations. The data will be grouped according to the formula in the formula. The outcomes of additional evaluation measures for negative, neutral, and positive tweets are presented in Table 9.

Table 9. Confusion Matrix Sentiment Analysis

Category Name	Precision	Recall	F-Score	Accuracy
Negative	0.79	0.71	0.75	76.70%
Neutral	0.72	0.87	0.79	
Positive	0.81	0.70	0.75	
Weighted Avg	0.77	0.76	0.76	

According to Tables 8 and 9, the Naive Bayes classifier has a recall measure of 0.71 for negative tweets, 0.87 for neutral tweets, and 0.70 for positive tweets. In addition, the experiment achieves 0.77 average weighted precision, 0.76 average weighted recall, and 0.76 average weighted f-score. This study demonstrates that the precision of sentiment analysis is 76%. These results indicate that feature selection using TF-IDF and increasing the number of polarities can also increase the precision, recall, and F-Score of the confusion matrix calculation in the study [17, 20]. This is because term weighting using TF-IDF can analyze and classify tweets more heterogeneously. This study presents a comprehensive discussion based on the results and discussion above. Table 10 shows the comparison of this study with previous research.

Table 10. Comparison of Research Results

References	Novelty	Result (Previous Study)	Result (This Study)
[18]	**Comparison:** The results of previous studies show that every increase in the amount of training data causes accuracy to increase. In this study, we investigate whether increasing the amount of training data causes an increase in accuracy and adds a 90%:10% ratio. **Novelty:** This research shows that the comparison of 70%:30% is the comparison with the highest level of accuracy, and there is an increase in accuracy compared to before.	**Comparison → Accuracy:** 60%:40% → 54.69% 70%:30% → 57.45% 80%:20% → 62.50%	**Comparison → Accuracy:** 70%:30% → 76.70% 80%:20% → 72.93% 90%:10% → 74.36%
[17, 19, 20]	**Comparison:** The results of previous studies show that the calculation of the Confusion Matrix value is below 70%. This study investigates whether adding the number of datasets and neutral polarity can increase the accuracy and calculation of the confusion matrix in classifying. **Novelty:** The results showed that calculating accuracy and confusion matrix values by adding the number of datasets and neutral polarity can produce accuracy, precision, recall, and f-measure values above 70%.	**According to [17] :** Dataset: 200 data Accuracy: 65% **According to [19] :** Accuracy Nave Bayes: 53.27% **According to [20] :** Accuracy Nave Bayes: 63.21% Precision: 59.11% Recall: 56.80% F-Measure: 57.96%	Dataset: 1000 Accuracy Nave Bayes: 76.70% Precision: 77% Recall: 76% F-Measure: 76%

4. CONCLUSION

The contribution of this paper is combines the discriminative multinomial nave Bayes (DMNB) method with the TF-IDF term weighting approach for classify tweet more heterogeneously and increase the accuracy. This paper also shows that the polarities neutral is needed for the evaluation of the Indonesian government for the best policies taken to handling COVID-19 for the future. The dataset consists of 1000 Indonesian tweets. According to data testing, the proposed approach has an average precision class of 77%, recall of 76%, and f-score of 76%. In addition, the accuracy is 76.7%. Sentiment Analysis using DMNB and TF-IDF on Twitter divides the Covid-19 response into three categories: positive, neutral, and negative, with positive sentiment at 28.7%, neutral at 43.9%, and negative at 27.4%. This means that the actions taken by the government in dealing with covid-19 in Indonesia show a neutral sentiment where the Indonesian government needs to evaluate the policies taken to deal with Covid-19 to create positive opinions to create solid cooperation between the government and the government. Residents in tackling the Covid-19 outbreak. It is hoped that further specific research can be carried out by looking at the polarity of handling Covid-19 in Indonesia using other methods and by adding emotes to the dataset. This research implies that the government is expected to pay more attention to policies based on the community's perspective so that they can make better policies in the future. From the dataset obtained, the influence of socialization of policies on the community also needs to be considered so that the community understands better and can collaborate to reduce the number of Covid-19 victims in Indonesia. Suggestions for future research are adding a more significant number of tweets to improve the results of classification accuracy and a dataset that can represent all tweets from Indonesian people in all regions to capture the overall sentiment of people in Indonesia. As well as using a dataset that is not limited to words but includes emotes and satirical words.

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6. DECLARATIONS

AUTHOR CONTIBUTION

This research was compiled by three writers who were divided into each task. Supangat conceives and designs works, collects, analyzes, and interprets data. Mochamad Yovi Fatchur Rochman prepared the articles. While Mohd Zainuri Bin Saringat carried out a critical revision of the article and final approval of the final version to be published.

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COMPETING INTEREST
I have no declare under financial, general, and institutional competing interests.

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