

Sentiment analysis on vaccine COVID-19 using word count and Gaussian Naïve Bayes

Nur Ghaniaviyanto Ramadhan, Faisal Dharma Adhinata

Department of Software Engineering, Faculty of Informatics, Institut Teknologi Telkom Purwokerto, Indonesia

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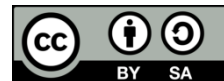
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ABSTRACT

Since the Coronavirus disease 2019 (COVID-19) pandemic hit the world, it had a significant negative impact on individuals, governments, and the global economy. One way to reduce the negative impact of COVID-19 is to vaccinate. Briefly, vaccination aims to enable the formed immune system to remember the characteristics of the targeted viral pathogen and be able to initiate an immune response that is rapid and strong enough to defeat future live viral pathogens. However, there are still many people in the world who are anti-vaccine. This certainly greatly hampers the process of accelerating the formation of the body's immune system widely in the community. Anti-vaccine people can be found on various social media platforms. Twitter was chosen as the data source because twitter is a common source of text for sentiment analysis. This study aims to analyze public sentiment on the COVID-19 vaccine through twitter in the form of tweets and retweets. This study uses the Gaussian Naïve Bayes method to see the results of the classification of sentiment analysis. The results obtained based on experiments prove that the Gaussian Naïve Bayes method can produce an average accuracy of 97.48% for each vaccine dataset used.

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Corresponding Author:

Nur Ghaniaviyanto Ramadhan

Department of Software Engineering, Faculty of Informatics, Institut Teknologi Telkom Purwokerto

Purwokerto, Indonesia

Email: ghani@ittelkom-pwt.ac.id

1. INTRODUCTION

Coronavirus disease 2019 (COVID-19) is an infectious disease caused by the novel coronavirus severe acute respiratory syndrome (SARS) Cov2, first identified in Wuhan, China in December 2019 [1]. At the beginning of August 2021 worldwide, the cumulative number of confirmed positive cases was 200,702,075, while the death toll was 263,985 [2]. The covid19 virus can be transmitted by close contact or even by droplets between individuals [3]. In 2020, since the COVID19 pandemic hit the world, it has had a significant negative impact on individuals, governments, and the global economy [4]. The whole world is now competing to reduce the negative impact on their respective countries. One way to reduce the negative impact of COVID-19 is to get vaccinated. Many COVID-19 vaccines are being circulated around the world under different brands such as Sinovac, Moderna, Sinoparhm and Pfizer. As of August 2021, global vaccine data shows 1,172,440,018 (15%) doses of vaccine have been administered [5]. In summary, vaccination aims to enable the immune system to be trained to remember the characteristics of the targeted viral pathogen and to be able to initiate an immune response that is fast and strong enough to defeat the viral pathogen withdraw in the future [6].

However, there are nevertheless many humans withinside the global who're anti-vaccine. This truly significantly hampers the procedure of increasing the formation of the body's immune gadget broadly

withinside the community. Anti-vaccine humans may be determined on numerous social media systems, consisting of Twitter. Twitter is one of the social media systems with 187 million each day lively customers withinside the 0.33 area of 2020 [7]. Twitter changed into selected because the statistics supply due to the fact Twitter is a not unusualplace supply of textual content for sentiment evaluation and sentiment evaluation on vaccination [8]-[10]. Sentiment evaluation has regularly been finished with the aid of using associated research. For example, for sentiment evaluation on COVID-19, picture sentiment airline reviews, political sentiment, FB comment, resort reviews, PC reviews, patron satisfaction/reviews, training e-sport, film reviews, polygamy or even sentiment evaluation may be used for product and carrier evaluation [11]-[20].

Several preceding research have mentioned comparable problems, together with in studies attempts to evaluate the category withinside the sentiment evaluation of Telkom merchandise from customer evaluations written withinside the shape of tweets on Twitter with the fashions utilized by k-nearest neighbor (KNN), Naïve Bayes, and textual content blob [21]. Focuses on assessing Indonesian perceptions thru a sentiment evaluation and could decide people's perceptions of the difficulty of polygamy [22]. Another paper offers an ensemble-primarily totally based version for facial express recognition (FER) that mixes numerous category fashions that paintings for sentiment evaluation of images [23]. Another looks at discusses the evaluation of English feedback at the Facebook platform the use of the Naïve Bayes method [24]. The uncooked information used on this technique are Tweets taken from Twitter concerning the COVID-19 vaccine, Pfizer, Moderna, and AstraZeneca. Assesses Indonesian public opinion thru evaluation of the COVID-19 vaccine social community in January 2021 [25].

Sentiment analysis using the Naïve Bayes algorithm with Twitter data crawl with the keyword 'COVID-19 vaccine' [26]. Collected data on Filipino sentiments regarding the Philippine government's efforts against COVID 19 using the social networking site Twitter. Natural language processing techniques are applied to understand common sentiments, which can assist governments in analyzing responses. Sentiments were annotated and trained using the Naïve Bayes model to classify English and Filipino tweets [26]. Analyzes the sentiments of people living in India concerning the COVID-19 vaccine. The COVID-19 pandemic has also coincided with social media companies experiencing an increase in traffic [27]. Research aims to use machine learning methods to extract topics and sentiments related to COVID-19 vaccination on Twitter using the latent dirichlet allocation (LDA) method [28]. Based on the presentation of several previous studies, then this study aims to analyze public sentiment on the COVID-19 vaccine (AstraZeneca, Moderna, Pfizer, Sinovac, and Sinopharm) through Twitter in the form of tweets and retweets using keywords which serves to analyze which type of vaccine has the most positive and negative sentiments along with the accuracy of the classification of the Gaussian Naïve Bayes model used.

2. METHOD

This study uses a dataset from Twitter. This study performs several data preprocessing techniques, feature extraction, and classification. Figure 1 is the system design used in this study. For a more detailed explanation, see the sub-section.

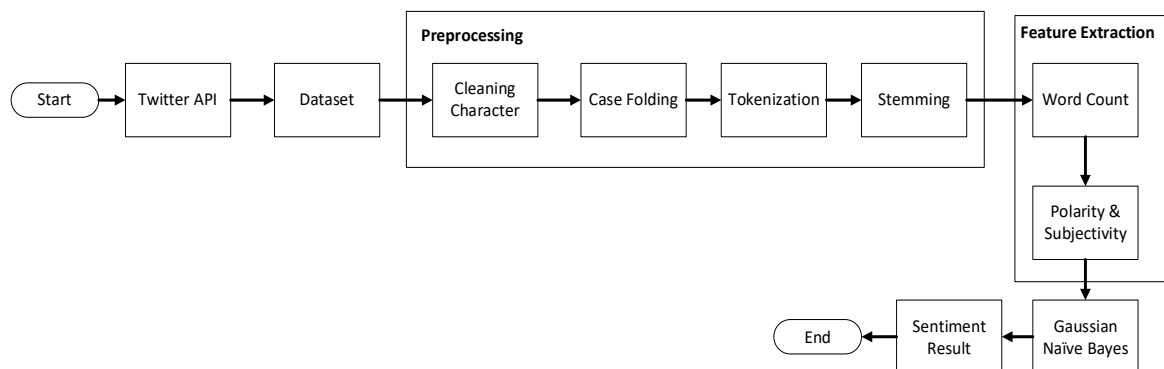


Figure 1. Design system

2.1. Twitter API and dataset

This initial process is carried out for getting access to the Twitter application programming interface (API). After access is obtained, then Twitter data is collected based on the keywords (#Vaccine Aztrazenecca,

#Vaccine Moderna, #Vaccine Pfizer, #Vaccine Sinopharm, and #Vaccine Sinovac) that have been entered. The dataset collection period is carried out from 7 August 2021-7 October 2021, with each total number of tweet data, can be seen in Table 1. Tweets used are from people all over the world.

Table 1. Dataset distribution

Vaccine Covid-19	Total Tweet
Aztrazeneca	2789
Moderna	2757
Pfizer	2688
Sinopharm	2749
Sinovac	2693

Table 1 shows the difference in the total number of tweets for each type of vaccine, even though the data collection period was carried out simultaneously. This happens for several reasons, such as, on certain days there are rarely users who tweet about the vaccine type, it could also be that on certain days the news about certain vaccines is not published, or the number of the same tweet is tweeted repeatedly so that it will be counted once tweets.

2.2. Pre-processing

This process will first clean up the characters, emoticons, and symbols in the tweet data. Then the case folding process is carried out which changes the sentences in the dataset to lowercase letters and only accepts letters a-z. Furthermore, the tokenization process will be carried out where tokenization is a process that ends with a stemming process which changes the affixes into basic words. So that the result of pre-processing is a word dictionary along with other features that will be used in the next stage.

2.3. Feature extraction

This process will perform feature extraction which will later be used for the classification process. The resulting features are the number of tweet words, polarity, and subjectivity. Polarity and subjectivity resulted from the calculation of the number of words. So, then the two features (polarity and subjectivity) will determine the value limits used for the classification process. The result of this process is in the form of limit values of polarity and subjectivity to determine the category of tweets including positive, negative, or neutral sentiment values which will be classified later.

2.3. Gaussian Naïve Bayes

In this process, classification will be carried out using a Gaussian Naïve Bayes machine learning model. Gaussian Naïve Bayes is a variant of Naïve Bayes which is calculated using a normal distribution. The Naïve Bayes method itself has recently been widely used in classification techniques, especially in social media networks such as Twitter by using several methods including Unigram Naïve Bayes, Multinomial Nave Bayes, and maximum entropy classification [29].

Gaussian Naïve Bayes itself allows classifying numerical data with Gaussian distribution and categorical data [30]. Gaussian Naïve Bayes is easiest because it only needs to estimate the mean and standard deviation of the training data [30]. Calculating Gaussian Naïve Bayes can be done with (1):

$$P(C|Z) = \frac{P(Z|C) \times P(C)}{P(Z)} \tag{1}$$

where (1) shows that *C* is the class label, *Z* is the applied attribute, while *P(Z|C)* is the probability of the previous class. *P(C)* is the probability that occurs on the class label. *P(Z)* is the probability that occurs in the applied attribute. In this classification, the processed data collection will be classified into three classes, namely positive, negative, and neutral.

$$mean (\mu) = \frac{\sum xi}{N} \tag{2}$$

N is the number of samples and *xi* is the value for each input variable in the training data.

$$std (\sigma) = \frac{\sqrt{\sum_{i=1}^N (xi - \mu)^2}}{N} \tag{3}$$

N is the number of samples, x_i is the i -th sample and \bar{x} is the average value.

When making predictions, this parameter can be added to the Gaussian probability density function (4) with a new entry for the variable.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{4}$$

$f(x)$ is a Gaussian Probability Density Function. As shown in (4) calculates the mean and standard deviation in the form of a numeric constant and is the input value for the input variable.

3. RESULTS AND DISCUSSION

This section will discuss the experimental results of this research. The number of sentiment categories obtained can be seen in Table 2. The AstraZeneca vaccine had the highest number of positive sentiments, while the Sinovac vaccine had the least number of positive sentiments. Moderna vaccines have the highest number of negative sentiments. If at the results of the number of positive, neutral, and negative sentiments, the AstraZeneca vaccine is the type of vaccine that has the best issue.

The results of the sentiment category from tweet obtained can be seen in Table 3. Figures 2-6 are examples of the word count form of the resulting sentiment category (positive and negative). Word count serves to represent a sentence or document into a value that is used for classification.

Table 2. Number of sentiment categories

Vaccine Covid-19	Number of Sentiment Categories		
	Positive	Neutral	Negative
Aztrazeneca	1177	942	670
Moderna	1098	904	755
Pfizer	1065	927	696
Sinopharm	1133	1185	431
Sinovac	1034	1133	526

Table 3. Sentiment category result

Username	Tweet	Sentiment category
@pakhead	New Turkish study claims that 3 doses of sinovac is more effective then 2 sino + 1 mrna.	Positif
@wchen	New England Journal of Medicine: Two doses of Pfizer, AstraZeneca vaccines effective against COVID Delta variant.	Positif
@MOH_TT	What about those who need to travel to the US or Canada and they got the Sinopharm vaccine which isn't accepted by the US or Canada?	Netral
@teddyboylcsin	Time for boosters, Sinovac antibodies are undetectable 6 months after inoculation.	Netral
@Reuters_Health	The U.S. Food and Drug Administration is expected to authorize a third booster dose of COVID-19 vaccines by Pfizer	Negatif
@esshimself	Clinics are charging RM 350 for sinovac two doses. Singapore clinics only charge SGD 20-50. Where does the money	Negatif

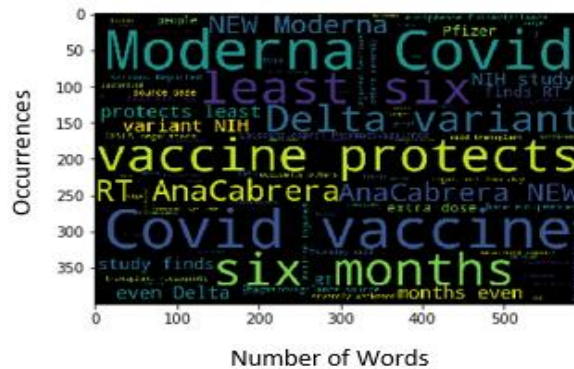


Figure 2. Moderna vaccine negative category word count

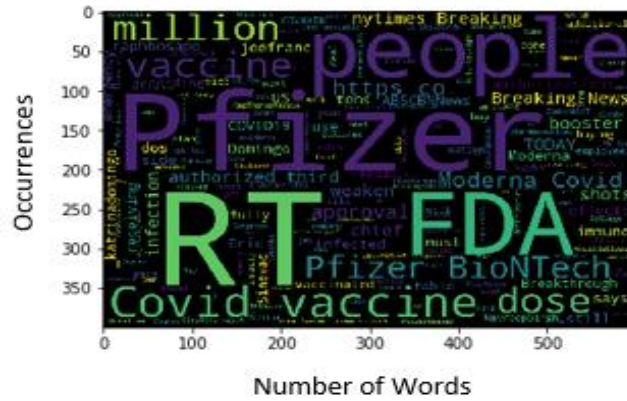


Figure 3. Pfizer vaccine negative category word count

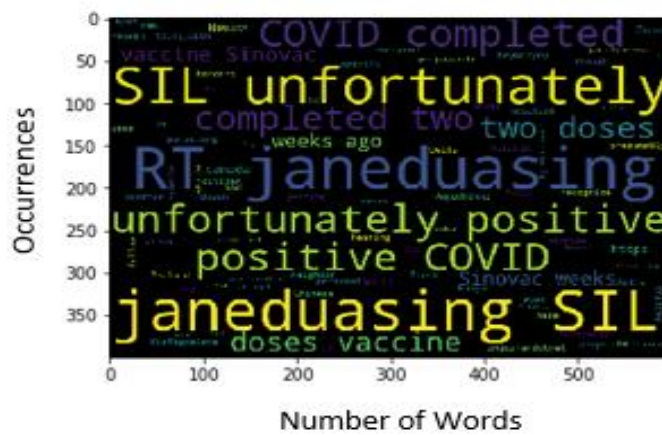


Figure 4. Sinovac vaccine negative category word count

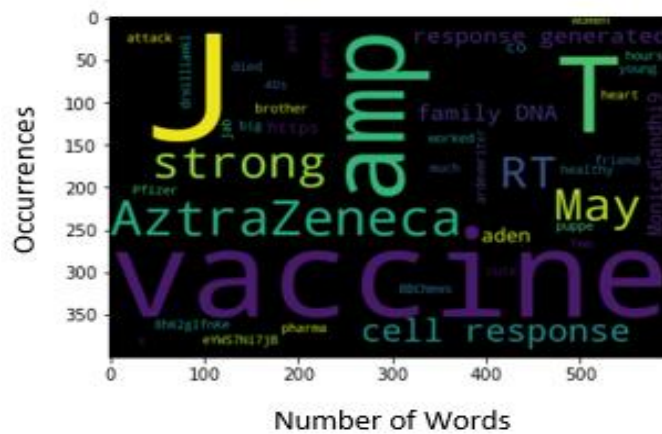


Figure 5. AztraZeneca vaccine positive category word count

The results of the average polarity and subjectivity of each type of vaccine in this study can be seen in Table 4. Based on the results of Table 4, then each type of vaccine will be classified based on the resulting sentiment to see the accurate results. The results of the comparison of sentiment accuracy obtained using the Gaussian Naive Bayes model and logistic regression can be seen in Table 5.

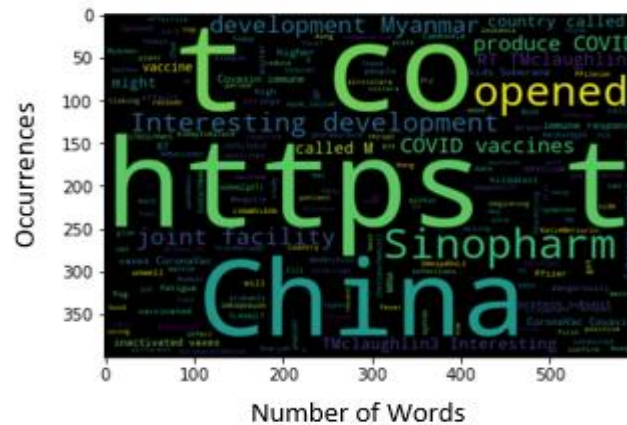


Figure 6. Sinopharm vaccine positive category word count

Table 4. Polarity and subjectivity result

Vaccine Covid-19	Polarity	Subjectivity
Aztrazeneca	0.089626687	0.321059181
Moderna	0.070549392	0.311492526
Pfizer	0.076261211	0.302357763
Sinopharm	0.118422537	0.271337923
Sinovac	0.082584714	0.271676892

Table 5. Accuracy result

Methods	Accuracy %				
	Aztrazeneca	Moderna	Pfizer	Sinopharm	Sinovac
Gaussian Naïve Bayes	98.9	97.8	97.6	97.5	95.6
Logistic Regression	91.6	95.8	94.2	94	91.9

It can be seen in the results of the table above that the proposed research method is superior to other methods used in all types of vaccine datasets used. This happens because the gaussian naive bayes process considers the mean and standard deviation in the probability calculation. Gaussian naive bayes also proves that a method that is very suitable for use in the case of sentiment analysis. For the type of vaccine that has the highest accuracy, namely Aztrazeneca at 98.9%, this indicates that the tweet used is indeed in the positive/neutral/negative category based on the polarity and subjectivity of this study. The accuracy of the proposed method of preprocessing-Gaussian naive Bayes has an average gap of 4% compared to the proposed method of preprocessing-logistic regression. This indicates the importance of a preprocessing process before determining the sentiment category.

The results of the accuracy of each type of vaccine are also influenced by the average polarity and subjectivity. The AstraZeneca vaccine type has an average polarity of 0.08 and a subjectivity of 0.32 which results in the highest accuracy compared to other types of vaccines. Sinovac vaccine types have an average polarity of 0.08 and 0.27 subjectivity resulting in the lowest accuracy compared to other types of vaccines. It can be seen from the example of the two types of vaccines which have the same average polarity value but differ in 0.04 subjectivity, the results of which differ inaccuracy of 3.3%. Another thing is seen in the average polarity value of Moderna and Pfizer which is the smallest compared to others, but the subjectivity value is 0.3, which can produce higher accuracy than the types of Sinovac and Sinopharm vaccines. While the Sinopharm vaccine has the highest average polarity but low subjectivity, its accuracy cannot exceed the AstraZeneca, Moderna, and Pfizer vaccines. So, it can be seen from the explanation above that the value of subjectivity has more influence on accuracy than the value of polarity.

4. CONCLUSION

Based on the experimental results that have been carried out, it proves that the proposed method of Gaussian Naïve Bayes is superior to other methods. The accuracy results produced by the Gaussian Naïve Bayes method also have a high average for all types of vaccine datasets, namely 97.48%. The value of

subjectivity has more influence on the accuracy results than the value of polarity. This proves that the proposed method in this study is very suitable for use in sentiment analysis problems. For further research, experiments can be carried out using other tree-based methods.

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BIOGRAPHIES OF AUTHORS



Nur Ghaniaviyanto Ramadhan     he received the bachelor's degree in informatics from Telkom University, Indonesia, in 2019, the master's degree in informatics from Telkom University, Indonesia, in 2021. He is a lecturer at Department of Software Engineering, Faculty of Informatics, Institut Teknologi Telkom Purwokerto, Indonesia. His research interests are in the areas of data mining, machine learning, artificial intelligence, and information science. He can be contacted at email: ghani@ittelkom-pwt.ac.id.



Faisal Dharma Adhinata     he received received his bachelor's degree in informatics in 2015 from the State University of Surakarta, Indonesia. He received his master's degree in computer science in 2020 from Gadjah Mada University, Indonesia. He has received the LPDP award from the Ministry of Finance of the Republic of Indonesia. He is a lecturer at Department of Software Engineering, Faculty of Informatics, Institut Teknologi Telkom Purwokerto, Indonesia. His research areas are in the fields of machine learning, computer vision, and image processing. He can be contacted at email: faisal@ittelkom-pwt.ac.id.