Accredited Ranking SINTA 2
Decree of the Director General of Higher Education, Research, and Technology, No. 158/E/KPT/2021
Validity period from Volume 5 Number 2 of 2021 to Volume 10 Number 1 of 2026

Published online on: **http://jurnal.iaii.or.id**

JURNAL RESTI
(Rekayasa Sistem dan Teknologi Informasi)
Vol. 7 No. 1 (2023) 161- 167 ISSN Media Electronic: 2580-0760

Comparison of Sentiment Analysis Methods Based on Accuracy Value Case Study: Twitter Mentions of Academic Article

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Abstract

The assessment of academic articles is based on the number of citations, but the number only is not enough. So now there is Altmetric which can measure the impact of academic articles from the number of citations and using social media, usually Twitter. Still, the number of mentions on Twitter is not enough because the expressions of the sentences vary. Mentions must be classified according to neutral, positive, and negative criteria. Sentiment analysis is performed on tweets to measure social media volume and attention related to research findings from academic articles. There are many sentiment analysis methods, so this study aims to compare sentiment analysis methods using Decision Tree, K-NN, Naïve Bayes, and Random Forest to get the most suitable methods. The evaluation method in this study uses the Confusion Matrix by searching for Accuracy, Precision, and Recall values. The results show that the most suitable sentiment analysis method is Naïve Bayes by obtaining the highest classification suitability value of the other methods, which has an actual positive sentiment value of neutral 2056, positive 1200, and negative 1292. In addition, Naïve Bayes gets the highest accuracy score of 95, 45%.

Keywords: *sentiment analysis, decision tree, k-nearest neighbors, naïve bayes, and random forest.*

1. Introduction

Humans are individual creatures and social beings who need to interact and communicate with each other because humans always want to be in touch with others and want to know the surrounding environment, that sense forces humans to need to share [1]. The development of human technology creates social media that can make it easier for humans to communicate. The relationship between communication and social media is very close because, with social media, communication becomes faster and easier for communities to share, communicate, and collaborate [2]. Researchers use social media to display their research so that it is easier to read and search. The social media used by researchers is Twitter.

Altmetrics stands for Alternative Metrics, which is a tool to measure the volume and attention of social media around research findings and can be used to complement traditional citation-based metrics such as the impact of a paper on the H-Index value of its author, Altmetrics is much faster and up to date compared to metrics traditional because traditional metrics are citation-based which can only provide information for a few years after publication. There are many Altmetrics data sources, including Twitter by counting Twitter posts that reference academic publications, Facebook is similar to Twitter but does not have the relevant API so that data collection is limited to only taking from Facebook pages that are public, Mendeley calculates the number of readers of academic publications on its website, Youtube counts mentions of academic research in comments but seems rare, and Reddit counts citations in Reddit posts but it's as rare as Youtube [3]. In this study, the data used is Twitter because on Twitter, the Altmetrics data source is constantly updated at any time [4]. In addition, the website altmetric.com Twitter has the most data compared to other social media, so it can help in terms of the accuracy of applying sentiment analysis methods.

Sentiment analysis research with the latest Altmetrics uses the Support Vector Machine method on Twitter mentions examining the impact or influence of Twitter social media on indexed papers from researchers. This study has an F1 score of 0.86 for positive sentiment and 0.97 for negative sentiment, and a score of good Accuracy is 0.96 [5]. However, the study only has two criteria for classification, namely positive and negative

Accepted: 16-12-2022 | Received in revised: 25-01-2023 | Published: 05-02-2023

reviews, but in fact, there are other criteria for mentions on Twitter that must be investigated. In addition, previous research using the Support Vector Machine method with TF-IDF weighting for sentiment analysis was used to detect Indonesian-language rumors on Twitter. This research began with data collection from Twitter, which was then carried out preprocessing, feature choosing, N-Gram modeling, category, and evaluation operating a confusion matrix. The outcomes of this study only got the highest accuracy value of 78.71 with the TF-IDF characteristic and an accuracy value of 76.26 without the TF-IDF characteristic [6]. The value of the test results is good, but to get the best and more accurate results, the value of the test results should be increased.

So, this study proposes using several sentiment analysis methods to compare which is best used for sentiment analysis on tweets used for Altmetric in measuring volume and attention from social media around research findings from a paper.

This research is expected to propose a sentiment analysis method that is most suitable for implementing sentiment analysis on tweets for Altmetric. Comparative sentiment analysis methods used to classify sentiment polarity in this study are Decision Tree, K Nearest Neighbors, Naïve Bayes, and Random Forest. The decision tree was chosen because previous research obtained good accuracy calculations, namely 80% with 79.96% Precision and 84% Recall from the implementation of this method for sentiment analysis on Twitter data regarding miscellaneous customer sentiments around several online marketplace locations in Indonesia. A Decision Tree is a relatively efficient technique for constructing classifiers from data [7].

Previous research has implemented K Nearest Neighbors to analyze Twitter user sentiment toward online learning. This method is used because it has a minimal error rate of 0.12% in sentiment analysis on Twitter for online learning [8]. At the same time, the Naïve Bayes method is selected for comparison because it is most usually operated to classify texts containing multidimensional training data sets and is easy to implement [9]. It uses the Random Forest method because previous research has proven that several variations of weighting procedures, such as Binary TF, Raw TF, Logarithmic TF, and TF-IDF for sentiment classification, provide good performance based on the calculation of Out-Of-Bag (OOB) error estimation. With a mean score of 0.829 [10].

The analysis of the OOB score ranges from 0 to 1, if the OOB score is higher, the more valuable the category performance, conversely the more subordinate the OOB score means a more harmful category performance, then the OOB score of 0.829 proves that the Random Forest method is a suitable method for sentiment analysis. So based on previous research, this study proposes to compare the sentiment analysis method used to classify the polarities contained in mention tweets with the Decision Tree, K Nearest Neighbors, Naïve Bayes, and Random Forest methods used to classify the polarities contained in mention tweets.

2. Research Methods

In this research, the system built can process tweet data taken from July 2020 to October 2022 with various scenarios of applying the sentiment analysis method to determine which sentiment analysis method is best for processing tweet data on Altmetric. The system starts by doing Data Crawling, Data Cleaning, Data Labeling, Preprocessing, TF-IDF Weighting, Sentiment Analysis Method, Prediction Model, and lastly, evaluation using the Confusion Matrix. The system flow can be seen briefly in Figure 1.

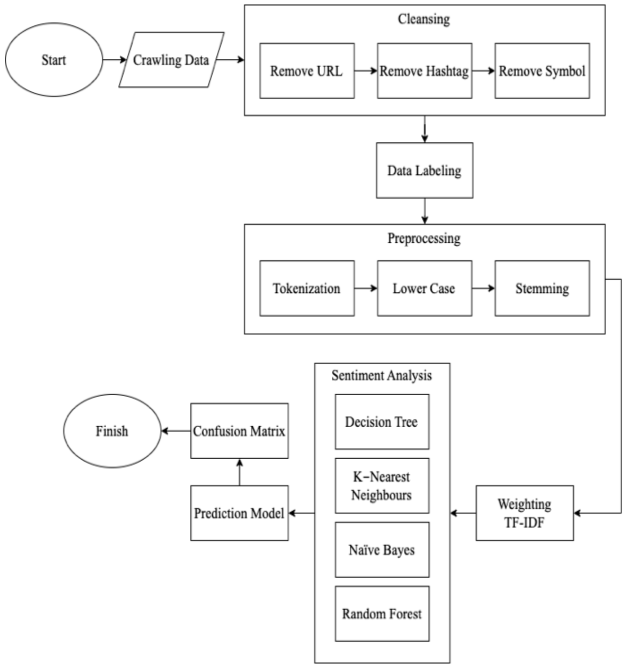

Figure 1. Design Workflow System

2.1 Crawling Data

This research begins with collecting data in the form of tweets mentioned from the Altmetric website using Instant Data Scraper, an extension application from Google Chrome which is then stored in CSV configuration [11]. Tweet data is in English, with 10,000 tweets discussing the paper The Proximal Origin of SARS-CoV-2, which has the highest score based on Altmetric website calculations [12]. The data taken is only the Twitter account's name, the tweet's mention, and the time the tweet was published. The data shown in this table is only 5 data out of 10,000 data that have been collected. The following is Table 1 illustration of data crawling outcomes.

DOI: https://doi.org/10.29207/resti.v7i1.4767

Table 1. Illustration of Data Crawling Results.

Name	Tweet	Posted time
@Ayjchan	Of course not.	28-Oct-2022
@philster612	Its not "man made". It is a Corona virus that has its zoonotic origins in bats. Heres the scientific breakdown.	28-Oct-2022
@Flix548	That is impossible. Just the spike protein binding to the ace2 receptor is suboptimal. Arguably the most important feature of the virus to infect us, is not optimal and incomplete.	28-Oct-2022
@sensiN23	Another factually challenged liar & propagandist hack peddling his factless conspiracy theory. Let's debunk: etc	28-Oct-2022
@_ocean	*need a break* In the meanwhile check these two cool papers. [1] KGA nature paper. [2] KGA cell press paper.	26-Oct-2022

2.2 Cleaning and Labeling Data

Then carry out the data cleaning process so that the data can be processed accurately by deleting URLs, hashtags, and symbols. The data cleaning process removes some tweets that do not have complete information, so the number of tweets that are ready to be processed is 4765 out of 10000 tweets. Similar words or sentences may have many meanings, sometimes even semantically. They are unrelated, so it is necessary to label the data to predict the most appropriate polarity classification [13]. In this study, the data was labeled operating VADER (Valence Aware Dictionary and Sentiment Reasoner) so that it did not take long to label it into positive, neutral, and negative polarity classifications. Labeling the three polarities minimizes the possibility of inaccuracies in the test results. Below is Table 2, an example of the effects of cleaning and labeling data using VADER.

Table 2. Cleaning and Labeling Data

Cleaned Data	Score	Label
There are really a lot of studies that say it is natural like this	0.769	Positive
So now we know that Fauci helped Andersen et al on their Proximal Origins paper that Nature publishe	0	Neutral
Off course there is evidence Here the virus is analyzed and it is seen that there are no artificial insertions in the virus	-0.308	Negative

2.3 Preprocessing

The preprocessing methods used in this research are tokenization, lowercase, and stem, intending to make it easier for machine-readable data to reduce ambiguity. Tokenization is a process to remove characters such as brackets and hyphens, lowercase which aims to make all text lowercase so that it is easy to analyze and stemming aims to remove prefixes or suffixes from words [14]. Here is Table 3, an example of the preprocessing result:

Table 3. Preprocessing

Tweet	Preprocessing Result
There are really a lot of studies that say it is natural like this	"really", "lot", "study", "say", "natur", "like"
So now we know that Fauci helped Andersen et al on their Proximal Origins paper that Nature published	"know", "fauci", "help", "andersen", "et", "al", "proxim", "origin", "paper", "natur", "publish"
Off course there is evidence Here the virus is analyzed and it is seen that there are no artificial insertions in the virus	"course", "evidence", "virus", "analys", "see", "artificial", "insert", "virus"

2.4 TF-IDF Weighting

TF-IDF is a preprocessing technique to calculate the most used word weights. The objective of using TF-IDF is to decrease the impact of little informational tokens that often occur in the data corpus by considering the features of unigram, bigram, and trigram [15]. Below is formula 1 to calculate the TF-IDF used:

$$TF - IDF(d,t) = TF(t)\ x\ IDF(d,t) \tag{1}$$

TF-IDF(d,t) is the weight of terms or words in the document, TF(t) is the number of occurrences of the term in the document, and IDF(d,t) is the number of terms in all documents.

2.5 Sentiment Analysis Methods

To determine the best performance, this study compares four sentiment analysis methods. The methods used are Decision Tree, K Nearest Neighbors, Naïve Bayes, and Random Forest. The primary idea of the Decision Tree is to divide the dataset into shorter subsets and gradually create a related tree so that it can handle numeric to categorical data [16]. The Naïve Bayes is used as a probability classifier which gives good results for text data analysis, such as sentiment analysis, with the main feature of getting a solid hypothesis from all conditions [17]. The Naïve Bayes calculation uses the Bayes algorithm approach with the following formula 2:

$$P(A \mid B) = \frac{P(B \mid A)\ P(A)}{P(B)} \tag{2}$$

Shows that P(A | B) is the hypothetical possibility of a particular target class. In contrast, P(A) is the possibility of the previous class, and P(B | A) is the possibility of a class based on the given hypothetical conditions. In contrast, P (B) is the possibility of a predictor. K-Nearest Neighbor for new object classification based on the closest learning data. The data or nearest neighbor is expressed by K, and the K-Nearest Neighbor method begins by calculating the Euclidean distance, sorting by Euclidean space, and determining the closest K classification [8]. The formula 3 used to calculate Euclidean length is:

$$d(x_i, x_j) = \sqrt{\textstyle\sum_{r=1}^{n}(a_r(x_i) - a_r(x_j))^2} \tag{3}$$

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Where d (x_i, x_j) represents the euclidean distance, x_i Represents the record to I, x_i Represents the record to j, and a_r Defines the data to r. Random forest is a costume learning approach for category and regression that blends predictions from several basic estimators created with a decision tree [10]. This algorithm was first suggested in 2001 by Leo Breiman and Adèle Cutler, representing a random forest pictorial that takes a Decision Tree as a unique predictor, as illustrated in Figure 2 [18].

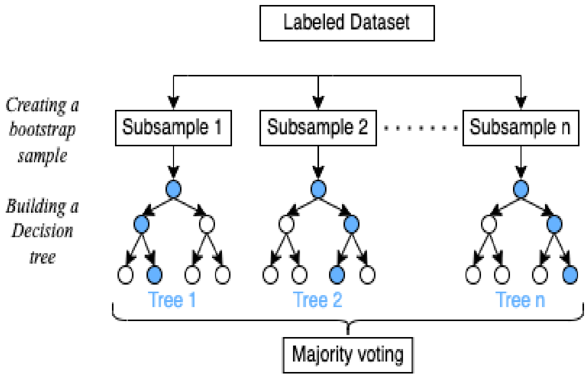

Figure 2. Random Forest

2.6 Prediction Model

Predictive models are sentiment predictions generated by the system in three polarities: neutral, positive, and negative. From the four scenarios of applying the sentiment analysis method, sentiment predictions have been obtained based on each technique.

On the prediction label, several labels are different from the initial label, affecting the performance results of sentiment analysis methods. Table 4 and Table 5 are examples of predictions obtained and are the results of this study.

Table 4. Prediction Label Naïve Bayes and Decision Tree

Tweet	Label	Prediction	
		Decision Tree	KNN
There are really a lot of studies that say it is natural like this	Positive	Neutral	Neutral
So now we know that Fauci helped Andersen et al on their Proximal Origins paper that Nature publishe	Neutral	Neutral	Neutral
Off course there is evidence Here the virus is analyzed and it is seen that there are no artificial insertions in the virus	Negative	Neutral	Neutral

Table 5. Prediction KNN and Random Forest

Tweet	Label	Prediction	
		Naïve Bayes	Random Forest
There are really a lot of studies that say it is natural like this	Positive	Neutral	Neutral
So now we know that Fauci helped Andersen et al on their Proximal Origins paper that Nature publishe	Neutral	Neutral	Neutral
Off course there is evidence Here the virus is analyzed and it is seen that there are no artificial insertions in the virus	Negative	Negative	Neutral

2.7 Confusion Matrix

To test the system, it is necessary to conduct an evaluation. In this study, using the Confusion Matrix is a helpful tool to measure how nicely the classification is executed, Figure 3 illustrates a multiclass classification Confusion Matrix with three classes, namely Positive, Neutral, and Negative [19].

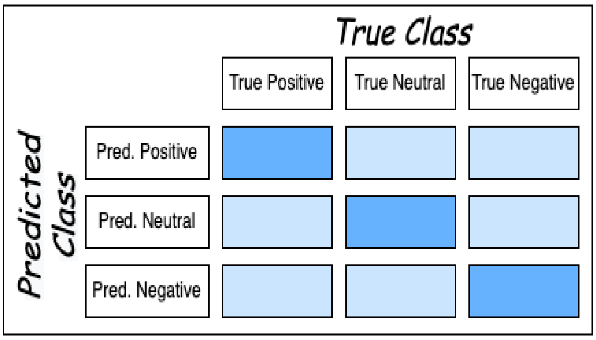

Figure 3. Confusion Matrix Multi-class Classification

The blue box shows the number of true positive and perfectly categorized models. The light blue box means the number of misclassified models.

In this study, the evaluation measurement of the system uses Accuracy, Precision, and Recall [6]. Accuracy to show the proximity of the estimate results to the actual value. Here's formula 4 for calculating Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (4)$$

Precision is operated to resolve the level of Accuracy between the ratio of correctly predicted positive observations asked and the responses provided by the system. Instruction 5 calculates Precision:

$$\text{Precision} = \frac{TP}{TP+TF} \quad (5)$$

The recall is used for measurements based on the percentage of perfectly predicted positive observances to all actual observances. Here's the recall formula 6:

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

DOI: https://doi.org/10.29207/resti.v7i1.4767

3. Results and Discussions

3.1 Dataset Result

The results of this study found that the most suitable sentiment analysis method for implementing sentiment analysis on Altmetric tweets is the Naïve Bayes method. The following Figure 4 predicts the results of the system that was built by displaying the results of the 4765 tweets that have been analyzed.

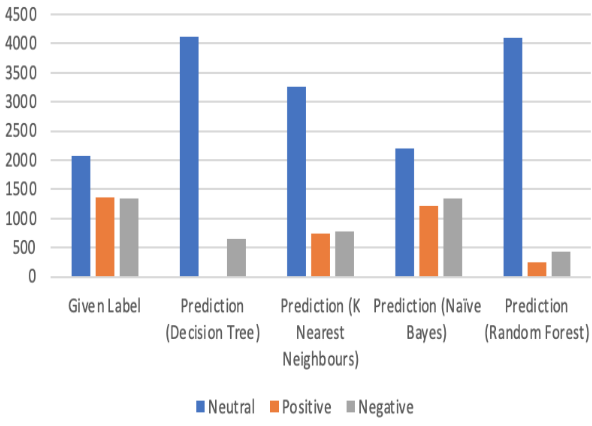

Figure 4. Prediction Results

Several prediction results are different from the given label from the four scenarios of applying sentiment analysis applied by the system. However, the prediction results from the Naïve Bayes method have very little difference with the label. To be more accurate, testing the system's prediction results is carried out.

3.2 Test Result

In this study, testing using the Confusion Matrix was carried out on each scenario applying the sentiment analysis method. Starting with testing the prediction results from the Decision Tree method. True positive results were obtained for 2066 neutral sentiments, true positive for 642 negative sentiments, but the true positive value for positive sentiments was 0 which means there was an error in the classification process resulting in a high difference between the initial sentiment and the predicted sentiment. The following is Table 6 Confusion Matrix for the Decision Tree method.

Table 6. Confusion Matrix Decision Tree

	true Neutral	true Positive	true Negative
pred. Neutral	2066	1365	692
pred. Positive	0	0	0
pred. Negative	0	0	642

Testing the prediction results using the K Nearest Neighbors method shows that there is several suitability for classifying sentiment labels which are more than the results of the Decision Tree method, which does not have a true positive value for positive sentiment. It can be glimpsed in Table 7 below.

Table 7. Confusion Matrix K-Nearest Neighbours

	true Neutral	true Positive	true Negative
pred. Neutral	2061	643	561
pred. Positive	2	713	17
pred. Negative	3	9	756

The test results for the Naïve Bayes method show a high true positive value and the model is perfectly categorized for each sentiment compared to other methods. Table 8 is the outcome of testing using the Confusion Matrix for the Naïve Bayes method.

Table 8. Confusion Matrix Naïve Bayes

	true Neutral	true Positive	true Negative
pred. Neutral	2056	115	26
pred. Positive	7	1200	16
pred. Negative	3	50	1292

The test results from the Random Forest method show that the true positive value for neutral sentiment is 2066. Still, in the Confusion Matrix results for the Random Forest method, there is a neutral sentiment class incorrectly classified as a positive sentiment class with a high value of 1118. Table 9 shows the test results from the Random Forest method.

Table 9. Confusion Matrix Random Forest

	true Neutral	true Positive	true Negative
pred. Neutral	2066	1118	907
pred. Positive	0	247	0
pred. Negative	0	0	427

After conducting the testing process on the four scenarios of applying the sentiment method, the values of Precision, recall and Accuracy were obtained. Table 10 shows the test results of the system results based on all the data that has been processed.

Table 10. Test Result

Methods	Precision			Recall			Accuracy
	pred. Neutral	pred. Positive	pred. Negative	true Neutral	true Positive	true Negative	
Decision Tree	50.11%	0%	100%	100%	0%	48.13%	56.83%
KNN	63.12%	97.4%	98.44%	99.76%	52.23%	56.67%	74.08%
Naïve Bayes	93.58%	98.12%	96.06%	99.52%	87.91%	96.85%	95.45%
Random Forest	50.5%	100%	100%	100%	18.1%	32.01%	57.50%

Finally, in the table of test results from the Decision Tree and Random Forest, several values reach 100%. Still, both of them in several evaluation categories obtain very small values, some are below 50.00%, so these two methods get the lowest accuracy value with an accuracy value of only 56.83% for the Decision Tree, and the accuracy value of the Random Forest method is only 57.50%. The accuracy value for the K Nearest Neighbors method is 74.08% which is the second highest accuracy value with scores above 50.00% for each evaluation category. However, the Naïve Bayes method scores above 85.00% for each evaluation category, so the Naïve Bayes method obtains the highest accuracy of 95.45%. So, it can be concluded based on the test results in Table 10 that the best application of the sentiment analysis method on tweets for academic articles is the Naïve Bayes method with an accuracy value of 95.45% and is the method that has the highest classification suitability between the given label and the predicted sentiment. However, the accuracy has not reached 100% due to data factors processed in the data cleansing and preprocessing processes. Besides that, perhaps because of the labeling factor in the initial data, which is done automatically using VEDER, there is a slight difference in the prediction labels generated by the system. But the accuracy value of 95.45% is included in the high score category and is close to perfect. The accuracy value using the Naïve Bayes method is 95.45, which is higher than the previous study using the Support Vector Machine by obtaining an accuracy value of only 78.71. Below is Figure 5, which shows that the sentiment analysis method using Naïve Bayes is the best method with the acquisition of Precision predictive Neutral 93.58%, Precision predictive Positive 98.12%, Precision predictive Negative 96.06%, Recall true Neutral 99.52%, Recall true Positive 87.9 %, Recall true Negative 96.85%, and accuracy value of 95.45%.

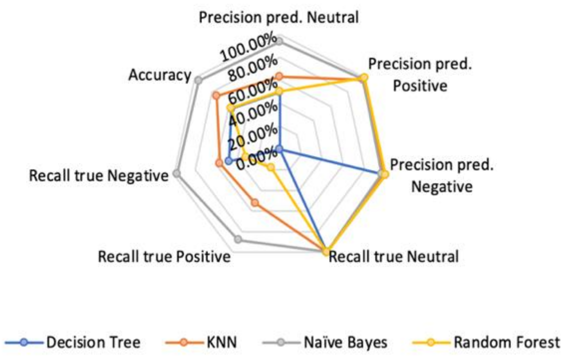

Figure 5. Test Results

4. Conclusion

The results of this study show that sentiment analysis using the Naïve Bayes method used to analyze tweets from Altmetric is the most suitable method by obtaining a higher classification suitability value compared to other methods, namely having a true positive sentiment value, Neutral 2056, Positive 1200, and Negative 1292. So, the Naïve Bayes method has the highest accuracy value of 95.45%. Whereas the Decision Tree method only gets an accuracy value of 56.83%, K Nearest Neighbors gets an accuracy value of 74.08% which is the second suitable method after the Naïve Bayes method, and the Random Forest method only gets an accuracy value of 57.50%. However, the Accuracy of the four methods can be improved by adding data and changing the pre-processing process. For future research, we can compare other sentiment analysis methods, such as Neural Networks and Logistic Regression.

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