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IMPLEMENTATION OF INFORMATION GAIN AND PARTICLE SWARM OPTIMIZATION ON SENTIMENT ANALYSIS OF COVID-19 HANDLING USING K-NN

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Abstract

In early 2020, a new virus from Wuhan, China, identified as the coronavirus or COVID-19, shocked the entire world. (Coronavirus Disease 2019). The government has made various attempts to combat this outbreak, even though the government's involvement in combating Covid-19 has many benefits and disadvantages. One of the most commonly debated subjects on Twitter is the Indonesian government's response to the Covid-19 virus. This research compares the k-nearest neighbor classification technique, the Information Gain feature selection with the K-Nearest Neighbor classification algorithm, and the Information Gain feature selection and Particle Swarm Optimization optimization with the K-Nearest Neighbor classification algorithm. Comparisons are performed to determine which method is more accurate. Because it is frequently used for text and data categorization, the K-Nearest Neighbor algorithm was selected. The K-Nearest Neighbor algorithm has flaws, including the ability to be fooled by irrelevant characteristics and being less than ideal in finding the value of k. The Information Gain feature selection could solve this issue by decreasing less critical terms. To optimize the K-Nearest Neighbor categorization an optimization method with the Particle Swarm Optimization algorithm is employed to maximize the K-Nearest Neighbor classification. According to the results of this research, the K-Nearest Neighbor categorization with Information Gain feature selection and Particle Swarm Optimization optimization is better than the K-Nearest Neighbor model without selecting features and without optimization. It is better than the K-Nearest Neighbor model with Information Gain selecting features, notably 87,33% with a value of K 5.

Keywords: *Sentiment Analysis, Covid-19, K-Nearest Neighbor, Information Gain, Particle Swarm Optimization*

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1. INTRODUCTION

The government's involvement in dealing with Covid-19 has many benefits and drawbacks, such as the imposition of large-scale social restrictions (PSBB). This causes the general public want to communicate different opinions. Time and space constraints make it challenging for people to share their views; however, the existence of social networks, such as Twitter, is a suitable location to express different opinions [1]. Twitter users frequently discuss public views of the Indonesian government's handling of the Covid-19 issue. Twitter is one method to gauge popular sentiment in Indonesia about how the government is handling COVID-19 [2].

Sentiment analysis is the process of comprehending and categorizing what is found in an article using text analysis techniques. Sentiment analysis is used to evaluate customers' or researchers' feelings, perceptions, and judgements about goods, services, or people. The benefit of this sentiment analysis can be done instantly, thereby saving time and resources [3].

The K-Nearest Neighbor (K-NN) algorithm is frequently used for text and data categorization. Previous research [4] used the K-NN technique to analyze popular opinion about the 2021 homecoming ban, with an accuracy of 86,67%. The existence or lack of unimportant characteristics, or if the weight of these features is not proportional to their importance for categorization, has a substantial effect on the K-NN algorithm's accuracy [5].

In a different study [6] on sentiment analysis of E-Wallet usage during a pandemic using Naïve Bayes Classifier and Information Gain resulted in an accuracy of 92%. Information Gain is one of the best methods in feature selection. One technique that is widely used for feature selection is Information Gain. In applications such as text classification, microarray data analysis, and image data analysis, Information Gain is a feature-selecting approach the simplest by rating characteristics. Information Gain works in lowering noise caused by unimportant features [7].

In addition, research conducted by [8] on ride-hailing sentiment analysis using the Support Vector Machine (SVM) algorithm with Term Frequency – Inverse Document Frequency (TF-IDF) weighting, resulted in an accuracy of 95.46%. Furthermore, the Particle Swarm Optimization (PSO) algorithm was added, resulting in an accuracy of 96.04%. A comparison of sentiment analysis classification techniques on the findings of this problem shows that the PSO-optimized SVM approach is superior to the SVM algorithm alone.

The K-Nearest Neighbor algorithm has the disadvantage that it is less than optimal in identifying the value of k and requires feature selection to achieve the best results [9]. Other drawbacks include the high computational cost of algorithms and gullibility with irrelevant features. This problem can be solved by selecting the Information Gain feature by eliminating irrelevant features and ranking important features to generate the best system evaluation value [10]. In addition, optimization methods using the Particle Swarm Optimization algorithm are applied to improve K-NN classification. In the data mining classification process, the PSO is used as a decision maker to determine the best solution.

In this research, the author used the K-Nearest Neighbor method along with the selection of the Information Gain feature and Particle Swarm Optimization to analyze Twitter users sentiment towards handling Covid-19.

2. RESEARCH METHOD

Figure 1 depicts the research phases. This research includes data collection phases, such as Preprocessing data, feature extraction using TF-IDF, feature selection using Information Gain, data sharing, classification using K-Nearest Neighbor, optimization using Particle Swarm Optimization, evaluation using Confusion Matrix. Data sharing consists of Train Data and Test Data. The data division is divided into 90:10.

In a different research [6] on sentiment analysis of E-Wallet usage during the pandemic using Naïve Bayes Classifier and Information Gain resulted in an accuracy of 92%. Information gain is one of the best methods for selecting features. One of the most widely used techniques for the selection of features is information gain. In applications such as text classification, microarray data analysis, and image data analysis, information gain is a feature selection approach. Based on the characteristics of the level, Information gain reduces noise caused by insignificant features [7].

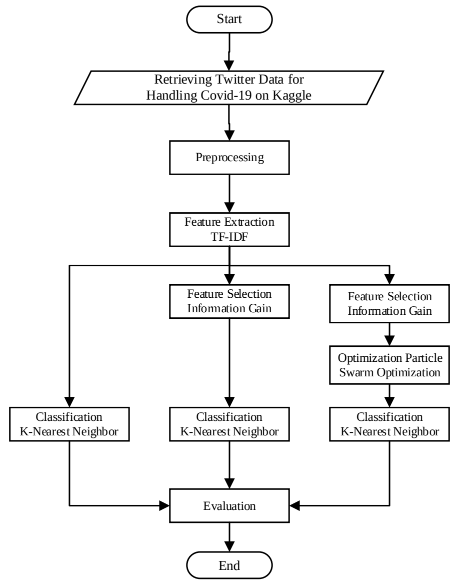

Figure 1. Research Flow

2.1 Data Collection

The research used Twitter data on opinions about the treatment of COVID-19 by the government in Indonesia. The data collected is obtained from link https://www.kaggle.com/dionisiusdh/covid19indonesian-twitter-sentiment, It was then selected, and a total of 1500 tweets were collected.

2.2. Preprocessing

In this research, preprocessing is divided into several steps, namely:

Labeling: In the process of labeling data, it is divided into two categories: (i) positive and (ii) negative.

Cleansing: The process clears the datasets from the link url, hashtag, username, symbol, email, bookmarks, and numbers.

Case Folding: Each word form is converted to a small letter, or lowercase.

Formalization: Non-standard terms are converted to standard words by the KBBI guidelines.

Stemming: This procedure returns the word to its fundamental shape or removes the substitutes.

Stopword Removal: This procedure gets rid of terms like "I," "rather," and "who" that have no real meaning.

2.3. TF-IDF

Inverse Document Frequency (TF-IDF) is a technique to calculate the significance of each word in a phrase based on the frequency with which it occurs across a set of documents. Term frequency is a statistic that measures how frequently a specific term appears. If the value of TF is higher, the higher the weight. IDF shows how often a particular term appears in each document. The higher the IDF value, the lower the TF. Once the data has been previously processed, it must be in a numerical format. TF-IDF is used to convert data into numerical form. The initial TF value of each word in the TF-IDF weight calculation is 1 [11]. The following formula can be used to obtain TF-IDF:

$$TFIDF_a = TF_a \text{ x } \log\left(\frac{N}{DFa}\right) \quad (1)$$

Information:
Tfa : the number of occurrences of each word in a document a
N : total number of documents
DFa : the total number of documents containing the word a
[12].

2.4. Information Gain

Information Gain is a very simple feature rating process, this method is widely used in reading category applications. The amount of information gained on each feature or Term of the category is measured by Information Gain.
Information Gain allows one to determine the value of each feature, which shows how effectively the feature distinguishes the important features from the sentiment category. Information gain is calculated based on how much influence a term has on classification [13].

2.5. Particle Swarm Optimization

The quickest and easiest optimization method is Particle Swarm Optimization, which involves simply adjusting a few parameters. Particle Swarm Optimization can be optimized through attribute selection, feature selection, and raising attribute weights for all attributes or factors used. [8]. In the data mining categorization process, Particle Swarm Optimization can help with decision making and finding the best answer. Particle Swarm Optimization is analogous to a flock of birds flying to a location to find food. They didn't know how to get there, but they knew how far away the food was. Therefore, following the last seen bird near the food is the most efficient method [14].

The benefits of particle swarm optimization include quick and straightforward convergence and ease of implementation. The method of discovering a solution based on the amount of particles of the Particle Swarm Optimization Algorithm is referred to as this. The community is evaluated at random, with a minimum and highest threshold. As they move across the search area, particles adjust to their best location (local best) and to their best position in the group as a whole (global best) [8].

2.6. K-Nearest Neighbor

To classify new data, the K-Nearest Neighbor (K-NN) method calculates the distance between each piece of data and its nearest neighbor, and then assigns each piece of data to one of those categories. K-Nearest Neighbor improves Nearest Neighbor classification method [13]. The K-NN approach has the advantage of working well with large datasets and is also strong against training data that is noise, i.e., data with a wide range of values, but can interfere with current data structures [9]. The distance on the K-Nearest Neighbor algorithm using Cosine Similarity is calculated using Equation 5:

$$\cos(D) = \frac{\sum_{i=1}^{n} Q_i D_i}{\sqrt{\sum_{i=1}^{n} (Q_i)^2}\sqrt{\sum_{i=1}^{n} (D_i)^2}} \quad (5)$$

Information:
$\cos(\theta QD)$: the resemblance of Q to document D
Q : test data
D : Training Data
n : amount of training data
[15].

2.7. Evaluation

Calculating the performance of the classification model is one way to determine the effectiveness of the system being built. The Confusion Matrix is one of the metrics used to calculate system performance and efficiency [12]. Confusion confusion matrix is a technique for evaluating the performance of classification algorithms. Applications of evaluation with Confusion confusion matrix will obtain an accuracy value, which is a percentage of the data that has been correctly classified by an algorithm. On the Confusion Matrix, metrics such as accuracy can be calculated to assess the effectiveness of the classification results used. Accuracy is the proportion of the true positive and true negative classification results of all documents using equation 6.

$$accuracy = \frac{TN+TP}{TN+FP+FN+TP} \text{ x } 100\% \quad (6)$$

Description:
True Negative (TN): the detected negative data is true
False Positive (FP): negative data detected positive data
True Positive (TP): positive data detected is true
False Negative (FN): positive data detected negative data
[13].

3. RESULT AND DISCUSSION

3.1. Data Collection

This research utilizes the Twitter dataset, which includes discussions about how the Indonesian government handles the COVID-19 virus. The data collected amounted to 1500 records, sourced from

Kaggle. Data can be downloaded at the link https://www.kaggle.com/dionisiusdh/covid19indonesian-twitter-sentiment.

3.2. Preprocessing

The first step is manual labeling based on the characteristics of the data used. In the process of labeling data, it is divided into two categories: (i) negative and (ii) positive.

Table 1. Labeling

Text	Label
Aku bingung pemerintah sebenarnya gimana ya? Serius apa ngga nanganin covid? https://twitter.com/ainunnajib/status/1260924890439315456Â â€¦	Negatif
hayuuuk Bersatu cegah Covid-19 w/ mengikuti aturan dri Pemerintah. . #ShalatIdDirumahAja pic.twitter.com/6bjLhMgBkZ	Positif

The second stage is Cleansing which is used to reduce Noise by removing unnecessary words. Words are removed, such as URL, hashtag (#), username (@username), numbers, email, and reading marks. The cleansing process can be seen in Table 2.

Table 2. Cleansing

Before Cleansing	After Cleansing
Aku bingung pemerintah sebenarnya gimana ya? Serius apa ngga nanganin covid? https://twitter.com/ainunnajib/status/1260924890439315456Â â€¦	Aku bingung pemerintah sebenarnya gimana ya Serius apa ngga nanganin covid
hayuuuk Bersatu cegah Covid-19 w/ mengikuti aturan dri Pemerintah. #ShalatIdDirumahAja pic.twitter.com/6bjLhMgBkZ	hayuuuk Bersatu cegah Covid w mengikuti aturan dri Pemerintah

The third stage is case folding, which is used to change the form of a word into a lowercase or small letter. The case folding process can be seen in Table 3.

Table 3. Case Folding

Before Case Folding	After Case Folding
Aku bingung pemerintah sebenarnya gimana ya Serius apa ngga nanganin covid	aku bingung pemerintah sebenarnya gimana ya serius apa ngga nanganin covid
hayuuuk Bersatu cegah Covid w mengikuti aturan dri Pemerintah	hayuuuk bersatu cegah covid w mengikuti aturan dri pemerintah

The fourth stage is a formalization, which serves to convert acronyms and terms that do not match the KBBI spelling into standard word forms that do match the KBBI spelling. Use a raw language lexicon that was especially made based on the data used at this step of formalization. Words that do not match the KBBI edition will be changed into terms that do on the basis of the dictionary that has already been produced. Figure 4 illustrates the formalization procedure.

Table 4. formalization

Before the formalization	After the formalization
aku bingung pemerintah sebenarnya gimana ya serius apa ngga nanganin covid	aku bingung pemerintah sebenarnya bagaimana ya serius apa tidak tangan covid
hayuuuk bersatu cegah covid w mengikuti aturan dri pemerintah	ayo bersatu cegah covid w mengikuti aturan dari pemerintah

The fifth stage is stemming, which is used to remove the imbuhan contained in the word or change the word back into its basic form. The Stemming process can be seen in Table 5.

Table 5. Stemming

Before Stemming	After Stemming
aku bingung pemerintah sebenarnya bagaimana ya serius apa tidak tangan covid	aku bingung pemerintah benar bagaimana ya serius apa tidak tang covid
ayo bersatu cegah covid w mengikuti aturan dari pemerintah	ayo satu cegah covid w ikut atur dari pemerintah

Stopword Removal is the sixth stage, and it is used to eliminate meaningless or non-standard words (stopwords) from Tweet. To delete words that do not have important meanings or are not basic, use a dictionary created based on the data used and the general dictionary of English accessed through the link on github masdevid https://github.com/masdevid/ID-Stopword. The stopword removal process can be seen in Table 6.

Table 6. Stopword Removal

before Stopword Removal	After Stopword Removal
aku bingung pemerintah benar bagaimana ya serius apa tidak tang covid	bingung pemerintah serius tang covid
ayo satu cegah covid w ikut atur dari pemerintah	cegah covid atur pemerintah

3.3. Features Of TF-IDF Extraction

The technique Term Frequency - Inverse Document Freqency is used to identify features (TF-IDF). Tf-Idf Or Term Frequency – Inverse Document Frequency is a calculation used to determine the weight of terms in a text. Table 7 shows an illustration of the outcome of extracting features from data that is already in Preprocessing on 1500 data points with 750 labels each.

Table 7. Example of TF-IDF Weighting Results

ambil	bantu	…	temu	zona	label
0	0,354994	…	0,265754	0	Negatif
0,463629	0	…	0	0	Negatif
…	…	…	…	…	…
0	0,328698	…	0	0	Positif

3.4. Feature Selection With Information Gain

The following procedure involves the selection of features using Information Gain, which is done using Tools RapidMiner. The Information Gain algorithm was used to pick functions, and a Threshold threshold of 0.01 was used to generate 1897 features from 1916 features.

3.5. Particle Swarm Optimization

To optimize the K-Nearest Neighbor classification and help improve the accuracy of the model created, we used optimization techniques with the Algorithm for Partitioned Arrays of Optimization (algoritm particle swarm optimization). Tools RapidMiner is used to implement the Particle Swarm Optimization algorithm. The value of the particle used is 10, with the number of iterations set at 30, and other parameter values set by default.

3.6. Division Of Data

Before categorizing, the data is first split into Training data and Testing data, where the division employs the Random Percentage Split method. The data sets in this research were separated into 90% Training data and 10% Testing data. The machine splits data at random.

3.7. Performance Comparison

On the K-Nearest Neighbor classification, the K parameter utilized for the manufacturing of K-Nearest Neighbor models, the K-Nearest Neighbors model using Information Gain, and the K-Nearest Neighbor model with the Information Gain feature selection and Particle Swarm Optimization optimization is an odd number between 1 and 10 and distance calculation utilizing Cosine Similarity.

Table 8. Accuracy Results

Model	Accuracy				
	K=1	K=3	K=5	K=7	K=9
K-NN	76,76%	74%	77,33%	79,33%	82,67%
Information Gain +K-NN	76%	75,33%	81,33%	82%	79,33%
Information Gain+ PSO+ K-NN	82%	84,67%	87,33%	86%	85,33%

According to table 8, the accuracy of the K-Nearest Neighbor model K=9 is 82.67% higher than the accuracy of the other K values. In the K-Nearest Neighbor model with the Information Gain feature selection, K=7 is 82% more accurate than the other K values. Then, on the K-Nearest Neighbor model with information gain selection and Particle Swarm Optimization optimization, K=5 was 87.33% more accurate than the other K values. The addition of the Particle Swarm Optimization optimization to the K-Nearest Neighbor classification with the selection of the Information Gain feature could indeed significantly enhance the precision; from the 5 tested K values, all experienced an improvement in accuracy ranging from 4% on k 7 to the highest 9.34% on k 3.

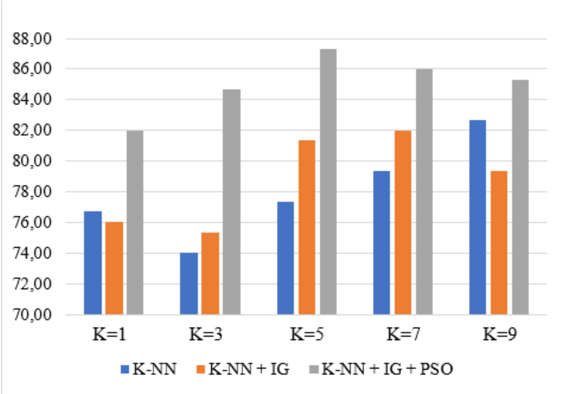

Figure 2. Comparison of accuracy

3.8. The Evaluation Related To Confusion Matrix

The Confusion Matrix is going to be utilized to determine accuracy during the evaluation stage. There are 52 negative data and 3 positive data predicted as negative data in the K-Nearest Neighbor classification K=9 with an accuracy of 82.67%. Then there are 23 negative data points and 72 positive data points that are regarded as positive data predictions. The accuracy is calculated as follows:

$$\text{Accuracy} = \frac{52+72}{52+23+3+72} \text{ x } 100\% = 82{,}67\%$$

With an accuracy of 82%, K=7 in the K-Nearest Neighbor classification with the selection feature Information Gain had 56 negative data and 8 positive data that were projected to be negative data. Then there are 19 negative data points and 67 positive data points that are regarded as positive data predictions. The accuracy is calculated as follows:

$$\text{Accuracy} = \frac{56+67}{56+19+8+67} \text{ x } 100\% = 82\%$$

In the K-Nearest Neighbor classification with the choice of Information Gain features and Particle Swarm Optimization optimization, K=5 with an accuracy of 87.33% had 62 negative data and 6 positive data predicted as negative data. There are 13 negative data and 69 positive data that are regarded positive data predictions. The calculation for accuracy is as follows:

$$\text{Accuracy} = \frac{62+69}{62+13+6+69} \text{ x } 100\% = 87{,}33\%$$

4. CONCLUSION

According to the findings, the K-Nearest Neighbor classification had the highest accuracy, with a K=9 value of 82.67%. The best accuracy in the K-Nearest Neighbor classification with the selection of Information Gains results attained is with a value of K=7 of 82%. The selection features Information Gain and Particle Swarm Optimization achieved the highest accuracy in the K-Nearest Neighbor classification, with a K=5 value of 87.33%. The K-Nearest Neighbor classification with the selection of Information Gain features and the Particle Swarm Optimization optimization is superior to the K-Nearest Neighbor classification without feature selection and without optimization as well as superior to that of K-Nearest Neighbors with the Information Gain feature selection. To acquire a significant impact, utilize different K values on the K-Nearest Neighbor classification method, as well as feature selection methods and other optimization methods.

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