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Comparison of Kernel Support Vector Machine Multi-Class in PPKM Sentiment Analysis on Twitter

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Abstract

PPKM is the Indonesian government's policy to deal with the spread of the coronavirus since early 2021. Until now, PPKM is still the main topic to prevent the spread of COVID-19. This policy has generated various responses from the public, especially on Twitter. A sentiment analysis process is needed to process the text obtained from Twitter. Sentiment analysis is a form of representation of text mining and text processing. This study aims to analyze public sentiment towards PPKM through data obtained from Twitter using the multi-class SVM algorithm. In implementing multi-class SVM, an analysis of the Polynomial and RBF kernels was carried out on the One Against One and One Against Rest methods which showed that the combination of One Against Rest and the Polynomial kernel obtained the best accuracy, which was 98.9%. Unlike the case with the combination of One Against One and Kernel RBF, which obtained the worst accuracy, 77.6%. The best model produces precision, recall, and f1-score values of 97%, 98%, and 97%. Based on the confusion matrix results, the best model has a positive class distribution = 912, neutral = 51, and negative = 26. Overall, the model that uses polynomial kernel produces higher accuracy, both applied to the One Against One and One Against Rest methods. In contrast, the model that uses the RBF kernel produces lower accuracy and is significantly different when applied to the One Against One and One Against Rest methods. The model results show that public sentiment towards the PPKM policy is positive to be continued consistently to suppress the spread of the COVID-19 virus.

Keywords: *PPKM, Support Vector Machine, One Against One, One Against Rest, Polynomial, RBF*

1. Introduction

In dealing with the Covid-19 pandemic, the Indonesian government has implemented various policies such as Large-Scale Social Restrictions (PSBB) [1] and the Enforcement of Restrictions on Community Activities (PPKM). The PPKM policy has been implemented to deal with the spread of the Covid-19 virus since early 2021. PPKM occurs in all areas in Indonesia, which are the point of spreading the Covid-19 virus infection [2].

Public opinion through Twitter can be used to conclude the current situation in an area [3]. In Indonesia, users generally access Twitter, reaching 59%, and it is ranked 5th most frequently used social media in 2020 [4]. The number of uploads on Twitter about PPKM has become a useful data set to serve as a supporting tool in policymaking. Sentiment analysis is needed to collect comments and uploads to obtain data on the trend level of public responses to this PPKM policy.

Sentiment analysis is a process of extracting attitudes, opinions, and emotions in text data [5]. Based on the approach process, sentiment analysis is divided into two, namely Machine Learning and Lexicon-based [6]. The Machine Learning approach is carried out by processing data that has previously been divided into positive data and negative data. The lexicon-based method is made by giving the sentiment value of a word based on the lexicon dictionary. To obtain public opinion on PPKM, sentiment analysis that can be used is machine learning to process text data that will be classified into positive, negative, or neutral sentiments.

Many sentiment analysis studies have been carried out, especially on the Support Vector Machine (SVM) method. The basic principle of SVM is to find a dividing hyperplane between positive and negative classes [7], whereas this study consists of three classes (positive, negative, and neutral) so that the SVM used was multi-class [8]. The effectiveness of this SVM algorithm can be quite good compared to other algorithms in the classification process, as evidenced by previous studies on the comparison of SVM and Naïve Bayes classification resulting in accuracy of 76.42%

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and 62.47% [9]. Other studies also support this by comparing the SVM and KNN methods with 95% and 80% accuracy [10]. The weakness in previous research is that there is no comparison of the SVM approach combined with the kernel. In SVM, several parameters can be configured to obtain optimal results [11], one of which is the kernel. Based on this, it is necessary to compare SVM kernels to find out the best kernel that can be used, especially in sentiment analysis.

This study aims to analyze sentiment on Twitter using the SVM method related to PPKM in Indonesia. Data is obtained from Twitter through the crawling technique, separated into training and test data. The training data consists of the attributes used for modeling the SVM classification, while the test data is used to evaluate the model results. This study compares the Polynomial kernel and RBF on the One Against One and One Against Rest approaches to obtain optimal accuracy results. Finally, the model with the best accuracy is analyzed to see the number of values in the positive, negative, and neutral classes to obtain the value of public sentiment towards the PPKM policy.

2. Research Methods

The stages carried out in this study can be seen in Figure 1.

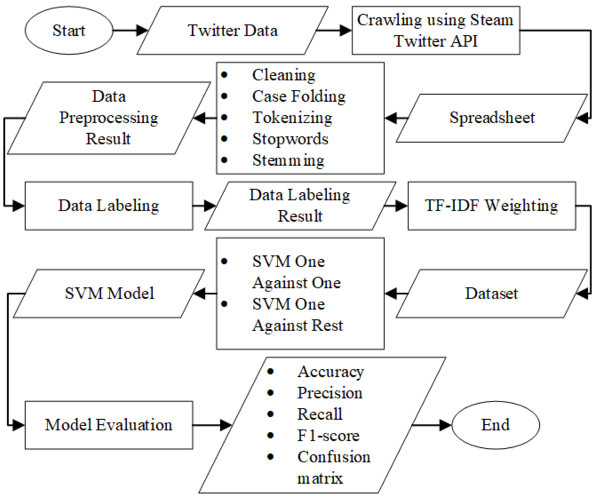

Figure 1. Research stage

The explanation of each stage in Figure 1 is explained as follows.

2.1 Data Collection

The tweet text dataset was obtained from Twitter social media through a crawling technique using the Python programming language. A key and an access token are required as proof of authentication using the Twitter developer method to perform the Steam Twitter API. In searching for data using the keyword "PPKM", the data obtained is stored in excel with .csv format. The following is an illustration of Twitter data crawling shown in Figure 2.

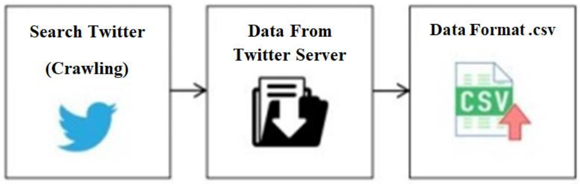

Figure 2. Data collection stage

2.2 Data Preprocessing

Data preprocessing is an initial data mining technique to convert raw data or commonly known as raw data collected from various sources, into cleaner information that can be used for further processing. This process can also be called the initial step to retrieve all available information by cleaning, filtering, and combining the data. Preprocessing data is very important because errors, redundancies, missing values, and inconsistent data reduce sentiment analysis results. The sequence of data preprocessing carried out is shown in Figure 3.

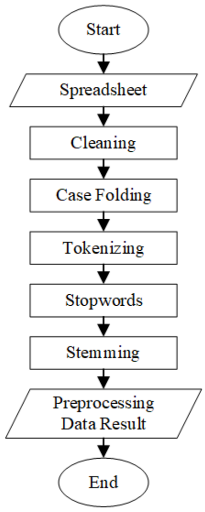

Figure 3. Data preprocessing stage

The explanation of each stage in Figure 3 is explained as follows.

a. Cleaning is a step that aims to remove the character or symbol link URL (http://site.com), username or mention(@username), hashtag (#), retweet, and emoticons. Three operations are performed to clean up unnecessary characters, namely removing numbers, punctuation, and whitespace.
b. Case Folding is a stage that aims to convert all responses into lowercase letters. In this process, the characters ‘A’-‘Z’ contained in the data are converted to characters ‘a’-‘z’. Meanwhile, other characters that are not letters and numbers, such as punctuation marks and spaces, are considered delimiters.
c. Tokenizing is data processed where punctuation marks will be removed to produce sentences/words

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that stand alone. Entities that can be referred to as tokens include words, numbers, symbols, punctuation marks, etc. That is, this stage aims to break down responses into word units.

d. Stopwords is a step that aims to eliminate common words that often appear in large numbers and have no meaning using a stoplist algorithm (removing less important words) or wordlist (saving essential words). An example in this study is the use of conjunctions such as 'dan', 'yang', 'serta', 'setelah', and others. Removing this stopwords can reduce index size and processing time. In addition, it can also reduce the noise level.
e. Stemming is the stage where each word will be changed from affixes to base words. This stage is needed to reduce the number of different indexes from one data so that a word with a suffix or prefix will return to its basic form. In addition, it is also to group other words that have the same basic word and meaning but have a different form because they get different affixes.

2.3. TF-IDF Weighting

The weighting stage is giving weight to each word by using the calculation of Term Frequency – Invert Document Frequency. This stage calculates the Term Frequency (TF) and Inverse Document Frequency (IDF) values for each token (word) in the dataset. In simple terms, the TF-IDF method is used to determine how often a word appears in the dataset. The TF-IDF weighting stages are shown in Figure 4.

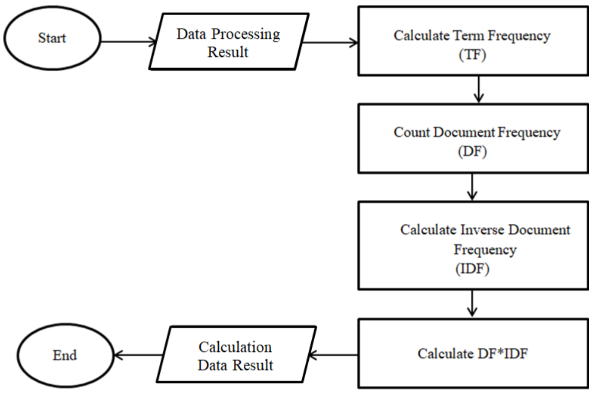

Figure 4. TF-IDF weighting stage

2.4 Support Vector Machine

Support Vector Machine is a classification algorithm that, in its working process, uses a hypothetical space consisting of a two-way linear function in a feature space that has high dimensions. Basically, SVM is used to classify data with only two classes [12] to find hyperplanes with optimal margins [13]. In the case of more than two classes, a different approach is needed from the two classes, especially in this study that uses three classes, namely positive, negative, and neutral. There are several multiclass SVM methods [7], namely One Against One (OAO) and One Against All (OAA).

The basic principle of the OAO method is to build (k-1)/2 binary SVM models (k is the number of classes), where each classification model is trained on data from two classes. Meanwhile, the basic concept of OAA is that k binary SVM models are built (k is the number of classes), where each i-th classification model is trained using all data to find solutions to problems. Basically, SVM is a linear hyperplane that only works on data that can be separated linearly. The kernel approach to the feature dataset is used for data whose class distribution is not linear. The kernel functions that will be used in this study include two, namely:

a. Polynomials, kernel functions representing the similarity of vectors in the feature space over the original variable polynomials, allow learning of non-linear models. Equation 1 is used to apply the polynomial kernel in SVM [8].

$$K(x,y) = (x^T.y + 1)^d \quad (1)$$

where, d is degree of polynomial

b. Radial Basis Function (RBF), kernel function whose value depends on the distance from the origin or some point. Equation 2 is used to implement the RBF kernel in SVM [8].

$$K(x,y) = \exp\left(-\frac{\|x,y\|^2}{2\sigma^2}\right) \quad (2)$$

where, $\sigma > 0$ is constant term

2.5 Confusion Matrix

Confusion Matrix is used to determine the effectiveness of the classification modeling, which consists of rows and columns that form a table containing labels from the prediction test data [14]. In this study, the confusion matrix consisting of True Positive (TP), True Negative (TN), and True Neutral (TNR) is a correct prediction based on actual data. False Positive (FP) is an error where the actual data labeled positive is predicted to be negative or neutral. False Negative (FN) is an error where the actual data labeled negative is predicted to be positive or neutral. False Neutral (FNR) is an error where the actual data labeled neutral is predicted to be positive or negative. To evaluate the model's performance, we used four aspects of the assessment, namely accuracy, precision, recall, and F1 score. Accuracy is the ratio of correctly classified sentiment samples to the total number of samples, as shown in equation 3 [15].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Precision is a measure of the positive ratio, the correctly predicted class of sentiment to the total number of positive classification predictions, which can be seen in equation 4 [15].

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

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The recall measures the actual positive ratio, correctly predicted sentiment class, as shown in equation 5 [15].

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

The F1 score measures the average precision and memory, which can be seen in equation 6 [15].

$$F1 = \frac{2\times Precision\times Recall}{Precision+Recall} \quad (6)$$

After obtaining the model with the best performance, the sentiment analysis results are visually displayed in the form of a graph. By visualizing the prediction results, the distribution of public opinion that is positive, negative, and neutral can be seen. The confusion matrix used in this study can be seen in Table 1.

Table 1. Confusion matrix

Actual	Prediction		
	Positive	Negative	Neutral
Positive	TP	FN	FNR
Negative	FP	TN	FNR
Neutral	FP	FN	TNR

3. Results and Discussions

Data collection in this study comes from Twitter data by registering an account to access the Twitter API. After registering an account, the consumer key, consumer secret, access token, and access token secret will be obtained. This is then used to access the Twitter library to get data according to the keywords entered, namely "PPKM".

3.1 Preprocessing Data Result

The dataset successfully obtained from Twitter through the crawling technique amounted to 5000 data between October 10, 2021, to December 2, 2021. The data preprocessing stage consisted of cleaning, case folding, tokenizing, stopword, and stemming. The data preprocessing stage is implemented using python programming, which utilizes the basic preprocessing library.

The first data preprocessing is cleaning, which removes punctuation marks, numeric numbers, and other unique symbols. The following is an example of the cleaning process shown in Table 2.

Table 2. Cleaning result

Before	After
RT @DS_yantie: Pemerintah tidak mau kecolongan lagi. Pelonggaran PPKM bukan berarti masyarakat bisa beraktivitas dengan bebas di tengah pandemic	Pemerintah tidak mau kecolongan lagi Pelonggaran PPKM bukan berarti masyarakat bisa beraktivitas dengan bebas di tengah pandemi

The next data preprocessing is case folding, which converts capital letters into lowercase letters. The following is an example of the case folding process shown in Table 3.

Table 3. Case folding result

Before	After
Pemerintah tidak mau kecolongan lagi Pelonggaran PPKM bukan berarti masyarakat bisa beraktivitas dengan bebas di tengah pandemi	pemerintah tidak mau kecolongan lagi pelonggaran ppkm bukan berarti masyarakat bisa beraktivitas dengan bebas di tengah pandemi

The next data preprocessing is tokenizing, which separates words based on spaces. Separation is done so that each word can be analyzed easily. The following is an example of the tokenizing process shown in Table 4.

Table 4. Tokenizing result

Before	After
pemerintah tidak mau kecolongan lagi pelonggaran ppkm bukan berarti masyarakat bisa beraktivitas dengan bebas di tengah pandemi	‘pemerintah’ ‘tidak’ ‘mau’ ‘kecolongan’ ‘lagi’ ‘pelonggaran’ ‘ppkm’ ‘bukan’ ‘berarti’ ‘masyarakat’ ‘bisa’ ‘beraktivitas’ ‘dengan’ ‘bebas’ ‘di’ ‘tengah’ ‘pandemi’

The next data preprocessing is stopword, which aims to change non-standard words into standard words according to the Big Indonesian Dictionary (KBBI). The following is an example of a stopword process shown in Table 5.

Table 5. Stopword result

Before	After
pemerintah tidak mau kecolongan lagi pelonggaran ppkm bukan berarti masyarakat bisa beraktivitas dengan bebas di tengah pandemi	pemerintah tidak mau colong lagi longgaran ppkm bukan berarti masyarakat bisa aktivitas dengan bebas di tengah pandemi

The next data preprocessing is stemming, which aims to remove words that are not descriptive or have no effect, such as ‘yang’, ‘ke’, ‘dari, etc. The following is an example of the stemming process shown in Table 6.

Table 6. Stemming result

Before	After
pemerintah tidak mau colong lagi longgaran ppkm bukan berarti masyarakat bisa aktivitas dengan bebas di tengah pandemic	perintah colong longgar ppkm berai masyarakat aktivitas bebas pandemi

The next data preprocessing is labeling, which aims to label data consisting of three classes: positive, negative, and neutral. Sentiment class labeling is done by acquiring the knowledge of Indonesian language experts, namely Mr. Jafar Fakhrurozi, S.Pd., M.Hum., who is a lecturer at the Teknokrat Indonesia University. The result is positive sentiment totaling 3547, negative sentiment totaling 585, and neutral sentiment totaling

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868. The following is the distribution of dataset class labeling shown in Figure 5.

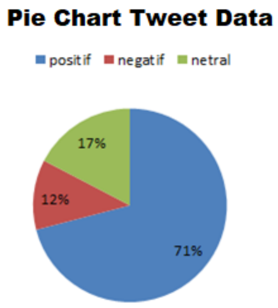

Figure 5. Labeling data

The last data preprocessing is TF-IDF weighting, which aims to convert text data into numeric data so that calculations can be carried out and calculate the weight of each word. The greater the weight of a word, the more important it is. In addition, the TF-IDF weighting is also useful for data filtering because words that have a weight >0 will be processed for the next stage, while words with a value of 0 will not be processed or displayed.

3.2 *Support Vector Machine Model*

The community's sentiment analysis on the PPKM policy is carried out by applying the SVM algorithm to a collection of data obtained through Twitter. The dataset generated through preprocessing the data is then partitioned into training data and test data using a random percentage of 80:20. The SVM algorithm classification modeling was carried out using the Python programming language version 3.7 by utilizing the Scikit-learn library version 0.21. In this study, four model variations were made as a comparison to obtain the best results, especially in accuracy. The model variation is based on the multiclass SVM method consisting of OAO and OAR combined with two kernels. The first and second models use the OAO method combined with the RBF kernel and polynomials. The third and fourth models use the OAR method combined with the RBF kernel and polynomial.

3.3 Model Evaluation

The evaluation was carried out on 1000 test data, 20% of the total data. The following are the results of the evaluation of the SVM method combined with the kernel on the values of accuracy, precision, recall, and F1-score of the class distribution values obtained, shown in Table 7.

Table 7. Evaluation result

Method	Kernel	Accuracy	Precision	Recall	F1-score
OAO	RBF	77.6%	76%	77%	76%
OAO	Polynomial	98.9%	96%	98%	97%
OAR	RBF	95.6%	93%	95%	94%
OAR	Polynomial	98.9%	97%	98%	97%

Regarding accuracy, it was found that implementation of the Polynomial kernel on the model is better than the RBF kernel, both in the OAO and OAR methods, which produce the same accuracy value, 98.9%. So, it can be said that the OAO and OAR methods have little effect on the Polynomial kernel. Unlike the case with the combination of the RBF kernel and the OAO method, which produces the lowest accuracy, 77.6%. However, implementation of the RBF kernel on the OAR method obtained a significantly different accuracy result from the OAO method, namely 95.9%. This can be caused by the incompatibility of the combination of the RBF kernel and the OAO method compared to the combination of the RBF kernel and the OAR method.

Regarding precision, it can be seen that the model with a combination of OAR and kernel polynomial methods obtained the highest value, which is 97%. This is due to the ratio of TP predictions to the overall positive predicted results being higher than other models. While the model with the lowest precision value is a combination of the OAO method and RBF kernel, which means the ratio of TP predictions compared to the overall predicted positive results is lower than other models.

Regarding recall, it can be seen that the model using the polynomial kernel produces the highest value, both combined with OAO and OAR methods. This shows that the polynomial kernel model has a better ratio of TP predictions than the overall TP data from the RBF kernel model. Meanwhile, the model with the lowest recall value is a combination of OAO method and the RBF kernel, which means that the prediction ratio of TP compared to the overall TP data is lower than other models.

Like the recall, in the f1-score, the polynomial kernel model produces the highest score, combined with OAO and OAR methods. This shows that the polynomial kernel model has better average precision and recall weighted comparison value than the RBF kernel model. In contrast, the model with the lowest f1-score value is a combination of the OAO method and RBF kernel, which means that the average comparison value of precision and recall is weighted lower than the other models.

Overall, the best model is a combination of the OAR method and kernel polynomial, which gets the highest value in all aspects, shown in Table 7. In comparison, the worst model is a combination of the OAO method and RBF kernel, which gets the lowest score in all aspects. Furthermore, the application of the polynomial kernel in both methods, both OAO and OAR, obtained similar results. This means that the polynomial kernel performance is more consistent than the RBF kernel, significantly different when applied to two different methods. A confusion matrix was used to see the class distribution as the best model, namely a combination of

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OAR method and a polynomial kernel. The confusion matrix results of the order of 3x3 can be seen in Table 8.

Table 8. Confusion matrix result

Actual	Prediction		
	Positive	Negative	Neutral
Positive	912	0	5
Negative	0	26	2
Neutral	3	1	51

Based on Table 8, it was found that the total correctness of predictions was 989, which resulted from the number of correct predictions being neutral = 51, positive = 912, and negative = 26. At the same time, the total prediction error is 11, which is the result of prediction errors from the actual class, whether neutral, positive, or negative. Errors in predictions can be caused by training data that do not fully represent the test data so that the prediction results do not match the actual data. However, with an accuracy that has reached 98.9%, it can be said that the resulting model is very good and can represent most of the data. The following is the final result of the public sentiment analysis towards PPKM, shown in Table 9.

Table 9. Sentiment analysis result

Class	Total
Neutral	51
Positive	912
Negative	26

Based on table 9, the results of the analysis on public sentiment contain more positive sentiments = 912, followed by neutral = 51, and finally negative = 26. It can be concluded that the PPKM policy has received a positive response from the public, so it is hoped that it will continue to suppress the spread of the coronavirus in Indonesia. Meanwhile, people who respond negatively are urged to continue to follow government regulations to reduce the space for spreading the COVID-19 virus.

4. Conclusion

This study applies multi-class SVM to sentiment analysis on PPKM policies obtained through Twitter data. The resulting SVM model uses two approaches, namely One Against Rest and One Against One, combined in two kernels, namely Polynomial and RBF. SVM One Against Rest combined with Polynomial kernel produces 98.9% accuracy while the combination with RBF kernel is only 95.6%. SVM One Against One combined with the Polynomial kernel resulted in an accuracy of 98.9%, but the combination with the RBF kernel was significantly different, namely 77.6%. It can be said that the polynomial kernel is better than the RBF kernel, both when applied to the One Against Rest and One Against One method. The results of the evaluation of the model with the best accuracy, namely the combination of the One Against One method and the Polynomial kernel, have a class distribution of positive = 912, neutral = 51, and negative = 26. It can be concluded that the sentiments of the Indonesian people through Twitter towards the PPKM policy during the pandemic are more leaning towards Positive. As a development for further research, optimization methods can be applied to the kernel that produces the lowest accuracy.

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