Sentiment Analysis of Public Perception Regarding the *Merdeka Belajar Kampus Merdeka* (MBKM) Policy on Twitter Using the K-Nearest Neighbor (K-NN) Method

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Abstract. This research aims to analyze public sentiment and perceptions of the *Merdeka Belajar Kampus Merdeka* (MBKM) policy through data obtained from social media Twitter. MBKM is a higher education policy in Indonesia that aims to provide tolerance and independence for students in choosing courses and accessing learning resources. The K-Nearest Neighbor (K-NN) method is used to classify sentiment based on text tweets related to MBKM. The steps in this research including tweet data containing keywords related to MBKM taken from Twitter, the text data is extracted, cleaned, and converted into a vector representation, and the K-NN model is drilled using the preprocessed tweet data. This model will classify sentiment into positive, negative, or neutral. Model performance is evaluated using metrics such as accuracy, precision, and recall. It is hoped that the results of this research will provide insight into how society responds to MBKM policies through social media platforms. With a further understanding of these sentiments, educational institutions can take appropriate actions to improve MBKM implementation. The algorithm was applied to 2000 tweet data with the keyword “MBKM”. The model training results prove that the negative precision score is 85%, neutral precision is 53%, positive precision is 70% and accuracy is 71%.

Keywords: Public Sentiment, MBKM, K-Nearest Neighbor

1 Introduction

Merdeka Belajar Kampus Merdeka (MBKM) is an innovation created by the Ministry of Education and Culture and launched a policy to transform the higher education system in Indonesia to produce more relevant graduates (Setiawan et al., 2023). The Independent Learning Program - Independent Campus is expected to be able to answer the challenges of higher education institutions to produce graduates who are in line with current developments, advances in science and technology, the demands of the business and industrial world, as well as the dynamics of society.

The implementation of MBKM presents a new phenomenon in the world of education. The positive impacts of MBKM include increasing learning motivation,

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developing competence, and improving character (Arsyad et al., 2022). To realize this positive impact, support is needed from various parties, including the government, universities, and lecturers. Weaknesses and inhibiting factors found in the implementation of MBKM, namely the unpreparedness of lecturers, lack of adjustments and training related to the implementation of MBKM, lack of facilities and infrastructure, and less than optimal learning systems.

Of course, there are some obstacles faced by universities when implementing MBKM (Yoga et al., 2022). There are many comments both pro and contra regarding the implementation of MBKM. For this reason, it is necessary to know the extent of public sentiment regarding the implementation of MBKM. Community sentiment can be grouped into two, those who feel that the implementation of MBKM provides a good solution and those who feel that it is not an effective solution.

To find out public sentiment, we can take and use data on social media. Social media is media that is a means of conveying opinions in public spaces through digital media. One thing that is often used as reference material is sentiment from the social media Twitter. With methods in the computer world known as machine learning, results can be obtained in the form of negative tweets, neutral tweets, and positive tweets. In this research, the K-Nearest Neighbor (K-NN) method was used to obtain a sentiment analysis of public perceptions of the Independent Learning Campus (MBKM) policy.

Other research on sentiment analysis on social media includes Sentiment Analysis About Airline Opinions in Twitter Documents Using the Support Vector Machine (SVM) algorithm which produces the best accuracy of 40% and precision of 40%, recall of 100%, and f- measure of 57.14%. This level of accuracy was obtained with a maximum number of iterations of 50 times with the implementation of the Lexicon-based feature (Pravina et al., 2019).

The second research is the analysis of public opinion sentiment regarding 2019 homecoming facilities and transportation on Twitter using the Naïve Bayes algorithm, Neural Network, KNN, and SVM. The results of public sentiment taken using the keyword Homecoming Hari Raya 2019 show that Twitter users give more positive opinions. The K-NN algorithm has higher accuracy than the SVM, Naïve Bayes and Neural Network algorithms for classifying sentiment analysis of English text with an accuracy value = 90.76% (Pertiwi, 2019).

The third research is a Comparison of Accuracy Between Convolutional Neural Networks and Naïve Bayes Classifiers in Sentiment Analysis on Twitter. This research found that the CNN Classifier model produced an accuracy of 0.88 or 88% while the NBC Classifier model produced an accuracy of 0.78 or 78% at the data testing stage (Sunarya et al., 2019). To examine public opinion of the *Merdeka Belajar Kampus Merdeka* (MBKM) policy—which is a revolutionary step for higher education in Indonesia—this study proposes a novel use of the K-Nearest Neighbor (K-NN) method. Although sentiment analysis has been used extensively in industries including transportation (Pertiwi, 2019) and airline services (Pravina et al., 2019), its use in government-driven educational reforms has not received as much attention. Furthermore, earlier research in related disciplines concentrated on general social media sentiment (Pravina et al., 2019); nevertheless, this study closes the gap in the literature by focusing specifically on how educational policies are perceived.

2 Methodology

2.1 Data Labeling

The data that has been collected is given a sentiment label as a requirement for carrying out the classification stage. Labeling was done manually by the researcher. Labeling is done by human power with the assumption that only living creatures can feel emotions or sentiments, whereas machines cannot. Label 0 means negative, label 1 means neutral, and label 2 means positive. The negative data in question is data that contains ridicule, harsh words, protests against MBKM, and rejection of the implementation of MBKM policies. Meanwhile, neutral data is tweet data that contains news, promotions, and other things that do not contain elements of sentiment in the typing. Positive data contains public support for the MBKM policy, tweets that remind people about the MBKM policy, and tweets that see it as progress in the field of education.

2.2 Data Preprocessing

After the data has been labeled, the data must go through the data preprocessing stage before the data is used for model training. Data preprocessing carried out includes Data Cleansing, Normalization, Tokenizing, Remove Stop-words, and Weighting. This is used for the preprocessing process, created as a function to make it easier and faster to apply to the data used. The data preprocessing stage presents a special challenge in this study as well because the tweets were written in Indonesian, necessitating the use of localized stop-word removal and tokenization techniques—a method that has not been extensively studied in previous sentiment analysis studies (Pravina et al., 2019; Pertiwi, 2019). The Manhattan and Euclidean distance metrics are additionally employed in this study to improve the K-NN algorithm's effectiveness in differentiating between the subtle sentiment categories.

2.3 Data Splitting

After the data is processed, the next stage is data splitting. The data will be divided into 2 parts, namely train data and test data. Data splitting is done with a ratio of 8:2, which means 80% train data and 20% test data. After splitting the data, 1600 train data and 400 test data were obtained. This process is carried out with the help of the Scikit-learn library.

2.4 KNN (K-Nearest Neighbor)

In this research, the machine learning model used is the KNN (K-Nearest Neighbor) model. Among the algorithms that are already well-known is the KNN algorithm. This group instance-based learning includes KNN. The KNN method is a lazy learning technique. In other words, this approach is applied when classifying data where the distance is small (Puspita & Widodo, 2020).

2.5 Tuning

The parameters used for tuning the model are the number of k, weights, and the distance formula. The number of k used is a number from 1 to 40 so that the prediction results are stable because in determining the label K-NN votes for the closest data. The weights used for tuning are uniform and distance. The difference is that with uniform weighting K-NN will only vote on the closest data amount without considering the distance, whereas with distance weighting the distance between the closest labels will be added up and the winner of the voting results is the label with the closest total distance. The distance formulas used for tuning parameters are Manhattan distance and Euclidean distance.

2.6 Training

The study optimized the K-NN model by a comprehensive parameter tuning technique with GridSearchCV, The GridSearchCV is used to extract the best parameters from the model. Hyperparameter tuning is the process of determining which parameters to add to the model to achieve the greatest performance (Darmawan & Dianta, 2023). which has not been frequently used in previous sentiment analysis studies on educational policies. In the training phase, we use the pipeline from Scikit-learn and also GridSearchCV from Scikit-learn for tuning and training the model. Pipelines are used to simplify the fitting process on data preprocessed with the K-NN algorithm. Meanwhile, GridSearchCV is used for model tuning to find the best model from several parameters using the cross-validation method.

2.7 Testing

After carrying out training, then carry out a prediction test on the test data, and then the prediction results are compared with the actual results using a confusion matrix. After making predictions, a confusion matrix visualization will be carried out so that it is easy to understand. An evaluation will also be carried out to find out the values of accuracy, precision, recall, and f1-score to find out how well the KNN model that has been trained performs.

Accuracy

Equation (1) is utilized to demonstrate the algorithm's performance through accuracy. (Maulidah et al., 2020)

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100\% \quad (1)$$

Precision

The ratio of genuine positive predictions (TP) to the total number of positive predictions made is known as precision. Use equation (2) to determine the mode's precision (Maulidah et al., 2020).

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{2}$$

Recall

Recall is defined as the ratio of all true positive data to true positive predictions (TP). To calculate the recall of the model, use the equation (3) (Maulidah et al., 2020).

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

F1-Score

The F1 Score uses a weighted average to measure recall and precision. Use equation (4) to determine the model's F1 Score (Maulidah et al, 2020).

$$\text{F1-Score} = 2 \times \frac{Precision \times Recall}{(Precision + Recall)} \tag{4}$$

Confusion Matrix

A confusion matrix is a table that lists the number of wrong test results and the number of correct test results (Normawati & Prayogi, 2021).

3 Result and Discussion

3.1 Result

Based on the confusion matrix Figure 1. The confusion matrix from the KNN model shows its performance across three categories: "Negative," "Neutral," and "Positive." The model demonstrates strong performance in predicting the "Positive" class, with 288 instances correctly classified. However, it struggles with distinguishing between the "Negative" and "Neutral" classes. While 60 "Negative" instances are accurately predicted, a significant number (81) are misclassified as "Positive" Similarly, "Neutral" predictions are less reliable, with only 19 correctly identified, while 43 are wrongly classified as "Positive" and 6 as "Negative." This suggests that the model may require further tuning, particularly to better distinguish between the "Negative" and "Neutral" categories, potentially through parameter adjustments or feature engineering.

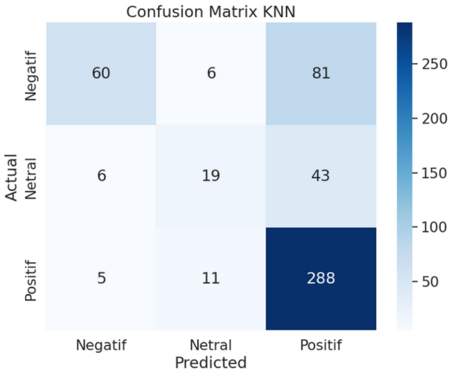

Figure 1. Confusion matrix

In Table 1 there are precision, recall and f1 scores for each class. This parameter is used as a benchmark for the reliability of the system to provide more accurate results.

Table 1. Table of test results

	Precision	Recall	f1-score
Negative	0.85	0.41	0.55
Neutral	0.53	0.28	0.37
Positive	0.70	0.95	0.80

Based on Table 1, the highest precision was achieved by the negative class, with a value of 0.85, followed by the positive class at 0.70, and the neutral class at 0.53. In terms of recall, the positive class ranked highest with a value of 0.95, followed by the negative class at 0.41 and the neutral class at 0.28. The highest F1-score was also recorded for the positive class at 0.80, with the negative and neutral classes achieving values of 0.55 and 0.37, respectively. The overall accuracy of the model is 0.71.

3.2 Discussion

This study explores the application of a KNN model for sentiment classification into three categories: negative, positive, and neutral. Analysis of the confusion matrix shows that the model performs well in predicting the positive sentiment. Precision scores indicate that the negative class achieves the highest value at 0.85, while recall is highest for the positive class at 0.95. Additionally, the positive class registers the top F1-Score of 0.80. The model's overall accuracy is 71%, surpassing the performance of the support vector machine model used in a previous study by (Arsyad et al., 2022). Compared to earlier research employing alternative algorithms, such as SVM, the model's precision and accuracy scores, especially for the negative and positive sentiment classifications, demonstrate notable gains, indicating that K-NN is a more appropriate technique for policy sentiment analysis.

This study extends the use of sentiment analysis to domains outside of the commercial sector by measuring public opinion toward government educational initiatives like MBKM through the use of the K-Nearest Neighbor (K-NN) algorithm. The K-NN approach outperformed other algorithms, like Support Vector Machines (SVM), which had lesser accuracy in previous sentiment analysis tasks (Pravina et al., 2019), with a model accuracy of 71%. This study emphasizes how policymakers may use social media sentiment analysis in real time to better understand public opinion and make data-driven judgments about educational changes. This work offers a novel framework for assessing policy impact through public sentiment, in contrast to previous studies (Pravina et al., 2019; Pertiwi, 2019) that focused on general sentiment topics. This unique perspective comes from the work's connection of sentiment analysis to a significant national educational initiative. To gain a deeper understanding of the acceptance of global education reform, future studies should expand on this by contrasting MBKM with other global education programs.

4 Conclusion

In this research, Sentiment Analysis of Public Perception Regarding the *Merdeka Belajar Kampus Merdeka* (MBKM) Policy on Twitter Using the K-Nearest Neighbor (K-NN) Method, the following were obtained. The model was trained using the split data that consisted of 80% for training and 20% for testing. Based on the experimental results, the highest accuracy was obtained on the k=40 the overall accuracy is over 0.71, the best precision was obtained by the negative class at 0.85, the best recall was obtained by the positive class at 0.95 and the best f1 score was obtained by the positive class at 0.80.

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