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Analysis of Public Sentiment Towards the Free Nutritious Meals Program on TikTok Social Media Using the K-Nearest Neighbor Algorithm

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ABSTRACT

The Free Nutritious Meals Program is currently one of the most talked about public policies, generating a wide range of responses from the public. One of the most active discussion forums is the social media platform TikTok, given that it has a large number of users and a relaxed and informal style of language. This study aims to examine public sentiment toward the MBG program through TikTok user comments, while also testing the performance of the K-Nearest Neighbor (KNN) algorithm in classifying sentiment as positive or negative. Research data was collected by crawling comments on several TikTok videos discussing Free Nutritious Meals during the period from September to November 2025. A total of 1,000 comments were obtained and then processed through data cleaning stages, such as data cleaning, case folding, normalization, tokenization, stopword removal, and stemming. To convert the text into numerical form, the Term Frequency–Inverse Document Frequency (TF-IDF) method was used. Meanwhile, sentiment labeling was done manually to maintain the quality of the training data. Model performance was evaluated using a confusion matrix with accuracy, precision, recall, and F1-score indicators. The test results showed that the best accuracy rate, which was 70.50%, was obtained at a K value of 4. From the sentiment analysis conducted, negative comments were found to outnumber positive sentiments. The criticism that emerged generally related to food quality and safety, inequality in program distribution, and a lack of transparency in information provided to the public. This study shows that the KNN algorithm is quite capable of being used for sentiment analysis on TikTok comment data, although it still has limitations in understanding the variety of informal language often used by users. Therefore, the results of this study are expected to provide public opinion-based input for policymakers, as well as a foundation for the development of sentiment analysis methods that are more suited to the characteristics of social media in future studies.

I. INTRODUCTION

The development of social media as a means of public interaction has become a digital platform and a forum for the public to express their opinions on current social issues and public policies. One platform that is very popular among various groups is TikTok. TikTok not only functions as a short video-based entertainment medium but has also developed into a very active public discussion space for expressing views, support, and criticism of government performance and policies [1] [2]. The high volume of user interactions in TikTok's comment section makes this platform a valuable source of data for understanding public opinion.

The diversity of public opinion that appears on social media requires a systematic analytical approach in order to be understood objectively. One approach that is widely used is sentiment analysis. Sentiment analysis is a method used to identify and classify public opinion into specific categories, such as positive and negative sentiment, based on text-based data [3]. Sentiment analysis can also provide an overview of the level of acceptance, forms of criticism, and public perception of policies being implemented by the government.

The free nutritious meal program is a public policy that has attracted public attention and sparked various reactions on social media, including TikTok. This program targets students and has a major impact on society. The free nutritious meal program is evaluated not only in terms of its policy objectives but also in terms of the quality of its implementation in the field. This has elicited various responses from TikTok users, showing positive sentiments in the form of appreciation for the free nutritious meal program, but also negative sentiments highlighting issues such as food quality, equitable distribution of funds, and transparency in program implementation. This situation makes the TikTok app an important platform for public criticism that needs to be analyzed using sentiment analysis methods.

Sentiment analysis research on social media has been widely conducted and developed by several researchers using various classification algorithms that are quite accurate in classifying data, such as Naive Bayes, Support Vector Machine (SVM), and many more. These methods have been applied to various applications such as TikTok, Twitter, Instagram, and YouTube [2] [4] [5]. In addition, previous studies have also integrated the K-Nearest Neighbor (KNN) algorithm with other approaches as a basis for comparison in measuring algorithm performance [2] [6]. However, most of these studies focus more on comparing algorithms, while studies that specifically evaluate the performance of the KNN algorithm independently on TikTok comment data related to public policy are still relatively limited. In fact, the characteristics of TikTok text, which tend to be informal, short, and varied, require a separate evaluation of the effectiveness of the classification algorithms used.

The selection of the K-Nearest Neighbor (KNN) algorithm in this study was based on methodological considerations and the characteristics of the data used. The K-Nearest Neighbor (KNN) algorithm is a relatively simple and effective distance-based classification algorithm for handling medium-sized datasets with features represented using TF-IDF [6] [7]. Compared to Naive Bayes, which relies on assuming independence between features, K-Nearest Neighbor (KNN) is considered capable of capturing the semantic proximity between documents. On the other hand, although Support Vector Machine (SVM) has superior performance in various studies, it also requires a more complex training process and greater computational resources. This makes it less than optimal for exploratory early-stage research, especially on short text data such as comments on the TikTok application [5] [8]. Thus, the application of the K-Nearest Neighbor (KNN) algorithm in this study aims to assess the ability of the K-Nearest Neighbor (KNN) algorithm in processing informal text characteristics on the TikTok application.

Based on the above explanation, this study aims to analyze public sentiment towards the Free Nutritious Meals Program through user comments on the TikTok application using the K-Nearest Neighbor (KNN) algorithm. This study not only focuses on measuring positive and negative sentiments, but also assesses the performance of the K-Nearest Neighbor (KNN) algorithm in classifying informal TikTok app comment data using evaluation metrics such as accuracy, precision, and recall. The results of this study are expected to broaden insights into social media-based public policy sentiment analysis, especially on the TikTok application, and provide data-based recommendations for policy makers to improve the quality of implementation and public communication strategies for the Free Nutritious Meals Program.

II. METHOD

This study uses machine learning-based sentiment analysis to identify and classify public opinion regarding the Free Nutritious Meals program on the TikTok app. The research methodology is structured as follows.

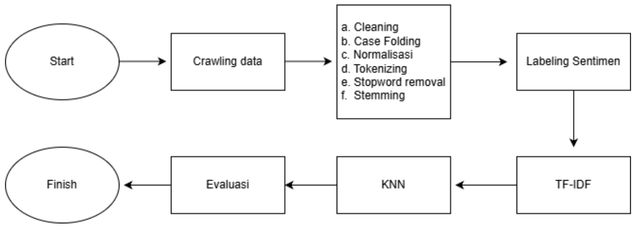


Figure 1. Research Flow

A. Data Collection

In this study, the data collected came from comments made by TikTok users discussing the Free Nutritious Meals program. The data collection process was carried out using the web crawling method on several video comments on the TikTok application. The data collection process took place from September to November 2025 with the aim of obtaining an initial overview of public opinion regarding the implementation of the program.

Approximately 1,000 comments were obtained in CSV format to facilitate the subsequent data processing stages. The selection of comments had the following criteria.

- Use Indonesian language
- Contain opinions on the Free Nutritious Meals program
- Not included in the categories of spam, promotion, and video content unrelated to the program discussed in this study.

The use of the TikTok application as a source of data is based on its position as a popular social media platform with a large number of users and a high level of public participation, especially in the form of comments on public policy issues. In addition, TikTok is known as a forum for public expression that is dominated by informal and spontaneous language, making it very interesting to analyze [1] [5] [9].

Figure 2. Data Crawling Stage

B. Text Processig

Text Processing is the process of preparing documents consisting of unorganized text and converting it into organized text so that it can be processed. The comment data obtained from the TikTok application is unstructured and contains non-standard elements such as numerous abbreviations, non-standard language, symbols, and emojis. Therefore, a text processing stage is needed to improve data quality before conducting sentiment analysis [10] [11] Text processing has the following stages.

1) Data cleaning

The first step is data cleaning, which involves removing symbols, links, URLs, numbers, user mentions, hashtags, meaningless emojis, and duplicate comments [10]. After this process is complete, the amount of data will be reduced from 1000 to 900 comments, which will then be used as the research dataset.

2) Case Folding

The second stage is case folding.This process standardizes the letter forms in a document by converting all capital letters to lowercase. This step is performed using the def lower text command [12]. The purpose of this process is to avoid differences in meaning caused by the use of capital letters and to ensure consistency of words before the analysis process.

3) Normalization

The normalization stage in the data preprocessing process is the stage of converting non-standard words, abbreviations, and regional slang on social media into a neater, more consistent format that is ready to be used for analysis using machine learning algorithms. This stage is very important because the TikTok application uses a lot of informal language [13].

4) Tokenizing

Tokenizing is the process of breaking text into small parts called tokens, such as words or characters. Tokenizing aims to facilitate the feature extraction process, where each token will be treated as a feature candidate in weight calculations using the TF-IDF method [13].

5) Stopword Removal

The stopword removal stage is carried out to remove common words that are not involved in the analysis process. If not removed, they will interfere with the analysis process and affect the classification results. Examples include the words “what,” “in,” “for,” and many more [11].

6) Stemming

Stemming is the process of converting words to their basic form by removing affixes, such as prefixes or suffixes. The stemming process is carried out using the Sastrawi library, a popular tool in Indonesian research for stemming and local language stopword removal. Using this tool has been proven to improve the accuracy of the classification system [14].

C. Labeling Sentimen

After the data from the crawling process is obtained and goes through the normalization stage, the next step is to label the data. TikTok videos containing public opinions about the Free Nutritious Meals program are labeled as positive or negative. The labeling process is done manually to create test data to assess the accuracy level of the sentiment analysis results [15]. Comments are categorized as positive if they contain elements of support, approval, or favorable assessment of the Free Nutritious Meals program. Conversely, comments containing criticism, complaints, dissatisfaction, or rejection of the Free Nutritious Meals program are included in the negative sentiment category.

Manual labeling was chosen based on the characteristics of comments on the TikTok application, which often use informal language. They contain sarcasm and are influenced by certain social factors, making them very difficult to analyze accurately by an automatic labeling system. Manual labeling is considered more accurate and capable of describing the true meaning of sentiment [15].

Based on the labeling results, there were 510 comments with positive sentiment and 488 comments with negative sentiment, indicating that the data was relatively balanced. Furthermore, the labeled data was used as training data and test data in the classification process using the K-Nearest Neighbor (KNN) algorithm.

D. TF-IDF

Data that has undergone text processing must then be converted into numerical or numerical form so that it can be easily analyzed by the K-Nearest Neighbor (KNN) algorithm. TF-IDF (Term Frequency-Inverse Document Frequency) is used to determine the most important or frequently appearing words in a data set or document, while distinguishing them from less relevant words. Each unique word in the document will be given a weight according to the TF-IDF calculation [5]. Mathematically, the TF-IDF weight is formulated as follows.

$$TF - IDF\ (t,d) = TF(t,d) \times IDF\ (t)$$

Where:

$$IDF(t) = \log\left(\frac{N}{df(t)}\right)$$

Explanation:

- TF (t,d) : frequency of term occurrence in document d
- df(t) : number of documents containing the term
- N : total number of documents

TF-IDF is used because it is able to give higher weight to words that are informative and rarely appear, as well as reducing the influence of words that appear frequently but are not very meaningful. This representation is very suitable for the K-Nearest Neighbor (KNN) algorithm, which depends on calculating the distance between feature vectors, so that the level of similarity between documents can be determined more accurately and precisely [6].

E. K-Nearest Neighbor (KNN)

The K-Nearest Neighbor (KNN) algorithm is one of the methods used to perform the classification process [16]. The K-Nearest Neighbor (K-NN) algorithm works by comparing training data that is closest to the test data [17]. In this study, KNN is used to classify the sentiment of comments on the TikTok application into two categories, namely positive and negative, based on the representation of TF-IDF weighted text features.

The selection of the K-Nearest Neighbor (KNN) algorithm is based on its simple concept, easy-to-understand classification process, and its ability to handle high-dimensional data. In addition, KNN does not require complex model training, making it very suitable for sentiment analysis on social media, which tends to use informal language. In this study, distance calculations used the Euclidean Distance method because this method is widely used to measure the degree of similarity between numerical vectors and is in accordance with the characteristics of TF-IDF features.

The stages of applying the K-Nearest Neighbor (KNN) method in this study are described as follows.

1) Determining the K Value

Determining the number of closest neighbors that will be used in the classification process, while also finding the best K value through the cross-validation method. In general, the K value is chosen as an odd number to avoid balanced classification results.

2) Calculating Distance

Measuring the distance between training data and test data using the Euclidean Distance method so that the process of comparing new sentences with all sentences in the training data runs smoothly.

3) Determining the Closest Neighbors

Based on the distance calculation results, a number of k data with the closest distance are selected. These data are considered the most relevant to the new data to be analyzed. This data will later be used as the basis for determining sentiment.

4) Determining the Class

Set the category based on the class that appears most frequently from K neighbors, then use the majority vote to classify the new data.

Although KNN has advantages in terms of simplicity and ease of interpretation, the KNN algorithm also has shortcomings in handling informal text in a semantic context, such as sarcasm and irony that often appear in comments on the TikTok application. These shortcomings are one of the factors that affect the accuracy of the algorithm, which is not yet optimal, so the classification results need to be analyzed further in the discussion chapter.

F. Evaluation

At this stage, the results of applying the K-Nearest Neighbor (KNN) classification algorithm are evaluated to see how well the model is able to classify the sentiment of TikTok comments on the Free Nutritious Meals program accurately and precisely. The evaluation is carried out using a confusion matrix, namely accuracy, precision, recall, and f1-score, to help indicate the level of accuracy. This evaluation approach aims to provide a more comprehensive overview of the model's performance, especially in handling the characteristics of social media sentiment data that has an unbalanced class distribution [12].

In this evaluation process, the first step is to determine and calculate the number of true positives, false positives, false negatives, and true negatives in each row of comment data. These values will be used to calculate the model's performance results, such as accuracy, precision, recall, and f1-score.

Accuracy calculation formula

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Precision calculation formula

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

Recall calculation formula

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

F1-score calculation formula

$$\textit{f1-score} = 2\text{x}\frac{Recall\ x\ Precision}{Recall\ x\ Precision} \tag{4}$$

Explanation:

- True Positive (TP) is a condition where positive sentiment is predicted correctly.
- True Negative (TN) is when negative sentiment is correctly predicted.
- False Positive (FP) is when data that actually has negative sentiment is predicted as positive sentiment.
- False Negative (FN) is when positive sentiment is predicted as negative sentiment

III. Result and Discussion

A. Data Collection

This study uses comment data from the TikTok application containing text and the crawling process using Website Crawling. The data obtained consists of 1,000 comments related to the Free Nutritious Meals (MBG) program, downloaded in CSV format.

The collected comments contained various public opinions, ranging from appreciation for the program to various criticisms regarding its implementation in the field. This study shows that the TikTok application serves as a dynamic public discussion forum for conveying public opinion on government policies, which is in line with the results of previous studies on various other social media applications [1] [2]. The following is an example of the collection in Table I.

TABLE I
Dataset

Text
anak saya dapat ayam yg udah busuk , nasi SDH busuk 😩😩😩
KENAPA MBG SEKOLAHKU DI LIBUR IN 💔 🥀

B. Text Processing

The text processing stage is carried out to evaluate the quality of comment data from the TikTok application before it is used in sentiment analysis. Considering that comments on the TikTok application are generally informal, contain abbreviations, spelling variations, and non-text elements, this stage plays a very important role in reducing noise and increasing the concentration of text representation. The results of each text processing stage not only show changes in the form of data, but also provide a strong basis for TF-IDF weighting and the performance of the K-Nearest Neighbor (KNN) algorithm in classifying data.

1) Data Cleaning

The initial stage of text processing is carried out through data cleaning to ensure that the comments on the TikTok application to be analyzed truly represent the opinions of the public in textual form. The raw data resulting from crawling still contains many URLs, emojis, numbers, symbols, duplicates, and empty columns that do not contribute to sentiment analysis. The existence of these non-text elements can interfere with the analysis process [10].

Based on the results of the data cleaning that has been carried out, the number of comments, which was initially 1000, has been reduced to 998 comments. This decrease indicates that some of the initial data is not suitable for further analysis. A comparison of the amount of data before and after can be seen in Figure 3 as follows.

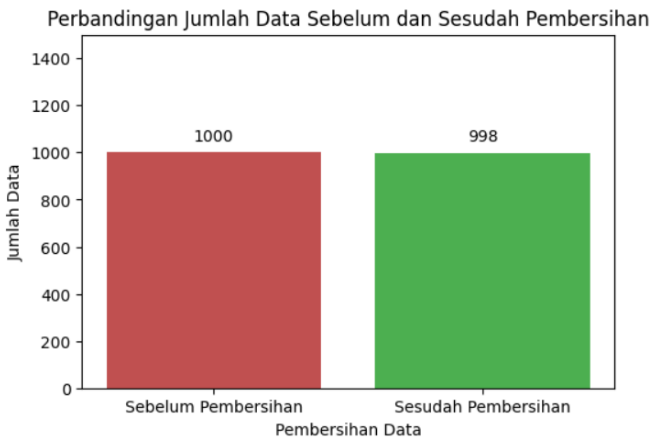


Figure 3. Amount of data after cleaning

Reducing the amount of data actually has a positive impact on the quality of the dataset because it can minimize distortion at the extraction stage using TF-IDF. In addition, a cleaner dataset will enable the K-Nearest Neighbor (KNN) algorithm to calculate the distance between documents accurately, thereby reducing classification errors due to irrelevant information.

An example of the text results after the data cleaning process is presented in Table II, where comments have been freed from symbols and non-text elements, making them easier to process in the next stage.

TABLE II
DATA CLEANING

Text
anak saya dapat ayam yg udah busuk , nasi SDH busuk
KENAPA MBG SEKOLAHKU DI LIBUR IN

2) Case Folding

After the data cleaning stage is complete, the data will begin to be processed using the case folding process. Case folding is the process of changing all capital letters in the comment text to lowercase letters. This stage aims to eliminate differences in word representation caused by variations in the use of capital and lowercase letters. Without case folding, words that use capital letters will have the same meaning as words that use lowercase letters, which will later be considered as two different features by the system.

The results of applying case folding are shown in Table III, which shows that all comments have been processed using case folding. This process can reduce feature redundancy and improve the consistency of text representation before weighting is performed.

TABLE III
CASE FOLDING

Text
anak saya dapat ayam yg udah busuk , nasi sdh busuk
kenapa mbg sekolahku di libur in

3) Normalization

The normalization stage is carried out to convert non-standard words, abbreviations, and excessive spaces into a more standard form of language. The language used on social media is very informal, often characterized by the use of abbreviations such as “yg”, ‘sdh’, or “udh”. If normalization is not carried out, it will cause fragmentation of features with the same meaning [14].

The results of normalization can be seen in Table VI below, where abbreviated words have been changed to their standard forms. This normalization helps improve the quality of text comprehension and ensures that words with similar meanings are represented consistently in the sentiment analysis process.

TABLE VI
NORMALIZATION

Text
anak saya dapat ayam yang udah busuk , nasi sudah busuk
kenapa mbg sekolahku di libur in

4) Tokenizing

After the normalization stage is complete, the next step is tokenizing to break the text into word units (tokens). Through this process, each word can be recognized as an independent feature that is then analyzed based on its frequency of occurrence. Tokenizing is also important in classification using the K-Nearest Neighbor (KNN) algorithm by utilizing feature representations in the form of word vectors.

The results of the tokenizing stage are shown in Table IV, which shows that each sentence in the comments has been parsed and separated using commas. With this stage, weight calculations can be performed precisely and accurately.

TABLE IV
TOKENIZING

Text
anak, saya, dapat, ayam, yang, udah, busuk, nasi, sudah, busuk
kenapa, mbg, sekolahku, di, libur, in

5) Stopword removal

The next step is stopword removal, which involves removing common words that have no meaning in determining sentiment. Words that often appear in the text are “and,” “in,” or “to.” The results of stopword removal are shown in Table V, which shows that common words have been removed, leaving only informative words.

TABLE V
STOPWORD REMOVAL

Text
anak, ayam, udah, busuk, nasi, busuk
mbg, sekolahku, libur, in

6) Stemming

Stemming is the final stage of text processing in this study. The stemming process is carried out to convert words into their root forms by removing prefixes, suffixes, or infixes. In this study, stemming was performed using the Sastrawi library, which was specifically designed for the Indonesian language and has been widely used in sentiment analysis research by previous researchers [14].

Table VI shows the results of stemming with words that have been simplified to their root form. This process aims to unify variations of words that have the same meaning so as to improve the consistency of features in the sentiment classification process.

TABLE VI
STEMMING

Text
anak ayam udah busuk nasi busuk
mbg sekolahku libur in

C. *Labeling Sentimen*

Comment data that has passed through text processing will then be labeled at the sentiment labeling stage. Sentiment labeling to classify public opinion is divided into two categories, namely positive and negative. The labeling process is done manually to maintain the accuracy of class determination, improve the characteristics of TikTok application comments, and emotional expressions that are difficult to recognize automatically.

The labeling results show that out of 998 comments, there are 510 positive sentiment comments and 488 negative sentiment comments. A balanced distribution of data between classes plays a role in minimizing the possibility of model bias towards one sentiment category. Thus, the classification model evaluation results obtained can represent the algorithm's performance more objectively.

A comparison between the number of positive and negative sentiments shown in Figure 2 shows that the proportions are almost equal. This condition indicates that there are critical responses from the public regarding the implementation of the Free Nutritious Food Program.

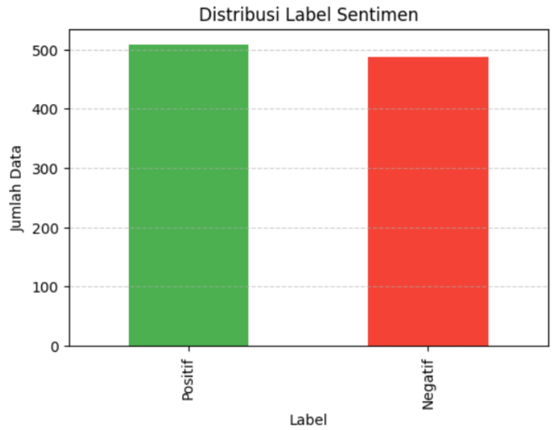


Figure 4. Comparison of Positive and Negative Sentiment

D. *TF-IDF*

At this stage, all comments that have passed through the previous processes are converted into numerical form using the TF-IDF method. This method is used to measure the level of importance of a word in a comment by considering the frequency of the word's appearance in a single document and its level of appearance in the entire document [5].

In general, the TF value indicates how often a word appears in a comment, while IDF indicates how rarely the word appears in the entire dataset. The TF value is then multiplied by the IDF value to produce the final TF-IDF weight value, so that words that appear frequently in a comment but are rarely used in other comments will have a greater weight than words that are more general in nature.

Based on the TF-IDF calculation results in this study, it can be seen that words related to the Free Nutritious Meals program have a fairly high weight. This study shows that user comments on the TikTok application focus on discussions of the Free Nutritious Meals program. Figure 5 below shows the weighting results using TF-IDF.

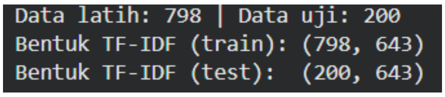
No	Kata	Frekuensi	TF	IDF	TF-IDF
269	makan	339	0.054484	2.261308	0.123205
19	anak	326	0.052395	2.477409	0.129803
284	mbg	307	0.049341	2.268400	0.111925
361	program	142	0.022822	3.046942	0.069538
396	sekolah	120	0.019286	3.262364	0.062919
129	enak	107	0.017197	3.321787	0.057125
170	ikan	101	0.016233	3.779620	0.061354
286	menu	98	0.015751	3.406945	0.053661
146	gizi	97	0.015590	3.395895	0.052941
179	jadi	83	0.013340	3.576021	0.047703

Figure 5. TF-IDF Results

The selection of TF-IDF as a representation method is based on its compatibility with the K-Nearest Neighbor (KNN) algorithm, which also works to determine data proximity by calculating the distance between features [6] [7]. However, TF-IDF weighting still has limitations in understanding deeper semantic meanings such as words containing sarcasm, puns, or implied messages that often appear in comments on social media, which can lead to errors in sentiment analysis. For example, a comment with a critical tone that uses words that appear neutral but have a negative meaning.

E. K – Nearest Neighbors Algorithm

Now we move on to testing and evaluating the algorithm, where we will see the results of the sentiment classification process using the K-Nearest Neighbors (KNN) algorithm to evaluate the model's ability to group texts into positive and negative classes. The dataset that went through the previous stage will be divided into 80% training data and 20% test data using the train_test_split function. This data division aims to ensure that the model is trained with sufficiently representative data and tested using data that has never appeared before. The following is the division of training data and test data.



```
Data latih: 798 | Data uji: 200
Bentuk TF-IDF (train): (798, 643)
Bentuk TF-IDF (test):  (200, 643)
```

Figure 6. Division Of Training Data And Test Data

The next step is to determine the highest K value. Based on the results of testing k values from 1 to 15, the highest accuracy is at K = 4 with an accuracy of 70.50% using the Euclidean metric. The decline in performance at k values above 4 shows that the more neighbors involved in the classification process, the greater the possibility of irrelevant data entering the majority voting process. This can cause the model to become less sensitive to locally patterned data. This condition is quite common in KNN algorithms, especially when used on high-dimensional text data such as TF-IDF representation results [6] [7]. Below is a graph of k value accuracy.

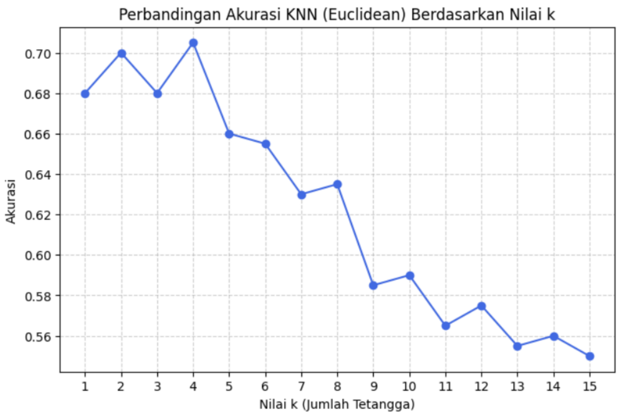


Figure 7. K-Value Accuracy Graph

In addition, the accuracy level in the moderate category can also be influenced by the nature of comments on the TikTok application, which are generally short, informal, and rich in linguistic diversity, such as puns, abbreviations, and the use of sarcasm. This makes it difficult for distance-based algorithms to understand sentiment broadly. It is not uncommon for comments that explicitly appear neutral or positive to actually imply negative meanings, thereby increasing the potential for errors during the classification process [12] [14].

Therefore, this study shows that although KNN can be used as an initial approach in sentiment classification on social media, this method still has many shortcomings in processing natural language used in applications such as TikTok. The results of this study are also consistent with previous studies showing that classical algorithms such as K-Nearest Neighbor (KNN) will show suboptimal performance when applied to unstructured social media data [5] [6].

F. Evaluation

Based on the results of testing the sentiment classification model using the K-Nearest Neighbor (KNN) algorithm with a K value of 4, an accuracy value of 70.50% was obtained. This value indicates that the model is capable of classifying the sentiment of TikTok comments on the Free Nutritious Food Program with a reasonable degree of accuracy, but it still has shortcomings in distinguishing sentiment precisely.

In the negative sentiment class, the model obtained a precision value of 80%, a recall of 53%, and an F1-score of 64%. The high precision value indicates that the negative sentiment predictions produced by the model are quite accurate, but the low recall value indicates that there are still many negative comments that are not detected by the system. This shows that the model is conservative in classifying comments as negative.

Conversely, in the positive sentiment class, the model showed better performance with a precision of 66%, a recall of 87%, and an F1-score of 75%. The high recall value indicates that the model is able to identify positive comments well. This condition shows that the model is more sensitive to language patterns that are supportive or positive than criticism or complaints.

The difference in performance between the positive and negative classes can be explained by the language characteristics on the TikTok app. Negative comments are often expressed in the form of sarcasm, irony, or insinuations that are difficult to capture using TF-IDF and KNN-based approaches, which only rely on word occurrence without understanding the semantic context in depth [12] [14]. In addition, comments on the TikTok application also contain a lot of informal language, abbreviations, and noise, which contribute to classification errors. The following are the results of the K-Nearest Neighbor (KNN) algorithm performance evaluation.

	precision	recall	f1-score	support
Negatif	0.80	0.53	0.64	98
Positif	0.66	0.87	0.75	102
accuracy			0.70	200
macro avg	0.73	0.70	0.69	200
weighted avg	0.73	0.70	0.70	200

Figure 8. KNN Performance Evaluation Results

Performance evaluation of KNN with K = 4 using a confusion matrix from the test data. This evaluation yielded four values divided into True Positive, True Negative, False Positive, and False Negative. These results show the confusion matrix test with 80% training data and 20% test data. The evaluation results show that the most classification errors occur in negative comments that are predicted as positive (False Negative).

This reinforces the research that the model still has difficulty in distinguishing between positive and negative comments. Although the accuracy value is quite good, the confusion matrix analysis shows that accuracy alone is not sufficient to represent the model's performance comprehensively [6] [9].

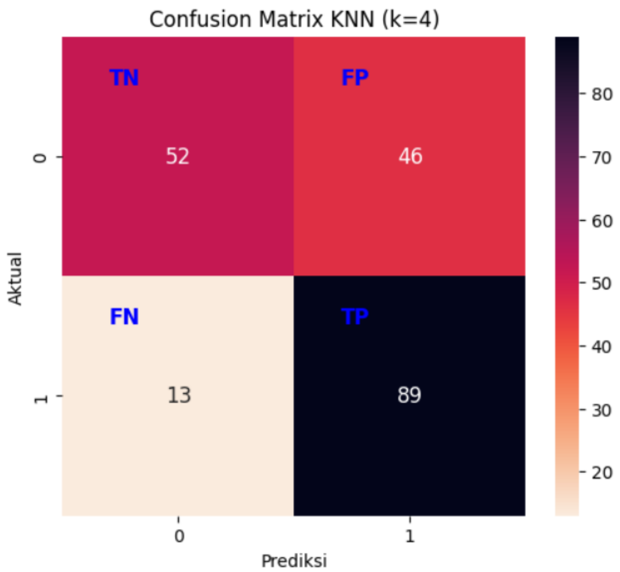


Figure 9. Confusion Matrix Results

IV. Conclusion

This study discusses public sentiment towards the Free Nutritious Food Program by analyzing user comments on the TikTok application. The analysis was conducted using the K-Nearest Neighbor (KNN) algorithm. The test results show that a value of K = 4 provides fairly good performance with an accuracy rate of 70.50%. In addition to accuracy, the evaluation was also carried out by measuring precision, recall, and F1-score to see the model's performance more comprehensively. Based on the analysis results, it shows that the number of positive responses is less than the negative ones. Most of the comments mention issues such as food quality, uneven program implementation in all schools, and lack of transparency regarding the distribution and supervision systems of the program.

This study contributes by evaluating the performance of the KNN algorithm in processing TikTok application comment data, which is known for its informal language, abbreviations, and diversity. The accuracy rate obtained shows that KNN is still quite effective for grouping sentiments in general, but KNN is not yet able to handle the complexity of language on social media. This can be seen from the challenges in handling the use of puns, abbreviations, sarcasm, and text interference. These results are also in line with previous studies which state that conventional classification methods often experience a decline in performance when applied to highly informal social media data [2].

The results of this study indicate that social media sentiment analysis can be used as a preliminary evaluation tool for public policy to identify widespread implementation issues. The prevalence of negative sentiment suggests that the implementation of the Free Nutritious Meals program still needs improvement, particularly in terms of supervision and communication with the public. When compared to previous studies that applied the KNN algorithm on other social media platforms, the performance of the model in this study can be considered adequate, but not as good as other methods such as Support Vector Machine and Random Forest [5]. Thus, this study is more appropriately positioned as a preliminary study that provides an overview of the sentiment trends of TikTok users, as well as a basis for further research with stronger methods and more diverse features.

The results of this study indicate that social media sentiment analysis can be used as a preliminary evaluation tool for public policy to identify widespread implementation issues. The emergence of more negative sentiments indicates that the implementation of the Free Nutritious Meals program still needs improvement, especially in terms of supervision and communication with the public. When compared to previous studies that applied the KNN algorithm to other social media applications, the performance of the model in this study can be said to be quite accurate and good, but not as good as other methods. Currently, the most superior classification methods are Support Vector Machine and Random Forest with high accuracy values [5]. Thus, this study is more appropriately positioned as a preliminary study that provides an overview of the amount of sentiment among TikTok users, as well as a basis for further research with stronger methods and more diverse features.

References

[1] R. Wijaya and A. Suwandhi, "Sentimen Komentar Universitas Pelita Harapan Pada TikTok Menggunakan Metode K-Nearest Neighbor," *JDMIS J. Data Min. Inf. Syst.*, vol. 2, no. 1, pp. 26–36, Feb. 2024, doi: 10.54259/jdmis.v2i1.2418.

[2] F. Fieryando and B. Kristianto, "Analisis Sentimen Terhadap TikTok Shop Dengan K-Nearest Neighbor, Decision Tree, dan Naive Bayes," *J. Buana Inform.*, vol. 15, no. 01, pp. 21–29, 2024, doi: 10.24002/jbi.v15i1.8205.

[3] S. Jurnalis Pipin and H. Kurniawan, "Analisis Sentimen Kebijakan

MBKM Berdasarkan Opini Masyarakat di Twitter Menggunakan LSTM," *J. SIFO Mikroskil*, vol. 23, no. 2, pp. 197–208, 2022, doi: 10.55601/jsm.v23i2.900.

[4] P. Algoritma, N. Bayes, D. A. N. S. V. M. Dalam, M. Prediksi, K. Siswa, and D. I. Smk, "No Title," vol. 2, no. April, pp. 38–45, 2023.

[5] R. Tangke, D. Tineke Salaki, W. Widsli Kalengkongan, and E. Ketaren, "Analisis Sentimen Aplikasi Tiktok Menggunakan Algoritma Support Vector Machine (Svm) Dan Random Forest," *J. TIMES*, vol. 13, no. 2, pp. 53–62, 2024, doi: 10.51351/jtm.13.2.2024762.

[6] D. Ardiansyah, A. Saepudin, R. Aryanti, E. Fitriani, and Royadi, "Analisis Sentimen Review Pada Aplikasi Media Sosial Tiktok Menggunakan Algoritma K-Nn Dan Svm Berbasis Pso," *J. Inform. Kaputama*, vol. 7, no. 2, pp. 233–241, 2023, doi: 10.59697/jik.v7i2.148.

[7] D. A. Lestari and D. Mahdiana, "Penerapan Algoritma K-Nearest Neighbor pada Twitter untuk Analisis Sentimen Masyarakat Terhadap Larangan Mudik 2021," *Inform. J. Ilmu Komput.*, vol. 17, no. 2, p. 123, 2021, doi: 10.52958/iftk.v17i2.3629.

[8] A. Halimi, K. Kusrini, and M. R. Arief, "Analisis Sentimen Masyarakat Indonesia Terhadap Pembelajaran Online Dari Di Media Sosial Twitter Menggunakan Lexicon Dan K-Nearest Neighbor," *COREAI J. Kecerdasan Buatan, Komputasi dan Teknol. Inf.*, vol. 2, no. 1, pp. 18–28, 2021, doi: 10.33650/coreai.v2i1.2283.

[9] N. Alvionika, S. Faisal, R. Rahmat, and A. F. N. Masruriyah, "Analisis Sentimen Pada Komentar Instagram Provider By.U Menggunakan Metode K-Nearest Neighbors (KNN)," *J. Algoritm.*, vol. 21, no. 2, pp. 50–63, Nov. 2024, doi: 10.33364/algoritma/v.21-2.1672.

[10] Syahril Dwi Prasetyo, Shofa Shofiah Hilabi, and Fitri Nurapriani, "Analisis Sentimen Relokasi Ibukota Nusantara Menggunakan Algoritma Naïve Bayes dan KNN," *J. KomtekInfo*, pp. 1–7, Jan. 2023, doi: 10.35134/komtekinfo.v10i1.330.

[11] I. Iwandini, A. Triayudi, and G. Soepriyono, "Analisa Sentimen Pengguna Transportasi Jakarta Terhadap Transjakarta Menggunakan Metode Naives Bayes dan K-Nearest Neighbor," *J. Inf. Syst. Res.*, vol. 4, no. 2, pp. 543–550, Jan. 2023, doi: 10.47065/josh.v4i2.2937.

[12] M. J. Palepa, N. Pratiwi, and R. Q. Rohmansa, "Analisis Sentimen Masyarakat Tentang Pengaruh Politik Identitas Pada Pemilu 2024 Terhadap Toleransi Beragama Menggunakan Metode K - Nearest Neighbor," *JIPI (Jurnal Ilm. Penelit. dan Pembelajaran Inform.*, vol. 9, no. 1, pp. 389–401, Feb. 2024, doi: 10.29100/jipi.v9i1.4957.

[13] N. Nur and F. Wajidi, "Analisis Sentimen Terhadap Komentar Game Mobile Legendsdi Play Store Dengan Menerapkan Metode K-Nearest Neighbors (KNN)," *J. Peqguruang Conf. Ser.*, vol. 7, no. 1, 2025, doi: 10.35329/jp.v7i1.

[14] Pius Deski Manalu, Mutiara Simanjuntak, and Chairil Umri, "Implementasi Algoritma Klasifikasi untuk Analisis Sentimen Media Sosial Tiktok Tahun 2025," *J. Tek. Inform. dan Teknol. Inf.*, vol. 5, no. 1, pp. 488–504, 2025, doi: 10.55606/jutiti.v5i2.5644.

[15] R. Puspitasari, "Kebijakan Baru Skripsi Pada Media Sosial," *JEISBI Vol. 05 Number 03, 2024 (Journal Emerg. Inf. Syst. Bus. Intell.*, vol. 05, no. 03, pp. 37–42, 2024.

[16] R. K. Dinata, H. Akbar, and N. Hasdyna, "Algoritma K-Nearest Neighbor dengan Euclidean Distance dan Manhattan Distance untuk Klasifikasi Transportasi Bus," *Ilk. J. Ilm.*, vol. 12, no. 2, pp. 104–111, 2020, doi: 10.33096/ilkom.v12i2.539.104-111.

[17] D. Kartini, A. Farmadi, M. Muliadi, D. T. Nugrahadi, and P. Pirjatullah, "Perbandingan Nilai K pada Klasifikasi Pneumonia Anak Balita Menggunakan K-Nearest Neighbor," *J. Komputasi*, vol. 10, no. 1, pp. 47–53, 2022, doi: 10.23960/komputasi.v10i1.2965.