

Type of
Contribution:

▶ Research Paper
Review Paper
Case Study

ENERGY: JURNAL ILMIAH
ILMU-ILMU TEKNIK
Special Issue 2025 pp 436-451
DOI: 10.51747/energy.si2025.257



E-ISSN: 2962-2565

This article
contributes to:



7 AFFORDABLE AND
CLEAN ENERGY



Sentiment Analysis of YouTube Comments Using the K-Nearest Neighbors (KNN) Method from an Axiological Perspective

Merinda Lestandy^{1,2*}, Syaad Patmanthara¹

¹ Department of Electrical Engineering and Informatics, Universitas Negeri Malang, 65145,
Indonesia

² Department of Electrical Engineering, Universitas Muhammadiyah Malang, 65144,
Indonesia

*merinda.lestandy.2505349@students.um.ac.id

Abstract

The rapid development of social media as a space for digital interaction has increased the need for sentiment analysis to understand public opinion in a systematic and measurable way. This study analyzes YouTube comment sentiment using the K-Nearest Neighbor (K-NN) method while also examining the axiological value of applying this technology in support of a more ethical digital ecosystem. The dataset consists of 8,200 YouTube comments obtained from Kaggle without predefined sentiment labels. The data were preprocessed through case folding, tokenization, stopword removal, stemming, and normalization. Initial sentiment labels were generated automatically using K-Means clustering to form two classes—positive and negative—and were partially verified manually. The labeled data were split into training and testing sets with ratios of 50:50, 60:40, 70:30, and 80:20, and evaluated using K-NN with k values of 3, 5, 7, and 9. Model performance was assessed using a confusion matrix with accuracy, precision, recall, and F1-score metrics. The results show that accuracy ranges from 0.95 to 0.96, with the best performance achieved at a 70:30 split and an optimal k value yielding 0.96 accuracy. Beyond technical contributions, this study highlights the ethical and practical value of sentiment analysis for interpreting public opinion, supporting fairer content moderation, and improving communication quality in social media environments.

Keywords: Sentiment Analysis, YouTube, K-Nearest Neighbor, K-Means, Text Preprocessing, Model Accuracy, Axiology

Article Info

Submitted:

2025-10-28

Revised:

2025-12-24

Accepted:

2025-12-25

Published:

2025-12-30



This work is
licensed under a
Creative
Commons
Attribution-
NonCommercial
4.0 International
License

Publisher

Universitas
Panca Marga

1. Introduction

The rapid development of social media has brought about significant changes in social interaction patterns, particularly among teenagers. Social media facilitates communication, accelerates the dissemination of information, and provides a means of self-expression. However, its presence also brings negative impacts, such as reduced social sensitivity and increased exposure to digital opinions, which can influence public perception [1], [2], [3]. Among the various growing platforms, YouTube has become one of the most popular social networks. Since its launch in 2005, YouTube has become the dominant video-sharing site globally, including in Indonesia, with a user penetration rate reaching 88% of all internet users in the country [4], [5]. The comments section on YouTube allows users to express their opinions and responses, which can include both positive and negative sentiments. These sentiments often serve as indicators of public opinion and can be used as material for digital evaluation [6], [7].

To understand public opinion from comments on social media platforms, sentiment analysis is a relevant approach. Sentiment analysis is a method for identifying and classifying emotional tendencies in text into positive or negative categories [8], [9], [10]. This technique is widely used to capture public opinion, evaluate service quality, or monitor responses to an issue. Various researchers have previously conducted research on sentiment analysis in social media comments. Ansori et al. examined comments on a culinary-themed YouTube channel using the Naive Bayes method and achieved 90.60% accuracy [11]. Another study by Dwi Wahyu et al. used the LVQ and Lexicon-Based Features methods to classify clickbait-related comments, but only achieved an accuracy of 54.54% [12], [13]. Siregar & Arianto applied the K-Nearest Neighbor (KNN) algorithm to classify training participant comments and reported an accuracy of 94.23% [14], [15]. Meanwhile, Ernawati & Wati used KNN for sentiment analysis of travel agent reviews with an accuracy of 87.00% [16].

Ontologically, this study defines sentiment as textual polarity reflecting evaluative orientation (positive or negative) toward a topic. It does not attempt to capture complex emotions such as irony, sarcasm, or mixed feelings. Thus, sentiment here is treated as a simplified representation of affective stance encoded in language.

Although various methods have been used, there is still room for research to explore more optimal applications of KNN across different objects and contexts. Previous research has shown that method performance is significantly influenced by dataset characteristics, preprocessing techniques, and the modeling parameters used. Furthermore, some previous studies have focused on specific platforms or content domains, requiring further investigation into their application to other

comment types, such as video comments from TikTok or other user groups. Several studies have also not explored the impact of varying the k value and data sharing ratio on model performance, even though these two parameters significantly influence the stability of classification results.

Based on this gap, this study proposes a sentiment analysis approach using the K-Nearest Neighbor method to classify user comments on social media. The KNN method was chosen based on its superior classification performance in various previous studies, ease of implementation, and its ability to work effectively on large datasets [17], [18], [19]. However, KNN also has weaknesses such as sensitivity to noise and the absence of weights in the features [20]. Therefore, precise parameter settings are required to achieve optimal performance. This research is expected to contribute by evaluating the application of KNN to different types of comment datasets and testing the effect of k value selection and train-test split ratio on classification results.

The main objective of this study is to analyze the sentiment of video comments on social media platforms using the KNN method and measure its performance based on model parameter variations. This study also introduces systematic preprocessing steps and an experimental scheme designed to obtain the best parameter configuration for the classification process. Therefore, this study is expected to provide new insights into the effectiveness of the KNN method in sentiment analysis on social media comment data, while expanding the scope of this method's application across different digital platforms.

From an axiological perspective, this research has significant utility in understanding how sentiment analysis technology can contribute to the formation of a more ethical and constructive digital ecosystem. Sentiment analysis is not only a technical process for classifying opinions, but also an effort to assess values, emotional tendencies, and the quality of human interactions in the digital space. By applying the KNN method to map positive and negative tendencies in social media comments, this research helps uncover communication patterns that have the potential to influence public opinion formation and social dynamics. The results can provide practical contributions in supporting content moderation, improving digital literacy, and encouraging more responsible media behavior. Thus, this research has benefits not only in the technical realm of computer science, but also in the ethical and social realms in efforts to improve the quality of interactions on social media.

2. Methods

The research method used in this study is systematically structured as shown in [Figure 1](#). The process begins with the acquisition of a YouTube comment dataset, which then undergoes a pre-processing stage to produce clean and structured text

data. The pre-processing stages include case folding, tokenizing, stopword removal, stemming, and text normalization. After the data is normalized, the next step is to apply the K-Means Clustering method to perform initial clustering. This process is necessary because the dataset lacks sentiment labels, so automatic clustering is used to form two sentiment categories: positive and negative. The resulting clusters are then used as the basis for the data labeling process, including partial data validation to ensure label accuracy.

The next stage is to divide the dataset into training and test data using several ratios, such as 80:20, 70:30, 60:40, and 50:50. The labeled dataset is then fed into the modeling stage using the K-Nearest Neighbor (KNN) algorithm, with several variations in the k value to achieve optimal performance. The model's predictions are then evaluated using a confusion matrix to obtain accuracy, precision, recall, and F1-score values. This entire process aims to determine the best parameter configuration capable of producing the most effective sentiment classification results, as visualized in **Figure 1**.

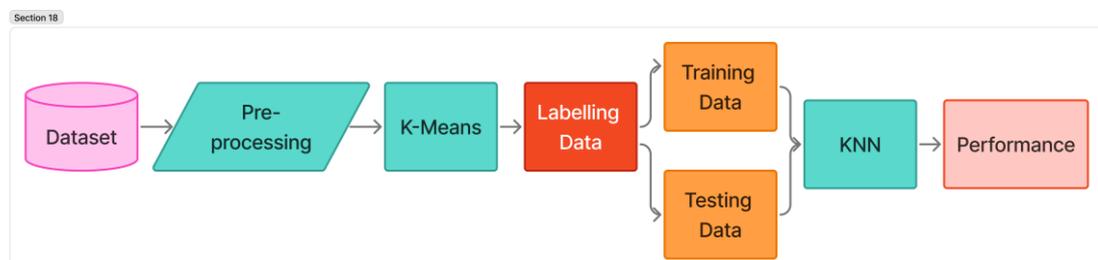


Figure 1. Research Method

The research dataset was obtained from the Kaggle platform, a YouTube comments dataset in CSV format with a total of 8,200 entries. The dataset is sourced from:

<https://www.kaggle.com/datasets/datasnaek/youtube?select=GBcomments.csv>

and initially lacks sentiment labels. Therefore, an initial labeling process using the unsupervised K-Means learning method is required to group comments into clusters based on text similarity characteristics. In this study, two main clusters were identified: a positive sentiment cluster and a negative sentiment cluster. After the clusters were formed, a portion of data from each cluster was randomly selected for manual verification to ensure the quality of the labeling before use in the classification stage.

2.1 Labeling

To reduce clustering bias, manual verification was conducted on a stratified 15% sample from each cluster. Two independent annotators reviewed the labels, and disagreements were resolved through discussion. Inter-annotator agreement

reached a Cohen's Kappa score of 0.82, indicating strong agreement. This step improves the reliability of the automatically generated labels.

The labeling process is necessary because the classification method used in this study is supervised learning, which requires labeled data as the basis for model learning. After the data is labeled, the next step is to divide the dataset into training data and testing data to support the model learning and evaluation process. This study used a 70% training data and 30% test data split ratio, a ratio commonly used in sentiment analysis research to maintain a balance between model generalization ability and performance evaluation quality.

The next stage is preprocessing and normalizing the text data before applying it to the model. The preprocessing stage includes text cleaning, normalization, special character removal, stopword removal, and other steps necessary to ensure the data is formatted uniformly and ready for use by the K-NN algorithm. This process is crucial because the quality of preprocessing directly impacts the feature representation and distance calculation results in the K-NN algorithm. Thus, all processed comments are expected to be represented in more informative and relevant vectors for classification purposes.

After all preprocessing, labeling, and data splitting stages are completed, the K-NN algorithm is then applied to classify comment sentiment. The K-NN model predicts sentiment labels based on the proximity between the training and test data vectors. The prediction results are then evaluated using a confusion matrix to comprehensively measure model performance using accuracy, precision, recall, and F1-score metrics. This evaluation aims to determine the effectiveness of the K-NN algorithm in classifying YouTube comments on the dataset used, while also providing insight into potential method improvements for future research.

From a philosophical perspective, the series of methods applied in this study are not merely technical procedures but also reflect how knowledge is constructed and the values it seeks to achieve. Epistemologically, the use of unsupervised algorithms like K-Means for the initial labeling stage and supervised learning like K-NN for the classification process demonstrates that this research progresses from pattern discovery to empirical evidence based on data. Meanwhile, from axiological perspective, the application of a systematic methodology to YouTube comments provides tangible benefits in generating a more accountable understanding of public opinion in the digital space. This method also provides social and ethical value, particularly in improving the quality of online communication, reducing bias in comment interpretation, and supporting a fairer content moderation process. Thus, the method used serves not only as an analytical tool but also as a means of presenting the values of truth and utility in social media studies.

2.2 Philosophical Paragraph

Epistemologically, this research adopts a data-driven empiricism, where knowledge about public sentiment is inferred from linguistic patterns in large-scale digital traces. However, the study acknowledges that algorithmic classification does not capture subjective meaning perfectly. The generated sentiment labels represent probabilistic interpretations rather than absolute truths. Therefore, the results are interpreted as approximations of collective tendencies, not definitive judgments of individual intentions.

Pre-processing

This stage is the initial stage in dataset processing, where data obtained from external sources is cleaned and reorganized to achieve a neat, consistent structure, ready for use in the next analysis stage. This initial processing is carried out to ensure that the dataset is free from noise, duplication, typos, and irrelevant elements. In this study, several preprocessing steps were applied, such as text cleaning, normalization, special character removal, and the removal of common words that have no informative value (stopwords). This stage provides an important foundation for systematic data processing and optimal performance when applied to classification methods in the next stage.

Case Folding

Case folding is the initial stage in text preprocessing, which aims to standardize all alphabetic characters into lowercase. At this stage, all capital letters are converted to lowercase, and non-letter characters, such as numbers, punctuation, and certain symbols, are removed to prevent interference with the analysis process. By applying case folding, each word in the text data will be identified consistently by the system, minimizing differences in meaning caused by spelling variations. Examples of text processing results before and after the case folding process can be seen in [Tabel 1](#).

Tabel 1. Case folding process

Before	After
When you have been doing online school all day and it would make you so happy if David Dobrik replied to you comment	when you have been doing online school all c and it would make you so happy if david dob replied you comment

Tokenizing

Tokenizing is the process of breaking down text into smaller units, which are usually words, but can also be phrases, sentences, or paragraphs, depending on the analysis requirements. This stage is crucial because text processing algorithms operate on tokens, the basic elements of data representation. Through tokenizing, each sentence in the text is broken down into more structured terms so that the

system can process it more effectively in the next analysis stage. Examples of text processing results before and after the tokenizing process are shown in [Tabel 2](#).

Tabel 2. Tokenizing process

Before	After	Number of word occurrence
Imagine getting a notification that says	'Imagine', 'getting', 'a', 'notification', 'that', 'says'	Image = 1 getting = 1 a = 1 notification = 1 that = 2 says = 1

Stopwords

Stopword removal is the process of filtering out words deemed to have no significant informational value in text analysis. After the tokenization stage produces a number of words, the stopwords removal process is applied to remove common words such as "and," "yang," "or," and other common words that do not contribute significantly to determining sentiment meaning. This process can be performed using a stopwords list, which removes irrelevant terms, or a wordlist, which stores words deemed important. This ensures that only meaningful and relevant words remain in the subsequent analysis stages. The stopwords process is shown in [Tabel 3](#).

Tabel 3. Stopword process

Before	After
When you have been doing online school all day and it would make you so happy if David Dobrik replied to you comment	when you have been doing online school all day and it would make you so happy if david dobrik replied you comment

Normalization

Data normalization is the process of adjusting the values or attributes in a dataset to ensure they are on a uniform scale and are not excessive. The goal is to ensure that each feature contributes proportionally to the analysis process, so that no attributes dominate due to differences in value ranges. By normalizing, the data becomes more organized, consistent, and of better quality for use in the modeling stage, especially in algorithms sensitive to distance calculations such as K-NN. This process helps improve model accuracy and stability during the classification stage.

Stemming

Stemming is a text processing process that aims to find the base form (root word) of each word appearing in the text. This process is important because Indonesian words can have various forms due to the addition of affixes such as prefixes, infixes, or suffixes. By applying stemming, all derived words can be returned to their base form, resulting in a more consistent feature representation and less fragmented by morphological variations. Stemming plays a significant role in

improving the quality of feature extraction, as the model will only process the most relevant and meaningful root terms. An example of the text processing process before and after stemming is shown in **Tabel 4**.

Tabel 4. Stemming process

Before	After
When you have been doing online school all day and it would make you so happy if David Dobrik replied to you comment	when you have been do online school all day a it would make you so happy if david dobrik re you comment

This study evaluates two representative metaheuristic algorithms: Particle Swarm Optimization (PSO) and Differential Evolution (DE). These algorithms are selected because they represent two dominant optimization paradigms in MPPT research. PSO is based on swarm intelligence and collective learning through velocity updating, while DE relies on evolutionary mutation and crossover mechanisms. Their widespread adoption in MPPT literature makes them suitable reference algorithms for examining not only numerical performance, but also the epistemic justification of simulation-based performance claims under partial shading conditions.

2.3 K-Means

K-Means was used in this study as an initial data clustering method because the comment dataset obtained did not have sentiment labels. Through a clustering process using the K-Means algorithm, each comment data point is grouped into clusters based on the proximity of text characteristics, thereby automatically generating initial sentiment labels. At each iteration, the position of the cluster center (centroid) is recalculated until all data points are in the most appropriate cluster based on their distance from the centroid. This process continues until the algorithm reaches convergence, when the centroid position no longer changes significantly. Thus, K-Means Clustering allows the formation of new clusters that represent specific sentiment groups, allowing previously unlabeled datasets to be used in the next classification stage [9]. The following are the steps of the K-Means algorithm:

- Determine the number of clusters (k), and randomly assign cluster centers (centroids).
- Calculate the distance of each object to the cluster center using the Euclidean distance using the following formula.

$$d_{ik} = \sqrt{\sum_{i,k=1}^n (x_i - c_k)^2}$$

Information:

d_{ik} = distance of object i to the center of cluster k

n = data dimension

x_i = coordinates of object i

c_k = coordinates of the data center (centroid)

- c. Group the data into clusters that are closest to the cluster center.
- d. Calculate the new cluster center using the following formula.

$$\mu_k = \frac{1}{N_k} \sum_{q=1}^{N_k} x_q$$

Information:

μ_k = centroid point of the k th cluster

N_k = number of data points in the k th cluster

x_q = q th data point in the k th cluster

- e. Repeat steps 2 to 4 until there are no more objects moving to other clusters [21].

2.4 K-Nearest Neighbor (K-NN)

The K-Nearest Neighbor (KNN) algorithm is a supervised learning method that works based on the principle of similarity or proximity between data. In this method, all training data is stored as a reference, so the classification process for new data is performed by comparing it to the training data with the most similar characteristics. KNN determines the class of new data by calculating the shortest distance between the data and a number of nearest neighbors in the training dataset. Therefore, the quality of the classification results is greatly influenced by the data representation and the distance measure used in the calculation process [22].

Although KNN is known as a simple yet effective classifier, this method also has several limitations that require consideration. One important factor is the selection of the k value, or the number of nearest neighbors. When the k value is too small, the model becomes very sensitive to noise, potentially resulting in unstable classifications. Conversely, if the k value is too large, the classification process can be disrupted due to the possible inclusion of neighbors from irrelevant classes, which can ultimately degrade model performance. Therefore, selecting the appropriate k value is a crucial aspect in ensuring optimal performance of the KNN algorithm. The KNN algorithm consists of several steps:

- a. Ensuring an odd value of k from multiple training data sources.
- b. Determining the nearest neighbors from the k distance processing data.
- c. Determining the class that emerged in the first step.
- d. Grouping results based on the same class.

In a clustering or classification system using the K-Nearest Neighbors (KNN) algorithm, the k value is a constant parameter specified by the user. This k value indicates the number of nearest neighbors used as a reference in determining the

class of a test data set. Thus, a data point will be classified based on the majority of the classes from the k training data sets that are closest to it. At this stage, KNN calculates the distance between the test point and all points in the training dataset, then selects the k points with the smallest distance as references in the classification process.

To measure the closeness between data sets, KNN generally uses a specific distance measure, with Euclidean Distance being one of the most frequently used in various studies. The use of this distance metric aims to obtain an accurate representation of the closeness between two points in the feature space. The following is the Euclidean distance measurement formula used in this study [23]:

$$D(x, y) = \sqrt{\sum_i (x_k - y_k)^2}$$

Description:

D = Euclidean distance

i = data variable

x_k = training data

y_k = test data

2.5 Confusion Matrix

The performance of the classification algorithm in this study was measured using a confusion matrix. A confusion matrix is an evaluation table that illustrates the number of test data correctly and incorrectly classified by the model. Through this table, researchers can more clearly see the distribution of model predictions relative to the actual classes, thereby identifying the algorithm's classification capability.

The confusion matrix provides information on the number of test data points in the true positive, true negative, false positive, and false negative categories. **Tabel 5.** provides a comprehensive overview of model performance by showing how many data points were correctly classified into the correct class and how many were incorrectly classified. Thus, the confusion matrix is a crucial evaluation tool for assessing the accuracy, precision, recall, and F1-score of the classification model implemented in this study.

Tabel 5. Confusion matrix

Current	Prediction	
	Positive	Negative
Positive	TP	FN
Negative	FT	TN

Description:

TP (True Positive) = quantity of class 1 inscriptions correctly grouped as class 1

TN (True Negative) = quantity of class 0 inscriptions correctly grouped as class 0

FP (False Positive) = quantity of class 0 inscriptions incorrectly grouped as class 1

FN (False Negative) = quantity of class 1 inscriptions incorrectly grouped as class 0

To calculate accuracy, precision, and recall as follows:

$$Accuracy = \frac{TP+TN}{Total}$$

$$precision = \frac{TP}{TP+FP}$$

$$recall = \frac{TP}{TP+FN}$$

3.Results and Discussion

This stage is the main process in system implementation, where classification modeling is performed using the K-Nearest Neighbor (KNN) method. At this stage, the model is built based on training data that has undergone preprocessing, normalization, and labeling. Modeling using KNN aims to identify proximity patterns between data so that the system can accurately classify sentiment on the test data. This process is the core of the entire research because it determines the model's effectiveness in classifying YouTube comments into positive or negative sentiment categories.

Next, a testing scenario stage is conducted to evaluate model performance by changing several parameters in the classification process. Testing is carried out by varying the ratio of the dataset to the training and test data, as well as modifying the k value, the number of nearest neighbors in the KNN algorithm. This scenario diversification is important to find the parameter combination that produces the most optimal results, considering that KNN performance is heavily influenced by the choice of k value and the proportion of training data.

In this study, the k values used were odd numbers, namely k = 3, 5, 7, and 9. The use of odd values aims to avoid the possibility of a tie or balanced classification results between classes. Furthermore, the dataset division ratio (split validation) was tested using proportions of 50%, 60%, 70%, and 80% for the training data. Each modeling scenario was evaluated based on its accuracy level and classification performance. The results of all tests are then presented in the following table to show the parameter combination that produces the best performance. The results of the K-NN test with different k values can be seen in [Tabel 6](#).

Based on the test results presented in the table, the first experiment with a 50:50 data split ratio showed the highest accuracy of 0.96 at k = 3, while the other k values (k5, k7, k9) yielded accuracies of 0.95. Negative precision reached 0.96 at k3 and k5, and 0.95 at k7 and k9. Meanwhile, the highest positive precision was achieved at k3

with a value of 0.91 and the lowest at k7 with a value of 0.87. For the recall metric, the negative recall value was 1.00, while the positive recall ranged from 0.55 to 0.45 at this ratio.

Tabel 6. K-NN test results with different k values

Ratio	Testing Parameters	K=3	K=5	K=7	K=9
50:50	Accuracy	0.96	0.95	0.95	0.95
	Precision	0.96	0.96	0.95	0.95
	Recall	0.91	0.90	0.87	0.88
60:40	Accuracy	1.00	1.00	0.99	0.99
	Precision	0.55	0.48	0.42	0.46
	Recall	0.95	0.95	0.95	0.95
70:30	Accuracy	0.96	0.96	0.96	0.96
	Precision	0.85	0.89	0.88	0.88
	Recall	0.99	0.99	0.99	0.99
80:20	Accuracy	0.44	0.49	0.47	0.46
	Precision	0.96	0.95	0.95	0.95
	Recall	0.97	0.96	0.95	0.95

In the second experiment with a 60:40 ratio, all tested k values yielded an accuracy of 0.95. Negative precision reached 0.96, while positive precision ranged from 0.85 to 0.89. For the recall metric, the negative recall value reached 0.99, while the positive recall ranged from 0.44 to 0.49. These results indicate relatively stable performance, although a decrease in the positive recall metric was observed.

The third experiment, with a 70:30 ratio, yielded an accuracy of 0.96 at k3, while other k values yielded 0.95 accuracy. The negative precision value at all k values was 0.96. For positive precision, the highest value was obtained at k3 at 0.91 and the lowest at k5 at 0.86. The recall metric ranged from 0.99 to 1.00, indicating excellent negative class recognition at this ratio.

In the fourth experiment, with a 80:20 ratio, an accuracy of 0.96 was achieved at all k values except k9, which yielded 0.95 accuracy. The negative precision value consistently remained at 0.96. For positive precision, all k values yielded a precision of 0.88, except for k5, which was slightly lower at 0.85. The negative recall value was 0.99 for most k values, except for k7, which reached 1.00. Meanwhile, the highest positive recall value was obtained at k3 with a value of 0.56, and the lowest values were at k7 and k9 with values of 0.46.

Overall, across all test scenarios, model accuracy ranged from 95% to 96%. This indicates that varying the ratio of training data to test data had an impact on model performance, although the difference was not significant. However, the table shows that certain ratios—specifically 70:30 and 80:20—tended to produce slightly higher accuracy at lower k values. Thus, it can be concluded that the choice of dataset ratio

and k value contributed to the variation in classification performance produced by the KNN model.

This study does not position sentiment analysis merely as a computational tool, but as a socio-technical system that mediates human expression. In the philosophy of technology, technology is not neutral; it shapes and is shaped by human values. Therefore, the KNN-based sentiment classification system developed in this study is viewed as a value-laden artifact that can influence how public opinion is interpreted, filtered, and governed in digital space. This perspective places sentiment analysis within the framework of philosophy of electrical and information engineering, where algorithms become part of the infrastructure that structures digital communication.

4. Conclusion

Based on the research results, it can be concluded that the sentiment analysis process for YouTube comments using the K-Nearest Neighbor (K-NN) method underwent a comprehensive preprocessing process, including case folding, tokenizing, stopword removal, stemming, and data normalization. The classification model was then tested using several training and test data split scenarios: 20%, 30%, 40%, and 50%, as well as varying the k value to assess the effect of these parameters on model performance. The test results showed that changes in the k value and the data split ratio directly affected the model's accuracy, precision, and recall.

Across all test scenarios, the best performance was achieved at a data split ratio of 70% for training and 30% for testing, with an accuracy value reaching 0.96 at that k value. This demonstrates that selecting the right parameters for K-NN significantly determines the quality of the classification results in sentiment analysis. Therefore, the K-NN method can be said to produce excellent results in YouTube comment sentiment clustering when supported by optimal preprocessing and appropriate model parameter selection.

From a philosophy of electrical and information engineering perspective, this study demonstrates that even a simple algorithm such as KNN can function as a technological mediator that shapes how digital discourse is interpreted. Therefore, engineering responsibility does not stop at model accuracy but extends to value-sensitive design, transparency, and social accountability. Future sentiment analysis systems should integrate ethical reflection as an integral design component, not as an afterthought.

Authors' Declaration

Authors' contributions and responsibilities - The authors made substantial contributions to the conception and design of the study. The authors took

responsibility for data analysis, interpretation, and discussion of results. The authors read and approved the final manuscript.

Funding - No funding information from the authors.

Availability of data and materials - All data is available from the authors.

Competing interests - The authors declare no competing interest.

Additional information - No additional information from the authors.

References

- [1] L. Yue, W. Chen, X. Li, W. Zuo, and M. Yin, "A survey of sentiment analysis in social media," *Knowl Inf Syst*, vol. 60, no. 2, pp. 617–663, 2019, doi: 10.1007/s10115-018-1236-4.
- [2] S. Chaudhary, K. Garg, P. Gupta, and A. K. Dwivedi, "Social Media Sentiment Analysis for Airline Customer Satisfaction," *Institute of Electrical and Electronics Engineers Inc.*, 2025, pp. 1519–1522. doi: 10.1109/ICDT63985.2025.10986313.
- [3] B. Pithava, A. Magar, and S. Bharti, "Unveiling Sentiment Dynamics: Emotion Detection in Social Media," *Institute of Electrical and Electronics Engineers Inc.*, 2024. doi: 10.1109/ICEC59683.2024.10837523.
- [4] N. Abel Laia and S. P. Barus, "Analisis Sentimen YouTube: 'Di Balik Ambisi Jokowi dalam IKN,'" *Jurnal Pustaka AI (Pusat Akses Kajian Teknologi Artificial Intelligence)*, vol. 5, no. 1, pp. 07–12, Apr. 2025, doi: 10.55382/jurnalpustakaai.v5i1.891.
- [5] V. S. Sherlin Solomi, S. N. Rajana, M. M. Kolluri, and W. J. William, "Deep learning based opinion mining on youtube," in *AIP Conference Proceedings*, American Institute of Physics, 2024. doi: 10.1063/5.0209061.
- [6] A. Rahman, F. Rahmat, M. Y. Fariqi, and S. Adi, "Metode Naive Bayes untuk Menganalisis Akurasi Sentimen Komentar di Youtube," 2020. [Online]. Available: <http://bit.ly/2u802Pe>
- [7] D. N. Larasakti, A. Aziz, and D. Aditya, "Analisis Sentimen Komentar Video Youtube Dengan Metode K-Nearest Neighbor," *Jurnal Ilmiah Wahana Pendidikan*, vol. 2023, no. 5, pp. 132–142, doi: 10.5281/zenodo.7728573.
- [8] M. Cindo, D. P. Rini, and E. Ermatita, "Literatur Review: Metode Klasifikasi Pada Sentimen Analisis," *Seminar Nasional Teknologi ...*, 2019, [Online]. Available: <http://seminar-id.com/prosiding/index.php/sainteks/article/view/124>
- [9] S. F. Pratama, R. Andrean, and ..., "Analisis Sentimen Twitter Debat Calon Presiden Indonesia Menggunakan Metode Fined-Grained Sentiment Analysis," *JOINTECS (Journal ...)*, 2019, [Online]. Available: <http://publishing-widyagama.ac.id/ejournal-v2/index.php/jointecs/article/view/1004>
- [10] M. R. Firdaus, F. M. Rizki, F. M. Gaus, and ..., "Analisis Sentimen Dan Topic Modelling Dalam Aplikasi Ruangguru," *J-SAKTI (Jurnal Sains ...)*, 2020, [Online]. Available: <http://ejournal.tunasbangsa.ac.id/index.php/jsakti/article/view/188>
- [11] K. B. Reddy, D. Sai Parthava Naidu, N. Deekshitha, and M. Srinivas,

- “Exploring Hybrid Approaches for Sentiment Classification: A Comparative Study of LSTM, Naive Bayes, and Bayesian Network on IMDB Reviews,” Institute of Electrical and Electronics Engineers Inc., 2025, pp. 221–227. doi: 10.1109/AIDE64228.2025.10987367.
- [12] “Comparative Analysis of Lexicon-Based Emotion Recognition of Text,” 2023, pp. 671–677. doi: 10.1007/978-981-19-5868-7_49.
- [13] Y. Dong and X. Zeng, “Lexicon-Enhanced Multi-Task Convolutional Neural Network for Emotion Distribution Learning,” *Axioms*, vol. 11, no. 4, 2022, doi: 10.3390/axioms11040181.
- [14] N. Ruhyana and D. Rosiyadi, “Klasifikasi Komentar Instagram untuk Identifikasi Keluhan Pelanggan Jasa Pengiriman Barang dengan Metode SVM dan Naïve Bayes Berbasis Teknik Smote,” *Faktor Exacta*, vol. 12, no. 4, p. 280, 2020, doi: 10.30998/faktorexacta.v12i4.4981.
- [15] R. Danyana Umrona, S. Naja Anwar, and R. Soelistijadi, “ANALISIS SENTIMEN KOMENTAR YOUTUBE TERKAIT KASUS PAGAR LAUT MENGGUNAKAN METODE KNN (K-NEAREST NEIGHBOR),” *Jurnal Informatika Teknologi dan Sains*.
- [16] S. A. Amira and M. I. Irawan, “Opinion Analysis of Traveler Based on Tourism Site Review Using Sentiment Analysis,” *IPTEK The Journal for Technology and Science*, vol. 31, no. 2, p. 223, 2020, doi: 10.12962/j20882033.v31i2.6338.
- [17] M. R. Firmansyah, R. Ilyas, and F. Kasyidi, “Klasifikasi Kalimat Ilmiah Menggunakan Recurrent Neural Network,” *Prosiding The 11th Industrial Research Workshop and National Seminar*, vol. 11, no. 1, pp. 488–495, 2020.
- [18] I. L. Rais and J. Jondri, “Klasifikasi Data Kuesioner dengan Metode Recurrent Neural Network,” *eProceedings of Engineering*, vol. 7, no. 1, pp. 2817–2826, 2020.
- [19] E. B. Nugroho, M. T. Furqon, and N. Hidayat, “Klasifikasi Pendonor Darah Menggunakan Metode Support Vector Machine,” *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer (J-PTIIK) Universitas Brawijaya*, vol. 2, no. 10, pp. 3860–3864, 2018.
- [20] N. K. Widyasanti, I. K. G. Darma Putra, and N. K. Dwi Rusjyanthi, “Seleksi Fitur Bobot Kata dengan Metode TFIDF untuk Ringkasan Bahasa Indonesia,” *Jurnal Ilmiah Merpati (Menara Penelitian Akademika Teknologi Informasi)*, vol. 6, no. 2, p. 119, 2018, doi: 10.24843/jim.2018.v06.i02.p06.
- [21] I. Kurniawan and A. Susanto, “Implementasi Metode K-Means dan Naïve Bayes Classifier untuk Analisis Sentimen Pemilihan Presiden (Pilpres) 2019,” *Jurnal Eksplora Informatika*, 2019, [Online]. Available: <https://eksplora.stikom-bali.ac.id/index.php/eksplora/article/view/237>
- [22] U. Kasanah, A. N., Muladi, M., & Pujiyanto, “Penerapan Teknik SMOTE untuk Mengatasi Imbalance Class dalam Klasifikasi Objektivitas Berita Online Menggunakan Algoritma KNN,” *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, vol. 1, no. 3, pp. 196–201, 2019.
- [23] M. Syarifuddin, “Analisis Sentimen Opini Publik Mengenai Covid-19 Pada Twitter Menggunakan Metode Naïve Bayes Dan Knn,” *Inti Nusa Mandiri*, vol. 15, no. 1, pp. 23–28, 2020.

- [24] M. R. Braun, P. Walton, S. B. M. Beck, and W. London, "Illustrating the relationship between the coefficient of performance and the coefficient of system performance by means of an R404 supermarket refrigeration system," *International Journal of Refrigeration*, vol. 70, pp. 225–234, 2016, doi: 10.1016/j.ijrefrig.2015.10.020.
- [25] Z. Ma, H. Bao, and A. P. Roskilly, "Thermodynamic modelling and parameter determination of ejector for ejection refrigeration systems," *International Journal of Refrigeration*, vol. 75, pp. 117–128, 2017, doi: 10.1016/j.ijrefrig.2016.12.005.