



A Performance Comparison of Machine Learning Algorithms in Text Analysis of the Free Lunch Program

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Received Jun 08th 2025; Revised Jul 06st 2026; Accepted Jul 13th 2026; Available Online Aug 01st 2026

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Abstract

The rise of public discourse on social policies in digital platforms necessitates accurate sentiment analysis to support data-driven policymaking. This study investigates the performance of three machine learning algorithms, Naive Bayes, Random Forest, and Support Vector Machine (SVM), in classifying public sentiment toward Indonesia's Free Lunch Program. Data were collected via web scraping of YouTube comment sections, preprocessed with standard Natural Language Processing (NLP) techniques, and transformed with TF-IDF vectorization. Each algorithm was evaluated using accuracy, precision, recall, and F1-score on a three-class sentiment classification task with classes positive, neutral, and negative. Results show that Random Forest outperformed the other models with an accuracy of 93.55%, followed by SVM at 82.54%, and Naive Bayes at 75.71%. Random Forest demonstrated strong consistency across all sentiment categories, while SVM also delivered competitive results, especially for neutral sentiment. Naive Bayes, although efficient, struggled with imbalanced data, particularly in detecting negative sentiment. These findings highlight the superiority of ensemble models, such as Random Forest, in handling complex sentiment tasks and provide a foundation for developing robust NLP-based public opinion analysis tools for social policy evaluation. Unlike previous studies that primarily focused on product reviews or political sentiment, this research provides a comparative evaluation of machine learning algorithms for analyzing public opinion on Indonesia's Free Lunch Program using YouTube comments. The findings contribute practical guidance for selecting appropriate sentiment classification models to support evidence-based public policy evaluation.

Keywords: Free Lunch Program, Machine Learning, Natural Language Processing, Public Opinion, Sentiment Analysis

1. INTRODUCTION

In the era of digital communication, the role of information technology has evolved from a tool for efficiency into a critical medium for civic engagement, political discourse, and policy evaluation. The exponential growth of user-generated content on platforms such as social media, online forums, and digital news portals has transformed the landscape of public opinion. These platforms now serve as real-time barometers of societal sentiment, where diverse perspectives on social programs and government initiatives are continuously expressed, debated, and amplified [1]. As such, the analysis of digital discourse has become increasingly vital in shaping evidence-based policies and fostering participatory governance.

A notable example of a social policy that has recently stirred extensive public discussion is Indonesia's Free Lunch Program, a government initiative aimed at combating child malnutrition and improving students' cognitive performance. While its intentions are broadly positive, the program has elicited mixed reactions. Supporters praise its potential to address systemic issues in education and nutrition, whereas critics raise concerns over logistical preparedness, long-term funding, and fair distribution. These opinions are not only

voiced in formal media but are prominently visible in the comment sections of YouTube videos, social media threads, and online forums. Such data, if properly analyzed, can serve as a valuable indicator of public sentiment and policy effectiveness [2], [3].

However, leveraging this wealth of unstructured data poses significant challenges. Manual analysis is not only time-consuming but also inherently limited in terms of human bias and scalability. To overcome this, researchers have increasingly turned to text mining and sentiment analysis, two interrelated disciplines within Natural Language Processing (NLP) that enable the extraction of meaningful insights from textual data [4]. Sentiment analysis, in particular, aims to classify opinions into categories such as positive, negative, and neutral, thereby providing actionable feedback for policymakers. When powered by machine learning (ML) algorithms, sentiment analysis becomes a scalable and statistically grounded method for analyzing public opinion at scale [5].

Among the various ML algorithms used in sentiment classification, Naive Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM) are frequently adopted due to their proven effectiveness in text-related tasks [6], [7]. Naive Bayes, grounded in probabilistic inference, is renowned for its simplicity and performance on high-dimensional data. Random Forest, an ensemble method combining multiple decision trees, offers robustness against overfitting and can model complex patterns. SVM, on the other hand, is a powerful classifier, especially well-suited to sparse, high-dimensional input spaces such as those produced by TF-IDF vectorization. Each algorithm has unique strengths, but their comparative performance often varies depending on the specific context, data characteristics, and classification objectives [8], [9].

Despite the growing number of studies comparing Naive Bayes, Random Forest, and Support Vector Machine, most previous research has focused on product reviews, e-commerce platforms, political campaigns, or international social media datasets [7], [8], [9], [10]. Although these studies consistently demonstrate the effectiveness of machine learning techniques for sentiment classification, their findings cannot be directly generalized to public policy discussions in Indonesia because policy-related discourse typically involves more diverse opinions, contextual expressions, and imbalanced sentiment distributions [2], [3], [11]. Furthermore, only a limited number of studies have examined sentiment toward the Free Lunch Program using Indonesian-language YouTube comments, leaving uncertainty regarding the most suitable classification algorithm for this specific domain [12], [13]. The novelty of this study lies in providing a comparative evaluation of Naive Bayes, Random Forest, and Support Vector Machine for multiclass sentiment classification of Indonesia's Free Lunch Program using YouTube comments. Unlike previous studies that mainly examined commercial products, political campaigns, or international datasets [8], [10], this research focuses on a government social policy in Indonesia and evaluates the effectiveness of three machine learning algorithms using Indonesian-language social media data. The findings provide practical recommendations for selecting suitable sentiment classification models to support evidence-based public policy evaluation and enrich the application of Natural Language Processing in public sector policy analysis [14], [15].

2. MATERIAL AND METHOD

2.1. Stage of Research

This research was conducted through several systematic stages to compare the performance of the Naive Bayes, Random Forest, and Support Vector Machine algorithms in analyzing public sentiment in comments regarding the Free Lunch Program [16]. The stages carried out in this study are shown in Figure 1.

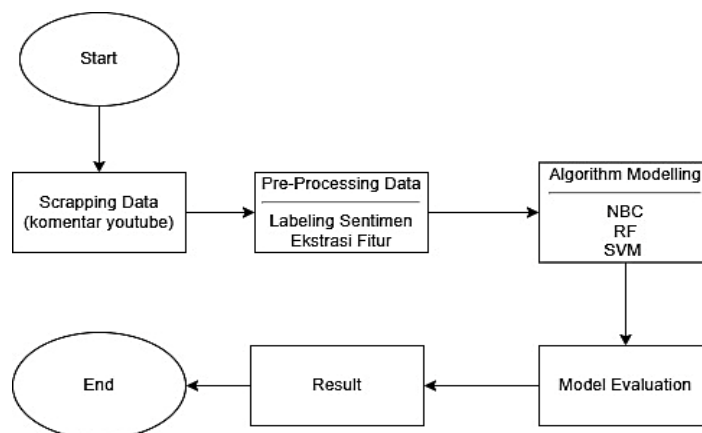


Figure 1. Research Methodology

This study is designed using a systematic approach, as illustrated by a methodological flowchart. The diagram serves as a visual representation of the entire research process, starting from problem formulation and

research objectives, data collection using scraping techniques, text data preprocessing, implementation of three classification algorithms (Naive Bayes, Random Forest, and SVM), model evaluation, as well as analysis and interpretation of classification results [17]. The presence of the flowchart makes the workflow clearer, more sequential, and easier to understand, especially in depicting the relationships between the important stages of the research. Each stage in the methodological diagram has interrelated roles and determines the success of sentiment classification using machine learning algorithms [18], [19].

2.2. Scraping Data

The dataset used in this study was obtained through web scraping of user comments from various digital platforms discussing the Free Lunch Program. The primary data source consists of comment sections on YouTube videos capturing public responses to the policy. The collected data consists of text comments expressing opinions, including those that support, oppose, or are neutral toward the government program [20]. The data collection process was conducted using Python libraries such as google-api-python-client [21]. Prior to analysis, the data underwent preprocessing steps to clean and normalize the text, ensuring the quality and relevance of the sentiment analysis.

2.3. Naïve Bayes Classifier

The Naive Bayes Classifier (NBC) is a probabilistic classification algorithm that relies on Bayes' Theorem and assumes that features are independent. In this study, NBC is used to predict comment sentiment based on the words that appear in the text. The probability that a comment belongs to a certain class is calculated using Equation 1.

$$P(C|X) = \frac{P(X|C) \cdot P(C)}{P(X)} \quad (1)$$

where $P(C|X)$ is the probability that a comment belongs to class C given the features X , $P(X|C)$ is the probability of the features X occurring in class C , and $P(C)$ is the prior probability of class C . NBC is known for its efficiency in handling high-dimensional data, such as text, and is often used as a baseline for sentiment classification [22], [23].

2.4. Random Forest (RF)

RF is an ensemble-based algorithm that constructs multiple decision trees to improve prediction accuracy [24], [25]. Each tree is trained on a different subset of the data using bootstrap sampling, and the final result is determined by majority voting. In this study, RF is used to classify public comments regarding the Free Lunch Program. RF is effective at handling interactions among features and can provide feature importance scores [26]. The impurity at each tree node is measured using the Gini Impurity Equation 2.

$$\text{Gini}(S) = 1 - \sum_{i=1}^n \rho_i^2 \quad (2)$$

where ρ_i is the proportion of elements in class i within subset S . RF has proven robust to noise and overfitting, especially with textual data [27].

2.5. Support Vector Machine (SVM)

SVM is a statistical learning algorithm that seeks the optimal hyperplane to separate two classes of data. SVM works by maximizing the margin between different classes in the feature vector space. In text classification [28], [29], SVM is highly effective because it can handle high-dimensional data, such as TF-IDF vectors. The SVM prediction equation 3.

$$f(x) = w^t x + b \quad (3)$$

where w is the weight vector, x is the feature vector of the data, and b is the bias. SVM can classify both linear and non-linear data using kernels and has been widely used in text classification and natural language processing.

2.6. Evaluation

The performance of the classification models was evaluated using four commonly adopted evaluation metrics: Accuracy, Precision, Recall, and F1-Score. These metrics were calculated from the confusion matrix to provide a comprehensive assessment of each algorithm's classification performance. Accuracy measures the overall proportion of correctly classified instances, while Precision evaluates the correctness of positive predictions. Recall measures the model's ability to identify all relevant instances, whereas the F1-Score

provides a balanced evaluation by considering both Precision and Recall [27][29]. Accuracy, precision, recall, and F1-Score are calculated as Equations 4-7.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (7)$$

These evaluation metrics were used to compare the performance of Naive Bayes, Random Forest, and Support Vector Machine in classifying public sentiment toward the Free Lunch Program.

3. RESULTS AND DISCUSSION

After training and testing the three classification algorithms on the dataset of comments related to the Free Lunch Program, model performance was evaluated using four main metrics: accuracy, precision, recall, and F1-score. The test data consisted of a number of comments that had undergone preprocessing and manual sentiment labeling to ensure the validity of the evaluation.

3.1. Scraping Data and Preprocessing Data

The results of this study demonstrate the performance of three machine learning algorithms in classifying sentiment in comments related to the Free Lunch Program into three categories: negative (0), neutral (1), and positive (2). The dataset consists of user comments that have undergone several preprocessing steps, including data cleaning, tokenization, stopword removal, and TF-IDF feature representation. The dataset was then split into training and testing sets using an 80:20 ratio with the Holdout Split method. The three algorithms tested, Naive Bayes, Random Forest, and Support Vector Machine, were evaluated using accuracy, precision, recall, and F1-score metrics to assess their effectiveness in classifying sentiment into the aforementioned categories. With the 80:20 data split, the algorithms exhibited varying performance levels. Overall, SVM and Random Forest tended to perform better than Naive Bayes, particularly in handling the complexity of textual data containing diverse public opinions.

3.2. Process Validity Algorithm

The prediction implementation in this study was carried out using three classification models: Naive Bayes, Random Forest, and Support Vector Machine. These models were used to process comment data on the Free Lunch Program, aiming to classify public sentiment as negative, neutral, or positive.

3.2.1. Naïve Bayes (TF-IDF, 80:20 split)

Displaying the validation results of the Naive Bayes Classifier implementation in Table 1.

Table 1. Naive Bayes Performance

Class	Precision	Recall	F1-Score	Support
0 (Negative)	100%	6,78%	12,70%	59%
1 (Neutral)	73,59%	99,13%	84,47%	343%
2 (Positive)	90,16%	44%	59,14%	125%
Accuracy	75,71%	75,71%	75,715%	0,76%

Table 1 shows the performance of the Naive Bayes Classifier (NBC) algorithm in classifying the sentiment of comments related to the Free Lunch Program into three classes: negative, neutral, and positive. The model achieved an overall accuracy of 75.71%, with performance varying across classes. The neutral class showed the best results with a Recall of 99.13% and an F1-Score of 84.47%, indicating that the model is very effective at recognizing neutral comments. Meanwhile, the negative class had a perfect Precision of 100% but a very low Recall of 6.78%, meaning the negative predictions are accurate, but many negative comments were not detected. For the positive class, Precision was high at 90.16%, but Recall was only 44%, showing that positive predictions are fairly accurate but incomplete in detecting all positive comments. Overall, Naive Bayes is effective at classifying neutral comments but less effective at recognizing negative and positive comments. These results highlight the challenges in handling imbalanced text data and the complexity of varied public opinions regarding the program.

3.2.2. Random Forest (TF-IDF, 80:20 split)

Showing the validation results of the Random Forest algorithm implementation in Table 2.

Table 2. Random Forest Performance

Class	Precision	Recall	F1-Score	Support
0 (Negative)	91,49%	72,88%	81,13%	59%
1 (Neutral)	92,18%	99,71%	95,80%	343%
2 (Positive)	99,08%	86,40%	92,31%	125%
Accuracy	93,55%	93,55%	93,55%	0,94%

This table presents the evaluation results of the Random Forest (RF) algorithm in classifying sentiment comments related to the Free Lunch Program, with three sentiment classes: negative (class 0), neutral (class 1), and positive (class 2). The evaluation was conducted using an 80:20 data split, with metrics including Precision, Recall, F1-Score, and Accuracy. Overall, the Random Forest algorithm demonstrated very good performance, achieving an accuracy of 93.55%, meaning most comments were correctly classified into their respective sentiment categories. The model showed high and consistent performance across all three classes. For the positive class (class 2), RF achieved a Precision of 99.08%, a recall of 86.40%, and an F1 Score of 92.31%, indicating that nearly all positive comments were recognized and that positive predictions were very accurate. Performance for the neutral class (class 1) was also very good, with a Precision of 92.18%, a recall of 99.71%, and an F1 Score of 95.80%, indicating that most neutral comments were correctly classified. Similarly, for the negative class (class 0), the model performed strongly, with a Precision of 91.49%, a recall of 72.88%, and an F1 Score of 81.13%.

3.2.3. Support Vector Machine (TF-IDF, 80:20 split)

Displaying the validation results of the Support Vector Machine algorithm implementation in Table 3

Table 3. Support Vector Machine Performance

Class	Precision	Recall	F1-Score	Support
0 (Negative)	81,08%	50,85%	62,50%	59%
1 (Neutral)	80,42%	99,42%	88,92%	343%
2 (Positive)	96,97%	51,20%	67,02%	125%
Accuracy	82,54%	82,54%	82,54%	0,83%

This table shows the performance of the Support Vector Machine (SVM) algorithm in classifying sentiment comments related to the Free Lunch Program into three classes: negative (class 0), neutral (class 1), and positive (class 2). Evaluation was conducted using an 80:20 data split with metrics including Precision, Recall, F1-Score, and Accuracy. Overall, the SVM algorithm achieved an accuracy of 82.54%, indicating that most comments were correctly classified. The model showed good performance with some variation between classes. For the positive class (class 2), the SVM achieved a Recall of 51.20% and a Precision of 96.97%, resulting in an F1-Score of 67.02%. For the neutral class (class 1), Precision was high at 80.42% with a Recall of 99.42%, yielding an F1-Score of 88.92%. The negative class (class 0) had a Precision of 81.08%, a recall of 50.85%, and an F1 Score of 62.50%, indicating moderate success in recognizing negative comments.

3.3. Comparison Accuracy of Algorithms

After evaluating each algorithm's performance on the data splits, the next step is to compare the algorithms to determine which achieves the highest accuracy. The comparison results are shown in Figure 2.

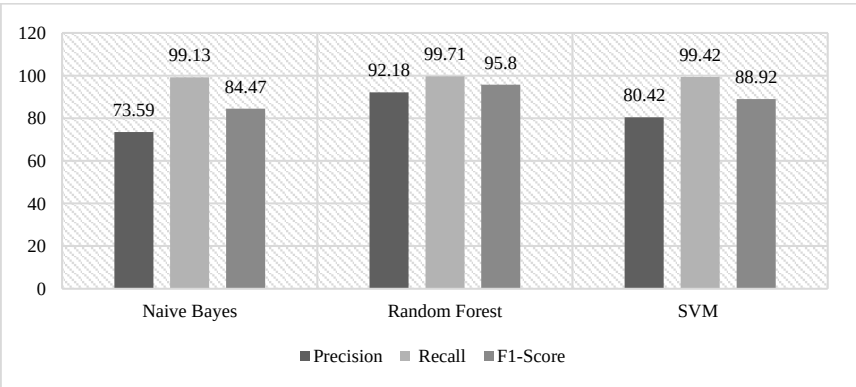


Figure 2. Comparison of Algorithm: Evaluation Metrics for Neutral Sentiment Class

The RF algorithm showed the best performance on the 80:20 split, achieving a Precision of 92.18%, a recall of 99.71%, and an F1-score of 95.80%. Support Vector Machine (SVM) also performed well, with a Precision of 80.42%, a recall of 99.42%, and an F1 Score of 88.92%. Meanwhile, the Naive Bayes Classifier (NBC) achieved a Precision of 73.59%, Recall of 99.13%, and F1-Score of 84.47%. To determine the overall best-performing algorithm, an additional comparison was conducted, as shown in Figure 3.

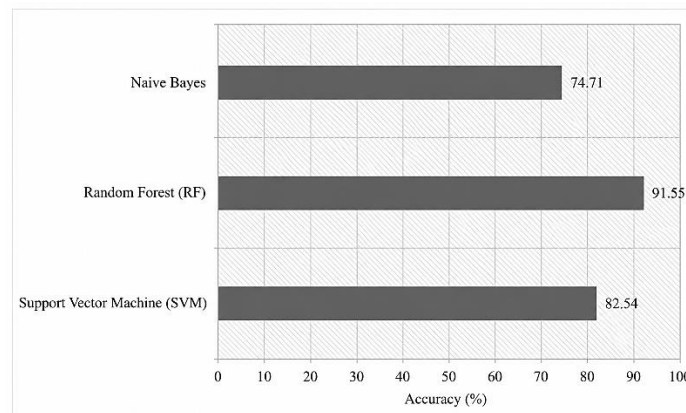


Figure 3. Model Accuracy Comparison

Based on the evaluation results with an 80:20 data split, the Random Forest (RF) algorithm demonstrated the best performance among the three tested algorithms, achieving an F1 score of 93.55%. This indicates that Random Forest is highly effective at classifying public sentiment comments about the Free Lunch Program with high accuracy. The advantage of this algorithm likely stems from its ability to combine multiple decision trees, thereby reducing the risk of overfitting and improving generalization on complex and varied textual data. In second place, the Support Vector Machine (SVM) algorithm also delivered solid results with an F1 score of 82.54%. SVM is known for its effectiveness at separating classes in high-dimensional spaces, making it well-suited for text classification tasks involving large, sparse TF-IDF features. Although slightly behind Random Forest, SVM still shows strong stability and consistency in recognizing positive, negative, and neutral sentiment patterns in the comments data. Meanwhile, the Naive Bayes algorithm performed lower, with an F1 score of 75.71%. Despite its advantages in training speed and computational efficiency, Naive Bayes has limitations in handling feature dependencies common in opinion text data, resulting in suboptimal performance compared to the other two algorithms, especially when classifying classes with an imbalanced data distribution.

This comparison of F1-Scores confirms that, in the context of three-class sentiment classification on social program comment datasets such as the Free Lunch Program, ensemble algorithms like Random Forest provide a significant advantage. However, SVM also remains a viable alternative with competitive performance. The choice of the best algorithm should still be tailored to specific needs, available computational resources, and the characteristics of the data used.

3.4. Discussion

The results demonstrate that the Random Forest (RF) algorithm achieved the highest classification performance, with an accuracy of 93.55%, outperforming Support Vector Machine (SVM) and Naive Bayes. This superior performance can be attributed to the ensemble learning mechanism of Random Forest, which combines multiple decision trees to improve prediction accuracy and reduce the risk of overfitting. Such characteristics enable Random Forest to effectively capture complex relationships among textual features represented by TF-IDF vectors, making it well-suited for multiclass sentiment classification involving diverse public opinions.

The findings of this study are consistent with previous research reporting that Random Forest generally provides better classification performance than Naive Bayes in sentiment analysis tasks. Pandey et al. found that Random Forest achieved higher accuracy because of its ability to model nonlinear relationships among textual features. Similarly, Fauzi et al. reported that Random Forest outperformed both SVM and Naive Bayes in classifying travel-related sentiment. However, unlike studies that focused on product reviews or tourism platforms, this research evaluates public sentiment toward a government social policy, thereby extending the application of machine learning algorithms to public policy analysis.

The characteristics of the dataset also influenced the classification results. The sentiment distribution was dominated by neutral comments, resulting in a class imbalance that affected the performance of the classification models. Random Forest demonstrated greater robustness in handling this imbalance because its ensemble structure reduces classification bias toward the majority class. In contrast, Naive Bayes showed relatively poor performance in identifying negative comments, mainly due to its conditional independence

assumption, which may not adequately capture contextual relationships among words in opinionated text. Although SVM achieved competitive results, its performance was slightly lower than Random Forest, particularly in detecting minority sentiment classes.

These findings indicate that Random Forest is a suitable approach for sentiment analysis in public policy evaluation using social media data. The model's ability to accurately classify public opinion may help policymakers understand community responses and identify public concerns about government programs. Furthermore, this study provides empirical evidence on the comparative performance of three widely used machine learning algorithms for analyzing Indonesian-language YouTube comments related to the Free Lunch Program. Future studies are encouraged to investigate hyperparameter optimization, ensemble learning strategies, cross-platform datasets, and deep learning approaches to further improve sentiment classification performance.

4. CONCLUSION

Based on the evaluation results of three machine learning algorithms, Naive Bayes, Random Forest, and Support Vector Machine in classifying public sentiment comments on the Free Lunch Program, it can be concluded that the Random Forest algorithm provides the best performance with the highest accuracy of 93.55%, followed by SVM with 82.54% accuracy, and Naive Bayes with 75.71%. Random Forest proves superior in handling complex and imbalanced text data, while SVM is also effective for high-dimensional data. The novelty of this study lies in comparing three machine learning algorithms for multiclass sentiment classification of Indonesia's Free Lunch Program using Indonesian-language YouTube comments, an area that has received limited attention in previous studies. The findings provide practical guidance for selecting appropriate machine learning models to support public policy evaluation. Future research may explore hyperparameter optimization, ensemble learning, and deep learning approaches, as well as larger datasets from multiple social media platforms.

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