

Sentiment Analysis of the Free Nutritious Meals Program using Linear Learner and Adaboost Algorithms

Muhammad Annash Ash Shidiq, Sriyanto Sriyanto

Faculty of Computer Science, Darmajaya Institute of Informatics and Business, Lampung,
INDONESIA

E-mail: annashidiq01@gmail.com, sriyanto@darmajaya.ac.id

| Submitted: February 23, 2026 | Revised: March 04, 2026 | Accepted: August 29, 2026 |

| Published: October 23, 2026 |

ABSTRACT

The government initiative through the Free Nutritious Meals Program is designed to intervene in the nutritional quality of the community, especially for students in schools. Given that this policy has sparked widespread discussion on social media platforms, this study aims to map public opinion trends through sentiment analysis. The main focus of this study is to apply a Logistic Regression-based Linear Learner algorithm integrated with the AdaBoost ensemble learning technique to classify text data. Primary data was collected from the Threads platform, which was then processed through a series of systematic stages including text preprocessing, feature extraction, and separation between training and test data for positive and negative sentiment categories. In this experiment, Logistic Regression acts as the base classifier, while AdaBoost is used as a strategy to optimize classification accuracy. Model performance evaluation was conducted comprehensively using accuracy, precision, recall, and F1-score parameters. The research findings confirm that adding the AdaBoost method to the Logistic Regression framework significantly improves classification quality compared to when the algorithm is used alone. The developed model was proven to produce higher metrics and a more stable distribution of values. Therefore, the synergy between Logistic Regression and AdaBoost is a reliable approach to evaluate public perception of public policy implementation.

Keywords: sentiment analysis, free nutritious meal program, logistic regression, adaboost, machine learning.

INTRODUCTION

The quality of human resources is a key pillar in achieving the vision of Indonesia Emas 2045. One of the major challenges facing the nation today is the issue of basic health, particularly stunting and malnutrition, which hinder the growth of children and toddlers. Responding to this urgency, the government launched the Free Nutritious Meals Program as a strategic measure targeting school children, toddlers, and pregnant and lactating mothers [1]. The long-term goal of this policy is to create a healthy, intelligent, and competitive generation. As a national public policy with a significant budget allocation, this program has sparked widespread discourse among the public [2], [3], [4]. Social media, especially the Threads platform, has become the main digital public space where people express their opinions in real time. This has created a massive flow of data, ranging from full support (pro) to criticism and concerns (con) regarding budget transparency and the effectiveness of implementation in the field. Since the success of the program is highly dependent on public acceptance, while opinions on social media are voluminous and unstructured, manual evaluation is difficult to carry out [5], [6]. Therefore, a sentiment analysis system is needed to accurately map public perception.

Various previous studies have attempted to map public perceptions of this policy, with the majority using data from social media platform X (Twitter). There are two contrasting sentiment trends: on the one hand, there is a predominance of negative sentiment, but on the other hand, there is also a predominance of positive sentiment. A study Arif [7] used lexicon-based Natural Language Processing (NLP) (TextBlob) on 657 tweets and found a 71.8% dominance of negative sentiment, reflecting public skepticism about the effectiveness and transparency of the budget. The analysis showed that criticism was more focused on technical and political aspects than on nutritional

substance. Another approach by Arfan & Badii [8] compared the BERT and SVM models on 1,000 data points. The BERT model proved to be superior at capturing language context with 86% accuracy, and confirmed the dominance of negative sentiment at 65.7%.

In contrast, a study by Aprianti et al. [9] that applied the Logistic Regression algorithm to 1,000 data points recorded an accuracy of 86.78% and found a predominance of positive opinions regarding the policy. A large-scale study by Nursakina et al. [10] using the KNN algorithm on 9,723 data points (72.27% accuracy) also indicated significant quantitative support from the public, with 3,955 positive opinions compared to 2,367 negative opinions. Additionally, Pratama et al. [11], which compared Decision Tree and Naïve Bayes on 643 tweets (best accuracy of Decision Tree 77.52%), revealed that despite support for nutritional improvement, negative opinions still emerged as a form of operational concern in the field.

From this study, it can be seen that the Linear Learner algorithm in the form of Logistic Regression has high effectiveness, simplicity, computational efficiency, and ease of interpretation of results. However, the performance of Logistic Regression alone still has the potential to be improved with ensemble learning techniques such as AdaBoost, which works by focusing learning on data that is difficult to classify to strengthen the base model. To date, studies discussing the application and evaluation of the combination of Logistic Regression and AdaBoost in sentiment analysis of the Free Nutritious Meals Program, specifically with data sources from the Threads platform, are still very limited. Therefore, this research is relevant to fill this gap in the literature while providing a comprehensive evaluation of public perception of government policies in a technical and objective manner.

RESEARCH METHODS

This study uses a quantitative approach to build a sentiment prediction model for the Free Nutritious Meals Program policy based on public opinion on the social media platform Threads. The method used is a Linear Learner algorithm in the form of Logistic Regression combined with the AdaBoost ensemble learning method to improve sentiment classification performance into three categories, namely positive, negative, and neutral. The data was obtained through purposive sampling by scraping relevant public discussions, then processed and analyzed using evaluation metrics such as accuracy, precision, recall, and F1-score. This study aims to evaluate the effectiveness of AdaBoost in improving the performance of Logistic Regression and to provide an objective picture of public perception of the Free Nutritious Meals Program policy as material for public policy evaluation.

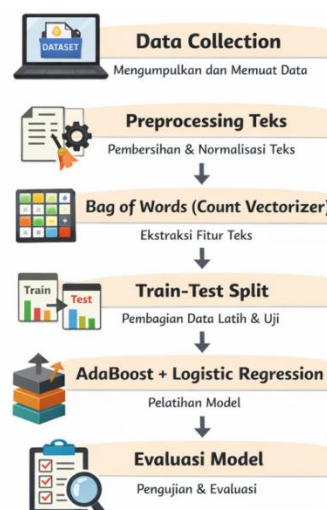


Figure 1. Research stages

Figure 1 shows the steps in this research process, namely data collection, data preprocessing, data mining consisting of two methods, lexicon-logistic regression and bert, evaluation, and comparison method.

Data Collection

At this stage, data was collected from comments on the Threads app about the free nutritious food policy from the start of the program until now using an additional Google Chrome application called Web Scraper, which generates XLS data.

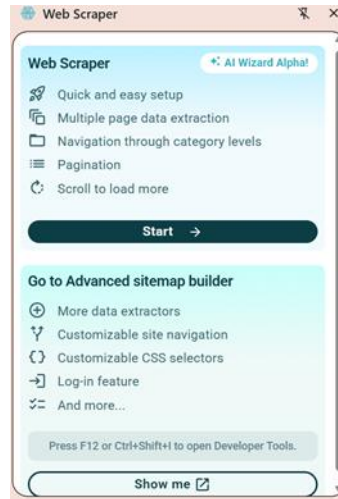


Figure 2. Web Scraper Application

Text Preprocessing

In an effort to prepare optimal data for the classification process, this study applied six stages of data preprocessing. The stages began with cleansing to eliminate non-informative attributes such as symbols, punctuation marks, and emojis. Next, case folding was performed to standardize all text to lowercase letters. The tokenizing process was then used to break sentences into single words. To maintain consistency of meaning, normalization is performed to correct spelling or typing errors. The next stage is stopword removal to filter out common words that have no contextual weight, and finally, stemming is used to reduce each word to its base form or root [12].

Bag of Words

Bag of Words (BoW) is a simple feature extraction technique in natural language processing that converts text into numerical representations (vectors) by counting the frequency of each word's appearance in a document. This method works by building a list of unique vocabulary from the entire data set, then recording how many times each word appears without regard to word order, grammatical structure, or sentence context. The end result is a matrix of numbers that allows machine learning algorithms to process text data, even though information about the relationships between words and their semantic meanings is lost in this simplification process. [13]

AdaBoost

AdaBoost stands for Adaptive Boosting, first introduced by Yoav Freund and Robert Schapire in 1996. This algorithm is an ensemble learning technique designed to convert a set of simple prediction models (weak learners) into one accurate and robust prediction model (strong learner). In practice, a weak learner is usually a basic model whose accuracy level only slightly exceeds random guessing. [14]

The working principle of the Adaboost algorithm consists of initializing weights with each observation in the dataset being given the same weight at the beginning.

$$\text{Weights } w_i = \frac{1}{N}$$

Then training weak models on weighted data (weak learners)

After that, calculating the model error $h_t(x)$ against the data weights using the equation

$$\epsilon_t = \frac{\sum_{i=1}^N w_i I(y_i \neq h_t(x_i))}{\sum_{i=1}^N w_i}$$

Assigning weights to weak models based on their errors using the equation

$$\alpha_t = \ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$$

Then, the observation weights are updated so that misclassified observations get higher weights using the equation

$$w_i \leftarrow w_i \exp(\alpha_t I(y_i \neq h_t(x_i)))$$

The final model is a combination of all models that have been weighted using the equation

$$H(x) = \text{sign}(\sum_{t=1}^T \alpha_t h_t(x))$$

Logistic Regression

Logistic regression is a classification algorithm in machine learning that is used to predict the probability of a categorical dependent variable. Logistic regression has high interpretability, but is less effective in handling data that is not linearly separable. In this method, the dependent variable is binary, i.e., it has a value of 1 (Yes) or 0 (No). Logistic Regression is a form of linear regression commonly used to map a number of numerical variables into binary or probabilistic variables. [15]

$$P(y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 + \beta_2 + \dots + \beta_p x_p)}}$$

Where:

$(y = 1|X)$ is the probability that the class is 1.

β is the coefficient learned by the model.

x is the input feature.

Evaluation

The evaluation process is used to determine the accuracy, precision, recall, and f-measure values stated in the multiclass confusion matrix table, which can be seen in Table [16].

Table 1. Confusion Matrix

Actual \ Predicted	Positive	Negative
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

then the accuracy, precision, recall, and F-1 score values can be calculated.

Accuracy describes how accurately the model classifies correctly.

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

Precision describes the accuracy between the requested data and the prediction results provided by the model.

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

Recall or sensitivity describes the model's success in finding information again.

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

F-1 Score describes the weighted average comparison of precision and recall. Accuracy is used as a benchmark for algorithm performance if our dataset has a very similar number of False Negatives and False Positives (symmetric). However, if the numbers are not similar, then we should use F1 Score as a benchmark.

$$F1\ Score = \frac{(2 * Recall * Precision)}{(Recall + Precision)}$$

RESULT AND DISCUSSION

Data Collection

A total of 4,593 reviews were collected from the comments section of Threads related to the free nutritious meal program. Examples of these comments are listed in the table below.

Table 2. comment threads

No.	Review
1	"This program is good actually, it's great. but, the execution needs to be corrected, from the 'kitchen' (internal operations) all the way to the staff. This includes the data collection of schools that are truly in need. It hasn't even been a year since it started; there is still a lot that needs attention and improvement. Remember: China took 10 years from their initial plan to succeed, and Japan took 8 years from their initial plan to succeed. "
2	:(Why is it that these schools tell their students to just stay quiet? It happened at my child's school yesterday, too. They recorded a video of a caterpillar in their food and shared it with the class group, which includes the teacher. The teacher then told them not to share it anywhere else."
...	...
4.593	Also, a friend's cousin got food poisoning from drinking the MBG (Free Nutritious Meal) milk because the expiration date wasn't checked. Oh my God, people's lives are at stake here. Mr. Prabowo, please double-check the MBG kitchens again.

A collection of comment data containing a lot of noise (interference) requires a preprocessing stage to remove the noise, perform normalization to produce standardized words, and apply stemming to obtain root words.

Data Preprocessing

To ensure data quality and consistency, the text undergoes a series of preprocessing procedures, including cleansing, case folding, normalization, tokenization, stopword removal, and stemming. Additional steps, such as duplicate data cleaning and removal of short words (three letters or less), are also performed because they are considered to have no significant informational value. The data preprocessing stages can be seen in Table 3.

Table 3. Preprocessing Process

Stages	Before	After
Cleansing	Auto Crying 🤔 🤔 Heartily very Younger Sibling Healthy always 🤔 🤔	Auto Crying Heartily very Younger Sibling Healthy always.
Case folding	Auto Crying Heartily very Younger Sibling Healthy always	auto crying heartily very younger sibling healthy always
Tokenizing	auto crying heartily very younger sibling healthy always	"auto", "crying", "heartily", "very", "younger", "sibling", "healthy", "always"
Normalization	"auto", "crying", "heartily", "very", "younger", "sibling", "healthy", "always"	"automatically", "crying", "heartily", "very", "younger", "sibling", "healthy", "always"

Stages	Before	After
Stopword removal	"automatically", "crying", "heartily", "very", "younger", "sibling", "healthy", "always"	"crying", "heartily", "healthy"
Stemming	"crying", "heartily", "healthy"	"cry" "hearty", "health"

Data Labeling

Data labeling in this study was carried out by classifying the data into two sentiment categories, namely positive sentiment and negative sentiment. Based on the labeling results, of all the data used, there were 738 data with positive labels and 3,854 data with negative labels. This distribution shows that the number of negative sentiment data is more dominant than positive sentiment, so that the dataset used has class imbalance characteristics.

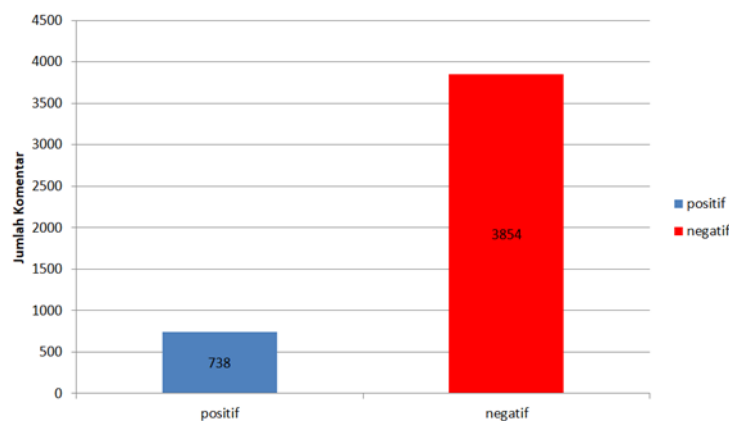


Figure 3. Sentiment Distribution of Positive and Negative Comments

Bag of Words

In this study, the Bag of Words (BoW) method was used to represent text data in the form of numerical vectors based on word frequency after going through the text preprocessing stage. The application of this method produced a feature matrix that represented the distribution of words in each document, so that the originally unstructured text data could be processed by the classification algorithm. The resulting feature representation shows that words with high frequency of occurrence play a role in distinguishing sentiment classes, even though this method does not consider the context and semantic relationships between words. The Bag of Words feature matrix is then used as input in the training and testing process of the classification model to evaluate the performance of the method proposed in this study.

Table 4. Python coding for bag of words

Script Python
<pre># ===== # 4. BAG OF WORDS (COUNT VECTORIZER) # ===== vectorizer = CountVectorizer(ngram_range=(1, 2), min_df=2, max_df=0.9) X_bow = vectorizer.fit_transform(df["teks_clean"])</pre>

Logistic Regression

In this study, sentiment analysis was performed using the Logistic Regression algorithm with TF-IDF feature representation, combined with the Bagging method to improve model stability. Logistic Regression was chosen because it is capable of performing binary classification effectively and has good interpretability in modeling positive and negative sentiments.

The evaluation was conducted with three data division scenarios, namely 70:30, 80:20, and 90:10 using a confusion matrix.

Table 5. Confusion Matrix Logistic Regression

Training data	Test data	True Positive	True Negative	False Positive	False Negative
70	30	47	1147	5	171
80	20	42	766	2	103
90	10	25	382	2	48

Based on the confusion matrix shown in Table 5, the model performance evaluation values were obtained, including accuracy, precision, recall, and F1-score, as presented in the following table.

Table 6. Logistic regression performance evaluation

Training data	Test data	Accuracy	Precision	Recall	F1-score
70	30	87	90	22	35
80	20	88	95	29	44
90	10	89	93	34	50

AdaBoost and Logistic Regression

This study uses the AdaBoost algorithm with Logistic Regression as a linear learner for text-based sentiment analysis using Bag of Words (BoW) feature representation. Each document is converted into a word frequency vector, then classified using Logistic Regression reinforced through the boosting mechanism in AdaBoost. The boosting process was carried out iteratively by increasing the weight of misclassified data, so that the final model was able to improve sentiment classification capabilities, especially for data that was difficult to predict.

Model performance was evaluated using the Accuracy, Precision, Recall, and F1-Score metrics, as well as a confusion matrix consisting of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Testing was conducted using several training and test data distribution scenarios, namely 70:30, 80:20, and 90:10, using a confusion matrix.

Table 7. Adaboost Logistic Regression Confusion Matrix

Training data	Test data	True Positive	True Negative	False Positive	False Negative
70	30	172	1103	54	49
80	20	109	755	16	39
90	10	52	383	3	22

Based on the confusion matrix shown in Table 4, model performance evaluation values were obtained, including accuracy, precision, recall, and F1-score, as presented in the following table.

Table 8. Adaboost logistic regression performance evaluation

Training data	Test data	Accuracy	Precision	Recall	F1-score
70	30	93	77	78	77
80	20	95	88	74	80
90	10	95	95	71	81

Evaluation and Comparison

The test results show that Logistic Regression (LR) as a single linear model produces a relatively stable accuracy value in the range of 87%–89% for all training and test data distribution scenarios. The high precision value (90%–95%) indicates that the model has a low positive prediction error

rate (low false positives). However, the low recall value, which only ranges from 22% to 34%, indicates that the model fails to identify most of the positive class samples (high false negatives). This condition causes the F1-score to be at a low value (35%–50%), which indicates an imbalance between precision and recall.

Statistically, this phenomenon is common in single linear models trained on datasets with imbalanced class distributions, where the loss function tends to prioritize the majority class. The application of AdaBoost with the Logistic Regression base learner resulted in a significant and more consistent improvement in performance across all evaluation metrics. The accuracy value increased to 93%–95%, indicating an overall decrease in classification error.

Furthermore, the recall value increased dramatically to a range of 71%–78%, indicating that the boosting mechanism successfully reduced false negative errors by focusing learning on previously misclassified data. From a machine learning perspective, AdaBoost adaptively adjusts sample weights so that difficult-to-predict instances have a greater contribution in the training process.

Moreover, the precision value in the ensemble method remained at a competitive level (77%–95%), despite experiencing a slight decrease in some scenarios compared to pure Logistic Regression. However, this trade-off resulted in a much higher and more stable F1-score, ranging from 77% to 81%, reflecting an optimal balance between precision and recall. Overall, these results show that AdaBoost + Logistic Regression has better generalization than single Logistic Regression, especially in the context of binary classification with unbalanced class distributions, because it is able to minimize linear model bias while increasing sensitivity to minority classes.

Discussions

The results of this study reinforce the findings of previous studies which state that the Logistic Regression algorithm is effective for use in text sentiment analysis due to its simplicity and computational efficiency [9].

However, unlike that study, which obtained relatively high recall values on more balanced datasets, this study shows that Logistic Regression experiences a significant decline in performance in terms of recall and F1-score when applied to datasets with high class imbalance, as also reported by Nursakina et al. [10]. This confirms that the performance of Logistic Regression is greatly influenced by data distribution and is not always optimal in class imbalance conditions.

Compared to lexicon-based approaches such as TextBlob [7] and classical models such as Naïve Bayes and Decision Tree [11], the supervised machine learning approach used in this study is able to provide more measurable evaluation control through precision, recall, and F1-score metrics. Furthermore, although deep learning models such as BERT are reported to have better contextual capabilities [8], their application requires greater computational resources. In the context of public policy analysis, the combination of AdaBoost and Logistic Regression offers an effective compromise between performance, interpretability, and computational efficiency.

The performance improvement obtained through the application of AdaBoost shows that ensemble methods are able to overcome the limitations of single linear models by increasing sensitivity to minority classes. Higher and more stable F1-scores across all data partitioning scenarios indicate that ensemble models have better generalization capabilities than Logistic Regression without boosting. These findings are consistent with ensemble learning theory, which states that strengthening weak models through adaptive mechanisms can produce models that are more robust to data variation and complexity.

In terms of policy implications, the results of this sentiment analysis provide an empirical picture of public perception of the Free Nutritious Meals Program, which is dominated by negative sentiment regarding implementation and oversight. This information can be used by the government as an early warning system to identify crucial issues developing in the digital public sphere. In addition, the use of classification models with balanced performance, such as AdaBoost + Logistic Regression, allows the government to obtain a more accurate mapping of public opinion, which can be used as a basis for formulating policy communication strategies, improving program governance,

and increasing the transparency and accountability of the implementation of the Free Nutritious Meals Program.

CONCLUSION

Based on the results of the research that has been conducted, it can be concluded that the Logistic Regression algorithm as a Linear Learner model is capable of classifying sentiment towards the Free Nutritious Meals Program with a fairly good level of accuracy. However, in a dataset with class imbalance characteristics, Logistic Regression tends to produce low recall and F1-score values, even though precision and accuracy are relatively high. This indicates that the model is less than optimal in detecting positive sentiment comprehensively due to the high number of false negatives. The application of the AdaBoost method with Logistic Regression as the base learner has been proven to significantly improve classification performance and provide a more balanced evaluation across all metrics. The adaptive boosting mechanism allows the model to pay more attention to data that is difficult to classify, thereby reducing the classification error rate and increasing sensitivity to minority classes. This is reflected in an increase in accuracy to 95%, recall to 78%, and a stable F1-score above 77% in all training and test data division scenarios. Thus, it can be concluded that the combination of AdaBoost and Logistic Regression has better generalization capabilities than Logistic Regression without ensemble, especially in the context of text-based sentiment analysis with an unbalanced class distribution. The model proposed in this study is effective for mapping public perceptions of public policy, so that the results of sentiment analysis can be used as material for evaluation and consideration in the formulation and refinement of the Free Nutritious Meals Program policy in the future.

REFERENCES

- [1] S. Ayu, F. Wahyuni, and Z. Risal, "Al-Kharaj : Jurnal Ekonomi , Keuangan & Bisnis Syariah Persiapan Menuju Indonesia Emas 2045 : Analisis Efektifitas Al-Kharaj : Jurnal Ekonomi , Keuangan & Bisnis Syariah," vol. 8, no. 1, pp. 538–546, 2026, doi: 10.47467/alkharaj.v8i1.10895.
- [2] A. Albaburrahim, A. P. A. Putikadyanto, A. N. Efendi, M. A. Alatas, S. Romadhon, and L. R. Wachidah, "Program Makan Bergizi Gratis: Analisis Kritis Transformasi Pendidikan Indonesia Menuju Generasi Emas 2045," *Entita J. Pendidik. Ilmu Pengetah. Sos. dan Ilmu-Ilmu Sos.*, pp. 767–780, May 2025, doi: 10.19105/ejpis.v1i.19191.
- [3] R. Qomarrullah, S. Suratni, L. Wulandari S, and M. Sawir, "Dampak Jangka Panjang Program Makan Bergizi Gratis terhadap Kesehatan dan Keberlanjutan Pendidikan," *Indones. J. Intellect. Publ.*, vol. 5, no. 2, pp. 130–137, Mar. 2025, doi: 10.51577/ijpublication.v5i2.660.
- [4] W. T. Aji, "Makan Bergizi Gratis di Era Prabowo-Gibran: Solusi untuk Rakyat atau Beban Baru?," *NAAFI J. Ilm. Mhs.*, vol. 1, no. 3, pp. 215–226, 2025.
- [5] G. Rota, "Threads by Meta: Redefining Social Media Dynamics, Challenges, and Unique Features. Professionals' Opinions and Social Media Users' Perceptions," 2024, *Universidade NOVA de Lisboa (Portugal)*.
- [6] F. Vasilopoulos, "Hanging by a Thread: Meta's New Platform, Threads, Sheds Light on the Slow Unraveling of Individual Privacy," *UIC L. Rev.*, vol. 58, p. 473, 2024.
- [7] M. W. Arif, "Analisis Sentimen Kebijakan Makan Bergizi Gratis di Media Sosial Menggunakan Natural Language Processing Berbasis Python TextBlob di Indonesia Teknik Informatika , Universitas Ngudi Waluyo , Indonesia Sentiment Analysis of Free Nutritious Meal Policy on S," vol. 5, no. 9, pp. 2463–2471, 2025, doi: 10.52436/1.JPTI.931.
- [8] U. Arfan and E. Badii, "Sentiment Analysis of Papuan Public Perceptions Toward the Free Nutritional Meal Program in Indonesia Analisis Sentimen Masyarakat Papua Terhadap Program Makan Gizi Gratis di Indonesia," vol. 5, no. October, pp. 1538–1546, 2025, doi: 10.57152/malcom.v5i4.2087.

- [9] N. N. Aprianti *et al.*, “Public Sentiment Analysis of the Free Nutritious Meals Program (MBG) on Social Media X Using the Naive Bayes Method,” vol. 9, no. 6, pp. 3929–3936, 2025.
- [10] Nursakina, F. Wajidi, and M. R. Rasyid, “Evaluasi algoritma KNN dan Naive Bayes untuk analisis sentimen kebijakan program makan bergizi gratis,” vol. 7, no. 2, pp. 83–97, 2025, doi: 10.37905/jji.v1i2.34418.
- [11] K. Y. Pratama, S. Achmadi, and K. A. Sari, “Analisis Sentimen Terhadap Makan Bergizi Gratis Pada Sosial Media X Menggunakan Metode Decicion Tree Dengan Pembanding Naive Bayes,” vol. 9, no. 6, pp. 11061–11067, 2025.
- [12] E. Mulyani, F. P. B. Muhamad, and K. A. Cahyanto, “Pengaruh N-Gram terhadap Klasifikasi Buku menggunakan Ekstraksi dan Seleksi Fitur pada Multinomial Naïve Bayes,” *J. Media Inform. Budidarma*, vol. 5, no. 1, p. 264, 2021, doi: 10.30865/mib.v5i1.2672.
- [13] A. D. M. Putri, N. Sulistianingsih, and R. Rismayati, “Pengaruh Teknik Representasi Teks Bag-of-Words dan TF-IDF terhadap Akurasi Klasifikasi Sentimen Teks Multi-Domain,” vol. 7, no. 4, pp. 675–688, 2025.
- [14] M. Erkamim, A. M. Tanniewa, and I. Ap, “Analisis Perbandingan Metode AdaBoost , Gradient Boosting , dan XGBoost Untuk Kalsifikasi Status Gizi Pada Balita,” vol. 6, no. 3, pp. 1799–1807, 2024, doi: 10.47065/bits.v6i3.5717.
- [15] A. Nanda and H. W. Perdana, “Perbandingan Efektivitas Random Forest , SVM , dan Logistic Regression dalam Deteksi Intrusi Jaringan,” vol. 12, no. 2, pp. 129–139, 2025.
- [16] S. K. Wardani and Y. A. Sari, “Analisis Sentimen menggunakan Metode Naïve Bayes Classifier terhadap Review Produk Perawatan Kulit Wajah menggunakan Seleksi Fitur N-gram dan Document Frequency Thresholding,” vol. 5, no. 12, pp. 5582–5590, 2021.