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The Influence of User Sentiment Analysis on the Free Nutritious Meal Program Using K-Nearest Neighbors and Logistic Regression Methods

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Abstract

The free nutritious meal program aims to reduce stunting, but its success relies on public support. This study analyzes public sentiment toward the program on social media X using K-Nearest Neighbors (KNN) and Logistic Regression (LR) algorithms with TF-IDF, a method to weigh important words. A total of 2,000 tweets were collected and preprocessed through cleaning, normalization, tokenization, stop word removal, and stemming. Exploratory Data Analysis (EDA) revealed predominantly positive sentiment, with class imbalance addressed using SMOTE, a data balancing technique. The KNN model achieved 78%–81% accuracy, with strong positive class performance, but weak negative class detection, due to data imbalance. Similarly, the LR model achieved 80%–81% accuracy, with positive recall ranging from 0.96 to 0.98 and negative recall ranging from 0.22 to 0.27, resulting in an F1-score below 0.38. Neutral sentiments had minimal impact. These results highlight model bias toward positive sentiments, underscoring the need for adaptive approaches to improve minority sentiment detection. The findings offer policymakers insights to address concerns about budget and implementation, enhancing trust in social programs.

Keywords

Free Nutritious Meal Program, K-Nearest Neighbours, Sentiment Analysis, Social Media X.

1. Introduction

Social media X (formerly Twitter) is one of the influential public communication channels in shaping opinions in the digital era. In Indonesia, the number of active users X in early 2024 is expected to reach approximately 24.7 million people, making it one of the key strategic discourse spaces that influence public perception. These platforms facilitate the rapid exchange of information. Still, they also have the potential to become a medium for the spread of hate speech, misinformation, and polarization of opinions, which can ultimately affect the effectiveness of public policies (Alam & Lucas, 2021; Febrilliani & Wibowo, 2025). One of the government's current strategic programs is the free nutritious meal program, which aims to reduce stunting rates and malnutrition problems still experienced by approximately 21.6% of children in Indonesia. The national target to reduce stunting to below 20% aligns with the WHO recommendations however, the success of this program is highly dependent on public support and participation. In the context of the digital era, public opinion on social media X is one of the indicators of policy acceptance as well as a potential space for resistance.

Several previous studies have shown how sentiment on social media X can influence public perception of policies. Research by Nugroho and Syarief (2023) demonstrates that the Natural Language Processing (NLP) approach and lexicon analysis effectively map the perception of user X, particularly on social issues in Indonesia. Similarly, the study of Septiani et al. (2022) confirms that the processing of social media data using machine learning algorithms can produce an in-depth understanding of public attitudes towards government policies. However, research that specifically highlights the analysis of social policy sentiment, such as free nutritious meal programs, is still limited in Indonesia. Some research in the field of text analysis on social media focuses more on electoral political issues or disasters, but not many have integrated linguistic, technological, and social aspects simultaneously to understand the acceptance of social policies based on sentiment data (Rahman & Wibowo, 2020; Putra et al., 2021)

To address this need, this study employed the TF-IDF (term frequency – inverse document frequency) method as a technique for extracting key word features from public comment data on social media platform X. The extracted data was analyzed using the K-Nearest Neighbors (KNN) algorithm and logistic regression, two classification methods that have proven to be effective for handling short texts and interpretation of results (Davidson et al., 2017; Kurniawan & Pratama, 2022). This approach is reinforced by the framework Theory of Planned Behaviour of Ajzen (1991), which explains how attitudes, subjective norms, and behavioural controls influence public responses in the digital space.

This study analyses public sentiment toward the free nutritious meal program on social media X using K-Nearest Neighbours (KNN) and Logistic Regression (LR) algorithms with TF-IDF feature weighting. Thus, this study offers novelty in the form of integrating TF-IDF, KNN, and logistic regression to analyse public sentiment towards the free nutritious meal program on social media X. The study's results are expected to serve as a basis for the government's consideration in designing a more responsive, inclusive, and data-driven digital communication strategy to enhance public acceptance of social policies in Indonesia.

2. Literature Review

2.1. The Role of Sentiment Analysis in Public Opinion Analysis

Sentiment analysis is a branch of Natural Language Processing (NLP) that aims to identify, extract, and classify opinions or emotions in text into categories such as positive, negative, or neutral (Liu, 2016). This technique is very relevant in understanding public responses, especially in the context of public policy. Social media provides direct access to diverse and real-time public opinion, making it a crucial source of data for evaluating the success of government policies (Happer et al., 2013). Sentiment analysis is a method of identifying, extracting, and categorising opinions or emotions expressed in text data, particularly from digital sources such as social media. According to Liu (2012), sentiment analysis focuses on recognising the polarity of positive, negative, or neutral opinions, making it an important instrument in understanding public perception. In the context of social policy, this approach serves as a bridge to capture people's aspirations, criticism, and support quickly and objectively.

As social media continues to grow rapidly, the volume of text data generated every second increases significantly. Happer et al. (2013) note that more than 70% of discussions related to public policy issues are now shifting to the digital space, making platforms such as social media X a rich source of sentiment data. Kumar and Sebastian (2012) emphasized that compared to conventional surveys, sentiment analysis is more efficient and cost-effective because it is able to process large-scale data in real-time.

Several previous studies also support the relevance of this approach. Mamo et al. (2024) show how sentiment analysis on platform X can describe users' attitudes towards technology topics, while Smith-Mutegi et al. (2025) utilise a similar approach to map public opinion regarding STEM education policy. In Indonesia, sentiment analysis has been widely applied to identify patterns in electoral political discourse and public responses to public health issues; however, its application to social policy programs, such as the free nutritious meal program, remains limited (Sari et al., 2021). Technically, the implementation of sentiment analysis generally begins with a pre-processing process of data, such as text cleaning, tokenisation, and keyword extraction using the TF-IDF technique. The TF-IDF result weights are then used as inputs (features) for classification algorithms such as KNN and logistic regression, which are effective in handling short-text data from social media (Davidson et al., 2017; Das et al., 2023).

While it offers the advantages of speed and scalability, implementing sentiment analysis presents its own challenges. Some of these are ambiguous word meanings, sarcasm, and variations in local language that can affect the accuracy of the classification (Liu, 2012). Therefore, it is necessary to select relevant algorithms and enrich the lexicon so that the results are valid and contextual. The integration between technical aspects and social understanding is key so that sentiment analysis not only produces polarity scores, but is also able to explain the dynamics of public opinion that influence policy success.

2.2. Logistic Regression as a Social Media Sentiment Classification Method

Logistic regression is a classification method used to predict the probability of a category or class, particularly in contexts where dependent variables are dichotomous or categorical. In this study, logistic regression was used to classify public sentiment into positive and negative categories based on text extracted from the social media platform X. The logistic regression model uses a logistic or sigmoid function to convert linear inputs into probability values between 0 and 1 (Briollais & Durrieu, 2017). This function is expressed in the form of the Equation below.

$$P(y = 1 \mid X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}}$$

Where to is the regression coefficient, and to is a predictor feature. The results of the sigmoid function are then compared with a specific threshold (generally 0.5) to determine the output class (James et al., 2013). Logistic regression is widely used in text classification due to its simple but effective ability in processing numerical features resulting from text extraction such as TF-IDF. According to Nibbering and

Hastie (2022), logistic regression offers a strong interpretation of the relationships between variables and can work optimally on large datasets with relevant features. In machine learning practice, logistic regression is combined with validation techniques such as test-practice data sharing and k-fold cross-validation to ensure that the model has good generalisation capabilities to new data. The evaluation of this model typically employs metrics such as accuracy, precision, recall, and F1-score to assess its classification performance (James et al., 2013).

2.3. K-Nearest Neighbours (KNN) and Term Frequency-Inverse Document Frequency (TF-IDF)

KNN is an agency-based classification algorithm that determines the label of a new data point based on the majority of its closest neighbours (Cover & Hart, 1952). Wijati et al. (2024) showed that KNN has a competitive accuracy with SVM in sentiment analysis of film reviews. In the context of social media, Ghiassi et al. (2013) and Romli et al. (2021) proved that KNN is effective in analyzing short texts such as tweets, especially with the support of methods such as cosine similarity. The advantages of KNN lie in the ease of implementation and the ability to handle data without certain distribution assumptions.

TF-IDF is a method of transforming text into numerical representation by giving weight to each word based on its frequency in the document and the uniqueness of the word throughout the document (Pravina et al., 2019). The TF formula indicates how often a word appears in a single document, whereas the IDF measures the opposite, namely how rarely the word appears across the corpus (Grossman & Frieder, 2004). When these two values are multiplied, a TF-IDF weight is generated, which is highly useful in text classification tasks such as sentiment analysis. TF-IDF assists machine learning algorithms, including KNN and logistic regression, in recognizing important words in the classification process (Salton et al., 1975). TF-IDF is a weighting method that combines term frequency (TF) and inverse document frequency (IDF) methods. TF itself is a measure of the frequency of the occurrence of a term in a document and also in all documents in the corpus. This term frequency is calculated by Equation below.

$$tf(i) = \frac{freq_i(d_j)}{\sum_{k=1}^{n} freq_k(d_j)}$$

Information:

t) = f (i *term frequency* to- i

$freq_i(d_j)$ = frequency of occurrence in i the document to j

Meanwhile, TF-IDF is a logarithm of the ratio of the number of all documents in the context of the corpus to the number of documents that have *the term* in question as systematically written in Equation below (Grossman & Frieder, 2004).

$$idf_i = log\frac{|D|}{|\{d: t_i \in d\}|}$$

The TF-IDF value is obtained by switching the two equations formulated with Equation below:

$$(tf - idf)_{ij} = tf_i(d_j) \cdot idf_i$$

By referring to the above theories and approaches, this research was built to combine the need to understand public opinion at large with the application of efficient and interpretive methods. The combination of TF-IDF as a feature extraction technique and the KNN algorithm as a classification method provides an appropriate analytical framework to comprehensively evaluate the community's response to the free nutritious meal program on social media X.

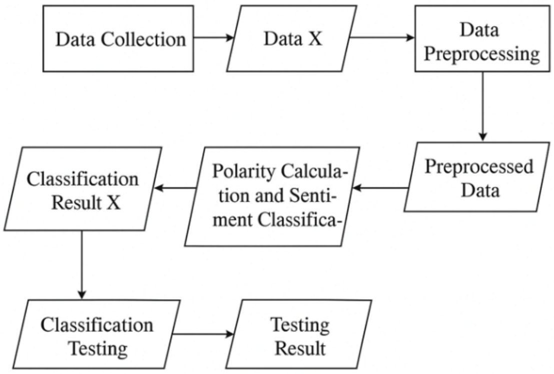

Figure 1. Research Procedure

Figure 1 shows the flow of the research process starting from the collection of data in the form of 2000 tweets related to the free nutritious eating program through the crawling method from social media X. The data obtained is then processed through a pre-processing stage that includes cleaning, normalization, tokenization, stopword removal, and stemming, in order to eliminate noise and simplify the structure of the text. The results of the preprocessing are used in the polarity calculation process using the InSet Lexicon-based lexicon approach to classify tweets into positive, negative, or neutral sentiments.

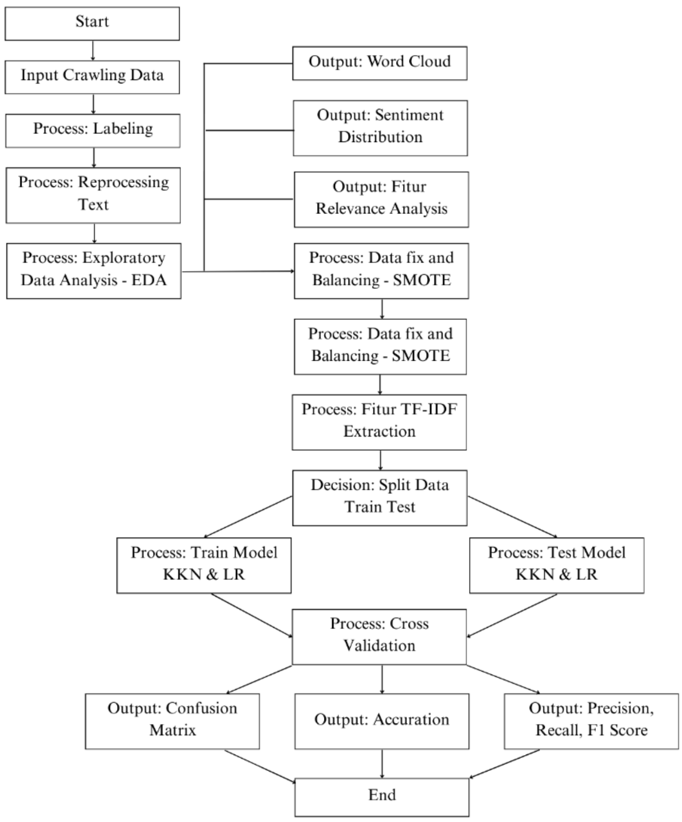

Figure 2. Research Flowchart

Figure 2 illustrates the workflow of text classification using machine learning, spanning from data collection (crawling) to model evaluation. After the data is collected and labelled, preprocessing is carried out to clean and prepare the data. The next stage is exploratory analysis (EDA), including word cloud visualisation, sentiment distribution, and feature analysis. Based on the EDA, data improvements are made such as class balancing using SMOTE, then features are extracted with TF-IDF. The data is then shared for training and testing, and used to train models such as KNN and logistic regression. After going through the cross-validation process, the model's performance is evaluated using a confusion matrix, as well as metrics such as accuracy, precision, recall, and F1-score, before drawing a conclusion.

3. Methods

This study employs an explanatory, quantitative approach to investigate the relationship between public sentiment on social media X and the free nutritious eating program, as described by Sugiyono (2013). Data was collected online through crawling using the Twitter API with the keyword "free nutritious meals" from November 28, 2024, to February 10, 2025, resulting in 2000 tweets in Indonesian. This process was carried out to capture public perceptions during the initial implementation of the program. The dataset is further labelled into three sentiment categories (positive, negative, neutral), either manually or semi-automatically (Hayaty & Pratama, 2023).

The classified data was then trained using two algorithms, KNN and logistic regression. Data representation is carried out using the TF-IDF method, allowing for numerical processing in machine learning algorithms. To overcome class imbalances, the Synthetic Minority Over-Sampling Technique (SMOTE) was used. Furthermore, the model formed was evaluated using k-fold cross-validation and confusion matrix techniques. The evaluation of classification results aims to measure the model's performance using accuracy, precision, recall, and F1-score metrics. This process helps determine the most optimal model for classifying public opinion of government programs. This diagram confirms the systematic relationship between the stages in sentiment analysis, from raw data input to classification performance validation.

The analysis stage begins with text preprocessing, which includes cleaning, normalisation, tokenisation stopword removal, and stemming (Angelina et al., 2023). EDA is used to evaluate data distribution, text length, as well as detect data outliers and imbalances (Josyula et al., 2024). To balance the distribution of sentiment classes, the Synthetic Minority Oversampling Technique (SMOTE) method is used, which produces synthetic data based on the distance between the nearest neighbours (Chawla et al., 2002). Furthermore, the data are represented in numerical form using the TF-IDF method (Salton et al., 1975; Rajaraman & Ullman, 2014).

The modeling was carried out using two algorithms: KNN and logistic regression. KNN works non-parametrically by determining labels based on the majority of the nearest neighbours using Euclidean distances (Cover & Hart, 1952). Meanwhile, logistic regression maps class probabilities using sigmoid functions (Hosmer et al., 2013). Model evaluation was carried out using k-fold cross-validation (k=10) as well as accuracy, precision, recall, and F1-score metrics calculated from the confusion matrix (Nibbering & Hastie, 2022; Wong, 2015). This evaluation ensures the reliability and stability of the model in classifying public sentiment towards the free nutritious meal program.

4. Results

A dataset of 2,000 tweets on the free nutritious meal program was collected from X and preprocessed through cleaning, normalisation, tokenisation, stop-word removal, and stemming. Exploratory analysis identified sentiment distribution and frequent words, with SMOTE applied to balance classes. Features were extracted using TF-IDF to highlight important terms for sentiment classification.

The dataset was split into training and testing with ratios of 70:30, 80:20, and 60:40, and validated using 10-fold cross-validation to avoid overfitting. Sentiment was classified using KNN and logistic regression with TF-IDF features. KNN achieved a test accuracy of up to 80.29%, while logistic regression reached 81.45%. Both models demonstrated competitive and consistent performance, supporting the accurate classification of sentiment in public communication strategies. The results of the KNN model evaluation in this study show a consistent performance pattern in three test data sharing scenarios, namely 20%, 30%, and 40%.

Table 1. Classification Report for KNN Methods

Scenario Data Test	Class	Accuracy	Recall	F1 Score	Support
KNN 20%:80% Data Test	Negative	0.73	0.15	0.25	127
	Positive	0.79	0.98	0.88	416
	Accuracy			0.79	543
	Macro Avg	0.76	0.57	0.56	543
	Weighted Avg	0.78	0.79	0.73	543
KNN 30%:70% Data Test)	Negative	0.74	0.20	0.31	173
	Positive	0.82	0.98	0.89	641
	Accuracy			0.81	814
	Macro avg	0.78	0.59	0.60	814
	Weighted avg	0.80	0.81	0.77	814
KNN 40%:60% Data Test)	Negative	0.82	0.11	0.19	258
	Positive	0.78	0.99	0.87	828
	Accuracy			0.78	1086
	Macro Avg	0.80	0.55	0.53	1086
	Weighted Avg	0.79	0.78	0.71	1086

Based on Table 1, the KNN model consistently showed very high recall for positive tweets (0.98–0.99) with strong F1-scores (0.87–0.89) across all test data splits, but its performance on negative tweets remained weak, with recall ranging only from 0.11 to 0.20 and F1-scores between 0.19 and 0.31. At a 20% test split, accuracy reached 79% but negative detection was very low; at 30%, accuracy improved to 81% with only slight gains for the negative class; and at 40%, accuracy dropped to 78% while negative recall fell drastically to 0.11. The macro-average F1-score also declined from 0.60 to 0.53, confirming that although KNN performs well for the majority class, it remains heavily imbalanced and struggles to capture minority sentiments effectively.

Based on Table 2, the KNN model shows consistent imbalance across test splits. In the 20% split, only 19 negative tweets were correctly classified while 108 were misclassified as positive, whereas 409 positives were accurately identified with only 7 errors. At 30%, performance peaked with 81% accuracy, where 629 of 641 positives were correctly predicted but only 34 of 173 negatives were detected, yielding a negative recall of 0.20 and F1-score of 0.31. In the 40% split, accuracy dropped to 78% with 822 of 828 positives classified correctly, but just 28 negatives detected while 230 were misclassified, reducing negative recall to 0.11. Although precision and recall for the positive class remain strong (precision 0.82, recall 0.98, F1-score 0.89), the very low performance on negative tweets shows that the model is biased toward the majority class despite SMOTE balancing.

Table 2. Confusion Matrix for KNN Methods

Scenario Data Test	Sentiment	Current: Negative (0)	Current: Positive (1)
KNN 20%:80% Data Test	Negative Predictions (0)	19	7
	Positive Predictions (1)	108	409
KNN 30%:70% Data Test	Negative Predictions (0)	34	12
	Positive Predictions (1)	139	629
KNN 40%:60% Data Test	Predicted Negative (0)	28	6
	Predicted Positive (1)	230	822

Evaluation of the performance of the logistic regression model in three test data sharing scenarios (20%, 30%, and 40%) showed a consistent pattern of results. In general, the accuracy of the model is quite high, ranging from 80% to 81%.

Table 3. Classification Report for Logistic Regression

Scenario Data Test	Class	Accuracy	Recall	F1 Score	Support
KNN 20%:80% Data Test	Negative	0.78	0.22	0.34	127
	Positive	0.80	0.98	0.88	416
	Accuracy			0.80	543
	Macro Avg	0.79	0.60	0.61	543
	Weighted Avg	0.80	0.80	0.76	543
KNN 30%:70% Data Test)	Negative	0.65	0.27	0.38	173
	Positive	0.83	0.96	0.89	641
	Accuracy			0.81	814
	Macro Avg	0.74	0.62	0.64	814
	Weighted Avg	0.79	0.81	0.78	814
KNN 40%:60% Data Test)	Negative	0.69	0.22	0.33	258
	Positive	0.80	0.97	0.88	828
	Accuracy			0.80	1086
	Macro Avg	0.75	0.59	0.61	1086
	Weighted Avg	0.78	0.80	0.74	1086

In Table 3, the LR model achieved 80% accuracy with a 20% test split, showing strong performance on positive tweets (precision 0.80, recall 0.98, F1-score 0.88) but weak detection of negatives, with recall only 0.22 and F1-score 0.34, yielding a macro-average F1 of 0.61. At 30%, accuracy improved slightly to 81%, with positive class performance remaining high (precision 0.83, recall 0.96, F1-score 0.89), while the negative class showed modest gains (precision 0.65, recall 0.27, F1-score 0.38), raising the macro-average F1 to 0.64. In the 40% test split, accuracy remained stable at 80%, with positive class results still strong (precision 0.80, recall 0.97, F1-score 0.88), but negative detection stayed weak despite slightly higher precision (0.69) as recall dropped back to 0.22, lowering its F1-score to 0.33 and keeping the macro-average at 0.61. These results indicate that while LR consistently excels in identifying positive sentiment, its ability to capture negative sentiment remains limited across all scenarios.

Table 4. Confusion Matrix for Logistic Regression

Scenario Data Test	Sentiment	Current: Negative (0)	Current: Positive (1)
KNN 20%:80% Data Test	Negative Predictions (0)	28	8
	Positive Predictions (1)	99	408
KNN 30%:70% Data Test	Negative Predictions (0)	47	25
	Positive Predictions (1)	126	616
KNN 40%:60% Data Test	Predicted Negative (0)	28	6
	Predicted Positive (1)	230	822

As shown in Table 4, the LR confusion matrix confirms the model's bias toward positive sentiment across all test splits. In the 20% set, only 28 of 127 negatives were correctly identified while 408 of 416 positives were accurate; in the 30% set, 47 of 173 negatives were detected while 616 of 641 positives were correct; and in the 40% set, just 56 of 258 negatives were captured while 803 of 828 positives were accurate. Accuracy remained stable at 80–81%, with positive sentiment showing consistently high precision and recall (0.96–0.98) and F1-scores above 0.88. However, negative sentiment recall stayed very low, peaking only at 0.27 with an F1-score of 0.38, indicating that despite LR's robustness, unequal data distribution continues to hinder minority class detection.

In this study, the feature extraction process was carried out using the Term Frequency-Inverse Document Frequency (TF-IDF) method to convert tweet text data into numerical representations that machine learning algorithms can process. TF-IDF calculates the weight of the importance of a word in a given document relative to the entire set of documents (corpus). This process helps the model in distinguishing words that are truly relevant to public sentiment towards free nutritious eating programs.

Inverse document frequency (IDF) is measured to find out how rarely a word appears in the entire document. If the total number of tweets is 2000 and the word "free" appears on 1500 tweets, then it is formulated with Equation below:

$$\text{idf}(\text{“free”}) = \log\frac{2000}{1500} = \log(1.333) \approx 0.12$$

This TF-IDF value is used to form the feature vector of each tweet. The vector then becomes an input for the KNN algorithm and logistic regression at the sentiment classification stage. The results of the TF-IDF implementation on this dataset successfully distinguished words with common but non-significant frequencies, and highlighted the keywords that actually contributed to the formation of public sentiment. Thus, the TF-IDF plays an important role in improving the accuracy and relevance of sentiment classification results.

At this stage, the word cloud visualization is made based on the results of pre-processing text data and word frequency calculation using the TF-IDF technique. Word cloud helps researchers see dominant word patterns as the basis for further sentiment classification.

Based on data collected from social media. In the overall word cloud, dominant words such as "program", "*makan*"/" meal", "*bergizi*"/" nutritious", "*gratis*"/"free", and "prabowo" indicate that the public discussion is indeed focused on the core topic of the policy and the figures associated with it. Meanwhile, when analysed based on central time, a clear difference can be seen. Word cloud positive sentiment shows community support through the emergence of words such as "*bagus*"/ "good", "*gizi*"/" nutrition", "*butuh*"/"need", and "*dukung*"/" support", which indicates the hope that this program can bring tangible benefits to the community, especially children. In contrast, the word cloud for negative sentiment shows the emergence of words such as "*enggak*"/"no", "*mbak*", "*korupsi*"/" corruption", "*pajak*"/ "tax", and "*anggaran*"/ "budget", which reflect the sceptical or critical tone of some of the public. This indicates that concerns exist regarding the program's implementation, particularly in terms of financing, effectiveness, and potential budget mismanagement. The difference in word patterns between positive and negative sentiments emphasises the importance of sentiment analysis as a tool to understand public opinion more deeply about a public policy.

5. Discussion

The findings show that public response to the free nutritious meal program on social media X is mainly positive and neutral, with fewer negative sentiments. This aligns with Anggriyani and Fakhriza (2024), who also found positive support for the program despite concerns over implementation. The use of KNN and logistic regression in this study proved effective in mapping public opinion, consistent with Irsansaputra and Udjulawa (2024), who demonstrated similar results using KNN with SMOTE. The accuracy of the models also supports Wong (2015), who highlights that k-fold cross-validation enhances classification reliability on unbalanced datasets.

Based on the results, the discussion highlights several important insights about public sentiment toward the free nutritious meal program and the performance of machine learning models in capturing it. Both KNN and logistic regression models achieved high overall accuracy, particularly in identifying positive sentiment, which demonstrates their effectiveness in detecting public support and favorable reactions toward the program. However, both models consistently struggled with negative sentiment classification, showing low recall and F1-scores for negative tweets across all test splits, indicating that minority or critical opinions remain underrepresented despite SMOTE balancing. This suggests that while automated sentiment analysis can reliably capture widespread positive reactions, additional strategies, such as advanced feature engineering, ensemble methods, or context-aware natural language models, may be needed to better detect critical or nuanced opinions.

The TF-IDF feature extraction proved effective in distinguishing relevant terms and emphasizing words that drive sentiment, ensuring that models focused on meaningful signals rather than high-frequency but non-informative words. Word cloud visualizations further corroborate the results, showing clear differences between positive and negative sentiment: supportive tweets highlighted words like "good," "nutrition," and "support," while critical tweets included terms such as "corruption," "tax," and "budget." This illustrates that sentiment analysis not only identifies general public opinion but also uncovers specific concerns and expectations related to the policy.

In text classification, TF-IDF played a key role in extracting relevant features, enhancing the performance of both algorithms. This supports the view of Das et al. (2023) that combining TF-IDF with simple classifiers can still yield strong results in social media sentiment detection. The findings also resonate with Liu (2016), who emphasised sentiment analysis as a valuable tool for capturing public opinion objectively, making it highly relevant for evaluating policies such as free nutritious meals. In line with Ilham and Priambodo (2024), the study further shows the importance of proper preprocessing, such as stopword removal and stemming, before classification.

These results confirm the observations of Attaulah and Soyusiawaty (2025) that public discourse on platform X reflects strong support for the free lunch program, while echoing Azhari and Parjito (2024) on the need for communication strategies to address remaining negative perceptions. Thus, sentiment analysis emerges not only as a technical method but also as a tool for adaptive policy evaluation (Sugiarti et al., 2024), providing insights for government efforts to monitor and strengthen public acceptance of the program. These findings suggest that while the program enjoys strong public support, policymakers should address critical opinions that are underrepresented in automated sentiment analysis. Combining advanced analysis techniques with tools like word clouds can help identify specific concerns, enabling more responsive communication, improved program implementation, and stronger public trust.

6. Conclusion

This study analysed public sentiment toward Indonesia's free nutritious meal program on social media X using K-Nearest Neighbours (KNN) and Logistic Regression (LR) with TF-IDF feature weighting. Analysis of 2,000 tweets revealed a predominantly positive sentiment, with key terms such as "free," "nutrition," and "program" dominating the discussions, while negative sentiments highlighted concerns about "budget," "tax," and "corruption." Neutral sentiments, although less prevalent, were included in the analysis but had a minimal impact. Both KNN and LR models achieved high accuracy (78%–81%), excelling in detecting positive sentiment (recall 0.96–0.99, F1-score 0.88–0.89) but struggling with negative sentiment (recall 0.11–0.27, F1-score below 0.38), even after SMOTE balancing, indicating a bias toward the majority class.

These findings offer policymakers actionable insights to strengthen public trust by addressing concerns about budget transparency and program implementation through targeted communication strategies. However, the models' weak performance in detecting negative sentiment highlights limitations due to data imbalance and the algorithms' sensitivity to short, noisy social media texts. Future research should explore advanced models, such as BERT or ensemble methods, to improve minority sentiment detection. It should also incorporate larger and multi-platform datasets, and investigate real-time sentiment tracking to enhance the robustness of policy evaluation.

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