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Article

Public Sentiment Analysis of Free Nutritious Meal Program Discourse on Social Media X Using Support Vector Machine N-Gram Features Based

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A B S T R A C T

The Free Nutritious Meal Program is a government policy aimed at improving the nutritional quality of society and has generated diverse public responses on social media. This study aims to analyze public sentiment toward the Free Nutritious Meal Program on social media X using the Support Vector Machine (SVM) algorithm with N-Gram features and Term Frequency–Inverse Document Frequency (TF-IDF) weighting. The data were collected through a crawling process from social media X, resulting in 1,014 tweets. After data cleaning, 931 tweets were obtained and labeled into two sentiment classes, namely positive and negative. The research stages include text preprocessing, N-Gram feature extraction (unigram and bigram), classification using the SVM algorithm, and model evaluation using the 10-Fold Cross-Validation method with the assistance of the RapidMiner tool. The experimental results show that the SVM model achieved an accuracy of 79.59%. Although the precision value for the negative class is relatively high, the recall and F1-score remain relatively low due to the imbalance in data distribution. Overall, the results indicate that public sentiment toward the Free Nutritious Meal Program on social media X is dominated by positive sentiment. The findings of this study are expected to serve as an initial evaluation for the government in understanding public perceptions of the implementation of the program.

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I. INTRODUCTION

The Free Nutritious Food Program is one of the Indonesian government's strategic policies aimed at improving the nutritional quality of the population, particularly children and vulnerable groups. This program is designed as an intervention to reduce the prevalence of stunting, improve health status, and support sustainable human resource development. Nutrition issues, especially stunting, remain a national challenge that directly impacts the quality of life and productivity of future generations, so the implementation of nutrition policies requires continuous and data-driven evaluation [1].

The success of a public policy is not only determined by technical planning and implementation, but also by the level of public acceptance and perception of the policy. Public perception plays an important role in shaping social support, compliance, and the sustainability of government programs. In this context, public opinion can be used as an initial indicator to evaluate the effectiveness of policies, especially in the early stages of implementation of a national program [2].

The development of information and communication technology has significantly changed the pattern of public communication. Social media has become the main space for the public to express their opinions, criticisms, and support for various social issues and government policies openly and in real-time. One of the social media platforms widely used to express public opinion is X. This platform generates large amounts of unstructured text data that reflects the attitudes and views of the public on current issues, including the Free Nutritious Food Program policy [3].

The large volume of unstructured opinion data on social media makes sentiment analysis an effective approach to understanding public attitudes. Sentiment analysis is part of data mining and natural language processing (NLP) that aims to classify opinions or texts into specific sentiment categories, such as positive and negative. In the context of public policy, sentiment analysis can be used as a data-based evaluation tool to capture public responses objectively and systematically [4].

Previous studies have applied sentiment analysis to examine public opinion on government policies and social issues using a machine learning approach. Some commonly used classification algorithms include Naïve Bayes, K-Nearest Neighbor, and Support Vector Machine (SVM) [5]. Among these algorithms, SVM is known to perform well in handling high-dimensional text data and is capable of producing relatively high accuracy in sentiment classification tasks [6], [7]. In addition, the use of N-Gram-based feature extraction methods allows the model to capture more complex word patterns and linguistic contexts than the unigram approach, thereby improving sentiment classification performance [8].

However, research that specifically analyzes public sentiment towards the Free Nutritious Food Program on social media X using the Support Vector Machine (SVM) algorithm based on N-Gram features with Term Frequency–Inverse Document Frequency (TF-IDF) weighting is still limited. In addition, the problem of sentiment data distribution imbalance in social media data is often overlooked, even though this condition can significantly affect the performance of classification models [9]. Therefore, research that specifically examines public perception of this policy using a comprehensive sentiment analysis approach is needed.

Based on this background, this study aims to analyze public sentiment towards the Free Nutritious Food Program on social media X using the Support Vector Machine (SVM) algorithm based on N-Gram features with TF-IDF weighting. This study is expected to provide an overview of public opinion trends regarding this policy and contribute as preliminary evaluation material for the government and policy makers in improving the effectiveness of the implementation of the Free Nutritious Food Program in the future.

II. LITERATURES REVIEW

Sentiment analysis is a branch of data mining and Natural Language Processing (NLP) that aims to identify, extract, and classify opinions or attitudes toward a particular object, topic, or

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event. These opinions are generally categorized into sentiment classes such as positive and negative based on the context and meaning contained in the text [10].

In the context of social media, sentiment analysis is widely used to understand public perceptions of social issues, products, and public policies. Data generated by social media users is spontaneous, real-time, and reflects public opinion on a large scale. Therefore, sentiment analysis becomes an effective approach for objectively measuring public responses by utilizing large volumes of available textual data [11].

Social media X is a microblogging-based social networking platform that allows users to express opinions, share information, and respond to issues in the form of short text messages. This platform is frequently used by the public to discuss various topics, including social issues and public policies, resulting in highly diverse opinion data [12].

The characteristics of data on social media X are generally unstructured and contain informal language, abbreviations, emoticons, and spelling errors. These conditions require appropriate preprocessing stages before the text data can be further analyzed. With proper processing, data from social media X can serve as a valuable source of information for sentiment analysis [13].

Text mining is the process of extracting information and knowledge from unstructured textual data using statistical, linguistic, and machine learning techniques. The main objective of text mining is to transform textual data into meaningful information that can be used for decision-making purposes [14].

The general stages in text mining include data collection, text preprocessing, feature extraction, and classification or clustering processes. In sentiment analysis, text mining plays an important role in transforming textual data into numerical representations that can be processed by machine learning algorithms [15].

Text preprocessing is the initial stage in text mining that aims to clean and prepare textual data before further analysis. This stage is conducted to reduce noise and improve data quality so that the classification process can perform optimally [16].

Common text preprocessing steps include case folding, tokenizing, stopword removal, and text normalization. Through proper preprocessing, textual data becomes more structured and ready for the feature extraction stage [17].

Feature extraction is the process of converting textual data into numerical forms that can be processed by machine learning algorithms. One commonly used feature extraction method in sentiment analysis is N-Gram. N-Gram divides text into sequences of words or tokens of length n, such as unigram ($n = 1$) and bigram ($n = 2$) [18].

The use of N-Gram features allows the model to capture context and relationships between words more effectively than using unigrams alone. In sentiment analysis, a combination of unigram and bigram features is often employed to represent phrases or word patterns that convey specific sentiment meanings [19].

TF-IDF is a word weighting method used to measure the importance of a term in a document relative to a collection of documents. Term Frequency (TF) represents the frequency of a term within a document, while Inverse Document Frequency (IDF) reflects the rarity of the term across the entire document corpus [20].

The use of TF-IDF aims to reduce the influence of frequently occurring but less informative words while emphasizing words that contribute significantly to distinguishing the sentiment of a text. This method has been proven effective in machine learning-based sentiment analysis [21].

Support Vector Machine (SVM) is a supervised learning algorithm used to address classification and regression problems by identifying an optimal hyperplane that separates data into different classes with the maximum margin [22].

In sentiment analysis, SVM is well known for its strong performance in handling high-dimensional text data and its relative robustness against overfitting. Consequently, SVM is widely

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used in text mining–based sentiment analysis research, particularly with linear kernels, which are efficient for textual data [23].

III. FRAMEWORK

This study is a quantitative research employing text mining and machine learning approaches aimed at analyzing public sentiment toward the Free Nutritious Meal Program on Social Media X. The classification method used is the Support Vector Machine (SVM) algorithm with N-Gram feature representation and Term Frequency–Inverse Document Frequency (TF-IDF) weighting, which has been proven effective in sentiment analysis of high-dimensional textual data [10].

The research workflow begins with data collection, followed by data cleaning, sentiment labeling, text preprocessing, feature extraction, SVM-based classification, and model performance evaluation. The overall research flow is visually presented in Figure 1.

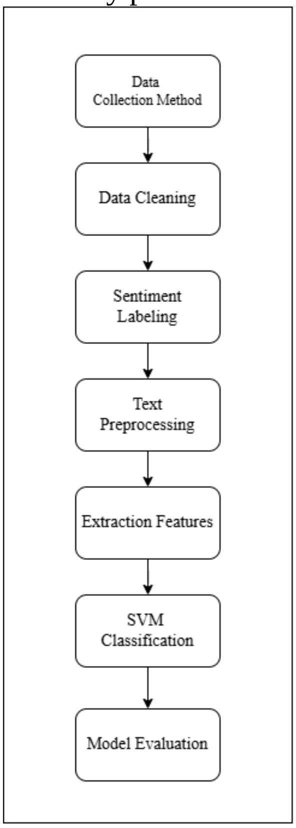

Figure 1. Research Flow

IV. METHODS

The research data were obtained through a crawling technique on Social Media X using keywords related to the Free Nutritious Meal Program. Data collection was conducted during the period of January–March 2025, resulting in 1,014 raw tweets that reflect public opinion toward the policy.

The data cleaning stage aims to eliminate irrelevant elements that may introduce noise into the sentiment analysis process. The data cleaning procedures include the removal of mentions (@username), hashtags (#), URLs, punctuation marks, non-alphabetic characters, and duplicate data. In addition, data records containing missing values are also handled. This stage is crucial for improving data quality before further analysis is conducted [24].

After the cleaning process, the number of data instances was reduced to 931 tweets that were ready for further processing. The technical implementation of the data cleaning stage using a series of operators in the RapidMiner software is comprehensively illustrated in Figure 2.

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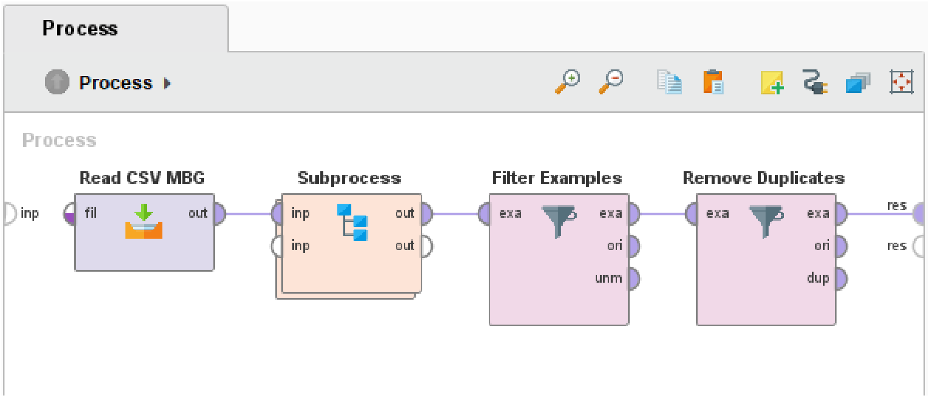

Figure 2. Data Cleaning Operators in RapidMiner

Furthermore, the detailed procedure for cleaning specific textual elements such as mentions, hashtags, and URLs was performed within a subprocess, as visualized in Figure 3.

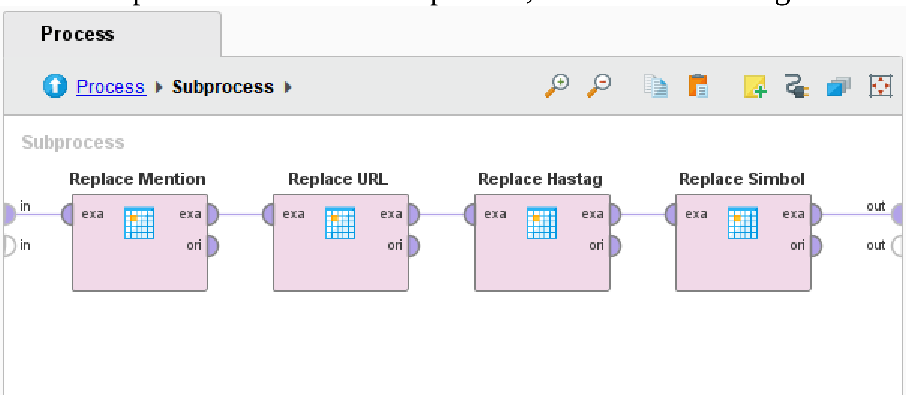

Figure 3. Detailed Text Sub-cleaning Process

The cleaned data were then manually labeled into two sentiment classes, namely positive sentiment and negative sentiment. The labeling process was carried out by considering the semantic context of each tweet and was used as training data in the development of the classification model. Manual labeling is still widely employed in sentiment analysis research because it can produce more accurate labels than automatic labeling, particularly for datasets of limited size [18]. The data distribution indicates an imbalance between the positive and negative sentiment classes.

The text preprocessing stage was implemented to ensure that raw textual data could be transformed into a structured and standardized format suitable for optimal processing by machine learning algorithms. This stage comprised three principal procedures. First, case folding was applied to convert all characters into lowercase, thereby eliminating inconsistencies caused by variations in letter capitalization and enhancing uniformity across the dataset [25]. Second, tokenization was performed to segment the continuous text into discrete word units or tokens, enabling the model to analyze linguistic components at a granular level. Third, stopword removal was employed to eliminate frequently occurring Indonesian words such as conjunctions, prepositions, and pronouns that carry minimal semantic value in sentiment classification tasks. Collectively, these preprocessing operations serve to reduce textual noise, decrease data dimensionality, and improve computational efficiency, ultimately contributing to enhanced classification performance as reported in previous studies [17]. The overall workflow, illustrating the transformation of raw text into a structured token collection through the Process Documents operator, is presented in Figure 4.

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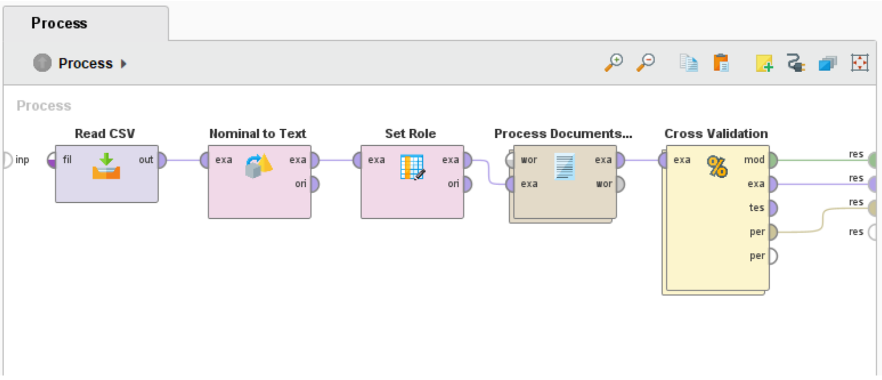

Figure 4. Text Preprocessing Operators

The preprocessed textual data were then transformed into numerical representations through feature extraction using the N-Gram approach, combining unigram and bigram features to capture broader word context. Subsequently, weighting was performed using the TF-IDF method to assign higher weights to terms with greater importance in distinguishing sentiment classes. The combination of N-Gram and TF-IDF has been proven effective in improving classification performance in text-based sentiment analysis [19]. The integration process between text preprocessing and N-Gram feature extraction with TF-IDF weighting within a RapidMiner subprocess is illustrated in Figure 5.

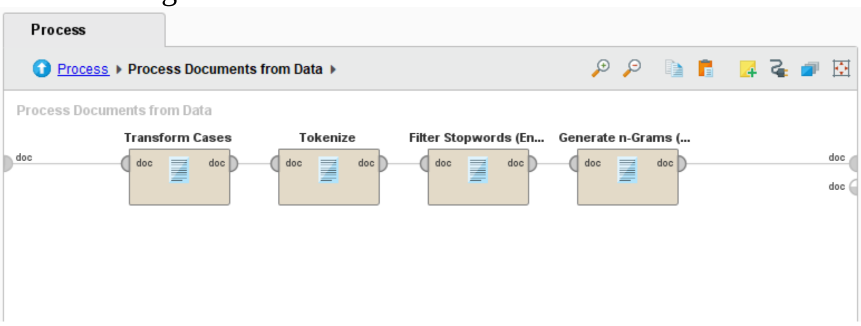

Figure 5. Text Preprocessing and Feature Extraction Stages

The sentiment classification process was performed using the Support Vector Machine (SVM) algorithm. This algorithm works by determining an optimal hyperplane that separates the data into positive and negative sentiment classes with the maximum margin. SVM was selected due to its stable performance in handling high-dimensional textual data and its ability to minimize the risk of overfitting in sentiment classification problems [10]. All classification processes in this study were conducted using the RapidMiner software.

Model performance evaluation was conducted using the 10-Fold Cross Validation method, in which the dataset was divided into ten subsets that were alternately used as training and testing data. This method aims to ensure the model's generalization capability and to avoid bias in the evaluation process [19]. The assessment of model performance and classification balance was carried out using accuracy, precision, recall, and F1-score metrics, as systematically illustrated in the operator configuration shown in Figure 6.

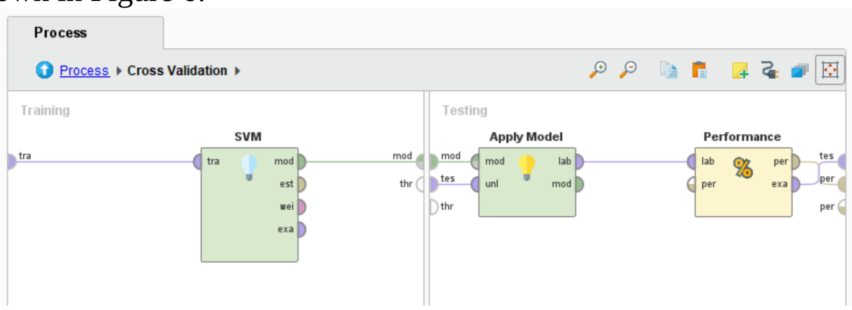

Figure 6. SVM Classification Model and Evaluation

V. RESULTS

This study applies the Support Vector Machine (SVM) algorithm with N-Gram features and TF-IDF weighting to classify public sentiment toward the Free Nutritious Meal Program on Social Media X. Model evaluation was conducted using the 10-Fold Cross Validation method on 931 tweets that were manually labeled into two sentiment classes, namely positive and negative.

Based on the data labeling results, a total of 683 tweets (73.36%) were classified as positive sentiment, while 248 tweets (26.64%) were classified as negative sentiment out of the 931 analyzed tweets. This distribution indicates that public opinion toward the Free Nutritious Meal Program on Social Media X is dominated by positive sentiment, suggesting a tendency of public support for the program. However, the substantial difference in the number of instances between the two sentiment classes indicates the presence of data imbalance (imbalanced dataset).

Based on the evaluation results using the 10-Fold Cross Validation method, the classification model achieved the following performance metrics:
Accuracy: 79.59% ± 3.06%
Classification Error: 20.41% ± 3.06%
Precision (negative class): 96.77%
Recall (negative class): 24.19%
F1-Score (negative class): 38.71%

The accuracy value indicates that the SVM model is capable of classifying public sentiment with a fairly good level of accuracy when applied to unstructured social media data.

Confusion Matrix

The confusion matrix is used to provide a more detailed overview of the classification model’s performance in classifying each sentiment class. Through the confusion matrix, the number of correct and incorrect predictions for each class can be identified, thereby assisting in analyzing the strengths and weaknesses of the model, particularly under conditions of imbalanced data distribution. The confusion matrix results of the SVM model are presented in Table 1.

Table 1. Results of the Confusion Matrix

	True Positif	**True Negatif**	**Precision**
Pred. Positif	681	188	78,37%
Pred. Negatif	2	60	96,77%
Recall	99,71%	24,19%	

Based on the table, the model is able to correctly classify most positive tweets; however, a considerable number of errors remain in classifying negative tweets as positive sentiment, indicating the model’s limitation in detecting the minority sentiment class.

VI. DISCUSSION

Based on the testing and evaluation results obtained, this section discusses the performance of the Support Vector Machine (SVM) algorithm in classifying public sentiment as well as the implications of the sentiment analysis results for the Free Nutritious Meal Program policy. The discussion focuses on the interpretation of the model evaluation metrics and their relevance in understanding public perception on Social Media X.

An accuracy value of 79.59% indicates that the combination of the SVM algorithm with N-Gram features and TF-IDF weighting is sufficiently effective in performing sentiment classification on unstructured social media data. SVM is known for its stable performance in handling high-dimensional textual data, particularly when combined with TF-IDF-based feature representations.

The use of N-Gram features allows the model to better capture word and phrase context compared to a unigram-only approach, thereby enhancing the model’s ability to distinguish

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sentiment patterns. However, the obtained accuracy value should be interpreted with caution due to the imbalanced distribution of sentiment data in this study.

The imbalance in data distribution, where positive sentiment instances are more dominant than negative sentiment instances, causes the model to be more optimized for classifying the majority class. This condition negatively affects the model's ability to detect the minority class, as reflected in evaluation metrics other than accuracy. Similar phenomena have also been widely reported in social media sentiment analysis studies involving imbalanced datasets.

The precision value for the negative class of 96.77% indicates that the model has a high level of confidence when predicting a tweet as negative sentiment. This suggests that the number of false positive errors is relatively low, meaning that the negative predictions produced by the model tend to be accurate.

In contrast, the recall value for the negative class, which is only 24.19%, indicates that the model has not been able to detect all tweets that actually express negative sentiment. The low recall value is primarily caused by the imbalance in data distribution, where the number of positive sentiment tweets is significantly higher than that of negative tweets. As a result, the model tends to be biased toward the majority class and overlooks some negative sentiment patterns.

This condition shows that although the model achieves high precision in predicting the negative class, its coverage in identifying all negative instances remains limited. Therefore, the use of evaluation metrics such as precision, recall, and F1-score is crucial to provide a more comprehensive assessment of model performance than relying solely on accuracy.

The F1-score for the negative class of 38.71% indicates that the balance between precision and recall has not yet reached an optimal level. Although the precision value is relatively high, the low recall significantly reduces the overall performance of the model for the negative class.

This result suggests that the model still faces difficulties in recognizing variations of negative sentiment patterns, particularly those that are implicit, ambiguous, or expressed using specific linguistic styles such as sarcasm. Therefore, further improvements are required, either through data balancing techniques or the exploration of more representative feature sets, to enhance the model's ability to detect negative sentiment more comprehensively [23].

The classification results indicate that public sentiment toward the Free Nutritious Meal Program on Social Media X is dominated by positive sentiment. This dominance suggests a relatively high level of public acceptance and support for the objectives and implementation of the program [19].

Nevertheless, the presence of negative sentiment that has not been optimally detected by the model indicates that there are still criticisms, concerns, or public dissatisfaction regarding certain aspects of the policy, such as implementation mechanisms, program distribution, or effectiveness in practice. Therefore, the results of this sentiment analysis can be utilized as an initial evaluation tool for the government to better understand public perception and to identify policy aspects that require further improvement.

VII. CONCLUSION

This study systematically examines public sentiment toward the Free Nutritious Meal Program as expressed on Social Media X by implementing a machine learning–based text classification framework. The research employs the Support Vector Machine (SVM) algorithm, which is widely recognized for its robustness in high-dimensional textual data, in combination with N-Gram feature extraction and Term Frequency–Inverse Document Frequency (TF-IDF) weighting to capture both contextual word patterns and term importance. A total of 931 tweets were collected and preprocessed through tokenization, normalization, stop-word removal, and vectorization before being used to train and evaluate the classification model. To ensure methodological rigor and generalizability, the performance was assessed using the 10-Fold Cross Validation technique, which minimizes bias by iteratively training and testing the model across different data partitions.

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The experimental results demonstrate that the proposed SVM-based approach achieves an overall accuracy of 79.59%, indicating a relatively strong capability in distinguishing between positive and negative sentiments related to the program. Notably, the precision for the negative sentiment class is comparatively high, suggesting that when the model predicts a tweet as negative, it is likely to be correct. However, the recall and F1-score for this class remain limited, reflecting the model's reduced ability to capture all negative instances present in the dataset. This performance discrepancy can be largely attributed to the imbalanced distribution of sentiment classes, where positive sentiment significantly outweighs negative sentiment. Such imbalance commonly leads to biased learning toward the majority class, a phenomenon well-documented in sentiment analysis literature.

Overall, the findings reveal that public perception of the Free Nutritious Meal Program on Social Media X is predominantly positive, indicating broad societal support and favorable responses toward the initiative. Nevertheless, the presence of underdetected negative sentiment highlights the need for methodological enhancements in future studies. It is recommended that subsequent research incorporate data balancing strategies such as Synthetic Minority Over-sampling Technique (SMOTE), random undersampling, or cost-sensitive learning to mitigate class imbalance issues. Additionally, model optimization through hyperparameter tuning, ensemble learning, or the integration of deep learning architectures such as LSTM or BERT-based transformers may further improve classification performance, particularly in capturing minority sentiment patterns. These improvements would contribute to a more comprehensive and accurate understanding of public opinion in policy-related social media discourse.

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BIOGRAPHY

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