Sentiment Analysis of Public Opinion on Indonesia's Free Nutritious Meals Program from X Platform

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***Abstract*— The rise of public policy discussions on social media platforms presents new opportunities to assess public sentiment through natural language processing. This study aims to analyze public opinion on Indonesian's Free Nutritious Meal Program using a sentiment classification approach. A total of 1,098 tweets were collected from the X platform and manually labeled into positive, neutral and negative categories. IndoBERT a pre-trained transformer model tailored for Bahasa Indonesia, was used to classify sentiments. To create a trustworthy classification model, the dataset was separated into training, validation, and testing sets. The findings indicated that the public are quite optimistic and supportive about the program. It is highlighted by the fact that positive attitude predominated, followed by negative and neutral sentiments. To support the result, the study also used visualizations including frequency charts and word clouds. These results offer actionable insights for policymakers to evaluate and improve program delivery. As future work, the integration of BERTopic is proposed to extract and explore topic level patterns within sentiment categories for more in-depth analysis. It is also advisable to incorporate methods for identifying and filtering out buzzer comments, in order to ensure that the analysis reflects genuine public opinion rather than artificially amplified narratives.**

Keywords—Sentiment Analysis, IndoBERT, Public Opinion, Free Nutritious Meal Program, X Platform

INTRODUCTION

The Free Nutritious Meal Program, that officially launched on January 6, 2025, is one of Indonesia's new President, Prabowo Subianto, priority policies to realize the golden Indonesia 2045. It aimed at overcoming malnutrition and stunting among Indonesian children by providing free, nutritious school meals to over 17 million elementary to high school students by the end of the year [1].

While the program expected to improve child welfare and stimulate the local economy, it has also sparked debates regarding its feasibility and sustainability. Critics have raised concerns about logistical challenges, funding sustainability, and regional food diversity needs. This lack of customization could lead to inefficiencies, food waste, and dissatisfaction among recipients [2].

The public's perception of this free nutritious meal program also became controversial. With the growth of social media, especially X platforms developed into a community space where members of the public, specialists, and even legislators gather to interact directly [3]. People react differently to the problem when they have this different point of view. But these discussions are extensive, varied, and frequently incoherent.

The discussion on X platform generate an unstructured data that can serve a valuable source for government to enhance the policy strategy making through social media analysis [4] Sentiment analysis, or opinion mining, is part of natural language processing (NLP) that aims to automatically identify, extract, and quantify the emotional tone and subjective information represented in the text data. This approach enables researchers to assess public satisfaction or dissatisfaction to the policies [5].

However, analyzing sentiment in social media present with several challenges, such as informal expressions, sarcasm, and the rapidly evolving slang and other unstructured data can lead to misinterpretation in the analysis process [6]. Despite these limitations, with implementation a robust sentiment analysis remains a powerful tool for policymaker improved policy strategies. [6].

This study aims to seeks the patterns regarding the Free Nutritious Meals Program. The insights obtained from this analysis can assist the governments to evaluating the program effectiveness with addressing public concerns, and guide data-driven decisions for the future improvements.

LITERATURE REVIEW

A. Free Nutritious Meal Program

The Free Nutritious Meal Program was initially proposed by President Prabowo Subianto, during his candidacy, as one of his priority initiatives aimed at addressing children's health and nutrition, given that the malnutrition rate in Indonesia is 21.5 percent in 2023, which is relatively high compared to other ASEAN countries [7]. It operates by providing free nutritious school meals to millions of children across Indonesia.

B. X Platform

Social media is a concept of technology that is designed to facilitate the public to interact and communicate through the internet. It plays a crucial function as a primary arena for public discourse, influencing perceptions and opinions regarding political programs and policy concerns [8]. One of the popular platforms is X. According to DataReportal,

the X platforms had approximately 24,69 million users in Indonesia in early of 2024 [9]. X was formerly an open forum for the public, specialists, and government officials to engage in discussions and served as a primary source of information regarding political developments [3].

C. Sentiment Analysis

Sentiment analysis is a natural language processing (NLP) technique used to determine the emotional tone behind textual data, typically classifying it into categories such as positive, neutral, and negative [10]. It is an essential tool for analyzing public opinion, particularly on social media platform like X.

Various approaches have been developed, ranging from rule-based systems to machine learning and deep learning techniques. An example of deep learning techniques is pretrained language models like BERT and IndoBERT [10].

IndoBERT is a language model pre-trained on large-scale Indonesian text corpora, making it particularly effective for sentiment analysis tasks involving Bahasa Indonesia. Several prior studies have successfully applied IndoBERT to analyze public sentiment. For example, the study titled *Analyzing Views on Presidential Candidates for Election 2024 Based on the Instagram and X Platforms with Text Clustering* demonstrates the effectiveness and adaptability of models like IndoBERT for analyzing sentiment and public opinion on social media [11].

METHODOLOGY

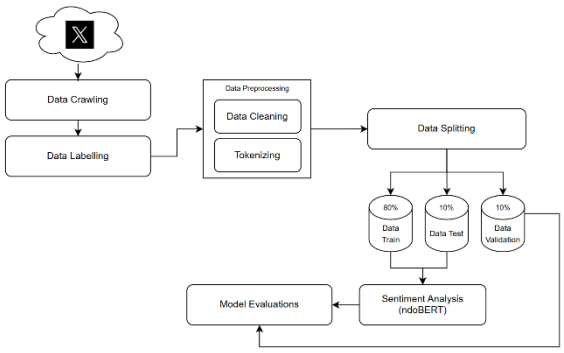

Fig.1 Research Flow

This research will be analyzing public opinions on Free Nutritious Meals Program by collecting data from platform X. These data will then be going through six stages of processing, namely: data crawling, preprocessing, classification, and lastly, evaluations.

A. Data Crawling

The first process is scraping data from X platforms; The data was collected from January 2025 to May 2025 using Tweet Harvest tool by Helmi Satria, which functions to extract the tweet data based on specific keyword automatically. This research extracts 1000 tweets, with specified keywords related to the topic – Free Nutritious Meals Program. This approach is widely used in the recent Indonesia social media research for its effectiveness in collecting data from X.

B. Preprocessing Data

Preprocessing data involves several steps, like data labeling, data cleaning, and feature extraction. By doing all these steps, it helps transform raw data into a structured format that are suitable for further analysis using machine learning models. Preprocessing data is a crucial step that need to be done to enhance the quality of datasets and facilitate more effective sentiment analysis.

a. Data Labeling

In this step, researchers will read each tweet and categorize them into 3 different sentiment labels namely positive, neutral, and negative manually [12] . The choice of label is done based on its emotional tone and sentiment expressed toward the program.

For tweets that contain keywords that express support and approval toward the program, they are labelled as positive. At the same time, for tweets that contain keywords that express dissatisfaction, disapproval, or criticism, will be labelled as negative. Whereas, for tweets that only present facts without clear sentiment will be labelled as neutral. This includes news headlines, general program descriptions, or discussions that neither express approval nor disapproval.

When all data have been labelled, then it is ready to be used as dataset for machine learning model training. With this dataset, it will help the model to learn how to distinguish and categorize textual data into different sentiments categories.

full_text	polarity
@ch_chotimah2 @prabowo Harusnya orang tua yang punya anak sekolah rame-rame menolak makan gratis bergizi..aja.	negative
Keluarga dan kroni presiden Prabowo dapat menu makan bergizi gratis. Anak sekolah dapat yg tak bergizi .bahkan rentan keracunan.	negative
@tomoseeker @apasihrit Makan siang bergizi gratis nihh. Makasii gesss	neutral
@kompascom Anak-anak dapet makan gratis dan bergizi tuh keren banget tinggal jaga kualitasnya aja lanjutkan MBG	positive
Program makan siang bergizi gratis bagi murid sekolah yang digagas pemerintah Prabowo-Gibran adalah langkah luar biasa untuk memastikan generasi muda tumbuh sehat dan cerdas. https://t.co/JVGTS9AHwQ	positive

Table 1 Data Labelling

b. Data Cleaning

When dataset is fully labeled, it will then undergo data cleaning. There are several steps of cleaning done, including removing symbols, eliminating irrelevant or duplicate comments, trimming whitespace, and standardizing data. This is done to ensure that the data will be more accurate when used for analysis. Data cleaning involves several steps:

- Removing punctuation, emojis, and symbols: This eliminates elements that could interfere with text analysis.
- Eliminating duplicate and irrelevant comments: Deleting comments that are duplicate and/or irrelevant to the topic discussed.
- Whitespace trimming: Reducing unnecessary spaces for consistency.
- Normalization: Process to converting categorical sentiment classes into standardized labels in spelling and formatting to ensure uniformity.

These preprocessing steps help improve the quality and structure of the data, making it more suitable for extracting useful features and classifying similar opinions.

c. Feature Extraction

At this step, the cleaned data is being converted into a format that machine learning models can work with. This process includes several steps, including label mapping, tokenization, vectorization, and data splitting.

- Tokenization: This involves splitting sentences into individual units or tokens, usually as word.
- Vectorization: After tokenization, text is converted into numerical vectors using TF-IDF which represent how often words appear in the dataset.
- Data Splitting: The dataset is divided into three parts: training (80%), testing (10%), and validation (10%) to ensure each class is balanced.

C. Classification Model

BERT Embeddings: Using pre-trained model from Hugging Face called 'ayameRushia/bert-base-indonesian-1.5G-sentiment-analysis-smsa' to capture the deeper meaning and context of each comment. This model converts entire sentences into numerical vectors that reflect their meaning.

D. Evaluation

Standard classification metrics are used while doing model evaluation. The metrics include accuracy, precision, recall, and F1-score, and confusion matrix with a weighted average to address class imbalance. These evaluation metrics attributes were calculated by comparing the true labels and predicted labels on both the validation and test sets.

The parameter on model training was using the Hugging Face 'TrainingArguments', with attributes such as batch size, epoch number, learning rate, evaluation, and checkpointing. The best model was chosen by looking at checkpoints with the highest F1-Score on the validation set.

RESULT

This research will be analyzing public opinions on Free Nutritious Meals Program by collecting data from platform X. These data will then be going through six stages of processing, namely: data scraping, preprocessing, classification, and lastly, evaluation.

A. Tweet Distribution per Category

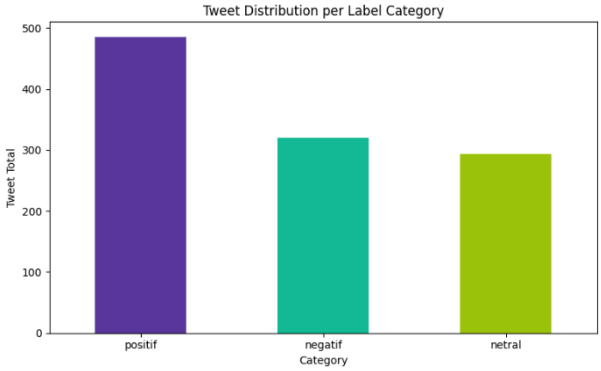

Fig.2 Tweet Distribution per Category

In this study, a total of 1,098 tweets were collected from the X platform to analyze public response to the Free Nutritious Meal Program. Each tweet was manually labeled into one of three sentiment categories positive, neutral, and negative. The labeling result showed that 486 tweets expressed positive sentiment, often containing support or optimism toward the program. Meanwhile, 294 tweets were categorized as neutral, typically conveying information or commentary without an apparent emotional tone. On the other hand, 320 tweets reflected negative sentiment, many of which raised concerns, criticism, or dissatisfaction regarding the implementation of the policy.

To prepare the dataset for the sentiment classification process, the labeled tweets were divided into three subsets: training, validation, and testing. The training set included 389 positive, 235 neutral, and 256 negative tweets. The validation set contained 49 positive, 29 neutral, and 32 negative tweets, while the test set comprised 48 positive, 30 neutral, and 32 negative tweets. This distribution was intentionally structured to maintain a balanced and representative split, allowing the model to learn effectively while being evaluated objectively. The proportions also reflect the diversity of public opinion and provide a solid foundation for the next stages of classification and visualization.

B. Model Performance

During training, the model was run for five epochs. The results are consistent with recent IndoBERT-based sentiment analysis studies. The best validation performance was achieved in the five epoch, with an accuracy of 84% with F1-socre of 0.84 indicating the model was able to correctly classify most of the tweets. The steady increase in performance epoch suggests the model remained stable without significant overfitting.

Epoch	Accuracy	F1-Score	Precision	Recall
1	0.78	0.77	0.77	0.78
2	0.80	0.80	0.80	0.80
3	0.82	0.82	0.82	0.82
4	0.83	0.83	0.84	0.83
5	0.84	0.84	0.84	0.84

Table 2. Metrics Evaluation Summary

On figure 5 shown the matrix confusion distribution consists of true positive, true neutral, and true negative instances against their corresponding predicted labels. The dataset used on the matrix is based on the predictions on the test set.

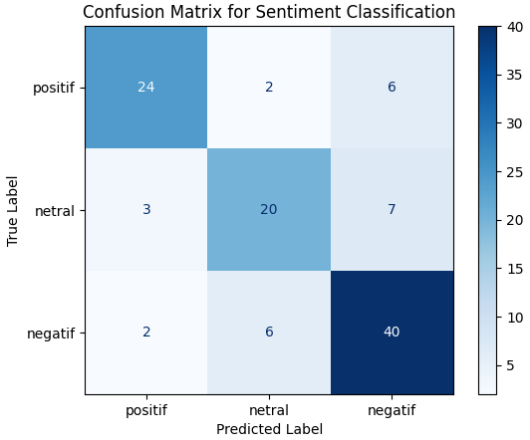

Fig.3 Confusion Matrix

The model accurately classified 24 out of 32 data labeled as positive, 20 out of 30 data labeled as neutral, and 40 out of 48 data labeled as negative. Most of the miss predicted predominantly happened between the neutral and negative classes, as well as between the positive and negative classes, which indicated the complexity and overlapping sentiment expression in social media discourse.

C. Visualization

Several visual tools are used to provide a clearer understanding of the textual data and sentiment distribution related to Indonesia's Free Nutritious Meals Program. A general word cloud is generated to display the most frequently occurring words across all tweets, offering a quick overview of the dominant topics and language used by the public.

Fig.4 Word Cloud Visualization per Category

To gain deeper insights, separate word cloud for each sentiment labels—positive, neutral, and negative—are also presented. These segmented visualizations help highlight the distinct vocabulary commonly associated with different opinions, revealing patterns such as supportive keywords in positive tweets or criticisms on negative ones.

Fig.5 Word Cloud of Frequently Used Word

Additionally, a bar chart of the top 20 most frequent words is included to provide a more quantitative view of word frequency that allows easier comparison between terms. These visualizations together support the interpretation and contextualization of the sentiment analysis result.

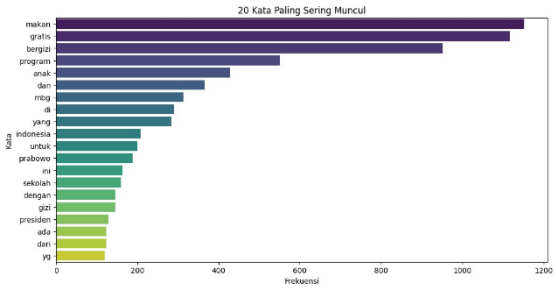

Fig.6 Top 20 Frequently Used Word

DISCUSSION

The findings indicate that public sentiment toward the Free Nutritious Meal Program is largely positive. This reflects growing support and optimism about the program's goals, especially in terms of improving student nutrition and addressing hunger. Still, some users expressed negative views, showing that concerns remain regarding the program's execution—particularly related to funding reliability, regional readiness, and distribution fairness.

IndoBERT performed well in handling informal Indonesian language, capturing sentiment with a strong F1 score of 0.84. However, the model occasionally struggled to distinguish between neutral and negative tones, which is understandable given the ambiguity and sarcasm often found in social media posts.

In the future, this research could expand by experimenting with other language models to assess and compare their performance. BERTopic may also be applied to uncover more targeted themes within each sentiment category, offering deeper and more context rich insights. Future studies should also consider the need to identify and exclude inauthentic accounts such as buzzer or bots to ensure that the findings truly reflect organic public opinion. That said, this study is not without its limitations. Potential digital manipulation, a relatively small dataset, and the inherent subjectivity in manual labeling all pose challenges that should be addressed to strengthen the reliability and broader applicability of future sentiment analysis.

CONCLUSION

To understand how the public is responding to Indonesia's Free Nutritious Meal Program, This study explores the use of IndoBERT for classifying sentiment in social media pots. Analysis of manually labeled tweets collected from platform X revealed that positive opinions were that most common. This trend reflects widespread skepticism, as many users expressed concerns about the feasibility of the program particularly regarding uneven distribution, funding sustainability and challenges in regional implementation.

While criticism was present, a considerable number of posts also reflected support. This suggests is still place hope and express a positive outlook toward the government's efforts to improve student nutrition and address hunger. The sentiment analysis result, combined with clear and accessible data visualizations, helped present a well-rounded picture of public perception toward the program as reflected on social media. With its ability to discern minute details in tweets written in Indonesian, IndoBERT provided insightful insights about how public initiatives are received online. This suggests that many members of the public. With its ability to discern minute details in tweets written in Indonesian, IndoBERT provided insightful insights about how public initiatives are received online.

AI USAGE DECLARATION

We declare that we use AI Tools Grammarly in this manuscript to check for grammar and paraphrasing. The result from AI is not used directly and it is under human supervision for error checking.

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