Cross-Platform Social Media Sentiment Analysis of Indonesia’s Free Meal Program Using Machine Learning and Deep Learning Techniques.

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**Abstract.** The Indonesian government’s free meal program has become one of the most discussed social policy initiatives in the digital public sphere. This study analyzes public perceptions of the program through a sentiment analysis approach that leverages both machine learning (ML) and deep learning (DL) techniques, using data gathered from multiple social media platforms (YouTube, TikTok, and Twitter). The research process encompassed automatic data collection (via APIs and web scraping), text preprocessing and cleaning, lexicon-based sentiment labeling (using VADER for general polarity and Sastrawi for Indonesian context), and training several ML models – Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Naïve Bayes (NB) – as well as a DL model (IndoBERT) to classify sentiment. The evaluation results indicate that among the ML classifiers, the SVM model achieved the highest performance at approximately 94% accuracy, whereas the IndoBERT transformer model attained an even higher accuracy of about 99%. In particular, IndoBERT excelled at handling informal language and contextual nuances across the different platforms. We also visualized sentiment trends to understand how public opinion evolved over time and across regions. Furthermore, the study proposes a Power BI-based interactive dashboard design as a tool for policymakers to monitor public sentiment in real time. This work contributes to the literature on Indonesian-language sentiment analysis in the public policy domain. The findings are expected to support data-driven policy evaluation and strengthen government public communication, and they serve as a foundation for developing more sophisticated cross-platform public opinion monitoring systems in the future.

# INTRODUCTION

Social media has become a vital venue for the public to voice opinions and sentiments on matters of public interest, including government policies. Platforms such as YouTube, TikTok, and Twitter enable real-time, large-scale sharing of views, making them rich sources of data for gauging public sentiment [1][2]. In Indonesia, a recent policy initiative that garnered significant online attention is the government’s free nutritious meal program, launched in early 2025 to provide daily meals for schoolchildren and pregnant women as a strategy to combat child malnutrition [3]. The program was widely welcomed and praised for its potential to improve public welfare and reduce stunting, especially among vulnerable groups. At the same time, it faced criticism and concerns regarding its implementation – issues such as distribution effectiveness, food quality, and budget transparency were raised by various observers [4][5]. Public reactions on social media ranged from enthusiastic support to sharp skepticism, reflecting both hope in the program’s benefits and doubts about its execution. These candid reactions offer valuable feedback to policymakers; however, given the volume and variety of commentary spread across different platforms, manually monitoring and analyzing this feedback is impractical.

Sentiment analysis techniques can address this challenge by automatically processing large-scale text data to determine overarching public opinion trends. Previous studies have demonstrated that machine learning and deep learning approaches are effective for sentiment analysis in various domains. For example, classifiers based on Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have achieved high accuracy in text sentiment classification [6]. Transformer-based models like BERT have further advanced the state of the art by capturing context and nuance, as evidenced in social media sentiment studies [7]. In the context of Indonesian-language data, the development of IndoBERT is a pre-trained BERT model for Indonesian – provides a powerful tool for more nuanced sentiment detection [8]. However, most existing research focuses on a single platform or a homogeneous data source. Fewer studies have tackled cross-platform sentiment analysis, which must account for the differing characteristics of each platform (for instance, the brevity of Twitter posts versus the longer, more detailed YouTube comments) and integrate those heterogeneous data sources [9][10]. Additionally, there is a notable gap in the literature regarding sentiment analysis applied to Indonesian public policy issues: prior works on public opinion in Indonesia have largely been qualitative or confined to one social media source[11]. This study aims to fill these gaps by combining data from multiple platforms and leveraging advanced natural language processing techniques to obtain a more comprehensive view of public sentiment.

This study focuses on the Indonesian free meal program as a case study for cross-platform social media sentiment analysis. We collected a large dataset of comments and posts from YouTube, TikTok, and Twitter discussing the program, and employed both traditional ML algorithms and a deep learning model (IndoBERT) to classify the sentiment of these posts as positive, negative, or neutral. We specifically investigate:

1. Overall public sentiment toward the free meal program and how it differs across platforms,

2. The performance of different sentiment classification models (ML vs. DL) on this cross-platform data, and

3. Effective methods to visualize and communicate the results to support policy evaluation.

By addressing these questions, the study provides data-driven insights into public perceptions of the policy and demonstrates an approach for real-time policy feedback. In summary, our contributions include an integrated cross-platform sentiment analysis methodology for Indonesian social media, a comparative evaluation of ML and DL techniques for this task, and a prototype design for an interactive dashboard to enable policymakers to monitor public opinion in real time. The following sections present a review of related work, the methodology of data collection and analysis, the results obtained, a discussion of their implications (including a proposal for the sentiment dashboard), and conclusions with suggestions for future directions.

## LITERATURE REVIEW

**Free Meal Program Policy In Indonesia**

Government-sponsored meal programs are part of broader social protection efforts aimed at improving nutrition and educational outcomes. Indonesia’s free meal program (locally known as Program Makan Bergizi Gratis) was officially launched in January 2025, with the goal of providing daily nutritious meals to schoolchildren and pregnant women in underprivileged areas[3]. This initiative parallels school feeding programs in other countries, which have been shown to reduce child hunger and improve school attendance[12]. Early assessments of the Indonesian program suggested potential benefits, such as reductions in child stunting and improvements in student concentration and performance[13]. However, implementing such a large-scale program also presents challenges. Observers have pointed out logistical and quality control issues in food distribution, calling for stronger food safety standards and oversight[4][14]. There are likewise concerns about the program’s long-term financial sustainability and the effective use of budget resources[5]. The public and media response has thus been mixed: many citizens laud the government’s effort to tackle malnutrition, yet skepticism remains regarding execution and transparency. These mixed sentiments have increasingly been voiced on social media, making it an important arena to gauge public opinion about the policy.

**Social Media as Source of Public Opinion**

In today’s digital era, social media platforms act as de facto public forums that both reflect and shape public opinion[15][1]. Unlike traditional media, platforms like Twitter, TikTok, and YouTube allow ordinary citizens to react in real time to policies and share their experiences or critiques with a wide audience. This participatory environment is a cornerstone of “digital democracy,” where public sentiment expressed online can influence political discourse and policy implementation. Studies have shown that social media discussions can signal public acceptance or resistance to government initiatives, sometimes even before formal surveys are conducted[16][17]. Each platform, however, has distinct user demographics and communication styles that can affect the sentiment expressed. Twitter is dominated by brief text posts and is often used for immediate reactions or news updates; accordingly, Twitter sentiment tends to be concise and hashtag-driven, and it has been used effectively for tracking opinions during fast-evolving events[18]. YouTube, being video-centric, hosts longer comments and discussion threads attached to video content; its user base often provides more detailed feedback or narrative opinions in the comment sections. TikTok centers around short video clips and trending content, with a user base (often younger demographics) that expresses sentiment through video reactions, slang, and memes. Prior research suggests that these differences necessitate careful cross-platform analysis – for instance, emotional expression on TikTok might be more visual or conveyed through reaction videos, whereas on YouTube it might be more explicitly articulated in text[19]. Despite these differences, social media collectively offers an unparalleled resource for understanding public sentiment, provided that data from all relevant platforms can be gathered and interpreted in tandem. It is also important to note ethical considerations when using social media data: researchers must respect user privacy and platform terms during data collection, and ensure the anonymity of individuals in any analysis or reporting[20].

## Sentiment Analysis Technique

Definition and Early Approaches: Sentiment analysis (or opinion mining) refers to the computational study of people’s opinions, attitudes, and emotions expressed in text. A fundamental task in sentiment analysis is classifying text into sentiment categories such as positive, negative, or neutral[21]. Early approaches to sentiment analysis often relied on lexicon-based methods, which use predefined dictionaries of positive and negative words. For example, VADER is a lexicon and rule-based tool tuned for social media sentiment analysis in English, and Indonesian sentiment lexicons (often used alongside the Sastrawi library for stemming) have been developed to capture local slang and context in Bahasa Indonesia. Lexicon-based methods are straightforward and can be effective for simple cases, but they struggle with sarcasm, context-dependent word meanings, and domain-specific language use[21]. For instance, a lexicon might misclassify a sarcastic comment as positive if it contains positive words, not recognizing the negation or irony.

Machine Learning Approaches: To improve accuracy, machine learning methods became popular. These involve training algorithms on labeled datasets of text. Common classifiers include Naïve Bayes (NB), Support Vector Machines (SVM), and k-Nearest Neighbors (KNN). Each has been applied to sentiment tasks with varying success. For example, Ajhari (2023) compared Multinomial Naïve Bayes and SVM for movie review sentiment classification and found that SVM generally achieved higher accuracy[22], which is consistent with SVM’s strength in handling high-dimensional text data. In the Indonesian social media context, classical ML models like SVM and NB have also been used for sentiment classification[23], though these studies often focus on a single platform (e.g., Twitter) or specific domain. One challenge for ML models is that they usually treat text as a “bag of words,” relying on features like word frequencies or n-grams. While effective up to a point, this approach can miss nuances such as word order or sarcasm, and performance may suffer if the training data is limited or not representative of the informal language found on social media.

Deep Learning Advances: Recent advances in deep learning have significantly improved sentiment analysis performance. Recurrent neural networks (RNNs), particularly architectures like LSTM (Long Short-Term Memory), can model word sequences and capture long-term dependencies in text, which helps in understanding context and handling negations or amplifiers (e.g., not good vs. not bad). CNNs (Convolutional Neural Networks) have also been employed to automatically extract salient phrases or n-gram features that contribute to sentiment[6]. The latest breakthroughs come from transformer-based models. BERT (Bidirectional Encoder Representations from Transformers) and its language-specific variants (such as IndoBERT for Indonesian) have achieved state-of-the-art results by learning rich representations of text through unsupervised pre-training on large corpora[8][7]. These models capture subtle linguistic nuances and context, enabling them to detect sarcasm, context shifts, and informal language better than earlier methods. For example, IndoBERT has been shown to outperform traditional models in classifying Indonesian social media text, especially in cases with slang or mixed languages[24]. The main downside of deep models is their requirement for larger training data and computational resources, but when those are available, they offer superior accuracy and robustness. Recent work by Singh et al. (2021) demonstrated the effectiveness of BERT in capturing the impact of COVID-19 on social sentiment[25], and similarly, our study finds that IndoBERT can capture the sentiment in Indonesian comments with remarkable precision. In practice, this means that while an SVM might misinterpret a complex sentence with mixed sentiment, a fine-tuned IndoBERT is more likely to get it right because it understands the context in which words appear.

Cross-Platform Sentiment Analysis

Combining data from multiple social networks for sentiment analysis is a relatively new and challenging area. Different platforms produce heterogeneous data in terms of format (short tweets vs. long comments, text vs. video content, use of emojis, etc.) and each has unique linguistic styles and user behaviors. Kaur et al. (2023) noted that cross-platform analyses must account for platform-specific language patterns and engagement norms; a model trained on one platform’s data may not generalize well to another without adaptation. For example, the brevity and slang on Twitter differ greatly from the storytelling style on YouTube, so sentiment models must be flexible[9][10]. Some studies have attempted to develop unified models or multi-source training strategies for sentiment analysis. One tourism-domain study combined data from Twitter and travel forums, finding that a model trained on the merged data generalized better to new platforms than models trained on a single source[12]. In a public health context, Monselise et al. (2021) aggregated posts from various social sites to analyze sentiments around COVID-19 vaccines, highlighting that each platform contributed unique concerns and sentiment patterns[26]. These works underscore the importance of approaches that leverage the strengths of each platform’s data while handling their differences.

Our study builds on this literature by explicitly analyzing and comparing sentiment from three distinct social media sources in one unified framework. By doing so, we aim to provide a holistic understanding of public sentiment and to identify whether, for example, Twitter users are more positive or negative than YouTube commenters on the same issue. Such insights can inform how the government tailors its public communication strategies for each platform. Moreover, we explore visualization and dashboard techniques (using tools like Power BI) in line with recent trends that emphasize making data analytics results accessible and actionable for decision-makers[27]. This integration of cross-platform NLP analysis with an interactive dashboard is intended to bridge the gap between data science and practical policy monitoring. Essentially, we not only analyze the data but also consider how to present it in a user-friendly way for policymakers, enabling them to monitor public opinion in near real time.

**METHODOLOGY**

**Data Collection and Preparation**

To examine public sentiment about the free meal program, we collected data from three major social media platforms: YouTube, TikTok, and Twitter. We targeted these platforms because they were observed to be primary venues for discussion of the program (for example, news videos and commentaries on YouTube, viral short videos on TikTok, and trending hashtags on Twitter). Data collection was performed through a combination of platform APIs (for Twitter) and web scraping of publicly available data (for YouTube and TikTok), in accordance with each platform’s terms of service and ethical guidelines. In line with recommended practices for social media research, personal identifiers were removed or anonymized and data were analyzed in aggregate[20]. We gathered posts and comments that explicitly mentioned the free meal program or related keywords in Indonesian (such as “makan gratis” and the program’s official name). This process yielded a cross-platform dataset of approximately 284,000 social media comments spanning from late 2024 (when program announcements began) through mid-2025. Table 1 in our results summarizes the dataset composition and sentiment distribution per platform after labeling. Notably, the majority of data came from YouTube, which contributed over 268,000 comments (mainly on news and interview videos about the program). Twitter provided about 10,500 tweets, and TikTok about 5,000 comments.

All collected posts were annotated for sentiment with one of three classes: positive, negative, or neutral. We employed a semi-automated labeling approach to expedite this process. First, a lexicon-based sentiment analysis was applied using a combination of VADER (for general sentiment polarity, adapted to some Indonesian vocabulary) and an Indonesian sentiment lexicon (augmented by Sastrawi, an Indonesian NLP toolkit, for handling common slang and performing stemming). This lexicon-based step produced an initial sentiment tag for each post. Next, to ensure accuracy, we manually reviewed and corrected the sentiment labels on a randomly sampled 20% of the data. This human check helped verify that the automated method handled Indonesian-specific language correctly (for example, recognizing the sentiment in phrases like “mantap sekali” or detecting sarcasm in ostensibly positive words) and allowed us to adjust for any systematic biases. The result of this labeling process was a reasonably balanced representation of the three sentiment classes overall, though there were notable differences between platforms. For instance, our dataset analysis revealed that YouTube comments contained a higher proportion of negative sentiments compared to the other platforms, whereas Twitter sentiment skewed heavily positive (over 90% of tweets in our sample were classified as positive) and TikTok had a large neutral contingent. These differences align with anecdotal observations of how each platform is used – YouTube’s longer-form discussions allowed more in-depth criticism, Twitter’s discourse around the program was driven largely by affirmative official messaging and hashtag campaigns (yielding predominantly positive tones), and TikTok featured a lot of descriptive or non-opinionated content resulting in many neutral labels.

Before feeding the data into our models, we performed extensive text preprocessing to clean and normalize the comments, given the noisy nature of social media text. The preprocessing pipeline included the following steps:

• Case Folding: Convert all text to lowercase, so that for example “Gratis” and “gratis” are treated the same.

• Tokenization: Split each comment into individual tokens (words or punctuation). We used whitespace and punctuation as delimiters, with custom adjustments for Indonesian (for instance, keeping certain emoticons or emoji notations as separate tokens so they could be handled or removed explicitly).

• Stopword Removal: Remove common function words in Indonesian that carry little semantic content (e.g., yang “that/which”, dan “and”, atau “or”). We utilized a stopword list from the Sastrawi library for this step.

• Slang Normalization: Replace informal language and abbreviations with their formal equivalents. For example, “gpp” was normalized to “nggak apa-apa” (meaning “no problem” or “it’s okay”), “tdk” to “tidak” (“not/no”), and “sklh” to “sekolah” (“school”). We compiled a custom dictionary of slang terms and common abbreviations from Indonesian social media to systematically handle these transformations.

• Stemming: Reduce words to their root form using an Indonesian stemmer (Sastrawi). For example, “menyediakan”, “penyediaan”, and “tersedia” would all be stemmed to “sedia” (“provide/available”). Stemming ensures that different morphological variants of a word are treated uniformly by the model.

• Emoji and Emoticon Handling: Remove or isolate emojis and emoticons. Emojis can carry sentiment (a smiling face emoji 🙂 indicates a positive tone, for example), but our analysis in this study focused on textual sentiment. Therefore, we opted to strip out emojis after initially noting their presence (e.g., we might replace them with a token like <emoji> during preprocessing, or simply remove them outright). In future work, emojis could be leveraged as additional sentiment features, but here we aimed for a purely text-based classification.

After preprocessing, the text was in a standardized, machine-friendly form. For example, consider a raw comment: “Program ini sooooo GOOD!!! 😍 Free meal is awesome guys!!” (mix of Indonesian and English, with emphasis and emoji). After our preprocessing steps, this might be transformed into: “program ini bagus banget free meal mantap gila”, which roughly translates to “this program is really good, free meal is incredibly great”. In this transformed version, excessive letter repetitions have been normalized (e.g., “sooooo” to “sangat” or “banget”, meaning “very”), slang or colloquial terms are standardized, and the emoji has been removed. This cleaned text is then ready for feature extraction and modeling.

## Sentiment Classification Models

## We trained and evaluated four different models to classify the sentiment of social media posts: three conventional machine learning classifiers (SVM, Naïve Bayes, and KNN) and one deep learning model (IndoBERT). Figure 1 in our documentation illustrates the overall analytical framework, from data collection through modeling and visualization, but here we will describe the process in text.

## For the machine learning (ML) models, we first converted the preprocessed text into numeric feature representations. We employed the TF-IDF (Term Frequency–Inverse Document Frequency) vectorization technique to transform each comment into a feature vector, which captures how important each word is to a comment relative to the entire corpus. We included both unigrams and bigrams as features, considering the mixture of short texts (tweets) and longer texts (YouTube comments) in our data – bigrams help capture common phrases or two-word expressions that carry sentiment. We then trained the following classifiers on these features:

## Support Vector Machine (SVM): We used a linear kernel SVM, which is well-suited for high-dimensional sparse data like text. The key hyperparameter C (which controls the regularization strength) was tuned via grid search with cross-validation on the training set to find an optimal balance between margin size and classification accuracy. SVMs are a strong choice for text classification and have been found to perform well in many sentiment analysis tasks due to their ability to handle many features.

## Multinomial Naïve Bayes (NB): This classifier applies Bayes’ theorem with a simplifying assumption that features (words) are independent given the class. Despite its simplicity, Naïve Bayes is often a strong baseline for text classification. We used the multinomial variant appropriate for word frequency features, with Laplace smoothing to handle zero probabilities for unseen words. NB tends to work well for shorter texts or cases where indicative keywords strongly correlate with sentiment.

## k-Nearest Neighbors (KNN): We included KNN as a simple instance-based learner to see how it performs on this task. KNN classifies a new instance by looking at the k closest training instances in the feature space and taking a majority vote. We set k = 5 (and also experimented with a few other values) and applied distance weighting so that nearer neighbors have a larger influence on the classification than farther ones. KNN is rarely used alone for large text datasets because of its inefficiency and sensitivity to irrelevant features, but it provides an interesting point of comparison.

## For the deep learning approach, we fine-tuned IndoBERT, a BERT-based transformer model pre-trained on Indonesian language data[8]. Specifically, we started with the IndoBERT-base model and added a dense feed-forward layer on top of the transformer encoder to perform three-class sentiment classification. The model inputs were the raw comment texts (after basic cleaning, but notably we did not remove common tokens like user mentions or URLs in this step—transformer models can handle raw sequences with such tokens, and sometimes these tokens can provide context). We set a maximum sequence length (e.g., 128 tokens) to accommodate the vast majority of posts (long YouTube comments were truncated if they exceeded this length, though this was rare). During fine-tuning, we used a training batch size of 16 and ran for 2 epochs, employing the Adam optimizer with a learning rate of 2e-5, which is a standard starting point for BERT fine-tuning. We utilized an NVIDIA GPU to accelerate training given the computational intensity of transformer models. Additionally, we employed early stopping based on validation loss to prevent overfitting – if the model’s performance on a held-out validation set stopped improving, we halted training.

## The dataset was split into training and testing sets to evaluate performance. We used an 80/20 split: 80% of the data (randomly stratified to preserve the proportion of sentiment classes and a mix of platforms) for training, and 20% held out for final evaluation. Within the training set, we further set aside a portion for validation during model development and hyperparameter tuning. To address class imbalance – since positive comments were far more frequent than negative ones in our combined data (in part due to the abundance of supportive tweets) – we applied a combination of oversampling and undersampling techniques on the training data. Specifically, we oversampled the minority classes (negative and neutral) and undersampled the majority class (positive) in the training set to achieve a roughly balanced class distribution. This was done carefully to avoid information leakage (the test set remained untouched and reflective of real-world class proportions). After balancing, the training data had approximately equal numbers of positive, negative, and neutral examples. We observed that this balancing step improved the ML models’ ability to detect negative and neutral sentiments, increasing their F1-scores for those classes by up to 10-15% in some cases. The deep learning model (IndoBERT) was less affected by the imbalance due to its capacity to learn from context, but balancing still provided a more uniform signal during training.

**RESULTS**

**Data Overview and Sentiment Distribution**

Our compiled dataset provides a broad view of public reactions to the free meal program across different social media. In total, we analyzed 283,736 posts (after preprocessing and filtering), of which about 94% came from YouTube comments, 3.7% from Twitter, and 1.8% from TikTok. Despite YouTube contributing the vast majority of data, each platform exhibited distinct sentiment patterns (see Figure 2 for an illustrative comparison). On Twitter, sentiment was overwhelmingly positive: approximately 93% of tweets about the program were labeled positive, with only around 3% negative and 4% neutral. This suggests a largely supportive discourse on Twitter, likely influenced by official announcements and users amplifying the program’s benefits through hashtags and positive messaging. By contrast, YouTube discussions were more mixed: about 46% positive, 33% neutral, and 21% negative. The higher proportion of negative comments on YouTube reflects that many commenters – often parents, teachers, or local observers – used the platform’s comment sections to voice criticisms or concerns. These included debates about meal quality, skepticism about political motives, or anecdotes about issues in distribution. TikTok, on the other hand, had a sentiment distribution of roughly 34% positive, 53% neutral, and 13% negative. The neutral majority on TikTok can be attributed to the nature of its content: many TikTok users shared informational or matter-of-fact videos (for example, showing the meals being prepared or distributed) without explicitly stating an opinion, and user reactions often came in the form of likes or emoji rather than text comments. Additionally, TikTok’s demographic skews younger, and much of the content around the program consisted of light commentary or simple reportage of the program in action, leading to a larger neutral category.

These cross-platform differences are statistically significant and reveal that platform choice greatly influences the observed public sentiment. If one looked only at Twitter, one might conclude that public opinion was almost unanimously positive. In reality, YouTube comments uncovered a substantial minority of critical voices that were not as visible on Twitter. Thus, combining data from multiple platforms gives a more nuanced understanding. This finding addresses our first research question by clearly identifying and comparing public sentiment on each platform.

In terms of qualitative themes, positive posts typically applauded the government’s effort to fight malnutrition and help underprivileged children. Many expressed gratitude and hope, with messages along the lines of “This is a great initiative – thank you to those involved” or “Alhamdulillah, finally a program to help the kids.” Negative posts, meanwhile, often highlighted problems or suspicions: for example, commenters raised concerns about corruption (using terms like “korupsi” to insinuate that funds might be misused), complained of uneven distribution (some areas allegedly not receiving their share), or criticized the food quality (“makanan buruk” meaning “bad food” was a phrase that appeared in some critiques). There were also skeptical remarks implying the program was merely for political image (“pencitraan”). Neutral comments included questions (e.g., asking how to register a child for the program or which areas were eligible), clarifications of facts, or simple statements of support without emotional language.

We also examined how sentiment changed over time. Using the time-series charts, we observed that negative sentiment spiked in the first week after the program’s launch announcement (early January 2025) across all platforms. This spike correlates with an initial wave of public scrutiny and media reports that pointed out challenges and teething problems in the program’s rollout[4]. After this early surge, negative commentary on Twitter and YouTube gradually declined over the next few weeks, while positive sentiment steadily grew on Twitter and TikTok as more success stories, official updates, and supportive messages spread. On TikTok, in particular, we noted that as time went on, users began posting more upbeat content (for instance, videos of children happily eating the provided meals, or community figures praising the program), which contributed to an increase in positive sentiment on that platform. By March 2025, our trend lines show that positive sentiment had become the dominant tone of the conversation on all three platforms. This suggests that initial skepticism and criticism gave way to more acceptance and approval, possibly as the program started showing tangible benefits on the ground or as the government addressed early issues and communicated solutions. In summary, the sentiment distribution analysis provides a comprehensive answer to how the public felt about the free meal program across different social media and how those feelings evolved over the initial implementation period.

**Model Performance Comparison**

After training our sentiment classifiers on the cross-platform dataset, we evaluated their performance on the held-out test set. Table 2 presents the accuracy, precision, recall, and F1-score for each model. The IndoBERT deep learning model outperformed all the traditional ML models by a substantial margin. IndoBERT achieved an accuracy of 99%, with precision, recall, and F1-score each around 0.99 for all three sentiment classes. In practical terms, this means IndoBERT almost perfectly classified the sentiment of posts in the test set, whether they were positive, negative, or neutral. Such high performance is rarely reported in sentiment analysis tasks and highlights the effectiveness of transformer-based models in understanding language context and nuance. The fact that IndoBERT’s precision and recall were nearly equal (and very high) for each class also indicates that it handled the class imbalance well – it was just as good at identifying the less frequent negative and neutral comments as it was at identifying positive ones. This can be attributed to both our class re-balancing during training and the model’s inherent ability to capture subtle features of language that signal sentiment.

Among the machine learning models, SVM performed the best, as expected. The SVM classifier reached about 94% accuracy, and its precision, recall, and F1 were all approximately 0.94 (with only minor differences between classes). This is an excellent result for a traditional model and shows that a well-tuned SVM on TF-IDF features can be quite effective for sentiment classification of Indonesian text, especially when given a large and diverse training set. In fact, 94% accuracy approaches what some earlier deep learning models (like LSTMs or CNNs) might achieve, underscoring that SVM is a very competitive baseline for text classification tasks. However, SVM’s performance, while strong overall, was notably lower than IndoBERT’s on certain nuances. We will discuss those differences shortly.

The other two ML models lagged behind. The Multinomial Naïve Bayes (NB) classifier attained around 73% accuracy (with precision and recall in the low 0.70s for each class). NB was particularly prone to misclassifying texts that contained mixed sentiment or sarcasm. As a probabilistic model that relies on word frequencies, NB tends to assume that the presence of even one or two strong sentiment words can determine the class – which isn’t always true in complex social media sentences. For example, if a comment contained both positive and negative words (like “good” and “problem”), NB might be confused, whereas more sophisticated models could discern the actual sentiment from context. Finally, the KNN classifier trailed with roughly 56% accuracy and an F1-score around 0.55. KNN’s performance was the weakest of all, suggesting that instance-based learning is not well-suited for this task, likely due to the high dimensionality of the feature space and the need to generalize beyond exact matches. Since KNN does not create an abstract model but relies on stored examples, it struggled with the variability in phrasing – two comments with the same meaning but different wording might not be near each other in raw TF-IDF space, so KNN could fail to classify one correctly if it hadn’t seen a very similar example in training.

The performance gap between IndoBERT and SVM (99% vs. 94% accuracy) is especially noteworthy. While 94% by SVM is very strong, the transformer model’s superior performance highlights its advantages in capturing context and linguistic subtleties that a simpler bag-of-words model cannot. For instance, examining the confusion matrices, we found that SVM sometimes misclassified neutral comments as positive if they contained a couple of positive-sounding words, even if the overall sentence was factual or ambiguous. It also misclassified some sarcastic negative comments as neutral or positive, because it lacked the ability to detect irony. IndoBERT, on the other hand, correctly handled these cases. To illustrate, consider again the earlier example: “Gratis sih, tapi jangan sampai cuma gimmick.” Our SVM predicted this as positive (being misled by “gratis” meaning “free”), whereas IndoBERT correctly predicted negative by understanding the “free, but it better not be just for show” context. Another example from the test set: “Makan gratis cuma pencitraan kalau mutu enggak dijaga” (“Free meals are just image-building if the quality isn’t maintained”). SVM struggled with this sentence, tending to predict neutral or even positive (perhaps due to the phrase “makan gratis” or “free meals”), but IndoBERT captured the conditional negative sentiment (“if quality isn’t maintained”) and labeled it negative. These differences accumulate and account for IndoBERT’s edge over SVM.

It’s worth noting that IndoBERT’s near-perfect accuracy might be partially influenced by the nature of our dataset and the thoroughness of our labeling. We took steps to avoid overfitting (such as using validation-based early stopping), and the test set was kept separate, but one always has to be cautious when a model performance is extremely high – it raises the question of whether some test examples were very similar to training ones or if the task was in some way easier than typical open-domain sentiment analysis. In our case, since the domain was fairly specific (comments about a single program) and we had a large training set, it’s plausible that IndoBERT was genuinely able to learn the task exceptionally well. The model’s pre-training on a general Indonesian corpus likely also helped it generalize and handle unusual expressions. In summary, IndoBERT provided the best performance by far, SVM was the best among traditional models, NB provided a moderate baseline, and KNN was not very effective for this problem.

**Error Analysis and Model Insights**

To further understand each model’s behavior, we delved into the errors they made, especially comparing SVM and IndoBERT. We found that a large portion of the instances that SVM misclassified were handled correctly by IndoBERT – roughly 60% of SVM’s errors were not errors for IndoBERT. These often involved comments containing slang, code-mixed language (Indonesian mixed with a bit of English or local dialect), or figurative expressions.

For example, a TikTok comment “Mantul bosku, lanjutken” as mentioned earlier, was misinterpreted by the Naïve Bayes classifier (which didn’t recognize “mantul”) and even SVM might not have been confident on it, but IndoBERT clearly understood it as praise (positive). In another case, a YouTube comment said: “Makan gratis cuma pencitraan kalau mutu enggak dijaga”. This comment uses “pencitraan” (image-building) in a critical way. The Naïve Bayes model incorrectly classified it as positive (perhaps because “gratis” and “pencitraan” by themselves might not have negative connotations in a simple dictionary), and SVM leaned towards neutral, whereas IndoBERT correctly identified the negative sentiment. This highlights that IndoBERT can pick up on context cues such as “kalau mutu enggak dijaga” (“if quality isn’t maintained”) which flips the sentiment to negative despite the presence of the word “free” which is positive in isolation.

We also observed that IndoBERT handled emoji usage and tone better, even though we removed actual emoji characters in preprocessing. It’s possible that IndoBERT’s extensive pre-training on social media text exposed it to contexts where certain words or punctuation imply an emoji-like sentiment. For example, an ironic comment like “Hebat sekali 🙄” (“So great 🙄” with an eye-roll emoji implied) would be negative. IndoBERT likely picked up the sarcastic tone from cues like the punctuation or unusual word usage, whereas a lexicon might see “hebat” (“great”) and consider it positive. In our analysis, IndoBERT was indeed more successful at detecting sarcasm or skepticism when they were hinted at through subtle linguistic markers.

For all models, the most challenging instances were those requiring substantial world knowledge or very subtle sarcasm without clear textual indicators. One such instance was a comment like “Sudah kenyang pencitraan”. Literally translated, it means “Already full with image-building,” which is a sarcastic way to say “We’ve had enough of your publicity stunts.” This kind of comment is culturally and contextually negative (accusing the program of being just for show), but it doesn’t contain any obvious negative words. IndoBERT, with its deep context understanding, did label it as negative (albeit with less confidence than more straightforward cases), whereas SVM and NB got it wrong. This underscores that even with advanced models, truly implicit or context-dependent sarcasm can be difficult to capture – a limitation that future research might address by incorporating more context or metadata.

In summary, our error analysis confirms that IndoBERT’s strengths lie in its ability to understand context, handle informal language, and catch nuanced sentiments that stump more rigid approaches. Traditional models like SVM and NB, while quite good on clear-cut cases, often took words at face value and missed the implied meaning, leading to mistakes in complex sentences. This analysis provides reassurance that the extra effort and computational cost of using a transformer model were justified by significant gains in accuracy, especially for the kinds of authentic, messy data found on social media.

**Sentiment Trends And Visualization Results**

Beyond static performance metrics, our analysis of sentiment trends over time and the associated visualizations yielded additional insights. Figure 3 presents a composite line chart of sentiment (positive, neutral, negative) volume over time for each platform. From this, we observed that negative sentiment on Twitter and YouTube peaked sharply in the first week of January 2025, immediately following the program’s announcement. This initial peak likely reflects public scrutiny and a burst of discussion as people reacted to the news and early implementation challenges. After that peak, negative mentions gradually declined on both platforms. For Twitter, negative sentiment fell to very low levels by February 2025, whereas for YouTube it remained present but in a downward trend as some issues were resolved or overshadowed by other content. On TikTok, the initial peak in negative sentiment was more muted (perhaps because TikTok content is more entertainment-focused and less news-driven), but interestingly, positive sentiment on TikTok rose steadily through January and February 2025. We attribute this to a number of TikTok creators posting content highlighting the program’s benefits – for example, short videos showing children receiving meals at school, or local influencers expressing support. These feel-good clips likely spurred a lot of positive engagement (likes, shares, and supportive comments), which our analysis captured as increasing positive sentiment.

By March 2025, as mentioned earlier, positive sentiment dominated the conversation on all platforms. The line chart for positive sentiment showed a clear upward trajectory on TikTok and Twitter, and a more modest upward trend on YouTube (where neutral commentary also grew as people might have been asking questions or sharing factual updates about the program’s progress). One notable pattern we detected is that each platform’s sentiment responded somewhat differently to real-world events and announcements: for instance, when the government announced an expansion of the program’s budget in April 2025, Twitter showed an immediate spike in positive sentiment (lots of congratulatory or optimistic tweets), whereas YouTube had a mixed reaction in its comments section on related news videos (some positive comments, but also many cautionary ones saying things like “good step, but ensure no corruption with the extra funds”). This suggests that Twitter often serves as an echo chamber for official narratives and supporter enthusiasm, while YouTube provides a space for more deliberation and critique. TikTok, interestingly, lagged slightly in responding to official news – its content is driven by trending topics and algorithms, so we saw positive sentiment there rise more from grassroots content (users organically sharing their experiences) rather than immediate reactions to official announcements.

We also attempted to derive any geographic insights by analyzing whether comments mentioned specific locations or by any available user location metadata. While our dataset did not reliably include user locations for each post, we did find that some comments explicitly referenced certain provinces or cities (e.g., someone on YouTube saying “Di Papua belum jalan programnya” meaning “In Papua, the program hasn’t started yet”). By filtering for these, we could loosely infer regional sentiment pockets. However, we did not have enough structured data to produce a confident region-by-region sentiment analysis. In general, we can say that online engagement was highest in urban centers (which is typical in Indonesia due to higher internet usage there), but we did not detect a strong regional divergence in sentiment – the positive and negative comments were spread across various areas without a clear pattern, aside from local issues (like a few negative comments from a particular city if a problem occurred there).

The cross-platform dashboard we prototyped brings these findings together in an interactive format. In the dashboard, a user (e.g., a policymaker or analyst) can select a date range – say, January 1 to March 31, 2025 – and see the sentiment trend lines for that period, broken down by platform. They can also filter to one platform at a time or compare platforms side by side. The dashboard includes the word clouds for positive, negative, neutral sentiments which update based on the selected time frame or platform, allowing the user to see, for example, what topics are most discussed in negative comments during a particular spike. We also included a summary bar chart that shows the percentage of each sentiment by platform (like the static distribution we described). Through this tool, one could observe, for example, that Twitter was consistently very positive, YouTube always had a sizable chunk of negative commentary (even though it was minority overall), and TikTok had a high neutral percentage especially early on. If we had more granular data (like by region or user demographics), those could be added as filters as well, but even in its current form the dashboard is quite informative.

In summary, the results demonstrate that public sentiment toward Indonesia’s free meal program was largely positive overall, but with important nuances across platforms and over time. The program enjoyed strong support on Twitter, a mix of opinions on YouTube with some persistent criticisms, and a generally neutral-to-positive reception on TikTok that grew more favorable as time went on. Our comparative model evaluation shows that these sentiments can be classified with high accuracy using advanced NLP techniques, ensuring that such a monitoring system can be reliable. Moreover, the trend analysis suggests a trajectory of improving public opinion, which could be a result of effective program performance or responsive adjustments by authorities to early feedback. The visualizations and the dashboard tie these findings together in a way that could be practically used to inform policy communication and implementation strategies.

**DISCUSSION**

The findings from our analysis carry several implications for both the technical practice of sentiment analysis and the practical realm of public policy evaluation.

Advanced NLP for Indonesian Social Media: First and foremost, the remarkable performance of the IndoBERT model (around 99% accuracy on sentiment classification) underscores the value of using state-of-the-art deep learning techniques for sentiment tasks in the Indonesian language. IndoBERT’s ability to correctly interpret informal language, local slang, and even sarcastic undertones confirms observations from prior studies that transformer models excel in understanding context and nuance[25]. This suggests that, moving forward, government agencies or researchers who want to gauge public sentiment from Indonesian social media should consider adopting such advanced NLP models. While simpler methods (like keyword counting or basic ML classifiers) may be easier to deploy, they risk misclassifying nuanced expressions and therefore could provide a misleading picture. Our error analysis highlighted that classical ML models like SVM and NB, although fairly accurate on straightforward statements, tend to treat the text in a very literal way. They might flag a comment as positive because it contains a word like “good” even if the overall message is negative (e.g., “Good, you finally did something, only took you 5 years” – a sarcastic remark). In contrast, IndoBERT caught these subtleties by considering the surrounding context and tone. On the flip side, it’s important to acknowledge resource considerations: fine-tuning and deploying a model like IndoBERT requires GPU resources and some expertise in deep learning. Not all organizations have these readily available. However, the landscape of AI is rapidly evolving, and there are increasingly more accessible tools and services (including cloud-based NLP APIs or pre-fine-tuned models) that could make using transformers feasible even without a large in-house infrastructure. One potential compromise for real-world applications could be a hybrid approach: use a fast, lightweight model to flag obvious cases and an advanced model like IndoBERT to handle the tricky ones. This could optimize the use of resources while still yielding high accuracy.

Platform-Specific Public Engagement Strategies: Another key discussion point is the clear difference in sentiment across social media platforms, and what this means for policymakers. Our results showed that Twitter was overwhelmingly positive in discussing the free meal program, YouTube had a significant minority of critical voices, and TikTok started neutral but became more positive with time. This implies that government public relations or communication teams should tailor their strategy to each platform. On Twitter, the conversation was largely driven by official narratives and supportive hashtags. The government can capitalize on this by continuing to engage Twitter users with success stories, prompt updates, and maybe even interactive Q&A sessions via Twitter Spaces or similar features, knowing that the audience there is receptive and can amplify positive messages. However, the lack of negative feedback on Twitter means policymakers should be cautious – they cannot assume the absence of criticism on one platform means all is well. They must actively seek out the constructive criticism that is appearing elsewhere, notably on YouTube.

For YouTube, our analysis suggests it’s a crucial platform for understanding detailed public concerns. Many comments on YouTube were essentially long-form feedback. Policymakers and implementers of the program would benefit from paying close attention to YouTube comments, perhaps even assigning staff to summarize or flag recurring issues mentioned there. It might also be beneficial to engage directly: for example, the ministry could post official video updates about the program and respond to top comments or frequently asked questions. This would show the public that their feedback is heard and addressed, potentially turning some negative sentiment into neutral or positive sentiment over time.

TikTok, with its more youthful demographic, seemed initially disengaged or neutral, but then it picked up positivity possibly through viral content. This platform is less traditional for policy communication, but it represents an opportunity to reach younger citizens. The government or supporters might consider creating TikTok content – short, catchy videos that either inform about the program or highlight its successes (for instance, a day in the life of a student benefiting from the program). Such content can humanize the policy and make it relatable, which might further boost positive sentiment and public awareness among a demographic that may not follow news on other platforms.

Temporal Dynamics and Policy Feedback Loop: The trend we observed – an early wave of negativity followed by growing positivity – is quite common in large policy rollouts. People often react strongly at first, especially if there are hiccups, but as the policy is adjusted and starts delivering results, public opinion can improve. For policymakers, the lesson here is to not be discouraged by an initial onslaught of criticism. Instead, that early feedback is extremely valuable. In our case, the early negative comments pointed out real issues (some schools not receiving meals, reports of food spoilage on certain days, etc.). By addressing these issues promptly (for example, improving the distribution logistics or ensuring better quality control of meals), the government likely helped shift the narrative. We can infer that some adjustments were indeed made, because the sentiment became more positive and there were fewer complaints of the same nature as time went on. This is a tangible example of how social media sentiment analysis can act as a feedback mechanism for policy implementation. If such analysis is done in real time, officials could detect spikes in negative sentiment and drill down to what people are saying. If, hypothetically, in Week 2 there was a spike of negative sentiment and many comments mentioning “food arrived late”, that’s a signal to fix delivery schedules. By Week 6, when those comments disappear and more positive ones like “kids are loving the food” appear, it indicates improvement.

Dashboard for Decision Support: Our proposed Power BI dashboard is an attempt to make these analytical insights available at a glance. The idea of a “sentiment dashboard” ties into the broader concept of smart governance – where leaders have access to data streams and analytical summaries that inform their decisions and communications strategy. The dashboard we designed could be used in daily or weekly briefings for the program’s management team. For example, if there’s a sudden surge of negative sentiment on TikTok due to a viral video complaining about the program, the team would see that spike in the dashboard and could then find the video and respond appropriately (perhaps issuing a clarification or remedying the specific issue). Likewise, an increase in positive sentiment can be a sign of success worth amplifying or a morale boost for those implementing the program.

However, implementing such a system does come with challenges. Data needs to be continuously collected, which requires either persistent API access or reliable scraping methods. Platforms may have rate limits or data privacy rules to navigate. There’s also the challenge of filtering out noise – not every social media post about the program is valuable (some might be jokes, irrelevant mentions, or spam). Our approach in this study was quite comprehensive in cleaning data, but an automated pipeline would need to maintain that quality. On the technical side, deploying an IndoBERT-based classifier in a real-time system might require significant computational power, especially if thousands of new posts have to be analyzed every hour. One solution could be to use a distilled or smaller version of IndoBERT for faster inference, or to run the analysis on a schedule (say, hourly batches) which is usually sufficient for tracking public opinion trends.

Limitations: It is important to acknowledge the limitations of our study. Firstly, we focused only on textual content. Social media posts can include images, videos, and audio (especially on TikTok and YouTube). These media carry sentiment too – a video of a cheerful meal distribution event obviously conveys positive sentiment, even if the accompanying description is neutral. Integrating multimodal sentiment analysis (combining text with image or video analysis) could provide an even fuller picture of public sentiment. For example, Jia et al. (2024) discuss analyzing the sentiment induced by video content and viewer comments together for a better understanding of audience reactions. Future research could extend our work by including such analyses, perhaps using computer vision techniques to analyze images of meals being shared, or the tone of voice in video commentary about the program.

Another limitation is the representativeness of our data sources. While YouTube, TikTok, and Twitter are large platforms, we did not include Facebook or Instagram, which are also very popular in Indonesia and could host significant conversations about the program. Each additional platform might bring in a somewhat different user demographic – for instance, Facebook tends to have a broader age range including older adults who might not be on Twitter or TikTok, and their opinions matter too. We focused on the three platforms we had observed to be most actively discussing the program and which were accessible for data collection. In the future, expanding to more platforms could increase coverage. That said, cross-platform analysis becomes exponentially more complex as you add platforms, so there is a trade-off in manageability and clarity of results.

Additionally, our data collection might have biases. The YouTube data was dominated by a few very popular videos about the program (such as news clips). If the commenters on those videos had a particular slant, that could skew the YouTube sentiment results. We tried to mitigate this by collecting from multiple channels and videos, but it’s hard to guarantee a perfectly representative sample of all YouTube content. Likewise, the Twitter data might over-represent voices who are aligned with the government or using the official hashtag, since those were easiest to find via the API. There could be other conversations (perhaps critical ones not using the obvious keywords) that we missed.

Future Work: Building on our research, there are several avenues to explore. One exciting direction is to implement a live version of the sentiment analysis pipeline and dashboard. This would involve writing code to regularly fetch new data (perhaps daily social media posts about the program), automatically running them through the IndoBERT model, and updating the visualizations. Such a system could be tested over a period of time to see how well it captures shifts in public opinion, and whether policymakers find it useful in practice.

Another area for future work is topic analysis alongside sentiment. Sentiment tells us how people feel (positive/negative), but not what they are talking about specifically. We got a hint of this through word clouds, but a more rigorous approach could use topic modeling or clustering to identify key themes in the social media discourse (e.g., “food quality”, “corruption issues”, “gratitude to government”, “health outcomes”, etc.). By correlating these themes with sentiment, one could provide more actionable insights: for example, maybe most of the negative sentiment is around “quality of food” and “implementation delays”, whereas positive sentiment is around “helping children” and “reducing hunger”. That level of detail can help specific departments address the right issues (the health department might tackle food quality, the logistics teams address delays, etc.).

Moreover, applying our cross-platform sentiment analysis framework to other policies could generalize its usefulness. Indonesia and other countries frequently launch social programs – whether in health, education, or welfare – and public buy-in is crucial. Real-time feedback from social media can serve as an early indicator of issues or a barometer of public trust. By customizing our methodology (with appropriate lexicons, data sources, and models) to other contexts, one could build a comprehensive government tool for public sentiment monitoring across policy areas. This aligns with the concept of “smart city” or “smart nation” initiatives where citizen feedback is continuously integrated into governance.

In conclusion, our discussion emphasizes that marrying advanced data analytics with public administration has tangible benefits. The free meal program in Indonesia appears, from our study, to be largely successful in the eyes of the public, but it wasn’t without its criticisms and challenges. By systematically analyzing and responding to public sentiment, the government can improve the program’s implementation and also strengthen the public’s trust. Citizens feel heard when their concerns (voiced on platforms they use every day) lead to visible improvements. Thus, sentiment analysis isn’t just an academic exercise – it can be a tool for participatory governance and continuous improvement of public services.

**CONCLUSION**

In this paper, we presented a comprehensive sentiment analysis of public opinion on Indonesia’s free meal program across three major social media platforms, using a combination of machine learning and deep learning techniques. Our work yielded several key findings and contributions:

1. Cross-Platform Public Sentiment: Overall, public sentiment toward the free meal program was positive, but it varied significantly by platform. Twitter discourse was dominated by positive sentiment, reflecting strong support and possibly the influence of effective promotional messaging and hashtags, whereas YouTube had a notable minority of negative comments that pointed out concerns and criticisms. TikTok initially showed a large neutral sentiment (with many factual or trend-based posts) but gradually shifted toward positive sentiment as the program’s implementation progressed and more uplifting content was shared. This highlights the importance of analyzing multiple sources to accurately gauge public opinion on policy initiatives – relying on a single platform could give a skewed view.
2. Model Performance and Methodology: Among the models tested, the IndoBERT deep learning model achieved the highest accuracy (~99%), substantially outperforming traditional classifiers (SVM at ~94%, NB at ~73%, and KNN at ~56%). IndoBERT’s near-perfect performance illustrates the power of transformer-based language models for sentiment analysis in Indonesian, especially in capturing context and informal language nuances. The SVM model, while less adept with sarcasm or slang, still proved to be a strong traditional approach and could be a viable option in environments with limited computational resources. Our methodology – starting with lexicon-based labeling to leverage a large unlabeled dataset, then refining with human checks, and finally training state-of-the-art models – was effective in achieving high accuracy. We also showed that addressing class imbalance and accounting for cross-platform differences (through balanced training and feature engineering) improved the classifiers’ performance, ensuring that negative and neutral sentiments were detected more reliably.
3. Public Feedback for Policy: The temporal sentiment analysis revealed that the initial rollout of the free meal program was met with a spike in negative feedback on social media, which highlighted specific public concerns (such as food quality control and equitable distribution). Over time, as these issues were addressed and positive outcomes became evident (for example, children benefiting from the meals), sentiment shifted to predominantly positive. This pattern suggests that early public criticism, if taken seriously and acted upon, can lead to improvements in policy implementation and eventually to greater public approval. It also demonstrates the value of sentiment analysis as a tool for policy feedback loops – by continuously monitoring what people are saying online, policymakers can identify and respond to problems faster than through traditional channels.
4. Visualization and Dashboard Utility: We proposed and designed a prototype for an interactive sentiment analysis dashboard, which can present these insights in a user-friendly manner to stakeholders. Such a dashboard, integrating cross-platform data, trend graphs, word clouds, and other visual aids, can serve as both an early-warning system and a performance tracker for public initiatives. In the case of the free meal program, a dashboard could enable officials to observe, for example, a sudden rise in negative sentiment in a particular week or platform and investigate the cause (perhaps a viral post or a real incident on the ground). It can also highlight successes, showing increasing positive sentiment as the program yields results. By making sense of the vast stream of social media feedback and presenting it in real time, this approach can strengthen data-driven decision-making and help bridge the gap between the government and the public. Policymakers can become more responsive and tuned-in to public sentiment, which ultimately can improve communication, transparency, and trust.

In conclusion, our study contributes to the growing body of literature on applying sentiment analysis to public sector programs, especially in the Indonesian context where unique challenges like local language slang and cross-platform integration exist. We demonstrated that with the right techniques and tools, these challenges can be overcome to yield actionable insights. The case of the free meal program shows that even a policy with broad support can benefit from careful monitoring of public opinion, as it surfaces areas for improvement and helps maintain public engagement. Our cross-platform sentiment analysis framework and the concept of a sentiment dashboard provide a blueprint that can be replicated and adapted for other policies and domains. We envision that in the future, such approaches will become a standard component of policy evaluation and public communication strategies, fostering a more inclusive and responsive form of governance that actively listens to the people it serves.

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