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Analyzing Public Sentiment Toward the Makan Bergizi Gratis (MBG) Program on TikTok Using SVM and IndoBERT

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Abstract— **Social media has become a major platform for the public to express opinions toward government programs. This study analyzes public sentiment toward Indonesia's Makan Bergizi Gratis (MBG) program using a text mining approach. A total of 11,730 TikTok comments related to the MBG program were collected and classified into positive, negative, and neutral sentiments. Two classification models were compared: a traditional Support Vector Machine (SVM) using TF-IDF features and a transformer-based model, IndoBERT. Experimental results show that IndoBERT outperforms the tuned SVM model, achieving an accuracy of 0.78 and a weighted F1-score of 0.78, compared to 0.73 accuracy and 0.73 F1-score obtained by the SVM. IndoBERT demonstrates better performance in handling neutral and context-dependent sentiments, indicating its effectiveness for analyzing Indonesian social media data related to public policy evaluation. This study contributes to the growing body of research on Indonesian sentiment analysis by providing an empirical comparison between classical machine learning and transformer-based models for analyzing public responses to government policies using social media data. The findings also highlight the importance of advanced language models in capturing linguistic nuances, informal expressions, and contextual meanings commonly found in online discussions, particularly on rapidly evolving social media platforms widely used by Indonesian users across different demographic and social backgrounds.**

Keywords—Sentiment Analysis; Text Mining; IndoBERT; Support Vector Machine; Public Policy; MBG

I. INTRODUCTION

Public policies often evoke diverse public responses, ranging from trust and support to criticism. To address malnutrition and promote balanced nutrition, the Indonesian government, through Badan Gizi Nasional (BGN), launched the Makan Bergizi Gratis (MBG) program in early 2025. The program prioritizes children's health while encouraging collaboration among local governments, cooperatives, and small businesses to ensure balanced nutrient distribution based on Angka Kecukupan Gizi (AKG) [1]. Institutional strengthening and transparency mechanisms, such as MBG Watch, have also been emphasized to support effective program implementation [2], [3].

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In the digital era, social media has become a primary platform for citizens to express opinions regarding government initiatives. Analyzing these online discussions provides valuable insights into public perception and acceptance of public policies. Natural Language Processing (NLP) and text mining techniques enable large-scale sentiment analysis to identify public opinion trends efficiently [4], [5]. Previous studies have shown that NLP-based sentiment analysis can effectively measure public trust toward government policies, achieving accuracy levels above 85% [4], [6].

Recent research in Indonesia further indicates that transformer-based models, such as IndoBERT and IndoBERTweet, outperform traditional approaches like Naïve Bayes and LSTM in sentiment classification tasks. Studies by Nugroho et al. [8] and Setiawan et al. [7] reported accuracy levels exceeding 80% when applying BERT-based models to Indonesian-language data. These findings suggest that contextual language models are better suited to capture linguistic nuances in social media text.

Research applying sentiment analysis to nutrition-related public policies remains limited. A recent study on the MBG program by Fatkhurrohman et al. [9] employed the SVM method on Twitter data and achieved an accuracy of 0.80; however, the model struggled to distinguish negative and neutral sentiments. Furthermore, most existing studies rely on a single modeling approach and primarily utilize Twitter datasets, leaving limited investigation into other social media platforms and limited comparison between classical machine learning and transformer-based models.

To address this gap, this study conducts a comparative analysis between SVM and IndoBERT using TikTok comment data related to the MBG program. By evaluating the performance of a classical machine learning model alongside a transformer-based model on the same dataset, this research aims to identify a more robust approach for sentiment classification while providing data-driven insights into public perception of the MBG policy in Indonesia's nutrition sector. The findings of this study are expected to contribute to the development of more effective NLP-based methods for analyzing public opinion on social media and to support evidence-based evaluation of government nutrition policies.

II. RELATED WORKS

The integration of NLP and sentiment analysis has become a core method for understanding public attitudes across various sectors. Suhas and Prarthana define sentiment analysis as a subfield of text mining that categorizes human opinions into positive, negative, or neutral sentiments [5]. Deep learning models like CNN, LSTM, and transformers have demonstrated superior performance in handling linguistically diverse and large-scale datasets.

In the Indonesian context, text mining still faces linguistic challenges due to informal language in social media. Kurniawan et al. proposed the GATA Framework to improve preprocessing quality via tokenization, normalization, and stemming [10]. Later, Asri et al. [11] refined this approach by combining IndoBERT and the INSET lexicon, resulting in higher sentiment classification accuracy [11].

Setiawan et al. compared LSTM and IndoBERTweet on Indonesian TikTok reviews and found that IndoBERTweet achieved 0.80 accuracy, surpassing LSTM's 0.78 [7]. Similarly, Nugroho et al. from Brawijaya University demonstrated that fine-tuning BERT with Indonesian datasets outperformed multilingual models, achieving 0.84 accuracy [8]. Further reinforcing this, Manoppo et al. (2025) used IndoBERT to analyze sentiment regarding a 12% VAT increase, collecting data from X, Instagram, and TikTok, and achieved a high accuracy of 0.8494 and an F1-score of 0.8437 [12].

Harwenda et al. conducted a systematic literature review summarizing the effectiveness of SVM, BERT, and Naïve Bayes across public policy studies, showing that BERT-based models deliver the best results for nuanced textual data [13]. Muhandhis and Ritonga also applied a Random Forest classifier to analyze TikTok sentiment on the Tapera policy, achieving 0.89 accuracy and emphasizing the dominance of negative sentiments in government-related discourse [14].

However, most previous studies focus on economic, political, or infrastructure topics [13]-[14]. Research on nutrition and social welfare policies, such as the MBG program, is an emerging area. For instance, Fatkhurrohman et al. applied the Support Vector Machine (SVM) method to analyze Twitter sentiment on the MBG program, finding a dominant positive sentiment and achieving 80% accuracy, though the model struggled with negative and neutral classes [9]. This highlights a need for more robust models. By incorporating both deep learning (IndoBERT) and traditional machine learning (SVM) approaches, this study aims to build on this existing work and contribute new insights into NLP applications for public policy evaluation, specifically in Indonesia's nutritional program context.

III. METHODOLOGY

Figure 1. illustrates the overall research methodology flowchart, which consists of nine main stages: (A) Research Design, (B) Data Source and Collection, (C) Sentiment Labelling, (D) Data Splitting, (E) Text Preprocessing, (F) Text Representation, (G) Handling Class Imbalance, (H) Modelling Approach, and (I) Evaluation Metrics.

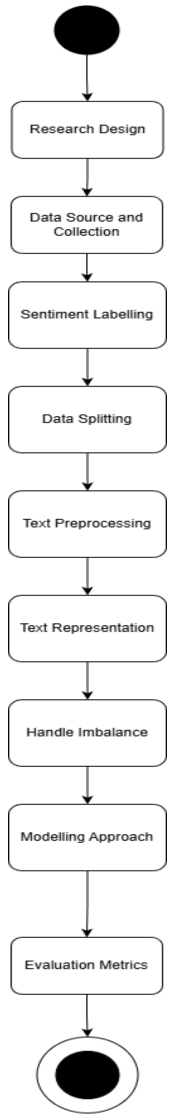

Figure 1. Nine Stages of Methodology

a. Research Design

This study adopts a quantitative text mining approach to analyze public sentiment regarding Indonesia's Makan Bergizi Gratis (MBG) program. The research employs a comparative modelling framework using two machine learning methods:

- Support Vector Machine (SVM) as a classical baseline classifier.
- IndoBERT, a transformer-based deep learning model specifically trained for the Indonesian language.

In this study, the transformer-based approach utilizes the IndoBERT-base model (indobenchmark/indobert-base-p1), which has been widely adopted in Indonesian natural language processing research for sentiment classification tasks. The comparative design allows performance evaluation between a traditional machine learning model and a contextual language model, an approach commonly adopted in recent Indonesian NLP studies [8]-[9],[11]-[12].

b. Data Source and Collection

The dataset consists of public comments collected from TikTok, extracted from three official videos related to the launch of the MBG program. Data collection was conducted through automated scraping using the Apify platform, implemented via the ApifyClient library in Python.

Although the scraping process was capable of retrieving multiple metadata attributes, this study utilizes only the comment text as the primary unit of analysis. Other attributes such as timestamps, video identifiers, and comment identifiers were excluded, as they were not required for the objectives of this text-based analysis.

Prior to analysis, a manual data cleaning process was applied to ensure topical relevance and data quality. Comments were reviewed and removed if they met one of the following criteria: (1) containing only emojis or non-textual symbols, (2) discussing topics unrelated to the MBG program, such as fuel prices, civil servant salaries, or other government policies not associated with nutrition or food assistance, or (3) duplicated entries. The filtering process was conducted by the two research authors based on content relevance, without applying a minimum word-count threshold, as short comments may still convey valid sentiment. This procedure follows common dataset refinement practices in Indonesian social media sentiment analysis [6], [15]. After cleaning, the final dataset consisted of 11,730 comments.

Video Sources:

- https://vt.tiktok.com/ZSfApJr81/
- https://vt.tiktok.com/ZSfAp8CEs/
- https://vt.tiktok.com/ZSfAgpPD7/

Dataset Source:

- https://drive.google.com/drive/folders/1wcZCeNU9Nv1vc4nrjsPwMyzLeM_xt9pm?usp=sharing

c. Sentiment Labelling

To construct a reliable sentiment dataset, this study employed a semi-automated annotation strategy that combined model-assisted labeling with human verification. Initial sentiment labels were generated using a pretrained IndoBERT-based sentiment classifier, specifically the IndoBERT-base-uncased checkpoint fine-tuned on publicly available Indonesian sentiment datasets consisting primarily of social media texts. This model was used solely as an auxiliary tool to accelerate the annotation process and was not treated as the ground truth.

The classifier assigned each comment into one of three categories: positive, negative, or neutral. Positive sentiment refers to comments expressing support, agreement, or favorable opinions toward the MBG program, while negative sentiment includes criticism, dissatisfaction, or rejection of the policy. Neutral sentiment represents comments that are informational, ambiguous, or do not express a clear emotional stance. Following automatic labeling, all annotations were manually reviewed by two human annotators with prior experience in Indonesian sentiment analysis. Approximately 30–40% of the automatically labeled samples were corrected, primarily due to contextual ambiguity, sarcasm, or implicit sentiment that the model failed to capture accurately. In cases of annotator disagreement, the final label was determined through discussion to reach consensus. This double-review process helps ensure annotation consistency and improves the reliability of the final sentiment labels.

To mitigate the risk of automatic label bias, the final sentiment labels used for model training and evaluation were entirely based on human judgment rather than the model's original predictions. Furthermore, the IndoBERT model used for automatic labeling was a pretrained classifier and was not fine-tuned on the MBG dataset, whereas the IndoBERT model evaluated in this study was trained from scratch using the manually verified labels. As both SVM and IndoBERT were evaluated on the same human-corrected annotations, any potential bias introduced during automatic labeling would affect both models equally. This human-in-the-loop annotation procedure minimizes model-induced bias and ensures labeling reliability and dataset validity, as commonly adopted in sentiment analysis research [4]–[6], [13].

d. Data Splitting

After completing the annotation process, the dataset was divided into three subsets: 70% for training, 15% for validation, and 15% for testing. This split was applied consistently to both the SVM and IndoBERT pipelines to ensure comparable evaluation across models. The decision to include a dedicated validation set aligns with standard practices in sentiment analysis and text classification, particularly when fine-tuning transformer-based models such as IndoBERT, which require ongoing performance monitoring during training to prevent overfitting [7], [11]-[12], [18]. A structured data split is also widely recommended in public opinion and sentiment analysis studies to maintain model generalization and ensure reliable performance assessment [4]-[6], [13]. By adopting this partitioning strategy, the study ensures that training, hyperparameter tuning, and final evaluation are conducted using non-overlapping data segments, thereby improving the robustness and reproducibility of the results.

e. Text Preprocessing

The preprocessing stage differed between the SVM and IndoBERT pipelines due to the distinct characteristics of classical machine-learning models and transformer-based architectures. For the SVM workflow, the text underwent comprehensive normalization, including lowercasing, slang dictionary standardization, stopword removal using an Indonesian stopword list, stemming with Sastrawi, and the removal of URLs, emojis, punctuation, numbers, and other non-alphabetic characters. This approach aligns with the GATA Framework and common preprocessing strategies in

Indonesian sentiment analysis research [9]-[11]. In contrast, IndoBERT did not employ stemming or stopword removal because transformer models rely on contextual embeddings rather than lexical simplification. Instead, preprocessing consisted of lowercasing (IndoBERT-base uncased), tokenization using BertTokenizer, and automated padding and truncation to a maximum sequence length of 128, including the insertion of special tokens such as [CLS] and [SLP]. This procedure follows established IndoBERT fine-tuning practices in prior studies [8], [12].

f. Text Representation

For the SVM classifier, text representation was performed using TF–IDF vectorization, which transforms the preprocessed text into a sparse numerical matrix based on term frequency and inverse document frequency values. This study utilized unigram and bigram features to capture both individual words and short contextual word pairs, while the remaining TF–IDF parameters followed the default settings provided by the scikit-learn library. TF–IDF is widely applied in traditional machine-learning–based sentiment analysis because it effectively distinguishes important terms from common ones in Indonesian text data, as demonstrated in previous studies on government policy sentiment and Indonesian user-generated content [6], [9], [15]. Meanwhile, IndoBERT did not require TF–IDF because transformer models generate contextual embeddings through multi-layer encoder representations that capture semantic meaning at the token and sentence levels [7]-[8], [12].

g. Handle Imbalance

The dataset exhibits a noticeable class imbalance, as shown in Figure 2. Negative sentiment dominates the dataset with approximately 37% of the total samples, followed by positive sentiment at around 32%. In contrast, neutral sentiment is significantly underrepresented, accounting for only about 13% of the data. To address the imbalanced distribution of sentiment classes in the dataset, both the SVM and IndoBERT models employ class-weighting strategies during training. Class weights are assigned based on the inverse frequency of each sentiment label, allowing the models to penalize misclassification of minority classes more heavily while reducing the influence of dominant labels. This approach is widely used in Indonesian sentiment analysis studies to mitigate bias in supervised learning models, especially when dealing with public opinion or social media datasets that naturally exhibit label imbalance [6], [9], [13].

For IndoBERT, the class-weighting mechanism is incorporated through a customized loss function using weighted cross-entropy. The loss function is defined in Equation (1) as follows:

$$L = -\sum_{i=1}^{C} W_i Y_i \, log \log(\hat{y}_i) \tag{1}$$

where C denotes the number of sentiment classes, represents the ground-truth label in one-hot encoding, yi is the predicted probability for class i, and wi is the class weight assigned to each sentiment category. The class weights are calculated using inverse class frequency in Equation (2):

$$W_i = \frac{N}{C \times n_i} \tag{2}$$

where N is the total number of samples and nin_ini is the number of samples belonging to class iii. This weighted loss formulation encourages the model to improve sensitivity toward minority classes without altering the original data distribution, in line with prior transformer-based sentiment analysis research [7]-[8], [12].

Meanwhile, the SVM model integrates class weights directly into the classifier's optimization process, enabling the adjustment of decision boundaries in favor of underrepresented sentiment classes. This strategy is commonly applied in traditional machine-learning workflows for Indonesian text mining tasks [9], [15].

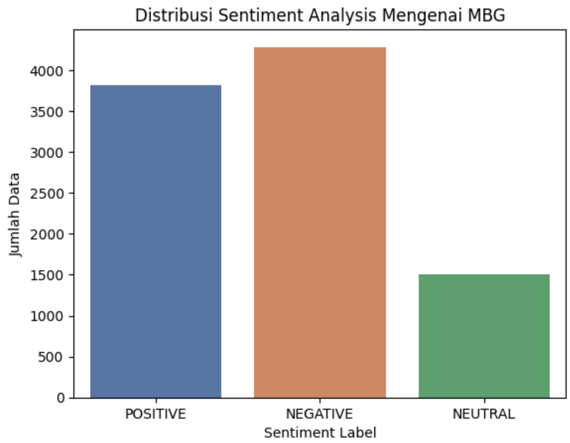

Figure 2. Distribution of sentiment classes in the MBG TikTok comment dataset, illustrating the class imbalance among positive, negative, and neutral sentiments

h. Modelling Approach

The sentiment classification stage in this study employs two modeling approaches: a traditional machine-learning pipeline using Support Vector Machines (SVM) and a transformer-based fine-tuning process using IndoBERT. For the SVM model, the workflow begins with TF–IDF vectorization to convert text data into numerical features, followed by class weight oversampling method to reduce class imbalance. A Linear Support Vector Classifier is then trained using these representations.

Hyperparameter tuning for the SVM model was conducted by evaluating several values of the regularization parameter C (0.01,0.1,1,10), which controls the trade-off between margin maximization and classification error. The optimal configuration was selected based on the highest weighted F1-score on the validation set, while other parameters were kept at their default settings to ensure model simplicity and reproducibility. SVM remains a widely used baseline in Indonesian sentiment analysis due to its strong performance on sparse textual features and its robustness across social media datasets [9], [13], [15].

In parallel, the IndoBERT model is fine-tuned using the IndoBERT-base architecture, where text is tokenized using the official IndoBERT tokenizer and fed into the BertForSequenceClassification model. To address class imbalance, a class weighted loss function is applied, consistent with previous Indonesian transformer-based sentiment studies showing improved recall for minority classes when weighting is incorporated [7]-[8], [11]-[12]. All transformer layers are fully fine-tuned rather than frozen, enabling IndoBERT to adapt deeply to the characteristics of the MBG sentiment corpus. Training, evaluation, and logging utilize the HuggingFace Trainer API, which provides a standardized and efficient pipeline for transformer fine-tuning. The model was trained using the AdamW optimizer with a learning rate of $2\,x\,10^{-5}$, a batch size of 8 per device, and 3 training epochs. A weight decay value of 0.01 was applied to improve regularization during training. Model evaluation was performed at the end of each epoch, and the best-performing model was selected based on the lowest validation loss.

Unlike SVM, no extensive hyperparameter tuning was applied to the IndoBERT model, as this study focuses on comparative model performance rather than exhaustive parameter optimization.

i. Evaluation Metrics

The performance of both the SVM and IndoBERT models was rigorously assessed using four standard classification metrics: Accuracy, Precision, Recall, and F1-Score [4]-[6]. The F1-Score was used as the primary benchmark for comparing the models, as it provides a single, robust score that balances the trade-off between precision and recall, which is essential in cases of class imbalance [12], [14].

IV. Result and Discussion

This study compares the performance of a hyperparameter-tuned Support Vector Machine (SVM) and IndoBERT for sentiment classification using accuracy, precision, recall, and F1-score metrics. Table I presents the overall F1-score comparison between the two models using both macro-averaged and weighted-average metrics.

Table 1. Performance Comparison of Svm and Indobert Models for Sentiment Classification of MBG-Related Tiktok Comments Using Macro F1-Score, Weighted F1-Score, and Accuracy Metrics

	F1-Macro Avg	*F1-Weighted Avg*	*Accuracy*
SVM	0.68	0.73	0.73
IndoBERT	0.74	0.78	0.78

As shown in Table I, IndoBERT achieves a higher macro-average F1-score (0.74) compared to SVM (0.68), indicating better balanced performance across all sentiment classes. Similarly, IndoBERT outperforms SVM in terms of weighted F1-score, achieving 0.78 versus 0.73.

The similarity between weighted F1-score and accuracy occurs because the weighted F1-score is influenced by class support. When dominant classes exhibit stable precision and recall, their contributions cause both metrics to converge, a common phenomenon in multi-class sentiment classification with moderately imbalanced data.

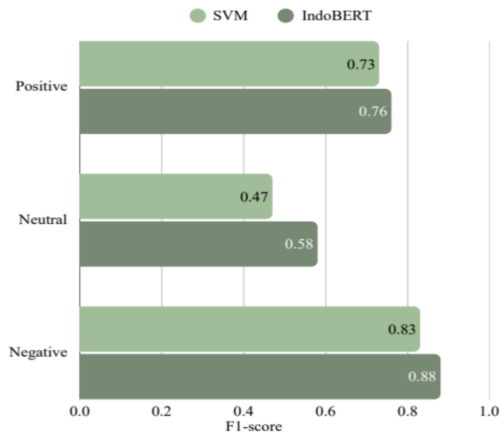

Figure 3. Comparison of F1-score between SVM and IndoBERT across the three sentiment classes (positive, neutral, and negative) on the MBG TikTok comment dataset

To further analyze model behavior, Figure 3. illustrates the F1-score comparison across sentiment classes (positive, neutral, and negative).

The SVM model performs well in identifying positive sentiment, achieving an F1-score of 0.83, indicating that lexically explicit expressions of support toward the MBG program are effectively captured by TF–IDF features. However, SVM shows a significant performance drop in the neutral sentiment class, with an F1-score of only 0.47, highlighting its limitation in handling ambiguous or context-dependent expressions.

In contrast, IndoBERT demonstrates more consistent performance across sentiment classes. The model achieves an F1-score of 0.88 for positive sentiment and 0.76 for negative sentiment. More importantly, IndoBERT substantially improves neutral sentiment classification, achieving an F1-score of 0.58, which represents a notable improvement over the SVM model. This result confirms IndoBERT’s ability to leverage contextual representations to better interpret nuanced sentiment expressions.

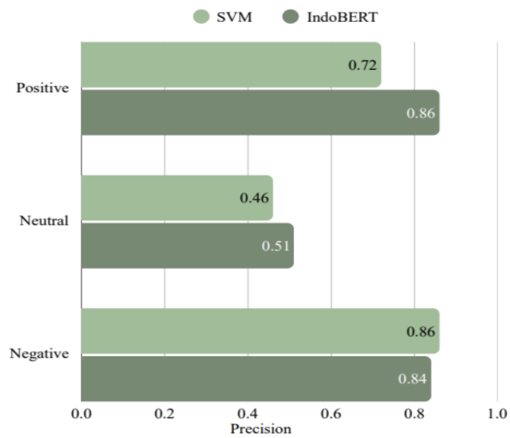

Figure 4. Comparison of Precision between SVM and IndoBERT across the three sentiment classes (positive, neutral, and negative) on the MBG TikTok comment dataset

Figure 4. presents the precision comparison between SVM and IndoBERTs for each sentiment class.

IndoBERT shows higher precision for positive sentiment (0.86) compared to SVM (0.72), indicating that predictions labeled as positive by IndoBERT are more reliable. For the neutral class, both models exhibit lower precision; however, IndoBERT still outperforms SVM (0.51 vs. 0.46), suggesting improved discrimination of neutral content.

For negative sentiment, both models achieve high precision, with SVM slightly outperforming IndoBERT. This suggests that explicit negative expressions are relatively easier to identify using both traditional and transformer-based approaches.

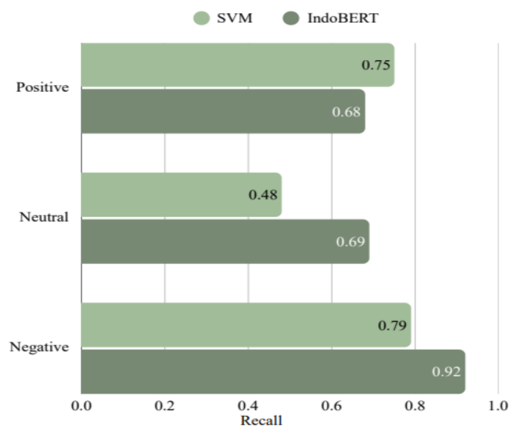

Figure 5. Comparison of Recall between SVM and IndoBERT across the three sentiment classes (positive, neutral, and negative) on the MBG TikTok comment dataset.

Figure 5. illustrates the recall performance of both models. IndoBERT achieves substantially higher recall for negative sentiment (0.92) and neutral sentiment (0.69) compared to SVM. This indicates that IndoBERT is more effective at capturing a larger proportion of relevant negative and neutral instances, as its contextualized representations enable the model to better interpret implicit sentiment expressions and linguistic nuances commonly found in Indonesian social media text, thereby reducing false negatives.

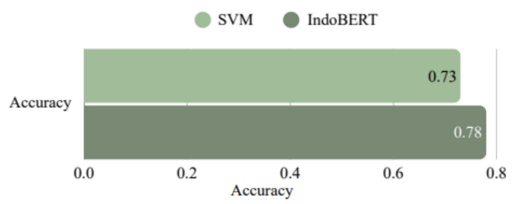

Figure 6. Accuracy comparison between the SVM and IndoBERT models for sentiment classification of MBG-related TikTok comments

In terms of overall accuracy, IndoBERT achieves 0.78, outperforming SVM's 0.73, as shown in Figure 6. This improvement aligns with the higher weighted and macro F1-scores observed earlier, reinforcing the robustness of the transformer-based approach.

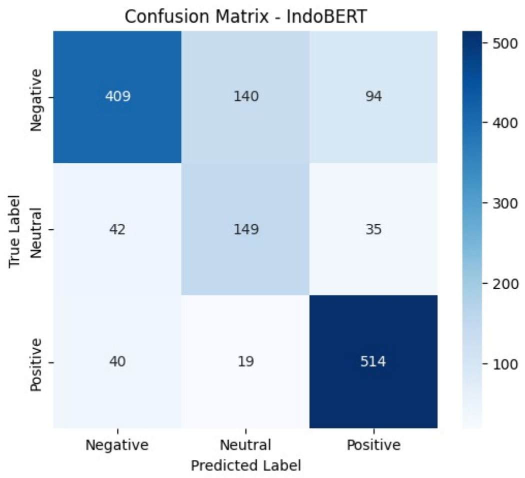

Figure 7. Confusion Matrix of the IndoBERT Model for MBG Sentiment Classification

To further analyze classification performance across sentiment categories, the confusion matrix of the IndoBERT model is presented in Figure 7. The results indicate that IndoBERT achieves strong performance in correctly identifying positive and negative sentiments, with 514 positive and 409 negative instances classified correctly. However, some confusion is observed between negative and neutral classes, as well as between neutral and positive sentiments. This pattern suggests that neutral comments often contain contextual or ambiguous expressions that are more difficult for the model to distinguish clearly.

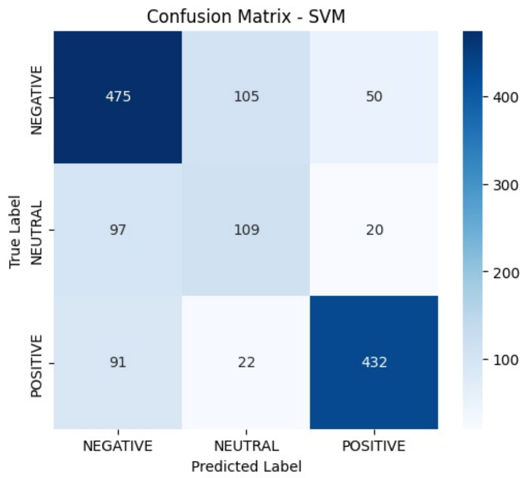

Figure 8. Confusion Matrix of the IndoBERT Model for MBG Sentiment Classification

To provide a clearer view of classification errors, the confusion matrix of the SVM model is shown in Figure 8. The matrix indicates that the SVM model performs reasonably well in identifying negative and positive sentiments, correctly classifying 475 negative and 432 positive instances. However, the model shows notable difficulty in distinguishing neutral comments, with many neutral samples misclassified as negative. This pattern suggests that traditional machine learning approaches relying on sparse textual features may struggle to capture contextual nuances in neutral or ambiguous social media comments.

V. CONCLUSION

The experimental results demonstrate that IndoBERT outperforms the SVM model across all evaluation metrics. Notably, IndoBERT showed superior performance in classifying neutral and context-dependent sentiments, highlighting its ability to capture semantic and contextual information within Indonesian social media text.

The findings also reveal that negative sentiment dominates public discussions regarding the MBG program, indicating critical public responses toward the policy's implementation. However, positive sentiment remains strongly present, suggesting that the program also receives support from segments of the public. These insights provide valuable feedback for policymakers in understanding public perception and improving communication strategies related to national nutrition programs. In addition, the findings demonstrate the potential of sentiment analysis techniques as a tool for monitoring public responses to government policies through social media data.

Despite its strong performance, this study has several limitations. The dataset was collected exclusively from TikTok, which may not fully represent public opinion across other social media platforms.

Future research may extend this work by incorporating data from multiple platforms, applying fine-tuning to the IndoBERT model, and exploring other transformer-based models to further improve sentiment classification accuracy. Such developments may contribute to the advancement of NLP-based tools for public opinion analysis and policy evaluation in Indonesia. Overall, this study confirms that transformer-based approaches are highly effective for analyzing public sentiment toward government policies in the Indonesian context.

REFERENCES

[1] Kementerian Kesehatan RI, "Pemerintah Perkuat Tata Kelola Program MBG, Keselamatan Anak Jadi Prioritas," [Online]. Available: https://kemkes.go.id/id/pemerintah-perkuat-tata-kelola-program-mbg-keselamatan-anak-jadi-prioritas. [Accessed: Okt. 22, 2025].

[2] Kementerian Pendayagunaan Aparatur Negara Dan Reformasi Birokrasi, "Kementerian PANRB Perkuat Kelembagaan BGN untuk Program MBG yang Semakin Kolaboratif," [Online]. Available: https://menpan.go.id/site/berita-terkini/kementerian-panrb-perkuat-kelembagaan-bgn-untuk-program-mbg-yang-semakin-kolaboratif. [Accessed: Okt. 22, 2025].

[3] Transparency International Indonesia, "MBG Watch Resmi Diluncurkan: Saatnya Publik Pantau Program Makan Bergizi Gratis," [Online]. Available: https://ti.or.id/mbg-watch-resmi-diluncurkan-saatnya-publik-pantau-program-makan-bergizi-gratis/. [Accessed: Okt. 22, 2025].

[4] B. He et al., "Analysis of online public opinion texts based on topic mining and sentiment analysis," Mathematical Modeling and Algorithm Application, vol. 2, no. 2, pp. 23–28, 2024.

[5] R. Suhas and T. Prarthana, "Sentiment analysis using text mining: A survey," International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), vol. 5, no. 8, Aug. 2023, doi: 10.56726/IRJMETS43989.

[6] E. M. Sipayung and B. Hakim, "Sentimen Kebijakan Pemerintah terhadap Kepercayaan Masyarakat Menggunakan Metode NLP Rule Based," JUSTIN (Jurnal Sistem dan Teknologi Informasi), vol. 12, no. 1, pp. 175–181, Jan. 2024, doi: 10.26418/justin.v12i1.72426.

[7] J. C. Setiawan, K. M. Lhaksmana, and Bunyamin, "Sentiment analysis of Indonesian TikTok review using LSTM and IndoBERTweet algorithm," JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika), vol. 8, no. 3, pp. 774–780, Sep. 2023, doi: 10.29100/jipi.v8i3.3911.

[8] K. S. Nugroho et al., "BERT fine-tuning for sentiment analysis on Indonesian mobile apps reviews," in Proceedings of the 10th International Conference on Digital Enterprise and Information Systems (DEIS), 2021, pp. 258–264, doi: 10.1145/3479645.3479679.

[9] F. Fatkhurrohman, B. I. Nugroho, and N. Fadillah, "Analisis Sentimen Program Makan Bergizi Gratis Pemerintah RI Melalui Twitter Menggunakan Metode SVM," Journal of Artificial Intelligence and Digital Business (RIGGS), vol. 4, no. 3, pp. 3906-3917, May 2025, doi: 10.31004/riggs.v4i3.2533.

[10] S. Kurniawan et al., "Text Mining Pre-Processing Using Gata Framework and RapidMiner for Indonesian Sentiment Analysis," IOP Conf. Series: Materials Science and Engineering, vol. 835, no. 1, p. 012057, 2020, doi: 10.1088/1757-899X/835/1/012057.

[11] Y. Asri et al., "Sentiment analysis based on Indonesian language lexicon and IndoBERT on user reviews PLN mobile application," Indonesian Journal of Electrical Engineering and Computer Science, vol. 38, no. 1, pp. 677–688, Apr. 2025, doi: 10.11591/ijeecs.v38.i1.pp677-688.

[12] M.R. Manoppo, I.C. Kolang, D. N. Fiat, R. M. C. Mawara, A. D. P. Sumarno, A. Yusup, and V. Tarigan, "Analisis Sentimen Publik di Media Sosial Terhadap Kenaikan PPN 12% di Indonesia Menggunakan IndoBERT," Jurnal Kecerdasan Buatan dan Teknologi Informasi, vol. 4, no. 2, pp. 152-163, Mei 2025, doi: 10.69916/jkbti.v4i2.322.

[13] R. W. Harwenda et al., "Sentiment analysis on government public policies: A systematic literature review," DIJEMSS: Dinasti International Journal of Education Management and Social Science, vol. 6, no. 5, pp. 4192–4204, Jun. 2025, doi: 10.38035/dijemss.v6i5.

[14] I. Muhandhis and A. S. Ritonga, "Public sentiment analysis on TikTok about Tapera policy using random forest classifier," Sistemasi: Jurnal Sistem Informasi, vol. 14, no. 1, pp. 354–365, Jan. 2025.

[15] A. A. Ningtyas et al., "Analisis sentimen komentar YouTube tentang prediksi resesi ekonomi tahun 2023 menggunakan algoritma Naïve Bayes," Bit (Fakultas Teknologi Informasi Universitas Budi Luhur), vol. 20, no. 1, pp. 9–16, Apr. 2023.