IMPLEMENTATION OF INDOBERT FOR PUBLIC SENTIMENT ANALYSIS TOWARD THE INDONESIAN GOVERNMENT'S FREE NUTRITIOUS MEAL PROGRAM

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ABSTRACT: The Free Nutritious Meal Program (MBG) is a government initiative aimed at improving public nutritional quality and reducing stunting rates in Indonesia. The implementation of this program has generated various public responses, particularly those expressed through social media platform X. Therefore, sentiment analysis is required to identify public opinion tendencies toward the program. This study aims to analyze public sentiment toward the Free Nutritious Meal Program using the Bidirectional Encoder Representations from Transformers (BERT) method, specifically the IndoBERT model. The dataset consists of 10,925 tweets collected through scraping using the X API and a public dataset from Kaggle. The data were processed through preprocessing stages including cleaning, case folding, and normalization. Sentiment labeling was conducted using a lexicon-based approach combined with manual labeling into three sentiment classes, positive, negative, and neutral. To address data imbalance, random oversampling was applied prior to model training. Model performance was evaluated using a confusion matrix with accuracy, precision, recall, and F1-score metrics. The results show that the IndoBERT model performs well in classifying public sentiment, achieving an accuracy of 90.2%, precision of 90.4%, recall of 90.2%, and an F1-score of 90.3%. Overall, public sentiment toward the Free Nutritious Meal Program is predominantly positive.

KEYWORDS: *Sentiment Analysis; IndoBERT; Free Nutritious Meal Program; Text Classification*

1.0 INTRODUCTION

Currently, stunting in toddlers is one of the nutritional problems experienced by toddlers around the world. According to the World Health Organization (WHO), stunting is a condition in which there are growth and development problems in children caused by chronic malnutrition and frequent illness, characterized by children who are shorter than other children of the same age [1]. According to WHO data in 2017, around 155 million toddlers worldwide, or 22.9%, were stunted. In addition, around 41 million toddlers (6%) were overweight and around 52 million toddlers (7.2%) were underweight [2]. In 2020, Indonesia was recorded as the country with the second-highest prevalence of stunting in Southeast Asia, after Timor Leste. Based on data from the 2022 Indonesian Nutrition Status Study (SSGI), the prevalence of stunting in Indonesia decreased from 24.4% in 2021 to 21.6%. Despite this decline, the figure is still above the target set by the World Health Organization (WHO), which is 20% [3]. With the high number of stunting cases in Indonesia, the government is implementing the Free Nutritious Meals Program (MBG), formerly known as Free Lunch.

MBG is one of the main programs implemented by the Prabowo–Gibran administration to help reduce malnutrition and support the improvement of human resources in Indonesia. This program focuses on children, students, and pregnant women as beneficiaries [4]. This program is one of the main programs of the Prabowo–Gibran administration, which is expected to create a healthy and high-quality generation in an effort to support the achievement of the Indonesia Emas 2045 vision.

One of the main challenges in implementing the free lunch program is the large budget required, which is estimated to cost up to Rp450 trillion, indicating the enormous scale of the program. This budget is a significant amount and poses a challenge in itself, even for a country with Indonesia's economic capacity [5]. This program has sparked controversy on a number of social media platforms, particularly X, due to its potential impact on various aspects of people's lives. Therefore, sentiment analysis was conducted to provide an overview of the public's response and perception of this policy.

Sentiment analysis is a technique in natural language processing (NLP) used to determine whether the sentiment contained in a text is positive, negative, or neutral [6]. In its application, several classification methods can be used, such as Naïve Bayes, Decision Tree, K-Nearest Neighbor (K-NN), Neural Networks, and Support Vector Machine (SVM), as well as transformer-based deep learning approaches [7][8]. This study will use the Bidirectional Encoder Representations from Transformers (BERT) method, which, based on test results, has been found to have better accuracy with bidirectional text reading so that it can understand the meaning of a word and capture the relationship between words that are far apart contextually [9]. Although IndoBERT has been widely used in sentiment analysis studies, most previous research focused on general topics such as product reviews, application reviews, and digital services. Research related to public sentiment toward the Free Nutritious Meal Program (MBG) is still limited, especially using IndoBERT combined with data balancing techniques such as Random Oversampling. Therefore, this study aims to analyze public sentiment toward the MBG program using IndoBERT to obtain more accurate classification results on Indonesian language social media data.

2.0 RELATED WORKS

Previous research in sentiment analysis has compared several classification methods, including Naïve Bayes, SVM, LSTM, and BiLSTM, which show differences in performance on large scale datasets [10]. Meanwhile, research on sentiment analysis has been conducted extensively using transformer methods such as BERT and IndoBERT for the majority of Indonesian words [11]. IndoBERT ability to process text bidirectionally gives it an advantage over traditional methods [12]. Related research, such as sentiment analysis of the relocation of Indonesia's capital city using the SVM method, obtained more balanced results compared to K-NN, which tended to produce unstable results [13]. Meanwhile, related research on data security sentiment analysis using the Naïve Bayes method obtained fairly low accuracy due to unbalanced data, and the accuracy increased again after the data was balanced [14].

Table 1: Comparison of Machine Learning and Deep Learning Methods

Method	Result
NB	Sentiment analysis of gaming products on Shopee with 1,000 reviews achieved 80.2% accuracy [15].
SVM	Sentiment analysis of Sayurbox app reviews on the Play Store with 3,382 reviews and a linear kernel achieved an accuracy of 89.2% [16].
K-NN	Sentiment Analysis of the Indonesian National Team in AFF 2024 with a total of 1,918 reviews, resulting in a final accuracy of 52.4% with [17].
LSTM	Sentiment analysis of the Grab app on the Play Store with a total of 2,000 reviews using SMOTE yielded an accuracy rate of 87% [18].

Based on previous studies, most sentiment analysis research used traditional machine learning methods such as Naïve Bayes, SVM, and K-NN, as well as several deep learning approaches such as LSTM and IndoBERT. However, studies discussing public sentiment toward the Free Nutritious Meal Program (MBG) are still limited. In addition, the application of Random Oversampling for handling imbalanced sentiment classes in MBG related datasets using IndoBERT has not been widely explored. Therefore, this study contributes by implementing IndoBERT combined with Random Oversampling to improve sentiment classification performance on Indonesian social media data related to the MBG program.

2.1 Bidirectional Encoder Representations From Transformers

BERT is an encoder-based Transformer model designed to represent text and understand the contextual relationships between distant words [9]. Since its introduction in 2018, BERT has had a major impact on the world of NLP with its excellent text comprehension. BERT uses Transformers that can learn the relationships between words using a mechanism called attention [19].

2.2 IndoBERT

IndoBERT is a BERT-based model that has been trained using a large Indonesian corpus. Its architecture is similar to BERT, with a transformer encoder stack. IndoBERT can be used as a sentiment analysis method to generate accurate representations of Indonesian text [20]. IndoBERT was trained with more than 220 million words from three sources, namely Wikipedia (74 million), Kompas, Tempo, and Liputan6 articles with a total of 55 million words, and the

Indonesia Web Corpus (90 million) words. IndoBERT itself has 3 models, namely IndoBERT-lite, IndoBERTbase, and IndoBERT-large, with each model having different layers, with two processes, namely pre-training and fine-tuning [21].

3.0 METHODOLOGY

This stage aims to provide a clear picture of the sentiment analysis process that was carried out. The overall research flow is shown in Figure 1.

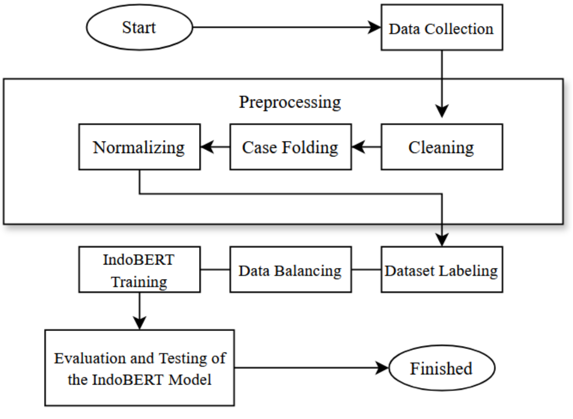

Figure 1: Research Design

3.1 Data Collection

Data collection was conducted using API-based scraping and the Kaggle public dataset. The data collected consisted of public tweets discussing the Free Nutritious Meals Program (MBG), with a total of 10,925 tweets.

3.2 Preprocessing

i. Cleaning

The process of deleting every blank line, punctuation mark, and other symbols so that the data used is valid later on.

ii. Case Folding

The process of converting each letter to lowercase so that every word is the same and facilitates text analysis.

iii. Normalizing

The process of correcting every word in every sentence that does not conform to the Kamus Besar Bahasa Indonesia (KBBI) dictionary.

3.3 Dataset Labeling

The collected data underwent a labeling process using a lexicon-based approach as the initial step to determine sentiment polarity based on an Indonesian sentiment dictionary. After the automatic labeling process, manual labeling was also conducted to verify and correct labels that were inconsistent with the sentence context. The sentiment labels were categorized into three classes: positive, negative, and neutral.

3.4 Data Balancing (Random Oversampling)

Random Oversampling is a technique used to address class imbalance in the classification process by increasing the amount of data in the minority class through random duplication of existing data until the class distribution becomes more balanced. This method was chosen because the neutral sentiment class had significantly fewer data compared to the positive and negative classes. Imbalanced data can cause the model to become biased toward the majority classes. Therefore, Random Oversampling was applied to improve the model's ability to learn all sentiment classes more effectively.

3.5 IndoBERT Training

The training process is carried out by refining the fine-tuning of the BERT model that has been trained using available specific data, so that the model's performance can be optimized. The batch size and number of epochs are carefully adjusted and the model's performance is monitored to avoid overfitting during the training process.

3.6 Evaluation and Testing of the IndoBERT Model

This evaluation process uses a number of metrics such as accuracy, precision, recall, f1-score, and confusion matrix. These metrics are used to describe the level of consistency and accuracy of the model in classifying tweets.

4.0 RESULT AND DISCUSSION

This section presents the research results covering the data collection and preparation process, sentiment labeling into three classes, and the results of training and evaluating the IndoBERT model in classifying sentiments related to the MBG program on the X platform.

4.1 Data Collection

Data was obtained from two main sources, the first source came from scraping on platform X, while the second source was obtained from a public dataset on Kaggle, with a total of 15,882 tweets as shown in Figure 2.

Number of Tweets: 15882

	tweet_id	text
0	1.981172e+18	Ini penyebab banyak murid2 keracunan MBG. Peng...
1	1.981172e+18	dapur mbg ada datanya ga sih\npemiliknya siapa...
2	1.981172e+18	ikan hiu makan mbg https://t.co/YIpGByVv7B
3	1.981172e+18	Ini penyebab MBG beracun. 📌📌📌📌
4	1.981172e+18	Program MBG menciptakan generasi muda yang seh...
...	...	...
15877	1.801110e+18	@tahilalats Kok ga ada yang pengen dapet makan...
15878	1.801110e+18	Ini makan siang yang bayar ya gaes. Udah kebay...
15879	1.801110e+18	yeuh si anying 02 ternyata. sekarang lu pikir ...
15880	1.801110e+18	makan siang gratis tuh program jelek banget bi...
15881	1.801110e+18	@are_inismyname @gibran_tweet @prabowo @bengke...

Figure 2: Total Datasets

4.2 Data Preprocessing

Data is cleaned through a process of cleaning, case folding, and normalization so that the sentence structure is neater and easier to process, as shown in Figure 3.

	text	cleaning	case_folding	normalization
0	Anak-anak di sekolah pasti senang! Makan bergi...	Anak anak di sekolah pasti senang Makan bergiz...	anak anak di sekolah pasti senang makan bergiz...	anak anak di sekolah pasti senang makan bergiz...
1	Program makan bergizi gratis bisa jadi contoh ...	Program makan bergizi gratis bisa jadi contoh ...	program makan bergizi gratis bisa jadi contoh ...	program makan bergizi gratis bisa jadi contoh ...
2	Program MBG penuhi asupan gizi anak bangsa #du...	Program MBG penuhi asupan gizi anak bangsa duk...	program mbg penuhi asupan gizi anak bangsa duk...	program mbg penuhi asupan gizi anak bangsa duk...
3	Manfaat Makan Bergizi Gratis (MBG) https://t.c...	Manfaat Makan Bergizi Gratis MBG	manfaat makan bergizi gratis mbg	manfaat makan bergizi gratis mbg
4	Program MBG (Makan Bergizi Gratis) bukan sekad...	Program MBG Makan Bergizi Gratis bukan sekadar...	program mbg makan bergizi gratis bukan sekadar...	program mbg makan bergizi gratis bukan sekadar...
5	Evaluasi dilakukan demi kebaikan bersama. Prog...	Evaluasi dilakukan demi kebaikan bersama Progr...	evaluasi dilakukan demi kebaikan bersama progr...	evaluasi dilakukan demi kebaikan bersama progr...
6	Program MBG terus jalan dengan pengawasan keta...	Program MBG terus jalan dengan pengawasan keta...	program mbg terus jalan dengan pengawasan keta...	program mbg terus jalan dengan pengawasan keta...
7	Setiap kotak makan dari program MBG bukan seka...	Setiap kotak makan dari program MBG bukan seka...	setiap kotak makan dari program mbg bukan seka...	setiap kotak makan dari program mbg bukan seka...
8	MBG menurunkan stunting itu gimana ceritanya w...	MBG menurunkan stunting itu gimana ceritanya w...	mbg menurunkan stunting itu gimana ceritanya w...	mbg menurunkan stunting itu bagaimana ceritany...
9	Di daerah saya mbg juga berdampak pada harga b...	Di daerah saya mbg juga berdampak pada harga b...	di daerah saya mbg juga berdampak pada harga b...	di daerah saya mbg juga berdampak pada harga b...

Figure 3: Preprocessing Results

Figure 3 shows data that has undergone preprocessing stages such as cleaning, where capital letters are converted to lowercase letters, punctuation marks and symbols are removed, and normalization, where non-standard words are simplified according to the rules.

4.3 Dataset Labeling

Each tweets is labeled as positive, negative, or neutral sentiment using a lexicon approach as a first step. After that, manual labeling is performed to correct or ensure the accuracy of the labels. An example of the dataset labeling process results is shown in Figure 4.

	Normalization	Sentiment
0	anak anak di sekolah pasti senang makan bergiz...	Positif
1	program makan bergizi gratis bisa jadi contoh ...	Netral
2	program mbg penuhi asupan gizi anak bangsa duk...	Netral
3	manfaat makan bergizi gratis mbg	Positif
4	program mbg makan bergizi gratis bukan sekadar...	Negatif
5	evaluasi dilakukan demi kebaikan bersama progr...	Netral

Figure 4: Data Labeling Results

4.4 Class Distribution

The results show that there is a significant difference in the neutral class, where there are only 1756 tweets or 17.6%. Therefore, data balancing is required before entering the modeling stage so that the model does not dominate in predicting one sentiment class. The following is a graph of the distribution of the dataset labeling results shown in Figure 5.

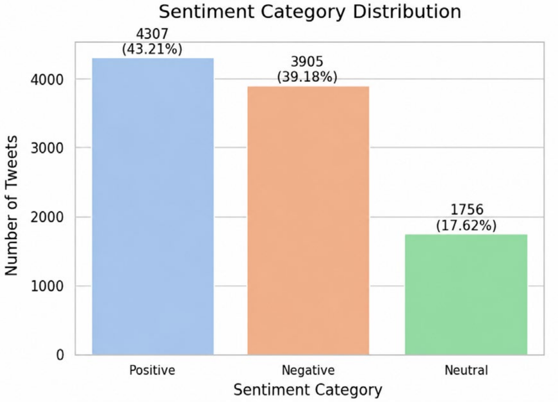

Figure 5: Data Labeling Results Chart

4.5 Data Balancing

This stage involves balancing the amount of data using Random Oversampling due to the uneven distribution of neutral classes. Uneven class distribution can cause the model to be biased towards the dominant class. The following graph shows the results of random oversampling, as shown in Figure 6.

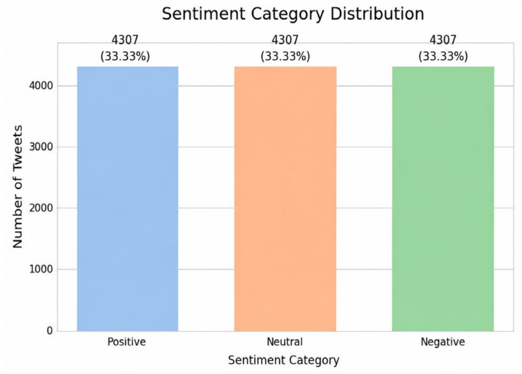

Figure 6: Random Oversampling Results Chart

4.6 IndoBERT Training

Model training was conducted using IndoBERT with a fine-tuning approach. The training process was carried out for 4 epochs, with a learning rate of 2e-5 and a batch size of 16. The following is an image of the IndoBERT model training results.

Epoch	Training Loss	Validation Loss	Accuracy
1	0.858100	0.615097	0.774468
2	0.537400	0.496511	0.860348
3	0.374100	0.459746	0.897485
4	0.207200	0.464623	0.902901

Figure 7: IndoBERT Model Training Results

Figure 7 shows the changes in training loss and validation loss values at each epoch. At the 4th epoch, there was a decrease of around 20% and a validation loss of 45%. The decrease in the values of both losses indicates that the model is increasingly able to understand data patterns. The decreasing training loss and validation loss indicate that the IndoBERT model was able to learn sentiment patterns effectively during the training process. The use of IndoBERT allows the model to understand contextual relationships between words in Indonesian language tweets, including informal expressions commonly found on social media platforms. In addition, the application of Random Oversampling helped reduce class imbalance, enabling the model to better recognize the neutral sentiment class during classification.

4.7 Evaluation and Testing of the IndoBERT Model

Based on the confusion matrix results shown in Figure 8, the IndoBERT model is able to classify positive sentiment quite well, with 795 data points correctly predicted as positive sentiment. In the neutral class, the model correctly classified 777 data points, and in the negative class, the model was able to classify 762 data points correctly, as shown in Figure 8.

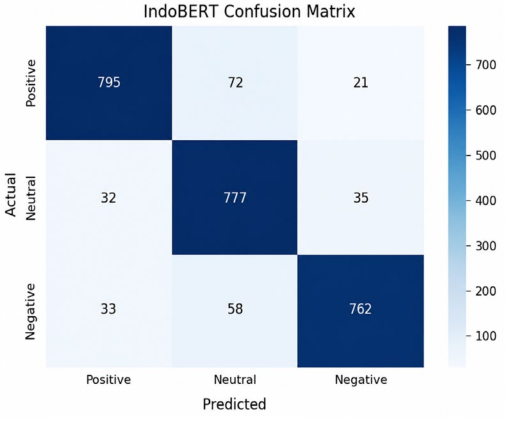

Figure 8: Confusion Matrix Results

Based on the evaluation results, the IndoBERT model obtained an accuracy score of 90.2%, which means that most of the test data was classified correctly. The precision value of 90.4% indicates that the sentiment prediction has a high level of accuracy, while the recall value of 90.2% shows that the model is able to recognize data in each sentiment class well. The F1-score value of 90.3% indicates a good balance between precision and recall, so that the model's performance can be said to be stable, as shown in Table 2.

Table 2: Model Evaluation

Model	Accuracy	Precision	Recall	F1-score
IndoBERT	90.2%	90.4%	90.2%	90.3%

The high evaluation scores indicate that IndoBERT performs effectively in classifying public sentiment toward the MBG program. This performance is influenced by the bidirectional contextual understanding capability of IndoBERT, which enables the model to capture semantic relationships between words more accurately compared to conventional machine learning methods. Furthermore, the balanced dataset contributed to improving the classification performance across all sentiment categories. As a complement to the evaluation, limited testing was also conducted using external test data that was not included in the training data or previous test data.

```
Text      : Sejauh ini MBG berjalan lancar di daerahku, masyarakat terbantu banget
Sentiment : Positif
-------------------------------------------------------------------
Text      : Anggaran MBG terlalu besar, tapi hasilnya tidak terlihat jelas.
Sentiment : Negatif
-------------------------------------------------------------------
Text      : menu mbg hari ini di sekolah ku
Sentiment : Netral
-------------------------------------------------------------------
Text      : Belum sempurna, tapi setidaknya MBG memberi solusi bagi masalah gizi
Sentiment : Positif
-------------------------------------------------------------------
Text      : MBG kelihatannya bagus, tapi kenyataannya banyak masalah di lapangan
Sentiment : Negatif
-------------------------------------------------------------------
Text      : Pelaksanaan MBG berbeda di tiap daerah, ada yang lancar ada yang tidak
Sentiment : Netral
-------------------------------------------------------------------
Text      : Banyak laporan makanan MBG basi dan tidak higienis
Sentiment : Negatif
-------------------------------------------------------------------
Text      : MBG menjadi solusi sementara untuk masalah gizi anak
Sentiment : Positif
-------------------------------------------------------------------
Text      : MBG mending dihentikan saja walaupun cukup membantu
Sentiment : Negatif
```

Figure 9: External Data Test Results

Figure 9 shows an example of the results of testing the IndoBERT model using external test data. Based on the results in the figure, the IndoBERT model is able to classify sentiment into three categories, namely positive, negative, and neutral, according to the content and context of the sentence.

5.0 CONCLUSION

Based on the results of the research that has been conducted, the BERT method, particularly IndoBERT, is able to work well in classifying public sentiment towards the Free Nutritious Meals Program (MBG). This can be seen from the accuracy, precision, recall, and F1-score values, which are above 90%, so it can be said that the model is quite reliable in recognizing sentiment in Indonesian-language tweet data. Recommendations for further research include developing sentiment analysis methods that take into account linguistic context, such as irony and sarcasm, to improve sentiment classification accuracy, and using other balancing techniques such as SMOTE.

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