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Sentiment Analysis and Topic Modeling Using BERT And LDA Methods (Case Study of Free Meal Program on Twitter)

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ABSTRACT

The Free Meal Program is one of the Indonesian government's strategic efforts to structurally address poverty and malnutrition (stunting). As a new policy with massive social and fiscal impacts, an in-depth evaluation is required to measure public acceptance. This study aims to categorize public sentiment into positive and negative categories and identify the dominant topics discussed on Twitter (X) regarding the program. The methodology involved crawling Twitter data, resulting in a total of 8,307 datasets. Sentiment labeling was performed automatically using the IndoBERT deep learning model, followed by topic modeling using the Latent Dirichlet Allocation (LDA) method for each sentiment category. The results of the topic modeling were validated through topic coherence tests using word instruction task and topic instruction task techniques. The results showed an imbalanced sentiment distribution, with 7,034 negative sentiments and 1,273 positive sentiments. LDA modeling successfully extracted 5 optimal topics for both sentiment categories. Positive sentiments included topics such as budget efficiency, the role of government institutions (National Police), technical implementation, and local economic empowerment. Meanwhile, negative sentiments encompassed concerns regarding state budget (APBN) priorities, health/poisoning issues, and the comparative urgency between the free meal program and the education and health sectors. The coherence test results showed an interpretation accuracy rate of 93% for keywords and 79% for topic relevance, indicating that the developed LDA model was optimal in extracting public opinion.

Keyword: Sentiment Analysis, Topic Modeling, BERT, LDA, Free Meal Program, Twitter.

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1. INTRODUCTION

Indonesia is an agrarian nation founded on the principles of Pancasila and the 1945 Constitution, with the primary objective of promoting the welfare of all its citizens. Based on Article 28C, Paragraph (1) of the 1945 Constitution, every citizen has the right to self-development and to benefit from science and technology to improve their quality of life [1]. Although the agricultural sector serves as a primary economic pillar, absorbing nearly 28.64% of the national workforce according to data from Statistics Indonesia (BPS), economic challenges remain a stark reality for much of the population across various regions [2]. Social inequality and structural poverty continue to pose significant obstacles for the government. Empirical evidence suggests that millions of residents still live below the poverty line and face

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difficulties accessing nutritious food, resulting in high stunting rates and a decline in children's health quality [3]. To bridge the contradiction between abundant natural resources and the reality of poverty, the government launched a strategic policy in the form of the Free Meals Program, aimed at improving national nutrition in a structured manner, particularly for school-aged children [4].

As a new policy with extensive fiscal and social implications, the Free Meals Program requires a transparent and data-driven evaluation mechanism. Public opinion serves as a crucial indicator for measuring the effectiveness and social acceptance of the program on the ground. Alongside technological advancements, social media has become a primary medium for the public to voice opinions instantaneously. The 2024 APJII report notes that over 79% of the Indonesian population, or approximately 221.5 million people, are now internet users, positioning digital platforms as a massive source of opinion data [5].

Twitter (X) was selected as the data source for this research due to its dynamic nature and its role as a central hub for conversations regarding political issues and public policy in Indonesia [6]. However, processing thousands of unstructured text data points from Twitter requires more sophisticated methods than simple manual keyword analysis. The primary challenges in social media sentiment analysis include understanding context, sarcasm, and the colloquial language (slang) frequently used by Indonesian netizens [7].

Previous research indicates that the use of Deep Learning methods, such as Bidirectional Encoder Representations from Transformers (BERT), offers significant advantages in understanding bidirectional sentence context, yielding higher accuracy compared to traditional methods like Naive Bayes [8], [9]. Furthermore, integration with Latent Dirichlet Allocation (LDA) allows researchers to not only determine sentiment polarity (positive/negative) but also automatically extract specific topics that are the focus of public attention [10], [11].

The novelty of this research lies in the application of the IndoBERT model—which has been pre-trained on an Indonesian corpus—combined with LDA to comprehensively dissect the issues surrounding the Free Meals Program. This study aims to provide an objective overview of sentiment distribution and the mapping of crucial issues. The results of this analysis are expected to serve as recommendations for policymakers to implement technical improvements to the program in order to achieve optimal public welfare targets.

2. METHODS

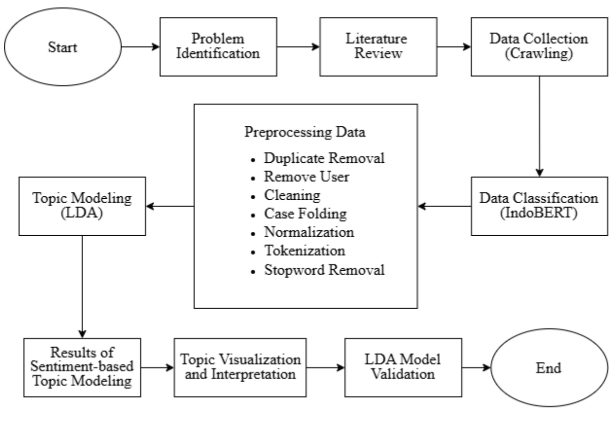


Figure 1. Research Framework

The research methodology follows a systematic framework designed to analyze public sentiment and key topics regarding the Free Meals Program. The process begins with problem identification and a literature review to establish a theoretical foundation, followed by data collection through web crawling. The extracted dataset undergoes automated classification using the IndoBERT model and a rigorous preprocessing phase, which involves duplicate removal, cleaning, normalization, and tokenization to ensure data quality. Subsequently, Topic Modeling is performed using Latent Dirichlet Allocation (LDA) to identify dominant themes [12]. The final stages involve the visualization, interpretation, and validation of the LDA model to ensure the accuracy and reliability of the research findings.

2.2 Problem Identification

In this stage, problem identification is conducted regarding the Free Meals Program. The process involves observing tweets on the social media platform Twitter (X), where preliminary observations reveal various issues circulating among the public. The opinions expressed by users contain diverse sentiments reflecting their perspectives on the program. Furthermore, a lack of clarity regarding these widespread issues necessitates the identification and categorization of discussion themes. This approach is essential to determine the primary discourse and core topics surrounding the Free Meals Program on Twitter.

2.3 Literature Review

Following the problem identification, a literature review was conducted to establish a theoretical and empirical foundation. This stage involved synthesizing information from academic articles, journals, and other relevant publications concerning sentiment analysis, topic modeling, and previous Twitter-based studies, specifically regarding the Free Meals Program. Furthermore, this study explored the implementation of Bidirectional Encoder Representations from Transformers (BERT) for sentiment classification and Latent Dirichlet Allocation (LDA) for topic discovery.

2.4 Data Collection

Data was acquired via web crawling from Twitter (X) using the Tweet Harvest tool within a Python environment on Google Colab. This tool utilizes authorization tokens and the Playwright library to extract relevant tweets. The collection period spanned from the start of the election campaign to March 2025, employing keywords such as *"Makan Gratis"*, *"#MakanBergiziGratis"*, *"Program Makan Gratis"*, and *"#MBG"*. This process yielded 8,974 tweets, capturing attributes such as usernames, tweet content, and user IDs. The resulting dataset was exported and stored in Comma Separated Values (CSV) format for further analysis.

2.5 Data Classification

At this stage, the raw crawled dataset underwent sentiment labeling into positive and negative categories using the IndoBERT model. IndoBERT is a BERT-based model specifically pre-trained on an Indonesian corpus to optimize performance for local linguistic nuances [13]. The classification process was conducted through the following steps:

1. Model Selection: The 'indobenchmark/indobert-base-p1' model from the HuggingFace Transformers library was utilized. An AutoTokenizer was employed to convert raw text into a compatible numerical format for the model.
2. Sentiment Prediction: A specialized function processed the data to predict sentiments based on the loaded model, categorizing each tweet as either positive or negative.
3. Visualization: The resulting sentiment distribution was visualized through charts to analyze and compare the proportions of each sentiment category.

2.6 Preprocessing Data

Following the classification stage, the labeled dataset underwent a preprocessing phase to transform raw text into a format suitable for analysis. This process focused on extracting essential attributes, specifically usernames and tweet content. Systematic cleaning and refining procedures were then applied to ensure the relevance and accuracy of the subsequent analytical results.

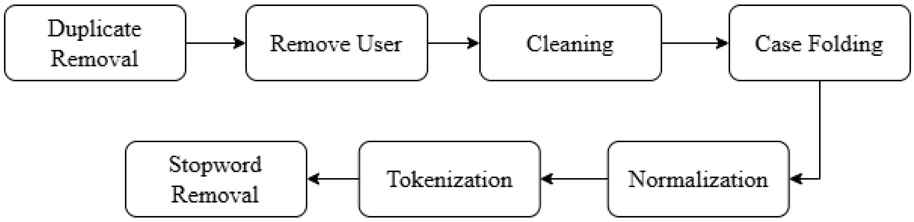


Figure 2. Preprocessing Pipeline

2.7 Topic Modeling

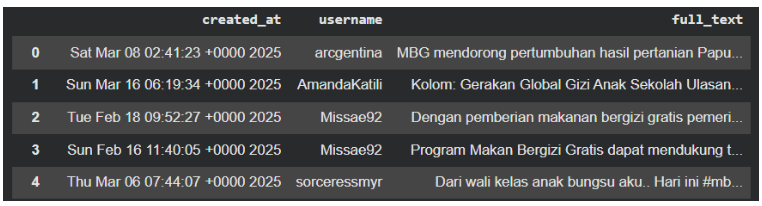
The development of the topic model utilized the Gensim library to extract primary themes from the preprocessed dataset. The process began with data preparation, where a dictionary and corpus were constructed as foundational inputs for the LDA algorithm. To ensure model quality, the optimal number of topics was determined by calculating the Coherence Score across a specific range of iterations; a higher score indicates greater thematic consistency and model optimality [14]. Once the LDA model was trained, the resulting topics were analyzed to provide a comprehensive overview of the public discourse [15]. Finally, the extracted themes were visualized using pyLDAvis, which offers an interactive graphical representation of the topic distribution, and Word Clouds to highlight the most prominent terms within each sentiment category.

3. RESULTS AND DISCUSSION

This section presents the results and detailed analysis of the research stages previously described. It elaborates on the systematic process of generating topic models for each sentiment category. The implementation was conducted using the Python programming language, with Google Colab serving as the primary computational platform for executing the analysis and modeling workflows.

3.1 Data Collection

Data acquisition was performed by crawling Twitter (X) content related to the free meals program. The process utilized the Tweet Harvest tool within a Python environment on Google Colab, employing a set of strategic keywords: *“Makan Gratis”*, *“Kebijakan Makan Gratis”*, *“Program Makan Gratis”*, *“Makan Bergizi Gratis”*, *“Makan Siang Gratis”*, *“#MBG”*, *“#MakanBergiziGratis”*, and *“#MakanBergiziGratisRamadhan”*.



	created_at	username	full_text
0	Sat Mar 08 02:41:23 +0000 2025	arcgentina	MBG mendorong pertumbuhan hasil pertanian Papu...
1	Sun Mar 16 06:19:34 +0000 2025	AmandaKatili	Kolom: Gerakan Global Gizi Anak Sekolah Ulasan...
2	Tue Feb 18 09:52:27 +0000 2025	Missae92	Dengan pemberian makanan bergizi gratis pemeri...
3	Sun Feb 16 11:40:05 +0000 2025	Missae92	Program Makan Bergizi Gratis dapat mendukung t...
4	Thu Mar 06 07:44:07 +0000 2025	sorceressmyr	Dari wali kelas anak bungsu aku.. Hari ini #mb...

Figure 3. Data Crawling Results

The crawling process yielded a consolidated dataset of 8,974 tweets. This raw data was subsequently filtered to retain three essential attributes required for the classification and analysis phases: created_at, username, and full_text. The full_text attribute serves as the primary textual data for subsequent natural language processing.

3.2 Data Classification with IndoBERT

The sentiment labeling process was executed using IndoBERT, a specialized variant of the BERT architecture optimized for Indonesian linguistic data. This stage categorized the collected tweets into two distinct sentiment classes: Positive and Negative. The implementation leveraged the Python ecosystem within the Google Colab platform, utilizing pre-trained transformer libraries to ensure high-accuracy classification.

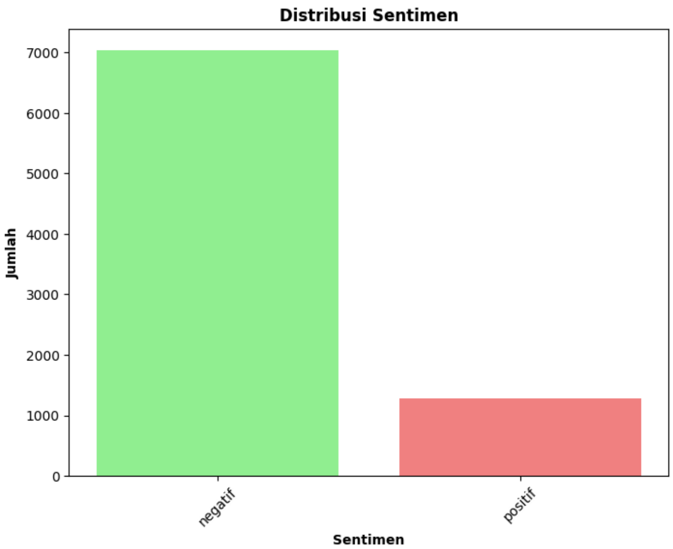


Figure 4. Data Classification Results

Out of the total dataset analyzed, negative sentiment predominantly characterized the discourse with 7,034 tweets, whereas positive sentiment accounted for a smaller portion with 1,273 tweets. This distribution suggests that the majority of digital conversation during the observation period contained criticisms, concerns, or dissatisfaction regarding the policy. These results provide a foundational sentiment polarity that will be further dissected through LDA topic modeling to identify the specific issues driving this predominantly negative response.

3.3 Preprocessing Data

3.3.1 Duplicate Removal

To ensure data integrity, the dataset was screened for duplicate or overlapping entries where identical values existed across multiple columns. The deduplication process focused specifically on the full_text column, resulting in the removal of redundant tweets to prevent bias in the analysis.

A deduplication process was implemented to maintain dataset quality and prevent analytical bias. By filtering the full_text column to remove redundant or overlapping entries, the dataset was refined from an initial count to a final total of 5,698 unique observations. This streamlined dataset, containing the attributes of username,

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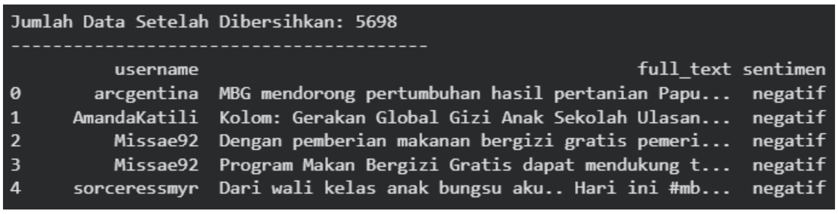
full_text, and sentiment, provides a more accurate representation of public discourse for the subsequent topic modeling phase.



```
Jumlah Data Setelah Dibersihkan: 5698
----------------------------------------
        username                                       full_text sentimen
0     arcgentina  MBG mendorong pertumbuhan hasil pertanian Papu...  negatif
1    AmandaKatili  Kolom: Gerakan Global Gizi Anak Sekolah Ulasan...  negatif
2       Missae92  Dengan pemberian makanan bergizi gratis pemeri...  negatif
3       Missae92  Program Makan Bergizi Gratis dapat mendukung t...  negatif
4   sorceressmyr  Dari wali kelas anak bungsu aku.. Hari ini #mb...  negatif
```

Figure 5. Duplicate Removal Results

3.3.2 Remove User

Remove User process was applied to the full_text data to eliminate usernames or mentions (e.g., @username) within the tweets. This step ensures that the analysis focuses strictly on the topical content of the discourse rather than interpersonal mentions, as illustrated in the following Table 1.

Table 1. Comparison of Remove User Results

Before Remove User	**After Remove User**
Kepala BP Taskin @budimandjatmiko soal Usul @KhofifahIP Makan Bergizi Gratis Pakai APBD. #MBG @kompascom @humasprovjatim https://t.co/6JV1Ns04Al	*Kepala BP Taskin soal Usul Makan Bergizi Gratis Pakai APBD. #MBG https://t.co/6JV1Ns04Al*
Legislator PKB @sahabat_arzeti Soroti Keluhan Variasi MenuÂ Program MBG Beberapa menu belum memenuhi standar gizi seimbang. Proporsi karbohidrat protein dan sayuran masih perlu diperhatikan. #SuaraPKB #MBG https://t.co/II7CJUtkMF https://t.co/n2dJn6Zkkh	*Legislator PKB Soroti Keluhan Variasi MenuÂ Program MBG Beberapa menu belum memenuhi standar gizi seimbang. Proporsi karbohidrat protein dan sayuran masih perlu diperhatikan. #SuaraPKB #MBG https://t.co/II7CJUtkMF https://t.co/n2dJn6Zkkh*

3.3.3 Cleaning

During the cleaning stage, the text underwent further refinement to remove symbols, emojis, punctuation, and other non-textual elements. This process ensures the dataset is noise-free and ready for analysis, as illustrated in Table 2.

Table 2. Comparison of Cleaning Results

Before Cleaning	**After Cleaning**
Dari wali kelas anak bungsu aku.. Hari ini #mbg -nya ttp dikasih tp dibawa ke rumah. Td jg tmnnya anak sulung aku bilang sebelum puasa kemarin ada anak kelasnya ada yg bolak balik ke toilet setelah makan MBG-nya. Ya Allah. https://t.co/qO0KQfq7p6	*Dari wali kelas anak bungsu aku Hari ini mbg nya ttp dikasih dibawa rumah tmnnya anak sulung aku bilang sebelum puasa kemarin ada anak kelasnya ada bolak balik toilet setelah makan MBG nya Allah*
Program makan bergizi gratis adalah langkah strategis pemerintah untuk mengatasi stunting di Papua. Mari kita dukung inisiatif ini demi masa depan anak-anak Papua yang lebih baik. #GiziAnak #PapuaCerdas #GenerasiSehat #MBG #MBGPapua https://t.co/HbIbZS8OHi	*Program makan bergizi gratis adalah langkah strategis pemerintah untuk mengatasi stunting Papua Mari kita dukung inisiatif ini demi masa depan anak anak Papua yang lebih baik GiziAnak PapuaCerdas GenerasiSehat MBG MBGPapua*

3.3.4 Case Folding

In the case folding stage, all text is converted into a uniform lowercase format to ensure consistency across the dataset. This process is essential for streamlining text analysis, as it allows the system to identify and group identical words regardless of their original capitalization. The results of this process are presented in Table 3.

Table 3. Comparison of Case Folding Results

Before Case Folding	After Case Folding
Pekarangan Pangan Bergizi atau merupakan program Kementerian Pertanian untuk menyukseskan Makan Bergizi Gratis yang menjadi program prioritas Presiden Prabowo Subianto dan Kabinet Merah Putih Apa itu Simak penjelasan singkatnya video ini fyp MBG	*pekarangan pangan bergizi atau merupakan program kementerian pertanian untuk menyukseskan makan bergizi gratis yang menjadi program prioritas presiden prabowo subianto dan kabinet merah putih apa itu simak penjelasan singkatnya video ini fyp mbg*
MBG adalah bukti nyata perhatian pemerintah dalam meningkatkan kualitas hidup rakyat Papua MBG	*mbg adalah bukti nyata perhatian pemerintah dalam meningkatkan kualitas hidup rakyat papua mbg*

3.3.5 Normalization

The text normalization phase involves converting abbreviations, slang, and non-standard terms into their formal Indonesian equivalents using a predefined dictionary stored in ‘kamuskatabaku.xlsx’. This process ensures linguistic consistency by replacing informal tokens with standardized vocabulary, as detailed in Table 4.

Table 4. Comparison of Normalization Results

Before Normalization	After Normalization
bukan mbg makanbergizigratis tapi oke dong dapet sarapan pax dari penginepan harga utk orang semalem mana kamarnya bersih bau terawat	*bukan mbg makanbergizigratis tapi oke dong dapat sarapan pax dari penginepan harga untuk orang semalem mana kamarnya bersih bau terawat*
pentingnya sosialisasi edukasi secara merata bagi masyarakat luas ttg program mbg utk saling mencerahkan program ini bukan ttg presiden atau tapi demi anak bangsa kemudian hari agar sehat cerdas mbg mbgpapua	*pentingnya sosialisasi edukasi secara merata bagi masyarakat luas tentang program mbg untuk saling mencerahkan program ini bukan tentang presiden atau tapi demi anak bangsa kemudian hari agar sehat cerdas mbg mbgpapua*

3.3.6 Tokenization

The tokenization process was performed to decompose the text sequences into smaller units, or tokens, to facilitate more efficient analysis in the subsequent stages. The results of this process are illustrated in Table 5.

Table 5. Comparison of Tokenization Results

Before Tokenization	After Tokenization
buah kurma khas timur tengah jadi menu utama program mbg sragen selama ramadan ramadanmubarak kurma mbg kabarterdepan mojokerto	*[‘buah’, ‘kurma’, ‘khas’, ‘timur’, ‘tengah’, ‘jadi’, ‘menu’, ‘utama’, ‘program’, ‘mbg’, ‘sragen’, ‘selama’, ‘ramadan’, ‘ramadanmubarak’, ‘kurma’, ‘mbg’, ‘kabarterdepan’, ‘mojokerto’]*
makan bergizi gratis mbg merupakan terobosan besar dalam pembangunan sumber daya manusia sejak usia dini mbg makanbergizigratis	*[‘makan’, ‘bergizi’, ‘gratis’, ‘mbg’, ‘merupakan’, ‘terobosan’, ‘besar’, ‘dalam’, ‘pembangunan’, ‘sumber’, ‘daya’, ‘manusia’, ‘sejak’, ‘usia’, ‘dini’, ‘mbg’, ‘makanbergizigratis’]*

3.3.7 Stopword Removal

The stopword removal stage involves eliminating non-essential words to retain only significant and relevant terms for the subsequent analysis. As illustrated in Table 6, this process refines the dataset by preserving meaningful keywords that contribute to more accurate topic modeling.

Table 6. Comparison of Stopword Removal Results

Before Stopword Removal	After Stopword Removal
[‘terus’, ‘kawal’, ‘program’, ‘bapak’, ‘presiden’, ‘prabowo’, ‘makan’, ‘bergizi’, ‘gratis’, ‘mbg’, ‘untuk’, ‘anak’, ‘anak’, ‘sekolah’, ‘kita’, ‘nantikan’, ‘generasi’, ‘masa’, ‘depan’, ‘yang’, ‘sehat’, ‘kuat’, ‘cerdas’, ‘dan’, ‘berdaya’, ‘saing’, ‘mbg’, ‘makanbergizigratis’]	*[‘kawal’, ‘program’, ‘presiden’, ‘prabowo’, ‘makan’, ‘bergizi’, ‘gratis’, ‘mbg’, ‘anak’, ‘anak’, ‘sekolah’, ‘nantikan’, ‘generasi’, ‘sehat’, ‘kuat’, ‘cerdas’, ‘berdaya’, ‘saing’, ‘mbg’, ‘makanbergizigratis’]*
[‘terus’, ‘kawal’, ‘program’, ‘bapak’, ‘presiden’, ‘prabowo’, ‘makan’, ‘bergizi’, ‘gratis’, ‘mbg’, ‘untuk’, ‘anak’, ‘anak’, ‘sekolah’, ‘kita’, ‘nantikan’, ‘generasi’, ‘masa’, ‘depan’, ‘yang’, ‘sehat’, ‘kuat’, ‘cerdas’, ‘dan’, ‘berdaya’, ‘saing’, ‘mbg’, ‘makanbergizigratis’]	*[‘kawal’, ‘program’, ‘presiden’, ‘prabowo’, ‘makan’, ‘bergizi’, ‘gratis’, ‘mbg’, ‘anak’, ‘anak’, ‘sekolah’, ‘nantikan’, ‘generasi’, ‘sehat’, ‘kuat’, ‘cerdas’, ‘berdaya’, ‘saing’, ‘mbg’, ‘makanbergizigratis’]*

3.4 Topic Modeling with LDA

3.4.1 Bigram and Trigram Models

In this research, Bigram (N=2) and Trigram (N=3) features are utilized to capture multi-word phrases with singular semantic meanings, such as *“makan gratis”*, which single words cannot represent. Using the Gensim library’s phrases module, frequently occurring word sequences are automatically identified and merged into single tokens based on frequency thresholds. This approach enriches the Corpus and Dictionary contextually, allowing the LDA model to generate more coherent, specific, and interpretable topics regarding the Free Meals Program, as detailed in Table 7.

Table 7. Bigram Trigram Results

Data Text	Bigram Trigram
pekarangan pangan bergizi program kementerian pertanian menyukseskan makan bergizi gratis program prioritas presiden prabowo subianto kabinet merah putih simak penjelasan singkatnya video fyp mbg	*[‘pekarangan’, ‘pangan’, ‘bergizi’, ‘program’, ‘kementerian’, ‘pertanian’, ‘menyukseskan’, ‘makan’, ‘bergizi’, ‘gratis’, ‘program’, ‘prioritas’, ‘presiden’, ‘prabowo_subianto’, ‘kabinet_merah_putih’, ‘simak’, ‘penjelasan’, ‘singkatnya’, ‘video’, ‘fyp’, ‘mbg’]*
kepala badan gizi nasional program makan bergizi gratis mbg berjalan ramadan paket mbg dibawa pulang dikonsumsi berbuka programmbg mbg makanbergizigratis kepalabgn badangizinasional metrotv	*[‘kepala_badan’, ‘gizi’, ‘nasional’, ‘program’, ‘makan’, ‘bergizi’, ‘gratis’, ‘mbg’, ‘berjalan_ramadan’, ‘paket’, ‘mbg’, ‘dibawa_pulang’, ‘dikonsumsi’, ‘berbuka’, ‘programmbg’, ‘mbg’, ‘kepalabgn’, ‘metrotv’]*

3.4.2 Dictionary and Corpus

In LDA topic modeling, the corpus serves as the primary structural input consisting of preprocessed text data, while the dictionary maps unique tokens to specific numerical IDs. This dictionary is essential for converting documents into a frequency-based Bag-of-Words (BoW) representation, enabling the LDA algorithm to effectively calculate probability distributions and identify latent topics.

3.4.3 Sentiment-Specific LDA Modeling

Following the data preparation phase, where context-rich bigram and trigram tokens were used to construct the corpus and dictionary, the Latent Dirichlet Allocation (LDA) model was developed separately for each sentiment segment previously classified by IndoBERT. This bifurcated approach ensures that the resulting topic maps specifically reflect the nuanced issues within both positive and negative public opinions regarding the Free Meals Program. To achieve optimal thematic granularity, the research utilized the Coherence Score (c_v) to determine the ideal number of topics (K), ensuring high-quality and interpretable results across the sentiment spectrum.

3.5 Sentiment Topic Modeling Results

3.5.1 Positive Sentiment Topic Modeling

Topic modeling for the positive sentiment category was optimized using the highest coherence score of 0.3427, which identified 5 distinct topics. This configuration, as detailed in Figure 7, ensures the most interpretable and semantically consistent thematic structure for the analysis.

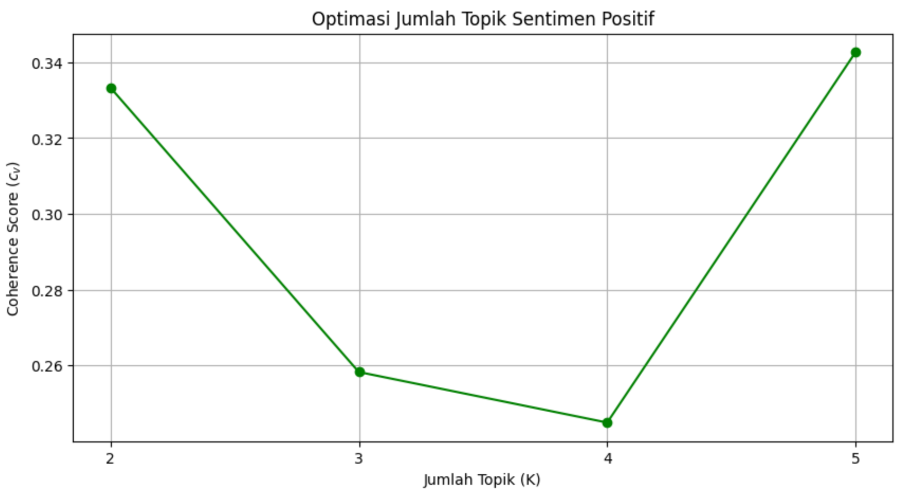


Figure 6. Positive Sentiment Coherence Score Graph

Based on the coherence score analysis, five topics were identified as the optimal configuration for the positive sentiment dataset, as this number yielded the maximum coherence value and the highest semantic interpretability. Following the model training, Table 8 presents the distribution of these five topics, each represented by the top 20 keywords and their respective probability weights.

Table 8. Positive Sentiment Modeling Output Results

Topic Model	Word Probability
1	0.046*"gratis" + 0.045*"makan" + 0.041*"butuh" + 0.027*"enak" + 0.027*"anak" + 0.019*"siang" + 0.014*"program" + 0.012*"dinas" + 0.012*"smk" + 0.010*"efisiensi" + 0.009*"anggaran" + 0.009*"prabowo" + 0.008*"kayaknya" + 0.007*"lulus" + 0.007*"ketimbang" + 0.007*"dengar" + 0.007*"stafsus" + 0.006*"industri" + 0.006*"jokowi" + 0.006*"berhasil"
2	0.017*"kalo" + 0.017*"polri" + 0.013*"polres" + 0.013*"kegiatan" + 0.013*"menunya" + 0.011*"laksankan" + 0.011*"sekadau" + 0.010*"masyarakat" + 0.007*"susu" + 0.007*"pemerintah" + 0.006*"kritik" + 0.006*"kota" + 0.006*"gratis" + 0.006*"keracunan" + 0.006*"kesehatan" + 0.005*"menjanjikan" + 0.005*"bantu" + 0.005*"makan" + 0.005*"juta" + 0.005*"sekolah"
3	0.107*"makan" + 0.093*"gratis" + 0.060*"siang" + 0.025*"orang" + 0.013*"kasih" + 0.011*"uang" + 0.011*"anak" + 0.010*"jalan" + 0.008*"pendidikan" + 0.008*"nanggung" + 0.007*"pengin" + 0.007*"pakai" + 0.007*"indonesia" + 0.007*"makanan" + 0.007*"sekolah" + 0.006*"lihat" + 0.006*"rakyat" + 0.006*"bikin" + 0.005*"gaji" + 0.005*"mikir"
4	0.049*"gratis" + 0.047*"makan" + 0.023*"cinta" + 0.020*"siang" + 0.020*"program" + 0.015*"komentar" + 0.013*"gizi" + 0.010*"harga" + 0.010*"anak" + 0.009*"sekolah" + 0.009*"evaluasi" + 0.009*"desa" + 0.008*"bikin" + 0.008*"gemborin" + 0.008*"setuju" + 0.008*"link" + 0.008*"tanah" + 0.007*"eceran" + 0.007*"penjual" + 0.007*"gembar"
5	0.086*"bergizi" + 0.062*"makan" + 0.056*"gratis" + 0.041*"program" + 0.037*"anak" + 0.015*"mbg" + 0.012*"sehat" + 0.010*"gizi" + 0.009*"pemerintah" + 0.009*"mendukung" + 0.009*"pekerjaan" + 0.009*"rumah" + 0.007*"ahli" + 0.007*"gunanya" + 0.007*"pastikan" + 0.007*"indonesia" + 0.007*"makanan" + 0.004*"menu" + 0.004*"dukung" + 0.003*"kebijakan"

3.5.2 Negative Sentiment Topic Modeling

Topic modeling for the negative sentiment category was optimized using the highest coherence score of 0. 4544, which identified 5 distinct topics. This configuration, as detailed in Figure 8, ensures the most interpretable and semantically consistent thematic structure for the analysis.

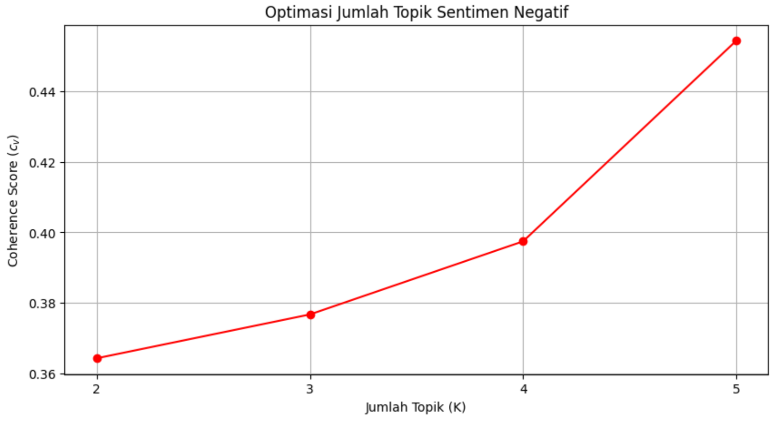


Figure 7. Negative Sentiment Coherence Score Graph

Based on the coherence score analysis, five topics were identified as the optimal configuration for the negative sentiment dataset, as this number yielded the maximum coherence value and the highest semantic interpretability. Following the model training, Table 9 presents the distribution of these five topics, each represented by the top 20 keywords and their respective probability weights.

Table 9. Negative Sentiment Modeling Output Results

Topic Model	Word Probability
1	0.113*"makan" + 0.108*"gratis" + 0.093*"bergizi" + 0.047*"anak" + 0.044*"program" + 0.026*"gizi" + 0.022*"dukung" + 0.015*"sehat" + 0.014*"indonesia" + 0.012*"mbg" + 0.011*"bikin" + 0.008*"bangsa" + 0.007*"siswa" + 0.007*"voucher" + 0.007*"langkah" + 0.007*"diskon" + 0.006*"papua" + 0.006*"sekolah" + 0.006*"mari" + 0.005*"makanan"
2	0.022*"polri" + 0.013*"sppg" + 0.013*"jakarta" + 0.013*"mending" + 0.012*"butuh" + 0.009*"masuk" + 0.008*"pemenuhan" + 0.007*"kapolri_resmikan_operasional" + 0.006*"kerja" + 0.006*"coba" + 0.006*"listyo_sigit" + 0.006*"kapolri_jenderal" + 0.005*"programnya" + 0.005*"dijadikan" + 0.005*"selatan" + 0.005*"keracunan" + 0.004*"pejaten" + 0.004*"meresmikan_operasional_satuan_pelayanan" + 0.004*"desa" + 0.004*"dapur"
3	0.081*"makan" + 0.078*"gratis" + 0.018*"anggaran" + 0.013*"prioritas" + 0.012*"negara" + 0.011*"kasih" + 0.009*"triliun" + 0.008*"utama" + 0.007*"enak" + 0.007*"dikasih" + 0.006*"uang" + 0.006*"malam" + 0.006*"klaim" + 0.005*"apbn" + 0.005*"bilang" + 0.005*"dana" + 0.004*"kebijakan" + 0.004*"bansos" + 0.004*"buka" + 0.004*"sukseskan"
4	0.073*"program" + 0.065*"gratis" + 0.064*"makan" + 0.062*"bergizi" + 0.021*"orang" + 0.021*"prabowo" + 0.021*"pemerintah" + 0.018*"mbg" + 0.017*"generasi" + 0.013*"indonesia" + 0.011*"presiden" + 0.010*"biar" + 0.010*"rakyat" + 0.009*"mendukung" + 0.008*"makanan" + 0.007*"masyarakat" + 0.007*"kalo" + 0.005*"nyata" + 0.005*"muda" + 0.005*"papua"
5	0.149*"gratis" + 0.144*"makan" + 0.107*"siang" + 0.020*"pendidikan" + 0.017*"kesehatan" + 0.016*"sekolah" + 0.007*"pakai" + 0.006*"menu" + 0.005*"jalan" + 0.005*"duit" + 0.005*"habis" + 0.004*"serangga" + 0.004*"lihat" + 0.003*"ayo" + 0.003*"investasi" + 0.003*"cari" + 0.003*"masjid" + 0.003*"cerah" + 0.003*"kepala" + 0.003*"wujudkan"

3.6 Visualization and Interpretation of Topics

The results of the topic modeling were visualized using word clouds to illustrate dominant keyword distributions and pyLDAvis to provide an interactive exploration of topic distances and term weightings. This approach facilitates a qualitative analysis by extracting specific themes and keywords for each sentiment, enabling a structured interpretation of the public discourse on social media.

3.6.1 Positive Sentiment

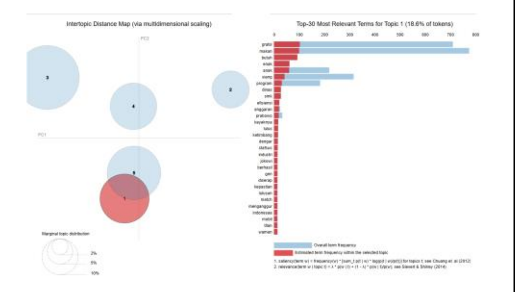
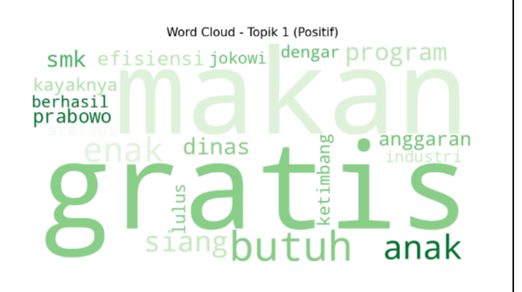
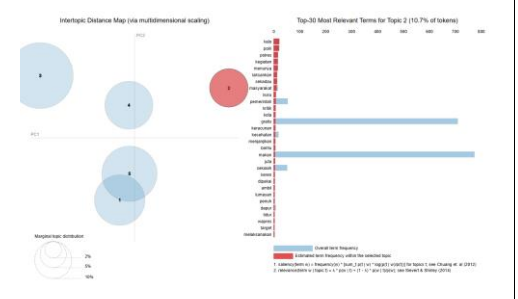
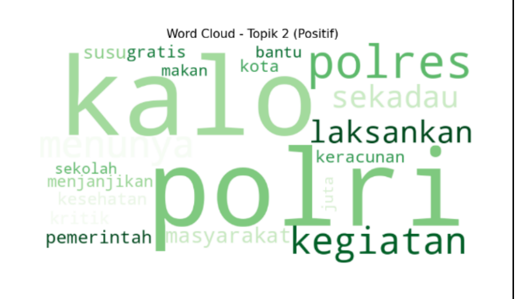
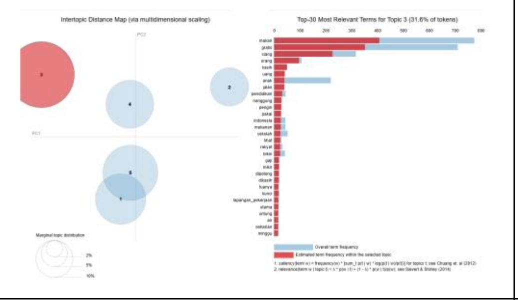
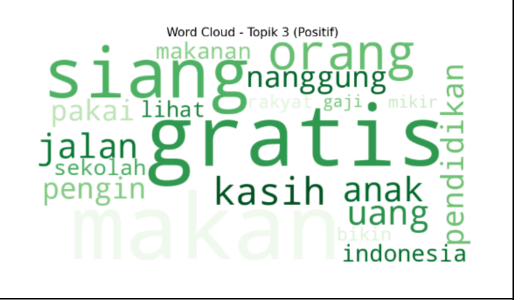
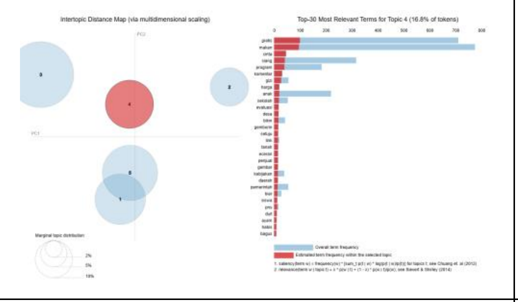
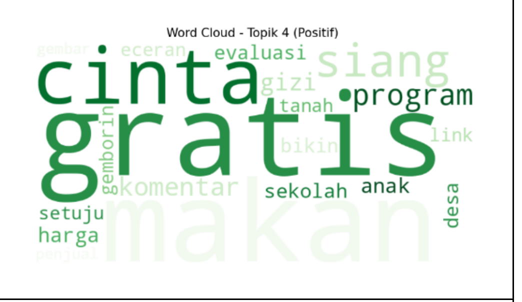
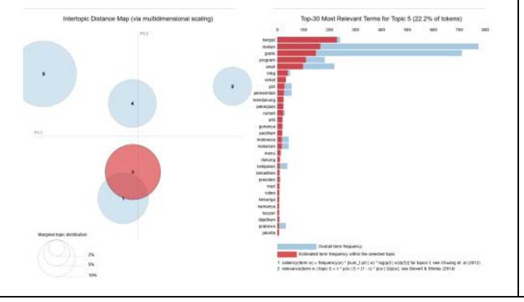
The following Table 10 presents the pyLDAvis visualizations and word clouds for each topic within the positive sentiment category.

Topic interpretations were derived from term weight distributions using pyLDAvis and Word Clouds. By analyzing the topic distribution across the sentiment dataset, the most dominant themes and their associated issues were identified, as summarized in Table 11.

Table 10. Topic Issue Positive Sentiment Results

Topic	**Topic Issues**	**Document Count**	**Percentage (%)**
Topic 1	Focus on efficiency and budget	147	18,13
Topic 2	Government institutions	95	11,71
Topic 3	Technical implementation	255	31,44
Topic 4	Program recipients	143	17,63
Topic 5	Benefits and nutrition of the MBG	171	21,09

Table 11. PyLDAvis and Wordcloud of Positive Sentiment

Topic	pyLDAvis	Wordcloud
1		
2		
3		
4		
5		

3.6.2 Negative Sentiment

The following Table 12 presents the pyLDAvis visualizations and word clouds for each topic within the negative sentiment category.

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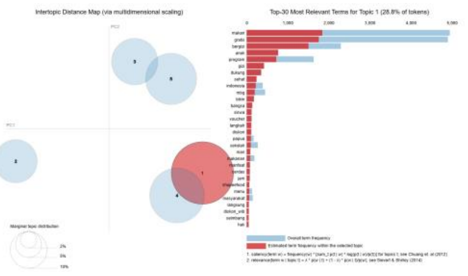
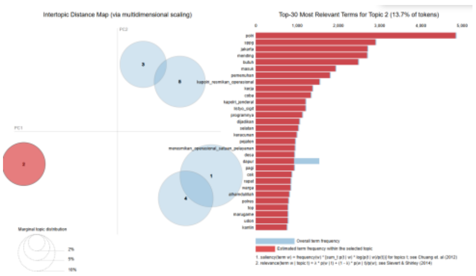
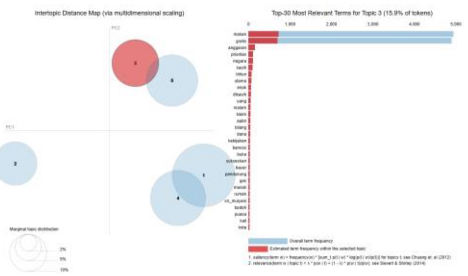
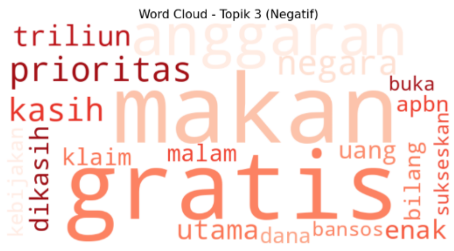
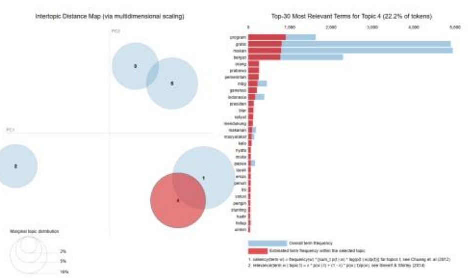
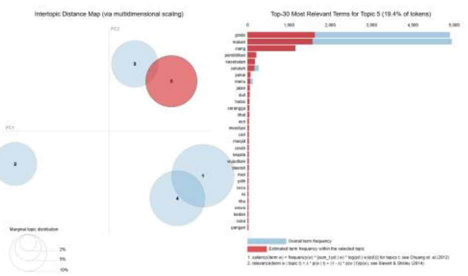
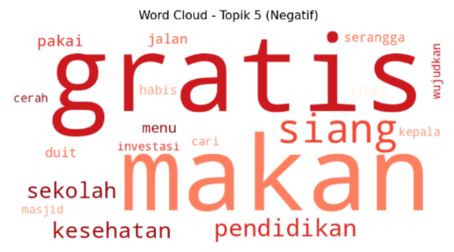
Table 12. PyLDAvis and Wordcloud of Negative Sentiment

Topic	pyLDAvis	Wordcloud
1		
2		
3		
4		
5		

Topic interpretations were derived from term weight distributions using pyLDAvis and Word Clouds. By analyzing the topic distribution across the sentiment dataset, the most dominant themes and their associated issues were identified, as summarized in Table 13.

Table 13. Topic Issue Negative Sentiment Results

Topic	Topic Issues	Document Count	Percentage (%)
Topic 1	MBG Program Nutrition	1,659	33,95
Topic 2	Nutrition Service Unit (SPPG)	541	11,07
Topic 3	Program Budget	648	13,26
Topic 4	Leadership Impact	1,018	20,83
Topic 5	Insect Menu	1,021	20,89

CONCLUSION

This research successfully classified public opinion on the Free Meals Program into two sentiment categories using IndoBERT, yielding 7,034 negative and 1,273 positive entries. By applying Latent Dirichlet Allocation (LDA), five optimal topics were extracted for each sentiment; the positive discourse was dominated by Technical Implementation (31.44%), while negative discourse centered primarily on MBG Program Nutrition (33.95%) and other critical issues such as budget and specific menu controversies. These findings provide a structured overview of public concerns and support, offering valuable data-driven insights for policy refinement.

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