



# Sentiment Analysis on the Allocation of the MBG Program Budget Using Support Vector Machine

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**Abstract**—Sentiment analysis is one of the applications of artificial intelligence and machine learning used to automatically identify and classify public opinions, particularly those expressed on social media. This approach is important for understanding public perceptions of a policy, as it provides a systematic, fast, and data-driven overview. With the increasing use of social media, sentiment analysis can be utilized as an evaluation tool to support transparency and more objective decision-making. One issue that has attracted public attention is the MBG (*Free Nutritious Food*) Program, a government initiative aimed at improving community nutrition. The budget allocation for this program has generated various responses from the public, including both support and criticism regarding its implementation and policy priorities. Therefore, an analysis that can comprehensively capture these diverse perspectives is necessary. This study aims to analyze public sentiment toward the MBG Program budget using data from the social media platform X (Twitter), which is known for its ability to represent real-time and dynamic public opinion. The dataset collected through crawling consists of 2,487 entries, and after preprocessing, 1,686 valid data points were obtained for analysis. Feature extraction was performed using the TF-IDF method, while sentiment classification was conducted using the Support Vector Machine (SVM) algorithm. Model evaluation was carried out using 5-Fold Cross Validation and Confusion Matrix. The results show that the developed model achieved an accuracy of 81.17%, indicating good performance in sentiment classification. For the negative class, the precision reached 85.48% and recall 98.76%. For the neutral class, the precision was 57.58%, recall 44.19%, and F1-score 49.98%. For the positive class, the precision was 75.00%, recall 15.79%, and F1-score 26.09%. These findings indicate that a machine learning-based approach can contribute to understanding public opinion and support more effective, data-driven government policy evaluation. This study contributes by demonstrating the effectiveness of the SVM algorithm in classifying public sentiment on policy-related issues, as well as by applying k-fold cross-validation and confusion matrix to provide a more comprehensive and reliable evaluation. The findings are expected to support data-driven policy evaluation and enhance understanding of public opinion toward government programs.

**Keywords:** Sentiment Analysis; Support Vector Machine; K-Fold Cross Validation; MBG Budget

## 1. INTRODUCTION

Sentiment analysis is a technique in text mining that aims to extract, understand, and classify opinions or sentiments expressed in textual data. This method is used to determine the polarity of a text, such as positive, negative, or neutral sentiment, based on emotional orientation. As part of text mining, sentiment analysis converts unstructured text into structured information that can provide meaningful insights [1]. Furthermore, text mining is included in data mining, which processes large volumes of textual data to discover patterns and knowledge [2]. With the rapid growth of digital data, efficient analytical approaches are required to process large-scale information and identify public opinion trends. The development of social media has significantly increased the availability of user-generated content, making it an important source for sentiment analysis. Social media platforms allow users to express their opinions openly, especially in the digital era where communication is highly dynamic [3]. One of the most widely used platforms is X (formerly Twitter), which serves as a medium for sharing opinions and engaging in public discourse [4].

Due to its real-time and open nature, X (Twitter) has become a valuable data source for capturing public sentiment toward various issues, including government policies [5]. Public responses on social media can reflect collective perceptions, support, or criticism, making them essential for understanding societal attitude [6].

One of the policy issues that has attracted public attention is the allocation of the government budget. The government budget is a financial plan that outlines estimated revenues and expenditures for a specific period and serves as a tool for planning, coordination, and control of government activities [7].

It also functions as an instrument of accountability and reflects policy priorities and development goals. Budget allocation refers to the distribution of financial resources to various programs or sectors in accordance with government priorities to ensure effective implementation [8].

A specific policy that has recently gained attention is the MBG (Makanan Bergizi Gratis / Free Nutritious Meals) Program, initiated by the Indonesian government under the administration of President Prabowo Subianto. This program aims to improve nutritional intake and enhance the quality of human resources, particularly among children and pregnant women [9].

The program involves a substantial budget allocation, reaching hundreds of trillions of rupiah, which has triggered diverse public responses, including both support and criticism regarding its effectiveness, priorities, and fiscal sustainability [10]. As a major public policy, the MBG Program budget becomes a relevant context for analyzing public sentiment [11].

However, despite the growing number of studies on sentiment analysis using social media data, research specifically focusing on public sentiment toward the MBG Program budget remains limited. Previous studies have generally examined sentiment on political issues, public services, or general government policies, but have not specifically addressed the MBG Program as a case study[12]. In addition, there is still a lack of research utilizing recent datasets from X (Twitter) to analyze public opinion in this specific policy context. Therefore, this study addresses this gap by providing a focused analysis of public sentiment toward the MBG Program budget using a machine learning approach [13].

This study aims to analyze public sentiment toward the MBG Program budget using the Support Vector Machine (SVM) algorithm, a supervised learning method that identifies the optimal hyperplane to separate data classes [14]

The data are collected from X (Twitter) and processed through preprocessing stages, including cleaning, tokenization, stopword removal, and stemming. Feature extraction is performed using the TF-IDF method. Model performance is evaluated using K-Fold Cross Validation [15]. And a Confusion Matrix to measure classification accuracy and error distributio [16]. In addition, data mining techniques are applied to extract patterns and insights from large dataset [17]. The results of this study are expected to provide valuable insights into public opinion and support data-driven evaluation of government policie [18]. Confusion Matrix also provides detailed evaluation metrics such as accuracy, precision, recall, and F1-score, which are essential for assessing the performance of classification models in each class and identifying potential misclassification pattern [19]. K-Fold Cross Validation is used to evaluate model performance by dividing the dataset into several subsets and performing repeated testing, resulting in a more stable performance estimation and reducing evaluation bias [20].

Several studies have shown that the Support Vector Machine (SVM) algorithm demonstrates strong performance in sentiment analysis. Sardin Nugroho found that sentiment toward Starlink was predominantly positive (56.3%), with the best SVM performance at  $k\text{-fold} = 7$ , achieving 76.22% accuracy, 77.48% precision, and 81.38% recall [21]. Sulthana also reported that the combination of SVM with Chi-Square feature selection and GridSearch resulted in high performance, with 93.4% accuracy, 0.93 precision, 0.95 recall, and 0.94 F1-score[22]. Meanwhile, Imanuddin identified a dominance of negative sentiment (73.4%) in the SatuSehat application, where SVM achieved 91% accuracy and up to 94% F1-score for the negative class[23].

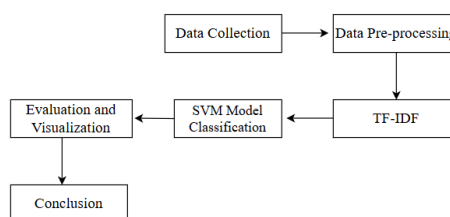
A more advanced approach was presented by Artia Irianti and Meldayang Agariana, who integrated BERT with SVM, resulting in a very high accuracy of 97% and an average cross-validation score of 97.25% [24]. In addition, Septini Shanty Dwi demonstrated that SVM is capable of effectively classifying public policy sentiment, achieving 86% accuracy, 0.85 precision, 0.84 recall, and 0.84 F1-score. Overall, these findings indicate that SVM consistently provides high and stable performance across various sentiment analysis contexts [25].

Based on the above, the contribution of this study lies in the application of the Support Vector Machine (SVM) algorithm to analyze public sentiment toward the MBG Program budget using recent data from the social media platform X (Twitter), as well as the use of k-fold cross-validation and a confusion matrix to provide a more comprehensive and reliable model evaluation.

## 2. RESEARCH METHODOLOGY

### 2.1 Research Stages

The research framework used in this study is illustrated in Figure 1. The process begins with data collection from the social media platform X (Twitter), followed by a data preprocessing stage that includes cleaning, tokenization, stopword removal, and stemming. Next, feature extraction is performed using the TF-IDF method to transform textual data into numerical representations. The processed data are then classified using the Support Vector Machine (SVM) algorithm. Finally, the model is evaluated and visualized using appropriate evaluation techniques, and conclusions are drawn based on the analysis results.



**Figure 1.** Research Framework

#### 2.1.1 Data Collection

In the data collection process, this study utilized data sources from the Twitter social media platform by applying crawling techniques. The data collection was conducted using the Python programming language with the assistance of the *snsrape* library, which was selected for its ability to access data automatically and efficiently according to research needs. This process was carried out using Google Colab.

The collected data consisted of public comments relevant to the issue of the Free Nutritious Meal Program budget, filtered using keywords such as “program,” “meal,” “free,” “budget,” “nutritious,” “allocation,” “budget,” and “funding” to ensure that the data obtained accurately represented public opinions or responses to the issue. The data collected were still in raw form and therefore required further processing. The researchers successfully collected a total of 2,236 comment data points through crawling, including public opinions, criticisms, and support for the program.

### **2.1.2 Data Pre-Processing**

Raw data from Twitter is usually not ready for immediate analysis. Therefore, data preprocessing is carried out. This stage aims to reduce noise such as emojis, URLs, punctuation marks, and mixed letters, which can interfere with the analysis process. Some important steps in preprocessing include: cleansing (removing unnecessary characters), case folding (standardizing text to lowercase letters), normalization (changing non-standard words to standard ones), tokenization (breaking text into words), stopword removal (removing common words such as “and” and “which”), and stemming (returning words to their basic form). By performing preprocessing, the text data becomes neater, more consistent, and easier for algorithms to process.

### **2.1.3 Term Frequency–Inverse Document Frequency (TF-IDF)**

At this stage, TF-IDF will give high weight to words that frequently appear in tweets about budget issues, but rarely appear in general topics. For example, if many tweets mention “budget waste,” then the word “waste” will be given significant weight because it is directly related to negative perceptions of the policy.

### **2.1.4 Data Analysis Using SVM**

Next, SVM constructs a hyperplane to separate data into positive, negative, or neutral sentiment classes. For example, tweets containing the words “budget waste” or “fund corruption” tend to be mapped to the negative class, while tweets with the words ‘transparent’ or ‘efficient’ are closer to the positive or neutral class.

### **2.1.5 Visualization and Interpretation**

The results of the analysis from both methods were then evaluated using k-Fold Cross Validation and a confusion matrix, such as accuracy, precision, recall, and F1-score. This evaluation provides a quantitative overview of the performance of the methods in classifying data. After evaluation, the research results were visualized to make them easier to understand. This visualization takes the form of a heatmap graph. This allows readers to immediately see the significant accuracy results of the SVM method. Interpretation of the results is carried out to give meaning to the evaluation figures.

### **2.1.6 Conclusion**

In this research framework, the conclusion stage is the final part that serves to bring together all research findings from the beginning to the end of the process. At this stage, the results of the Support Vector Machine (SVM) method in conducting sentiment analysis are presented.

## **3. RESULT AND DISCUSSION**

This chapter will outline the topics to be discussed, including data analysis, pre-processing data, analysis results, and design. The discussion is as follows:

### **3.1 Analisis Data**

When processing this data, researchers used Google Colab. The dataset was taken from platform X, which contains tweets, both responses and opinions. This data was collected using web crawling techniques with a time frame ranging from January to December 2025. Based on the crawling results, which produced 2,487 data points, 1,686 data points were selected after going through a filtering stage to remove sentences containing sarcasm, insinuations, and duplicate data. After crawling, the dataset was saved in Comma Separated Values (CSV) format and represented as unstructured text data. Each row of data represents one tweet as one document, while each column represents its constituent attributes, such as tweet text, upload date, and sentiment label.

### **3.2 Data Pre-Processing**

At this stage, the data obtained from the previous crawling process will undergo preprocessing because it is still unstructured text that contains a lot of noise. Therefore, the data needs to be cleaned of all irrelevant or unnecessary elements. The following describes the pre-processing stages.

#### **a. Cleaning**

The results of the text cleaning process are presented in Table 1. This stage removes unnecessary elements such as punctuation, URLs, mentions, hashtags, and other irrelevant characters. As shown in the table, the original text is simplified by eliminating noise, resulting in cleaner and more structured data for further processing.



**Table 1.** Cleaning Results

<i>Posts</i>	<i>Cleaning Text</i>
The BGN meal menu is designed so that each age group can receive adequate and safe nutrition in accordance with the Ministry of Health's recommendations #MenuMBGBergizi <a href="https://t.co/P6iP555Atn">https://t.co/P6iP555Atn</a>	The BGN meal menu is designed so that each age group can receive adequate and safe nutrition in accordance with the Ministry of Health's recommendations MenuMBGBergizi
MBG's reckless program has affected many people...	MBG's reckless program has affected many people.
MBG is a food agency, not an education agency, therefore funding education for MBG violates the law. MBG must be legally revoked!	MBG is a food agency, not an education agency. Therefore, funding education for MBG violates the law. MBG must be legally dissolved.

b. *Case Folding*

The results of the case folding process are shown in Table 2. This step converts all characters into lowercase to ensure consistency in the text data. As illustrated, all uppercase letters in the previous stage are transformed into lowercase, making the data more uniform and easier to analyze.

**Table 2.** Results Case Folding

<i>Cleaning Text</i>	<i>Case Folding</i>
The BGN meal menu is designed so that each age group can receive adequate and safe nutrition in accordance with the Ministry of Health's recommendations MenuMBGBergizi	The menu is designed so that each age group can get adequate and safe nutrition in accordance with the Ministry of Health's recommendations.
MBG's reckless program has affected many people.	The reckless program has affected many people.
MBG is a food agency, not an education agency. Therefore, funding education for MBG violates the law. MBG must be legally dissolved.	MBG is a food agency, not an education agency. Therefore, funding education for MBG violates the law. MBG must be legally dissolved.

c. *Tokenization*

The tokenization results are presented in Table 3, where sentences are split into individual tokens or words. This process allows each word to be analyzed independently. As shown in the table, each sentence is transformed into a list of tokens that represent meaningful textual features.

**Table 3.** Results tokenizing

<i>Case Folding</i>	<i>Tokenization</i>
The menu is designed so that each age group can get adequate and safe nutrition in accordance with the Ministry of Health's recommendations.	['menu', 'eat', 'made', 'so that', 'every', 'group', 'age', 'can', 'get', 'nutrition', 'suitable', 'and', 'safe', 'according to', 'recommendations', 'Ministry of Health']
The reckless program has affected many people.	['program', 'ugly', 'uglyness', 'mbg', 'create', 'many', 'that', 'affected', 'impact']
MBG is a food agency, not an education agency. Therefore, funding education for MBG violates the law. MBG must be legally dissolved.	['mbg', 'that', 'affairs', 'food', 'not', 'affairs', 'education', 'by', 'therefore', 'funding', 'education', 'for', 'mbg', 'violates', 'law', 'invitation', 'mbg', 'must', 'cancel', 'for', 'the sake of', 'law']

d. *Stopword Removal*

The results of the stopword removal process are presented in Table 4. This stage removes common words that do not carry significant meaning, such as conjunctions, prepositions, and filler words. As shown in the table, words such as “and”, “to”, and “so that” are eliminated, resulting in more meaningful and relevant tokens for sentiment analysis.

**Table 4.** Results *Stopword Removal*

<i>Tokenization</i>	<i>Stopword Removal</i>
['menu', 'eat', 'made', 'so that', 'every', 'group', 'age', 'can', 'get', 'nutrition', 'suitable', 'and', 'safe', 'according to', 'recommendations', 'Ministry of Health']	['menu', 'eat', 'made', 'so that', 'every', 'group', 'age', 'can', 'get', 'nutrition', 'suitable', 'safe', 'according to', 'recommendations', 'Ministry of Health']
['program', 'ugly', 'uglyness', 'mbg', 'create', 'many', 'many', 'that', 'affected', 'impact']	['program', 'ugly', 'uglyness', 'mbg', 'create', 'many', 'who', 'affected', 'impact']



Tokenization	Stopword Removal
['mbg', 'that', 'affairs', 'food', 'not', 'affairs', 'education', 'by', 'therefore', 'funding', 'education', 'for', 'mbg', 'violates', 'law', 'invitation', 'mbg', 'must', 'cancel', 'for', 'the sake of', 'law']	['mbg', 'affairs', 'food', 'not', 'affairs', 'education', 'therefore', 'funding', 'education', 'mbg', 'violates', 'law', 'invitation', 'mbg', 'must', 'cancel', 'for', 'the sake of', 'law']

e. *Stemming*

The results of the stemming process are shown in Table 5. This step converts words into their root forms to ensure consistency and reduce variation in word usage. As illustrated in the table, words with different forms but similar meanings are reduced to their base forms, improving the effectiveness of text analysis.

**Table 5.** Result Stemming

Stopword Removal	Stemming
['menu', 'eat', 'made', 'so that', 'every', 'group', 'age', 'can', 'get', 'nutrition', 'suitable', 'safe', 'according to', 'recommendations', 'Ministry of Health']	['menu', 'eat', 'bgn', 'make', 'so', 'each', 'group', 'age', 'can', 'nutrition', 'suitable', 'safe', 'appropriate', 'recommendation', 'Ministry of Health']
['program', 'ugly', 'uglyness', 'mbg', 'create', 'many', 'who', 'affected', 'impact']	['program', 'ugly', 'uglyness', 'mbg', 'make', 'many', 'that', 'affected', 'impact']
['mbg', 'affairs', 'food', 'not', 'affairs', 'education', 'therefore', 'funding', 'education', 'mbg', 'violates', 'law', 'invitation', 'mbg', 'must', 'cancel', 'for', 'the sake of', 'law']	['mbg', 'manage', 'food', 'not', 'manage', 'educate', 'because', 'cost', 'educate', 'mbg', 'violate', 'law', 'law', 'mbg', 'must', 'cancel', 'for the sake of', 'law']

f. *Normalization*

The normalization results are presented in Table 6. This stage standardizes text by correcting inconsistent word forms, abbreviations, or informal language into a uniform format. As shown in the table, non-standard words are transformed into their standardized forms, making the data more consistent and suitable for further analysis.

**Table 6.** Result Normalization

Stemming	Normalisasi
['menu', 'eat', 'bgn', 'make', 'so', 'each', 'group', 'age', 'can', 'nutrition', 'suitable', 'safe', 'appropriate', 'recommendation', 'Ministry of Health']	['menu', 'eat', 'bgn', 'make', 'so', 'each', 'group', 'age', 'can', 'nutrition', 'suitable', 'safe', 'appropriate', 'recommendation', 'Ministry of Health']
['program', 'ugly', 'uglyness', 'mbg', 'make', 'many', 'that', 'affected', 'impact']	['program', 'ugly', 'uglyness', 'mbg', 'create', 'many', 'who', 'affected', 'impact']
['mbg', 'manage', 'food', 'not', 'manage', 'educate', 'because', 'cost', 'educate', 'mbg', 'violate', 'law', 'law', 'mbg', 'must', 'cancel', 'for the sake of', 'law']	['mbg', 'manage', 'food', 'not', 'manage', 'educate', 'because', 'cost', 'educate', 'mbg', 'violate', 'law', 'law', 'mbg', 'must', 'cancel', 'for the sake of', 'law']

**3.3 Word Weighting (TF-IDF)**

The results of TF-IDF weighting are presented in Table 7. This method assigns higher weights to terms that are important but appear less frequently, while terms that appear more frequently but carry less significance receive lower weights. As shown in the table, certain terms such as “*menu*”, “*food*”, and “*public*” have different TF-IDF values across documents (D1–D4), indicating their varying importance in each document. For example, the term “*mbg*” has a high weight in D3, suggesting that it is a key term in that document. Similarly, the term “*public*” has a significant weight in D4, reflecting its relevance in representing the content of that document. These results demonstrate that TF-IDF effectively transforms textual data into numerical features that capture the importance of each term, thereby improving the performance of the classification model.

**Table 7.** Result TF-IDF

Term	TF-IDF			
	D1	D2	D3	D4
Menu	1,9163	0	0	0
Eat	1,5108	0	0	1,5108
Make	1,9163	0	0	0
.....	.....	.....	.....	.....
Mbg	0	1,5108	4,5324	0
Cost	0	0	1,9163	0

Term	TF-IDF			
	D1	D2	D3	D4
Citizens	0	0	0	3,8326

### 3.4 Data Splitting

Data splitting is the process of dividing a dataset into two parts, namely training data and test data, where the amount of training data is larger than the test data. In this study, an 8:2 split ratio was used, meaning that 80% of the entire dataset was used as training data, while the remaining 20% was used as test data. From the total dataset, 1.349 data points were used as training data, and 337 data points were used as test data.

### 3.5 Labelling

Labeling stage in this study uses the Lexicon-Based Sentiment Labeling method with a rule-based approach. Unlike general lexicon approaches, this study constructs a custom lexicon specifically tailored to the Indonesian language context and the research topic, which focuses on government programs. The lexicon consists of four main components: a list of positive words, negative words, negative phrases (two-word expressions), and negation words.

Positive words include terms that represent appreciation, benefits, public satisfaction, and program success, such as “good,” “helpful,” “beneficial,” and “successful.” Meanwhile, negative words cover various forms of criticism, including poor evaluations (“bad,” “chaotic”), program failure (“failed,” “stalled”), mis-targeting (“not evenly distributed,” “unfair”), as well as budgetary and political issues such as “wasteful,” “corruption,” and “image-building.” In addition, negative phrases such as (“not,” “appropriate”) or (“less,” “optimal”) are used to capture meanings that cannot be represented by a single word. A list of negation words such as “not,” “no,” and “not yet” is also applied to reverse the sentiment polarity within a sentence.

The labeling process is carried out by calculating sentiment scores based on the occurrence of words or phrases in the lexicon. Each preprocessed token is examined: if it belongs to the positive list, the score increases, while if it belongs to the negative list, the score decreases. Additional rules are applied for two-word phrases and negation to improve accuracy in capturing simple contextual meanings.

### 3.6 Classification using Support Vector Machine

Support Vector Machine (SVM) is the algorithm used in this study to perform sentiment analysis. The output produced consists of three categories: positive class, negative class, and neutral class. The parameters used in the SVM model in this study include  $\alpha_i = 0$ ,  $C = 1$ ,  $\gamma = 0.1$ , and  $\lambda = 0.01$ .

### 3.7 Model evaluation

At this stage, the model evaluation uses two methods, namely K-Fold Cross Validation and Confusion Matrix. The use of K-Fold Cross Validation aims to obtain a more accurate, stable, and representative evaluation of the model across the entire dataset. Meanwhile, the confusion matrix is used to provide a more detailed performance analysis for each class, allowing the model’s weaknesses to be identified more specifically, especially in cases of imbalanced data.

#### a. K-Fold Cross Validation

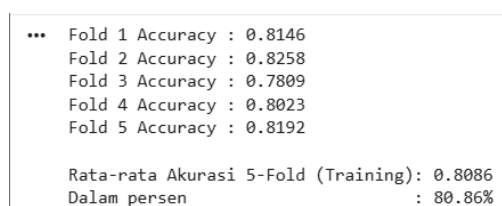
The dataset is divided into 5 folds with equal proportions of data. In each iteration, one fold is used as test data, while the other four folds are used as training data. The training and testing process is performed five times until all data has been used once as test data. Each iteration produces an evaluation metric in the form of accuracy. The results of the model evaluation using k-fold cross-validation are shown in Figure 2 below.

$$CV_k = \frac{1}{k} \sum_{i=1}^k K_i \tag{1}$$

$$CV_5 = \frac{1}{5} \sum_{i=1}^5 0.8146 + 0.8258 + 0.7809 + 0.8023 + 0.8192$$

$$CV_k = \frac{1}{5} \times 4.0428$$

$$CV_k = 0.8086$$



**Figure 2.** K-Fold Cross Validation Display

#### b. Confusion Matrix

A confusion matrix is used to determine the distribution of model predictions against actual data. This matrix consists of four main components, namely True Positive (TP), True Negative (TN), False Positive (FP), and False

Negative (FN). Through a confusion matrix, it is possible to determine the amount of data that has been classified correctly and the amount that has been predicted incorrectly. The results of the model evaluation using confusion matrix are shown in Table 8 and Figure 3 below.

**Table 8.** Classification Results in the Confusion Matrix

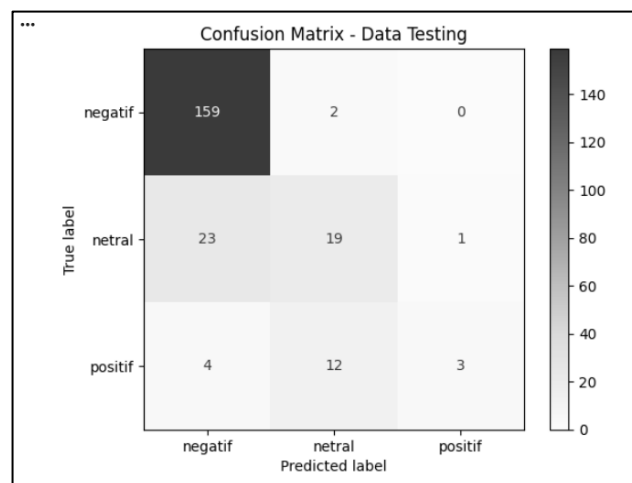
Actual Class (i)	Predicted Class (j)		
	Negative	Neutral	Positive
Negative	159	2	0
Neutral	23	19	1
Positive	4	12	3

$$Accuracy = \frac{159+19+3}{223} \times 100\% = 81.17\%$$

$$Precision = \frac{159}{159+27} = 85.48\%$$

$$Recall = \frac{159}{159+2} = 98.76\%$$

$$F1 - Score = 2 \times \frac{0.8548 \times 0.9876}{0.8548 + 0.9876} = 91.66\%$$



**Figure 3.** Confusion matrix visualization results

### 3.3 Discussion

Based on the results of testing with 2,487 data points, which were then pre-processed to 1,686 data points, and evaluated using K-Fold Cross Validation and a confusion matrix by dividing the data into 1. Test results using K-Fold Cross Validation and confusion matrix, on the Negative label, obtained a Precision value of 85.48%, Recall of 98.76%, and F1-Score of 91.66%. For the Neutral label, there was a Precision of 57.58%, Recall of 44.19%, and F1-Score of 49.98%. For the Positive label, there was a Precision of 75.00%, Recall of 15.79%, and F1-Score of 26.09%.

## 4. CONCLUSION

The evaluation results show that the Support Vector Machine (SVM) model achieved an accuracy of 81.17%, indicating that the model is able to correctly classify most of the test data. However, relying solely on accuracy is not sufficient to fully represent the model's performance, as it does not reflect performance across individual sentiment classes. Further analysis reveals that the model's performance is uneven across classes. In the negative class, the model demonstrates excellent performance, with a precision of 85.48%, recall of 98.76%, and an F1-score of 91.66%. The high recall indicates that the model is highly effective in identifying almost all negative sentiment data. This may be due to clearer negative linguistic patterns or a stronger representation of negative features in the dataset and lexicon. In contrast, the performance in the neutral class is moderate, with a precision of 57.58%, recall of 44.19%, and an F1-score of 49.98%. This suggests that the model still struggles to distinguish neutral sentiment from other sentiment classes. The ambiguous nature of neutral data and the lack of strong sentiment indicators are likely contributing factors. The most significant limitation is observed in the positive class. Although the precision reaches 75.00%, the recall is very low at 15.79%, with an F1-score of 26.09%. This indicates that the model fails to detect a large portion of positive sentiment data, even though its predictions are relatively accurate when it does classify instances as positive. This condition suggests that the model is biased toward the negative class. The implications of these findings

suggest that the current approach still requires substantial improvement. For future research, several concrete steps are recommended: (1) applying data balancing techniques such as oversampling (e.g., SMOTE) or undersampling to address class imbalance; (2) performing data augmentation, particularly for underrepresented classes such as the positive class; (3) improving labeling quality by combining lexicon-based methods with manual annotation or adopting supervised labeling approaches; and (4) exploring alternative algorithms or deep learning-based approaches that are better at capturing contextual language patterns, such as LSTM or transformer models. In conclusion, this study demonstrates the effectiveness of the SVM algorithm in sentiment analysis while highlighting its limitations in handling class imbalance. The use of k-fold cross-validation and confusion matrix contributes to a more comprehensive evaluation, providing valuable insights for improving sentiment classification models in future research.

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