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Public Sentiment Analysis on Ethanol-Blended Fuel News Using Support Vector Machine and Naïve Bayes

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ABSTRACT

The increasing discourse surrounding ethanol-blended fuel policy in Indonesia has generated substantial public opinion across digital media platforms. Understanding this public sentiment is essential for policymakers and stakeholders in formulating effective communication strategies and evidence-based policy decisions. This study aims to (1) implement Support Vector Machine (SVM) and Naïve Bayes algorithms for classifying public sentiment toward ethanol-blended fuel news and (2) compare the performance of both algorithms using accuracy, precision, recall, and F1-score metrics. A total of 1,492 YouTube comments were collected through web scraping and preprocessed using case folding, tokenization, normalization, and stemming. Features were extracted using Term Frequency–Inverse Document Frequency (TF-IDF), and sentiments were classified into positive, negative, and neutral categories. Model performance was evaluated using a confusion matrix and the aforementioned metrics. Results show that SVM achieved a higher test accuracy of 73% and mean cross-validation accuracy of 72.05%, while Naïve Bayes obtained 61% and 64.94%, respectively. SVM also demonstrated superior weighted precision on the test set (0.72 vs. 0.65), whereas Naïve Bayes achieved higher macro recall (0.50 vs. 0.37) and macro F1-score (0.47 vs. 0.35). Cross-validation results showed a similar pattern. A Paired T-Test confirmed statistically significant differences between the models across all evaluation metrics (accuracy $p=0.00016$, precision $p=0.039$, recall $p<0.001$, F1-score $p<0.001$). This study contributes to Indonesian-language sentiment analysis in the renewable energy policy domain and provides insights into public perception of the national ethanol fuel blending program.

INTRODUCTION

Bioethanol (C_2H_5OH) is a renewable fuel produced through fermentation of biomass containing sugars, starch, or cellulose, such as sugarcane, cassava, corn, and sorghum. Various Life Cycle Assessment (LCA) studies demonstrate that bioethanol possesses significant potential in reducing greenhouse gas emissions compared to fossil fuels, particularly when produced from lignocellulosic feedstocks and biomass waste, contributing toward a transition to more sustainable energy systems (Soleymani Angili, Grzesik, Rödl, & Kaltschmitt, 2021). In Indonesia, the utilization of bioethanol as a blending component in motor vehicle fuel has received national policy support as part of efforts to achieve energy security and reduce dependence on petroleum imports (Dinh Xuan, Vu Minh, Hoa, Duc, & Nguyen Duy, 2022).

Experimental studies show that addition of bioethanol blends to gasoline reduces carbon monoxide (CO) emission levels as the proportion of ethanol in the mixture increases, although under certain conditions NOx levels tend to increase due to higher combustion temperatures (Dinh Xuan et al., 2022). The use of bioethanol as a fuel additive can also potentially increase the octane number, improving thermal efficiency and reducing engine knocking, while opening economic opportunities for the agricultural sector through increased demand for domestic bioenergy feedstocks . Indonesia has significant potential for bioethanol development supported by availability of raw materials such as sugarcane, cassava, corn, and agricultural biomass, yet implementation still requires policy support, investment, and adequate distribution infrastructure (Alloysius Joko Purwanto & Dian Lutfiana, 2024).

The widespread circulation of news and public opinion regarding ethanol-blended fuel across various digital platforms drives the need for systematic mechanisms to identify, classify, and map public sentiment. Sentiment analysis is a branch of Natural Language Processing (NLP) that aims to extract and classify opinions, emotions, or attitudes contained in text into positive, negative, or neutral categories (Wankhade, Rao, & Kulkarni, 2022). This research has clear urgency as the government and stakeholders require empirical evidence on public perception as a basis for decision-making. With its ability to automatically process thousands of comments and news articles, sentiment analysis systems can provide a more objective picture of public views on ethanol-blended fuel policy, supporting effective communication strategy formulation (Lin & Nuha, 2023).

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The development of natural language processing (NLP) has progressed rapidly with the rise of machine learning and deep learning approaches, enabling automated extraction of insights from large volumes of unstructured text. Social media platforms, particularly YouTube, represent rich repositories of spontaneous public opinion where user express views on policies, products, and societal issues (Angdresey, Sitanayah, & Tangka, 2025). The comment section of YouTube videos discussing energy policy provides especially valuable data as it captures immediate, unfiltered public reactions to fuel policy announcements and news coverage. Analyzing these reactions systematically can provide policymakers with real-time feedback on policy acceptance and identify specific concerns requiring targeted communication efforts (Danyal et al., 2024).

Support Vector Machine (SVM) is a supervised learning algorithm that works by finding the optimal hyperplane to separate data classes in high-dimensional feature space (Gasparetto, Marcuzzo, Zangari, & Albarelli, 2022). Naïve Bayes is a probabilistic classification algorithm based on Bayes' Theorem with an independence assumption between features, offering fast computation and simple implementation (Wankhade et al., 2022). Research shows SVM consistently produces better classification performance than Naïve Bayes on various Indonesian sentiment datasets (Wahid, Sanatang, & Andayani, 2025). However, no prior study specifically compares SVM and Naïve Bayes in analyzing public sentiment toward bioethanol-blended fuel policy in Indonesia.

This research is therefore conducted to fill that gap by comparing the performance of both algorithms on renewable energy policy domain data, aiming to: (1) implement SVM and Naïve Bayes algorithms for sentiment classification of public opinion toward ethanol-blended fuel news; and (2) analyze and compare the performance of both algorithms to determine the most optimal model based on accuracy, precision, recall, and F1-score metrics.

LITERATURE REVIEW

Sentiment Analysis

Sentiment analysis is a computational process for identifying and classifying opinions in text into positive, negative, or neutral polarities. This field is widely applied to understand public perception of an issue, product, or policy through social media data (Rodríguez-Ibánez, Casánez-Ventura, Castejón-Mateos, & Cuenca-Jiménez, 2023).

Support Vector Machine (SVM)

SVM is a supervised learning algorithm that seeks the optimal hyperplane with the largest margin to separate data classes. For data that cannot be separated linearly, SVM uses a kernel function that maps the data into a higher-dimensional space. The Radial Basis Function (RBF) kernel is widely used in text classification because it can handle non-linear relationships between features (Nurkholis, Alita, & Munandar, 2022). For multi-class classification, SVM applies one-vs-rest or one-vs-one strategies.

Naïve Bayes

Naïve Bayes is a probabilistic classification algorithm based on Bayes' Theorem with an assumption of independence between features. The Multinomial Naïve Bayes variant is highly suitable for text classification because it works well with frequency- or weight-based word features such as TF-IDF. Although the independence assumption is rarely fully met, Naïve Bayes remains popular because it is fast, simple, and competitive (Danyal et al., 2024). Laplace smoothing is applied to prevent the zero-probability problem.

Natural Language Processing and TF-IDF

Natural Language Processing (NLP) is a branch of artificial intelligence that enables computers to understand and process human language. In sentiment analysis, unstructured text must be converted into a numerical representation through feature extraction. Term Frequency–Inverse Document Frequency (TF-IDF) is a weighting method that measures the importance of a word in a document relative to the entire corpus, so that overly common words receive lower weights (Supriyono, Wibawa, Suyono, & Kurniawan, 2024).

Class Balancing and Evaluation

On imbalanced datasets, models tend to be biased toward the majority class. The Synthetic Minority Over-sampling Technique (SMOTE) addresses this by creating synthetic minority-class samples through interpolation of the k-nearest neighbors. Model evaluation uses a confusion matrix that is derived into accuracy, precision, recall, and F1-score. On imbalanced data, macro-average-based metrics are more representative for assessing a model's ability to recognize all classes fairly (Helmud, Helmud, Fitriyani, & Romadiana, 2024; Jude Chukwura Obi, 2023).

Related Work

Wahid et al. (2025) compared SVM and Naïve Bayes on Indonesian-language reviews using TF-IDF and SMOTE, with SVM being more accurate. (Angdresey et al., 2025) analyzed YouTube comment sentiment using BERT labeling, oversampling, and Multinomial Naïve Bayes. (Zulfikar, Atmadja, & Pratama, 2023) applied Multinomial Naïve Bayes for public policy sentiment. Unlike these studies, the present research focuses on the energy policy domain

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(ethanol-blended fuel), which is still rarely studied, by combining validated IndoBERT labeling, SMOTE, and statistical significance testing.

METHOD

This study uses a quantitative experimental approach. The selection of SVM and Naïve Bayes refers to previous research showing their superiority in text classification (Gasparetto et al., 2022; Wahid et al., 2025). The research stages are presented in Figure 1.

Data were collected through web scraping using the youtube-comment-downloader library from 12 YouTube videos discussing ethanol-blended fuel, with a target of 1,500 comments. After initial cleaning (removal of emojis, URLs, mentions, hashtags, symbols, and numbers), 1,493 valid comments were obtained. The attributes collected include comment text, video identity, username, number of likes, and upload time.

Sentiment labeling was performed automatically using the pre-trained IndoBERT model (w11wo/indonesian-roberta-base-sentiment-classifier) into three classes: negative, neutral, and positive. To ensure label quality, validation was conducted on 150 random samples that were manually labeled, measured using accuracy and Cohen's Kappa (Angdresey et al., 2025).

Complete preprocessing was applied in five stages using the Sastrawi library: cleaning and case folding, tokenization, normalization of non-standard words, stemming with the Nazief-Adriani algorithm, and stopword removal (Khairunnisa, Adiwijaya, & Faraby, 2021). Feature extraction used the TF-IDF Vectorizer (max_features=5,000, ngram_range (1,2), sublinear_tf=True) fitted only on the training data to prevent data leakage. As an illustration, the original comment "batas max etanol 20%.? wkwkwk bener2 langsung rusak mesin" became "batas max etanol rusak mesin" after preprocessing. One comment was eliminated during initial cleaning because it produced empty text after noise removal, leaving 1,492 valid comments. No additional records were removed during the Sastrawi preprocessing stage.

The dataset was split using a stratified train-test split of 80:20. Because the class distribution was highly imbalanced, SMOTE was applied only to the training data. The SVM model was trained with an RBF kernel (C=1.0, gamma=scale, class_weight=balanced), while Naïve Bayes used Multinomial Naïve Bayes with Laplace smoothing (alpha=1.0). Evaluation used a confusion matrix and the accuracy, precision, recall, and F1-score metrics (Sujon, Hassan, Choi, & Samad, 2025). The accuracy equation is shown in (1), precision in (2), recall in (3), and F1-score in (4).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (4)$$

In addition to evaluation on the test set, 10-Fold Stratified Cross Validation was performed for a more reliable performance estimate, along with a Paired T-Test to determine the statistical significance of the performance difference between the two models at a significance level of 0.05.

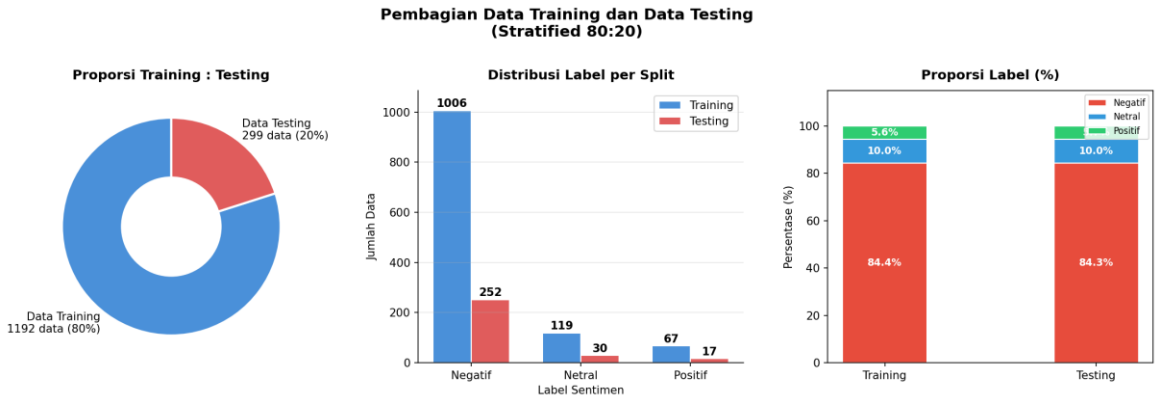


Figure 1. Research Stages

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The research workflow consists of seven sequential stages. The process begins with data collection via web scraping from YouTube videos discussing ethanol-blended fuel policy. The collected data then undergoes preprocessing, which includes cleaning, tokenization, normalization, stemming, and stopword removal. Following preprocessing, sentiment labeling is performed automatically using the pre-trained IndoBERT model, with label quality validated against 150 manually annotated samples. The labeled dataset is subsequently subjected to feature extraction using TF-IDF vectorization. To address class imbalance, SMOTE is applied exclusively to the training data after an 80:20 stratified split. Both the SVM and Naïve Bayes models are then trained on the balanced training data and evaluated on the original test data using accuracy, precision, recall, and F1-score metrics, followed by 10-Fold Cross Validation and a Paired T-Test for statistical comparison.

RESULT

Label Validation

The validation of IndoBERT labeling against 150 manual samples produced an accuracy of 83.33% and a Cohen's Kappa of 0.5886 (Moderate category). This value is above the threshold of 0.41, so the IndoBERT labels are feasible to use as training data, as shown in Figure 2.

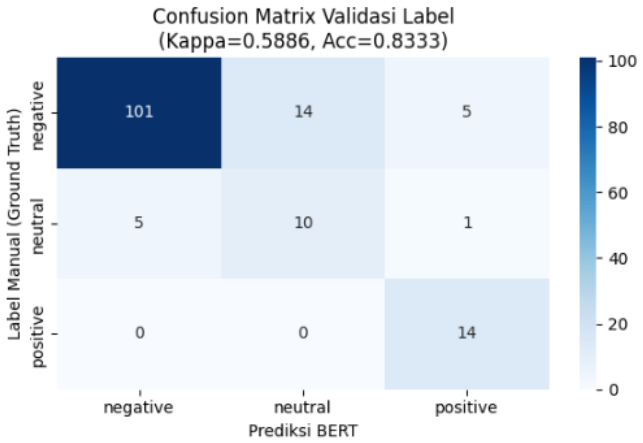


Figure 2. Confusion Matrix of IndoBERT Label Validation

Figure 2 presents the confusion matrix comparing IndoBERT-generated labels against 150 manually annotated samples. The matrix reveals that IndoBERT correctly classified the majority of negative and neutral comments, while showing relatively lower accuracy on the positive class, which is consistent with its minority representation in the dataset. The overall agreement between automatic and manual labels reached 83.33%, with a Cohen's Kappa of 0.5886, categorized as moderate agreement. This level of agreement is considered acceptable for automatic labeling in sentiment analysis tasks, confirming that the IndoBERT labels are sufficiently reliable to serve as ground truth for model training.

Label Distribution

After labeling, the sentiment distribution across 1,492 comments showed significant class imbalance as presented in Table 1. The negative class strongly dominates, while the positive class is the minority.

Table 1. Dataset Label Distribution

Class	Count	Percentage
Negative	1,258	84.32%
Neutral	150	10.05%
Positive	84	5.63%
Total	**1,492**	**100%**

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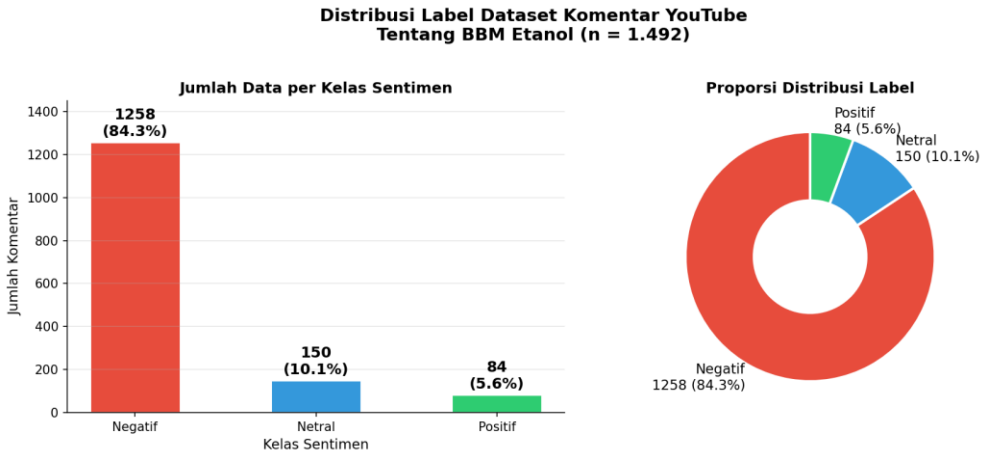


Figure 3. Dataset Label Distribution

Figure 3 visualizes the class distribution of the 1,492 labeled comments. The chart clearly illustrates the severe imbalance in the dataset, with the negative class comprising 84.32% of all samples (1,258 comments), followed by the neutral class at 10.05% (150 comments), and the positive class as the clear minority at only 5.63% (84 comments). This highly skewed distribution reflects the nature of public discourse on social media, where users are more inclined to express criticism or concern than neutral or positive responses toward energy policy. This imbalance necessitates the application of SMOTE during model training to prevent classifier bias toward the dominant class.

Data Split

The dataset was divided into training and testing subsets using a stratified train-test split with a ratio of 80:20, ensuring that the class proportions in each subset remained consistent with the original distribution. This stratified approach is particularly important in the context of imbalanced datasets, as it prevents any single fold from being disproportionately dominated by the majority class. As a result, the split produced 1,192 training samples and 299 testing samples, with the class distribution in both subsets proportionally preserved, as presented in Table 2. To address the severe class imbalance present in the training data, the Synthetic Minority Over-sampling Technique (SMOTE) was applied exclusively to the training set after the split, generating synthetic samples for the minority classes through interpolation between existing data points. This process balanced the training data to 1,006 samples per class, resulting in a total of 3,018 balanced training samples. Importantly, the testing data were kept in their original imbalanced state throughout the entire evaluation process to ensure that model performance was assessed under realistic and representative conditions.

Table 2. Training and Testing Data Distribution

Class	Train	Test	Total
Negative	1,006	252	1,258
Neutral	119	30	150
Positive	67	17	84
Total	**1,192**	**299**	**1,492**

Model Evaluation

After data splitting and SMOTE application, both models were trained and tested. The SVM confusion matrix (Figure 4) shows that the model correctly classified 249 of 252 negative comments but failed to recognize the positive class. Naïve Bayes (Figure 5) showed a more evenly distributed prediction.

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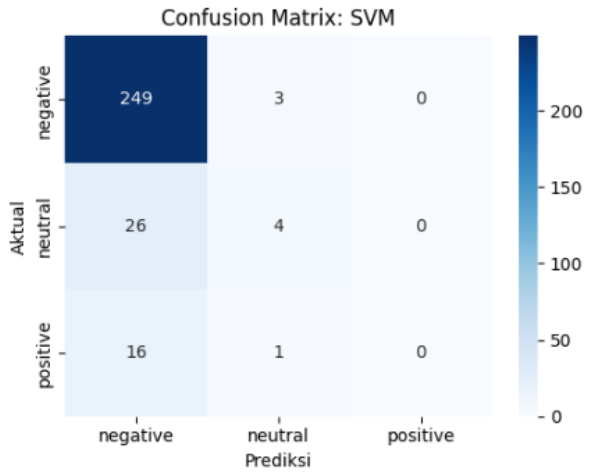


Figure 4. Confusion Matrix of the SVM Model

As shown in Figure 4, the SVM model demonstrated a strong ability to correctly predict the negative class, with 249 out of 252 negative test samples classified accurately. However, the model entirely failed to identify any positive-class samples (17 instances), predicting all of them as either negative or neutral. This behavior reflects the tendency of SVM to prioritize the majority class, even when SMOTE and balanced class weights are applied, particularly when the original minority class is extremely limited in size. The neutral class showed partial recognition, with some samples correctly classified and others misclassified as negative.

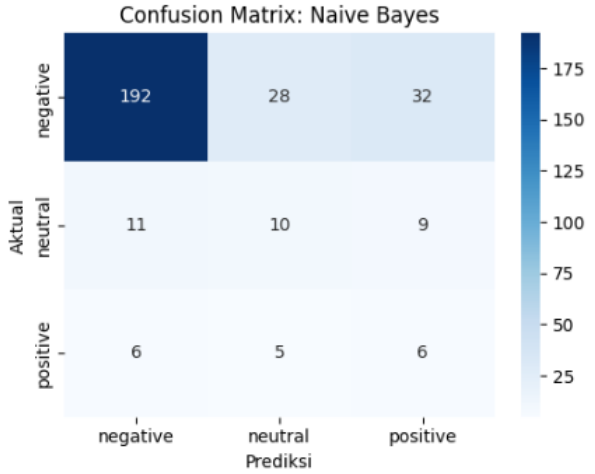


Figure 5. Confusion Matrix of the Naïve Bayes Model

Figure 5 illustrates the confusion matrix of the Naïve Bayes model, which shows a more balanced prediction pattern across all three sentiment classes compared to SVM. While Naïve Bayes correctly classified fewer negative samples than SVM, it successfully identified a portion of the neutral and positive samples, demonstrating greater sensitivity toward minority classes. This characteristic is reflected in its higher macro recall and macro F1-score. The more distributed predictions of Naïve Bayes suggest that the Multinomial variant, combined with TF-IDF features and SMOTE, is better suited for multi-class sentiment classification on highly imbalanced datasets.

The comparison of the evaluation metrics of both models on the test data is presented in Table 3. SVM is superior in accuracy, while Naïve Bayes is superior in precision, recall, and F1-score.

Table 3. Comparison of Evaluation Metrics

Metric	SVM	Naïve Bayes
Accuracy	0.73	0.61
Precision (weighted)	0.72	0.65
Recall (macro)	0.37	0.50
F1-Score (macro)	0.35	0.47

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The 10-Fold Cross Validation testing and the Paired T-Test are presented in Table 4. SVM achieved a mean accuracy of 72.05%, while Naïve Bayes achieved 64.94%.

Table 4. 10-Fold Cross Validation and Paired T-Test Results

Metric	SVM (CV Mean)	NB (CV Mean)	p-value
Precision	0.6279	0.6838	0.039*
Recall	0.3591	0.5296	<0.001*
F1-Score	0.3344	0.5011	<0.001*
Accuracy	0.7205	0.6494	0.00016*

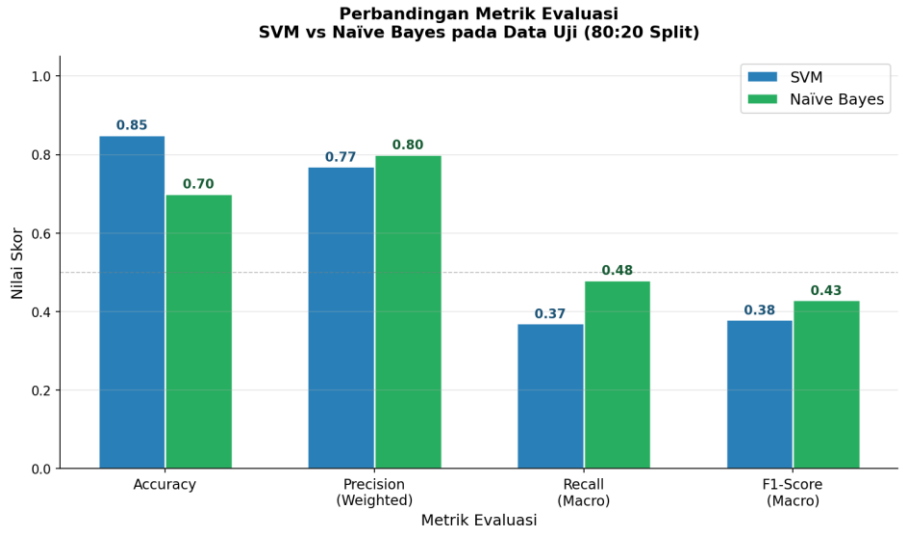


Figure 6. Comparison of Evaluation Metrics: SVM vs Naïve Bayes

Figure 6 presents a side-by-side bar chart comparing the evaluation metrics of SVM and Naïve Bayes on the test set. The visualization confirms that SVM outperforms Naïve Bayes in accuracy (0.73 vs. 0.61) and weighted precision (0.72 vs. 0.65), indicating its strength in overall correct predictions and majority-class precision. Conversely, Naïve Bayes achieves higher macro recall (0.50 vs. 0.37) and macro F1-score (0.47 vs. 0.35), reflecting its superior ability to detect all sentiment classes, including the minority positive class. These contrasting profiles underscore that the choice of the optimal model is contingent on the evaluation objective prioritized by the researcher.

The distribution of metric values across the 10-Fold Cross Validation is shown as a boxplot in Figure 7. SVM shows lower accuracy variability, indicating better consistency, while Naïve Bayes has a wider range in recall.

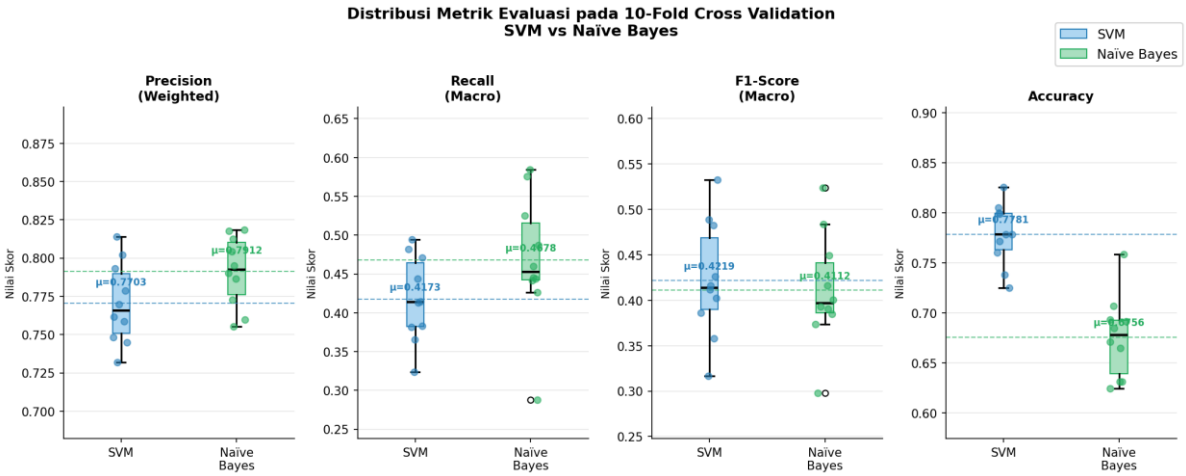


Figure 7. Distribution of Evaluation Metrics across 10-Fold Cross Validation

Figure 7 displays the distribution of metric values for both models across 10 cross-validation folds in the form of boxplots. For accuracy, SVM exhibits a narrower interquartile range and fewer outliers compared to Naïve Bayes, indicating more consistent performance across folds. In contrast, Naïve Bayes demonstrates a wider spread in recall values, suggesting greater variability in its ability to identify minority-class samples depending on the fold composition.

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The F1-score distribution further confirms that Naïve Bayes achieves consistently higher median macro F1-score values, reinforcing its advantage in balanced multi-class classification. These distributions validate that the performance differences observed on the test set are representative of the models' general behavior, not artifacts of a particular data split.

Sentiment Interpretation

Analysis of the dominant words shows patterns consistent with the sentiment distribution. In negative comments, words such as "busuk" (rotten), "rusak mesin" (engine damage), "mahal" (expensive), and "pertamina" stand out, indicating public concern about fuel quality, vehicle engine impact, and trust in institutions. Neutral comments tend to be factual and descriptive, while positive comments generally express support for the national energy security program and renewable energy development.

DISCUSSION

The results show that the selection of the best model depends on the metric used as a reference. SVM achieved the highest accuracy (73%), but this value is misleading because it was achieved primarily through predictions of the dominant negative class, while the model failed to recognize the positive class (recall=0.00). This is consistent with the characteristic of SVM, which tends to be biased toward the majority class on highly imbalanced datasets, even though SMOTE and balanced class_weight have been applied.

Conversely, Naïve Bayes showed more balanced performance in recognizing all three classes, reflected in higher macro recall and macro F1-score, as well as higher weighted precision in the cross-validation setting. These results are in line with (Angdresey et al., 2025; Zulfikar et al., 2023), who showed that Multinomial Naïve Bayes is effective for multi-class sentiment analysis. Unlike (Wahid et al., 2025), who placed SVM as the best model based on accuracy, this study emphasizes the importance of macro metrics on imbalanced datasets.

The Paired T-Test reinforced these findings: the accuracy difference was statistically significant ($p=0.00016$) in favor of SVM, the precision difference was also significant ($p=0.039$) in favor of Naïve Bayes, and the recall and F1-score differences were also statistically significant ($p<0.001$), confirming that Naïve Bayes is substantially better at recognizing minority classes. The dominance of negative sentiment (84.32%) indicates that public communication regarding the ethanol-blended fuel policy has not been effective.

The finding that SVM failed to recognize the positive class despite the application of SMOTE indicates that class imbalance handling at both the data and algorithm levels has not been sufficient to overcome the extreme imbalance, because the very limited number of original minority-class samples is the main limiting factor. The practical implication is that model selection must be tailored to the analysis objective: if the goal is to quickly measure the dominant tendency of public opinion, SVM is adequate; however, if the goal is to understand the full sentiment distribution including minority voices, Naïve Bayes is more representative. For policymakers, the dominance of negative sentiment underscores the need to strengthen evidence-based public communication.

This study has several limitations. First, the dataset is highly imbalanced, with a very limited number of positive-class samples (84 samples). Second, the automatic IndoBERT labeling has a Moderate level of agreement (Kappa=0.5886), so there is still potential for labeling errors. Third, the data come only from YouTube comments, so they do not yet represent all social media platforms.

CONCLUSION

This study successfully implemented and compared the Support Vector Machine and Naïve Bayes algorithms in analyzing public sentiment toward ethanol-blended fuel news. Public opinion was dominated by negative sentiment (84.32%), indicating high public concern about the policy. Based on the performance comparison, SVM was superior in test set accuracy (73%) and weighted precision (0.72), while Naïve Bayes was superior in macro recall (0.50) and macro F1-score (0.47).

The 10-Fold Cross Validation and Paired T-Test showed that SVM was significantly more accurate, while Naïve Bayes was more balanced in recognizing all classes. Therefore, for this highly imbalanced dataset, Naïve Bayes provides more comprehensive classification performance, while SVM is more suitable when the main objective is to maximize accuracy. Future research is recommended to add minority-class data, try other balancing techniques such as ADASYN, perform hyperparameter tuning, and compare transformer-based models.

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