International Journal of Informatics and Computation (IJICOM)
Vol. 7, No.1, 2025
ISSN: 2685-8711, E-ISSN: 2714-5263 DOI: 10.35842/ijicom

Sentiment Classification of Student Opinions on AI Utilization Using Naive Bayes Algorithm

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Abstract

The rapid advancement of technology has encouraged the use of Artificial Intelligence in various sectors, including higher education. Among students, AI was used to support learning activities, although it posed ethical concerns such as technological dependency and the risk of plagiarism. This study aimed to examine students' sentiment toward the use of AI in academic contexts. Data were collected through an online survey with a total of 498 responses, consisting of 347 positive sentiments and 151 negative sentiments. The classification process employed the Multinomial Naïve Bayes (MNB) algorithm using training data proportions of 60%, 70%, 80%, and 90%, along with combinations of unigram, bigram, and trigram features. The highest accuracy of 0.84 was obtained using 90% training data with the combination of all three features. As a comparison, the Random Forest algorithm achieved its highest accuracy of 0.86 using unigram features with the same training proportion. The results showed that both algorithms performed well in sentiment classification, with Random Forest slightly outperforming. Furthermore, the findings revealed variations in students' adherence to academic ethics regarding the use of Artificial Intelligence.

Keywords:
Sentiment Analysis, Academic Ethics, Multinomial Naïve Bayes, Random Forest, Artificial Intelligence

1. Introduction

The advancement of technology in recent years has significantly transformed various aspects of daily human life, making activities more efficient and accessible. In the context of higher education, students are encouraged to actively explore knowledge by utilizing available technological tools. One of the increasingly adopted technologies is Artificial Intelligence, which refers to a system developed using computer programming that is capable of performing intelligent tasks similar to human reasoning and perception [1]. AI has demonstrated the potential to support adaptive learning, especially when students struggle to comprehend the materials presented in class. In such situations, AI can provide access to supplementary materials or practice exercises tailored to students' needs [2]. However, consistent use of AI can lead to over-reliance, causing a decline in students' analytical skills. This dependency may further result in misuse, such as copying AI-generated answers without understanding or evaluating them, as the process only requires users to input a prompt and receive relevant responses in return [3].

The dual impact of AI, both positive and negative, necessitates careful consideration regarding its use in academic environments. As active members of the academic community, students are expected to uphold ethical behavior by established institutional rules [4]. Therefore, students have a critical role in evaluating the use of AI to support their learning while maintaining academic integrity [5]. Reviews from students who utilize AI can

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serve as valuable insights for others in selecting appropriate AI tools for academic purposes. Sentiment analysis, or opinion mining, is a method used to interpret and process textual data to classify sentiments as either positive or negative. One of the most commonly applied techniques is the Naïve Bayes Classifier, known for its simplicity and ability to deliver high classification performance in text processing tasks [6].

This study also compares the performance of the Multinomial Naïve Bayes model with that of the Random Forest algorithm, which is an ensemble method involving decision trees to produce accurate classification results [7]. Based on the issues presented, this research proposes sentiment analysis of student perspectives on the use of AI in higher education. The results aim to help students make informed decisions in integrating AI into their studies and to contribute to the formulation of ethical and strategic regulations on AI use in academic contexts.

2. Related Works

Previous studies have employed various machine learning algorithms to analyze sentiment related to a wide range of topics. A study applied the Naïve Bayes Classifier method to analyze sentiment regarding public opinion on the COVID-19 vaccination program organized by the Indonesian government. The dataset consisted of 2,000 Twitter posts, with 78% labeled as positive, 13% as negative, and 8% as neutral. The model's accuracy was evaluated under four training data scenarios: 60%, 70%, 80%, and 90%. The highest accuracy, 0.86, was achieved when using 90% of the data for training. However, the study did not explore variations in N-Gram features to evaluate their impact on the model's accuracy [8].

Another study employed the Naïve Bayes Classifier algorithm to analyze public sentiment toward ChatGPT, using 2,884 entries collected from the X application, categorized into positive, negative, and neutral sentiments. The research achieved an accuracy of 87.175043%. However, it did not address ethical aspects of AI usage in the context of higher education and was limited to only one AI tool, namely ChatGPT, whereas various types of AI have now emerged. Moreover, the study did not implement N-Gram features or explore different training data proportions, resulting in no comparison to determine the most optimal accuracy [9].

To analyze public sentiment toward the Jakarta International Stadium (JIS), a work explored MNB and RF using 2,971 data entries collected from Google Maps. The results showed that Naïve Bayes outperformed Random Forest, achieving an accuracy of 83% compared to 81%. However, the study did not implement N-Gram features or variations in training data proportions to assess their impact on model performance [10]. Another work analyzed public opinion sentiment toward the Pekanbaru government using the Naïve Bayes Classifier, K-Nearest Neighbor, and Decision Tree algorithms. The results showed that the Naïve Bayes Classifier achieved the highest accuracy at 100%, outperforming the other algorithms. This serves as the rationale for selecting Naïve Bayes Classifier as the primary model in this study [11].

Another study explored K-Nearest Neighbor to perform sentiment analysis on beauty product reviews using N-Gram features, including Unigram, Bigram, Trigram, and a combination of Unigram, Bigram, and Trigram. The training and testing data were split into 60%, 70%, and 80%. The results showed that the highest accuracy of 98.6% was achieved with an 80:20 data split using Trigram N-Gram features. However, the study did not fully optimize the training and testing data split by implementing a 90% training data proportion [12].

3. Proposed Method

The process of conducting sentiment analysis using the MNB algorithm as the primary model and Random Forest as a comparison model regarding the use of AI involves several systematically executed stages, as illustrated in Fig. 1.

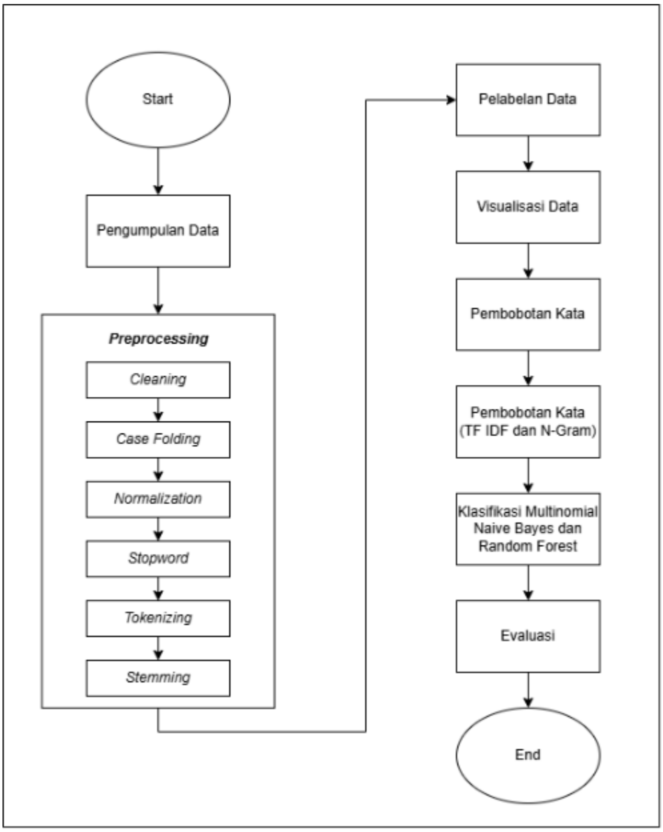

Fig. 1. Flowchart for sentiment analysis

Fig. 1 illustrates the workflow of a sentiment analysis system employing text classification methods using MNB and Random Forest. The process begins with data collection, followed by a comprehensive preprocessing phase that includes cleaning, case folding, normalization, stop-word removal, tokenization, and stemming. Once preprocessing is complete, the data undergoes labeling and visualization to understand distribution and trends. Feature extraction is then conducted using term weighting techniques such as TF-IDF and N-Gram models to convert textual data into numerical representations. These features are input into classification models for MNB and MNB for supervised learning. Finally, the models are evaluated to determine classification performance, completing the analytical cycle.

3.1 Data Collection

In this study, we gathered data using a survey based on a questionnaire created with Google Forms, which could be accessed by the respondents of this study, namely university students across Indonesia who are actively using Artificial Intelligence. The targeted minimum number of respondents is 500.

3.2 Preprocessing

The preprocessing stage involves several processes to clean or filter the data from unnecessary elements, aiming to make the data more structured and refined for optimal algorithm implementation [13]. The preprocessing begins with data cleaning, which aims to remove irrelevant elements such as hashtags, emoticons, numbers, duplicate data, excessive spaces, and symbols, as their presence holds no meaningful value [9]. The second step is case folding, which converts all text in the dataset to lowercase letters to maintain data consistency [14]. The third step is normalization, which transforms abbreviated or non-standard words into meaningful standard words according to the Indonesian Dictionary [15]. The fourth step is stop-word removal, which involves eliminating words considered meaningless or insignificant in the dataset [16]. The fifth step is tokenizing, a process that separates the text into individual words (tokens) based on whitespace [8]. The next step is stemming, which reduces each word to its root form by removing affixes [17].

3.3 Data Labelling

The data labeling stage is the first step after importing the data into Google Colaboratory. The sentiment labels consist of two classes: positive and negative. If the satisfaction score is 1, 2, or 3, it will be labeled as "Negative," whereas scores of 4 and 5 will be labeled as "Positive" [18].

3.4 Data Visualization

The data visualization phase is a form of representation in which the dataset is visualized using diagrams, graphs, and other graphical media [9]. The goal of this phase is to present the information in the dataset through visuals such as word clouds and bar charts for better understanding.

3.5 Word Weighting

TF-IDF, or Term Frequency-Inverse Document Frequency, is a combination of two methods: Term Frequency (TF) and Inverse Document Frequency (IDF), used to identify the correlation between words and documents by assigning a weight to each word. This method is widely used for word weighting due to its effectiveness and efficiency in achieving accurate results [19]. TF is used to calculate the frequency of words that appear frequently in a document. Once the TF and IDF values are obtained, the TF-IDF score is calculated by multiplying the TF value by the IDF value, as shown in (1), with the details provided in Table 1.

$$W_t = TF_{r,d} \times IDF_t \tag{1}$$

Table 1. TF-IDF Formula

Notation	Description
W_t	$Term\ Frequency - Inverse\ Document\ Frequency$
$TF_{r,d}$	$Term\ Frequency$
IDF_t	$Inverse\ Document\ Frequency$

In addition to the TF-IDF method, this study also implements the N-Gram feature in the word weighting stage. The N-Gram method is a sequence of words extracted from the beginning to the end of a sentence based on the value of *n*. N-Grams are categorized based on the number of words they contain. Common types of N-Grams include Unigram (consisting of a single word), Bigram (consisting of two words), and Trigram (consisting of three words) [12].

3.6 MNB Classification

Naïve Bayes is used as an algorithm model for discrete data, making it relevant for sentiment classification tasks involving texts or documents. The most commonly applied model of the Bayes algorithm in text or document classification is the MNB, as this model utilizes the principle of frequency or the occurrence of a word [20]. This model operates by requiring training data to calculate probability values. These probabilities are then used during the classification process by computing the likelihood of each attribute for every class in the testing data. The class with the highest probability is selected as the predicted label. The probability calculation follows Bayes' Theorem and is expressed using the following (2), with the details provided in Table 2.

$$P(V_j|a_i) = \frac{P(a_i|\, V_j)\, P(V_j)}{P(a_i)} \tag{2}$$

Table 2. Naive Bayes Formula

Notation	Description
$P(V_j\|a_i)$	$The\ probability\ of\ category\ j\ given\ the\ occurence\ of\ feature\ i$
$P(a_i\|V_j)$	$The\ probability\ of\ feature\ i\ occuring\ in\ category\ j$
$P(V_j)$	$The\ probability\ of\ the\ occurence\ of\ category\ j$
$P(a_i)$	$The\ probability\ of\ the\ occurence\ of\ feature\ i$

3.7 Random Forest Classification

The Random Forest algorithm is one of the machine learning algorithms that involves a combination of decision trees as the basis for classification, making it part of the ensemble learning method. This algorithm is used for both classification and prediction tasks. The prediction results are obtained by combining the outputs of each tree using a majority vote approach for classification [21]. Random Forest offers several advantages, including good classification performance, the ability to efficiently handle large-scale datasets, relatively low error rates, and the capability to effectively estimate missing data [22].

3.8 Evaluation

To calculate the success rate of the accuracy indicator, an evaluation step is required to measure the accuracy level. The evaluation of the classification system's performance in this study uses the Confusion Matrix method to obtain values of accuracy, precision, recall, and F1-Score for the applied model. The confusion matrix is presented in the form of a table that provides information on the comparison between the model's predicted classification results and the actual classification results, thereby illustrating the model's performance in the classification process [23]. The use of the confusion matrix in the model evaluation stage is due to its ease of interpretation and effectiveness in assessing the performance of the applied model [12]. The four components produced in a confusion matrix can be seen in Table 3.

Table 3. Confusion Matrix

		Predicted Values	
		Positive	**Negative**
Actual Values	**Positive**	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

The calculation process for accuracy, precision, recall, and F1-Score values is carried out using formulas as shown in (3), (4), (5), and (6).

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{3}$$

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

$$F1-Score = 2 \times \frac{Recall \times Precision}{Recall+Precision} \tag{6}$$

4. Experimental Setup

1) Data Collection

Data collection was carried out using a questionnaire created through the Google Forms platform, which was distributed to active university students currently pursuing their studies in Indonesia. The data was successfully collected over 30 days, from November 20, 2024, to December 20, 2024, with a total of 517 respondents. Once the responses were collected, the questionnaire results were downloaded in CSV file format and processed using Google Colaboratory.

2) Preprocessing

In this study, we apply a series of preprocessing steps to the survey data to ensure it is clean, structured, and suitable for sentiment analysis. First, we perform cleaning to remove duplicate entries and eliminate irrelevant characters or symbols that may introduce noise. Next, we carry out case folding by converting all text to lowercase, promoting consistency across the dataset. In the normalization step, we standardize the text by correcting non-standard words, abbreviations, and typographical errors. We then remove stopwords of common words that do not significantly contribute to sentiment detection. Using tokenization, we split the text into individual units or tokens, typically based on whitespace. Finally, we conduct stemming to reduce each word to its root form, utilizing the Sastrawi library. These preprocessing actions enhance the dataset's quality and improve the performance of the sentiment classification model. After the preprocessing stage, a total of 498 data entries were ready for analysis. The results of the preprocessing process are presented in Table 4.

Table 4. Result of Preprocessing

No	Step	Result
1	Data Collection	Saya dlu sering pake ai, karena mudah dan praktis namun ketika saya tau jawaban yg saya berikan yg bersumber dari ai itu rata rata salah dan nilai akademik saya menurun. Saya pun tidak mau lagi pake ai karena ketidak akuratan tsb Mudah digunakan Kesulitan dalam memahami jawaban, Respon yang lambat, Memerlukan keterampilan teknis dalam menggunakannya Nilai saya sedikit menurun Penggunaan gratis
2	*Cleaning*	Saya dlu sering pake ai karena mudah dan praktis namun ketika saya tau jawaban yg saya berikan yg bersumber dari ai itu rata rata salah dan nilai akademik saya menurun Saya pun tidak mau lagi pake ai karena ketidak akuratan tsb Mudah digunakan Kesulitan dalam memahami jawaban Respon yang lambat Memerlukan keterampilan teknis dalam menggunakannya Nilai saya sedikit menurun Penggunaan gratis
3	*Case Folding*	saya dlu sering pake ai karena mudah dan praktis namun ketika saya tau jawaban yg saya berikan yg bersumber dari ai itu rata rata salah dan nilai akademik saya menurun saya pun tidak mau lagi pake ai karena ketidak akuratan tsb mudah digunakan kesulitan dalam memahami jawaban respon yang lambat memerlukan keterampilan teknis dalam menggunakannya nilai saya sedikit menurun penggunaan gratis
4	*Normalization*	saya dahulu sering pakai ai karena mudah dan praktis namun ketika saya ngerti jawaban yang saya berikan yang bersumber dari ai itu rata rata salah dan nilai akademik saya menurun saya pun tidak mau lagi pakai ai karena ketidak akuratan tersebut mudah digunakan kesulitan dalam memahami jawaban respon yang lambat memerlukan keterampilan teknis dalam menggunakannya nilai saya sedikit menurun penggunaan gratis
5	*Stopword*	pakai ai mudah praktis ngerti bersumber ai salah nilai akademik menurun tidak pakai ai ketidak akuratan mudah kesulitan memahami respon lambat keterampilan teknis menggunakannya nilai menurun penggunaan gratis
6	*Tokenizing*	['pakai', 'ai', 'mudah', 'praktis', 'ngerti', 'bersumber', 'ai', 'salah', 'nilai', 'akademik', 'menurun', 'tidak', 'pakai', 'ai', 'ketidak', 'akuratan', 'mudah', 'kesulitan', 'memahami', 'respon', 'lambat', 'keterampilan', 'teknis', 'menggunakannya', 'nilai', 'menurun', 'penggunaan', 'gratis']
7	*Stemming*	pakai ai mudah praktis ngerti sumber ai salah nilai akademik turun tidak pakai ai tidak akurat mudah sulit paham respon lambat terampil teknis guna nilai turun guna gratis

3) Classification and Evaluation Scenario

We conducted data labeling using a Likert scale ranging from 1 to 5 to classify sentiment polarity. We labeled reviews with scores of 1, 2, and 3 as negative sentiment, and those with scores of 4 and 5 as positive sentiment. As a result, we obtained 347 reviews classified as positive and 151 as negative. To explore patterns in the labeled data, we performed data visualization using a word cloud to represent frequently occurring terms and a bar chart to display student responses regarding the ethical use of AI. These visual tools enabled us to identify trends and dominant themes within the sentiment-labeled dataset.

For the word weighting process, we applied the Term Frequency-Inverse Document Frequency (TF-IDF) method, limiting the features to a maximum of 700. We experimented with various n-gram configurations, including unigram, bigram, trigram, and their combinations, with the highest classification performance obtained using unigram and combined n-gram features. We then implemented the Multinomial Naive Bayes (MNB) classifier using training data proportions of 60%, 70%, 80%, and 90%, and found the best accuracy using 90% training data with the combined n-gram configuration. Similarly, for the Random Forest classifier, we tested the same training ratios and achieved the highest accuracy using 90% training data, but with unigram features. Finally, we conducted an evaluation using a confusion matrix to calculate accuracy, precision, recall, and F1-score. The results indicated that the Random Forest model outperformed the MNB model in terms of overall classification accuracy.

5. Results and Analysis

This section presents the core findings of the study, focusing on the data obtained through the applied methods. The results are reported in the form of tables, charts, and figures to illustrate the key outcomes relevant. The data labeling process resulted in a quantitative distribution of two sentiment categories, as shown in Fig. 2.

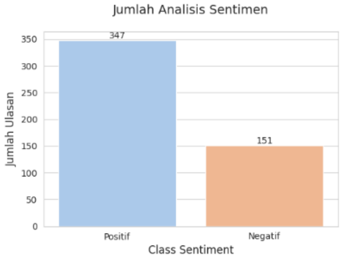

Fig. 2. Data Labeling Visualization

The bar chart distinctly illustrates the distribution of sentiment labels, with the majority of reviews concentrated in the positive category. The striking difference in numbers between positive and negative reviews suggests a robust, favorable trend in the dataset. This visualization supports the conclusion that, overall, the sentiment reflected in the data leans towards the positive.

Fig. 3. Positive Word Cloud Visualization

This word cloud prominently features words frequently found in reviews expressing positive sentiment, including terms like "*motivasi*", "*mampu*", "susun", and "*ajar*", as illustrated in Fig. 3. The variations in font size and placement underscore the crucial role these terms play in crafting a supportive positive narrative. Overall, the visualization in Fig. 3 evidences that the dataset predominantly exhibits a positive sentiment.

Fig. 4. Negative Word Cloud Visualization

In the negative sentiment word cloud presented in Fig. 4, most words reflect negative sentiment, such as "salah", "*turun*", "*lambat*", "*kecewa*", and "kacau", yet there are also positive terms like "*aman*", "*ringan*", and "*suka*". Therefore, this visualization effectively illustrates the frequently occurring words within the negative sentiment category.

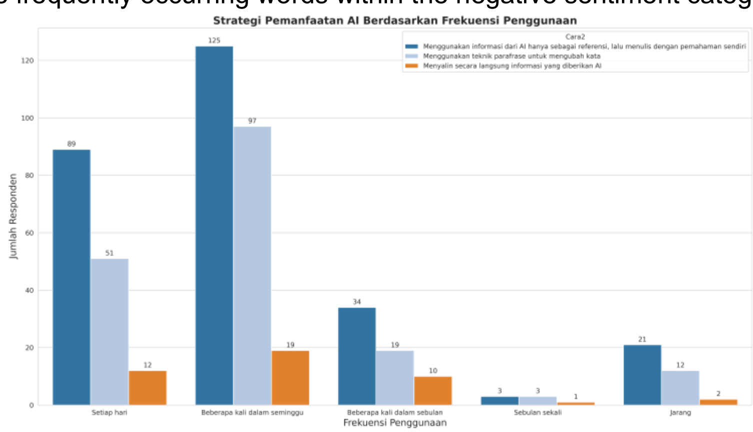

Fig. 5. Ethics of AI Usage

The visualization shown in Fig. 5 indicates that the majority of respondents use AI as a reference to generate ideas, which are then understood and developed using their comprehension. This strategy is predominantly chosen by respondents who interact with AI several times a week. Meanwhile, the technique of paraphrasing AI-generated responses is mostly applied by those who use AI daily. However, there are still 44 students in this study who tend to directly copy the answers provided by AI.

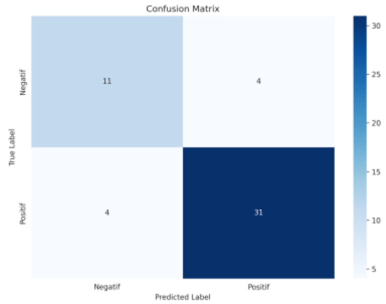

Fig. 6. Confusion Matrix of MNB

The confusion matrix for the highest accuracy achieved with the MNB model, using a 90% training data split and a combination of unigram, bigram, and trigram, is shown in Fig. 6. This accuracy result indicates that the model correctly classified 42 instances, while there were 8 misclassifications. Overall, the findings suggest that the model is quite balanced in classifying the two sentiment classes, despite some prediction errors.

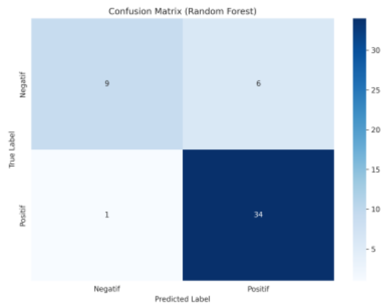

Fig. 7. Confusion Matrix of Random Forest

The confusion matrix for the highest accuracy obtained with the Random Forest model, using a 90% training data split and unigram, is shown in Fig. 7. The results reveal that 43 instances were correctly classified, and there were 7 misclassifications. Notably, the majority of these misclassifications occur in predicting the negative sentiment, with only 1 positive instance being incorrectly classified, which suggests that the Random Forest model is more effective at recognizing positive sentiment.

Akurasi pada Data Test: 0.84
Laporan Klasifikasi:

	precision	recall	f1-score	support
Negatif	0.73	0.73	0.73	15
Positif	0.89	0.89	0.89	35
accuracy			0.84	50
macro avg	0.81	0.81	0.81	50
weighted avg	0.84	0.84	0.84	50

Fig. 8. Performance of MNB

Akurasi pada Data Test (Random Forest): 0.86
Laporan Klasifikasi (Random Forest):

	precision	recall	f1-score	support
Negatif	0.90	0.60	0.72	15
Positif	0.85	0.97	0.91	35
accuracy			0.86	50
macro avg	0.88	0.79	0.81	50
weighted avg	0.86	0.86	0.85	50

Fig. 9. Performance of Random Forest

The accuracy results of the MNB model are shown in Fig. 8, with the highest accuracy of 0.84 achieved using a combination of unigram, bigram, and trigram features, and a training data proportion of 90%. In comparison, the Random Forest (RF) model, as presented in the Figure, achieved a higher accuracy than the primary model (MNB), reaching an optimal accuracy of 0.86 using 90% training data with unigram features. Thus, the Random Forest algorithm demonstrates superior performance in classifying positive sentiments, indicated by its lower False Negative value compared to MNB. However, MNB shows a strength in classifying negative sentiments due to its relatively lower False Negative value for that class.

6. Conclusion

Based on the experimental results, the RF algorithm demonstrates superior performance in sentiment classification compared to the MNB algorithm, achieving the highest accuracy of 0.86 when applying unigram features with 90% training data. MNB obtained an accuracy of 0.84 using a combination of unigram, bigram, and trigram with the same proportion of training data as the Random Forest model. The findings of this study indicate that n-gram features significantly influence the improvement of classification outcomes. In addition, a larger proportion of training data (90%) applied to both models yields the most optimal accuracy compared to smaller training data sizes.

In terms of AI usage ethics, the study reveals that 8.8% or 44 out of 498 student respondents have not yet demonstrated awareness of applying academic ethics when utilizing AI-generated information. These students tend to directly copy responses from AI without understanding or modifying them, which raises the risk of plagiarism. Therefore, the results of this study are expected to serve as a foundation for the establishment of academic ethical regulations in AI usage, highlighting the existence of ethical violations in the use of educational technology. Future research is encouraged to explore other algorithmic approaches by experimenting with different training data proportions and n-gram types, as well as other factors that may enhance model performance.

Acknowledgment

We would like to express our sincere gratitude to the Islamic University of Indonesia for providing the opportunity, support, and academic facilities for me to conduct this research. We also extend our thanks to the respondents who took the time to share their experiences with the researcher.

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