Scientific Journal of Informatics
Vol. 11, No. 3, Aug 2024

p-ISSN 2407-7658 https://journal.unnes.ac.id/journals/sji/index e-ISSN 2460-0040

Comparative Performance of SVM and Multinomial Naïve Bayes in Sentiment Analysis of the Film 'Dirty Vote'

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Abstract.
Purpose: The purpose of this research is to analyze and compare the performance of two machine learning models, Support Vector Machine (SVM) and Multinomial Naive Bayes, in conducting sentiment analysis on YouTube comments related to the film "Dirty Vote."
Methods: The study involved collecting YouTube comments and preprocessing the data through cleaning, labeling, and feature extraction using TF-IDF. The dataset was then divided into training and testing sets in an 80:20 ratio. Both the SVM and Multinomial Naive Bayes models were trained and tested, with their performance evaluated using accuracy, precision, recall, and F1-score metrics.
Result: The results revealed that both models performed well in classifying sentiments, with SVM slightly outperforming Multinomial Naive Bayes in terms of accuracy and precision. Particularly, SVM showed superior performance in detecting positive comments, making it a more reliable model for this specific sentiment analysis task.
Novelty: This study contributes to the field of sentiment analysis by providing a detailed comparative analysis of SVM and Multinomial Naive Bayes models on YouTube comments in the context of an Indonesian film. The findings highlight the strengths and weaknesses of each model, offering insights into their applicability for sentiment analysis tasks, particularly in analyzing social media content. This research also suggests potential future directions, including the exploration of advanced NLP techniques and different models to enhance sentiment analysis performance.

Keywords: Sentiment analysis, Dirty vote, SVM, Multinominal naïve bayes
Received July 2024 / **Revised** August 2024 / **Accepted** September 2024

INTRODUCTION

Information and communication technology development has brought significant changes in various aspects of human life. With the rapid growth of the internet and the emergence of various media platforms, movie viewers can express their opinions and reviews about the films they watch [1]. The film "Dirty Vote" is a documentary on YouTube that portrays the issue of electoral fraud in Indonesia. Viewers are shown depictions of fraud in various elections, where politics becomes an arena for personal interests. The film is used as a public awareness campaign, encouraging active participation in monitoring the election process so that the public could report potential fraud and ensure votes were counted correctly [2]. The release of this film has sparked both supportive and opposing opinions among the Indonesian public regarding electoral fraud. The numerous reviews in the YouTube comment section reflect viewers' diverse perceptions and sentiments towards the film [3]. Sentiment analysis, or opinion mining, is the process of using Natural Language Processing (NLP) to identify and classify opinions within a text into categories such as positive, negative, or neutral [4], [5]. Sentiment analysis can help analyze the public's or an individual's opinions about a product or service [6].

Several studies have been conducted on the application of sentiment analysis using various algorithms. The study [7] focused on analyzing existing movie reviews on IMDb. The study found that IMDb visitors cannot immediately see whether the movie review has positive or negative reviews. This sentiment analysis method is used to classify whether the film falls into the positive or negative category. Using the SVM algorithm, the study produced an accuracy of 86.5%, a precision value of 90.67%, and a recall of 91.62%. Meanwhile, the study [8] focused on analyzing the sentiment of twitter users' responses to the Covid-19 vaccination action. The study found that the researchers wants to see whether the vaccination action gets a

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DOI: [10.15294/sji.v11i3.10290](https://doi.org/10.15294/sji.v11i3.10290)

positive or negative response from the community. The test used two keywords, namely "vaksinmerah putih" and "vaksinsinovac". The test can result in people having a positive response to vaccination actions. The test results used the Naïve Bayes method with a result of 66% on the keyword "vaksinsinovac" and 89% positive on the keyword "vaksinmerah putih". Meanwhile, the results of the SVM test produced 96% positive on the keyword "vaksinovac" and 98% positive on "vaksinmerah putih". The study [7] only used the SVM algorithm and did not mention the title of the film being tested, while the study [8] used the SVM and Naïve bayes algorithms, and mentioned the keywords used for the test.

In the study [9], the researchers focused on the classification of public responses on Twitter regarding the discourse on the relocation of the Indonesian capital. The study aims to find out the tendency of public sentiment that exists in the controversy of the discourse on the relocation of the Indonesian capital. The Support Vector Machine (SVM) method is used to classify positive and negative sentiment classes, then evaluation and validation are carried out using the Confusion Matrix. Thus resulting in 96.68% accuracy, 95.82% precision, 94.04% recall, and 0.979 AUC. Furthermore, in the study [6], the researchers focused on the classification of Twitter users' responses on Biznet internet services. Using the Support Vector Machine (SVM) algorithm, researchers compared and tested which kernels could provide the best performance results on the SVM algorithm. The results of the test showed that the SVM algorithm using the two kernels had an influence on the performance of the SVM and produced consistent performance in terms of accuracy, precision, and recall. The difference is that the study [6] focuses on testing SVMs using 2 kernels, while the study [9] uses a confusion matrix.

Research [10] applied sentiment analysis to beauty product reviews. The study found that the number of reviews on beauty products is too large so that it cannot be assessed manually. In addition, the study was conducted to find out whether the use of DF-Tresholding and N-gram algorithms could affect the accuracy level of the Naive Bayes Classifier algorithm. The sentiment analysis conducted aims to classify reviews to make it easier for consumers to buy suitable products. The study used the Naïve Bayes Classifier method and feature selection using N-gram and DF-Tresholding algorithms to reduce the feature dimensions in the data. The results of the study showed the highest accuracy value on the combination of unigram and bigram of 49%, precision of 0.23, recall of 0.26, and f-measure of 0.24. Furthermore, the study [11] focused on customer satisfaction of 3 Indonesian digital banks, namely Bank Jenius, Jago, and Blu. The problem of this research is that because of the existence of digital banks, customer satisfaction may not be noticed. Therefore, this study aims to measure the level of customer satisfaction of the 3 banks based on twitter data. The sentiment analysis of this study uses 9 stand-alone classifications and 2 ensemble methods, namely hard voting and soft voting. This study found that bank jago obtained more positive sentiment of 86.62%. while Bank Jenius received 43.50% negative sentiment, and Bank Blu 44.46% neutral sentiment.

In the study [12] researchers focused on analyzing the sentiment of customer reviews in various Jordanian restaurants. The problem is, customer review data usually has imbalanced data because the sentiment can be biased towards positive or negative reviews. Therefore, the researchers combined the Support Vector Machine (SVM) with Particle Swarm Optimization (PSO) to overcome imbalanced data. In addition, the researcher also used 2 other oversampling techniques, namely SMOTE, AVM_SMOTE, ADASYN, and borderline-SMOTE. Thus, the result of the test is that the PSO-SVM approach is more effective and superior to other approaches. On the other hand, the k-NN algorithm has the worst results because it produces data complexity on examples and dimensions. These three studies have similarities in the application of sentiment analysis and both handle the imbalanced data that occurs. The difference between the three studies is in the context and methods used. The research [10] focuses on beauty product reviews and uses the Naive Bayes Classifier method with the selection of N-gram and DF-Tresholding algorithm features. The study [11] focused on customer satisfaction in three Indonesian digital banks using 9 standalone classifications and 2 ensemble methods. While the study [12] focused on restaurant customer reviews in Jordan by combining SVM and PSO methods.

In conclusion, various studies have shown that sentiment analysis is an essential step in understanding public perception of a film. This research aims to identify the dominant sentiment in Youtube comments related to the film “Dirty Vote” and compare the performance of two classification models, specifically Support Vector Machine (SVM) and Multinominal Naive Bayes. These models will be used to analyze public sentiment, and their performance will be evaluated using metrics such as accuracy, precision, recall, and F1-score [13]. The results will then be compared with each other. The main objective of this study is to provide a deeper understanding of which model performs more accurately in analyzing the sentiment of

"Dirty Vote" comments. Additionally, this research will identify the classification model that delivers the best performance, with the ultimate goal of providing practical recommendations for the development of more accurate and relevant sentiment analysis in the future.

METHODS

The sentiment analysis process for this study involves six steps as illustrated in Figure 1. The process begins with data acquisition, where YouTube Comments about the film "Dirty Vote" are collected. The data was then cleaned and prepared in the preprocessing stage. Next, Feature Extraction is performed using TF-IDF to convert the text into numerical values. The data was then Labeled with sentiment categories and classified using two models, Support Vector Machine (SVM) and Multinominal Naive Bayes, in the Model Classification step [14]. Finally, the models performances were evaluated using metrics like accuracy and precision in the model evaluation stage.

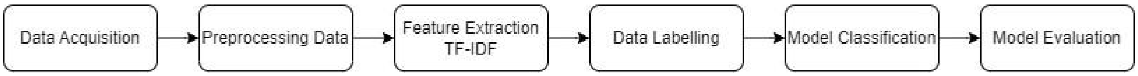

Figure 1. System flow design

Dataset acquisition

The data used in this study is YouTube comment data due to with drawals on the YouTube server. The comment data is obtained by utilizing the API (Application Interface) feature that YouTube has provided [15], [16]. The API is used to retrieve video comment data from YouTube's servers and then collect the data in a file in CSV format [17]. While collecting YouTube comment data, the researcher used the ID of the intended video. Then, the process of collecting comment data is taken from users who have commented on the video using the YouTube API. Then, the YouTube server will retrieve the comment data that matches the video ID entered. Furthermore, the comment data obtained from the YouTube server is saved into a CSV format file.

Figure 2. Dataset acquisition flow

In this study, the total comment data taken were 1000 comments. Comments taken were then saved for text preprocessing and labeling into two classes: positive and negative.

Table 1. Sample comment dataset

Comment
MAU NGAKAK DIKASIH NIH VIDIO BUAT PILIH YANG CERDAS MALAH PILIH 02, SEMANGAT DIRTY VOTE SEKARANG SUDAH TERBUKTI TUNGGU SAMPAI TAHUN BERIKUTNYA DAN SETERUSNYA INDONESIA BAKALAN SUSAH😡👊
Biarkan filem ini menjadi sejarah tuntunan atas kebenaran itu sendiri memanusiakan manusia seutuhnya tidak membela pihak mana pun
Kalian semua yg komen dan ada disini sedang di giring ke saling benci satu sama lain, bukannya secara gars besar politik itu tidak ada yg jujur ,siapapun itu selma ada di dunia politik ..jadi jngan lah terpecah belah ,semoga saja indonesia ini menjadi lebih baik .

Preprocessing

Data preprocessing is processed to process raw data into ready-to-use data [9]. In this study, the dataset obtained is unstructured data, so it needs to be processed first so that the collection of essential words can be detected in sentiment analysis [18], [19]. The preprocessing process in this study has several stages, namely data cleaning, case folding, stopword removal, tokenization, and Stemming [19].

Data cleaning and case folding

The first stage, data cleaning, focused on removing extraneous elements from the text. The first stage is data cleaning, it cleans up the text by removing unnecessary characters such as numbers, URLs, extra spaces, and punctuation, which do not contribute to the sentiment analysis [20]. Additionally, inconsistencies such as mixed case usage are addressed by converting all text to lowercase, ensuring uniformity across the dataset [19], [21], [22]. An example of the result of Data Cleaning anad Case Folding can be seen ini Table 2 below:

Table 2. Sample data cleaning and case folding

Before	After
Film edukasi yang keren. Mencerdaskan bangsa tentang kebusukan pemimpin negara saat ini. Tapi kita bisa apa sekarang. Tinggal tunggu pengadilan akhirat untuk pemimpin dzolim ðŸ¦‰ðŸ¦‰ðŸ¦‰	film edukasi yang keren mencerdaskan bangsa tentang kebusukan pemimpin negara saat ini tapi kita bisa apa sekarang tinggal tunggu pengadilan akhirat untuk pemimpin dzolim

Tokenization

Following data cleaning, tokenization breaks down the text into smaller, manageable units called tokens [22]. This process enables the machine to handle and analyze the text more efficiently by separating it into individual words or phrases. An Example of tokenizing result process can be seen in Table 3 below:

Table 3. Sample tokenization

Before	After
film edukasi yang keren mencerdaskan bangsa tentang kebusukan pemimpin negara saat ini tapi kita bisa apa sekarang tinggal tunggu pengadilan akhirat untuk pemimpin dzolim	['film', 'edukasi', 'yang', 'keren', 'mencerdaskan', 'bangsa', 'tentang', 'kebusukan', 'pemimpin', 'negara', 'saat', 'ini', 'tapi', 'kita', 'bisa', 'apa', 'sekarang', 'tinggal', 'tunggu', 'pengadilan', 'akhirat', 'untuk', 'pemimpin', 'dzolim']

Stopward removal

In the stopword removal stage, common but unimportant words that frequently appear in the text but do not contribute meaningful information to the sentiment analysis are removed. This helps to reduce noise and focus on words that carry significant sentiment value. An example of stopword removal result can be seen in Table 4 blow:

Table 4. Sample stopword removal

Before	After
['film', 'edukasi', 'yang', 'keren', 'mencerdaskan', 'bangsa', 'tentang', 'kebusukan', 'pemimpin', 'negara', 'saat', 'ini', 'tapi', 'kita', 'bisa', 'apa', 'sekarang', 'tinggal', 'tunggu', 'pengadilan', 'akhirat', 'untuk', 'pemimpin', 'dzolim']	['film', 'edukasi', 'keren', 'mencerdaskan', 'bangsa', 'kebusukan', 'pemimpin', 'negara', 'tinggal', 'tunggu', 'pengadilan', 'akhirat', 'pemimpin', 'dzolim']

Stemming

Finally, the stemming stage involves reducing words to their root forms using a stemmer algorithm. This process helps in standardizing the words by stripping suffixes and prefixes, thereby consolidating various forms of a word into a single base form [23]. By following these preprocessing steps, the dataset is refined and prepared for accurate sentiment classification. An example of stemming result can be seen in Table 5 below:

Table 5. Sample stemming

Before	After
['film', 'edukasi', 'keren', 'mencerdaskan', 'bangsa', 'kebusukan', 'pemimpin', 'negara', 'tinggal', 'tunggu', 'pengadilan', 'akhirat', 'pemimpin', 'dzolim']	['film', 'edukasi', 'keren', 'cerdas', 'bangsa', 'busuk', 'pimpin', 'negara', 'tinggal', 'tunggu', 'adil', 'akhirat', 'pimpin', 'dzolim']

Feature extraction (TF-IDF)

This process calculates the inverse document frequency (IDF) first. After the IDF results are known, look for the TF-IDF weight value, where the term frequency value is transferred to the inverse document frequency value for each term [24]. The results of the TF-IDF calculation can be used to perform text analysis, document grouping, and index creation [22], [25]. The TF-IDF calculation formula is as follows (1).

$$wt,d = wtf\ x\ idft \quad (1)$$

Description:

N = Total text of the document

$wtft$ = Word weights

tft,d = The number of words or terms that appear in the document

dft = The number of documents containing a word or term
$idft$ = Inverse Weight
wt,d = TF-IDF Weight

Feature extraction with TF-IDF helps highlight words that have important weight in the comment text. These words have a high probability of containing useful information for further analysis. The table 6 below shows some words with the highest TF-IDF scores in the dataset.

Table 6. Sample TF-IDF score

Word	TF-IDF Score
pj	0.046625
kpu	0.063262
langgar	0.052598
putus	0.060804
gubernur	0.066368
desa	0.06901
kepala	0.080621
presiden	0.080621
bansos	0.07059
wenang	0.074574
netral	0.072415
kontroversi	0.13523

Data labelling

The sentiment classification in this study uses the VADER Lexicon to regulate only positive and negative sentiment [26]. Positive sentiment is assigned to values above zero, while negative sentiment is assigned to values below zero. The classification results showed a total of 45 positive reviews and 955 negative reviews. The table 7 below shows some sample comment label.

Table 7. Sample data labelling

Cleaned_comment	Negative	Positive	Compound	Sentiment
ngakak kasih nih vidio pilih cerdas pilih semangat dirty vote bukti tunggu indonesia susah	0.182	0	-0.4404	negatif
film dirty vote sebar tenang jelang h coblos kemas himbauan hukum yaa ya propaganda licik kedok edukasi juta rakyat indonesia jawab coblos prabowo tps tps februari unggul prabowo gagal total propaganda licik	0.198	0	-0.7096	negatif
si bodoh yg munafik percaya per dokumenter sebar hoax depan mata fakta	0.16	0	-0.2732	negatif

Model classification

The model classification stage is carried out after the dataset has been preprocessed and given a sentiment label. This study compares two classification models often used in data analysis, SVM (Support Vector Machine) and Multinominal Naive Bayes, with test data and training data of 80:20.

Support vector machine

Support Vector Machine (SVM) is a classification method that separates classes from data by relying on supporting vectors [19], [27]. SVM works by getting a hyperplane that separates the two classes and maximizes the margin of the two classes [28]. This study uses a linear kernel to find a linear hyperplane that maximizes the margin between different classes. The hyperplane is presented as linear equations as follows (2).

$$\mathrm{w} \cdot \mathrm{x} + b = 0 \tag{2}$$

Description:
w = Weight Vector.
x = Feature vector.
b = bias.

Multinomial naïve bayes

Naive Bayes is a method of classifying by predicting future opportunities based on experience [18]. This model classification is carried out by calculating the probability of comments in the positive or negative sentiment class using the training process results [24]. This study uses multinominal naïve bayes that are suitable for data with features that represent the number or frequency [21], [22]. In addition, multinominals are very commonly used in text classification, where the feature is a TF-IDF representation or word count. In the application of Multinominal Naïve Bayes, equation (3) is used:

$$P(w_i|c_j) = \frac{\text{count}(w_i,c_j)+1}{(\sum_{weV} \text{count}(w_i,c_j))+|V|} \tag{3}$$

Description:
$P(w_i|c_j)$ = The probability of a wi word appearing in the cj category
count(w_i,c_j) = The number of occurrences of the word wi in the cj category
+1 = Given to avoid zero
$\sum_{weV} \text{count}(w_i, c_j))$ = The sum of all words in the CJ category
$+|V|$ = the sum of all unique words in all categories

Model evaluation
In this study, a model evaluation was carried out on the performance of the Support Vector Machine (SVM) and Naive Bayes multinominal methods. This model was evaluated using a confusion matrix to evaluate the prediction results against the training data [29]. The following is a table of confusion matrix [6].

Table 2. Confusion matrix table

Actual	**Prediction**	
	True	**False**
True	TP	FN
False	FP	TN

Description :
TP = Number of correct positive predictions
TN = Number of correct negative predictions
FP = Number of false positive predictions
FN = Number of false negative predictions

YouTube dirty vote comment data was tested using the division of 80% training data and 20% test data. From the confusion matrix, it can get the accuracy, precision, recall, and F1-Score values [30].

Accuracy
Accuracy measures how often the model makes correct predictions. The formula for accuracy is given by equation (4):

$$Accuracy = \frac{\text{TP+TN}}{\text{Total}} \tag{4}$$

Precision
Precision measures how many positive predictions are correct compared to all the positive predictions made. Precision formulas are written with equations (5):

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \tag{5}$$

Recall
The recall measures how many positive cases the model actually detects. Precision formulas are written with equations (6):

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{6}$$

F1 - score
F1 – Score is a harmonic average of precision and recall. Precision and recall are given a balance, especially if there is an imbalance between the number of positive and negative cases.

$$F1 - Score = 2 \,.\frac{Precision\ .\ Recall}{Precision+Recall} \tag{7}$$

RESULTS AND DISCUSSIONS
The primary focus of this study's evaluation is on how well the Support Vector Machine (SVM) and Multinominal Naive Bayes algorithms perform when used for sentiment analysis on YouTube comments about the movie "Dirty Vote". This study looks at how well the models produced by these algorithms match the predicted classification results from the training data that has been processed. If there are discovered

differences between the predicted and actual outcomes. If differences are discovered between the predicted and actual outcomes, further research is needed to determine the underlying causes and raise the accuracy of the model. This research created a test scenario in which the dataset was split into training and testing sets on an 80:20 rasio after undergoing preprocessing, labeling, and feature extraction using TF-IDF. To measure each model's effectiveness, a confusion matrix was used, and the key performance metrics accuracy, precision, recall, and F1-Score were calculated. Table 8 provides a detailed comparison of the Multinominal Naive Bayes and SVM models.

Table 8. Classification model comparison result

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
SVM	0.955	0.96	0.95	0.94
Naive Bayes	0.95	0.90	0.95	0.93

The confussion matrix in Figure 3 illustrates how well the SVM model classified the negative comments. It properly identified 190 cases as true negatives (TN) and produced no false positives (FP). However, the SVM had some trouble processing the positive remarks, which resulted in nine false negatives (FN) and only one true positive (TP). Despite this, the performance metrics were generally strong, with an F1-Score of 94%, an accuracy of 95.5%, a precision of 96%, and a recall of 95%. These findings suggest that while the SVM model has difficulty identifying positive comments, it is highly effective at accurately classifying the sentiment of comments, particularly negative ones.

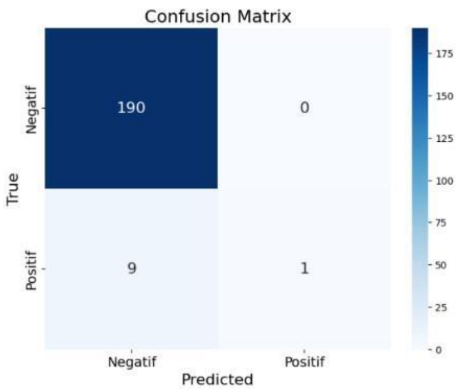

Figure 3. Confusion matrix SVM

As shown in the confusion matrix in Figure 4, the Multinomial Naive Bayes model exhibited similar accuracy in identifying negative comments, with 190 true negatives (TN) and no false positives (FP). However, this model had significant problems identifying positive comment. As a result, there were 10 false negatives (FN) and 0 true positives (TP). This suggests that the model's ability to detect positive sentiments is limited, which could potentially affect the overall sentiment analysis in cases where a large portion of the dataset is made up of positive comments. The model achieved performance scores of 93% for F1-Score, 90% for precision, 95% for recall, and 95% for accuracy. Although the precision and F1-Score are slightly lower than those of the SVM, these metrics still indicate excellent performance, especially in terms of recall.

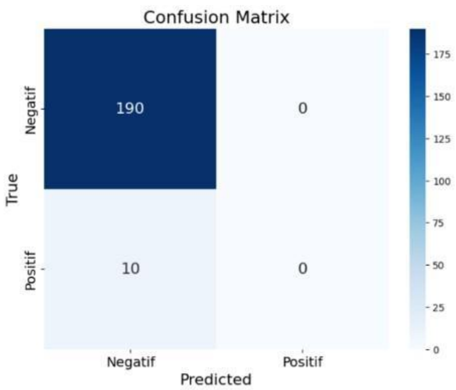

Figure 4. Confusion matrix multinomial naïve bayes

This study also showed how the dataset sentiments were distributed. The sentiment data revealed a significant difference in the distribution of sentiment labels, with 955 negative comments and only 45 positive comments. The model's performance may have been influenced by this imbalance, particularly in its ability to accurately identify positive comments. Figure 5 displays a graphical representation of this sentiment distribution.

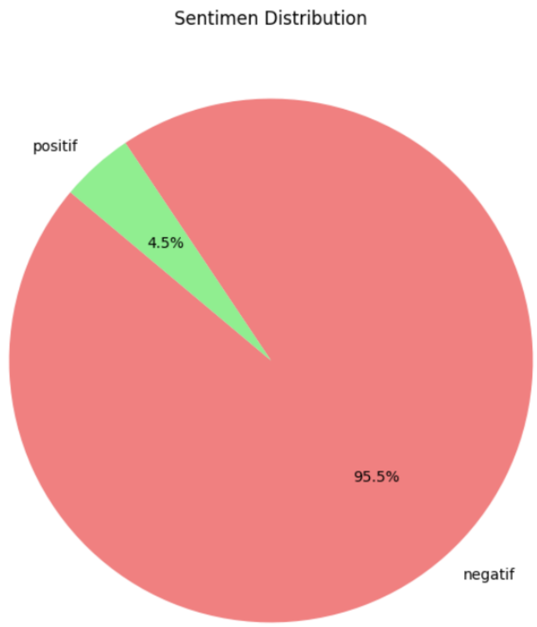

Figure 5. Sentiment distribution

When comparing to Multinominal Naive Bayes and SVM models, both prove effective for sentiment analysis, especially when it comes to identifying negative comments. However, the SVM model generally performs more effectively, especially in terms of precision, which makes it more dependable option for applications where sentiment categorization accuracy is crucial. The SVM model may perform better on balanced datasets that include both positive and negative sentiments, as evidenced by its slight advantage in detecting positive comments. Despite being slightly less accurate, the Multinomial Naive Bayes model provides a quicker and more straightforward option while still achieving strong performance metrics This model may be better suited for large-scale sentiment analysis tasks where computational speed is a concern and a minor loss of precision is acceptable

Overall, this research contributes valuable insights into the performance of different machine learning models for sentiment analysis, providing a foundation for future studies to build upon. By understanding the strengths and limitations of these models, researchers and practitioners can make more informed decisions when selecting tools for sentiment analysis in various contexts.

CONCLUSION

This study concludes that while both the Support Vector Machine (SVM) and Multinominal Naive Bayes models demonstrate strong performance in sentiment analysis of YouTube comments related to the "Dirty Vote" film, the SVM model proves to be superior in terms of accuracy and precision, particularly in detecting positive comments. The evaluation using the confusion matrix highlights that the SVM model is more effective than the Multinomial Naive Bayes model in classifying positive sentiments, making it a more reliable option for this specific task. Future research can focus on improving sentiment analysis by addressing challenges such as the detection and handling of informal language commonly found in online comments. Employing advanced natural language processing (NLP) techniques, such as word embeddings and pre-trained models, could enhance the understanding of sentiments in the Indonesian context. Additionally, conducting comprehensive comparisons with various other classification models could provide deeper insights into the performance of sentiment analysis models. These advancements are expected to yield more accurate and relevant results in analyzing sentiments expressed in YouTube comments related to the "Dirty Vote" film and similar contexts.

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