



# Sentiment Analysis of Film Audience for IPAR ADALAH MAUT Using Support Vector Machine

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## Abstract

This study aims to analyze user sentiment on social media X (formerly Twitter) toward the film Ipar Adalah Maut using the Support Vector Machine (SVM) method. The data were collected through a crawling process using the sncrape library, focusing on tweets containing keywords related to the film title. The preprocessing stages included data cleaning, case folding, tokenization, stopword removal, and stemming, while feature extraction was performed using Term Frequency Inverse Document Frequency (TF-IDF). Sentiment was classified into two categories, namely positive and negative, using the SVM algorithm. The results showed that the model achieved 100% accuracy on the training data and 82% accuracy on the testing data, indicating good generalization performance, although there is a potential risk of overfitting due to the gap between training and testing results. These findings demonstrate the effectiveness of SVM in analyzing sentiment related to film discussions on social media and provide a basis for future research by incorporating larger and more balanced datasets.

**Keywords:** Sentiment Analysis, SVM, TF-IDF, Ipar Adalah Maut, Social Media.

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## 1. Introduction

The development of the film industry in the digital era cannot be separated from the role of social media as a platform for public expression. Films are no longer merely a form of entertainment but also a medium that generates diverse emotional responses from audiences. One film that has attracted significant public attention is Ipar Adalah Maut, which gained viral popularity even before its official release and sparked widespread discussions among society [1]. This phenomenon indicates that audience opinions toward a film are highly diverse and widely distributed, especially on social media platforms such as X (Twitter). However, the massive volume of opinion data generated daily presents a major challenge, as it is difficult to analyze manually [2]. Therefore, an automated approach is required to process and classify these opinions effectively. Sentiment analysis emerges as a relevant solution to understand public opinion trends, whether they are positive or negative. The main problem addressed in this study is how to accurately identify and classify audience sentiment toward the film and how the chosen method can optimally handle large-scale textual data.

Based on the background described above, this study focuses on two main research problems: how public sentiment toward Ipar Adalah Maut is represented through social media, and how effective the chosen method is in classifying such sentiment. The importance of this research lies in the need to understand public perception objectively and in a data driven manner. Opinions shared on social media are often subjective, unstructured, and difficult to interpret without technological assistance [3]. Moreover, the diversity of language, the use of slang, and the emotional context within textual data present additional challenges in sentiment analysis. Therefore, a method capable of handling the complexity of textual data efficiently is required. This study is expected to provide a comprehensive overview of audience responses to the film while also serving as a reference for the film industry in evaluating their works. Thus, sentiment analysis not only functions as a classification tool but also as a strategic source of information for decision-making based on public opinion [4].

Various previous studies have demonstrated that sentiment analysis is an effective approach for processing text-based opinions. Research by Al-shufi and Erfina (2021) showed that the Support Vector Machine (SVM) algorithm can classify reviews of streaming applications with high accuracy, reaching 92.67% on certain platforms [5]. Furthermore, a study by Khairudin et al. (2023) on the Shopee application proved that SVM could achieve an accuracy of up to 98% with an F1-score of 0.98 [6]. Another study by Hibatullah (2021) revealed that the use of SVM combined with Information Gain feature selection improved accuracy to 86.12% while reducing overfitting [7]. Meanwhile, Nuraliza (2022) also demonstrated the effectiveness of SVM in analyzing movie reviews, achieving accuracy above 88% [8]. In addition, the combination of TF-IDF and SVM in the study by Ristiana and Jumaryadi (2021) resulted in good performance, with an accuracy of 85%. These findings indicate that SVM is a consistent and reliable method for text classification tasks [9].

Although numerous studies have proven the effectiveness of the SVM method in sentiment analysis, several research gaps remain to be addressed. Most previous studies have focused on product or application reviews, while research specifically analyzing sentiment toward films using social media data is still relatively limited, particularly in the context of the Indonesian language. Additionally, some studies do not provide detailed explanations of preprocessing stages, even though these stages significantly influence classification results. Other common issues include overfitting and data imbalance, which can negatively impact model performance. Therefore, this study aims to fill these gaps by analyzing audience sentiment toward Ipar Adalah Maut using data from social media platform X and applying a comprehensive and systematic preprocessing approach. By adopting this method, the results are expected to be more accurate and representative in capturing public opinion [10].

To address the identified problems, this study employs the Support Vector Machine (SVM) method as the primary algorithm for sentiment classification. This method is chosen due to its strong capability in handling high-dimensional data and its consistently high accuracy in previous studies. The research process begins with data collection through a crawling technique on social media platform X using keywords related to the film. The collected data then undergoes preprocessing stages, including cleaning, case folding, tokenizing, stopword removal, and stemming [11]. Subsequently, feature extraction is performed using the Term Frequency-Inverse Document Frequency (TF-IDF) method to convert textual data into numerical representations. The dataset is then divided into training and testing data to train and evaluate the SVM model. Evaluation is conducted using a confusion matrix with metrics such as accuracy, precision, recall, and F1-score. This approach is expected to produce an optimal classification model.

This study aims to identify the overall sentiment of the public toward the film Ipar Adalah Maut and to evaluate the effectiveness of the Support Vector Machine method in sentiment classification. In addition, this research seeks to contribute to the development of sentiment analysis, particularly for Indonesian-language data derived from social media [12]. The findings are expected to provide benefits for various stakeholders, including researchers, film industry practitioners, and the general public. For the film industry, the analysis results can serve as an evaluation tool to better understand audience responses to their productions. For future researchers, this study can be used as a reference for further development of sentiment analysis methods [13].

## **2. Research Methods**

This study employs a text mining approach using the Support Vector Machine (SVM) method as the primary algorithm in sentiment analysis, with the object of study being the film Ipar Adalah Maut. According to research by Khairudin (2023), the Support Vector Machine (SVM) method has proven effective in analyzing sentiment on social media, particularly Twitter. This method is capable of accurately classifying user opinions based on comments related to films and produces a reliable SVM model for sentiment classification based on tweet data [6]. The research data were obtained through a crawling process on the X platform, consisting of user comments related to the film Ipar Adalah Maut. Furthermore, the data were processed and classified into two sentiment categories, namely positive and negative, using the Support Vector Machine method.

### **2.1. Sentiment Analysis**

According to Hibattullah (2021), sentiment analysis is a field of study that focuses on natural language processing, computational linguistics, and text mining [7]. This field, also known as opinion mining, examines individual opinions or perspectives toward entities, events, or specific attributes through computational approaches. Its primary objective is to determine the polarity of a text, whether it is positive or negative. Sentiment analysis can be conducted at several levels, including document level, sentence level, and entity level. At the document level, the goal is to determine whether the overall text expresses a positive or negative sentiment. At the sentence level, the analysis focuses on identifying the polarity of individual statements, while at the entity or aspect level, it evaluates sentiment toward specific entities or attributes.

### **2.2. Crawling**

Data collection was carried out through a crawling process on the social media platform X (formerly Twitter) using the Python programming language with the assistance of the `snsrape` library. This method utilizes web scraping techniques to retrieve tweets based on the keyword "Iparadalahmaut." The selection of platform X is based on the diversity of user opinions and the availability of an API that allows data access through token-based authentication Styawati (2021). From this crawling process, a total of 1,001 Indonesian-language tweets were collected as the research dataset [14].

### **2.3. Preprocessing**

The initial stage of analysis involves preprocessing to ensure that the text data are clean and standardized before further analysis [15]. This process consists of several main steps:

#### **1. Cleaning**

This stage aims to remove irrelevant elements or noise, such as HTML characters, emoticons, hashtags (#), user mentions (@username), retweets (RT), URLs, and website addresses.

#### **2. Case Folding**

At this stage, all text is converted into lowercase to standardize the writing format. Additionally, non-alphabetic characters such as numbers and punctuation are removed as they do not contribute to the analysis.

### 3. Tokenizing

This process breaks down text into smaller units in the form of words or tokens, allowing the data to be processed in a more structured manner in subsequent stages [16].

### 4. Stopword Removal

This step involves removing common words (stopwords) that do not carry significant meaning in sentiment analysis, such as conjunctions or pronouns [16].

### 5. Stemming

The final step is transforming words with affixes into their root forms according to Indonesian morphological rules. This ensures that words with different forms are treated as having the same meaning [15].

The preprocessing stage aims to prepare text data so that they are cleaner, more consistent, and ready for further text mining and sentiment analysis processes.

## 2.4. Labeling

According to Musfiroh (2021), a lexicon is a collection of words or phrases that have been assigned specific sentiment values, either positive or negative. In sentiment analysis, a lexicon serves as a reference for determining text polarity; therefore, this approach is known as lexicon-based [17]. The process is carried out by matching words in the text with entries in the sentiment dictionary. Thus, positive and negative labels depend on the values defined in the lexicon dictionary.

## 2.5. Data Splitting

The data splitting stage is conducted to divide the dataset into two parts, namely training data and testing data, with the aim of reducing the risk of overfitting and ensuring a more objective evaluation of the model's performance [18]. The training data are used to build the model by learning patterns from the text, while the testing data are used to evaluate the model's ability to generalize to new data. In this study, the data are divided using an 80% training and 20% testing ratio, following common practices in machine learning-based sentiment analysis.

## 2.6. TF-IDF Weighting

TF-IDF (Term Frequency-Inverse Document Frequency), according to Husada and Paramita (2021), is a widely used term weighting method in information retrieval and text analysis [19]. This technique combines two main components: Term Frequency (TF), which represents the number of times a word appears in a document, and Inverse Document Frequency (IDF), which measures the importance of a word by considering how frequently it appears across the entire collection of documents. After undergoing the preprocessing stage, the data are divided into two parts using a data splitting technique, consisting of 80% training data and 20% testing data [20]. This stage is conducted to separate the data used for model training and the data used for model evaluation. Subsequently, the data are transformed into numerical representations using the TF-IDF method, allowing each word to be assigned a specific weight that can be processed by classification algorithms [16].

## 2.7. Support Vector Machine

According to Pohan (2022), Support Vector Machine (SVM) is a supervised learning method introduced by Vapnik in 1995 and further developed by Joachims in 1998. SVM is recognized as one of the classification algorithms with a strong theoretical foundation and high performance, particularly in text processing and sentiment analysis tasks [21]. In principle, SVM works by separating data into two classes using a hyperplane that acts as a decision boundary. This hyperplane is determined in such a way that it maximizes the margin, which is the distance between the closest data points from each class and the separating boundary. The larger the margin, the better the model's ability to generalize to new data. This characteristic makes SVM more robust in avoiding overfitting compared to several other classification methods [7].

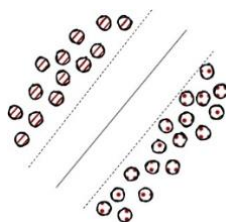


Fig. 1: Hyperlane Visualization

## 2.8. Confusion Matrix

According to Nuraliza (2022), the performance evaluation of a classification model is conducted using a confusion matrix, which represents the comparison between actual labels and predicted labels generated by the model [8]. The confusion matrix consists of four main

components: True Positive (TP), which is the number of positive class data correctly predicted; True Negative (TN), the number of negative class data correctly predicted; False Positive (FP), the number of negative data incorrectly predicted as positive; and False Negative (FN), the number of positive data incorrectly predicted as negative. Based on these components, several commonly used evaluation metrics can be calculated, including:

### 1. Accuracy

Accuracy measures the overall percentage of correct predictions, both for positive and negative classes. Although widely used, this metric can be misleading when the dataset is imbalanced.

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

### 2. Precision

Precision indicates the proportion of predicted positive instances that are actually positive. This metric emphasizes the correctness of positive predictions.

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

### 3. Recall

Recall measures the model's ability to correctly identify all actual positive instances. In other words, it emphasizes the completeness of positive predictions.

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

### 4. F1-Score

The F1-score is the harmonic mean of precision and recall. This metric is used to balance precision and recall, especially when dealing with imbalanced datasets.

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

	Asli	Asli
Pred	TP	FP
Pred	FN	TN

Fig. 2: Confusion Matrix

## 3. Results and Discussion

### 3.1. Data Source

In this study, the data used were obtained from the social media platform X (Twitter), which represents public opinions and responses toward the film *Ipar Adalah Maut*. This data was selected because of its real-time nature and its ability to reflect direct responses from users. The total amount of raw data successfully collected was 1,001 tweets. The selection of X as the data source is also based on the popularity of this platform as a dynamic public discussion space. With its open and interactive nature, X allows users to express their opinions freely, thereby providing diverse and relevant data to be analyzed in the context of sentiment.

### 3.2. Data Collection Technique

Data collection was carried out using a crawling method with the assistance of the Google Colab platform, which supports integration with Python libraries. To retrieve the data, the Tweepy library was used, which is connected to the Twitter API. The keyword used in the search was "iparadalahmaut," so that only tweets relevant to the study were collected. The data collection process was conducted over a period of one month to ensure that the data were representative. This crawling approach allows for the collection of large amounts of data quickly and systematically. By utilizing APIs and Python libraries, researchers can extract tweets automatically without the need for manual recording, thereby ensuring greater efficiency in time and accuracy of the data.

### 3.3. Auth Token Retrieval

Before the crawling process can be carried out, a Twitter Auth Token is required as an official authentication key to access data from the X server. This token is stored in the variable `twitter_auth_token` and is used each time the data retrieval function is called. This authentication ensures that the crawling process is conducted legally and verified in accordance with Twitter API regulations. The presence of an authentication token also serves as a security mechanism so that only verified accounts can access the data. Thus, the data collection process not only follows technical procedures but also complies with ethical standards for data usage on social media platforms.

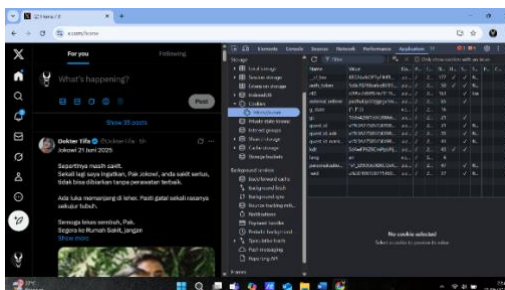


Fig. 3: Auth Token Retrieval

### 3.4. Library Installation

Before the data collection process is carried out, the initial step that needs to be prepared is the research environment. At this stage, several Python libraries are installed, such as `pandas`, which is used as the main foundation for data processing. In addition, system adjustments are also required because the data retrieval tool used (`tweet-harvest`) is built based on `Node.js`, so `Node.js` along with all its dependencies must be installed beforehand. The installation process is carried out in stages, starting from updating the repository, adding the key for the `Node.js` repository, to verifying the success of the installation by checking the version. This stage is important to ensure that all dependencies are properly installed so that the system can run JavaScript-based web scraping integrated with Python. With this preparation, the process of crawling data from social media platform X can run more optimally and with minimal technical obstacles.

### 3.5. Crawling Process

After the environment has been successfully prepared, the next stage is the data retrieval or crawling process. In this study, the tool used is `tweet-harvest` version 2.6.1, which is executed using the `npx` command. The keyword used in the search is "iparadalahmaut," chosen because it is relevant to the research topic focusing on public opinions toward the film *Ipar Adalah Maut*. In order for the data obtained to better match the research needs, the search is complemented with several additional filters. The time filter is set from June 1, 2024, to December 1, 2024, so that only tweets within that time range are collected. In addition, the setting `lang:id` is applied so that only Indonesian-language tweets are retrieved. The maximum amount of data is set to 600 tweets in each execution, with the process carried out twice. To increase relevance, the search mode is directed to the LATEST tab, so that the system only records the most recent tweets that appear according to the keyword.

### 3.6. Data Viewing

The final stage of the data collection process is to display the crawling results that have been stored in file form. In this study, the data obtained from the scraping process are stored in the file `iparam.csv`. To read the file, the `pandas` library is used to load the data into a dataframe structure. By utilizing a dataframe, the content and structure of the data can be visualized more systematically, allowing researchers to ensure that the data have been successfully collected according to the defined search parameters. This process is also important for conducting an initial check on data quality before entering the preprocessing stage, in order to ensure the feasibility of the data used in sentiment analysis.

Table. 1: Crawling Results

No	id str	created at	Favorite count	full text
1	1,86066E+18	Sun Nov 24 12:26:06 +2024	0	Bru di nnton sdikit film ipar adalah maut mengantuk maa wkwkwkwk
2	1,86066E+18	Sun Nov 24 12:08:08 2024	0	@HabisNontonFilm Ipar adalah maut noh film yang bener2 merusak mental
3	1,86065E+18	Sun Nov 24 11:45:16 +0000 2024	1	@gurlfromisland Yang gak realistis dari film ipar adalah maut adalah ceritanya di Semarang Hawanya panas kaya gitu kok bisa hs tu loh. Padahal cuddle lebih enak kalau hawanya adem Harusnya latar cerita di Magelang suaminya akpol atau Jogja yang hs udah j Nonton Ipar adalah maut di Gereja njir emang agak lain kelar latihan buat Natal bukannya pada pulang malah nobar film penuh emosi wkwk <a href="https://t.co/4mtYossJPO">https://t.co/4mtYossJPO</a>
4	1,86065E+18	Sun Nov 24 11:35:24+0000 2024	0	
5	1,86063E+18	Sun Nov 24 10:08:29 +0000 2024	0	Davina Karamoy Aktris yang membintangi film Ipar Adalah Maut sekaligus Penyanyi Indonesia menggunakan audio WHO di video tiktok terbarunya Jangan lupa tinggalkan komentar positif dan

6	.....	.....	.....	gunakan audio Who sebanyak-banyaknya di Tiktok! https://t.co/QAKa55xS0k https://t.co/myrl9BsCEa
1001	1,85178E+18	Fri Nov 08 11:21:52 +0000	0	nobar film ipar adalah maut sama keluarga yay or nay?
		2024		

### 3.7. Preprocessing

The preprocessing stage is an important step in sentiment analysis because it functions to prepare the data so that it can be processed more effectively in the modeling stage. Data obtained from social media platform X are generally still in raw form and contain many irrelevant elements. Therefore, a series of preprocessing steps is required so that the text becomes clean, consistent, and ready for feature extraction. The preprocessing stages in this study include:

#### 1. Cleaning

Data cleaning is carried out by removing irrelevant elements such as mentions, hashtags, retweet symbols (RT), links, numbers, and punctuation. The goal is to reduce noise so that only essential information remains in the text.

#### 2. Case Folding

All letters in the text are converted into lowercase to standardize word representation. Thus, words such as "Film" and "film" will be treated as the same entity.

#### 3. Tokenizing

This process breaks text, which was originally in the form of sentences or paragraphs, into smaller units called tokens (generally words). Tokenization is important to make the data more structured and analyzable individually.

#### 4. Stopword Removal

Stopwords are common words such as "and," "or," "which," that do not carry significant meaning in sentiment analysis. This step aims to remove these words so that only meaningful words are retained.

#### 5. Stemming

The stemming process converts affixed words into their root forms, for example, the word "watching" becomes "watch." In this way, various morphological variations of a word can be recognized as the same semantic entity, thereby reducing data complexity.

Through these stages, unstructured text data are transformed into clean, consistent data ready for feature extraction and sentiment classification modeling.

**Table. 2:** Sample Preprocessing Results

No	Sebelum/Text	Sesudah/Text_Cleaned
1.	Bru di nnton sedikit film ipar adalah maut mengantuk maa wkwkwkwk	bru nnton sedikit film ipar maut antuk maa wkwkwkwk
2.	@HabisNontonFilm Ipar adalah maut noh film yang bener2 merusak mental	ipar maut noh film bener rusak mental
3.	@gurlfromisland Yang ngak realistis dari film ipar adalah maut adalah ceritanya di Semarang Hawanya panas kaya gitu kok bisa hs tu loh. Padahal cuddle lebih enak kalau hawanya adem Harusnya latar cerita di Magelang suaminya akpol atau Jogja yang hs udah j	ngak realistis film ipar maut cerita semarang hawa panas kaya gitu hs tu loh cuddle enak hawa adem latar cerita magelang suami akpol jogja hs udah j
4.	Nonton Ipar adalah maut di Gereja njir emang agak lain kelar latihan buat Natal bukannya pada pulang malah nobar film penuh emosi wkwk	nonton ipar maut gereja njir emang kelar latih natal pulang nobar film penuh emosi wkwk

### 3.8. Labeling

The labeling stage is carried out using a lexicon-based approach. The preprocessed data are analyzed based on a list of positive and negative words compiled in an Indonesian lexicon. Each comment is assigned a polarity score and then categorized into two classes, namely positive and negative. The final result of this process is a dataset that already has sentiment labels, making it ready for use in the classification modeling stage.

**Table. 3:** Labelling

No	text_cleaned	text_preprocessed	polarity_score	polarity
----	--------------	-------------------	----------------	----------

1	download film ipar maut nonton ngecek film asli nggak jd langsung liat scene tengah eh scene aw awww	['download', 'film', 'ipar', 'maut', 'nonton', 'ngecek', 'film', 'asli', 'nggak', 'jd', 'langsung', 'liat', 'scene', 'tengah', 'eh', 'scene', 'aw', 'awww']	10	positive
2	Jarang bgt nnton film indo selain horor tp ipar adalah maut bagus si bener2 bikin mewek	['jarang', 'bgt', 'nnton', 'film', 'indo', 'horor', 'tp', 'ipar', 'maut', 'bagus', 'si', 'bener', 'bikin', 'mewek']	-22	negative
3	barusan aku sama pacarku nonton ipar adalah maut pas nonton pacarku bilang lebih serem film ini daripada film horor awkwkwkwkwk ngakak banget	['barusan', 'pacar', 'nonton', 'ipar', 'maut', 'pas', 'nonton', 'pacar', 'bilang', 'rem', 'film', 'film', 'horor', 'awkwkwkwkwk', 'ngakak', 'banget']	-18	negative
4	seru bgt live reaction film ipar adalah maut pada emosi semua tengah malem wkwkwkwk gas jadwalkan nobar selanjutnya asalkan jangan film horror	['seru', 'bgt', 'live', 'reaction', 'film', 'ipar', 'maut', 'emosi', 'malem', 'wkwkwkwk', 'gas', 'jadwal', 'nobar', 'film', 'horror', 'aja']	-3	negative

Next, the polarity\_score is calculated, which is the difference between the number of positive and negative words based on the sentiment dictionary. This value is then used to determine the label in the polarity column with categories positive and negative. The labeling results are visualized in the form of a bar chart to show the data distribution in each category, and also serve as the basis for the model training stage using the Support Vector Machine (SVM) algorithm.

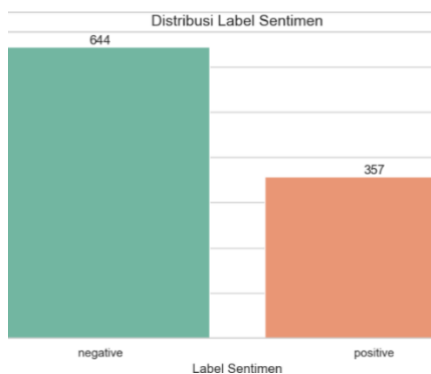


Fig. 4: Polarity Diagram

### 3.9. TF-IDF Weighting

At this stage, the labeled dataset stored in the file dataset\_labelfilm6.xlsx is loaded for further processing. This dataset already contains opinions that have been labeled with sentiment, making it ready to undergo numerical representation using the Term Frequency (TF) and Term Frequency-Inverse Document Frequency (TF-IDF) methods. One of the initial outputs displayed is the Term Frequency (TF) value for a particular tweet, which shows how often words appear in that text. The TF results are then visualized in graph form to provide a clearer picture of word distribution and to ensure that the text representation process has been carried out properly before entering the classification stage.

```

TF untuk tweet pada indeks 50:
Term                TF
-----
ipar                0.1111
maut                0.1111
mrindik            0.1111
banget             0.1111
film               0.1111
udah               0.1111
x                  0.1111
lepas              0.1111
earphone           0.1111
    
```

Fig. 5: Term Frequency

After calculating Document Frequency (DF) using the calc\_DF function, the document frequency value for each term in the tweet collection is obtained. This DF value indicates the number of documents (tweets) that contain a particular word, not the total number of occurrences. Thus, DF helps in understanding the distribution of a word across the entire corpus. The results are displayed in the form of tables and graphs to visualize DF distribution, making it possible to identify which words frequently appear in many tweets and which ones appear

rarely. This visualization also serves as the basis for TF-IDF calculation, since DF directly influences the Inverse Document Frequency (IDF) value for each term.

Term	DF
bru	2
nnton	9
sdikit	1
film	516
ipar	522
maut	523
antuk	1
maa	1
wkwkwkwk	3
noh	2

Fig. 6: DF results

### 3.10. Support Vector Machine

At this stage, the Support Vector Machine (SVM) algorithm is applied to classify sentiment in the dataset. The process begins by dividing the data into two parts, namely training data (80%) and testing data (20%), with the aim of maintaining a balanced class distribution. The text features represented in TF-IDF form are used as input, while the polarity column is used as the target label consisting of two classes, positive and negative.

The SVM model is trained using a linear kernel, which is effective in handling text classification problems. After training is completed, the model is tested on the testing data to evaluate its generalization capability. The evaluation process uses precision, recall, F1-score, and accuracy metrics, which provide a comprehensive overview of the model's performance in recognizing sentiment patterns in the data. The evaluation results serve as the main reference for assessing how well the model can be used to analyze public opinion toward the film Ipar Adalah Maut.

Table. 4: SVM Results

	precision	recall	f1-score	support
negative	0,79	0,99	0,88	129
positive	0,97	0,51	0,67	72
accuracy			0,82	201
macro avg	0,88	0,75	0,77	201

The hyperplane visualization of the Support Vector Machine (SVM) algorithm is displayed after dimensionality reduction using Principal Component Analysis (PCA) into two dimensions. The blue and red areas represent the two sentiment classes, negative and positive, separated by the decision boundary. This separating line is the hyperplane, which is the optimal boundary formed by SVM to maximize the margin between the two classes, enabling more accurate sentiment classification.

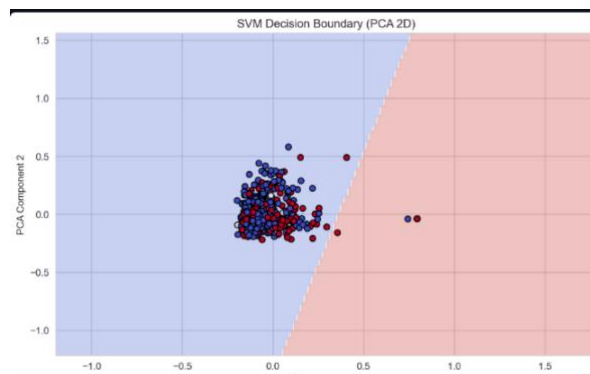


Fig. 7: Visualisasi Hyperlane

The bar chart of sentiment results shows the distribution of data based on the assigned sentiment labels. From the visualization, it can be seen that negative sentiment data are more dominant than positive sentiment data. This finding indicates that audience responses to the film Ipar Adalah Maut tend to be negative. In addition, this chart provides an overview of the data proportions used in the classification process and helps in understanding sentiment tendencies within the dataset.

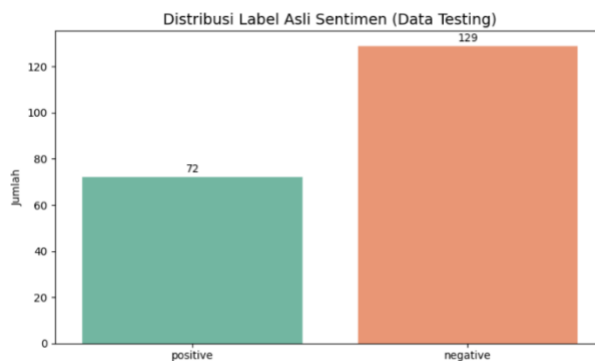


Fig. 8: SVM Bar Chart Visualization

Based on the test results, it can be concluded that the SVM model used in this study is capable of classifying user sentiment with fairly good performance. The accuracy value obtained indicates that the model can be relied upon in processing the analyzed review data. However, the noticeable difference between precision and recall in the positive class indicates that the model still has difficulty consistently identifying all positive sentiment data. This issue is likely influenced by data imbalance, where the number of positive and negative sentiment data is not evenly distributed. Therefore, improving data distribution or applying balancing methods can be considered in future research so that the model can better recognize all sentiment classes.

### 3.11. Confusion Matrix

Accuracy is not the only metric that can be used to evaluate the performance of classification models in machine learning. In some cases, accuracy may appear high but does not necessarily reflect the overall capability of the model, especially when the dataset is imbalanced. Therefore, a confusion matrix is used as a more detailed evaluation tool. The confusion matrix provides an overview of the number of correctly and incorrectly predicted data for each sentiment class. Through this matrix, it can be observed how the Support Vector Machine (SVM) model classifies testing data into positive and negative classes. The visualization of the confusion matrix on the testing data shows the model's performance more comprehensively and serves as the basis for analyzing the strengths and weaknesses of the model in distinguishing between sentiment classes.

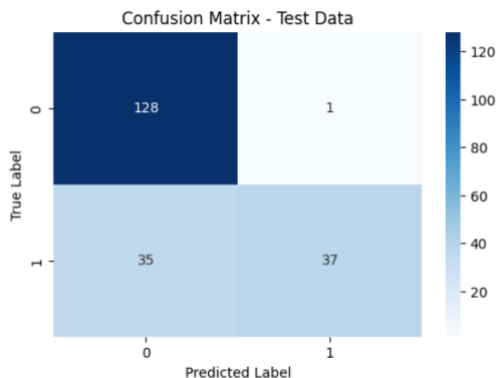


Fig. 9: Confusion Matrix

The confusion matrix visualization on the testing data shows that the SVM model is able to recognize negative sentiment quite well, where 128 negative data points are correctly classified and only 1 negative data point is incorrectly classified as positive. However, for the positive class, the model's performance is still less optimal. Out of the total positive data, only 37 are correctly classified, while 35 are incorrectly categorized as negative. This finding indicates that although the model is quite reliable in predicting negative sentiment, it still faces difficulties in distinguishing some positive data.

## 4. Conclusion

Based on the research on audience sentiment analysis toward the film *Ipar Adalah Maut* using the Support Vector Machine (SVM) method, it can be concluded that public opinion regarding the film tends to be diverse. Some reviews express positive appreciation for the storyline and the issues presented, while others contain criticism regarding the film's presentation or its mismatch with audience expectations. These results indicate that sentiment analysis is capable of capturing a wide spectrum of opinions, ranging from appreciation to criticism. Quantitatively, the developed SVM model achieved an accuracy of 82%. This value indicates that SVM is fairly effective in classifying public opinions, particularly in identifying negative sentiment.

However, there are still challenges in consistently identifying certain positive sentiments. The imbalance in the number of data and the complexity of language used in social media opinions are factors that are likely to influence the model's performance. Thus, this study confirms that SVM can serve as a relevant approach for analyzing public opinion toward films and other cultural works, especially within the context of social media, which is characterized by spontaneous expressions and informal language. The results of this analysis are

expected to contribute to academic research while also providing valuable insights for film industry practitioners and researchers in understanding public sentiment trends.

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