Analysis of Vina Film Sentiment on Social Media X Using The Naïve Bayes Method

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ABSTRACT

The increasingly rapid development of technology and information, one of which is the internet. Where users can share opinions and discuss various topics or problems around them, namely social media One of the news items that frequently appears as a trending topic on X is the Vina film controversy. However, with the large amount of review data available, it will be difficult to process manually. Therefore, sentiment analysis is needed to see whether people's tendencies toward the Vina film case are positive or negative. The stages carried out were data collection taken via web scrapping with an initial amount of data of 833 and processed through the preprocessing stage, including cleaning, case folding, normalization, stopword removal, tokenization, and stemming, the data became 830. The application of the Naïve Bayes algorithm in this research uses the probability method to classify and predict 664 training data and 166 test data, with the help of the Python library. The accuracy calculation results show quite good performance with TF-IDF weighting producing an accuracy of 78%, precision of 80%, and recall of 90%, f1-score of 84%. Analysis from this research shows that the dominance of negative sentiment is 517 while positive sentiment is 313. The amount and quality of training data play an important role in system quality, where high data quality provides better accuracy in predicting sentiment classes.

Keywords: Sentiment Analysis; Naïve Bayes; TF-IDF; Data Mining; Web Scrapping

1. INTRODUCTION

The increasingly rapid development of technology and information, one of which is the internet. Where users can share opinions and discuss various topics or problems around them, namely social media X. X remains popular because it allows users to be more expressive and be themselves (Nurhakim, Widiastiwi, & Chamidah, 2022). Topics related to films are interesting material to discuss in the media. Through film reviews, viewers can find out which films are good quality (Hibattullah & Faraby, 2021). A film review can provide information that can be used to determine the quality of the film (Razaq, Nurjanah, & Nurrahmi, 2023). This form of representation can be in the form of support, rejection, criticism, or neutral. Social reality in films is a sign in the form of text that contains a series of actions in real life that are motivated by social constructs and created by individuals (Novianti, Musa, & Darmawan, 2022).

Many netizens provide opinions through tweets, comments, or criticism of current issues that become trending news. One of the news items that often appears is trending the topic in X is the Vina film controversy. The public considers this film not worth showing because it is considered unethical and disrespectful to victims who are no longer alive. This film also received criticism from film critics that this film violated ethics and was immoral. In fact, this film was threatened with being boycotted because it was considered to be exploiting an event. After its release, various reviews appeared, especially on X, giving both negative and positive opinions. Therefore, this research focuses on analyzing the sentiment of these reviews using the Naive Bayes algorithm method, with the aim of understanding whether people think the film is worth watching or not.

Text Mining is a mining process carried out by a computer to obtain something new, previously unknown, or to rediscover implicitly implied information. Text Mining attempts to find and extract important information from various data sources by exploring and identifying patterns that are considered interesting (Nurhakim et al., 2022). Text Mining can provide solutions to problems such as processing, organizing, grouping, and analyzing unstructured large amounts of text (Santoso, 2021). Text Preprocessing is part of text mining which is done to remove noise in sentences. Text Preprocessing aims to avoid imperfect data, interference with data, and inconsistent data (Sari & Wibowo, 2019).

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Text preprocessing transforms text data that is not structured or haphazard into structured data. At the preprocessing stage, the cleaning process is carried out that is case folding, cleaning, normalization, stopword removal, stemming, and tokenizing (Wandani, 2021).

Naive bayes classifier is an algorithm for simple classification, efficiency, and computing high, and accuracy classification especially for dimensional data. The naive bayes classifier algorithm is capable of classifying data or text (Ikhsan & Kurniawan, 2023). Classification of this naïve bayes algorithm can give high accuracy and is also fast in processing the data contained in its very large number (Normawati & Prayogi, 2021). In this way, the naïve bayes algorithm can shorten classification time (Tanggraeni & Sitokdana, 2022). Naïve bayes algorithm process with calculation statistics based on probability emergence every word used processing language naturally that will be categorized as to in sentiment positive, negative or neutral. Formula equality from calculation naïve bayes probability (Asyer & Pakereng, 2023). From billions of tweet data on done analysis sentiment for find How many percentage sentiment positive and how much percentage negative sentiment towards a person, company, institution, group, or a situation certain areas. Analysis sentiment can help in analyzing word data with the method count words and classify them using the naïve bayes algorithm (Legiawati, Hermanto, & Ramadhan, 2022). Therefore, research focused on the analysis of sentiment review the use method naive bayes algorithm, with an objective understanding is public looked at the film worthy watched or not. Study this also involves analysis level accuracy TF-IDF frequency on each sentiment, aims to increase film quality based review Twitter users (X).

2. LITERATURE REVIEW

2.1 Text Mining
Text mining can be interpreted as a stage of extracting knowledge that is carried out intensively on a collection of documents over time by applying various analytical tools. Applying the same principles as data mining, text mining seeks to find and extract important information from various data sources by exploring and identifying patterns that are considered interesting.

2.2 Sentiment Analysis
Sentiment analysis or opinion mining is a branch of text mining that studies the sentiments in an opinion text. The basic principle of sentiment analysis is to classify a text whether the text is positive, negative or neutral. Sentiment analysis or opinion mining refers to the broad field of natural language processing, computational linguistics and text mining which aims to analyze a person's opinions, sentiments, evaluations, attitudes, judgments and emotions. In terms of terms, sentiment analysis is the detection of attitudes towards objects or people. From billions of tweets on Twitter, sentiment analysis can be carried out to find out what percentage of positive sentiment and what percentage of negative sentiment towards a person, company, institution, group, or a particular situation.

2.3 Film
Film can be interpreted as a form of fragmentary depiction of life in society. This form of representation can be in the form of support, rejection, criticism, or neutral. Apart from that, films are a mirror of life that has given birth to reality with a biased view. Social reality in films is a sign in the form of text that contains a series of actions in real life which are motivated by social constructs and created by individuals (Novianti et al., 2022).

2.4 Web Scrapping
Web data scrapping is a process carried out to collect review data from social media X using the Python programming language. The results of this web scrapping obtained 1000 records of review data on the X application with the hashtag Vina film.

Retrieves information from playstore and saves the information in a dominant record using the "Write Excel" operator by simply separating the data. And then do the labeling. partition the information data into several assessment classes that will be utilized at the next stage. There are two classes of opinion classes used, namely specifically negative and positive. The reason for this tagging cycle is to separate the dataset into 2 parts, into setup information and testing information

2.5 Naive Bayes Classifier
The naïve Bayes algorithm processes with statistical calculations based on the probability of occurrence of each

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word using natural language processing which will be categorized into positive, negative or neutral sentiment. The data that is input into the Naïve Bayes algorithm is in the form of comments from Playstore users which have gone through a pre-processing and translation process. The Naïve Bayes algorithm will calculate the weight of each word and produce a sentiment output for each comment that will lead to positive or neutral sentiment.

Formula equality from calculation naïve bayes probability :

$$P(X|Y) = \frac{P(Y|X) \times P(X)}{P(Y)} \tag{1}$$

2.6 TF-IDF

TF-IDF (Term Frequency-Inverse Document Frequency) is an algorithm method that gives weight to text. TF is the frequency with which a word appears in a document, while IDF is the inverse value of documents containing that word. TF and IDF will be multiplied to produce the weight value of the word.

3. METHOD

The study uses the method quantitative which is the investigation systematic of a phenomenon by collecting as much data as possible to be measured using technique statistics, mathematics, or computing. In future research done will apply the naïve bayes algorithm to analyze sentiment about Vina film on social media X. Following is a staged process in implementation naïve bayes algorithm.
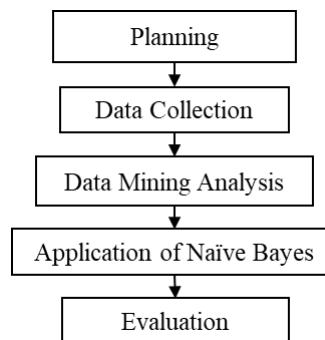

Fig. 1 Framework Study

This research process begins with planning, namely determining the topic that will be discussed. The topic of this research is analysis of sentiment towards the Vina film on social media X using the Naïve Bayes method. Next, data collection from X using web scrapping, then data mining analysis consists of preprocessing, labeling, tf-idf weighting of split data, then application of naive bayes and evaluation, the following is an explanation of the stages of this research.

3.1. Data Collection

Review data collection from X applications using web scrapping is performed with Google Colaboratory tools and languages Python programming. The data resulting from scrapping is the opinion latest on x about the film Vina. During the process of retrieving Twitter data, keywords is in the position of the Twitter trending topic or in the position discussion the most frequently tweeted was "vina film". Data was taken using data in Indonesian and taken from May 8, 2024 – June 8, 2024. The results of the scrapping process will be changed to in .csv extension for then processed using Python programming. The amount of data obtained from the scrapping result is 833 opinion data on the X application regarding the Vina film. Then the data is shared in 2 parts that is information preparation and information testing. Data is shared amounting to 80% training data and 20% testing data. Testing data is used to evaluate the outcomes of the training that has been done, whereas training data is used to train the system to detect the pattern it is searching for (Saputra et al., 2021).

3.2. Data Mining Analysis

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Data mining analysis was carried out based on the data obtained from the data collection process. The flow of data mining analysis is represented by flowchart symbols consisting of connectors, input/output, processes, flow lines, decisions, defined processes, terminal points, connectors, and preparation (Rosaly & Prasetyo, 2020). Following is a flowchart that illustrates input, process, and output so that the study structured, can seen in the picture following.
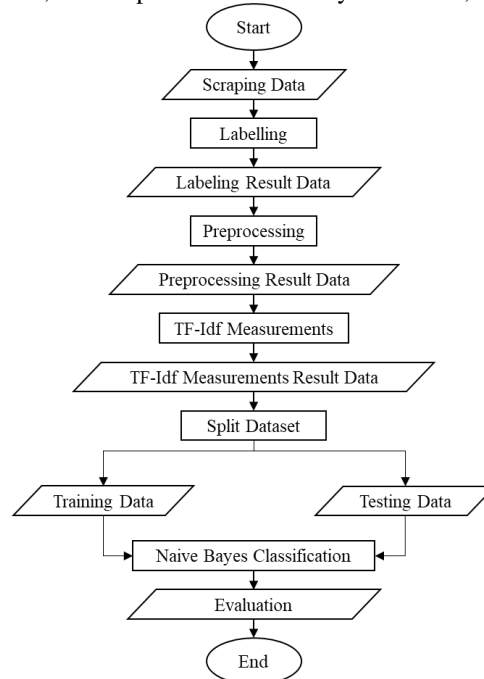

Fig. 2 Naïve Bayes Classification Flowchart

In Figure 2 it is explained starts with performing data scraping. After all the data is there obtained then done data labeling later done the preprocessing stage aims to ensure that the data is still raw and can cleaned. The preprocessing stage consists of from cleaning, case folding, normalization, stopword removal, stemming, and tokenizing.

a. Cleaning that is deletion of stopwords needs to be carried out so that researchers can focus on other words more important (Naraswati et al., 2021). Deleting punctuation marks and keywords that have been applied also removes some unimportant words that have been previously defined (Salsabila, Alim Murtopo, & Fadhilah, 2022), for example numbers, symbols, emojis, and punctuation marks.

b. Case folding is a step to uniformize all the letter shapes in the dataset into lowercase letters in the dataset which is called the case folding process. The only characters that can be changed to lowercase are the letters "a" to "z", characters other than that will be considered delimiters (Legiawati et al., 2022).

c. Normalization refers to words or phrases used in informal conversations that often have a specific meaning or significance in certain circles. These slang words may not be standard or official, but they are often used in everyday communication, especially in social media, online chats or informal conversations. To interpret those slang words, a slang dictionary is used, which turns those slang words into real words. For example, "organization" is changed to person..

d. The tokenizing stage involves chunking the input string into each word that makes it up. Tokenization also plays a role in eliminating certain characters (Muhammad Rizal, Martanto, & Hayati, 2024). The results of tokenizing change the data which was previously still in the form of sentences and will be broken down into word by word forms (Rahma, Garno, & Sulistiyowati, 2022).

e. Removal of stop words is the process of picking out important words from results tokenizing. There is an algorithm stoplist therein a purpose for throwing out words that aren't important and a working wordlist as a place to save important words. A throwaway word is a word that isn't descriptive, for example that, and, in, and from (Normawati & Prayogi, 2021).

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f. At the stemming stage, the process of removing all the affixes in the word so that it forms a basic word. The main goal of management is to reduce the different word variants of the text to a more general form, so that words of the same root can be recognized as a single whole...

This research uses two sentiments, namely positive sentiment and negative sentiment. The next stage is feature extraction which is the process of changing words into numbers and weight the word values using TF-IDF to simplify the naïve bayes classification process. TF-IDF (Term Frequency-Inverse Document Frequency) is something method algorithm that provides weight to text. TF is the frequency a word appears in document, while IDF is inverse value of documents containing these words. TF and IDF will be multiplied to produce the weight value of the word. Then the data is shared into test data and training data.

3.3. Application of Naïve Bayes

The dataset that has been passed preprocessing and extraction features, next will next with the learning process (learning) using method naive bayes classification. After the data is successfully trained then will be testing to use test data for test results accuracy classification is carried out, so that the dataset is obtained will be classed using confusion matrix.

3.4. Evaluation

After testing then stage model evaluation to determine level of accuracy, precision, recall, and f1 score with objective know the performance of the model and visualize results from analysis sentiment using pie charts and word cloud.

4. RESULT AND DISCUSSION

4.1. Data Preprocessing

The scraper product data must go through a preprocessing phase before being analyzed. The purpose of the preprocessing step is to transform the original data without much structured and proprietary noise into clean data ready for processing. Data preprocessing process including cleaning, usage folding, filtering, tokenization, slang word conversion, end words, derivation. After all operations are completed, the table may contain empty cells due to the entire cell text selection process. Therefore rows are checked and deleted if there are empty text cells.

4.2. Term Frequency-Inverse Documente (TF-IDF) Weighting

After preprocessing, the next stage of label and sentiment cleaning is the TF-IDF weighting stage, in which the weight technique is calculated for each word in the document data, and then each word is multiplied by the IDF. The following is an example of calculating the TF-IDF value.

Table 1
Training Data Sample

Sentiment Train	Class
['skandal' 'artis' 'film' 'vina' 'ramai' 'lolos' 'uji' 'batas' 'umur' 'redup' 'jelas' 'ditimpa' 'gaduh']	Negative
['vina' 'eky' 'viral' 'film' 'ribet' 'berantas' 'instansi' 'kinerja']	Positive
['film' 'vina' 'pikir' 'angkat' 'film' 'sorot' 'netizen' 'alur' 'terduga' 'kebuka' 'kelam' 'polisi' 'tangani' 'bongkar']	Negative

After determining the TF value, determine the DF value. The DF value is obtained from the number of documents where a term (t) appears. Scandal is worth 1 because of all the documents it only appears in D1. Film has a value of 3 because the word film appears in D1, D2, and D3. Following are example results of TF and DF calculations from training data.

Table 2
TF and DF Values from Training Data

Term	TF			DF
	D1	D2	D3	
skandal	1	0	0	1
artis	1	0	0	1
film	1	1	1	3

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vina	1	1	1	3
ramai	1	0	0	1

Once the TF (thermal frequency) value is obtained, the next step is to find the IDF value. Below is the formula to determine the IDF value of each word. Following is sample in apply formula mentioned in the first and second data :

$$\text{Skandal } IDF = \log\left(\frac{D+1}{df+1}\right) + 1 = \log\left(\frac{3+1}{1+1}\right) + 1 = \log(2) + 1 = 1.301 \qquad (1)$$

$$\text{Film } IDF = \log\left(\frac{D+1}{df+1}\right) + 1 = \log\left(\frac{3+1}{3+1}\right) + 1 = \log(1) + 1 = 1.000 \qquad (2)$$

The following is an example of the results of the IDF data value calculation carried out.

Table 3
IDF Values From Training Data

Term	DF	IDF
skandal	1	1.301
artis	1	1.301
film	3	1.000
vina	3	1.000
ramai	1	1.301

After TF and IDF values are obtained Then can calculated For the TF-IDF value . Following is sample in apply formula mentioned in the first and second data :

Skandal W=TF×IDF=1×1.301=1.301

Film W=TF×IDF=3×1.000=3.000

Following is an example results calculation TF-IDF value of the data carried out.

Table 4
TF-IDF Values From Training Data

Term	TF-IDF		
	D1	D2	D3
Skandal	1.301	0	0
Artis	1.301	0	0
Film	3.000	3.000	3.000
Vina	3.000	3.000	3.000
ramai	1.301	0	0

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	term	idf	tf_0	tf_1	tf_2	tf_3	tf_4	tf_5	tf_6	tf_7	...	tf_820	tf_821	tf_822	tf_823	tf_824	tf_825	tf_826	tf_827	tf_828	tf_829
0	aa	5.622813	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.393484	0.421454	0.0	0.0	0.0
1	abadi	6.028279	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	0.0
2	abai	5.622813	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	0.0
3	abang	4.641984	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	0.0
4	about	6.028279	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
195	bambang	6.028279	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	0.0
196	ban	5.622813	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	0.0
197	banding	5.111988	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	0.0
198	bandingkn	6.028279	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	0.0
199	bandung	6.028279	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	0.0

200 rows × 832 columns

Fig. 3 TF-IDF Results

4.3. Splitting

Splitting is stages where the dataset will be shared into training data (training) and test data (testing). In the analysis carried out, the comparison between training data and test data is 8:2. In the first dataset there are 830, therefore that's the training data on the first dataset amounted to 664 while the test data amounted to 166.

4.4. Naive Bayes Classification

The dataset that has gone through preprocessing and extraction features, next is classified with naive Bayesian algorithm. The first step in the classification process is to divide the data into training data and test data. The study uses an 8:2 ratio to compare training and test data. The training data is used to learn the positive and negative features and differences of another class, while the test data is used to determine the success if it is correctly classified.
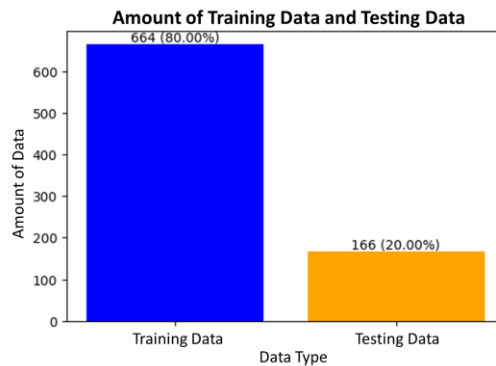

Fig. 4 Distribution Data and Test Data

Total initial dataset study analysis Vina film sentiment on social media X uses naive Bayesian algorithm consisting of 833 data. However, the remaining data after the pre-processing step was a total of 830 data. In this study, the comparison between training data and experimental data is 8:2. The total training data is thus obtained from at least 664 data, while the test data has a total of 805 data. The training process generates a symbolic weight for each word in each category using the TF-IDF weighting method.

Determination sentiment done with method count probability training data and test data documents. This process is implemented in functions MultinomialNB with compare every weights on testing data with training data. The result every this training document totaled probability word weight positive and probability the negative. Furthermore weight test documents compared. If the weight document probability positive more big so results classification sentiment is positive whereas if weight probability negative so results classification sentiment is negative.

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Table 5
Example of Training Data

Sentiment Train	Class
skandal artis film vina ramai lolos uji batas umur redup jelas ditimpa gaduh	Negatif
vina eky viral film ribet berantas instansi kinerja	Positif
film vina pikir angkat film sorot netizen alur terduga kebuka kelam polisi tangani bongkar	Negatif

In the positive sentiment training data, it is known that the number frequency whole sentiment postive is 8 and sum vocabulary whole sentiment positive is 8. Meanwhile in the training data negative sentiment is known that the total frequency of negative sentiment is 27 and total vocabulary whole sentiment negative is 24. The data form can be seen in Table 6.

Table 6
Example of Training Data Sentiment Positive and Negative

Positive		Negative	
Term	Frequency (n_k)	Term	Frequency (n_k)
Vina	1	skandal	1
Eky	1	artis	1
Viral	1	film	3
Film	1	vina	2
Ribet	1	ramai	1

By using the previous sample data as training data, 1 test data is determined as follows.

Table 7
Example of test Data

Sentiment Test	Kelas
['kaget' 'film' 'vina' 'usut' 'horor' 'adegan']	?

The classification steps were started by calculating the prior probability, conditional probability and posterior probability. In the classification process, applying the naive bayes algorithm to the test data is as follows.

Calculation prior probability value

$$P(\text{Class}|\text{Sentiment}) = \frac{\text{Number of Class X}}{\text{Number of Sentiments}} \qquad (2)$$

Using the equation above, we will obtain the probability of each class in sentiment

P (Positive | Sentiment) $= \frac{1}{3} = 0.3$

P (Negative | Sentiment) $= \frac{2}{3} = 0.6$

Probability from every term can searching for with use formula:

$$P(x_i|V_j) = \frac{n_k+1}{n+|\text{vocabulary}|} \qquad (3)$$

Using the equation above, we will obtain the probability of the terms in each class of sentiment. By calculating the probability values for all sentiment categories, there is a change in the probability values for each term in the training data. Changes are made by combining the total vocabulary of all training data sentiments. In the test data classification

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stage, the terms listed in Table 9, and the frequency of the test data will be classified, looking for their probability values by comparing and matching with the terms in the positive and negative sentiments of the training data. If there are similar terms between the training data and the test data, then the same probability value is calculated to be 1, and if they are not the same then the frequency is calculated to be 0. Based on the probability value of the test data on positive sentiment above, the V map value for sentiment positive is as follows:

$$V_{map} = \frac{armax}{(positive)}\Pi_i{}^{13}{=}1\, P(x_i|V_j)P(V_j) = ((0.062)(0.125)(0.125)(0.062)(0.062)(0.062)) * (0.3)$$
$$= 6.9264075e-8$$

Based on the probability value of the test data on negative sentiment above, the V map value for negative sentiment are as follows:

$$V_{map} = \frac{armax}{(positif)}\Pi_i{}^{13}{=}1\, P(x_i|V_j)P(V_j) = ((0.019)(0.08)(0.06)(0.019)(0.019)(0.019) * (0.6)$$
$$\mathbf{= 3.7532448e-10}$$

Implementation of naïve bayes algorithms. The classification process will train the model that was created during the training process to make predictions on predetermined test data.

```
Multinomial Naive Bayes Accuracy: 0.7771

Multinomial Naive Bayes Confusion Matrix:
[[105  11]
 [ 26  24]]
```

Fig. 5 Naïve bayes Process

Here is a wordcloud of positive and negative sentiment.

Fig. 6 Wordcloud for Positive Reviews

Fig. 7 Wordcloud For Negative Reviews

4.5. Evaluation

The purpose of this process is to determine the ability of the system that has been created to carry out sentiment analysis in the case of the film Vina. The tools used in this research are Google Colab and Python as the programming language. The results of the sentiment analysis carried out will be presented in the form of a classification report, which goes through classification report can determine the level of accuracy of the research conducted. After testing sentiment using a naïve bayes algorithm, the sentiment classification results will be obtained in the form of sentiment labels. The resulting classification labels will be compared with the actual labels so that the accuracy, precision, recall, and f1-score values of the model used on the dataset will be known.

Fig. 8 Confusion Matrix

In Figure 8 it can be calculated how much big accuracy, precision, recall, f1-score values respectively use equality following.

$$Accuracy = \frac{104+26}{104+11+25+26} \times 100\% = 78\%$$

$$Precision = \frac{104}{104+25} \times 100\% = 80\%$$

$$Recall = \frac{104}{104+11} \times 100\% = 90\%$$

$$F1 - score = \frac{2 \times 80 \times 90}{80+90} \times 100\% = 84\%$$

Overall, the values above can be presented in classification report. Below is presented the classification report from the analysis process using naïve bayes methods.

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```
Negatif        0.80      0.91      0.85       116
Positif        0.69      0.48      0.56        50

accuracy                           0.78       166
macro avg      0.74      0.69      0.71       166
```

Fig. 9 Classification Reports

From the calculation results above, it can be seen that the total number of test data is 166 data and the accuracy value is 78%, precision is 80%, recall is 90%, f1-score is 84%.
This research was conducted with the aim of testing degree of accuracy of the constructed system. The results of this study show that the NBC was able to provide a good level of accuracy that will help students and researchers analyze the public's opinions on this topic.

4.6. Sugestions
The following are suggestions and input from the author for future researchers who will conduct similar research on sentiment analysis, namely that a special, more complete dictionary needs to be created to handle non-informative words contained in the content of comments with multiple training models and an increasing number of datasets. There is a need for development using other algorithmic methods whose results can be compared and analyzed. To get more optimal classification results, more test data and training data need to be added.

5. CONCLUSION
Based on the sentiment analysis results of social media X on the case of the film Vina using the Naive Bayes algorithm, it can be concluded that the application of Naive Bayes in this work leverages probabilistic methods for classification and model creation. The study employed X to demonstrate the effectiveness of the Naive Bayes algorithm in sentiment analysis models related to the film Vina. Predictions from 664 training data and 166 test data using the Python library yielded 517 instances of highly negative emotions and 313 instances of highly positive emotions. The accuracy calculation results using the Naive Bayes method for emotion classification were notably good, evidenced by an 83% accuracy rate when comparing the 8:2 split between training and test data. The precision values were 78% and 80%, recall was 90%, and the F1 score was 84%. For future research, it is recommended to conduct testing with multiple training models and to enhance classification outcomes by incorporating more extensive training and test datasets.

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