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Sentiment Analysis on Application X on the Use of Red Oil Using the Naïve Bayes Method

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ABSTRACT

Red oil, as an alternative to traditional cooking oil, has gained public attention through reviews on App X. However, questions arise about how public sentiment is towards red oil and how the Naïve Bayes algorithm can classify positive and negative sentiments. This study aims to analyze user sentiment towards red oil using the Naïve Bayes method. The dataset used consists of 1,200 comments collected through the scrapping technique in 2024. After going through the process of removing duplicate comments, the number of data becomes 1,189. Before running the Naïve Bayes algorithm, the data is divided into test data and training data, with 238 data as test data and 951 data as training data. The analysis process involves pre-processing stages such as text cleaning, tokenization, and normalization, followed by word weighting with the TF-IDF method. The Naïve Bayes algorithm is applied for the classification of positive and negative sentiments. The results showed that 1,147 comments were positive sentiment, while 42 comments were negative sentiment with a total accuracy of 88.66%, then precision of 95.41%, recall of 92.44% and F1- 93.91% and it was found that the sentiment comments on the use of red oil had a greater positive polarity than negative polarity. This analysis provides important insights for producers and stakeholders regarding public perception of red oil, which is useful for strategic decision making, such as improving product quality and marketing campaigns. This method is expected to be a reference for further studies in the field of text classification and natural language processing.

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1. INTRODUCTION

President Joko Widodo (Jokowi) has just inaugurated a red cooking oil factory located in Deli Serdang Regency, North Sumatra. In the inauguration on Thursday, March 14, 2024, Jokowi hoped that this mill could provide added value for oil palm farmers, not only in North Sumatra, but also throughout Indonesia. As palm oil production in Indonesia continues to grow, the red palm oil industry is also expanding. The government supports the downstream development of palm oil products to create high-value derivatives for both domestic and global markets. Various funding programs and sustainable research efforts further contribute to this initiative [1].

Red cooking oil is considered a natural, non-GMO, trans-fat-free product processed at low temperatures, making it suitable for direct and indirect consumption [2]. However, challenges such as its bitter taste, strong aroma, and deep red color affect consumer acceptance. Despite these issues, red oil offers many benefits and is widely used in margarine, vegetable cheese, fat substitutes, natural soap, and skincare products.

This study aims to analyze public sentiment toward red oil based on social media comments using the Naïve Bayes method. The key issue is understanding consumer perception whether positive or negative and how it influences market acceptance. The findings are crucial for producers, policymakers, and marketers in improving product quality, addressing consumer concerns, and designing better marketing and educational strategies. Ultimately, this research contributes to the sustainable growth of the red oil industry by aligning production and marketing efforts with consumer expectations.

In recent years, red palm oil, which has not gone through a long refining process, has attracted the attention of the public. Processed palm oil is claimed to have a higher nutritional content than cooking oil, making it increasingly popular as an alternative to cooking oil. Because it uses fewer resources during its production process, red oil is considered more environmentally friendly. However, the presence of red oil on the market caused controversy among the public, as did many new innovations. Many users of the X app express their opinions on the benefits, quality, and sustainability of red oil, which can be seen in its various reviews and discussions [3].

The X application is a significant platform because it provides a space for the public to share their experiences and views related to the products they use, including red oil [4]. These user reviews contain a wide range of sentiments, both positive and negative, that reflect the views of the public at large. Positive sentiment includes aspects of better health and sustainability of the product, while negative sentiment is often related to issues of price, taste, and availability in the market. Sentiment analysis on red oil through this application can provide a comprehensive picture of public views and help producers, consumers, and governments in making more informative decisions. The naïve bayes method is a classification method from machine learning that has the advantage of using training data samples to estimate the parameters involved in the classification process can be presented quickly, and obtain high accuracy [5].

Research conducted by Muhammad Muslimin, et al. (2023) analyzed public sentiment on Twitter regarding the increase in the price of staples using the Naïve Bayes Classifier method. The data was retrieved from Twitter via netlytic.org with the keyword "staples" and labeled using TextBlobs. The 2070 tweets, 2.8% had positive sentiment and 97.2% were negative. After preprocessing, 934 tweets were left with 3.43% positive sentiment and 96.57% negative. The classification results showed an accuracy of 94.38%, precision 59.67%, recall 67.93%, and F-measure 62.32% [6].

Next Research conducted by Naufal Fakhri Zakaria, et al. (2023) analyzed the sentiment of the 2023 recession issue in Indonesia using the Naïve Bayes method with an accuracy of 77%, precision 0.42, recall 0.43, and f1-score 0.42. The labeling results showed that 87.4% of the data (1982 tweets) were labeled neutral, 7.7% (175 tweets) were negative, and 4.9% (112 tweets) were positive. This study concludes that Indonesian people tend to be neutral towards the issue of the 2023 recession [7].

While these studies focused on general economic issues such as rising staple prices and recession concerns, this research specifically analyzes public sentiment toward red oil, a newly emerging product in the market. Unlike previous research, which primarily assessed reactions to economic conditions, this study aims to understand consumer perceptions of red oil, which is crucial for product acceptance and industry development. Additionally, this study employs the Naïve Bayes algorithm in combination with the TF-IDF method for feature extraction, ensuring a more refined classification process. The findings will provide valuable insights for stakeholders in the palm oil industry, helping them refine marketing strategies and address consumer concerns effectively.

Based on the above research in this study to analyze public sentiment towards red oil, the Naive Bayes method was chosen as the main classification technique. This method is known to be effective in dealing with text classification problems and is able to provide quite good results in the context of sentiment analysis [8]. The use of Google Colabs as an analytics platform supports the interactivity required in the data processing process and allows for easy visualization of analysis results. The platform is also integrated with various libraries that support the Naive Bayes algorithm, speeding up and simplifying the analysis process [9].

2. RESEARCH METHOD

This study uses a quantitative methodology where this research method reveals phenomena holistically-contextual by collecting data from natural phenomena. The use of quantitative methodologies produces more measurable data [10]. There are several stages that must be passed to conduct this research, including the figure 1.

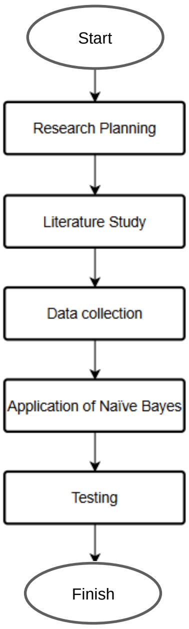

Figure 1. Research Stage

The initial stage carried out in this study is the existence of research planning. This research was carried out by applying the Naïve Bayes method in the sentiment analysis process regarding the use of red oil whose data source comes from the X application and produces high and good method accuracy. The next stage is to conduct a literature study by reading and understanding several previous researches, be it in the form of journals, articles, theses, or theses that are related to the research that is currently being conducted. The following is the theory used about this research.

Machine Learning was first introduced in 1959 by Arthur Samuel, a computer expert from the United States, when he was still working at IBM. He mentioned that Machine Learning is a system that can predict data, and make decisions using various algorithms without the need for reprogramming [11]. Machine learning is a science that makes the system can automatically learn on its own without having to be repeatedly programmed by humans [12]. Machine Learning itself is one of the disciplines in artificial intelligence or often known as Artificial Intelligence (AI) [13].

Text Mining is the stage in finding information in a large collection of texts, which can automatically identify interesting patterns and relationships in textual data. Text mining is a form of research that is very interdisciplinary, such as in the fields of data, natural language processing, machine learning and information retrieval [14]. Sentiment analysis is one of the sciences of data mining, with the aim of analyzing, understanding, processing, and extracting textual data in the form of opinions about entities such as products, services, organizations, or certain topics used in the process of extracting some information in line with the required datasets [15].

Sentiment classification with a Lexical-Based approach using Valence Aware Dictionary and Sentiment Reasoner (VADER) is an analysis method that utilizes a dictionary of positive, negative, or neutral sentiment-oriented words, designed for informal texts such as social media. VADER allows computers to understand sentiment by relying on the polarity score of words in lexicons, where the intensity of emotions can be adjusted through word reinforcement or punctuation. This approach makes it easy to analyze customer opinions regarding products or services, thanks to its ability to handle informal language, emoticons, and punctuation, making it an effective solution for accurate social media data analysis [16]. Python is a well-known programming language that has many benefits to support object-oriented programming and can run in a wide variety of platform operating systems such as PCS, Macintosh, UNIX [17].

Data collection is a condition where data is successfully collected by scraping data on the X application about the use of red oil with the keyword #minyakmerah. With the scrapping, more than 1000 data were obtained that will be used in the sentiment analysis classification process using the Naive Bayes method. Before the classification began, the TF-IDF was used to obtain the correct weighting value for each term in each research document. Furthermore, the data were classified using the Naive Bayes Classifier method in sentiment analysis about the use of red oil. The following is the flowchart used in this study.

Naïve Bayes is one of the most effective and efficient machine learning and data mining algorithms [18]. Although the assumption that the attributes in the data are independent, the classification performance Naïve Bayes Although the assumption of attribute independence is rare in actual data, if violated, the algorithm can still produce good classification results. Naïve bayes It is an implementation of probabilistic machine learning algorithms using Bayes' theorem calculation techniques [19].

$$P(H|X)^{\wedge =} = \frac{p(H|X).P(H)}{P(X)} \tag{1}$$

In the Naïve Bayes classification formula, X represents the data class that has not been validated, while H refers to a specific data class. The probability P(H|X) indicates the likelihood of a hypothesis H being true given the evidence X. Additionally, P(H) represents the prior probability of H, whereas P(X|H) denotes the probability of the data occurring under a given hypothesis. Finally, P(X) is the overall probability of the data occurring. The testing stage in this sentiment analysis research uses the Confussion Matrix method which will later obtain accuracy, recall and f-1 score values from the classification that has been carried out.

Confusion Matrix is an instrument used to evaluate the performance of the classification model that has been produced. At confusion matrix, the results of the prediction class will be compared with the results of the actual data class, the results will then be used to calculate the accuracy value, Precipitation, Recall, and F-Score [20]. Accuracy, precision, recall and F1-Score are described in equations (2), (3), (4) and (5).

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \text{ x } 100\% \tag{2}$$

$$\text{Precision} = \frac{TP}{FP+TP} \text{ x}100\% \tag{3}$$

$$\text{Recall} = \frac{TP}{FN+TP} \text{ x } 100\% \tag{4}$$

$$\text{F1-score} = \frac{2 * (\text{recall} * \text{precision})}{(\text{recall} + \text{precision})} \text{ x } 100\% \tag{5}$$

In the confusion matrix, True Positive (TP) refers to cases where both the predicted and actual values fall within the positive category. True Negative (TN) occurs when both the predicted and actual values belong to the negative category. False Positive (FP) happens when a prediction classifies a data point as positive, while the actual value belongs to the negative category. Conversely, False Negative (FN) arises when a prediction categorizes a data point as negative, even though the actual value is positive.

3. RESULTS AND ANALYSIS

In this study, the author collected data from the X application (formerly Twitter) using a web scraping technique. The dataset consists of 1,200 comments discussing public opinions on the use of red oil. After preprocessing, which involved removing duplicate entries, the dataset was reduced to 1,189 comments. The preprocessing steps included text cleaning, case folding, normalization, tokenization, stopword removal, and stemming to ensure data consistency and improve classification performance.

The sentiment classification was conducted using the Naïve Bayes algorithm, with feature extraction performed using the Term Frequency-Inverse Document Frequency (TF-IDF) method. Sentiment labeling was carried out using the VADER Lexicon, categorizing comments into positive and negative sentiments. The dataset was then split into training and testing sets, with 951 comments used for training and 238 comments for testing.

The experiments involved evaluating model performance based on accuracy, precision, recall, and F1-score using a confusion matrix. The results of the classification provide insights into public sentiment regarding red oil, which is further analyzed to understand consumer perception and its implications for stakeholders in the palm oil industry.

3.1. List of User Sentiment Towards the Use of Red Oil

The comments used were obtained from the X application (Twitter) where the scrapping process was carried out in October 2024 and the tool used was Google Colabs. An example of the review used is shown in the table 1.

Table 1. Example of Comments on the Use of Red Oil

No.	Username	CA	FC	Full_text
1	SanRi70842	Wed Sep 25 11:04:04 +0000 2024	13	Minyak merah ku rasa kualitasnya masih bnyk diragukan. Takut ada efek jangka panjang buat kesehatan.

No.	Username	CA	FC	Full_text
2	dinulfadli_	Wed Sep 25 08:40:01 +0000 2024	0	Aku lebih sukak minyak yg biasa daripada minyak merah. Engga terbiasa sama rasa dan aromanya.
3	Claudiaratri	Wed Sep 25 08:23:11 +0000 2024	0	Gue mending pakai minyak biasa aja sih, minyak merah tuh nggak appealing.

The next step is to drop unused data such as "username", "CA" and "FC" so that it is obtained as shown in the table 2.

Table 2. Comment Data

No.	Full_text
1	Minyak merah ku rasa kualitasnya masih bnyk diragukan. Takut ada efek jangka panjang buat kesehatan @ezasybani
2	Aku lebih sukak minyak yg biasa daripada minyak merah. Engga terbiasa sama rasa dan aromanya @elisa_jkt #minyakmerah
…	…
1200	@Qodridio enggak mas disini saya belajar kalau sambal matah itu hanya: 1. bawang merah 2. sereh 3. cabe rawit 4. minyak kelapa 5. terasi 6. daun jeruk 7. jeruk limau setelah semua dicampur lalu diaduk aduk menggunakan tangan agar juice dari bawang merahnya keluar

After carrying out the process of removing irrelevant data (drop), the next step in this study is to filter the comment data to eliminate duplicate entries. This step aims to ensure that each comment analyzed is unique, so that the results of the analysis become more accurate and representative. As in the following table, which initially had 1200 data became 1188 comments, that it is obtained as shown in the table 3 and figure 2.

Table 3. Comment Data on the Results of Deleting Duplicate Entries

No.	Full_text
1	Minyak merah ku rasa kualitasnya masih bnyk diragukan. Takut ada efek jangka panjang buat kesehatan @ezasybani
2	Aku lebih sukak minyak yg biasa daripada minyak merah. Engga terbiasa sama rasa dan aromanya @elisa_jkt #minyakmerah
3	Gue mending pakai minyak biasa aja sih, minyak merah tuh nggak appealing @lala22_ #minyakmerah
…	…
1189	@Qodridio enggak mas disini saya belajar kalau sambal matah itu hanya: 1. bawang merah 2. sereh 3. cabe rawit 4. minyak kelapa 5. terasi 6. daun jeruk 7. jeruk limau setelah semua dicampur lalu diaduk aduk menggunakan tangan agar juice dari bawang merahnya keluar

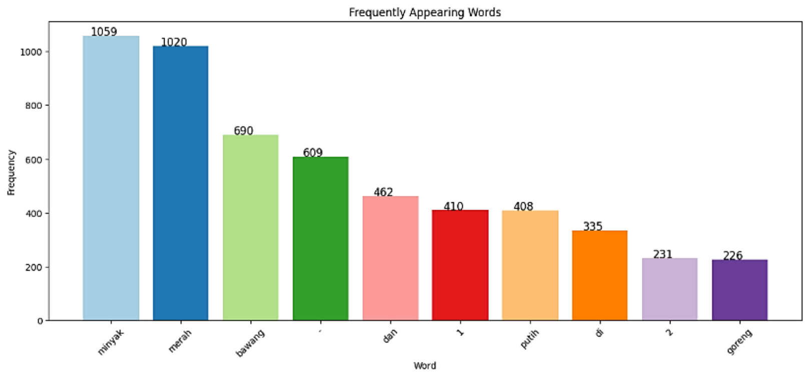

Figure 2. Frequently Occurring Words

The words that appear most frequently in the comments dataset are shown in the bar graph above. The most commonly used words are "and", "1," "white", "6," "2," and "fried". Other words that are frequently used are "oil", which is used 1,059 times, followed by "red", which is used 1,020 times, and "onion", which is used 690 times. These graphs provide an overview of the topics or themes that are frequently discussed in the comments and help us understand the dominant keywords in the dataset.

3.2. Pre-processing

The first stage is text cleaning which aims to clean the comment data that has been obtained. The components that are cleaned are meaningless or irrelevant components for the data classification process. Remove any existing links or emoticons. In the case of sentiment analysis classification, here are the cleaning procedures that can be used. Examples of data before and after the cleaning process can be seen in Table 4.

Then the case folding process is the process of converting all letters in the text to lowercase letters to equalize their shape. This step is important so that variations in the use of capital letters, such as "Indonesia" and "Indonesia," are not perceived differently by the machine. With case folding, text data becomes more consistent and text analysis, such as classification, becomes more accurate.

Furthermore, the normalization stage is carried out into standard Indonesian according to KBBI, by changing words such as "yg" to "yang," "ga" to "no," and so on. In this study, the normalization process was carried out using an Indonesian *normalisasi.csv* file accessed from GitHub. After the normalization process, the text is then carried out by dividing it into words or symbols related to the use of red oil. For example, "oil" means oil, "red" means red, and "fried" means fried, among other things. Common terms like "and", "or", or "in" are usually ignored in text. A process called "tokenization" in which text is divided into specific units or tokens.

In text, stopwords are common words that appear frequently, but usually do not provide significant meaning for analysis, such as "and", "or", "in", and "which." In research on the use of red oil, these words were ignored, and the analysis focused only on more relevant words, such as "oil", "red", and "fried". Eliminating stopwords helps to simplify data and improve efficiency and accuracy in the text analysis process.

In Natural Language Toolkit (NLTK), steaming is one of the preprocessing steps used to reduce words to their basic form, also known as word roots. It is an important part of the text preprocessing pipeline in Natural Language Processing (NLP). This process lowers the variation of words with the same meaning and makes it easier to analyze other texts, such as text classification, sentiment analysis, and document grouping, that it is obtained as shown in the table 4.

Table 4. Text Pre-processing

No.	Stages	Result
1	Initial Data	Minyak merah ku rasa kualitasnya masih bnyk diragukan. Takut ada efek jangka panjang buat kesehatan @ezasybani
2	Cleaning	Minyak merah ku rasa kualitasnya masih bnyk diragukan Takut ada efek jangka panjang buat kesehatan
3	Case Folding	minyak merah ku rasa kualitasnya masih bnyk diragukan takut ada efek jangka panjang buat kesehatan
4	Normalization	minyak merah ku rasa kualitasnya masih banyak diragukan takut ada efek jangka panjang buat kesehatan
5	Tokenizing	['minyak', 'merah', 'ku', 'rasa', 'kualitasnya', 'masih', 'banyak', 'diragukan', 'takut', 'ada', 'efek', 'jangka', 'panjang', 'buat', 'kesehatan']
6	Stopwords	['minyak', 'merah', 'ku', 'kualitasnya', 'diragukan', 'takut', 'efek', 'jangka', 'kesehatan']
7	Steamming	minyak merah ku kualitas ragu takut efek jangka sehat

3.3. Sentiment Labeling Using VADER Lexicon

VADER Lexicon was used to label positive and negative sentiments in this study. VADER calculates the mixed score of each text from -1 to +1, and with the threshold rule, text with a mixed score of >= 0 is labeled "Positive" and text with a mixed score of <= 0 is labeled "Negative". This method allows for simpler identification of sentiment polarity and concentrates the analysis on only two categories, that it is obtained as shown in the table 5.

Table 5. Labeling Results

No.	Steamming	Sentimen_Score	Label
1.	minyak merah ku kualitas ragu takut efek jangka sehat	0.0	Positive
2.	sukak minyak minyak merah engga biasa aroma minyakmerah	0.0	Positive
3.	mending pakai minyak sih minyak merah tuh nggak appealing minyakmerah	0.0	Positive
4	minyak merah hmm insecure kualitas sih	-0.4215	Negative
5	dapet minyak merah murah tuh lifesaver banget nggak kalah minyak	0.5859	Positive
…	…		…
1189	minyak merah doang stabilin harga minyak penggunaanminyakmerah republikindonesia	0	Positive

In Table 10, there are several comments with positive and negative values. This process is carried out until all datasets. The number of positive comments is 1147 comment data and the total negative sentiment is 42 comments. The number of positive and negative comments is shown in the following figure 3, where the process is carried out using python programming in google colaboratory.

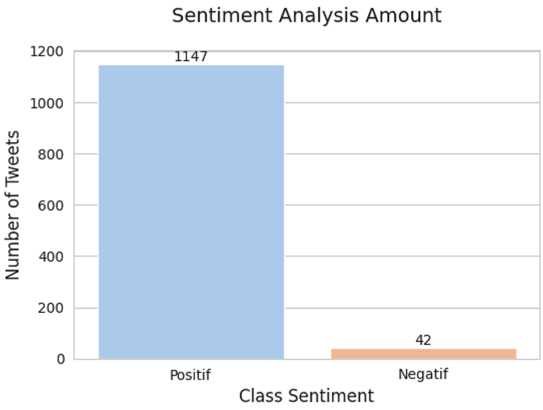

Figure 3. Visualization of the Amount of Sentiment Analysis

3.4. Word Weighting Using TF-IDF

The initial step is to calculate the TF value of all words contained in the text (counting how often the word appears). Using 3 sentences, namely:

1. my red oil is of doubtful quality for fear of healthy long-term effects
2. Cooking vows using red oil are delicious authentic
3. hmm red oil is insecure quality

TF and IDF values are calculated for each word in a user's comment in the X (Twitter) app. After obtaining the TF value for each word, the next step is to calculate the TF-IDF value by multiplying the TF and IDF values of each word. The TF and IDF calculation methods for each word are presented in this section.

$$\mathrm{tf-\ idf}_{t,d} = \mathrm{tf}_{td}\mathrm{xidf}_{t}$$

$$\mathrm{tf-\ idf}_{(minyak,D1)} = \mathrm{tf}_{miyak,D1}\mathrm{xidf}_{minyak} = \frac{1}{3}\mathrm{x}\, 0 = 0$$

$$\mathrm{tf-\ idf}_{(merah,D1)} = \mathrm{tf}_{merah.D1}\mathrm{xidf}_{merah} = \frac{1}{3}\mathrm{x}\, 0 = 0$$

$$\mathrm{tf-\ idf}_{(ku.D1)} = \mathrm{tf}_{ku.D1}\mathrm{xidf}_{ku} = \frac{1}{3}\mathrm{x}\, 0.477 = 0.159$$

$$\mathrm{tf-\ idf}_{(kualitas.D1)} = \mathrm{tf}_{kualitas.D1}\mathrm{xidf}_{kualitas} = \frac{2}{3}\mathrm{x}\, 0.176 = 0.059$$

$$\mathrm{tf-\ idf}_{(ragu.D1)} = \mathrm{tf}_{ragu.D1}\mathrm{xidf}_{ragu} = \frac{1}{3}\mathrm{x}\, 0.477 = 0.159$$

$$\mathrm{tf-\ idf}_{(sumpah.D2)} = \mathrm{tf}_{sumpah.D2}\mathrm{xidf}_{sumpah} = \frac{1}{3}\mathrm{x}\, 0.477 = 0.159$$

The TF-IDF value calculation process is not described in detail for each step in the entire sample text used. However, the final results of the IDF calculation for all words have been summarized and presented in the form of a table below, to provide a comprehensive overview of the weight of each word in the analysis, that it is obtained as shown in the table 6.

Table 6. TF-IDF Table

Word	Document	TF-IDF
Minyak	1.2.3	0
Merah	1.2.3	0
Ku	1	0.159
Kualitas	1.3	0.059
Ragu	1	0.159
Sumpah	2	0.159
Masak	2	0.159
Pakai	2	0.159
Tuh	2	0.159

Word	Document	TF-IDF
Enak	2	0.159
Authentic	2	0.159
Hmm	3	0.159
Insecure	3	0.159
Sih	3	0.159

3.5. Calculation of the Naïve Bayes model and finding accuracy

The initial step is to calculate the TF value of all words contained in the text (counting how often the word appears). Using 3 sentences, namely:

The total data used in the sentiment analysis study on the use of red oil with the Naïve Bayes Algorithm was 1,189 data. This data is divided into training data and test data with a ratio of 80% for training data and 20% for test data. The training data totaled 951 data, while the test data consisted of 238 data. In the training process, the weight of each word in each class is calculated using the TF-IDF method. Using the previous 3 sample data as training data, 1 test data was selected as the table 7.

Table 7. Sample Training Data

Data Training	Sentiment
giimana kabar minyak merah katanya murah	Positive
minyak merah hmm insecure kualitas sih	Negative
dapet minyak merah murah tuh lifesaver banget enggak kalah minyak	Positive

Sentiment classification is done automatically using the Naive Bayes algorithm, which uses the MultinomialNB function, which compares the weight of each word in the document. This is done by calculating the likelihood of the test data document based on the possible words present in the training data. As a result, each training document will have a balanced number of positive and negative word probabilities, as shown in the table 8.

Table 8. Word Weighting on Training Data

No.	Vocabulary	Tf (Positive)	Tf (Negative)
1.	Gimana	1	0
2.	Kabar	1	0
3.	Minyak	2	1
4.	Merah	2	1
5.	Katanya	1	0
6.	Murah	1	0
7.	Hmm	0	1
8.	Insecure	0	1
9.	Kualitas	0	1
10.	Sih	0	1
11.	Dapet	1	0
12.	Tuh	1	0
15.	Lifesaver	1	0
16.	Banget	1	0
17.	Enggak	1	0
18.	Kalah	1	0
Term Total		12	4

In conclusion, there are 12 words with positive values and 4 words with negative values, for a total of 18 words. The class classification process begins by calculating the probability of prior, probability, and posterior probability. The following are the stages of the classification process using the Naïve Bayes algorithm on the training data.

1. Calculation of probability values

$$P\ (Class \mid Comments) = \frac{Number\ of\ Class\ X}{Number\ of\ Comments}$$

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

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

P (Negative | Comments) = = $0.3\frac{1}{3}$

2. Calculation of Conditional Probability Value:

$$P\ (Term \mid Class) = \frac{Total\ TF - IDF\ Term\ weight\ in\ Class + 1}{TF - IDF\ Weight\ Class + Total\ TF - IDF\ Weight}$$

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

a. Probability of the word "oil"
P(Honest | Positive) = = = 0.1$\frac{2+1}{12+18}\frac{3}{30}$

P(Honest | Negative) = = = 0.091$\frac{1+1}{4+18}\frac{2}{22}$

b. Probability of the word "red"
P(Urgency | Positive) = = = 0.1$\frac{2+1}{12+18}\frac{3}{30}$

P(Urgency | Negative) = = = 0.091$\frac{1+1}{4+18}\frac{2}{22}$

c. Probability of the word "cheap"
P(Anies | Positive) = = = 0.067$\frac{1+1}{12+18}\frac{2}{30}$

P(Anies | Negative) = = = 0.045$\frac{0+1}{4+18}\frac{1}{22}$

Next is to take test data, namely by classifying test data by multiplying all opportunities. Higher values represent a new class of data, as shown in the table 9.

Table 9. Test Data Used

Test Sentiment
minyak merah murah cuy worth it daily cooking oke

In the test data "cheap red oil cuy worth it daily cooking okay" which is included in the training data are the words "oil" and "red".

3. Calculation of posterior probability values

$$P\ (Comments \mid Class) = P_{Term\ 1} x \ldots x P_{Term\ n} x\ P\ (Class|Comments)$$

P (Test | Positive) = P(positive) x P(oil|positive) x P(red|positive)
= 0.3 x 0.1 x 0.1
= 0.003

P (Test | Negative) = P(negative) x P(oil|negative) x P(red|negative)
= 0.3 x 0.091 x 0.091
= 0.0058

The conclusion is that because P(Test | Negative) is greater than P(Test | Positive), then the comment is more likely to be classified as "Negative".

After sentiment testing using the Naive Bayes algorithm, the next step is to conduct an evaluation using a confusion matrix to calculate accuracy, precision, recall, and F1 score by comparing the result classification label with the actual label on the sentiment dataset related to the use of red oil, as shown in the figure 4. The results of the sentiment analysis were then visualised in the form of a Wordcloud to facilitate the analysis and reading of the research results. The Wordcloud of the sentiment results can be shown in figure 5 and figure 6.

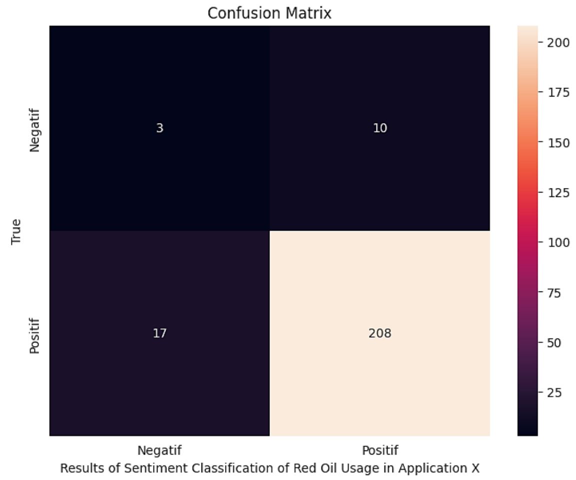

Figure 4. Confusion Matrix

Figure 5. Wordcloud Positive

Figure 6. Wordcloud Negatives

In figure 4 the classification results for finding accuration, precision, recall and F1-score follow the table 10 and the confusion matrix result as table 11.

Table 10. Determination of TP, FP, TN and FP Values

Label	Value
True Positive (TP)	208
False Positive (FP)	10
True Negative (TN)	3
False Negative (FN)	17

Table 11. Confusion Matrix Results

Accuracy: 0.88				
	Precision	Recall	F1-Score	Support
Negative	0.15	0.23	0.18	13
Positive	0.95	0.92	0.94	225
Accuracy			0.89	238
Macro avg	0.55	0.58	0.56	238
Weighted avg	0.91	0.89	0.90	238

3.6. Discussion

The results of this study show that public sentiment toward red oil is largely positive, with 1,147 positive comments and only 42 negative ones. The Naïve Bayes model combined with TF-IDF achieved high accuracy (88.66%), precision (95.41%), recall (92.44%), and F1-score (93.91%), indicating reliable sentiment classification. Compared to previous studies, which found predominantly negative or neutral sentiment on economic issues, this research reveals a more favorable consumer perception, likely due to the nature of the topic. While positive sentiment highlights consumer interest in red oil's benefits, negative comments point to concerns about taste, aroma, and availability. These findings suggest that producers and marketers should focus on improving product quality and educating consumers to boost acceptance. The study's strength lies in its effective machine learning approach, but limitations include reliance on social media data, which may not represent all demographics. Future research should explore deep learning techniques and additional data sources for a more comprehensive analysis of consumer sentiment.

4. CONCLUSION

Based on the results of the research, I conducted a sentiment analysis on application X about the use of red oil using the Naïve Bayes method. Before the analysis begins, the scraping process is carried out to collect data, where the total initial data obtained amounts to 1,200. After going through the process of deleting duplicate comments, the number of data became 1,189. Before running the Naïve Bayes algorithm, the data was divided into test data and training data, with 238 data as test data and 951 data as training data.

The labeling process used is the VADER Lexicon method. The way this method works is by assigning a polarity score to each word or phrase in the text, where the score value ranges from -4 to +4 to indicate the intensity of the emotion. A positive score indicates positive sentiment, while a negative score indicates negative sentiment. In addition, VADER is capable of handling various elements that affect sentiment intensity, such as the use of reinforcement words (e.g., "very"), negation words (e.g., "no"), punctuation (e.g., "!" or "?"), and capitalization. Thus, VADER can provide an accurate sentiment classification based on the total polarity score obtained, where a positive score indicates positive sentiment and a negative score indicates negative sentiment.

The classification results were obtained with total accuracy = 0.8866 or 88.66%, precision = 0.9541 or 95.41%, recall of 0.9244 or 92.44% and F1-score of 0.9391 or 93.91% and obtained in the sentiment comments of the use of red oil positive polarity is greater than negative polarity. Where the positive score was 1147 comments, 42 negative comments with a total of 1189 sentiment comment datasets obtained from X (Twitter).

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