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Comparison of Naïve Bayes and K-Nearest Neighbor for Iphone 16 Youtube Sentiment

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Abstract
Sentiment analysis plays an important role in understanding public opinion toward technological products, particularly in the context of social media such as YouTube. This study aims to analyze the sentiment of user comments on an iPhone 16 review video published by the GadgetIn YouTube channel, as well as to compare the performance of the Naïve Bayes and K-Nearest Neighbor classification algorithms. The data were collected through a crawling process, resulting in 2,499 comments, which were then split into training data (80%) and testing data (20%). The methodology includes text cleaning, tokenization, normalization, and term weighting using the TF-IDF method. The experimental results show that the Naïve Bayes algorithm achieved an accuracy of 73%, with precision, recall, and F1-score each reaching 72%, outperforming KNN, which only achieved 65% accuracy. Most comments were neutral; positive comments generally focused on design and performance, while negative comments mainly highlighted price and comparisons with other products. These findings indicate that the Naïve Bayes algorithm is more suitable for sentiment analysis of unstructured YouTube comment data..

Keywords—*Sentiment Analysis, iphone 16, Naïve Bayes, K-Nearest Neighbor*

1 Introduction

The rapid development of the smartphone industry has made it one of the most competitive sectors in the global technology landscape.One of the most talked-about products is the iphone 16, officially launched by Apple Inc. in early 2025. This product has captured public attention, particularly in Indonesia, where Youtube serves as one of the most popular social media platforms for watching product reviews and expressing opinions[1]. One of the iPhone 16 review videos uploaded by the channel GadgetIn garnered thousands of user comments, reflecting diverse perspectives on the product's features, price, and performance. These comments are unstructured, often using informal language, abbreviations, and other non-formal expressions. This makes large-scale opinion analysis challenging, necessitating a technology-based approach to efficiently and objectively classify sentiments.

One applicable method is machine learning-based sentiment analysis, which enables the system to categorize comments into positive, negative, and neutral. Two commonly used text classification algorithms are Naïve Bayes and K-Nearest Neighbor. Naïve Bayes is a simple yet effective probabilistic algorithm for text data, while KNN classifies based on data similarity, though it is sensitive to data volume and nearest-neighbor parameters [2][3]. Previous studies have compared these two algorithms in various contexts. In sentiment analysis of Youtube comments regarding the development of Indonesia's new capital city (IKN), Naïve Bayes achieved an accuracy of 60%, significantly outperforming KNN, which only reached 23% [4]. Conversely, research on Vidio app reviews from the Google Play Store showed that KNN performed better, with an accuracy of 74.92%, while Naïve Bayes achieved 71.32% [5]. This demonstrates that the performance of each algorithm heavily depends on data characteristics.Although many studies have evaluated Naïve Bayes and KNN, there has been limited research specifically comparing the two in analyzing Youtube comments on the latest technology products. Therefore, this study aims to address that gap by focusing on sentiment classification of user comments on iphone 16 review videos from the GadgetIn channel.

2 Research methods

The process in this research involves the application of the Knowledge Discovery in Databases (KDD) method. KDD is a step in extracting potential, hidden, and previously unknown information from a dataset. The workflow of the research follows stages including data selection, preprocessing, transformation, data mining, evaluation, and knowledge presentation[6].

2.1 *Data Selection*

Data collection was conducted through a crawling process on the comment section of the iPhone 16 review video from the GadgetIn Youtube channel to extract comments relevant to the research topic. After collecting the data, sampling was performed to ensure the relevance and quality of the data to be analyzed. Subsequently, each comment was manually labeled into positive, neutral, or negative sentiment categories to support accurate sentiment classification during the modeling stage[7].

2.2 *Preprocesing*

Preprocessing aims to clean and prepare raw text data before feature extraction. This stage includes several sub-processes[8][9]:

- Case folding: Converting all characters to lowercase.
- Cleansing: Removing special characters, numbers, emojis, and irrelevant symbols.
- Tokenizing: Splitting sentences into individual words (tokens).
- Normalization: Transforming informal words, slang, or abbreviations into their standard forms.
- Stopword removal: Eliminating common words with little significance in classification.
- Stemming: Reducing words to their root forms to simplify the data.

2.3 *Transformation*

The copyright before feature extraction was carried out, the preprocessed data was divided into training and testing sets to support model development and evaluation. In the next stage, the textual data was transformed into numerical form using the TF-IDF (Term Frequency-Inverse Document Frequency) method.The formula used for TF-IDF is as follows[10]:

$$TF - IDF(t) = tf_{t,d} \times \log\frac{N}{df_t} \quad (1)$$

In this formula, $tf_{t,d}$ refers to the number of times the term t appears in document . The variable N indicates the total number of documents in the dataset, while df_t represents how many documents contain the term t. This calculation gives higher scores to terms that frequently appear in a specific document but are rare across the entire collection, thus helping distinguish significant words for sentiment classification.

2.4 *Data Mining*

Data mining is a process used to discover hidden patterns and new knowledge from large datasets by utilizing statistical techniques or artificial intelligence methods. In this study, data mining is applied to build a sentiment classification model that categorizes comments into three sentiment classes: positive, neutral, and negative. The algorithms employed are Naïve Bayes and K-Nearest Neighbor[11][12].

2.4.1 Naïve Bayes

Naïve Bayes is a classification method based on probability, assuming that each feature is independent of the others[13]. The probability equation used in this algorithm is expressed as:

$$P(H|X) = \frac{P(X|H) \times P(H)}{P(X)} \quad (2)$$

In this equation, $P(H|X)$ represents the probability of hypothesis H (the sentiment class) given the data X (the word features). The term $P(X|H)$ refers to the probability of observing X if H is true, $P(H)$ denotes the prior probability of H, and $P(X)$ is the overall probability of X. This calculation helps determine the sentiment class with the highest likelihood based on the word patterns found in the comments.

2.4.2 K-Nearest Neighbor

K-Nearest Neighbor is a classification algorithm that groups data based on proximity[14]. The Euclidean distance formula used in this algorithm is:

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (3)$$

In this formula, d(x,y) denotes the distance between data points x and y, n represents the number of features, while x_i and y_i are the values of the i-th feature in x and y, respectively. A smaller distance indicates a higher likelihood that the data points belong to the same class. Thus, KNN predicts the sentiment of a comment by analyzing its similarity to training data with known classes.

2.5 *Evaluation*

The evaluation stage in this research aims to assess the performance of the sentiment classification model and to determine how accurately it predicts sentiment categories. Evaluation is carried out using a confusion matrix, which summarizes the model's predictions by displaying the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) outcomes[15]. This matrix helps identify how well the model distinguishes between different sentiment classes and where misclassifications occur. The model's accuracy is calculated as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

In this equation, accuracy measures the proportion of all predictions that are correct.

Precision is calculated using the formula:

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

This metric indicates how many of the predictions labeled as positive are truly positive.

Recall is computed as:

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

Recall measures how many actual positive cases are correctly identified by the model.

The F1-Score, which balances precision and recall, is determined by the following formula:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (7)$$

This score provides a single metric that reflects the model's overall effectiveness in handling both precision and recall.

2.6 Knowlage Presentation

The final output is presented through visualizations, including bar charts and word clouds, to illustrate the sentiment distribution and frequently occurring words in each sentiment class. This stage facilitates the interpretation of public sentiment towards the iPhone 16. A wordcloud is used to display the most frequently occurring words, where words with higher frequencies appear in larger font sizes, making it easier to identify dominant themes or opinions within each sentiment category[16].

3 Results and Discussion

3.1 Data Selection

Data was collected through a crawling process on the comment section of the iPhone 16 review video from the GadgetIn Youtube channel using the Youtube Data API v3. After data collection, sampling was performed at a rate of 2%, resulting in a dataset of 2,499 comments for analysis. Subsequently, the comments were manually labeled into three sentiment categories: positive, neutral, and negative, to ensure that the labels accurately reflected the actual context of each commen.

3.2 *Preprocesing*

At this stage, the labeled data is processed through several text preprocessing steps, which are shown in Table 1.

Table 1 Case Folding Results Data

Review Before Case Folding	Review After Case Folding
di iBox kapan ya keluarnya ?	di ibox kapan ya keluarnya ?
Setelah ip resmi dijual di indo apakah IP gen 15 turun harga ?	setelah ip resmi dijual di indo apakah ip gen 15 turun harga ?
Untuk series ip menurutku kamera yg paling bagus…	untuk series ip menurutku kamera yg paling bagus…

All characters are converted to lowercase to standardize the data and avoid differences caused only by capitalization. After this step, cleansing is performed as shown in the table 2.

Table 2 Cleansing Results Data

Review Before Cleansing	Review After Cleansing
di ibox kapan ya keluarnya ?	di ibox kapan ya keluarnya
setelah ip resmi dijual di indo apakah ip gen 15 turun harga ?	setelah ip resmi dijual di indo apakah ip gen turun harga
untuk series ip menurutku kamera yg paling bagus…	untuk series ip menurutku kamera yg paling bagus

Cleansing removes unnecessary elements from the text, such as punctuation marks, numbers, emojis, and extra spaces. Next, tokenization is carried out as presented in the table 3.

Table 3 Tokenization Results Data

Review Before Tokenization	Review After Tokenization
di ibox kapan ya keluarnya	['di', 'ibox', 'kapan', 'ya', 'keluarnya', '']
setelah ip resmi dijual di indo apakah ip gen turun harga	['setelah', 'ip', 'resmi', 'dijual', 'di', 'indo', 'apakah', 'ip', 'gen', 'turun', 'harga', '']
untuk series ip menurutku kamera yg paling bagus	['untuk', 'series', 'ip', 'menurutku', 'kamera', 'yg', 'paling', 'bagus']

Tokenizing splits the text into separate words (tokens) to make it easier for further analysis. After separating the words, normalization is conducted as indicated in the table 4.

Table 4 Normalization Results Data

Review Before Normalization	Review After Normalization
['di', 'ibox', 'kapan', 'ya', 'keluarnya', '']	['di', 'ibox', 'kapan', 'ya', 'keluarnya', '']
['setelah', 'ip', 'resmi', 'dijual', 'di', 'indo', 'apakah', 'ip', 'gen', 'turun', 'harga', '']	['setelah', 'iphone', 'resmi', 'dijual', 'di', 'indonesia', 'apakah', 'iphone', 'gen', 'turun', 'harga', '']
['untuk', 'series', 'ip', 'menurutku', 'kamera', 'yg', 'paling', 'bagus']	['untuk', 'series', 'iphone', 'menurutku', 'kamera', 'yang', 'paling', 'bagus']

Normalization converts non-standard words or abbreviations into their standard forms according to linguistic rules, ensuring more consistent meaning. This is followed by stopword removal as shown in the table 5.

Table 5 Stopword Removal Results Data

Review Before Stopword Removal	Review After Stopword Removal
['di', 'ibox', 'kapan', 'ya', 'keluarnya', '']	['ibox', 'kapan', 'keluarnya', '']
['setelah', 'iphone', 'resmi', 'dijual', 'di', 'indonesia', 'apakah', 'iphone', 'gen', 'turun', 'harga', '']	['iphone', 'resmi', 'jual', 'indonesia', 'iphone', 'gen', 'turun', 'harga', '']
['untuk', 'series', 'iphone', 'menurutku', 'kamera', 'yang', 'paling', 'bagus']	['series', 'iphone', 'menurutku', 'kamera', 'paling', 'bagus']

Stopword removal eliminates common words that carry little significance in analysis, such as "untuk "di," or "ya." Finally, stemming is performed as displayed in the table 6.

Table 6 Stemming Results Data

Review Before Stemming	Review After Stemming
['ibox', 'kapan', 'keluarnya', '']	ibox kapan keluar
['iphone', 'resmi', 'jual', 'indonesia', 'iphone', 'gen', 'turun', 'harga', '']	iphone resmi jual indonesia iphone gen turun harga
['series', 'iphone', 'menurutku', 'kamera', 'paling', 'bagus']	series iphone turut kamera paling bagus

Stemming reduces words to their root forms by removing affixes, making the word forms more consistent.

3.3 *Transformation*

In the data mining stage, the dataset was divided into training and testing sets with an 80:20 ratio, resulting in 1,942 training data points and 486 testing data points. This partitioning process was carried out using the train_test_split module from the sklearn.model_selection library. After the data split, TF-IDF calculations were performed to transform the textual data into numerical vectors for subsequent sentiment classification, as shown in Equation (1) and presented in the table 7.

Table 7 TF-IDF Calculator

Term	D1	D2	D3	DF	D/DF	IDF
Ibox	1	0	0	1	3	0.4771213
Kapan	1	0	0	1	3	0.4771213
Keluar	1	0	0	1	3	0.4771213
iphone	0	2	1	2	1.5	0.1760913
resmi	0	1	1	1	3	0.4771213
jual	0	1	0	1	3	0.4771213
indonesia	0	1	0	1	3	0.4771213
gen	0	1	0	1	3	0.4771213
Turun	0	1	0	1	3	0.4771213
Harga	0	1	0	1	3	0.4771213
Series	0	0	1	1	3	0.4771213
Turut	0	0	1	1	3	0.4771213
Kamera	0	0	1	1	3	0.4771213
Paling	0	0	1	1	3	0.4771213
bagus	0	0	1	1	3	0.4771213

3.4 *Data Mining*

The subsequent stage involves applying the Naive Bayes and KNN algorithms. Samples of the training and testing data are presented in Table 8 and Table 9.

Table 8 SampleTesting Data

D	Comment	Category
D1	iphone plus kamera bagus	Positive
D2	tidak suka iphone ribet lebih baik samsung	Negative
D3	batrei nya awet bagus	Positive
D4	kalo iphone e gimana	Neutral

Table 9 SampleTest Data

D	Comment	Category
D1	Lucu warna iphone plus	?

3.4.1 Naïve Bayes

The first stage in Naive Bayes calculations is to determine the prior probabilities for each sentiment class. These calculations can be performed using Equation (2) and are summarized in Table 10.

Table 10 Prio Probablitiy

Prior Probability		
$P_{(Positive)}$	$P_{(Neutral)}$	$P_{(Negative)}$
$\frac{2}{4} = 0.5$	$\frac{1}{4} = 0.25$	$\frac{1}{4} = 0.25$

After calculating the prior probabilities, the next step is to determine the conditional probabilities for each word in the vocabulary with respect to every sentiment class. For instance, the probability of the word.

Probability of the word 'iphone'

$$P(a_{iphone} \mid V_{Positive}) = \frac{2+1}{8+18} = \frac{3}{26} = 0.115$$

$$P(a_{iphone} \mid V_{Neutral}) = \frac{1+1}{4+18} = \frac{2}{22} = 0.0909$$

$$P(a_{iphone} \mid V_{Negative}) = \frac{1+1}{7+18} = \frac{3}{25} = 0.08$$

Probability of the word 'plus'

$$P(a_{plus} \mid V_{Positive}) = \frac{1+1}{8+18} = \frac{2}{26} = 0.077$$

$$P(a_{plus} \mid V_{Neutral}) = \frac{0+1}{4+18} = \frac{1}{22} = 0.0455$$

$$P(a_{plus} \mid V_{Negative}) = \frac{0+1}{7+18} = \frac{1}{25} = 0.04$$

Probability of the word 'lucu'

$$P(a_{lucu} \mid V_{Positive}) = \frac{0+1}{8+18} = \frac{1}{26} = 0.0385$$

$$P(a_{lucu} \mid V_{Neutral}) = \frac{0+1}{4+18} = \frac{1}{22} = 0.0455$$

$$P(a_{lucu} \mid V_{Negative}) = \frac{0+1}{7+18} = \frac{1}{25} = 0.04$$

Probability of the word 'warna'

$$P(a_{warna} \mid V_{Positive}) = \frac{0+1}{8+18} = \frac{2}{26} = 0.0385$$

$$P(a_{warna} \mid V_{Neutral}) = \frac{0+1}{4+18} = \frac{1}{22} = 0.0455$$

$$P(a_{warna} \mid V_{Negative}) = \frac{0+1}{7+18} = \frac{1}{25} = 0.04$$

After determining the conditional probabilities, the next stage is to calculate the posterior probabilities for each sentiment class. This is achieved by multiplying the prior probability of the class by the product of the conditional probabilities for all words in the test sentence. The class with the highest posterior probability is then selected as the predicted sentiment category.

Positive Class

P(Positive|X)×P(lucu|Positive)×P(warna|Positive)×P(iphone|Positive)×P(plus|Positive)×P(Positive)

Substitute the values:

=0.0385×0.0385×0.115×0.077×0.5 = 0.00000655

Neutral Class

(Neutral|X)×P(lucu|Neutral)×P(warna|Neutral)×P(iphone|Neutral)×P(plus|Neutral)×P(Neutral)

Substitute the values:

=0.0455×0.0455×0.0909×0.0455×0.25 = 0.00000214

Negative Class

P(Negative|X)×P(lucu|Negative)×P(warna|Negative)×P(iphone|Negative)×P(plus|Negative)×P(Negative)

Substitute the values:

=0.04×0.04×0.08×0.04×0.25 = 0.00000128

Based on the calculation results, the class with the highest posterior probability is Positive, indicating that the sentence "lucu warna iphone plus" is categorized as a positive sentiment.

3.4.2 K-Nearest Neighbor

In K-Nearest Neighbor, the initial step involves computing the Euclidean distances from the test document to each training document, as shown in Equation (3) and summarized in Table 10.

Table 11 KNN Caculator

D	Category	Caculator $\sum(xi - yi)^2$	Euclidean distance
D1	Positive	$(1-1)^2+(1-1)^2+(0-0)^2+(0-0)^2+(0-0)^2+(0-0)^2+(0-0)^2+(1-0)^2+(1-0)^2 = 4$	$\sqrt{4} = 2.000$
D2	Negative	$(1-0)^2+(1-0)^2+(1-1)^2+(1-0)^2+(1-0)^2+(1-0)^2+(1-0)^2+(0-1)^2+(0-1)^2 = 6$	$\sqrt{6} = 2.449$
D3	Positive	$(1-0)^2+(1-0)^2+(1-0)^2+(1-0)^2+(0-1)^2+(0-1)^2+(0-1)^2+(0-1)^2+(0-1)^2 = 8$	$\sqrt{8} = 2.828$
D4	Neutral	$(0-1)^2+(1-1)^2+(0-0)^2+(0-0)^2+(0-0)^2+(0-0)^2+(0-0)^2+(1-0)^2+(1-0)^2 = 4$	$\sqrt{4} = 2.000$

Using K-Nearest Neighbor with k=1, the test sentence “lucu warna iphone plus” was compared to all training documents. The closest neighbor was found to be document D1, which belongs to the Positive category.

3.5 Evaluation

Following the completion of the modelling stage, the next step is model evaluation, where a confusion matrix is used to assess the accuracy of the constructed model. The structure of the confusion matrix can be seen in Figure 1 and Figure 2.

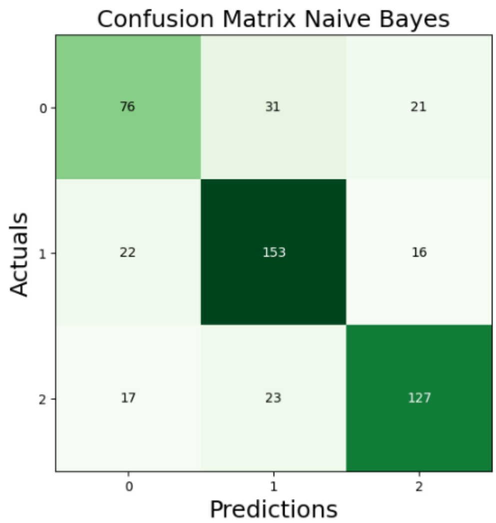

Figure 1 Confusion Matrix Naïve Bayes

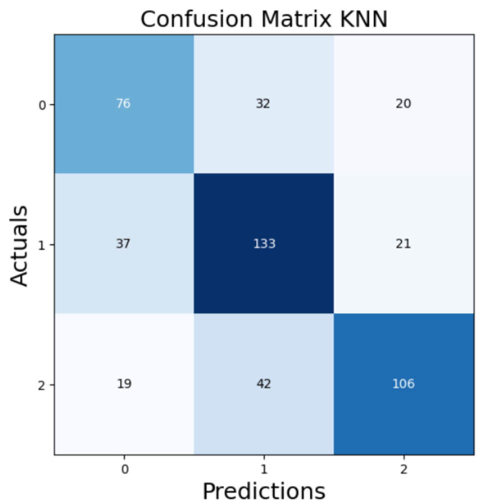

Figure 2 Confusion Matix K-Nearest Neighbor

The classification results will be displayed in the form of a confusion matrix. The evaluation results of each algorithm can be seen in Table 12 and are calculated based on Equation (4) for Accuracy, Equation (5) for Precision, Equation (6) for Recall, and Equation (7) for F1-Score.

Table 12 Confusion Matrix

	Naïve Bayes			K-Nearest Neighbor		
	Positive	Neutral	Negative	Positive	Neutral	Negative
Accuracy	73%			65%		
Precision	77%	74%	66%	72%	64%	58%
Recall	76%	80%	59%	63%	70%	59%
F1-score	77%	77%	63%	68%	67%	58%

3.6 Knowlage Presentation

The analysis of the test data showed that 808 instances were classified as positive sentiment, 987 as neutral sentiment, and 636 as negative sentiment. These results will be visualized in the form of a bar chart, as shown in Figure 3.

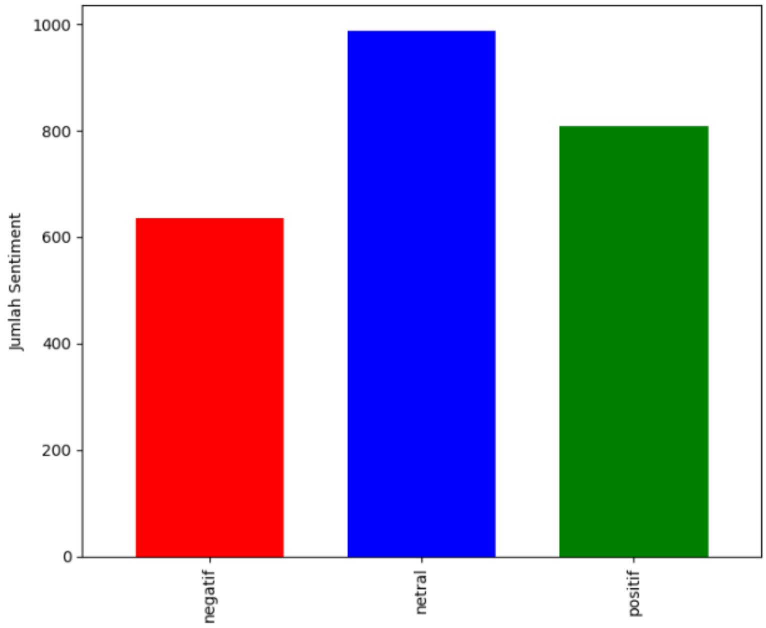

Figure 3 Visualisation Data

The following visualization presents a wordcloud that illustrates the most frequently used words in positive comments. Figure 4 shows a visual representation of terms associated with favorable sentiments toward the iPhone 16 product. Words such as “bagus”, “banget”, “pakai”, “iphone”, and “beli” appear prominently, indicating their frequent usage. The word “bagus” reflects a positive perception of the product’s quality, while “banget” emphasizes the users’ high level of enthusiasm or admiration. Meanwhile, the words “pakai” and “beli” suggest that many comments stem from firsthand experience or a strong desire to own the product. Terms like “worth”, “keren” (cool), and “mantap” (great) also appear in large font sizes, signifying praise related to the price, design, and performance of the iphone 16. Overall, this wordcloud indicates that YouTube users generally express favorable opinions about the iphone 16, particularly in terms of quality, design, and functionality.

Figure 4 Wordcloud Positive

The wordcloud in Figure 5 displays frequently occurring words found in comments with neutral sentiment, such as “iphone,” “beli”, “pakai”, “baru”, and “indonesia.” The larger size of these words indicates that the topics being discussed tend to be descriptive or informative in nature, without conveying clear emotional tones. Several comments also reflect the delivery of general information or factual content related to the product and the smartphone industry. Overall, this wordcloud represents neutral comments, where users primarily share information, questions, or light opinions without strong emotional expression.

Figure 5 Wordcloud Neutral

A wordcloud illustrating negative sentiment in user comments is shown in Figure 6. Among the most prominent terms are “tidak”, “mahal”, “beli”, “android,” “samsung,” and “telat” , indicating frequent expressions of dissatisfaction or criticism regarding the iPhone 16. The word “tidak” frequently appears in contexts such as “not worth buying,” “not meeting expectations,” or “not significantly different from previous models.” Other words like “mahal” and “telat” reflect user complaints about high prices and late release. The presence of “android” and “samsung” suggests comparisons with competing products that are perceived as more favorable. Overall, this wordcloud illustrates the negative perceptions found in user comments, particularly regarding pricing, features, and the iPhone 16's position relative to its competitors.

Figure 6 Wordclou Negative

3.7 Discussion

The results of this study indicate that the Naïve Bayes algorithm outperforms K-Nearest Neighbor in classifying sentiment in YouTube comments on the iPhone 16. Naïve Bayes achieved an accuracy of 73%, while KNN reached only 65%. This finding aligns with the characteristics of Naïve Bayes, which excels in text classification due to its probabilistic approach and the assumption of feature independence. In contrast, the lower performance of KNN may be attributed to its sensitivity to data dimensionality and its reliance on distance metrics, which are less effective when dealing with sparse text features such as those generated by TF-IDF. Furthermore, sentiment distribution analysis revealed that neutral comments were the most dominant, followed by positive and negative ones. The wordcloud visualization supports these findings: neutral comments tend to be descriptive and factual, positive comments emphasize product design and performance, while negative comments frequently highlight price concerns and comparisons with competing products like Samsung and Android-based devices. These results reinforce that the Naïve Bayes algorithm is more suitable for analyzing large-scale textual data on social media, and they highlight the importance of selecting the appropriate algorithm based on the specific characteristics of the dataset.

4 Conclusion

The Naïve Bayes algorithm demonstrated better performance than K-Nearest Neighbor in classifying sentiment in YouTube comments on the iPhone 16 review video. Naïve Bayes achieved an accuracy of 73%, while KNN obtained only 65%. Most of the analyzed comments fell into the neutral sentiment category, followed by positive and negative sentiments. Positive comments generally highlighted aspects of design and performance, while negative comments were mostly related to price and comparisons with other products. Naïve Bayes proved to be more suitable for high-dimensional and unstructured text data. The accuracy obtained in this study was also higher than that reported in a previous study [4] using similar algorithms on YouTube comment data, indicating that data characteristics and preprocessing steps play a significant role in the effectiveness of classification models.

5 Suggestion

Future research may consider developing sentiment analysis models by applying alternative algorithms that have the potential to yield better results in handling informal and unstructured comment data. It is also recommended to broaden the data scope by collecting comments from multiple videos or channels to achieve more generalizable outcomes. Improvements in the preprocessing stage particularly in handling slang and regional terms could also enhance the model's accuracy.

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