Metris
Jurnal Sains dan Teknologi
p-ISSN: 1411 - 3287
e-ISSN: 2808 - 4810

Metris: Jurnal Sains dan Teknologi 26 (2025) 39 – 50
http://ejournal.atmajaya.ac.id/index.php/metris

Identification of Inconsistent Reviews and Ratings on Apps Using Sentiment Analysis: Case Study on Indonesian Digital Media Platform

Ahmad Aulia Zakiyal Fikri, Hafidz Ridho*

Department of Systems and Industrial Engineering, Faculty of Industrial Technology and Systems Engineering, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia

Article Info

Article history:

Received
13 June 2025

Accepted
05 July 2025

Keywords:
Sentiment analysis, digital media, naïve bayes classifier, word cloud.

Abstract

Reviews and ratings on apps store show how users perceive an app. This is an important aspect that companies must pay attention to in order to plan improvement strategies. However, there is an inconsistency between reviews and ratings, which makes it difficult to take corrective action. Detikcom, one of the main players in the digital media industry in Indonesia, also faces this similar problem. On Google Play Store platform, it is known that Detikcom's 1-star rating (13%) is one of the highest compared to its competitors. However, the inconsistency between ratings and reviews can be found frequently in the review section. Reflecting on this case, this study focuses on building a model that can identify sentiment using the Naïve Bayes Classifier method and identifying the main driving factors of each sentiment category using K-means Clustering and word cloud. Based on the results of the developed model, the tendency of Detikcom user sentiment is generally positive (67.16%) with a test accuracy of 87.84%. The presence of positive sentiment is based on keywords such as “accurate”, “trusty”, and “up to date”, while negative sentiment is based on keyword “ads”.

1. INTRODUCTION

Along with the development of the times and regulations in Indonesia, public information is now a human right accessible to all citizens (Kominfo Indonesia, 2008). According to a survey conducted by Annur in 2023, 27.5% of the population in Indonesia access public information from digital media news (Annur, 2023).

One of the main players in the Indonesian digital news sector is Detikcom, which has managed to acquire 65% of digital news users in Indonesia (Pahlevi, 2022). Detikcom is a digital media outlet with a breaking news concept under CT Corp. As of December 2020, Detikcom recorded more than 17 billion page views, 462 million visitors, and 162 million user accounts enjoying video content.

Despite various achievements, Detikcom has several shortcomings based on user reviews on the Google Play Store platform. Detikcom has the second highest percentage of 1-star ratings (13%). This indicates that Detikcom's 1-star rating is one of the highest compared to its competitors, Kompas ID (2%) and Liputan6 (10%). Additionally, 45% of reviewers complained about the presence of intrusive ads that obstruct news content. However, there are many inconsistencies between ratings and reviews found in the review section, e.g. 5-star rating with bad reviews, 1-star rating with good reviews, and also many empty reviews. This causes complexity in the analysis. A comprehensive tudy should so be conducted so that important reviews are not lost when the filtering process is carried out.

This issue presents an urgency for Detikcom, as a player in the digital media industry, to take mitigation actions. The presence of ads on an application page significantly impacts the ease of access for digital media users (Newman, 2023). Ease of access is a key parameter

*Corresponding author. Hafidz Ridho
Email address: hafidz.ridho@its.ac.id

for someone choosing a digital media platform (Tamara, Kisata, & Rosenanda, 2020). This indirectly leads to a decrease in page views and the number of daily active users, which are key performance indicators, as users become uncomfortable accessing the digital news service.

Based on these problems, this study aims to conduct sentiment analysis to identify the sentiment trends from user reviews. Sentiment analysis generally involves processing text data to obtain emotional information contained in opinion texts (Imam, Pramono, & Dahlan, 2012). Several studies have been conducted to provide a framework for analyzing user sentiment. Naïve bayes classifier combined with Term Frequency-Inverse Document Frequency (TF-IDF) is the common method for a sentiment analysis (Ismaturrahmi, Khadafi, & Amirullah, 2025) (Razaq, Nurhanah, & Nurrahmi, 2023) (Muzaki, Febriana, & Cholifah, 2024). More advanced methods such as AdaBoost, XGBoost, and artificial neural networks also can be utilized to classify reviews based on polar emotions (Khan, Khan, & Malik, 2024).

On the subject of incosistent rating and reviews, (Aljrees, *et al.*, 2024) provided a framework to handle this problem using transfer learning approaches to predict numerical ratings based on reviews. The results of this study proved that the proposed model was able to provide more authentic ratings based on user reviews. Study by (Eser & Sahin, 2024) proposed a Transformer-based Models to classify reviews into positive, neutral, and negative sentiment and followed by XLM-RoBERTa to predict apps ratings. These two studies considered both reviews and ratings on the sentiment analysis. However, there is a need to analyze both aspect simultaneously. By doing so, the analysis is not only focused on reviews that have low ratings, but also on reviews that have inconsistencies in ratings to get the authentic sentiments.

The sentiment analysis in this study is conducted using the Naïve Bayes Classifier method. This method is chosen due to the limited runtime capacity on the researcher's Google Colab. Despite its low complexity, the results of this method can compete with more complex models such as Decision Tree, Support Vector Machine, and Artificial Neural Network (Sfenrianto, Purnamasari, & Bahaweres, 2016).

Furthermore, this study identifies the factors causing sentiment by utilizing the K-Means Clustering algorithm and word cloud. The K-Means Clustering algorithm is used to identify distinguishing characteristics between text data clusters formed from each sentiment. Meanwhile, the use of word cloud in this study aims to identify keywords that frequently appear in user reviews for each sentiment (positive, neutral, and negative).

Based on the outputs of this process, this study also provides policy recommendations for PT Trans Digital Media. These policies focus on how the company can use the analysis results for business processes, particularly in the development of the Detikcom application.

2. METHODOLOGY

This study proposes sentiment analysis framework as explained by Figure 1. Sentiment analysis is a process or method that automatically understands, extracts, and processes text data to obtain emotional information contained in opinion texts (Imam, Pramono, & Dahlan, 2012). Sentiment analysis has several uses, one of which is identifying public opinion trends towards an object, product, or service. Various classification algorithms can be applied in sentiment analysis, such as Naïve Bayes (NB), Support Vector Machine (SVM), and Artificial Neural Network (Chandani, Satria, & Purwanto, 2015). The implementation of the analysis was performed using Python programming. The package and library features in the analysis include "NumPy", "Pandas", Scikit-Learn", "Google Play Scrapper", "NLTK", "Gensim", and "Sastrawi" were utilised. Detailed explanation about the methodology is explained in the next subchapters.

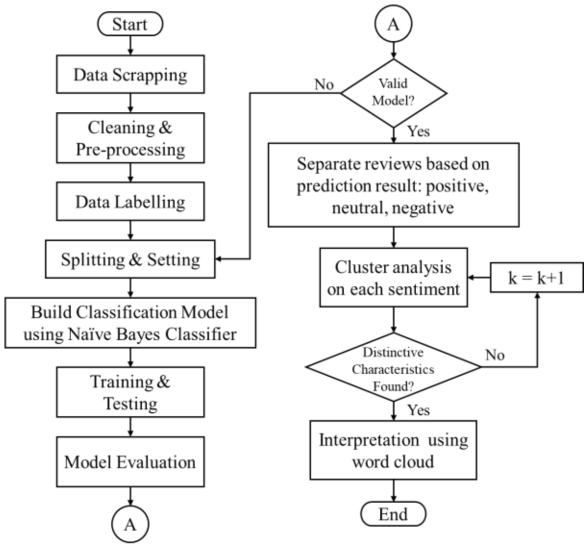

Figure 1.
Sentiment analysis framework

2.1 Data Scrapping

The first step in this study was to collect data using Google Play Scraper. The Google Play Scraper API were applied in Python to retrieve user reviews for a specific application on the Google Play Store platform. Adjustments made in the data scraping process focus on the context of the data to be obtained, including language (Indonesian), country (Indonesia), recency (latest), the amount of data to be retrieved (15,000 data points), and rating (all ratings).

The output file format from data scraping was in .csv format, which had been normalized and displays only the necessary information. By doing so, further processing in the stages of data cleaning, tokenization, stemming, and modeling can be done with ease. The output examples from the data scraping process is shown in Table 1.

2.2 Data Pre-Processing

The data preprocessing stage consisted of data cleaning, text tokenization, and text stemming. During the data cleaning stage, uppercase letters were converted to lowercase, and stopwords, emojis, punctuation, foreign characters, and words using non-ASCII alphabet characters (A-Z) were eliminated.

Table 1.
Data scrapping output examples (first 5 rows)

	User Name	Score	At	Content
0	*Google User*	5	2024/06/15 02:04:55	*Bagus*
1	*Google User*	1	2024/06/14 16:10:39	*Terlalu banyak iklan*
2	*Google User*	4	2024/06/14 08:17:42	4 *dulu*
3	*Google User*	5	2024/06/13 07:11:09	Infinix GT 20 PRO 5G./6/29/2024
4	*Google User*	5	2024/06/12 12:30:53	*Sangat membantu menambah informasi dan wawasan*

The tokenization stage aimed to break down sentences in the document into a list of strings containing the set of words forming a sentence. This ensures that the model analyzes not the entire sentence but each word composing the user review sentence. The library used for document tokenization is Gensim version 4.2.0.

The stemming stage aimed to find and replace each syllable in the tokenized document with its root syllable. For example, some words were not root words, such as "beritanya," where the root word was "berita" with the suffix "-nya". The output examples of the data preprocessing stage was a data frame as shown in Table 2.

2.3 Classification Using Naïve Bayes Classifier

Naïve Bayes is a statistical classifier that can predict the probability of a data tuple belonging to a certain class, based on probability calculations (Berrar, 2018). Despite its low complexity, the results of this method can compete with more complex models such as Decision Tree, Support Vector Machine, and Artificial Neural Network (Sfenrianto, Purnamasari, & Bahaweres, 2016). Bayes' theorem is the foundational rule of the Naïve Bayes classifier. Bayes' theorem is presented in Eq. 1.

$$P\left(C_j|X\right) = \frac{P\left(X|C_j\right) \times P\left(C_j\right)}{P\left(X\right)} \tag{1}$$

Where C_j is the category of text to be classified, and $P\left(C_j\right)$ is the prior probability of the respective category. Meanwhile, X is a text document represented as a set of words (*W1, W2, ..., Wn*), where *W1* is the first word, *W2* is the second word, and so on.

The application of the Naïve Bayes Classifier model was conducted through three main stages: initial labeling process, selection of data splitting ratio, and definition of the Naïve Bayes Classifier model. This stage began with the initial data labeling process. In this process, the "score" criteria, or in this case, the star rating given by the user, was used. If the star rating given was less than 3, the document will be labeled as negative. If the rating given was 3, the document will be labeled as neutral. If the rating given was more than 3, the document will be labeled as positive. This label served as the prior probability needed to perform classification using the Naive Bayes Classifier method. The output examples of the initial labeling process is shown in Table 3.

Table 2.
Data preprocessing output examples

	Content	Score	Text_clean	Tokenize_text	Text_stem
0	Informatif, edukatif, energi positif.	5	Informatif, edukatif, energi positif.	[Informatif, edukatif, energi, positif]	Informatif, edukatif, energi, positif
1	Dulu sangat bagus dn slalu update beritanya tp…	3	Dulu sangat bagus dn slalu update beritanya tp…	[Dulu, sangat, bagus, dn, slalu, update, berita, tpi, s…]	Dulu, sangat, bagus, dn, slalu, update, berita, tpi, s…
2	Berita update	5	Berita update	[Berita, update]	Berita, update
3	Banyak berita gak pentingnya malahan yg lagi r…	3	Banyak berita gak pentingnya malahan yg lagi r…	[Banyak, berita, gak, pentingnya, malahan, yg, lagi, rame, g…]	Banyak, berita, gak, penting, malah, yg, lagi, rame, g…
4	Bagus	5	Bagus	[Bagus]	Bagus
5	Beritanya selalu up to date	5	Beritanya selalu up to date	[Beritanya, selalu, up, to, date]	Berita, selalu, up, to, date

Table 3.
Labelling output examples

	Content	Score	Text_stem_indo	Label
0	Informatif, edukatif, energi positif.	5	Informatif, edukatif, energi, positif	Positive
1	Dulu sangat bagus dn slalu update beritanya tp…	3	Dulu, sangat, bagus, dn, slalu, update, berita, tpi, s…	Neutral
2	Berita update	5	Berita, update	Positive
3	Banyak berita gak pentingnya malahan yg lagi r…	3	Banyak, berita, gak, penting, malah, yg, lagi, rame, g…	Neutral
4	Bagus	5	Bagus	Positive
5	Beritanya selalu up to date	5	Berita, selalu, up, to, date	Positive

In the data-splitting process, several combinations of splitting ratio were performed, as explained in Table 4.

Table 4.
Scenarios for splitting ratio.

Scenario	Experimented Ratio
1	70% - 30%
2	75% - 25%
3	80% - 20%
4	85% - 15%
5	90% - 10%

The test accuracy value was prioritized as the primary parameter considered, given that the goal of this research was to predict sentiment in a document. Using the best data split ratio, the Naïve Bayes Classifier model was then applied to the reviews. Sentiment prediction outputs presented as a new data frame, as the example explained in Table 5.

Table 5.
Prediction output examples.

	Content	Score	Text_stem_indo	Label	Prediction
0	Informatif, edukatif, energi positif.	5	Informatif, edukatif, energi, positif	Positive	*Positive*
1	Dulu sangat bagus dn slalu update beritanya tp…	3	Dulu, sangat, bagus, dn, slalu, update, berita, tpi, s…	Neutral	*Negative*
2	Berita update	5	Berita, update	Positive	*Negative*
3	Banyak berita gak pentingnya malahan yg lagi r…	3	Banyak, berita, gak, penting, malah, yg, lagi, rame, g…	Neutral	*Positive*
4	Bagus	5	Bagus	Positive	*Positive*
5	Beritanya selalu up to date	5	Berita, selalu, up, to, date	Positive	*Positive*

2.4 Model Validation

After defining the Naïve Bayes algorithm, a performance test was applied. Performance measurement is the final stage in text classification. In this stage, the results of the experiment were evaluated. Many measurement methods have been used, such as precision and recall, error, accuracy, and others (Handayani & Pribadi, 2015). The evaluation of the text classification results in each category can be shown in Table 6.

Table 6.
Confusion matrix

		Actual	
		YES	NO
Predicted	YES	TP – True Positive	FP – False Positive
	NO	FN – False negative	TN – True Negative

Four parameters explained in Table 6 can be used to calculate these 4 evaluation metrices:

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

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

$$Precision = \frac{TP}{TP+FN} \quad (4)$$

$$F1\ Measure = \frac{2 \times Precision \times Recall}{Precision \times Recall} \quad (5)$$

2.5 Cluster Analysis For Each Sentiment

After analyzing sentiment using the Naïve Bayes Classifier, the reviews in each sentiment category were clustered to determine the factors causing those sentiments. K-Means clustering is a method used in the clustering process to determine the best way to divide objects, such as documents, into groups called clusters (Tan, Steinbach, & Kumar, 2005). Each cluster formed optimized partition criteria, such as the distance function and similarity function. The Euclidean distance was used as the distance measure in the K-Means approach to highlight the similarity between each cluster with the smallest distance and the highest similarity. The Euclidean distance between point $a = (a_1, a_2, a_3, \ldots, a_k)$ and point $b = (b_1, b_2, b_3, \ldots, b_n)$ determined using the following formula:

$$d(b_i, a_t) = \sqrt{\sum_{j=1}^{l}(b_{ij} - a_{tj})^2} \tag{6}$$

The clustering process used 5 clusters (K=5). This process produced a scatter plot that shows the vector of each document and the cluster distribution of the analyzed reviews. At this stage, the PCA (Principal Component Analysis) method was also used to reduce the dimensionality of the clustering

2.6 Word Cloud

After clustering analysis was done, the frequently occurring words in all reviews were mapped into a Word Cloud to be more interactive for analysis in the Discussion.

3. RESULT AND DISCUSSION

The focus of this chapter is to discuss the output from the running process of the developed model. Several discussion points focus on how to get appropriate data splitting ratio, the clustering results of documents in each sentiment, and the word cloud generated by the model.

In order to get the appropriate data splitting ratio, an experiment was conducted to measure the testing and training accuracy of different ratios as explained by Table 7.

Table 7.
Experiment results on splitting ratio.

Experimented Ratio	*Test Accuracy*	*Train Accuracy*
70% - 30%	0.8669807	0.86294302
75% - 25%	0.8686406	0.86164199
80% - 20%	0.8741588	0.85969044
85% - 15%	**0.8784208**	**0.85868102**
90% - 10%	0.8781965	0.86069986

Based on Table 7, it can be observed that there is a distinctive pattern in accuracy values among the 5 variations of data split ratios. Figure 2 shows a bar chart depicting the pattern of differences in accuracy values for each train-test data ratio.

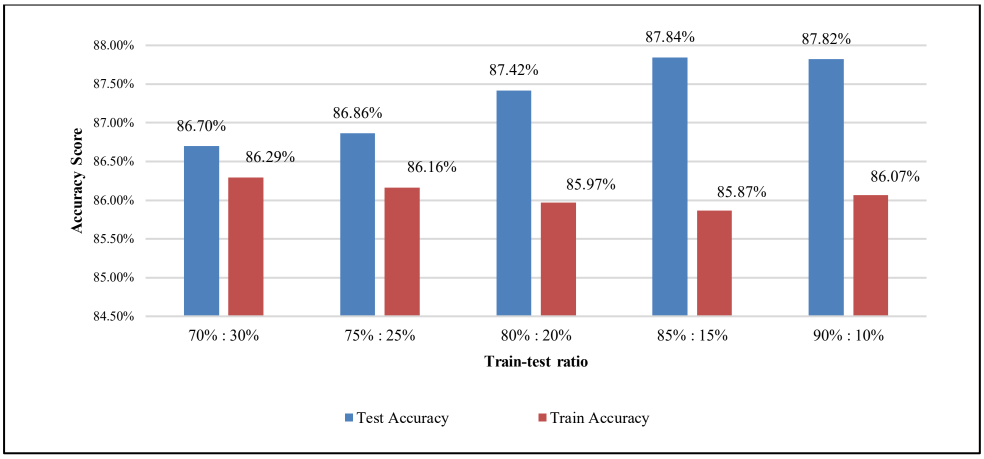

Figure 2.
Accuracy comparison on different train-test ratio

Based on Figure 2, it can be observed that the test accuracy value increases along with the train data ratio. It reaches its peak at 0.8784 with a train data ratio of 85% and then decreases to 0.8781 when the train data ratio is 90%. Additionally, it can be seen that the train accuracy value is lower than the test accuracy. This indicates that the developed model is slightly underfitting for the given splitting ratio. However, since the model is intended to predict sentiment, the test accuracy value was prioritized in this case. Considering this, the researcher decided to use the Naïve Bayes Classifier algorithm with a train-test data split ratio of 85% and 15%.

Figure 3 shows the model validation results for the Naïve Bayes Classifier model with an 85%-15% train-test data split ratio. Based on this result, it can be justified that the model is valid. The sentiment tendency of user comments on the Detikcom application on the Google Play Store tends to be positive, with a positive sentiment percentage of 67.16% (1,497 out of 2,229 test data) and an accuracy of 87.84%, as shown in Figure 2. This positive sentiment trend likely occurs due to the high percentage of 4 and 5-star ratings (80% of all reviews), which, in the initial labeling algorithm, are categorized as reviews with positive sentiment. Meanwhile, the percentage of negative review is only 28.85% (644 test data).

```
MultinomialNB Accuracy: 0.8784208165096455
MultinomialNB Precision: 0.8784208165096455
MultinomialNB Recall: 0.8784208165096455
MultinomialNB f1_score: 0.8784208165096455
confusion_matrix:
 [[ 552    1   91]
 [   42    0   46]
 [   89    2 1406]]
=====================================================

              precision    recall  f1-score   support

     Negatif       0.81      0.86      0.83       644
      Netral       0.00      0.00      0.00        88
     Positif       0.91      0.94      0.93      1497

    accuracy                           0.88      2229
   macro avg       0.57      0.60      0.59      2229
weighted avg       0.85      0.88      0.86      2229
```
Figure 3.
Validation result.

The output generated by the Naïve Bayes Classifier model (Table 5) indicates that the model predicts sentiment not based on rating or sentiment label but rather on the frequency of keywords. This can be seen from the differences in sentiment of a document in the 'label' and 'prediction' columns of the data frame. This output also supports the previous statement, where the model validation achieved an imperfect accuracy value. Additionally, it can be observed in Table 8 that the Naïve Bayes Classifier model does not produce neutral sentiment predictions, even though there is an option for neutral sentiment in the prior probability (label). This can occur because the amount of data labeled as neutral is too small (103 documents), as shown in Figure 3. Therefore, the analysis conducted using the output from the Naïve Bayes Classifier model in this research are focusing only on negative and positive sentiments.

Table 8.
Sentiment Prediction Result.

	Predicted Sentiment		
Rating	Negative	Neutral	Positive
1-2 stars	500	0	110
3 stars	46	0	46
4-5 stars	106	0	1421

The data that has been labeled with sentiments (negative, neutral, and positive) by the Naïve Bayes Classifier model is then be clustered using K-Means Clustering for each sentiment. The output from the clustering process is a scatter plot, as shown in Figure 4 for negative sentiment and Figure 5 for positive sentiment. At this stage, the PCA (Principal Component Analysis) method is also used to reduce the dimensionality of the clustering. The *x* and *y* axes on both scatter plots represent first two Principal Components that had been identified to represent all the variables used, which is the “bag of words”. The characteristics of each cluster are presented in Table 9.

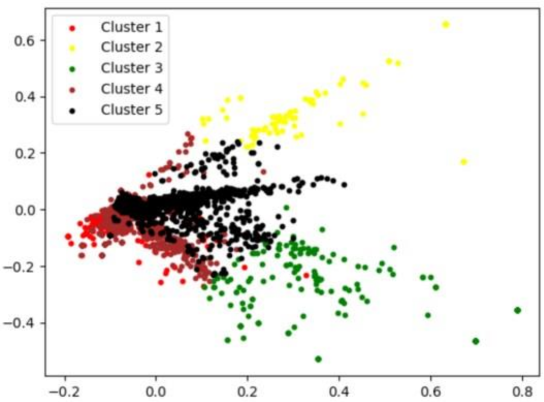

Figure 4.
Scatter plot for reviews that have Negative Sentiment.

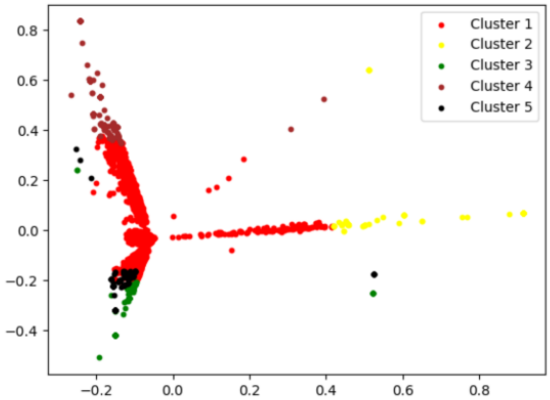

Figure 5.
Scatter plot for reviews that have Positive Sentiment.

Table 9.
Distinctive Characteristics on Each Cluster.

Sentiment	Cluster Number	Distinctive Characteristics
Negative	*Cluster 1*	'laggy, 'uninstall', 'update'
	Cluster 2	'ads, 'login', 'news
	Cluster 3	'lots, 'ads'
	Cluster 4	'not', 'neutral', 'obscured, 'stand
	Cluster 5	'much 'ads
Positive	*Cluster 1*	'accurate', 'trusted', 'update'
	Cluster 2	'ok'
	Cluster 3	'good'
	Cluster 4	'great'
	Cluster 5	'awesome'

Based on the results of the clustering process, it can be concluded that clusters for comments with negative sentiment tend to have less distinct differentiators and are generally centered on a single keyword, namely 'ads'. In contrast, clusters for comments with positive sentiment tend to have distinct differentiating keywords, but all clusters in the positive sentiment can be interpreted as expressions of user satisfaction.

To support the researchers' findings in the clustering process, a word cloud algorithm was developed using the reviews used for clustering as input. The results of the word cloud algorithm can be seen in Figure 6 for negative sentiment and Figure 7 for positive sentiment. Moreover, Table 10 provides the translation for the most frequent words, since the reviews are all written in Bahasa Indonesia.

Figure 6.
Word cloud for negative sentiments.

Figure 7.
Word cloud for positive sentiments.

Table 10.
Word cloud translation.

No	Sentiment	Word	Translation
1	Negative	*iklan*	Advertising
2	Negative	*nya*	(Suffix, no meaning)
3	Negative	*media*	Media
4	Negative	*di*	(Suffix, no meaning)
5	Negative	*saya*	I
6	Positive	*bagus*	Great
7	Positive	*mantap*	Awesome
8	Positive	*nya*	(Suffix, no meaning)
9	Positive	*akurat*	Accurate
10	Positive	*terpercaya*	Trusted

Based on the Word Cloud in Figure 6, it can be seen that one of the frequently occurring words in negative comments is ‘ads’. Meanwhile, according to the Word Cloud results in Figure 7, the frequently occurring words in positive comments are commendatory words such as ‘great’, ‘good’, ‘ok’, and ‘awesome’. Additionally, in the Word Cloud for positive comments, there are specific words that indicate why users are positive towards the Detikcom application, such as ‘trusted,’ ‘up-to-date,’ and ‘accurate.’

From this analysis, it can be concluded that most negative comments from Detikcom users are based on the keyword ‘ads’, while positive comments from Detikcom users are based on the keywords ‘trusted’, ‘up-to-date’, and ‘accurate’.

Based on the analysis and modeling that has been conducted, the researchers recommend several actions that PT Trans Digital Media can take to demonstrate a commitment to improving user satisfaction in a customer/user-centric manner. As identified by the developed model, the main issue causing negative sentiment among Detikcom users is advertisements. On the other hand, the basis for positive sentiment among Detikcom users is accurate, trusted, and up-to-date news content.

The above interpretation highlights the strengths (positive sentiment) and weaknesses (advertisements) of the Detikcom application product that must be considered when planning and developing the product. Referring to these strengths and weaknesses, Detikcom can implement Ads Management that focuses on highlighting news content deemed accurate, reliable, and up-to-date by most users. This can be done by replacing pop-up ads with static ads aligned with the content so that they do not cover it. Thus, negative user sentiment can be minimized while maximizing positive sentiment, which correlates with user satisfaction.

4. CONCLUSION

Based on the research objectives and the modeling process conducted, it can be concluded that the Naïve Bayes Classifier model with a data-split train & test ratio of 85% and 15% is the best option for sentiment analysis on user reviews of the Detikcom application on the Google Play Store platform, achieving an accuracy rate of 87.84%. The tendency of sentiment in the data obtained is positive, with a percentage of 67.16% from the testing data. Moreover, it was found that most negative comments by Detikcom users are based on the keyword "ads" with indistinct differentiating characteristics between comments. In contrast, positive comments by Detikcom users are based on the keywords "trusty", "up-to-date", and "accurate" with distinct differentiating characteristics between comments. Lastly, researchers recommend that PT Trans Digital Media implement Ads Management focused on highlighting news content on the Detikcom platform. There are several recommendations for further research to overcome the weaknesses in this study, such as doing hyperparameter tuning, proposed cleaning framework to detect slang of a particular language, or using a classification model that not only understands words based on patterns, but also the meaning and context of a word or sentence such as the BERT Classification Model with the consequence of a runtime that requires large capacity.

ACKNOWLEDGEMENT

The authors gratefully acknowledge financial support from the Institut Teknologi Sepuluh Nopember forthis work, under project scheme of the Publication Writing and IPR Incentive Program (PPHKI) 2024.

REFERENSI

1. Aljrees, T., Umer, M., Saidani, O., Almuqren, L., Ishaq, A., Alsubai, S., . . . Ashraf, I. (2024). Contradiction in text review and apps rating: prediction using textual features and transfer learning. Peer Computer Science, 10, e1722.
2. Annur, C. M. (2023, May 30). Media Sosial, Sumber Informasi Utama Masyarakat Indonesia. Retrieved from Databoks: https://databoks.katadata.co.id/datapublish/2023/05/30/media-sosial-sumber-informasi-utama-masyarakat-indonesia. Accessed March 29, 2024.
3. Berrar, D. (2018). Bayes' Theorem and Naive Bayes Classifier. In Encyclopedia of Bioinfor-matics and Computational Biology (pp. 403-412). Elsevier.
4. Chandani, V., Satria, R., & Purwanto. (2015). Komparasi Algoritma Klasifikasi Machine Learning dan Feature Selection pada Analisis Sentimen Review Film. *Journal of Intelligent System*, 1(1), 56-60.
5. Eser, G., & Sahin, C. (2024). Sentiment Analysis and Rating Prediction for App Reviews Using Transformer-based Models. *International Journal of Advanced Natural Sciences and Engineering Researches*, 8, 372-379.
6. Handayani, F., & Pribadi, F. S. (2015). Implementasi Algoritma Naïve Bayes Classifier dalam Pengklasifikasian Teks Otomatis Pengaduan dan Pelaposan Masyarakat melalui Layanan Call Center 110. *Jurnal Teknik Elektro*, VII(1), 19-24.
7. Imam, F. R., Pramono, S. H., & Dahlan, E. A. (2012). Implementasi Opinion Mining (Analisis Sentimen) untuk Ekstraksi Data Opini Publik pada Perguruan Tinggi. *Jurnal EECCIS (Electrics, Electronics, Communications, Controls, Informatics, Systems)*, 6(1), 37-43.

8. Ismaturrahmi, Khadafi, M., & Amirullah. (2025). Implementation of Web-Based Sentiment Analysis Application on Movie Reviews Using the Naive Bayes Algorithm. *Journal of Informatics Engineering and Software Applications,* 1(1), 129-138.
9. Khan, M., Khan, M. Q., & Malik, F. (2024). Optimized Sentiment Classification of Google Play Store App Ratings Using Advanced Machine Learning Models. *VFAST Transactions on Software Engineering*, 12(4), 252-266.
10. Kominfo Indonesia, K. (2008). Undang-undang (UU) Nomor 14 Tahun 2008 tentang Keterbukaan Informasi Publik. Jakarta: Kementerian Kominfo.
11. Muzaki, A., Febriana, V., & Cholifah, W. N. (2024). Analissi Sentimen pada Ulasan Produk di E-Commerce dengan Metode Naive Bayes. *Jurnal Riset dan Aplikasi Mahasiswa Informatika (JRAMI),* 5(4), 758-765.
12. Newman, N. (2023). Reuters Institute Digital News Report 2023. London: Reuters Institute for the Study of Journalism.
13. Pahlevi, R. (2022, June 16). Ini Media Online Paling Banyak Dikonsumsi Warga Indonesia. Retrieved from Databoks: https://databoks.katadata.co.id/teknologi-telekomunikasi/statistik/ea656802a0af1bf/ini-media-online-paling-banyak-dikonsumsi-warga-indonesia Accessed March 29, 2024.
14. Razaq, M. T., Nurhanah, D., & Nurrahmi, H. (2023). Analisis Sentimen Review Film Menggunakan Naive Bayes Classifier dengan Fitur TF-IDF. e-Proceeding of Engineering, 10(2), 1698-1712.
15. Sfenrianto, Purnamasari, I., & Bahaweres, R. B. (2016). Naïve Bayes Classifier Algorithm and Particle Swarm Optimization for Classification of Cross Selling (Case Study: PT TELKOM Jakarta). 2016 4th International Conference on Cyber and IT Service Management (pp. 1-4). Bandung: IEEE.
16. Tamara, D., Kisata, P., & Rosenanda. (2020). Consumer Behavior Towards DIgital and Printed Media in Indonesia. *Psychology and Education*, LVII(9), 241-245.
17. Tan, P.-N., Steinbach, M., & Kumar, V. (2005). Introduction to Data Mining. Pearson.