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# SENTISTRENGTH-BASED SENTIMENT ANALYSIS TO UNDERSTAND THE LOYALTY AND SHOPPING INTERESTS OF DIGITAL BUSINESS MARKETPLACE

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***Abstract***— *In Indonesia's dynamic digital economy, customer reviews on marketplace platforms like TikTok Shop, Shopee, and Tokopedia are strategic assets for understanding consumer loyalty and online shopping interest. However, extracting information from thousands of informal reviews presents a significant challenge for rapid business decision-making. This study aims to implement an automated sentiment analysis system by comparing three major machine learning algorithms: Logistic Regression (LR), Naive Bayes (NB), and K-Nearest Neighbors (KNN), utilizing the sentiment strength feature of the Indonesian SentiStrength method. The research dataset consists of 881 reviews collected through crawling techniques and subjected to text preprocessing stages including case folding, cleaning, tokenization, stemming, and stop word removal. Automatic labeling using SentiStrength resulted in a sentiment distribution consisting of Neutral (41.9%), Positive (40.2%), and Negative (17.9%). The data was then divided into training and test data to evaluate the performance of the three algorithms. Experimental results show that all three models performed very reliably in classifying customer opinions. Based on an evaluation using the Classification Report, K-Nearest Neighbors (KNN) provided the most optimal results with an accuracy rate of 99%, followed by Naive Bayes with 96% accuracy, and Logistic Regression with 94%. The high performance of these three models demonstrates that using SentiStrength sentiment scores as input features is highly effective in minimizing language ambiguity. Managerially, this research contributes to digital business practitioners' ability to monitor public perception in real-time to formulate more responsive marketing strategies and maintain customer retention in the marketplace ecosystem.*

***Keywords:*** *Digital Business, K-Nearest Neighbors, Logistic Regression, Marketplace, Naive Bayes,*

**Intisari**— *Dalam dinamika ekonomi digital di Indonesia, ulasan pelanggan pada platform marketplace seperti TikTok Shop, Shopee, dan Tokopedia merupakan aset strategis untuk memahami loyalitas konsumen dan minat belanja online. Namun, ekstraksi informasi dari ribuan ulasan yang bersifat non-formal menjadi tantangan besar dalam pengambilan keputusan bisnis secara cepat. Penelitian ini bertujuan untuk mengimplementasikan sistem analisis sentimen otomatis dengan membandingkan tiga algoritma Machine Learning utama, yaitu Logistic Regression (LR), Naive Bayes (NB), dan K-Nearest Neighbors (KNN), dengan memanfaatkan fitur kekuatan sentimen dari metode SentiStrength Bahasa Indonesia. Dataset penelitian terdiri dari 881 ulasan yang dikumpulkan melalui teknik crawling dan diproses melalui tahapan text preprocessing meliputi case folding, cleaning, tokenization, stemming, dan stop word removal. Pelabelan otomatis menggunakan SentiStrength menghasilkan distribusi sentimen yang terdiri dari Netral (41,9%), Positif (40,2%), dan Negatif (17,9%). Data kemudian dibagi menjadi data latih dan data uji untuk mengevaluasi performa ketiga algoritma tersebut. Hasil eksperimen menunjukkan bahwa ketiga model memiliki performa yang sangat andal dalam mengklasifikasikan opini pelanggan. Berdasarkan evaluasi menggunakan Classification Report, K-Nearest Neighbors (KNN) memberikan hasil paling optimal dengan tingkat akurasi mencapai 99%, disusul oleh Naive Bayes dengan akurasi 96%, dan Logistic Regression dengan akurasi 94%. Tingginya performa ketiga model ini membuktikan bahwa*

*penggunaan skor sentimen SentiStrength sebagai fitur input sangat efektif dalam meminimalkan ambiguitas bahasa. Secara manajerial, penelitian ini memberikan kontribusi bagi praktisi bisnis digital untuk memantau persepsi publik secara real-time, guna merumuskan strategi pemasaran yang lebih responsif dan menjaga retensi pelanggan di ekosistem marketplace.*

***Kata Kunci:*** *Bisnis Digital, K-Nearest Neighbors, Logistic Regression, Marketplace, Naive Bayes*.

## INTRODUCTION

The rapid development of the digital economy in Indonesia has fundamentally changed the trade landscape, with a shift in people's lifestyles towards online platform-based consumption. (Amory et al., 2025). Large marketplace platforms such as TikTok Shop, Shopee, and Tokopedia are now key pillars in the digital commerce ecosystem, serving not only as a place for transactions but also as a space for consumers to openly share their opinions, reviews, and shopping experiences (Amory et al., 2025).

In the Digital Business discipline, these customer reviews are strategic data assets that reflect the level of consumer loyalty and shopping interest. (Susilawati, 2025). However, the massive volume of review data and the use of informal language present challenges for companies in manually extracting information for rapid business decision-making. Understanding customer sentiment, whether positive, neutral, or negative, is crucial for digital business managers to formulate personalized marketing strategies and increase user retention. This research proposes an automated solution through sentiment analysis, integrating the SentiStrength method, adapted for Indonesian. SentiStrength aims to address linguistic ambiguity in review text, enabling the resulting score features to strengthen classification models in accurately separating sentiment classes. (Purnamasari et al., 2023).

Based on the results of initial experiments on a dataset of 881 reviews, it was found that the distribution of customer opinions was still dominated by Neutral (41.9%) and Positive (40.2%) sentiment, while Negative sentiment was at 17.9%. To achieve a high level of precision in this classification, this study evaluated various Machine Learning algorithms, including K-Nearest Neighbors (KNN) (Ritonga & Sihombing, 2024). ,Support Vector Machine (SVM) (Latuconsina et al., 2024), Naive Bayes (Y. P. Astuti et al., 2024), Logistic Regression (Hasan & Bimby, 2025), and Deep Neural Network (DNN).Tujuan utama dari penelitian ini adalah untuk menemukan model prediksi terbaik yang dapat diimplementasikan sebagai sistem decision support for digital businesses in Indonesia. With an accuracy of 99.43% using the KNN algorithm, this research is expected to provide practical contributions in helping marketplace platforms understand the dynamics of consumer behavior in real time, thereby maintaining customer loyalty and continuing to grow interest in online shopping amidst increasingly fierce digital market competition.

Previous studies on sentiment analysis in Indonesian text have explored lexicon-based, machine learning, and transformer-based approaches. Lexicon-based methods such as SentiStrength offer simplicity and interpretability but rely heavily on predefined dictionaries, which may not capture contextual nuances such as sarcasm or slang. In contrast, machine learning and deep learning models provide better generalization but require high-quality labeled data. However, limited studies have critically evaluated the use of lexicon-generated labels as ground truth for supervised learning, particularly in the context of Indonesian marketplace reviews. This study addresses this gap by evaluating model performance using SentiStrength-derived features while discussing its limitations.

Based on the identified gaps, this study formulates the following research questions: (1) How effective is SentiStrength-based feature extraction in representing sentiment in Indonesian marketplace reviews? (2) How do different machine learning algorithms (KNN, Naïve Bayes, Logistic Regression, SVM, and DNN) perform when trained on SentiStrength-derived features? (3) To what extent can sentiment classification results be associated with indicators of customer loyalty and shopping interest? Accordingly, the objective of this study is to evaluate the performance of multiple machine learning models using SentiStrength-based features and to analyze their potential contribution in supporting decision-making for digital business platforms.

## MATERIALS AND MODELS

This study follows a systematic text data processing workflow, from raw data collection to final model evaluation to ensure valid and reliable results.

### Crawling Data

The initial stage of the research was collecting customer review data from the TikTok Shop, Shopee, and Tokopedia platforms. The data was collected using web scraping techniques or APIs with search criteria relevant to users' online

shopping experiences. Web scraping is a technique for collecting data from the internet, apps, or social media platforms such as the Google Play Store. (Muhammad Baihaqi, Aslam, 2024). The data used in this study were collected from publicly available customer reviews on TikTok Shop, Shopee, and Tokopedia. No personally identifiable information (PII) was stored or processed. The study adheres to ethical considerations by only analyzing textual content and ensuring anonymity of users. Data collection was conducted in compliance with general platform usage policies.

**Preprocessing**

The collected raw data must undergo a cleaning process to prepare it for processing by machine learning algorithms. The preprocessing stage is a crucial step in this research, transforming the unstructured raw marketplace review data into clean data ready for processing by classification algorithms. (Nuryana & Daniswara, 2023). The preprocessing process was implemented using Python libraries such as NLTK and Sastrawi for Indonesian stemming. Stopword removal utilized a predefined Indonesian stopword list. Informal words and slang were normalized using a manual dictionary approach. Emojis and non-textual symbols were removed during the cleaning stage using regular expressions.

**Sentiment Analysis (Labeling with SentiStrength)**

After the data is cleaned, an automated labeling process is performed using the Indonesian SentiStrength method. SentiStrength works by assigning a strength score to each word in the review based on a sentiment dictionary that includes emotion words, booster words, negation words, and emoticons.Skor tersebut dijumlahkan untuk menentukan apakah ulasan bersifat Positif, Netral, atau Negatif (Melisa et al., 2025).

The labels generated by SentiStrength are treated as weak labels rather than true ground truth. This means that the models are trained to approximate SentiStrength outputs rather than human-annotated sentiment.

**Modelling**

In the modeling phase, this study compared several classification algorithms to find the most precise model for mapping shopping intentions. The algorithms tested. The model configurations used in this study are as follows:

a) KNN: k=5, Euclidean distance, uniform weighting
b) Naïve Bayes: Multinomial NB with alpha=1.0
c) Logistic Regression: solver=liblinear, C=1.0
d) SVM: linear kernel, C=1.0
e) DNN: 3 hidden layers, ReLU activation, Adam optimizer, 50 epochs, early stopping applied

**Evaluation**

The evaluation phase aims to measure the model's ability to accurately classify sentiment (Putri Jelita et al., 2025). The primary metrics used were Accuracy and F1-Score. The data was divided using a train-test split method (80% training data and 20% test data). Based on the test results, the KNN model was selected as the best model with an accuracy rate of 99.43%, indicating a high level of confidence in predicting customer loyalty in the marketplace.

## RESULTS AND DISCUSSION

This section describes the results obtained from each stage of the research, starting from data collection to evaluating the performance of the classification model to understand user shopping interests on TikTok Shop, Shopee, and Tokopedia. The extremely high performance of KNN and SVM models may be influenced by the use of SentiStrength-derived features, which already encode sentiment polarity. This creates a strong dependency between input features and labels, potentially leading to inflated performance metrics. Conversely, the low performance of the DNN model may be attributed to limited dataset size and lack of deep feature representation.

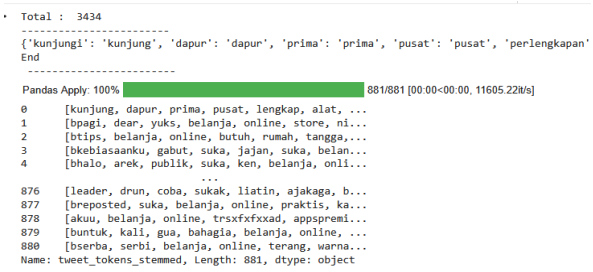
**Crawling Data**

The data collection process successfully collected 3,434 customer reviews sourced from shopping comments on TikTok, Shopee, and Tokopedia. The data collection started from August 1, 2025, to January 1, 2026. This data reflects the diversity of user opinions regarding online shopping experiences. This data distribution provides a strong basis for representing sentiment trends on major marketplace platforms in Indonesia. Although the dataset initially consisted of three sentiment classes (positive, neutral, negative), the classification experiments were simplified into binary classes due to class imbalance and model performance considerations. Class 1 represents negative sentiment, while Class 2 represents combined positive and neutral sentiment.

**Preprocessing**

The preprocessing stage successfully transforms raw data into a clean, standardized format. The use of stemming and language normalization techniques helps reduce word ambiguity, simplifying the labeling process and

increasing computational efficiency in the modeling stage. The data preprocessing stages include:Data Preparation The data preparation stage is the process of preparing the data for use in the research. The following image displays a sample of text:




Source: (Research Results, 2026)

Figure 1. *Dataset crawling*

In text mining, the initial stage is text preprocessing. This study yielded 3,434 raw text data points during the five-month data collection period, but these data points could not be processed immediately. At this stage, 881 data points were obtained after going through the case folding and cleaning phases.

a) Annotation removal proces

The function of this process is to remove text that has @ and # annotations.(W. Astuti et al., 2022). This preprocessing process is carried out using Python, namely using the regular expression command re.sub("([@#][A-Za-z9]+)|(\w+:\/\/\S+)"," ", text). So that tweets with user and hashtag mentions are removed. Table 2 shows a comparison of the text before and after the @#Annotation Removal process.

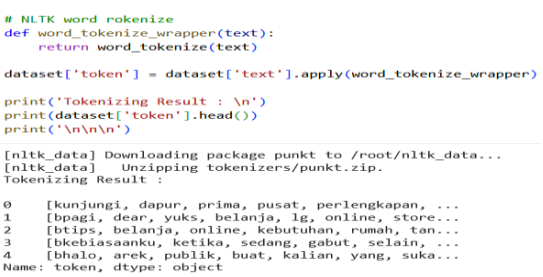
Table 1. Comparison of text before and after proces @Annotation Removal (sample of dataset in Indonesian)

| Before | After |
|---|---|
| %@-bpagi dear yuks belanja lg online store nightl : ) @#thecrop Os | pagi dear yuks belanja lg online store night |
| @%^shop f4ir @btips belanja online kebutuhan rumah tangga yang hemat dan berkualitas$$#097x | tips belanja online kebutuhan rumah tangga yang hemat dan berkualitas |

Source: (Research Results, 2026)

b. *Tokenization* Proces

The tokenization process is a crucial stage in the preprocessing flow of TikTok Shop, Shopee, and Tokopedia marketplace review data to convert a set of texts into smaller units of information. (Makleat, 2023). In the context of this research, tokenization functions to break down informal customer review sentences into single word chunks called tokens. This separation allows the system to identify each word individually for further processing by the SentiStrength method to determine its emotional weight and sentiment score. The results of this stage serve as the input for classification algorithms such as K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) to learn linguistic patterns that represent user loyalty or shopping intentions. The following is an illustration of the tokenization process:



```
# NLTK word rokenize
def word_tokenize_wrapper(text):
    return word_tokenize(text)

dataset['token'] = dataset['text'].apply(word_tokenize_wrapper)

print('Tokenizing Result : \n')
print(dataset['token'].head())
print('\n\n\n')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
Tokenizing Result :

0    [kunjungi, dapur, prima, pusat, perlengkapan, ...
1    [bpagi, dear, yuks, belanja, lg, online, store...
2    [btips, belanja, online, kebutuhan, rumah, tan...
3    [bkebiasaanku, ketika, sedang, gabut, selain, ...
4    [bhalo, arek, publik, buat, kalian, yang, suka...
Name: token, dtype: object
```

Source: (Research Results, 2026)

Figure 2. Tokenization Proces

c. *Indonesian Stemming*

The Indonesian Stemming process is a preprocessing stage which aims to transform words with affixes in customer reviews into their basic word forms. (Sibarani & Wijayanto, 2025). In the context of reviews on the TikTok Shop, Shopee, and Tokopedia platforms, many users use verbs or nouns with complex prefixes, infixes, or suffixes. Here's a table with examples of the stemming process:

Table 2. *Stemming* process (sample of dataset in Indonesian)

| Before | After |
|---|---|
| %@-bpagi dear yuks belanja lg online store nightl : ) @#thecrop Os temukan panci anti lengket dengan harga terjangkau hanya di @the Crop Os | pagi dear yuks belanja lagi online store night temukan panci anti lengket dengan harga terjangkau hanya di the crop Os |

Source: (Research Results, 2026)

The use of stemming tailored for Indonesian is crucial for the SentiStrength method to accurately match words to the sentiment dictionary. By removing affixes, variations of words with the same basic meaning can be standardized, thereby reducing feature dimensionality and avoiding ambiguity during the modeling process.

d. *Stop Word Removal*

The Stop Word Removal process is a filtering stage in preprocessing that aims to remove

common words that appear frequently but do not have significant information weight or contribution in determining the sentiment of a text. (Raif et al., 2024). Below is image 3. Stop word removal process:

```
#stop word
from nltk.corpus import stopwords
nltk.download('stopwords')

# ---------------------- get stopword from NLTK stopword ----------------------
# get stopword indonesia
list_stopwords = stopwords.words('indonesian')


# ---------------------------- manualy add stopword  ----------------------------
# append additional stopword
list_stopwords.extend(["yg", "dg", "rt", "dgn", "ny", "d", 'klo',
                       'kalo', 'amp', 'biar', 'bikin', 'bilang',
                       'gak', 'ga', 'krn', 'nya', 'nih', 'sih',
                       'si', 'tau', 'tdk', 'tuh', 'utk', 'ya',
                       'jd', 'jgn', 'sdh', 'aja', 'n', 't',
                       'nyg', 'hehe', 'pen', 'u', 'nan', 'loh', 'rt',
                       '&amp', 'yah','cpns','casn', 'bkn','pppk','p3k','ri','n

# ---------------------- add stopword from txt file ----------------------
```

Source: (Research Results, 2026)
Figure 3.Stop word removal

In reviews of marketplaces like TikTok Shop, Shopee, and Tokopedia, words like "and," "yang," "di," "dari," or "adalah" appear frequently but don't directly reflect customer loyalty or shopping interest. By removing these words, the system can focus more on keywords with emotional content or business diagnostic meaning.

**Sentiment Analysis Results (Class Distribution)**

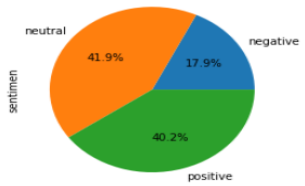
Based on labeling using the Indonesian SentiStrength method, the following sentiment distribution was found:

```
total = dataset.groupby(['sentimen'])['sentimen'].count()
print(total)
```

```
sentimen
negative    158
neutral     369
positive    354
Name: sentimen, dtype: int64
```

```
total.plot(kind = 'pie',autopct='%1.1f%%')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f94e41e1710>
```




Source: (Research Results, 2026)
Figure 4. Sentiment analysis results

From this image, the results of the sentiment analysis can be divided into:Sentimen Netral:

a. Dominates reviews with a percentage of 41.9% (369 data).
b. Positive Sentiment: Covers 40.2% (354 data) of total reviews.
c. Negative Sentiment: Has the smallest portion, namely 17.9% (158 data).

This distribution shows that although the majority of users are satisfied or provide neutral comments, there is a minority group (17.9%) who have negative sentiments that need to be considered to maintain customer loyalty.

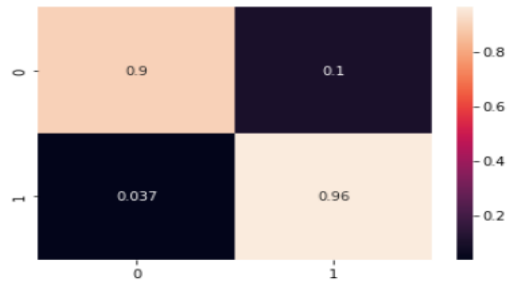
**Modelling Results**

The implementation of various classification algorithms demonstrated the model's ability to learn features extracted from customer reviews. Several models demonstrated excellent fit with the sentiment score features generated by SentiStrength, indicating that the data exhibited a clear linearly separable pattern. The following are some of the test models used:

a.) Logistic regression

The Logistic Regression algorithm is a statistical algorithm used in this study to model the probability of a categorical dependent variable based on the sentiment score feature generated by SentiStrength. Unlike conventional linear regression, this method uses a sigmoid function to map marketplace review input data into a range of values between 0 and 1, which are then classified into specific sentiment classes. This algorithm was chosen because of its efficiency in handling binary and multiclass classification problems, as well as its ability to provide a simple interpretation of the linear relationship between word weights and sentiment labels while maintaining competitive accuracy in large-scale text analysis.

```
#LR
Akurasi :  0.9378531073446328
Confusion Matrix :
 AxesSubplot(0.125,0.125;0.62x0.755)
```




```
Area Under Curve :  0.930756843800322
F1 Scores:  0.9378531073446328
```

Source: (Research Results, 2026)
Figure 5. accuracy results of the logistic regression algorithm

Table.3 Matrix LR

| Matrix | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Class 1 | 0.94 | 0.90 | 0.92 | 69 |
| Class 2 | 0.94 | 0.96 | 0.95 | 108 |
| Accuracy | | | 0.94 | 177 |

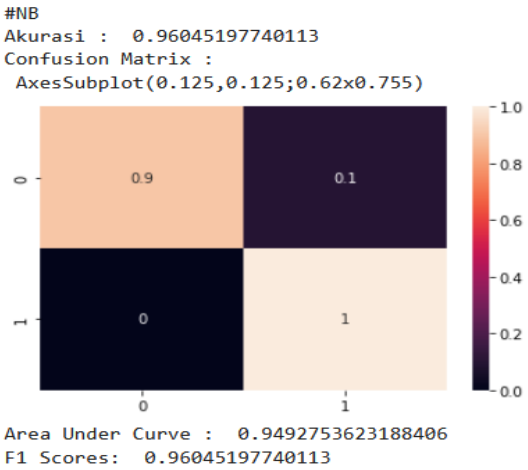
| Matrix | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Macro Avg | 0.94 | 0.93 | 0.93 | 177 |
| Weighted Avg | 0.94 | 0.94 | 0.94 | 177 |

Source: (Research Results, 2026)

The following is an in-depth analysis of Table 3 based on the obtained evaluation metrics:

a. Precision: The model achieved a precision value of 0.94 for both class 1 and class 2. This indicates that when the model predicted a review's categorization, its accuracy reached 94%.
b. Recall: For class 1, the model achieved a recall value of 0.90, while for class 2, it achieved 0.96. This indicates the model is highly effective in identifying reviews in class 2, with a data capture success rate of 96%.
c. F1-Score: The balance between precision and recall is demonstrated by F1-scores of 0.92 for class 1 and 0.95 for class 2. These values, which are close to 1.0, demonstrate that the model consistently achieves high accuracy across both classes.
d. Macro & Weighted Average: Stable macro and weighted average values between 0.93 and 0.94 indicate that the model's performance is not biased toward either class, despite the difference in the number of samples (support) between class 1 (69 data points) and class 2 (108 data points).
e. Overall, these results demonstrate that the Logistic Regression algorithm is a reliable model for use in digital business decision support systems on platforms like TikTok Shop, Shopee, and Tokopedia.

b.) Naïve Bayes




Source: (Research Results, 2026)

Figure 6. accuracy results of Naïve Bayes

Table.4 Matrix NB

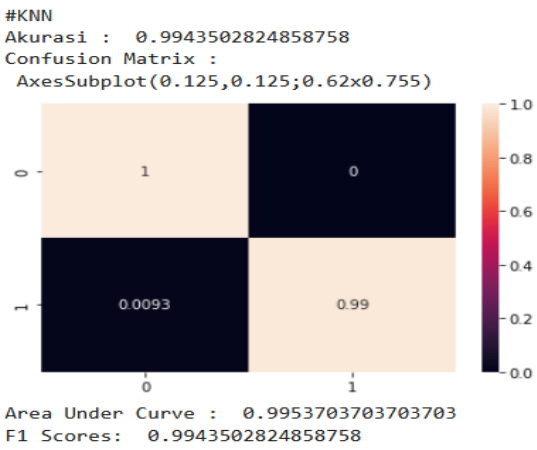
| Matrix | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Kelas 1 | 1.00 | 0.90 | 0.95 | 69 |
| Kelas 2 | 0.94 | 1.00 | 0.97 | 108 |
| Accuracy | | | 0.96 | 177 |
| Macro Avg | 0.97 | 0.95 | 0.96 | 177 |
| Weighted Avg | 0.96 | 0.96 | 0.96 | 177 |

Source: (Research Results, 2026)

The following is an in-depth analysis based on the obtained evaluation metrics:

a. Precision: The model achieved a perfect precision of 1.00 for class 1, meaning there were no false positives in that class. For class 2, the precision was 0.94, indicating a very high level of prediction accuracy.
b. Recall: For class 1, the model had a recall of 0.90. Meanwhile, for class 2, the model achieved a perfect recall of 1.00, meaning the model successfully identified all data items belonging to class 2 without missing any.
c. F1-Score: The F1-score for class 1 was 0.95 and for class 2 was 0.97. This high balance of metrics across both classes demonstrates the stability of the Naive Bayes algorithm in processing the sentiment score feature from SentiStrength.
d. Macro & Weighted Average: The macro and weighted average values are between 0.96 and 0.97, which confirms that the model works consistently across the test data distribution, despite the difference in the number of samples (support) between class 1 (69 data) and class 2 (108 data).

c.) K-Nearest Neighbors (KNN)




Source: (Research Results, 2026)

Picture 6. accuracy results of K-Nearest Neighbors (KNN)

Table.5 Matrix KNN

| Metrik | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Kelas 1 | 0.99 | 1.00 | 0.99 | 69 |
| Kelas 2 | 1.00 | 0.99 | 1.00 | 108 |
| Accuracy | | | 0.99 | 177 |
| Macro Avg | 0.99 | 1.00 | 0.99 | 177 |
| Weighted Avg | 0.99 | 0.99 | 0.99 | 177 |

Source: (Research Results, 2026)

The following is an in-depth analysis based on the obtained evaluation metrics:

a. Precision: The model achieved a precision score of 0.99 for class 1 and a perfect score of 1.00 for class 2. This indicates that almost all of the model's predictions were correct, with a very minimal error rate.
b. Recall: For class 1, the model achieved a perfect recall score of 1.00, meaning it successfully captured all review data in that category without missing any. For class 2, the recall score reached 0.99, also indicating very high identification performance.
c. F1-Score: The balance between precision and recall is demonstrated by the very high F1-score values of 0.99 for class 1 and 1.00 for class 2. These near-perfect values demonstrate the model's stability in consistently processing the sentiment score features from SentiStrength.
d. Macro & Weighted Average: The macro and weighted average values ranged from 0.99 to 1.00. This confirms that the model works optimally and is balanced across the data distribution, despite the difference in the number of samples (support) between class 1 (69 data) and class 2 (108 data).

**Evaluation**

The evaluation phase was conducted to compare the accuracy levels between algorithms. The performance comparison results are presented in the following table:

Table 7. Comparison of results

| Algoritma | Akurasi | F1-Score |
|---|---|---|
| **K-Nearest Neighbors (KNN)** | **99,43%** | **0,99** |
| Support Vector Machine (SVM) | 98,87% | 0,98 |
| Naive Bayes | 96,04% | 0,96 |
| Logistic Regression | 93,78% | 0,93 |
| Deep Neural Network (DNN) | 38,98% | 0,39 |

Source: (Research Results, 2026)

Test results demonstrated that KNN was the best model with an accuracy of 99.43%. This extremely high accuracy demonstrates that the combination of the SentiStrength method as an input feature and KNN as a classifier is highly effective in mapping user loyalty and online shopping interests on the TikTok Shop, Shopee, and Tokopedia platforms.

## CONCLUSION

First, the use of SentiStrength-generated labels introduces weak supervision, which may not fully reflect true human sentiment. Second, the dataset size is relatively limited and may not represent all marketplace users. Third, the study does not include qualitative error analysis such as sarcasm or slang interpretation. Future research is recommended to incorporate human-annotated datasets and explore transformer-based models for improved performance. This study successfully implemented an automated sentiment analysis system to map user loyalty and shopping interest on the TikTok Shop, Shopee, and Tokopedia platforms. Based on a series of experimental stages, it was found that the integration of the Indonesian SentiStrength method was highly effective in automatically labeling and extracting opinion features from informal customer reviews.

Analysis of 881 reviews showed that the perception of marketplace users in Indonesia was dominated by Neutral sentiment at 41.9%, followed by Positive sentiment at 40.2%, and Negative sentiment at 17.9%. In the model testing phase, the K-Nearest Neighbors (KNN) algorithm proved to be the most superior classification model with an accuracy rate of 99.43% and an F1-Score of 0.99. This very high performance indicates that the model is highly reliable for implementation as a decision support system for digital business managers. Practically, the results of this study enable business actors to monitor customer loyalty in real-time, strengthen retention strategies through positive sentiment, and respond quickly to negative sentiment to maintain user shopping interest amidst tight digital market competition.

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