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Sentiment Analysis of Scar Removal Product Reviews Using the Naïve Bayes Algorithm

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Abstract

Scar removal products are widely sought after by consumers to address skin issues caused by wounds or injuries. On Shopee, user reviews reflect consumer experiences and provide valuable insights for improving product quality. This study aims to analyze user sentiment using the Naïve Bayes algorithm. The research begins with dataset collection and text preprocessing. Reviews are labeled using the Inset Lexicon, which calculates polarity scores to classify sentiments as positive or negative. The dataset is divided into training and testing sets (80%:20% ratio) and represented using TF-IDF. The Naïve Bayes algorithm is then applied for sentiment classification. Model evaluation shows 92% accuracy, with excellent performance in identifying positive sentiments (F1-Score: 0.96). However, the model performs poorly in classifying negative sentiments (F1-Score: 0.31). Confusion matrix visualization and Word Cloud are used for further evaluation. This study contributes to store managers by enhancing product quality, optimizing data-driven marketing strategies, and improving product competitiveness in the market.

Keywords: *Sentiment Analysis; Naïve Bayes; Product Reviews; Scar Cream Removal; Shopee.*

1. Introduction

The rapid development of e-commerce and evolving trends offer significant opportunities for businesses to expand [1]. Shopee, as one of the most widely used e-commerce platforms, offers a variety of products, including skincare items such as scar The removal treatments marketed by the karinadlatr store. Amid intense competition among sellers, customer reviews serve as a crucial source of information for improving marketing strategies and product quality [2]. However, these reviews are often unstructured and vary in language, expression, and sentence length, making manual analysis inefficient and time-consuming [3]. Without a systematic approach, these reviews risk being underutilized.

One way to address this challenge is sentiment analysis using Machine Learning, which enables automatic categorization of customer opinions into positive and negative sentiments. Several previous studies have demonstrated the effectiveness of the Naïve Bayes algorithm in sentiment analysis for various e-commerce product categories. For instance, a study on face mask product reviews on Tokopedia achieved an accuracy of 88% [4]. Another study on sentiment analysis of Samsung smartphone product reviews on Shopee reported an accuracy of 87% [5]. Meanwhile, a similar study on Shopee's Amreta store showed a high accuracy of 97.16% [6]. These studies emphasize the importance of sentiment analysis in helping sellers identify issues in customer reviews and optimize their services.

Most sentiment analysis research in e-commerce has focused on electronics, fashion, or cosmetics, while the scar removal product category remains underexplored. Additionally, common sentiment labeling methods often rely on manual approaches or customer ratings. This study introduces a novel contribution by utilizing the InSet Lexicon dictionary for sentiment labeling. Furthermore, this research evaluates the effectiveness of the Naïve Bayes algorithm in classifying user sentiment using multiple evaluation metrics.

The primary objective of this study is to analyze sentiment in scar removal product reviews on Shopee's karinadlatr store using the Naïve Bayes algorithm. This research is expected to provide deeper insights into customer opinions regarding scar removal products and demonstrate how Machine Learning-based sentiment analysis can enhance business competitiveness.

1.1. Sentiment Analysis

Sentiment analysis is a method of converting qualitative data into quantitative insights using Machine Learning algorithms, allowing for the classification of reviews into positive, negative, or neutral sentiments [7].

1.2. Naïve Bayes

The Naïve Bayes algorithm is widely used in sentiment analysis due to its advantages in handling large volumes of textual data and achieving relatively high accuracy. This algorithm is a probabilistic machine learning method that calculates probabilities based on Bayes' Theorem [8].

1.3. Inset Lexicon

The Inset Lexicon dictionary, compiled by Fajri Koto and Gemal Y. Rahmaningtyas, is a linguistic resource containing 3,609 positive and 6,609 negative Indonesian words, where each word is assigned a polarity score ranging from -5 to +5 for sentiment analysis [9].

1.4. Confusion Matrix

The Confusion Matrix works by comparing the model's predicted results with the actual or true classes, producing a matrix that shows the number of correct and incorrect predictions [10].

1.5. Wordcloud

A word cloud is a visual representation that displays the frequency of word occurrences in a text collection. In a word cloud, the font size reflects how often a word appears in the text; the larger the font size, the more frequently the word appears, and vice versa [11].

2. Research Methodology

This study employs the Naïve Bayes algorithm as the primary method for data analysis, executed through several well-organized and interrelated stages to achieve the research objectives. The methodology consists of the following steps:

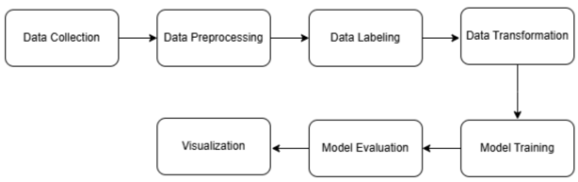

Fig. 1: Research Methodology

Figure 1 illustrates the research methodology flow, which includes data collection, preprocessing, labeling, and data transformation as preparation for model training, followed by evaluation. The results are then visualized to aid in the interpretation process.

2.1. Data Collection

Product review data was manually collected from the karinadlatr store on Shopee. A total of 1,174 reviews were obtained in Excel format and converted into CSV for easier processing.

2.2. Data Preprocessing

This stage aims to clean and structure the text for further analysis. The steps include:

1. Text Cleaning: Removing irrelevant elements such as URLs, punctuation, numbers, and non-ASCII characters while converting text to lowercase [12].
2. Tokenization: Splitting text into the smallest meaningful units (tokens) [13].
3. Stopword Removal: Eliminating words that do not contribute significant meaning to the analysis [14].
4. Stemming: Converting words into their root form by removing affixes [15].

2.3. Data Labeling

Data labeling was performed using the InSet Lexicon dictionary, where Sentiment classification was determined based on the total polarity score: scores greater than or equal to zero were labeled as positive, while scores below zero was labeled as negative.

2.4. Data Transformation

User review data is converted into a numerical format using the TF-IDF technique to calculate the weight of each word in a document, considering both the word's frequency within the document and its distribution across the entire dataset [16]. This transformation aims to help the model distinguish meaning between reviews and facilitate text data analysis more effectively.

2.5. Model Training

The transformed review data is then divided into two parts: training data and test data. This ensures that the model can learn patterns from the training data while evaluating its performance on unseen test data. During this stage, parameter optimization is also performed using

GridSearchCV, a technique used to determine the best parameter combinations for the model based on scores obtained through cross-validation [17].

2.6. Model Evaluation

This stage is conducted on the test data to assess how well the trained model can make accurate predictions on new, previously unseen data. The evaluation is performed using several metrics, including:

1. Accuracy
   Accuracy measures how well the model correctly predicts the outcomes [18]. It is calculated using the following formula 1:

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Data}} \quad (1)$$

2. *Precision*
   Precision measures the model's accuracy in predicting positive-labeled data [19]. It is calculated as follows 2:

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

   Where:
   TP = *True Positives*
   FP = *False Positives*

3. *Recall*
   Recall measures the precentage of actual instances that the model correctly identifies [20]. It is calculated as follows 3:

$$Recall = \frac{\text{TP}}{\text{TP}+FN} \quad (3)$$

   Where:
   TP = *True Positives*
   FN = *False Negatives*

4. *F1-Score*
   F1-Score represents the harmonic mean of *precision* and *recall*, calculated using the following formula 4:

$$F1 - Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \quad (4)$$

2.7. Visualization

The results were visualized using Confusion Matrix and Word Cloud.

3. Results and Discussion

The analysis results obtained from each stage of the research methodology will be explained in detail and comprehensively.

3.1. Data Collection Results

The dataset was obtained from the Shopee platform, specifically from the Karinadlatr store. Data collection was conducted manually by recording the reviews in Microsoft Excel. The collected dataset consists of 1,174 review entries. Table 1 below presents a sample of the dataset.

Table 1: Dataset Review

No	Review
1	Penasaran banget dari dulu udah laser juga bekas luka gak ilang Nemu produk ini jadi coba aja dulu siapa tau cocok order 2 langsung kaka
2	Udah ku pake beberapa kali sih, semoga bermanfaat. Makasih ya seller. Harganya mahal tapi semoga ampuuuuh yaaaa
3	Barang sesuai pesanan ☺

Table 1 presents a portion of the dataset containing user reviews of scar removal products from the Karinadlatr store on Shopee.

3.2. Data Preprocessing Results

Data pre-processing is crucial for sentiment analysis as it transforms review texts into more organized, clean, and analyzable data. This process involves several steps, with the first stage being text cleaning, which aims to remove irrelevant elements such as URLs, punctuation, numbers, and non-ASCII characters. Additionally, all text is converted to lowercase. The results after text cleaning can be seen in Table 2.

Table 2: Cleaning Text Results

No	Before	After
1	Penasaran banget dari dulu udah laser juga bekas luka gak ilang Nemu produk ini jadi coba aja dulu siapa tau cocok order 2 langsung kaka	penasaran banget dari dulu udah laser juga bekas luka gak ilang nemu produk ini jadi coba aja dulu siapa tau cocok order langsung kaka

2	Udah ku pake beberapa kali sih, semoga bermanfaat. Makasih ya seller. Harganya mahal tapi semoga ampuuuuh yaaaa	udah ku pake beberapa kali sih semoga bermanfaat makasih ya seller harganya mahal tapi semoga ampuuuuh yaaaa
3	Barang sesuai pesanan ☺	barang sesuai pesanan

Table 2 presents the results of the text-cleaning process, producing cleaner and more structured data, which facilitates further analysis. Next, the tokenization process is performed to divide the text into its smallest meaningful units, known as tokens. The results after tokenization can be seen in Table 3.

Table 3: Tokenization Results

No	Before	After
1	penasaran banget dari dulu udah laser juga bekas luka gak ilang nemu produk ini jadi coba aja dulu siapa tau cocok order langsung kaka	'penasaran', 'banget', 'dari', 'dulu', 'udah', 'laser', 'juga', 'bekas', 'luka', 'gak', 'ilang', 'nemu', 'produk', 'ini', 'jadi', 'coba', 'aja', 'dulu', 'siapa', 'tau', 'cocok', 'order', 'langsung', 'kaka'
2	udah ku pake beberapa kali sih semoga bermanfaat makasih ya seller harganya mahal tapi semoga ampuuuuh yaaaa	'udah', 'ku', 'pake', 'beberapa', 'kali', 'sih', 'semoga', 'bermanfaat', 'makasih', 'ya', 'seller', 'harganya', 'mahal', 'tp', 'semoga', 'ampuuuuh', 'yaaaa'
3	barang sesuai pesanan	'barang', 'sesuai', 'pesanan'

Table 3 illustrates the tokenization process, where words are separated based on spaces. After tokenization, the stopword removal process is applied to filter out irrelevant words, eliminating terms that do not contribute meaningful information to sentiment analysis. The results after stopword removal are shown in Table 4.

Table 4: Stopword Results

No	Before	After
1	'penasaran', 'banget', 'dari', 'dulu', 'udah', 'laser', 'juga', 'bekas', 'luka', 'gak', 'ilang', 'nemu', 'produk', 'ini', 'jadi', 'coba', 'aja', 'dulu', 'siapa', 'tau', 'cocok', 'order', 'langsung', 'kaka'	'penasaran', 'laser', 'bekas', 'luka', 'ilang', 'nemu', 'produk', 'coba', 'cocok', 'order', 'langsung', 'kaka'
2	'udah', 'ku', 'pake', 'beberapa', 'kali', 'sih', 'semoga', 'bermanfaat', 'makasih', 'ya', 'seller', 'harganya', 'mahal', 'tp', 'semoga', 'ampuuuuh', 'yaaaa'	'pake', 'kali', 'semoga', 'bermanfaat', 'makasih', 'seller', 'harganya', 'mahal', 'semoga', 'ampuuuuh', 'yaaaa'
3	'barang', 'sesuai', 'pesanan'	'barang', 'sesuai', 'pesanan'

Table 4 presents the results of stopword removal, which eliminates irrelevant words from the text. This is followed by the stemming process, which converts words into their root forms. The results after stemming are displayed in Table 5.

Table 5: Stemming Results

No	Before	After
1	'penasaran', 'laser', 'bekas', 'luka', 'ilang', 'nemu', 'produk', 'coba', 'cocok', 'order', 'langsung', 'kaka'	'penasaran', 'laser', 'bekas', 'luka', 'ilang', 'nemu', 'produk', 'coba', 'cocok', 'order', 'langsung', 'kaka'
2	'pake', 'kali', 'semoga', 'bermanfaat', 'makasih', 'seller', 'harganya', 'mahal', 'semoga', 'ampuuuuh', 'yaaaa'	'pake', 'kali', 'moga', 'manfaat', 'makasih', 'seller', 'harga', 'mahal', 'moga', 'ampuuuuh', 'yaaaa'
3	'barang', 'sesuai', 'pesanan'	'barang', 'sesuai', 'pesan'

Table 5 demonstrates the results of stemming, where words with similar meanings are simplified into their root forms. This process enhances efficiency and accuracy in the sentiment analysis stage.

3.3. Data Labeling Result

Data labeling is performed using the Inset Lexicon dictionary, which contains a collection of words with specific weight values that indicate positive or negative sentiment. The labeling process begins by calculating the polarity score for each product review based on the words found in the dictionary. Words present in the lexicon will either increase or decrease the total polarity score, depending on whether they have a positive or negative sentiment. As a result, each review is assigned a label of "positive" if its polarity score is greater than or equal to zero, and "negative" if the polarity score is less than zero. The results of the labeling process using the Inset Lexicon dictionary are presented in Table 6.

Table 6: Labeling Data Results

No	Review	Polarity Score	Sentiment
1	'penasaran', 'laser', 'bekas', 'luka', 'ilang', 'nemu', 'produk', 'coba', 'cocok', 'order', 'langsung', 'kaka'	1	positive
2	'pake', 'kali', 'moga', 'manfaat', 'makasih', 'seller', 'harga', 'mahal', 'moga', 'ampuuuuh', 'yaaaa'	16	positive
3	'barang', 'sesuai', 'pesan'	5	positive

Table 6 presents the results of the polarity score calculation using the Inset Lexicon dictionary to determine positive and negative labels. Out of a total of 1,174 reviews, 1,069 were categorized as positive**,** while 105 were categorized as negative**.** This indicates that positive sentiment is more dominant than negative sentiment in the reviews of the scar removal product.

3.4. Data Transformation Results

Data transformation was carried out using the TF-IDF (Term Frequency-Inverse Document Frequency) technique, which enables a deeper analysis of text content by identifying more meaningful words. The results of the data transformation process are shown in Figure 2**.**

abis	adain	adakan	adha	admin	adminnya	after	afternya	aga
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Fig. 2: TF-IDF Results

Figure 2 illustrates the outcome of the data transformation process using the TF-IDF technique.

3.5. Model Training and Evaluation Results

During the model training phase, the Naïve Bayes algorithm was developed using training and testing data, with a proportion of 80% for training data and 20% for testing data, amounting to 939 training samples and 235 testing samples. This split follows common practices in Machine Learning research to ensure that the model can learn patterns from the training data and be evaluated on unseen data. To enhance model performance and prevent overfitting or underfitting, optimization was conducted using GridSearchCV, which searches for the best parameters through 5-fold cross-validation**.** The model evaluation results are presented in Table 7.

Table 7: Evaluation Results

Class	*Precission*	*Recall*	*F1-Score*	*Support*
Negative	0.80	0.19	0.31	21
Positive	0.93	1.00	0.96	214
Accuracy			0.92	235
Macro Avg	0.86	0.59	0.63	235
Weighted Avg	0.91	0.92	0.90	235

Table 7 presents the classification results of the Naïve Bayes algorithm with GridSearchCV optimization, achieving an accuracy of 92%. Based on the Classification Report, the model demonstrates excellent performance in identifying positive sentiment, with precision, recall, and F1-score values of 0.93, 1.00, and 0.96, respectively. However, the model's performance in detecting negative sentiment is relatively lower, with a precision of 0.80, recall of 0.19, and F1-score of 0.31, indicating that the model struggles to detect all negative sentiment data effectively. The macro average scores are precision: 0.86, recall: 0.59, and F1-score: 0.63. The low recall value in the macro average suggests that the model is less effective in consistently detecting minority sentiment. Meanwhile, the weighted average scores are precision: 0.91, recall: 0.92, and F1-score: 0.90, indicating that the model performs exceptionally well in handling the dominant sentiment.

Overall, the Naïve Bayes model, optimized using GridSearchCV, achieved an accuracy of 92%, demonstrating its ability to correctly classify most of the reviews. The Classification Report reveals that the model performs exceptionally well in identifying positive sentiment, with a precision of 0.93, recall of 1.00, and F1-score of 0.96, meaning nearly all positive reviews were correctly identified without any being missed. However, the model's performance on negative sentiment is weaker, with a precision of 0.80, recall of 0.19, and F1-score of 0.31, indicating that many negative reviews were misclassified as positive. This imbalance is reflected in the macro average scores (precision: 0.86, recall: 0.59, and F1-score: 0.63), highlighting the model's difficulty in detecting negative sentiment due to the smaller amount of negative data. On the other hand, the weighted average scores (precision: 0.91, recall: 0.92, and F1-score: 0.90) indicate that the model performs well in handling the dominant sentiment, which is positive reviews. While the Naïve Bayes algorithm successfully meets the research objective of classifying sentiment with high accuracy, it still has limitations in detecting negative reviews effectively.

This study compares its findings with research [4], which also used the Naïve Bayes classification model for sentiment analysis on mask products in Tokopedia. Despite using the same algorithm, differences in context and dataset led to variations in accuracy. The previous study achieved 88% accuracy for mask products, while this study, which focuses on scar removal products in e-commerce, attained a higher accuracy due to the dominance of positive sentiment in the dataset. These differences indicate that the context of the product influences the model's performance, even when the same algorithm is applied. This finding supports the idea that product type and usage context play a crucial role in improving sentiment analysis accuracy.

3.6. Visualization Results

The visualization was carried out using two main approaches: the Confusion Matrix, which was used to analyze the performance of the classification model, and the Word Cloud, which illustrated the distribution of words in positive and negative sentiment reviews.

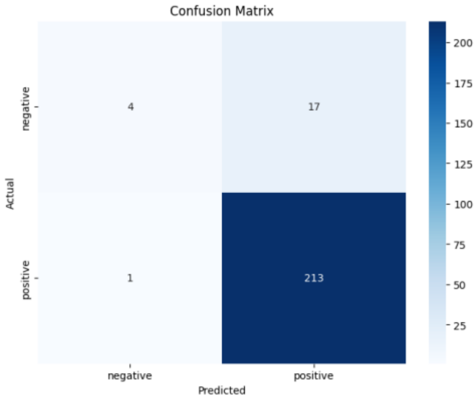

Fig. 3: Visualization Confusion Matrix

Figure 3 presents the visualization of the Confusion Matrix based on a total of 235 test data points. The results indicate that 213 positive reviews were correctly classified, while only 4 negative reviews were accurately identified. However, the model misclassified 17 negative reviews as positive and incorrectly labeled 1 positive review as negative. These findings suggest that while the model performs well in identifying positive sentiment, it struggles to accurately detect negative sentiment.

Fig. 4: Word Cloud Positive

Fig. 5: Word Cloud Negative

Figures 4 and 5 present the word cloud visualization for positive and negative reviews. The word cloud for positive reviews highlights dominant words such as "bagus" (good), "cocok" (suitable), "alhamdulillah" (thank God), "coba" (try), and "cepat" (fast), reflecting customer satisfaction with the product's quality and delivery speed. In contrast, the word cloud for negative reviews features words like "jelek" (bad), "gatal" (itchy), "kecewa" (disappointed), "buruk" (poor), and "mahal" (expensive), indicating that many consumers expressed dissatisfaction due to unmet expectations, particularly regarding scar treatment and skin-related issues.

These findings provide valuable insights for the owner of the Karinadlatr store to enhance marketing strategies and product quality. Based on positive reviews, the store can emphasize product advantages, such as its effectiveness for certain customers and fast delivery, in promotional strategies. Meanwhile, the complaints in negative reviews can serve as an evaluation point to improve the product formulation for better scar removal effectiveness and to educate customers on realistic expectations based on their skin conditions. Additionally, the store owner may consider adjusting pricing strategies or offering discount programs to increase market competitiveness, as well as strengthening customer service to address consumer complaints, ultimately improving customer satisfaction and loyalty.

4. Conclusion

This study successfully achieved its objectives by implementing the Naïve Bayes algorithm, which proved effective in classifying positive sentiment with an accuracy of 92%. The model demonstrated a precision of 0.93, recall of 1.00, and an F1-score of 0.96 for positive sentiment. However, for negative sentiment, the precision was 0.80, recall was 0.19, and the F1-score was 0.31, indicating a weakness in identifying negative sentiment, likely due to data imbalance.

Overall, this sentiment analysis provides valuable insights for the owner of the Karinadlatr store in understanding consumer perceptions of scar removal products. Negative reviews can be used as feedback to improve product quality and services, particularly in evaluating product effectiveness based on customer complaints.

Based on the findings of this study, future research is recommended to address data imbalance using techniques such as SMOTE or undersampling to improve the representation of minority classes and achieve a more balanced model performance. Additionally, more advanced feature representation techniques, such as word embeddings (Word2Vec, GloVe, or BERT), can be explored to better capture the contextual meaning of words.

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