p–ISSN: 2723 – 6609 e-ISSN: 2745-5254
Vol. 5, No. 11, November 2 024 http://jist.publikasiindonesia.id/

Sentiment Analysis on Skincare Product Reviews Using Lexicon-Based and Comparison of SVM Kernel

Lutfiana Sinta Lestari[1*], Tri Sutrisno[2], Irvan Lewenusa[3]
Universitas Tarumanegara, Indonesia
Email: lutfiana.535210065@stu.untar.ac.id[1*], tris@fti.untar.ac.id[2], irvanl@fti.untar.ac.id[3]
*Correspondence

ABSTRACT

The skincare industry has seen remarkable growth in recent years, fueled by increasing public awareness of skincare and beauty. As awareness of the importance of skincare grows, skincare products are becoming more popular. The skincare brands available on the market today are diverse. However, not all skincare products offer the same quality, and some are more suitable for specific skin types or concerns, depending on the ingredients used and product formulation. To help consumers understand skincare reviews, this study conducts sentiment analysis on skincare products, identifying whether reviews tend to be positive, negative, or neutral. The sentiment analysis utilizes a lexicon-based approach with comparisons of various SVM kernels, including linear, polynomial, RBF, and sigmoid. Additionally, this research applies the Term Frequency-Inverse Document Frequency (TF-IDF) for word weighting. The study results indicate that the best performance was achieved with the Sigmoid and Linear kernels when no oversampling technique was applied. The results for the linear kernel without balancing achieved 81.83% accuracy, 77.46% precision, 81.83% recall, and 79.53% F1 score. Meanwhile, the Sigmoid kernel yielded 81.83% accuracy, 77.39% precision, 81.83% recall, and 79.53% F1-score.

Keywords: sentiment analysis, SVM kernel, lexicon-based, skincare products.

Introduction

Industry skincare has experienced significant growth in recent years, driven by increasing public awareness of skincare and beauty. Where everyone wants to have an attractive and pleasing appearance. An attractive appearance is not only from the clothes or accessories worn but having healthy skin is also support for appearance. Skincare is one of the facial skin treatments that can be done to maintain and maintain a healthy skin condition. By doing facial skincare, is a form of appreciation and concern for yourself and others to support your appearance to be attractive (Sinaga & Hutapea, 2022). The use of skincare is one of the efforts to achieve an attractive appearance through skin health.

With the increasing public awareness of the importance of skincare, skincare products are becoming increasingly popular. The various skincare brands circulating in the market today are very diverse. However, not all skincare products have the same quality, and some of them are more suitable for skin types with specific concerns depending on the ingredients used and how the product is formulated. An individual's skin type and condition can affect how the skin reacts to the skincare used. Before consumers decide to buy a skincare product, consumers should know their skin type and condition. This can be done by reading the results of reviews from other consumers who have purchased the product.

According to the results of a survey conducted in December 2019 in the US, the majority of internet users 76% place the same level of trust between online reviews and recommendations from family or friends in making purchase decisions. Several reviews about skincare products can help consumers assess whether the quality of the skincare brand is worth using or not. This is because not all skincare brands have good quality and everyone has a different skin type. Even the same skin type is not necessarily compatible with the same skincare. (Kamal, 2021). Following Figure 1 is sales data for Brand Skincare Best Selling Local Online.

Figure 1
Sales Data of the Best-Selling Local Skincare Brand Online

Based on sales data from Compas. Id quoted from various e-commerce platforms in the April-June 2022 period, sales for local skincare brands are said to be quite great. Throughout the April-June 2022 period, total sales on the marketplace reached IDR 292.4 billion with a total transaction of 3.8 million. The Something skincare brand managed to become the best-selling skincare brand in e-commerce with a total revenue of IDR 53.2 billion. Followed by Scarlet with IDR 40.9 billion and Ms Glow with IDR 29.4 billion. This data shows the dominance of local brands in the Indonesian skincare industry.

Reviews and opinions about several skincare brands are the focus of research to identify whether there are trends in positive, negative, and neutral sentiments. By classifying reviews, it can help consumers assess the quality of products and find products that match their skin type. So this study focuses on sentiment analysis of skincare product reviews. The following in Figure 2 is an example of a review of a skincare product.

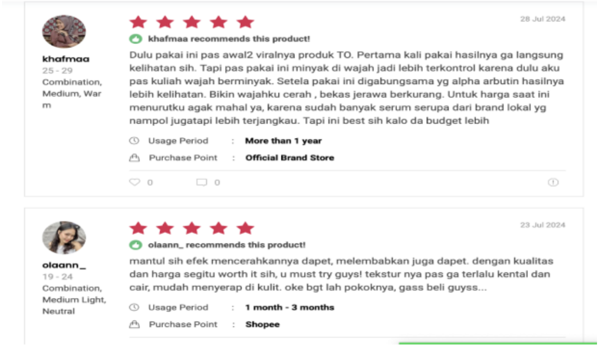

Figure 2
Skincare Review on Female Daily Forum

Based on the reviews above, there are many forms of phrases in expressing positive or negative feelings from a product review. Phrases like "bounce is a brightening effect" indicate user satisfaction with the quality of the product, especially in terms of its scent and effect on the skin. In the context of the embedding lexicon, these phrases can be considered part of the Natural Language Processing (NLP) which is used to understand user sentiment. Lexicon embedding can be used to get information about a word or phrase that is positive or negative. Where the lexicon sentiment is a list of lexical features that are generally labeled according to positive or negative semantic orientation (Bonta, Kumaresh, & Janardhan, 2019). With a lexicon-based approach that uses sentiment words, it is essential to describe and understand the emotional aspects of written communication, therefore lexicon-based techniques are used to carry out labeling of existing data into positive, negative, and neutral.

In research on text classification using the lexicon-based approach, Oktaviana et al (2022) also conducted. (Oktaviana, Sari, & Indriati, 2022). The study discusses sentiment analysis on online lecture policies during the pandemic. The problem behind this research is that there are policies issued by the government to minimize the spread of COVID-19, these policies result in contributions to the community and many end up having opinions on social media. So to find out the polarity of public opinion regarding online lecture policies during the pandemic, the study conducted a sentiment analysis using the Lexicon and Support Vector Machine (SVM). The result of this study is that there is an increase after using lexicon-based features, namely with an accuracy value of 60%, a precision value of 56%, a recall value of 75%, and an f1-score of 64%, compared to the classification process without Lexicon Based Feature which only produces an accuracy value of 48%, a precision value of 46%, a recall value of 58%, and an f1-score value of 52%. Where the evaluation value increased by 12% compared to the SVM method which did not use the lexicon-based approach.

Other research conducted by Arsi & Waluyo (2021) (Arsi & Waluyo, 2021) Discussed the sentiment analysis of the discourse on the relocation of the Indonesian capital. The problem behind this study is that there are pros and cons related to the relocation of the Indonesian capital on social media such as Twitter (X). So the study conducted a sentiment analysis related to the discourse on the relocation of the Indonesian capital using the SVM algorithm. The result of this study is to produce an accuracy of 96.68%, Precision of 95.82%, Recall of 94.04%, and AUC of 0.979.

Based on the description above, this study will conduct sentiment analysis using lexicon-based with a comparison of kernels in SVM such as linear, polynomial, RBF, and Sigmoid. The use of the SVM algorithm for classification in this study is because previous studies have shown that the SVM method is one of the effective techniques for text classification, including sentiment analysis. SVM works by separating data into different classes using Hyperplane (Annur, Murtopo, & Fadilah, 2022). Meanwhile, in this study, word weighting will use the Term Frequency-Inverse Document Frequency (TF-IDF). The TF-IDF technique aims to overcome these limitations by giving weight to the relationship of a word (term) on a document. (Lestandy, Abdurrahim, & Syafa'ah, 2021). The TF-IDF method has the advantage of its ability to give the right weight to the terms in the document. By combining TF and IDF scores, the TF-IDF method can identify the most relevant terms in the document. (Annisa, Kalifia, Bisnis, Humaniora, & Yogyakarta, 2024). While lexicon-based in this study is used for labeling by extracting opinion sentences automatically using a dictionary of opinion words that will be used as a reference in the classification. (Roiqoh, Zaman, & Kartono, 2023) So with this research hope that can add insight related to sentiment analysis in product reviews skincare, and find out which kernel on the SVM method has the best performance.

Method

In classifying, it will be website-based using the Python programming language and using the Flask framework. In the first process of creating a system, it is necessary to know the needs that will be applied to the system.

The system that will be designed will later apply a comparison of the kernels of SVMs such as linear, polynomial, RBF, and sigmoid. This aims to determine the best performance in the sentiment analysis process for skincare product review data totaling 3000 data.

The dataset that has been collected will only use feature review and then positive, negative, and neutral labeling using lexicon-based, and preprocessing. Furthermore, datasets were distributed with a proportion of 80% training data and 20% testing data. Furthermore, data imbalance is handled and without data imbalance is handled. The method used in handling data imbalances is SMOTE. Then classification is carried out using a comparison of SVM kernels. Finally, an evaluation was carried out using a confusion matrix with the values of accuracy, precision, recall, and f1-score. The process in the system design uses the waterfall method which consists of requirement analysis, design, development, and testing.

After that, an elaboration was carried out regarding the creation of a classification system for sentiment analysis based on the previous draft. The following is an explanation of the stages:

1. Dataset collection is carried out before creating the system. The dataset used is user review/review data on skincare products. The dataset was obtained through the female daily website with a total of 3000 data.
2. The creation of the user interface is carried out based on the previously designed interface design which includes the interface design of the admin and user modules.

Classify sentiment analysis on skincare product reviews. The first process carried out is preprocessing using case folding, data cleaning, tokenizing, normalization, stopword, and stemming. Then labeling is carried out using lexicon-based, and weighting using TF-IDF. Then split the data. The distribution of datasets was carried out by dividing the data into 80% training data and 20% testing data. Then an oversampling process was carried out using SMOTE. Next, the implementation of the SVM kernel was carried out. After the model creation is completed, the performance of each kernel will then be evaluated. The creation of the model will later be implemented using the Python programming language with the Flask framework. The last stage is to test the system and validate the results using confusion matrix evaluation metrics, namely accuracy, precision, recall, and f1-score.

Results and Discussion

Testing on sentiment analysis in skincare product reviews using lexicon-based and comparison of SVM kernels implemented in website-based is by using confusion matrix evaluation, black box testing, and UAT. Confusion matrix by knowing the value of accuracy, precision, recall, and f1-score. Blackbox testing is used to test the functionality of the system so that the system can run properly and minimize errors. Meanwhile, by using UAT to ensure that the application will be built according to user needs, it is easy to use as a sentiment analysis on skincare product reviews by users.

Testing on the dataset is carried out using kernel comparison, in each kernel data balancing is carried out without using data balancing. The following in Figure 3 to Figure 11 are the results obtained in each kernel and the process of using balancing and without balancing.

The following in Figure 3 is the result of the classification of linear kernels without using data balancing.

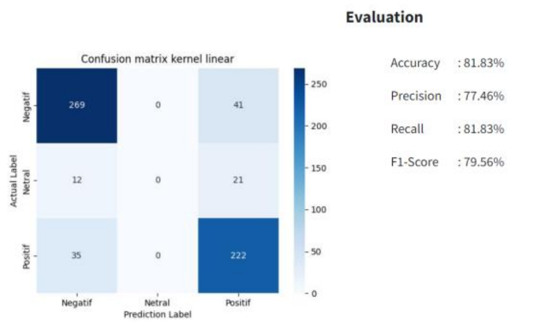

Figure 3
Linear kernel results without using data balancing

The following in Figure 4 is the classification of polynomial kernels without using data balancing.

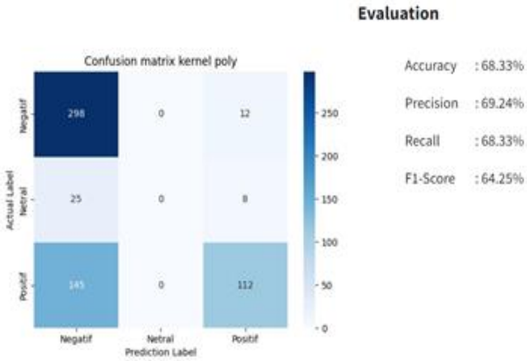

Figure 4
Polynomial kernel results without using data balancing

The following in Figure 5 is the classification result of the RBF kernel without using data balancing.

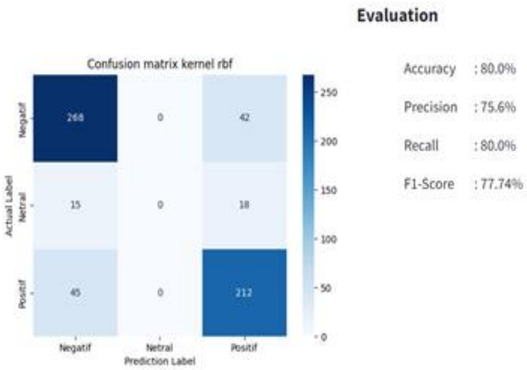

Figure 5
RBF kernel results without using data balancing

The following in Figure 6 is the classification result of the sigmoid kernel without using data balancing.

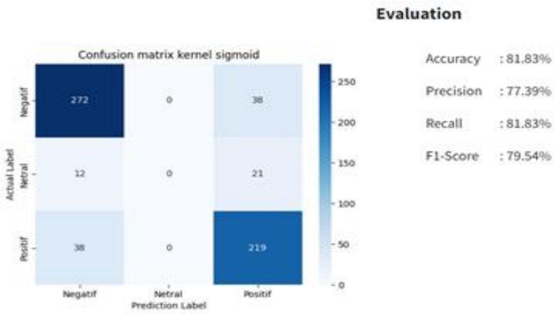

Figure 6
Sigmoid Kernel Results Without Using Data Balancing

The following in Figure 7 is the result of the classification of linear kernels using data balancing.

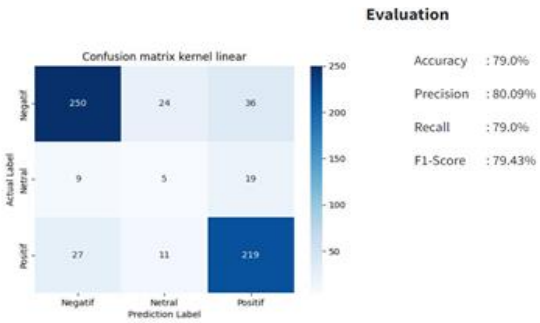

Figure 7
Linear Kernel Results Using Data Balancing

The following in Figure 8 is the result of the classification of polynomial kernels using balancing data.

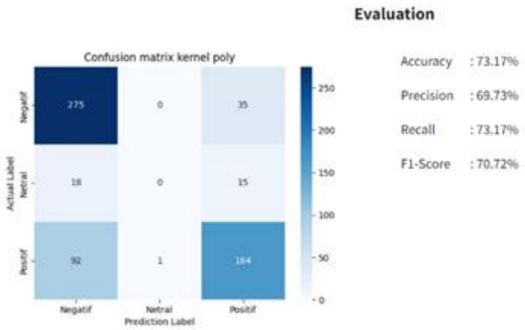

Figure 8
Polynomial Kernel Results Using Data Balancing

The following in Figure 9 is the classification of the RBF kernel using balancing data.

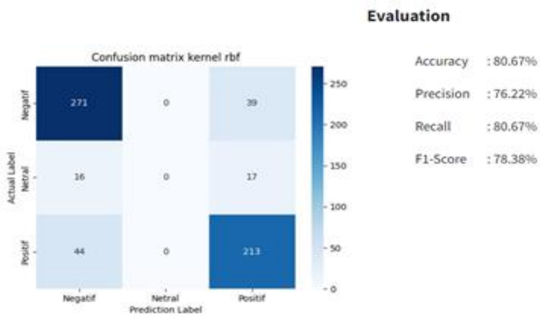

Figure 9
RBF Kernel Results Using Data Balancing on Users

The following in Figure 10 is the classification of sigmoid kernels using data balancing.

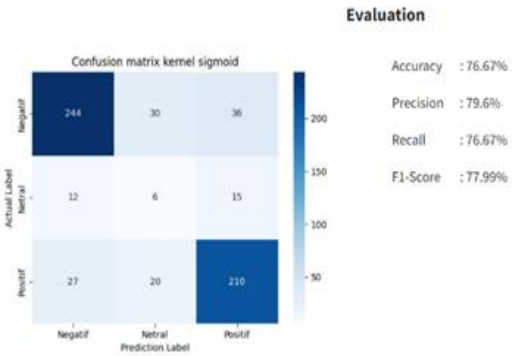

Figure 10
Sigmoid Kernel Results Using Data Balancing

In testing using black box testing, a scenario or system test design is created on each model of the skincare product sentiment analysis system that has been made. In addition, evaluations were also carried out by distributing questionnaires and filled out by application users.

From the results of the research that has been carried out, this study analyzes the sentiment of skincare products using an SVM kernel comparison. The dataset used in this study came from the female daily website which amounted to 3000 data. The labels used in this study consist of 3 (three) labels, namely positive, negative, and neutral. In its implementation, after the dataset input, namely preprocessing, labeling, TF-IDF weighting, splitting the data by dividing it into a proportion of 80% data train and 20% test data. Furthermore, an oversampling process is carried out or without an oversampling process. The method used to overcome the data imbalance is the SMITE technique. Furthermore, the classification process using SVM was carried out using a comparison of 4 (four) kernels, namely RBF, Linear, Sigmoid, and Polynomial, and continued with an evaluation using a confusion matrix. From the results of the confusion matrix with the values of accuracy, precision, recall, and f1-score. The results obtained vary, as shown in Table 1 below.

Table 1
Comparison Results

Kernel	Confusion Matrix	Without using Balancing	Using Balancing
Linear	Accuracy	81.83%	79%
	Precision	77.46%	80.09%
	Recall	81.83%	79%
	F1-score	79.56%	79.43%
Kernel	Confusion Matrix	Without using Balancing	Using Balancing
Polynomial	Accuracy	68.33%	73.17%
	Precision	69.24%	69.73%
	Recall	68.33%	73.17%
	F1-score	64.25%	70.72%
RBF	Accuracy	80%	80.67%
	Precision	75.6%	76.22%
	Recall	80%	80.67%
	F1-score	77.74%	78.38%

Sigmoid	Accuracy	81.83%	76.67%
	Precision	77.39%	79.6%
	Recall	81.83%	76.67%
	F1-score	79.54%	77.99%

Based on Table 1, the best performance is obtained on Sigmoid and Linear kernels when not using *oversampling techniques.* The results obtained on the linear kernel without balancing were 81.83% on accuracy, 77.46% on precision, 81.83% on recall, and 79.53% on f1-score. Meanwhile, in the sigmoid kernel, it was 81.83% in accuracy, 77.39% in precision, 81.83% in recall, and 79.53% in f1-score. Meanwhile, in polynomial kernels and RBF, the highest results were obtained when applying the oversampling technique. In the polynomial kernel it was obtained by 73.17% in accuracy, 69.73% in precision, 73.17% in recall, and 70.72% in f1-score. In the kernel, RBF was obtained by 80.67% on accuracy, 76.22% on precision, 80.67% on recall, and 78.38% on f1-score.

Conclusion

Based on the implementation process and discussion that has been carried out, it is concluded that to compare the SVM kernel using lexicon embedding in website-based skincare product sentiment analysis, this study is applied using the Python programming language. After the dataset input was carried out, the steps taken included preprocessing, labeling, TF-IDF weighting, and data division into a proportion of 80% of the data train and 20% of the data. Furthermore, an oversampling process was carried out without oversampling, where the method used to overcome the data imbalance was the SMATE technique. After that, a classification process using SVM was carried out by comparing four kernels, namely RBF, Linear, Sigmoid, and Polynomial, which was followed by evaluation using a confusion matrix.

The performance results of each SVM kernel show that the best performance is obtained in the Sigmoid and Linear kernels when not using the oversampling technique. The Linear kernel produces an accuracy of 81.83%, a precision of 77.46%, a recall of 81.83%, and an f1-score of 79.53%, while a Sigmoid kernel produces an accuracy of 81.83%, a precision of 77.39%, a recall of 81.83%, and an f1-score of 79.53%.

As a suggestion for future research development, other oversampling methods such as the Adaptive Synthetic Sampling Approach (ADASYN) can be applied. Thus, the best classification model for conducting sentiment analysis can be known through a comparison of oversampling techniques applied to various SVM kernels.

Bibliography

Annisa, Luthfiyah, Kalifia, Anna Dina, Bisnis, Fakultas, Humaniora, Dan, & Yogyakarta, Universitas Teknologi. (2024). Analisis Teknik TF-IDF Dalam Identifikasi Faktor-Faktor PenyebabDepresi Pada Individu. *January*, *2*, 302–307.

Annur, Ahsinil Amal, Murtopo, Aang Alim, & Fadilah, Nurul. (2022). Analisis Sentimen Aplikasi E-Learning Selama Pandemi Covid-19 Dengan Menggunakan Metode Support Vector Machine Dan …. *IJIR*, *3*(2), 9–17.

Arsi, Primandani, & Waluyo, Retno. (2021). Analisis Sentimen Wacana Pemindahan Ibu Kota Indonesia Menggunakan Algoritma Support Vector Machine (SVM). *Jurnal Teknologi Informasi Dan Ilmu Komputer*, *8*(1), 147. https://doi.org/10.25126/jtiik.0813944

Bonta, Venkateswarlu, Kumaresh, Nandhini, & Janardhan, N. (2019). A Comprehensive Study on Lexicon-Based Approaches for Sentiment Analysis. *Asian Journal of Computer Science and Technology*, *8*(S2), 1–6. https://doi.org/10.51983/ajcst-2019.8.s2.2037

Kamal, Willy Wildan. (2021). *Analisis Sentimen Ulasan Produk Skincare Menggunakan Metode Support Vector Machine (Studi Kasus: Forum Female Daily)*. 65.

Lestandy, Merinda, Abdurrahim, Abdurrahim, & Syafa'ah, Lailis. (2021). Analisis Sentimen Tweet Vaksin COVID-19 Menggunakan Recurrent Neural Network dan Naïve Bayes. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *5*(4), 802–808. https://doi.org/10.29207/resti.v5i4.3308

Oktaviana, Natasya Eldha, Sari, Yuita Arum, & Indriati, Indriati. (2022). Analisis Sentimen terhadap Kebijakan Kuliah Daring Selama Pandemi Menggunakan Pendekatan Lexicon Based Features dan Support Vector Machine. *Jurnal Teknologi Informasi Dan Ilmu Komputer*, *9*(2), 357–362. https://doi.org/10.25126/jtiik.2022925625

Roiqoh, Salsabila, Zaman, Badrus, & Kartono, Kartono. (2023). Analisis Sentimen Berbasis Aspek Ulasan Aplikasi Mobile JKN dengan Lexicon Based dan Naïve Bayes. *Jurnal Media Informatika Budidarma*, *7*(3), 1582–1592. https://doi.org/10.30865/mib.v7i3.6194

Sinaga, Ricka Putri Yani Br, & Hutapea, Joan Yuliana. (2022). Analisis pengaruh brand image, harga, dan review product terhadap keputusan pembelian skincare wardah pada mahasiswa unai. *Jurnal Ekonomi, Sosial & Humaniora*, *3*(08), 12–25.