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Sentiment Analysis of Shopee App Usage Reviews Using Metaheuristic Algorithm Optimization

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Abstract

Sentiment analysis is widely used to classify opinions expressed in textual data; however, many previous studies employing Support Vector Machine (SVM) do not explicitly address parameter optimization, which can lead to suboptimal classification performance. To address this research gap, this study integrates Particle Swarm Optimization (PSO) to optimize key SVM parameters for sentiment analysis of Shopee application reviews. The dataset consists of 1,000 Indonesian language user reviews collected from the Google Play Store between January and August 2025. Text preprocessing was conducted prior to feature extraction using the Term Frequency–Inverse Document Frequency (TF-IDF) method. PSO was applied to optimize the kernel parameters, penalty parameter (C), and gamma value of the SVM model. The results demonstrate that PSO-based optimization significantly improves classification performance, increasing accuracy from 86.0% to 90.0%, precision from 86.9% to 90.6%, recall from 87.6% to 91.2%, and F1-score from 87.2% to 90.9%. Additionally, positive reviews are dominated by keywords such as “cheap,” “fast,” and “free shipping,” while negative reviews frequently contain terms such as “error” and “slow.” These findings confirm that PSO effectively enhances SVM performance and provides reliable insights into user sentiment toward e-commerce applications.

Keywords: Sentiment Analysis, Particle Swarm Optimization (PSO), Support Vector Machine (SVM), Shopee, Parameter Optimization.

1. Introduction

The rapid development of information and communication technology in the digital era has driven a paradigm shift in various sectors of life, particularly in the economic and trade sectors. This paradigm shift is demonstrated by the shift in buying and selling patterns from conventional to digital, utilizing internet technology. The use of digital technology in trade activities has had a significant impact on how businesses offer products and how consumers obtain goods and services. This situation demands a trading system that can provide speed, convenience, and efficiency in the transaction process, thus adapting to the increasingly dynamic needs of modern society. E-commerce emerged as a manifestation of these technological developments and provided a solution for people to conduct online buying and selling transactions (Permata et al., 2022). Through e-commerce platforms, consumers can search for products, compare prices, and make transactions without having to visit a physical store. With e-commerce, distance and time constraints are no longer barriers to trading, as the entire transaction process can be carried out anytime and anywhere using digital devices connected to the internet, making e-commerce a rapidly growing sector and playing a crucial role in the development of the digital economy (Steven et al., 2023).

One e-commerce platform that has experienced significant growth and has a very large user base in Indonesia is Shopee. The Shopee application offers various features designed to enhance user convenience in making transactions, such as an easy-to-use interface, diverse digital payment systems, and promotional programs including free shipping and cashback (Idris et al., 2023). In addition, Shopee provides integrated logistics services that support efficient product delivery to consumers. These features have positioned Shopee as one of the most downloaded and widely used e-commerce applications on the Google Play Store, reflecting strong user interest and trust (Amalia et al., 2023). The high level of application usage has led to an increasing number of user reviews on the Google Play Store. These reviews represent direct feedback from users, containing both positive and negative experiences related to application performance, transaction processes, delivery services, and product suitability (Huda et al., 2023).

The information contained in user reviews is valuable for application managers as it can be used to evaluate service quality and identify areas requiring improvement. Through systematic analysis of user reviews, service providers can better understand user satisfaction and dissatisfaction. However, the large volume of reviews and their unstructured textual nature make manual analysis inefficient and subjective. Therefore, computational approaches capable of automatically processing and analyzing large-scale textual data are required. One widely adopted method is sentiment analysis, a branch of Natural Language Processing (NLP) that aims to classify opinions or emotions expressed in text into sentiment categories such as positive and negative (Utami et al., 2022).

In sentiment analysis research, various machine learning algorithms have been applied to classify textual data, one of which is the Support Vector Machine (SVM). SVM is well known for its ability to handle high-dimensional data such as TF-IDF-based text representations and has been widely used in sentiment classification tasks (Idris et al., 2023). Despite its advantages, SVM performance is highly dependent on parameter selection, including kernel parameters and regularization values. Inappropriate parameter settings can result in suboptimal classification accuracy (Kumar et al., 2022).

To overcome this challenge, the application of parameter optimization methods is required to enhance the performance of the Support Vector Machine (SVM) classifier. Particle Swarm Optimization (PSO), a metaheuristic algorithm inspired by swarm intelligence, has been widely recognized as an effective approach for optimizing classification model parameters (Putra et al., 2023). Previous research has demonstrated that PSO can substantially improve classification outcomes by identifying optimal parameter configurations (Andriana et al., 2021). Nevertheless, studies that specifically apply PSO to tune SVM parameters for sentiment analysis of Indonesian-language Shopee application reviews remain limited. Consequently, this research aims to integrate PSO for optimizing SVM parameters in the sentiment analysis of Shopee user reviews obtained from the Google Play Store during the period from January to August 2025.

2. Methods

This study uses a quantitative approach with sentiment analysis to analyze user-generated reviews on the Shopee application sourced from the Google Play Store. The dataset used in this study consists of 1,000 Indonesian-language user reviews collected from January to August 2025. The quantitative approach is considered appropriate because this study focuses on numerical representations obtained from text feature extraction and on the evaluation of classification models using measurable performance indicators. The entire research process is implemented systematically, including data collection, text pre-processing for data cleaning and normalization, feature weighting using TF-IDF, sentiment classification using the SVM algorithm, parameter tuning with PSO, and model evaluation using a confusion matrix.

The initial stage of the research began with data collection using web scraping techniques on Shopee app user reviews on the Google Play Store. This data collection process generated 1,000 user reviews, which served as the research dataset. These reviews were then labeled with positive and negative sentiment based on the context of the sentences they contained. The labeling process ensured that each piece of data had a clear class before being used in the machine learning process. With this labeling, the classification model could learn word patterns that represent each sentiment class. The labeled data was then divided into training and testing data, allowing the classification process and model performance evaluation to be conducted separately and objectively.

After the data collection and labeling process is complete, the next stage is text preprocessing. The preprocessing stage aims to clean the data of irrelevant elements and standardize the text format so that it can be processed computationally. The preprocessing process begins with case folding, which converts all letters in the review text to lowercase. This step is carried out to avoid differences in word representation due to the use of capital letters. Next, the tokenization process is carried out, which breaks the review sentence into word tokens based on spaces and punctuation. The resulting tokens still contain common words that do not have a significant impact on sentiment analysis, so a filtering process is carried out to remove stopwords such as "and", "which", "in", and other common words. The final preprocessing stage is stemming, which converts affixed words into basic words using an Indonesian stemming algorithm. This process aims to unify variations of words with similar meanings into a single basic form, thereby reducing data complexity and improving feature quality.

After completing the preprocessing stage, the textual data is converted into numerical features through a weighting mechanism based on the Term Frequency–Inverse Document Frequency (TF-IDF) method. This method evaluates the importance of words by comparing their frequency in a specific document to their presence in the full collection of documents. The Term Frequency (TF) component indicates how frequently a term occurs within a single review, while the Inverse Document Frequency (IDF) component measures how uncommon the term is across the dataset. In this study, the calculation of TF is defined by the following equation:

$$TF_{t,d} = \begin{cases} 1 + log(F_{t,d}), & if\ F_{t,d} > 0 \\ 0, & if\ F_{t,d} = 0 \end{cases}$$

Where $F_{t,d}$ is the frequency of occurrence of term t in document d Next, the Inverse Document Frequency value is calculated using the equation:

$$IDF_t = log\left(\frac{N}{df_t}\right)$$

Where N represents the total number of review documents and df_t is the number of documents containing the term t. The final TF-IDF weight is obtained by multiplying the TF and IDF values as follows:

$$TFIDF_{t,d} = TF_{t,d} \times IDF_t$$

The results of the TF-IDF calculation produce a numeric feature matrix that represents each review in vector form, which is then used as input in the classification process.

The classification stage was performed using the Support Vector Machine (SVM) algorithm. SVM works by finding the optimal hyperplane that can separate positive and negative sentiment data with the maximum margin. In the initial stage, classification was performed without parameter optimization (baseline SVM). The SVM parameters used at this stage were default, so the classification results still had the potential for error due to suboptimal parameters. The baseline SVM classification results were then evaluated using a confusion matrix to determine the performance of the initial model.

From the baseline SVM classification results, a confusion matrix is constructed to obtain the values of True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). These components are subsequently utilized to assess the model’s performance. The evaluation measures, including accuracy, precision, recall, and F1-score, are calculated based on the following equations:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision \times Recall}$$

The baseline evaluation results show that the accuracy of the SVM model before optimization was at 86.0%, which was the basis for comparison before parameter optimization was carried out.

To enhance the classification performance, the parameters of the Support Vector Machine (SVM) were optimized through the application of Particle Swarm Optimization (PSO). Within this framework, each particle represents a candidate solution defined by a specific combination of SVM parameters, namely the values of C and γ. At the beginning of the optimization process, particle positions and velocities are initialized randomly, followed by a fitness evaluation based on the classification accuracy produced by the SVM model. Since classification accuracy is employed as the objective function, the particle that yields the highest accuracy is regarded as the optimal solution. The PSO iterative procedure is then conducted by updating the velocity and position of each particle according to the following equations:

$$v_i{}^{(t+1)} = w.v_i{}^{(t)} + c_1c_2\left(pbest_i - x_i{}^{(t)}\right) + c_2r_2\left(gbest - x_i{}^{(t)}\right)$$

$$x_i{}^{(t+1)} = x_i{}^{(t)} + v_i{}^{(t+1)}$$

Where v_i is the velocity of the i-th particle i-th x_i is the particle's position, w is the inertial weight, c_1 and c_2 are the acceleration constants, and r_1 and r_2 are random numbers between 0 and 1. This process is carried out repeatedly until it reaches the maximum number of iterations or the best solution convergence.

The PSO iteration results show that the best parameter combination is obtained at the highest fitness value. These optimal parameters are then reused in the SVM classification process. The SVM model resulting from PSO optimization is then evaluated using a confusion matrix. Based on the SVM + PSO confusion matrix results, the obtained values are TP = 500, FP = 52, FN = 48, and TN = 400.

Based on these values, the accuracy calculation is obtained as follows:

$$Accuracy = \frac{500 + 400}{1000} = 0{,}90 = 90{,}0\%$$

The precision value is calculated as:

$$Precision = \frac{500}{500 + 52} = 0{,}9058 = 90{,}6\%$$

The recall value is obtained from:

$$Recall = \frac{500}{500 + 48} = 0{,}9124 = 91{,}2\%$$

Meanwhile, the F1-score value is calculated using the equation:

$$F1 - Score = 2 \times \frac{0{,}9058 \times 0{,}9124}{0{,}9058 + 0{,}9124} = 0{,}909 = 90{,}9\%$$

The results of this evaluation show that the application of PSO succeeded in significantly improving the performance of the SVM model compared to the model before optimization.

3. Result and Discussion

3.1 Data Description and Preprocessing Results

This part of the study elaborates on the experimental outcomes of sentiment analysis conducted on Shopee user reviews by employing an SVM classifier optimized through Particle Swarm Optimization (PSO). The dataset comprises Indonesian-language reviews collected from the Google Play Store during the period from January to August 2025. Prior to model training, the raw textual data underwent an extensive preprocessing workflow, which included data cleansing, case folding, token segmentation, removal of stopwords, and stemming. These processes played a critical role in reducing textual noise, standardizing the data format, and ensuring that the extracted features accurately represented the underlying sentiment expressed by users.

The scraping process successfully retrieved a large number of reviews that varied in length, writing style, and sentiment polarity. Many reviews contained informal language, abbreviations, and typographical errors, which justified the necessity of preprocessing. After cleaning, irrelevant symbols, numbers, and duplicated entries were removed, resulting in a more structured dataset suitable for computational analysis.

3.2 Feature Extraction Using TF-IDF

After the preprocessing stage, the processed text data is represented numerically through the application of the TF-IDF weighting technique. The weighting strategy evaluates each term based on how frequently it appears in a given document and how rarely it appears across the entire corpus. As a result, words with higher discriminative values play a more prominent role in sentiment classification tasks. Examples of term frequency values and their corresponding TF-IDF scores are presented in Table 1.

The TF-IDF representation enabled the SVM classifier to effectively distinguish between positive and negative sentiment patterns. Words such as *“Cheap”*, *“Fast”*, and *“Free shipping”* appeared with high TF-IDF scores in positive reviews, whereas terms like *“Error”*, *“Slow”*, and *“Incorrect”* were dominant in negative reviews. This result confirms that TF-IDF successfully captures meaningful linguistic features relevant to sentiment polarity.

Table 1.

Sample TF-IDF Feature Representation

Term	TF	IDF	TF-IDF
Cheap	0.085	1.21	0.103
Fast	0.072	1.34	0.097
Error	0.091	1.56	0.142
Slow	0.064	1.48	0.095

The values presented in Table 1. demonstrate how the TF-IDF weighting mechanism emphasizes sentiment-relevant terms within the dataset. Words such as *error* and *lambat* obtain relatively higher TF-IDF scores because they frequently appear in negative reviews while remaining less common across the entire corpus. Conversely, positive sentiment indicators such as *murah* and *cepat* also show significant weights, indicating their importance in distinguishing favorable user experiences. This result confirms that TF-IDF effectively captures discriminative linguistic features that are essential for sentiment classification.

3.3 Classification Results Using SVM (Before Optimization)

Baseline sentiment classification was conducted using a standard SVM classifier without the incorporation of parameter optimization techniques. The model was trained on TF-IDF–based features and evaluated using a confusion matrix in combination with commonly used performance indicators such as accuracy, precision, recall, and F1-score. Table 2 summarizes the confusion matrix results of the baseline SVM model.

An accuracy of 86.0% was obtained by the baseline model, indicating satisfactory performance in classifying the majority of reviews. However, several misclassifications were identified, especially for reviews containing ambiguous or mixed sentiment expressions. This observation served as the basis for employing PSO to optimize SVM parameters and enhance the classification results.

Table 2.
Confusion Matrix – SVM Baseline

Actual / Predicted	Positive	Negative
Positive	430	70
Negative	65	435

Table 2. illustrates the classification performance of the baseline SVM model before parameter optimization. The model correctly classified a large portion of both positive and negative reviews, as reflected by the high values of true positives and true negatives. However, the presence of false positives and false negatives indicates that some reviews with ambiguous sentiment expressions were misclassified. These results suggest that while the baseline SVM provides acceptable performance, further optimization is necessary to improve decision boundary precision.

3.4 Optimization Results Using PSO-SVM

In this study, Particle Swarm Optimization (PSO) was utilized to optimize critical parameters of the SVM classifier, namely the kernel configuration, the penalty parameter (C), and the gamma value. The optimization began by initializing particles with randomly assigned positions and velocities, which were subsequently updated through iterative interactions between individual best (pbest) and overall best (gbest) solutions. The integration of PSO resulted in a substantial enhancement of the SVM model’s performance, with accuracy increasing to 90.0% and corresponding improvements observed in precision, recall, and F1-score. Table 3 reports the performance evaluation of the optimized model, confirming the role of PSO in strengthening SVM-based classification.

Table 3.
Evaluation Results of PSO-SVM Model

Metric	SVM Baseline	PSO-SVM
Accuracy	86.0%	90.0%
Precision	86.9%	90.6%
Recall	87.6%	91.2%
F1-Score	87.2%	90.9%

As shown in Table 3, the performance of the standard SVM model is compared with that of the PSO-optimized SVM model. The results indicate that parameter optimization using PSO consistently improves all evaluation metrics. Higher accuracy signifies improved classification performance, whereas the increases in precision and recall demonstrate enhanced robustness in detecting both sentiment categories. In addition, the improved F1-score highlights a more balanced trade-off between precision and recall, supporting the effectiveness of PSO in strengthening SVM-based sentiment analysis.

Discussion

Overall, the results obtained in this study indicate that the integration of Particle Swarm Optimization (PSO) with the Support Vector Machine (SVM) algorithm provides a substantial improvement in sentiment classification performance compared to the baseline SVM model. The increase in accuracy from 86.0% to 90.0% demonstrates that parameter optimization plays a critical role in enhancing the generalization capability of the SVM classifier when applied to high-dimensional text data. This improvement is not merely numerical but reflects a more optimal separation of sentiment classes, as evidenced by the balanced values of precision, recall, and F1-score obtained after optimization.

Methodologically, the implementation of the TF-IDF scheme plays a crucial role in mapping textual review data into informative numerical features while preserving word significance. The weighting mechanism emphasizes terms that are prominent in individual reviews but relatively infrequent across the entire dataset, contributing to a more discriminatory feature representation. Such a transformation is crucial for SVMs, given their reliance on the geometry of the feature space to construct an effective separating hyperplane. Without proper weighting, important sentiment-containing terms can be overshadowed by common but less informative words.

The baseline SVM results reveal that although SVM is inherently robust for text classification tasks, the use of default parameters may limit its performance. In this study, the baseline model still misclassified a noticeable number of reviews, particularly those containing ambiguous expressions or mixed sentiments. This limitation underscores the sensitivity of SVM performance to the selection of hyperparameters, especially the penalty parameter (C) and the kernel parameter (γ). Improper parameter values may lead to underfitting or overfitting, which in turn affects the classifier's ability to generalize to unseen data.

The implementation of PSO effectively addressed this limitation by systematically searching for the optimal combination of SVM parameters. Through iterative updates of particle positions and velocities, PSO was able to explore the solution space efficiently and converge toward parameter values that maximized classification accuracy. The iterative process ensured that each particle learned not only from its own best experience (pbest) but also from the global best solution (gbest), resulting in a cooperative search mechanism. This characteristic makes PSO particularly suitable for optimization problems involving complex, non-linear search spaces such as SVM parameter tuning.

The confusion matrix results after optimization further confirm the effectiveness of the proposed approach. The increase in True Positive and True Negative values indicates that the optimized model achieved better recognition of both positive and negative sentiments, while the reduction in False Positive and False Negative values suggests improved reliability in classification decisions. This balanced improvement is crucial in sentiment analysis applications, where misclassification can lead to misleading interpretations of user opinions and potentially incorrect decision-making by stakeholders.

In the context of user reviews for the Shopee application, these findings have important practical implications. A more accurate sentiment classification model enables stakeholders to better understand user satisfaction and dissatisfaction patterns, identify recurring issues, and evaluate the impact of application updates or service changes. By leveraging the PSO-optimized SVM model, organizations can extract more reliable insights from large volumes of user-generated text data, thereby supporting data-driven decision-making processes.

Overall, this study confirms that combining SVM with PSO optimization significantly enhances sentiment analysis performance on Indonesian-language reviews. The results align with previous studies that highlight the effectiveness of metaheuristic optimization techniques in improving machine learning models. However, this research further contributes by providing a detailed implementation and evaluation within the context of Indonesian e-commerce application reviews, thus enriching the existing body of knowledge and offering a practical framework for future sentiment analysis studies.

4. Conclusion

The results of this study confirm the successful implementation of sentiment analysis on Shopee user reviews sourced from the Google Play Store using an SVM classifier enhanced with Particle Swarm Optimization (PSO). The dataset comprised 1,000 Indonesian-language reviews collected from January to August 2025 and labeled into positive and negative sentiment categories. The research methodology was carried out in a sequential manner, encompassing data collection, text cleaning and preprocessing, feature weighting using TF-IDF, sentiment classification with SVM, optimization of model parameters using PSO, and performance assessment through confusion matrix analysis. The evaluation results reveal that the baseline SVM achieved an accuracy of 86.0%, while the optimized SVM model reached 90.0% accuracy, along with notable improvements across precision, recall, and F1-score metrics. This evidence highlights the effectiveness of PSO in improving the classification performance of SVM for sentiment analysis tasks in e-commerce applications.

Despite these promising results, this study has several limitations. First, the dataset used in this research was limited to 1,000 reviews collected from a single platform, namely the Google Play Store, which may not fully represent the overall opinions of Shopee users across different platforms or regions. Second, this study focused only on binary sentiment classification (positive and negative), without considering neutral sentiment or more fine-grained emotion categories. In addition, the analysis relied on the TF-IDF feature extraction method, which may not fully capture semantic relationships between words in complex textual data.

Future research can address these limitations by expanding the dataset size and incorporating reviews from multiple platforms, such as social media or other application stores, to obtain more comprehensive sentiment insights. Further studies may also explore multi-class sentiment classification or emotion-based analysis to capture more nuanced user opinions. Moreover, advanced feature extraction techniques or deep learning-based models, such as word embeddings or transformer-based architectures, can be integrated with metaheuristic optimization methods to further improve sentiment classification performance.

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