Jurnal Mandiri IT
Vol. 15 No. 1, July (2026), pp. 37-42

ISSN 2301-8984 (Print), 2809-1884 (Online)
Published by Institute of Computer Science

Analysis of user satisfaction with the seabank app using support vector machines (SVM)

Eko Yulianto[1], Nanang Nuryadi[2], Taufik Asra[3]
[1]Information System Department, Universitas Bina Sarana Informatika, Jakarta, Indonesia
[2]Computer Technology Department, Universitas Bina Sarana Informatika, Kampus Kota Tegal, Indonesia
[3]Software Engineering Department, Universitas Bina Sarana Informatika, Jakarta, Indonesia

ARTICLE INFO

Article history:

Received May 20, 2026
Revised May 30, 2026
Accepted Jun 9, 2026

Keywords:

Sentiment Analysis;
SMOTE;
Support Vector Machine;
Text Mining;
TF-IDF.

ABSTRACT

The development of financial technology (fintech) in Indonesia has driven the rapid growth of digital banks, one of which is SeaBank. User satisfaction with the SeaBank app is a crucial indicator for maintaining customer loyalty amid intense competition. This study aims to analyze user satisfaction with the SeaBank app based on reviews on the Google Play Store using the Support Vector Machine (SVM) method. Review data was classified into positive sentiment (satisfied) and negative sentiment (dissatisfied). The research stages included data collection, rating-based labeling, text preprocessing (including normalization of banking colloquial language), feature extraction using TF-IDF, handling imbalanced data with SMOTE, and classification using an RBF Kernel SVM. The results show that the application of SMOTE successfully addressed class imbalance, and SVM hyperparameter optimization yielded an accuracy of 89.14% with an F1-Score of 88.75%. The analysis findings indicate that the majority of users are satisfied with the convenience of free transactions, but there are significant complaints regarding OTP delays and errors in the login system.

Corresponding Author:

Eko Yulianto,
Information System,
Universitas Bina Sarana Informatika,
Jalan Kramat Raya No. 98, Senen, Jakarta Pusat, DKI Jakarta, 10410, Indonesia
Email: eko.eui@bsi.ac.id

1. INTRODUCTION

Digital transformation in Indonesia's banking sector has accelerated dramatically, marked by the emergence of digital banks offering services without physical branches (Khoirunisa et al., 2023) SeaBank, a banking entity under the Sea Group (Shopee) ecosystem, has emerged as a market disruptor by offering convenient financial transactions integrated with e-commerce platforms (Prabowo et al., 2025). In this highly competitive industry, user satisfaction is the key to business sustainability (Priatna, 2024).

One method for measuring user satisfaction in real-time and in an expressive manner is through the analysis of reviews published on the Google Play Store (Sanjaya et al., 2023). These reviews contain unstructured opinions, complaints, and suggestions, thus requiring further processing using text mining and Natural Language Processing (NLP) techniques (Hamzah, 2026). Sentiment analysis serves as a technique to classify such text into positive or negative polarity (Ariansyah & Kusmira, 2021).

Various algorithms have been used for sentiment classification, but Support Vector Machines (SVMs) have proven superior in handling high-dimensional data such as text (Lowell et al., 2025). SVMs work by finding the optimal hyperplane that maximizes the margin between classes (Setyawan, 2024). However, the main challenge in analyzing app review sentiment is data imbalance, where positive reviews often dominate, as well as the high use of slang and banking abbreviations that can reduce model accuracy (Shevira et al., 2022). The standardization of this slang and banking terminology is a crucial step in improving the quality of sentiment analysis (Mahendra et al., 2023). Without standardization, feature extraction methods like TF-IDF suffer from *feature sparsity*, where variations of the same complaint (e.g., "lemot", "lola", "nge-lag") are treated as separate, weak features instead of consolidating their weight under a single root word like "lambat" (slow). Furthermore, standardizing domain-specific terminology—such as transforming "gagal trf" into "gagal transfer"—ensures accurate semantic mapping. This prevents the system from misclassifying highly negative reviews as neutral simply because the core complaint words were unrecognizable to standard stemmers, thereby directly improving the model's precision and recall in identifying true user dissatisfaction.

Previous studies, such as those conducted by (Pratama et al., 2023) and (Ardiansyah et al., 2025), have applied SVM to various applications; however, several research gaps make SeaBank a highly relevant object of study in the context of digital banking sentiment analysis. First, most prior research focuses on traditional banks with physical legacy systems, whereas SeaBank represents a *digital-first bank* (neo-bank) where the application is the absolute sole point of interaction, making app reviews a much more critical indicator of satisfaction. Second, SeaBank possesses a unique cross-platform vocabulary due to its deep integration with the Shopee e-commerce ecosystem—a specific dynamic that previous studies have not explored. Third, there is a methodological gap; many prior studies highlight high overall accuracy metrics while ignoring the *accuracy paradox* caused by imbalanced data, a gap this study addresses through the application of SMOTE. Finally, SeaBank is in a phase of aggressive user growth, providing a timely snapshot of user sentiment regarding specific infrastructural growing pains. To address these gaps, few have specifically explored the SeaBank app by comprehensively implementing an approach to handle imbalanced data using SMOTE and colloquial normalization (Pratiwi et al., 2025). Therefore, this study proposes an analysis of user satisfaction with the SeaBank application using SVM with hyperparameter optimization to produce a classification model that is accurate, unbiased, and capable of providing a realistic picture of user sentiment (Darmawan & Dianta, 2023).

2. RESEARCH METHOD

This study adopts a Knowledge Discovery in Databases (KDD) approach. The research workflow is shown in Figure 1 (Shevira et al., 2022).

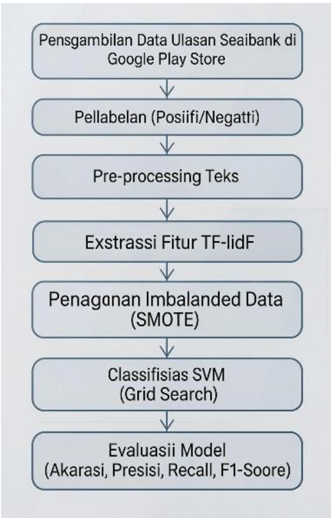

Figure 1. Sentiment analysis research workflow

Data Collection and Labeling

The data was collected using web scraping techniques on the SeaBank app review page on the Google Play Store, yielding 8,500 raw data points. Labeling used a rating-based approach, where 4- and 5-star ratings were labeled "Positive," 1- and 2-star ratings were labeled "Negative," and 3-star (neutral) ratings were ignored (Widodo et al., 2025). The rationale for using ratings as the primary reference for sentiment classification lies in their efficiency and scalability; manual annotation by human experts on thousands of reviews is highly time-consuming and prone to subjective inter-annotator bias. In contrast, app store ratings serve as an immediate, objective quantitative proxy provided by the users themselves to summarize their overall satisfaction. Furthermore, excluding the 3-star (neutral) ratings ensures the establishment of a strict binary margin, preventing ambiguous data from confusing the SVM's hyperplane during the training process.

Text Pre-processing

The text is stripped of special characters, converted to lowercase, tokenized, and stemmed using the Sastrawi library (Pardede & Darmawan, 2025). A crucial step is the application of a slang normalization dictionary customized for fintech terms (for example: “gagal top up” becomes “gagal isi saldo”) (Irawanto, 2026).

Classification and Evaluation

The data was split in an 80:20 ratio (training: testing). The rationale behind utilizing an 80:20 split is to achieve an optimal balance between model learning and evaluation reliability. Because text data transformed via TF-IDF results in high-dimensional features, the SVM algorithm requires a substantial volume of data (80%) to adequately map complex decision boundaries without underfitting. Simultaneously, retaining a 20% unseen test set provides a sufficiently large and statistically reliable sample to stabilize the evaluation metrics (Accuracy, Precision, Recall, F1-Score) when estimating the model's real-world generalization performance. On the training data, SMOTE was applied to balance the classes (Riza & Kurniawan, 2024). Next, an RBF Kernel SVM model was trained using Grid Search optimization for the parameters C Є {0.1, 1, 10} and γ Є {0.01, 0.1, 1}. Evaluation was performed using a Confusion Matrix to calculate Accuracy, Precision, Recall, and F1-Score (Islamey et al., 2026).

3. RESULTS AND DISCUSSIONS

Initial Data Distribution and SMOTE Implementation

Table 1 shows that the initial data set is highly skewed, with positive reviews accounting for 82.35% of the total (Sanjaya et al., 2023).

Table 1. The implementation of SMOTE

Sentiment Class	Initial Data Volume	Initial Percentage	Data Volume After SMOTE
Positive	5.600	82,35%	5.600
Negative	1.200	17,65%	5.600
Total	6.800	100%	11.200

This 82:18 imbalance could cause the model to predict only “Positive” in an attempt to achieve high accuracy (the accuracy paradox). Using the SMOTE technique, the minority class (negative) data was synthesized until it matched the size of the majority class (5,600 data points), resulting in a total synthetic dataset of 11,200 for the training process (Cahya et al., 2023).

SVM Hyperparameter Optimization

The search for the optimal parameters using grid search with cross-validation yielded the results shown in Table 2(Wainer & Fonseca, 2021).

Table 2. Results of the SVM hyperparameter grid

Kernel	Grade C	Value	Validation Accuracy (CV)
Linear	1	-	84,20%
RBF	1	0.1	85,40%
RBF	10	0.1	89,05%
RBF	10	1	86,15%

According to Table 2, the combination of the RBF kernel with C = 10 and γ = 0.1 yields the highest validation performance. A high C value indicates that the model imposes a heavy penalty on classification errors, resulting in a very strict decision boundary to distinguish between complaint and praise keywords (Harjanta et al., 2024).

Model Evaluation

The model with optimal parameters was tested on 20% of the test data (1,360 original data points, without SMOTE) (Mahendra et al., 2023). The results of the confusion matrix are summarized in Table 3.

Table 3. Matrix for the Test Data

Current \ Predictions	Negative Forecast	Predicted to be Positive
Negative News	198 (True Negative)	42 (False Positive)
Current Positive	105 (False Negative)	1.015 (True Positive)

Based on this matrix, evaluation metrics were calculated to assess how robust the model is to imbalanced data under real-world conditions (Hermawan et al., 2025) (Table 4).

Table 4. SVM model evaluation metrics

Metrics	Formula	Results
Accuracy	(TP+TN)/Total	89,14%
Presisi (Negatif)	TN/(TN+FP)	82,50%
Recall (Negatif)	TN/(TN+FN)	65,37%
F1-Score (Negatif)	2x(PresxRecall)/(Pres+Recall)	73,02%
F1-Score (Positif)	-	93,48%

The overall accuracy reached 89.14%, meaning the model successfully classified nearly 9 out of 10 reviews correctly and outperformed the accuracy of similar studies without SMOTE, which averaged between 80% and 84%(Lowell et al., 2025). The positive F1-Score is very high (93.48%), indicating that the model is excellent at recognizing praise. Although the negative Recall is slightly lower (65.37%) due to the fact that negative data is indeed very scarce in the real world, the negative precision (82.50%) shows that when the model classifies a review as a “complaint,” that prediction is highly reliable (Mardiyanto et al., 2023). The lower recall value for negative sentiment compared to positive sentiment is primarily attributed to the inherent characteristics of the real-world test set. Although SMOTE was applied to balance the training data, the 20% testing set retained the original, heavily skewed distribution. Because the model is evaluated against a significantly smaller pool of actual negative instances, and because SMOTE synthesizes data by interpolating between existing minority samples rather than generating entirely new linguistic contexts, the model remains slightly biased toward the majority class boundaries. Consequently, when encountering novel or atypical phrasing of complaints in the real-world test data, the model tends to miss these rare negative expressions (False Negatives), thereby depressing the negative recall score.

Analysis of SeaBank User Satisfaction Levels

Based on the interpretation of the TF-IDF features with the highest weights in each class, the following qualitative findings regarding user satisfaction can be concluded:

Sources of Satisfaction (Positive):

The keywords with the highest weight are “free,” “transfer,” “easy,” “fast,” and “Shopee.” This indicates that SeaBank’s strategy of offering interbank transfer services with no administrative fees and direct integration with ShopeePay balances is highly appreciated by users and serves as its primary Unique Selling Proposition (USP), setting it apart from competitors.

Sources of Dissatisfaction (Negative):

The main keywords in the negative category are “OTP,” “long,” “failed,” “error,” and “login.” These findings indicate that while SeaBank’s transaction features are quite good, its security infrastructure and servers remain the primary source of complaints. The implications of these negative sentiment findings for the development of the app's security and authentication infrastructure are critical. The frequent complaints regarding OTP delays and login errors signal that the back-end authentication mechanisms are acting as a bottleneck, struggling to scale with the bank's rapid user growth. For developers, this necessitates an immediate strategic pivot from merely expanding front-end transactional features to reinforcing back-end reliability. Practical development steps must include optimizing SMS gateway routing to reduce OTP latency, implementing fallback authentication methods (such as push notifications or biometric logins to bypass SMS delays), and enhancing server load balancing to prevent login crashes during peak traffic. If these security infrastructural bottlenecks are not promptly addressed, they pose a severe risk of high churn rates, as users will likely abandon the app despite its attractive free-transfer benefits (Setiawan & Hasan, 2025).

4. CONCLUSION

This study successfully analyzed user satisfaction with the SeaBank app using the Support Vector Machine (SVM) algorithm. The application of banking colloquial text normalization, TF-IDF feature extraction, and handling of imbalanced data using SMOTE proved effective in improving modeling quality. Test results show that the RBF Kernel SVM model with parameter optimization ($C = 10$, $\gamma = 0.1$) is capable of classifying review sentiment with 89.14% accuracy and an excellent average F1-Score. Substantively, SeaBank users' satisfaction levels are generally very high, driven by free transfer features and e-commerce integration. However, there is a significant satisfaction gap in technical aspects, particularly regarding OTP system delays and login failures. For developers, these findings can serve as strategic recommendations to prioritize improvements to the authentication server infrastructure in the future. The implications of these findings for the development of SeaBank's customer retention strategies are twofold. Firstly, management must aggressively leverage its identified Unique Selling Proposition (USP)—free transfers and seamless Shopee ecosystem integration—as the primary anchor for loyalty programs, potentially transforming highly satisfied users into brand advocates through targeted referral incentives. Secondly, and more critically, the retention strategy must urgently pivot from relying solely on promotional acquisition (such as cashbacks) to operational risk mitigation. Because authentication friction (OTP delays and login errors) directly blocks user access and triggers immediate frustration, it poses a severe threat of customer churn. Therefore, SeaBank should implement proactive customer success interventions, such as automated in-app troubleshooting or direct customer support outreach triggered by failed login attempts, to salvage the user experience before frustration leads to app abandonment. Furthermore, several directions for future research can deepen our understanding of user satisfaction regarding digital banking services. First, transitioning from binary sentiment classification to Aspect-Based Sentiment Analysis (ABSA) would allow researchers to automatically extract and evaluate sentiment toward specific granular features (e.g., UI design, transaction speed, customer service) rather than evaluating the entire review as a single entity. Second, exploring advanced deep learning architectures, such as transformer-based models like IndoBERT, could potentially capture deeper contextual nuances and complex sarcasm in Indonesian colloquial language better than the traditional SVM-TF-IDF approach. Finally, conducting a longitudinal sentiment analysis by tracking review dynamics across multiple platforms (e.g., Twitter/X, the Apple App Store, and in-app surveys) over time would provide a more holistic and dynamic understanding of how user satisfaction fluctuates in response to specific application updates, policy changes, or competitor movements.

REFERENCES

Ardiansyah, D., Aryanti, R., & Fitriani, E. (2025). Analisis Sentimen Pengguna GoPay pada Layanan Keuangan Digital dengan Perbandingan Naïve Bayes dan SVM. *Profitabilitas*, *5*(2), 83–89.

Ariansyah, A., & Kusmira, M. (2021). ANALISIS SENTIMEN PENGARUH PEMBELAJARAN DARING TERHADAP MOTIVASI BELAJAR DI MASA PANDEMI MENGGUNAKAN NAIVE BAYES DAN SVM. *Faktor Exacta*, *14*(3), 100. https://doi.org/10.30998/faktorexacta.v14i3.10325

Cahya, L. D., Luthfiarta, A., Krisna, J. I. T., Winarno, S., & Nugraha, A. (2023). Improving multi-label classification performance on imbalanced datasets through smote technique and data augmentation using indobert model. *Jurnal Nasional Teknologi Dan Sistem Informasi*, *9*(3), 290–298.

Dhea Khoirunisa, Nia Desy Arifiani, Muhammad Rizqi Maulana, & Endang Kartini Panggiarti. (2023). Analisis Peran Otoritas Jasa Keuangan (Ojk) dalam Mengawasi Pelayanan Pada Perusahaan Financial Technology (Fintech) di Indonesia. *Inisiatif: Jurnal Ekonomi, Akuntansi Dan Manajemen*, *2*(3), 127–132. https://doi.org/10.30640/inisiatif.v2i3.1108

Hamzah, M. (2026). Penerapan Natural Language Processing (NLP) dalam analisis sentimen pada media sosial. *JICR: Journal Of Informatics and Computer Research*, *1*(1).

Harjanta, A. T., Herlambang, B. A., & Fahmi, S. (2024). Analisis Sentimen Review Pelanggan Lazada dengan Sastrawi Stemmer dan SVM-PSO untuk Memahami Respon Pengguna. *J-INTECH*, *12*(02), 330–339.

Hermawan, M. A., Faqih, A., & Dwilestari, G. (2025). Implementasi Akurasi Model Naive Bayes Menggunakan Smote Dalam Analisis Sentimen Pengguna Aplikasi Brimo. *Jurnal Informatika Dan Teknik Elektro Terapan*, *13*(1).

Irawanto, I. (2026). Penerapan Natural Language Processing (NLP) dalam Analisis Sentimen pada Media Sosial. *Journal of Informatics and Computer Research (JICR)*, *xx, No. xx*. https://doi.org/10.1007/s41060-018-0111-1

Islamey, R., Winiarti, S., & Riadi, I. (2026). Analisis Komparatif Random Forest dan Support Vector Machine untuk Klasifikasi Tingkat Keparahan Serangan Siber. *Euler: Jurnal Ilmiah Matematika, Sains Dan Teknologi*, *14*(1), 1–14.

Lowell, A., Lowell, A., Candra, K., Indra, E., & Informasi, S. (2025). *JURNAL MEDIA INFORMATIKA [JUMIN] Perbandingan Metode Support Vector Machine (SVM) Dan Naive Bayes Pada Analisis Sentimen Ulasan Aplikasi OVO*.

Mahendra, M. H., Murdiansyah, D. T., & Lhaksmana, K. M. (2023). Analisis Sentimen Tweet COVID-19 menggunakan K-Nearest Neighbors dengan TF-IDF dan Ekstraksi Fitur CountVectorizer. *Dike*, *1*(2), 37–43.

Maisat Eka Darmawan, Z., & Fauzan Dianta, A. (2023). Implementasi Optimasi Hyperparameter GridSearchCV Pada Sistem Prediksi Serangan Jantung Menggunakan SVM. *Teknologi*, *13*(1), 8–15. https://doi.org/10.26594/teknologi.v13i1.3098

Mardiyanto, R. O., Kusrini, K., & Wibowo, F. W. (2023). Analisis Sentimen Pengguna Aplikasi Bank Syariah Indonesia dengan menggunakan Algoritma Support Vector Machine (SVM). *TEKNIMEDIA: Teknologi Informasi Dan Multimedia*, *4*(1), 9–15.

Pardede, J., & Darmawan, D. (2025). Perbandingan Algoritma Stemming Porter, Sastrawi, Idris, Dan Arifin & Setiono Pada Dokumen Teks Bahasa Indonesia. *Jurnal Teknologi Informasi Dan Ilmu Komputer*, *12*(1), 69–76.

Pratama, M. R., Ramadha, Y. R., & Komara, M. A. (2023). Analisis sentimen BRImo dan BCA mobile menggunakan support vector machine dan lexicon based. *Jutisi: Jurnal Ilmiah Teknik Informatika Dan Sistem Informasi*, *12*(3), 1439–1450.

Pratiwi, F. S., Agung Barata, M., & Ardianti, A. D. (2025). IMPLEMENTASI METODE SMOTE DAN RANDOM OVER-SAMPLING PADA ALGORITMA MACHINE LEARNING UNTUK PREDIKSI CUSTOMER CHURN DI SEKTOR PERBANKAN. *Jurnal Sistem Informasi Dan Informatika (Simika)*, *8*(1). https://www.kaggle.com/datasets/gauravtopre/bank-customer-churn-dataset/data

Priatna, W. (2024). Dampak Pengambilan Sampel Data untuk Optimalisasi Data tidak seimbang pada Klasifikasi Penipuan Transaksi E-Commerce. *The Indonesian Journal of Computer Science*, *13*(2).

Setiawan, A., & Hasan, F. N. (2025). Analisis Sentimen Tanggapan Pengguna Aplikasi Bale by BTN Menggunakan Metode Support Vector Machine (SVM). *STORAGE: Jurnal Ilmiah Teknik Dan Ilmu Komputer*, *4*(4), 315–326.

Setyawan, M. F. (2024). Implementasi Support Vector Machine (SVM) pada Klasifikasi Jenis Tanah Memanfaatkan Fitur RGB. *SISFOTENIKA*, *14*(2), 175–184.

Shevira, S., Made, I., Suarjaya, A. D., & Wira Buana, P. (2022). Pengaruh Kombinasi dan Urutan Pre-Processing pada Tweets Bahasa Indonesia. In *JITTER-Jurnal Ilmiah Teknologi dan Komputer* (Vol. 3, Number 2).

Tania Puspa Rahayu Sanjaya, Ahmad Fauzi, & Anis Fitri Nur Masruriyah. (2023). Analisis sentimen ulasan pada e-commerce shopee menggunakan algoritma naive bayes dan support vector machine. *INFOTECH: Jurnal Informatika & Teknologi*, *4*(1), 16–26. https://doi.org/10.37373/infotech.v4i1.422

Wainer, J., & Fonseca, P. (2021). How to tune the RBF SVM hyperparameters? An empirical evaluation of 18 search algorithms. *Artificial Intelligence Review*, *54*(6), 4771–4797.

Widodo, A., Agus Herlambang, B., & Renaldy, R. (2025). Optimizing Support Vector Machine (SVM) for Sentiment Analysis of Blu by BCA Reviews with Chi-Square. In *Journal of Applied Informatics and Computing (JAIC)* (Vol. 9, Number 5). http://jurnal.polibatam.ac.id/index.php/JAIC