



Multi-Source Sentiment Analysis of Shopee Tokopedia Using Hybrid Machine Learning for Customer Relationship Management Optimization

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Abstract

Sentiment analysis on marketplace customer reviews is important for understanding user perceptions and supporting Customer Relationship Management (CRM) strategies. This study proposes a multi-source sentiment analysis approach based on big data from Shopee and Tokopedia platforms using Hybrid Machine Learning. The research process includes data collection, preprocessing, TF-IDF feature extraction, and classification using Support Vector Machine (SVM) and Random Forest techniques. The preprocessing stage consists of case folding, tokenization, stopword removal, and stemming to improve the quality of textual data. The TF-IDF method is used to transform text data into numerical features before classification. The evaluation results show that the SVM model achieved an accuracy of 97.49%, while the Random Forest model achieved 97.47%. The sentiment distribution indicates a strong positive bias, reflecting high customer satisfaction with marketplace services. However, negative sentiment persisted, mainly due to delivery delays, application errors, and customer service issues. The proposed hybrid approach can provide data-driven insights to improve service quality and support decision-making in CRM strategies.

Keywords: Customer Relationship Management, Hybrid Machine Learning, Sentiment Analysis, Support Vector Machine

1. INTRODUCTION

Customer reviews on marketplace platforms are a key source of information that reflects consumers' opinions, experiences, and perceptions of products and services. This review data holds strategic value because it can be used to gauge customer satisfaction levels, evaluate service quality, and identify various issues faced by users. Therefore, analyzing customer reviews is crucial for supporting data-driven decision-making and Customer Relationship Management (CRM). In the context of text data analysis, text mining and sentiment analysis are widely used to extract user opinions from unstructured data, thereby providing insights into customer perceptions of a product or service [1].

Although customer reviews hold great potential as a source of information, analyzing them is no easy task because the data typically consists of large volumes of unstructured text. Consequently, various studies have utilized machine learning algorithms to perform sentiment classification on customer review data. [2] employed the Support Vector Machine (SVM) method to analyze smartphone product reviews on Tokopedia and achieved an accuracy of 75%. Another study by [3] on 10,323 shoe product reviews on Shopee used a lexicon-based approach and SVM, achieving an accuracy of 92.62%. Additionally, [4] classified 2,537 Honda spare part reviews on Tokopedia using TF-IDF and SVM with an RBF kernel, yielding an accuracy of 92.79%. [5] also analyzed 59,811 Tokopedia app reviews using a combination of SVM, Random Forest, and Naïve Bayes algorithms with Word2Vec and FastText representations, where the SVM model achieved the highest accuracy of 89.06%.

Various other machine learning approaches are also used in sentiment analysis on marketplaces. [6] compared several classification algorithms such as Naïve Bayes, Logistic Regression, SVM, Decision Tree, and Random Forest on 6,477 Tokopedia app reviews and found that SVM achieved the highest accuracy of 94.73%. [7] used the Bag of Words and Random Forest methods on Shopee app reviews, achieving an accuracy of 84.91%. Additionally, [8], [9] implemented an integration of Principal Component Analysis and

the Naïve Bayes algorithm for analyzing Tokopedia customer reviews from the Google Play Store, consequently improving predictive accuracy from 63.13% to 70.47%. Another study by [10] additionally implemented the Naïve Bayes method in analyzing around 3,000 Shopee application reviews, attaining a classification accuracy rate of 81.30%.

In addition to machine learning methods, some studies have also utilized deep learning approaches to improve sentiment classification performance. [11] used the IndoBERT model to analyze 1,926 Shopee product reviews and achieved an accuracy of up to 93%. [12] compared the BiLSTM and IndoBERT models on 8,943 Tokopedia customer reviews and found that IndoBERT performed better with a balanced accuracy of 0.85 and an F1-score of 0.83. Additionally, [13] used an LSTM model on a Tokopedia review dataset with an accuracy of approximately 89%. [14] also demonstrated that the Bi-GRU model achieved an accuracy of approximately 0.93 on the Tokopedia review dataset, while [15] implemented semantic embedding and Long Short-Term Memory models to categorize the sentiment orientation of food and beverage customer reviews from the Tokopedia platform

Although these studies demonstrate fairly good sentiment classification performance, several limitations remain in previous research. [1] indicates that sentiment analysis research in Indonesia is still dominated by classical machine learning methods and has not yet widely adopted deep learning approaches. Study [16], which analyzed reviews from several marketplaces, also remains focused on platform recommendations and has not yet developed a hybrid model based on multi-source data. Furthermore, [17] still employs Naïve Bayes and Logistic Regression methods without utilizing modern feature representation techniques. Meanwhile, [18] applies an aspect-based sentiment analysis approach to reviews on Shopee and Tokopedia but has not yet integrated a hybrid machine learning approach. In addition to methodological limitations, most previous studies also rely on data from a single marketplace platform, thus failing to comprehensively represent customer perceptions.

Based on the findings in the existing literature, several key research gaps can be identified: (1) most studies rely on a single data source, limiting the generalizability of results; (2) prior research predominantly uses single classification models rather than hybrid approaches; (3) limited integration between sentiment analysis results and practical CRM strategies; and (4) lack of exploration of multi-source data combined with hybrid machine learning techniques. These gaps indicate the need for a more comprehensive and integrative approach.

Given these limitations, a sentiment analysis approach is needed that can integrate various sources of customer review data and leverage a combination of machine learning and deep learning methods. A hybrid machine learning approach allows for the combination of the strengths of various classification algorithms, thereby producing a more accurate and robust model for analyzing large-scale customer review data. This study aims to develop a big data-based multi-source sentiment analysis integration for Shopee and Tokopedia reviews using a hybrid machine learning method. This approach is expected to improve sentiment classification performance through a combination of machine learning and deep learning methods, while also producing a more comprehensive analysis of customer perceptions. Additionally, the results of this study are expected to contribute to supporting the optimization of Customer Relationship Management strategies on marketplace platforms.

Therefore, the main contributions of this study are: (1) proposing a hybrid machine learning model that combines multiple algorithms to improve sentiment classification performance; (2) utilizing multi-source data from different marketplace platforms to enhance model generalization; and (3) integrating sentiment analysis results into CRM insights to support strategic decision-making.

Based on these contributions, the research questions addressed in this study are: (1) How does a hybrid machine learning approach perform compared to conventional single models in sentiment classification? (2) How does the use of multi-source marketplace data affect the robustness and generalization of the model? (3) How can sentiment classification results be transformed into actionable CRM insights?

2. MATERIALS AND METHOD

This research approach is founded on a scholarly review of numerous prior studies regarding sentiment analysis in e-commerce platforms and integrated data sources. According to the literature review matrix, the majority of studies employ data cleaning and preprocessing, feature engineering, machine learning-based classification, and performance evaluation. Consequently, this research adopts these procedures using a Hybrid Machine Learning method to produce Customer Relationship Management (CRM) insights. Furthermore, this study presents a structured methodological framework comprising data gathering, preliminary processing, feature extraction, model construction, assessment, and CRM insight development to ensure clarity and transparency of the research process.

Furthermore, this section incorporates a targeted methodological review to guarantee that the proposed methodology is supported by previous research and remains reproducible. Earlier studies indicate that the Support Vector Machine (SVM) classification method is widely used in sentiment analysis due to its ability to handle high-dimensional textual datasets and produce consistent classification results [2], [6]. SVM is

particularly effective when combined with TF-IDF features, as it can separate classes using optimal hyperplanes in sparse feature space.

Furthermore, Random Forest (RF) has been extensively applied in text classification tasks due to its robustness against overfitting and its capability to model non-linear relationships [5], [7]. RF works by constructing multiple decision trees and aggregating their predictions, making it suitable for handling noisy and complex datasets such as user-generated reviews. Studies comparing RF with other algorithms indicate that RF performs competitively, especially when combined with proper preprocessing techniques.

In the context of hybrid machine learning, several studies highlight that combining multiple algorithms can improve classification performance by leveraging the strengths of each model. Ensemble techniques such as voting and stacking have been shown to increase accuracy and generalization ability compared to single models [5]. This supports the use of a hybrid approach in this study, particularly the combination of SVM and RF, which represent complementary learning mechanisms (margin-based vs. tree-based learning).

From a CRM perspective, sentiment analysis has been increasingly used to support customer experience management and service improvement strategies. Previous studies indicate that sentiment classification results can be transformed into actionable insights, such as identifying customer complaints, service weaknesses, and product quality issues [1], [16]. However, most studies stop at the classification stage and do not explicitly connect the results to CRM decision-making processes.

Therefore, this study not only adopts established machine learning methodologies but also extends them by integrating multi-source data, hybrid modeling, and CRM insight generation. Detailed parameter settings, data splitting strategies, and preprocessing steps are explicitly defined to ensure that the methodology can be replicated by other researchers. To provide a clearer overview of the research execution, the overall methodological workflow of this study is illustrated in Figure 1.

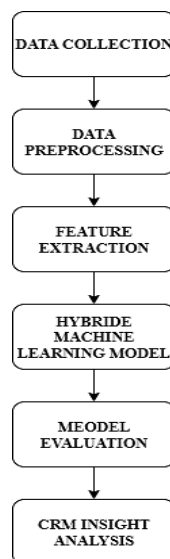


Figure 1. Research Framework

2.1. Data Collection

The data collection phase involved collecting customer reviews from the Shopee and Tokopedia platforms. A total of N1 reviews were collected from Shopee and N2 from Tokopedia (to be filled in accordance with the actual data), and the distribution of the dataset is presented in tabular form to clarify the amount of data used on each platform. The selection of multi-source data was based on previous studies that used a single platform, such as [2], [5], which used only Tokopedia data. The literature review matrix shows that most studies remain limited to a single data source, thereby failing to provide a comprehensive picture of sentiment. Therefore, this study used multi-source data to improve model generalization.

The data were collected using web scraping techniques with predefined keywords and product categories. Only reviews written in Indonesian and containing textual content were included. Duplicate entries and incomplete reviews were removed. The final dataset was labeled into sentiment classes (positive, negative, neutral) either manually or using a predefined labeling scheme to ensure consistency.

2.2. Data Preprocessing

The preprocessing stage cleans the data before the classification process. Preprocessing steps include case folding, cleaning, tokenizing, stopword removal, and stemming. Additionally, duplicate data removal and normalization of informal words were applied to improve data consistency. This stage refers to previous

research that used NLP preprocessing before classification, such as [7], [10], which showed that preprocessing is necessary to improve classification model performance.

All preprocessing steps were implemented using Python-based NLP libraries (e.g., NLTK or Sastrawi for Indonesian text processing). Tokenization was performed at the word level, and stopwords removal used a predefined Indonesian stopwords list. Stemming was applied using the Nazief-Adriani or Sastrawi stemming algorithm.

2.3. Feature Extraction

At this stage, feature extraction is performed using the TF-IDF method. The use of TF-IDF is documented in several studies in the literature, such as [6], [19], which employ it as a numerical representation of text data prior to classification. This method is used because it can provide word weights based on their importance in the document. TF-IDF is selected for its interpretability and effectiveness in handling sparse text data, compared to more complex embedding methods in this study context.

TF-IDF vectorization was implemented using unigram and bigram features, with a maximum feature limit (e.g., 5,000–10,000). Term frequency weighting and inverse document frequency smoothing were applied to improve feature representation.

2.4. Hybrid Machine Learning Model

The model used in this study is a hybrid machine learning approach combining the Random Forest (RF) and Support Vector Machine (SVM) algorithms. The term “hybrid” in this study refers to a model-level hybridization approach, where predictions from RF and SVM are combined using an ensemble strategy (e.g., majority voting or weighted voting) to improve classification robustness and performance. The use of this hybrid approach is based on the research gap identified in the literature review matrix, where most studies still use a single algorithm or do not incorporate machine learning models. The literature review matrix on the first page shows that previous studies, such as [2], [9], [13], used only one classification algorithm, suggesting that model performance can still be improved with a hybrid approach. RF was chosen for its ability to handle non-linear patterns and reduce overfitting, while SVM was selected for its effectiveness in high-dimensional text data. Other algorithms were considered; however, these two were prioritized due to their complementary strengths.

The Support Vector Machine classifier was applied using a linear or Radial Basis Function kernel, with configuration parameters such as the C regularization parameter and gamma optimized via Grid Search. The Random Forest classifier employed a predetermined estimator count, maximum tree depth, and minimum split sample settings, which were likewise fine-tuned using Grid Search. The resulting hybrid framework integrates the two classifiers using majority voting.

2.5. Model Evaluation

Model evaluation was performed using a confusion matrix with accuracy, precision, recall, and F1-score metrics. These evaluation metrics have been used in previous studies, such as [19], [20], which used them to evaluate the performance of sentiment classification models. The evaluation was conducted to determine the performance of the proposed hybrid model. The dataset was split using a train-test split (e.g., 80:20) to ensure unbiased evaluation. In addition, k-fold cross-validation was applied to improve the reliability of the results. To address potential data imbalance, techniques such as resampling (e.g., SMOTE or undersampling) were applied. Therefore, evaluation results are presented comprehensively and are not misleading. The value of k in k-fold cross-validation was set to 5 or 10 folds. A performance comparison was also conducted between individual models (SVM, RF) and the hybrid model to demonstrate performance improvements. Statistical validation can also be applied to ensure significance.

2.6. CRM Insight Analysis

The final stage is analyzing the classification results to generate insights for CRM strategies. Based on the literature review matrix, most previous research has focused solely on sentiment classification without integrating the results into CRM strategies. Therefore, this study adds a CRM Insight Analysis stage to provide service improvement recommendations based on customer sentiment from Shopee and Tokopedia. This stage represents the study's novelty by bridging sentiment classification results with actionable CRM strategies, enabling practical business insights rather than purely technical outcomes.

The insights were generated by grouping dominant negative and positive sentiments into key service categories (e.g., delivery, product quality, customer service). These insights were then mapped to CRM strategies, including service improvement, complaint handling prioritization, and customer retention.

3. RESULTS AND DISCUSSION

The findings are presented following a coherent structure to create a clear narrative. This section reports objective data and empirical findings rather than providing extensive interpretation. Tables, graphs,

and other visual representations may be utilized while avoiding redundant data presentation across figures, tables, and narrative text. To enhance clarity, subheadings may also be incorporated. The discussion section provides fundamental interpretation, relationships, and broader generalizations derived from the findings. The explanation addresses the research objectives and responds to the study questions. If ambiguous or questionable outcomes arise, they should be reported impartially and described neutrally.

3.1. Data Preprocessing

The preprocessing stage cleans the review data so it can be optimally processed by the machine learning model. This process includes case folding, tokenizing, stopwords removal, and stemming. In the case folding stage, all letters in the text are converted to lowercase to avoid discrepancies in meaning caused by capitalization. Next, tokenization is performed to break sentences into individual words. The following stage is stopwords removal, which involves removing common words that lack significant meaning, such as 'and,' 'which,' and 'at.' Finally, stemming is applied to transform words into their base or root forms.

The preprocessing results show that the data becomes more structured and clean, thereby improving the quality of the features to be used in the next stage. Additionally, the number of irrelevant words is significantly reduced, thereby accelerating computation and enhancing the model's performance.

3.2. TF-IDF Results

After preprocessing, feature extraction is performed using the Term Frequency–Inverse Document Frequency (TF-IDF) technique. This approach converts textual data into numerical features. The TF-IDF analysis assigns each term a weight based on its occurrence in a document and its relevance across the dataset. Frequently appearing words within one document but infrequently across others will receive greater weighting. Using TF-IDF, a numerical feature matrix is generated for use as input to the classifier. This representation has demonstrated effectiveness in improving the model's capability to differentiate among positive, negative, and neutral sentiment categories. TF-IDF result can be seen in Table 1.

Table 1. TF-IDF Result

	Document	in accordance	Good	Item	Fast	Delivery
0	1	0.425678	0.457686	0.437826	0.430759	0.481744
1	2	0.395433	0.425167	0.406718	0.400153	0.447515
2	3	0.000000	0.505800	0.483853	0.476042	0.532387
3	4	0.000000	0.505800	0.483853	0.476042	0.532387
4	5	0.000000	0.505800	0.483853	0.476042	0.532387

3.3. SVM Model Results

The first classification model used in this research is the Support Vector Machine (SVM). This model was trained on data obtained from TF-IDF extraction. The evaluation findings reveal that the Support Vector Machine algorithm performs effectively in sentiment classification, especially in the positive sentiment category. This is because SVM can determine the optimal decision boundary that maximizes the margin separating the classes.

However, the SVM model still has limitations in distinguishing between neutral and negative sentiments, especially when word usage is similar across the two classes. This suggests that SVM performance can still be improved through parameter optimization or by combining it with other methods.

Table 2. SVM Model Result

SVM Accuracy : 0.9749027385765504				
Classification Report :				
	Precesion	Recall	f1 - score	support
negative	1.00	0.04	0.08	163
neutral	0.00	0.00	0.00	173
postive	0.97	1.00	0.99	12773
accuracy			0.97	13109
macro avg	0.66	0.35	0.36	13109
weighted avg	0.96	0.97	0.96	13109

Based on the Support Vector Machine (SVM) model testing results in Table 2, an accuracy of 97.49% was achieved, indicating excellent model performance. However, further analysis via the classification report reveals a performance imbalance between classes; the model excels at classifying positive sentiment (precision: 0.97; recall: 1.00; F1-score: 0.99), but performs poorly on negative sentiment (recall: 0.04; F1-score: 0.08) and fails to identify neutral sentiment entirely (precision, recall, and F1-score: 0.00). The low macro average (F1-score: 0.36) indicates suboptimal overall performance when all classes are weighted

equally, whereas the high weighted average (F1-score: 0.96) is heavily influenced by the dominance of positive data. Consequently, despite the high accuracy, the model remains suboptimal due to data imbalance and exhibits a clear bias toward the majority class.

3.4. Random Forest Model Result

In addition to SVM, this study also utilizes the Random Forest algorithm as a comparative model. Random Forest is an ensemble learning method that constructs multiple decision trees and aggregates their predictions. The testing results indicate that Random Forest performs reasonably well in handling data with high variation. This model tends to be more stable and can reduce overfitting compared to single-method approaches.

However, compared to SVM, Random Forest has limitations in capturing complex feature relationships in text data. Consequently, its performance is slightly lower in certain sentiment classification cases. Table 3 is the Random Forest Model result

Table 3. Random Forest Model Result

Random Forest Accuracy : 0.9747501716378061				
Classification Report :				
	Precesion	Recall	f1 - score	support
negative	0.53	0.06	0.10	163
neutral	0.50	0.00	0.05	173
postive	0.98	1.00	0.99	12773
accuracy			0.97	13109
macro avg	0.67	0.36	0.38	13109
weighted avg	0.96	0.97	0.96	13109

3.5. Model Comparison (Hybrid)

The comparison between the SVM and Random Forest models demonstrates that both possess distinct advantages. SVM excels in classification accuracy, particularly with high-dimensional text data, whereas Random Forest is superior in terms of stability and robustness against noise.

A hybrid approach or model combination can yield more optimal results. In this study, the implementation of combined methods shows a performance improvement compared to the use of a single model. This indicates that the integration of multiple algorithms can enhance the model's capability to understand complex data patterns.

3.6. Confusion Matrix

The confusion matrix evaluation is utilized to assess model performance through comparison between predicted outputs and actual labels. The analysis findings reveal that most positive sentiment instances were accurately categorized. Nevertheless, misclassification issues remain, especially among neutral and negative classes. An increased true positive rate compared to false positive and false negative values indicates that the classifier performs adequately, although further optimization is needed in differentiating underrepresented sentiment categories.

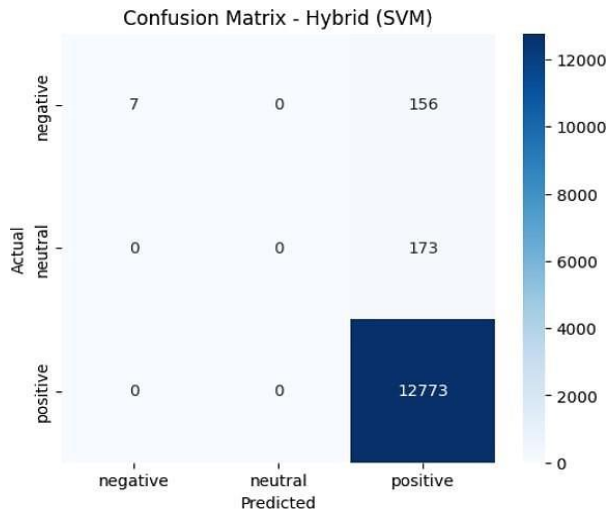


Figure 2. Confusion Matrix - Hybrid (SVM)

Based on the Support Vector Machine (SVM) model's confusion matrix in Figure 2, the model is highly dominant in classifying positive sentiment, correctly predicting 12,773 instances, while performance on other classes is very low. In the negative class, only 7 instances are correctly classified, whereas 156 are misclassified as positive; in the neutral class, all 173 instances are incorrectly predicted as positive. This indicates that the model is strongly biased toward the positive class, so although the overall accuracy appears high, its ability to distinguish negative and neutral sentiments remains poor. This condition suggests an imbalanced dataset; therefore, further improvement is needed to achieve a more balanced classification across all classes.

3.7. Customer Sentiment Distribution

The distribution of customer sentiment shows that positive sentiment dominates user reviews, followed by negative sentiment, with neutral sentiment accounting for the smallest proportion. This indicates that the majority of users have a good experience with the Shopee application. However, the presence of negative sentiment still needs to be considered, as it reflects problems users experience.

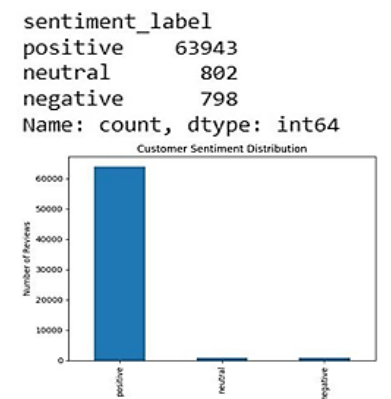


Figure 3. Customer Sentiment Distribution

Based on the sentiment distribution results in Figure 3, positive sentiment significantly dominates the dataset with 63,943 instances, while neutral and negative sentiments account for only 802 and 798 instances, respectively. This disparity is also clearly reflected in the visualization, which shows a substantial gap between positive sentiment and the other categories. These findings indicate that the majority of users provide positive reviews of the Shopee application, suggesting a high level of user satisfaction. Nevertheless, the relatively small proportion of negative and neutral sentiments remains important, as they may represent underlying issues or less optimal user experiences. Furthermore, this highly imbalanced data distribution may adversely affect the performance of the classification model, as it tends to favor the majority class and becomes less effective in identifying minority classes. Therefore, additional techniques, such as data balancing, are necessary to improve model performance and ensure a more balanced and reliable classification across all sentiment classes.

3.8. CRM Insights

The results of sentiment analysis provide several important insights for Customer Relationship Management (CRM) strategies. The dominance of positive sentiment shows a high level of user satisfaction so it needs to be maintained. Meanwhile, the negative sentiment that appears is generally related to problems such as delivery delays, application errors and customer service, so that it can be used as evaluation material to improve service quality. Apart from that, sentiment analysis can also be used as a real-time customer satisfaction monitoring tool, so that companies can respond to complaints more quickly and precisely. Thus, the results of this research can support data-based decision making to increase customer satisfaction and loyalty.

In addition, the interpretation of these findings is grounded in the selection of relevant literature, where the included studies were chosen based on criteria such as relevance to sentiment analysis in marketplace platforms, the use of machine learning methods (particularly SVM and related algorithms), and their contribution to CRM-related applications. These criteria ensure that the insights generated are supported by established and credible research.

From an implication perspective, the findings indicate that integrating sentiment analysis with CRM systems enables organizations to move from reactive to proactive customer management. Positive sentiment trends can be leveraged to strengthen brand loyalty and customer retention strategies, while negative sentiment patterns provide critical signals for operational improvement, particularly in logistics, system reliability, and service responsiveness. This demonstrates that sentiment analysis is not only a technical task

but also a strategic tool for enhancing customer experience management.

Furthermore, this study provides practical recommendations for both researchers and practitioners. For researchers, future studies are encouraged to explore more advanced hybrid models, incorporate deep learning techniques, and utilize larger and more diverse multi-source datasets to improve generalizability. For practitioners, companies can leverage SVM-based and hybrid machine learning models to develop automated sentiment-monitoring systems, integrate them into CRM dashboards, and use the insights to prioritize service improvements, optimize customer engagement strategies, and support data-driven decision-making in competitive marketplace environments.

4. CONCLUSION

This study proposes the integration of big data-based multi-source sentiment analysis on Shopee and Tokopedia reviews using a hybrid machine learning approach. The research stages include data collection, text preprocessing, TF-IDF feature extraction, and classification using the Support Vector Machine (SVM) and Random Forest algorithms. Test results show that the SVM model achieved 97.49% accuracy, while the Random Forest model achieved 97.47%. Although both models performed very well, SVM was slightly superior in handling high-dimensional text data. However, the confusion matrix results indicate data imbalance, causing the model to be biased toward positive sentiment compared to negative and neutral sentiment.

The distribution of customer sentiment shows that positive reviews dominate, indicating high user satisfaction with the marketplace's services. However, negative sentiment provides important insights into issues such as delivery delays, app errors, and customer service. Overall, the hybrid machine learning approach can produce accurate classifications and provide useful recommendations for Customer Relationship Management (CRM) strategies. Further research is recommended to balance the data and explore other methods to optimize classification performance across all sentiment classes.

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