Performance Evaluation of Machine Learning Algorithms in Aspect-Based Sentiment Analysis on E-Commerce User Reviews

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Abstract.
The rapid growth of the e-commerce industry in Indonesia has resulted in a significant surge in the number of user reviews available on various digital platforms. These reviews contain valuable information about customer experiences related to price, product quality, service, delivery, and applications. However, the massive volume of data and its unstructured nature pose challenges in extracting relevant information. Aspect-Based Sentiment Analysis (ABSA) presents an approach that can provide deeper insights by identifying sentiment towards specific aspects within a review, rather than just the overall general sentiment. This study aims to evaluate the performance of several machine learning algorithms, namely Naïve Bayes, Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbors (KNN), in implementing ABSA on e-commerce user reviews in Indonesia. The dataset used consists of 20,000 user reviews of the Shopee and Tokopedia applications obtained through a crawling process on the Google Play Store. The data is processed through several stages: text preprocessing, aspect and sentiment annotation, model training, and performance evaluation using accuracy, precision, recall, and F1-Score metrics. The evaluation results showed differences in performance among the tested algorithms. Naïve Bayes achieved an accuracy of 82.5%, KNN achieved 84.6%, Random Forest 87.1%, while SVM provided the best performance with an accuracy of 89.3% and an F1-Score of 88.3%. This difference in performance indicates that algorithms that are better able to handle high-dimensional text representations, such as SVM, are superior in aspect-based sentiment classification compared to other methods. Thus, this study not only provides a comprehensive overview of the effectiveness of machine learning algorithms in sentiment analysis in the e-commerce sector but also provides a practical basis for developing recommendation systems, improving customer service, and enhancing user experience strategies on digital platforms. This research is expected to serve as a reference in the application of machine learning to support the growth of the e-commerce industry in Indonesia.

Keywords: *Aspect-Based Sentiment Analysis (ABSA); E-Commerce; Machine Learning and Sentiment Analysis.*

1. INTRODUCTION

E-commerce has become one of the largest pillars of the digital economy in Indonesia, with business revenues ranking highest among other ASEAN countries at Rp. 778.8 trillion [1]. With this development, Indonesia is now the largest e-commerce market in Southeast Asia. This is in line with the strategy of the Government of the Republic of Indonesia as stated in the Asta Cita of President Prabowo Subianto and Vice President Gibran Rakabuming to encourage the creative industry by creating new sources of economic growth through the development of the digital economy.

The growth of e-commerce businesses in Indonesia is inseparable from the ever-expanding user base. According to the Ministry of Trade's Data and Information Systems Center (PDSI Kemendag), the number of e-commerce users has increased by 69% in the last five years, from 38.7 million users in 2020 to 65.6 million in 2024, and is expected to continue to increase to 99.1 million users in 2029 [2]. This indicates the increasing interest in using e-commerce in the country. Various e-commerce platforms exist to make it easier for users to conduct online transactions more personally and efficiently [3], [4]. Shopee ID, Tokopedia, Lazada ID, Blibli, and Bukalapak are the largest and most popular e-commerce platforms in Indonesia.

Most e-commerce platforms provide customer reviews that reflect users' experiences and satisfaction with products and services. These reviews cover various dimensions, such as price, product quality, customer service, and availability [5]. For potential buyers, these reviews serve as a valuable source of information in the decision-making process [6], [7], [8], [9]. For manufacturers and service providers, reviews can be used

to evaluate and improve product quality and customer experience [10]. However, as the number of e-commerce users increases, so does the volume of unstructured review data. This large volume of data presents a challenge, as potential consumers must manually review various reviews before making a purchasing decision [11], [12]. In the era of Big Data and Artificial Intelligence (AI), the ability to understand and extract relevant information from unstructured data is crucial [13]. On the other hand, the human ability to summarize and extract insights from massive user reviews is challenging, making it difficult to identify relevant and useful information [14]. In this context, sentiment analysis comes as a solution to transform unstructured data into organized and meaningful information [15], [16], [17], [18].

The main goal of sentiment analysis is to identify whether customers are satisfied or dissatisfied based on the opinions they express in reviews [19]. However, most sentiment analysis approaches are still conducted at the document or sentence level, which tends to provide a general overview without considering the differences in sentiment towards specific aspects within a single text [20], [21], [22], [23]. This approach becomes inadequate when a single review covers opinions on several different aspects, for example, a customer likes the product quality but is dissatisfied with the delivery service. Therefore, a more in-depth approach is needed, namely Aspect-Based Sentiment Analysis (ABSA). ABSA focuses on identifying opinions towards a specific entity and its aspects, such as performance, price, or service. This approach allows the system to extract and classify sentiment towards each aspect separately, thus providing richer and more specific insights [24], [25].

In this case, various methods have been applied to the task of sentiment analysis, ranging from traditional machine learning algorithms such as K-Nearest Neighbors, Logistic Regression, Naïve Bayes, Random Forest, and Support Vector Machine [26], [27]. The purpose of this study is to evaluate the performance of several machine learning algorithms in carrying out Aspect-Based Sentiment Analysis (ABSA) on e-commerce user reviews in Indonesia. The research question asked is which machine learning algorithm shows the best performance in classifying sentiment based on aspects.

II. METHODS

This research method is designed to evaluate the performance of machine learning algorithms in aspect-based sentiment analysis (ABSA) on e-commerce user reviews. This study uses a quantitative approach with systematic research stages to ensure valid and accountable results. Broadly speaking, the research stages consist of six main steps: data collection, data preprocessing, aspect and sentiment annotation, machine learning algorithm application, model performance evaluation, and result analysis.

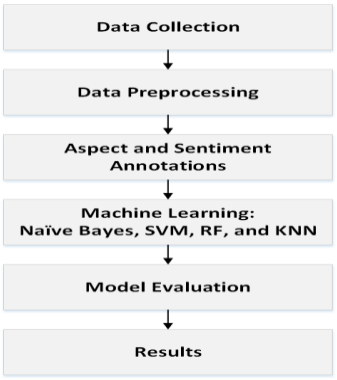

Fig. 1. Research Stage

Data was obtained from popular e-commerce platforms in Indonesia, particularly Shopee and Tokopedia, which offer user review features. Reviews were collected by considering frequently occurring aspects, such as price, product quality, delivery service, and interactions with sellers. The collected data was stored in text format and cleaned of duplicates. The collected review data was then further processed to prepare it for use in model training. This process involved several stages: cleaning the text from irrelevant symbols or characters, converting capital letters to lowercase, removing stopwords, stemming or lemmatization, and tokenization. Next, text representation was performed using TF-IDF methods and word

embeddings, converting the text into numeric vectors understandable by machine learning algorithms. In the Aspect and Sentiment Annotation stage, each review was annotated based on its aspects and the polarity of the expressed sentiment (positive, negative, or neutral). The annotation process can be performed manually or semi-automatically using a sentiment dictionary. The goal of this stage is to build a labeled dataset that can be used in model training and testing.

Several machine learning algorithms were selected for evaluation in this study, namely Naïve Bayes, Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN). Each algorithm was trained using preprocessed training data. The selection of these algorithms was based on literature demonstrating their relevance and effectiveness in sentiment analysis tasks. To measure the algorithms' performance, this study used evaluation metrics such as accuracy, precision, recall, and F1-score. The use of these metrics is important to provide a more comprehensive picture of the strengths and weaknesses of each algorithm. Cross-validation was also applied to ensure the reliability of the results. The final stage was analyzing the performance evaluation results of each algorithm. This analysis aimed to answer the research question regarding the most optimal algorithm for use in the context of ABSA in e-commerce reviews. Furthermore, the practical implications of the research results are also discussed, particularly regarding their contribution to the development of recommendation systems and improving service quality on e-commerce platforms. By going through these six stages, this research is expected to provide a deeper understanding of the effectiveness of machine learning algorithms in classifying aspect-based sentiment, while also providing a real contribution to the development of data analysis technology in the e-commerce sector.

III. RESULT AND DISCUSSION

This research dataset consists of 20,000 user reviews of the Shopee and Tokopedia apps obtained through a crawl of the Google Play Store. The collected reviews were annotated based on the platform, the aspects examined (price, product quality, service, delivery, and app), and the polarity of sentiment (positive versus negative).

Table 1. Dataset

Platform	Amount	Positive	Negative	Aspects
Shopee	10.000	6.000	4.000	Price, Product Quality, Service, Delivery, Application
Tokopedia	10.000	5.800	4.200	Price, Product Quality, Service, Delivery, Application
Total	20.000	11.800	8.200	five main aspects of e-commerce users

The data distribution in Table 1 shows that positive reviews dominate, with a total of 11,800 positive reviews compared to 8,200 negative reviews. This indicates that, in general, user satisfaction with both e-commerce platforms is relatively high. However, the significant number of negative reviews remains valuable evaluation material for identifying weaknesses in service, product quality, and the application system used. Proportionally, Shopee contributed 10,000 reviews, with a distribution of 6,000 positive and 4,000 negative, while Tokopedia also contributed 10,000 reviews, with a distribution of 5,800 positive and 4,200 negative. This balance of data between the two platforms provides a strong basis for conducting a comparative analysis of the performance of machine learning algorithms in Aspect-Based Sentiment Analysis (ABSA) tasks.

Table 2. Data Preprocessing

ID	Original Review	Preprocessing Results
1	“Very fast shipping, only 2 days to arrive □□”	fast delivery, 2 days to arrive
2	“Product prices on Shopee are cheaper than other stores, so great!!”	Shopee product prices are cheap compared to other stores, great
3	“The application often crashes when opening a promo, please fix it immediately!!!”	The application often crashes, open promo, please fix it immediately

4	“The item arrived defective, poor quality and did not match the description □”	The item arrived defective and was of poor quality as described.
5	“Friendly customer service and very fast response, satisfied shopping at Tokopedia”	Friendly customer service, fast response, satisfied with shopping on Tokopedia

Table 2 shows that each user review underwent a significant transformation after going through the preprocessing stage. Irrelevant elements such as emojis (👍, 😠), punctuation (!, ,), and repeated words were removed. Furthermore, words were changed to lowercase, stopwords were removed, and stemming was applied to make sentences more concise while still maintaining their core meaning. For example, the review "Super fast delivery, only 2 days to arrive 👍👍" was transformed into the much simpler and more informative "fast delivery 2 days to arrive." This makes it easier for machine learning algorithms to recognize sentiment patterns without being disturbed by noise. Thus, the preprocessed dataset is ready for use in the next stage, namely training and evaluating aspect-based sentiment analysis models.

Table 3. Aspect and Sentiment Annotations

ID	Ulasan	Aspects	Sentiment
1	fast delivery, 2 days to arrive	Delivery	Positive
2	Shopee product prices are cheap compared to other stores, great	Price	Positive
3	The application often crashes, open promo, please fix it immediately	Application	Negative
4	The item arrived defective and was of poor quality as described.	Product Quality	Negative
5	Friendly customer service, fast response, satisfied with shopping on Tokopedia	Service	Positive

Table 3 displays the results of aspect and sentiment annotation of five user review samples after going through the preprocessing stage. From this table, we can see that the Delivery Aspect → review "fast delivery, arrived in 2 days" is labeled positive because it reflects satisfaction with the speed of service. The Price Aspect → review "Shopee product prices are cheap compared to other stores, great" is categorized as positive because it emphasizes the price advantage. The Application Aspect → review "application often crashes, open promo, please fix immediately" is categorized as negative because it indicates a complaint about the application's performance. The Product Quality Aspect → review "item arrived defective, poor quality as described" is labeled negative because it contains disappointment with the product. The Service Aspect → review "customer service is friendly, fast response, satisfied shopping on Tokopedia" is categorized as positive because it indicates satisfaction with customer service. These annotation results indicate that each review can be clearly mapped to a specific aspect, allowing the study not only to assess the general sentiment polarity but also to highlight specific dimensions of the user experience. This is important in supporting aspect-based sentiment analysis (ABSA), the main focus of the study.

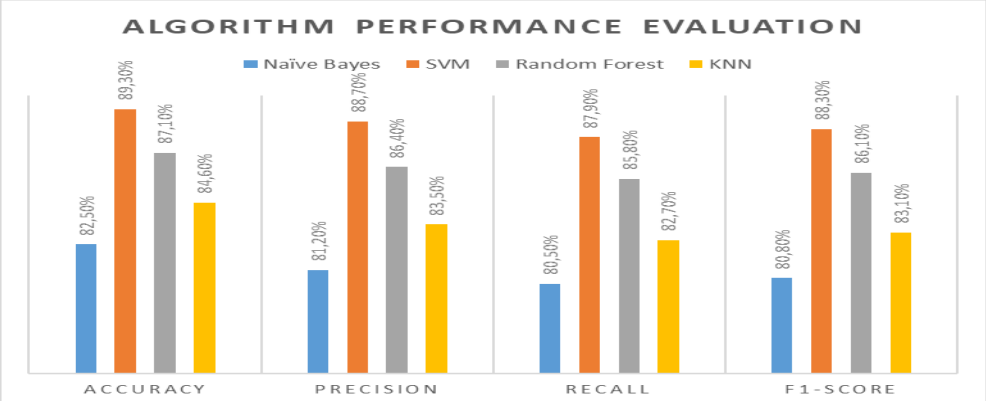

Fig. 2. Algorithm Performance Comparison

Figure 2 presents the performance evaluation results of four machine learning algorithms—Naïve Bayes, Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbors (KNN)—based on four key metrics: Accuracy, Precision, Recall, and F1-Score. The highest accuracy score was achieved by SVM at 89.3%, followed by Random Forest at 87.1%, KNN at 84.6%, and Naïve Bayes at 82.5%. This difference indicates the variation in the algorithms' ability to classify data overall. In the precision metric, SVM again recorded the highest score at 88.7%, followed by Random Forest at 86.4%, KNN at 83.5%, and Naïve Bayes at 81.2%. These results illustrate the extent to which the algorithms are able to correctly identify positive and negative reviews compared to the number of positive predictions made. For recall, SVM achieved 87.9%, Random Forest 85.8%, KNN 82.7%, and Naïve Bayes 80.5%. This value indicates the proportion of reviews that were correctly classified from the entire actual review data. In terms of F1-Score, SVM recorded a value of 88.3%, followed by Random Forest with 86.1%, KNN with 83.1%, and Naïve Bayes with 80.8%. This metric shows the balance between precision and recall achieved by each algorithm. Overall, the graph shows a variation in performance across each metric, with each algorithm displaying different levels of effectiveness in handling aspect-based sentiment analysis on Shopee and Tokopedia user reviews.

A comparison of the performance results of the four algorithms in Figure 2 shows significant differences in each evaluation metric. SVM consistently achieved the highest scores across all metrics, with a significant gap compared to the other algorithms. This is particularly evident in precision (88.7%) and F1-Score (88.3%), demonstrating SVM's ability to accurately and consistently balance the identification of positive and negative reviews. Random Forest ranked second in almost all metrics, with relatively stable values. In accuracy (87.1%) and recall (85.8%), Random Forest performed close to SVM, although the difference in precision was larger (86.4% compared to 88.7%). This indicates that Random Forest is quite effective in handling the variety of review data, especially when the evaluated aspects involve more complex contexts. KNN showed intermediate performance with accuracy (84.6%) and F1-Score (83.1%), which were higher than Naïve Bayes, but still below Random Forest and SVM. The most noticeable differences are in precision (83.5%) and recall (82.7%), which tend to fluctuate due to KNN's sensitivity to the choice of neighbor size and noisy data. Naïve Bayes consistently produced the lowest scores across all metrics, with an accuracy of 82.5% and a recall of 80.5%. Despite its simplicity, this algorithm shows limitations in capturing the complex word variations and sentence contexts of user reviews. The most striking difference is seen in precision (81.2%), which is the lowest among the four algorithms.

From this comparison, it can be seen that performance differences are primarily influenced by how each algorithm processes text representations. Algorithms capable of handling high feature dimensions and varying word contexts, such as SVM and Random Forest, tend to show better results. Conversely, simpler algorithms like Naive Bayes are more susceptible to performance degradation, particularly in precision and recall.

While this study successfully evaluated the performance of several machine learning algorithms in aspect-based sentiment analysis of e-commerce reviews, several limitations are worth noting. First, the dataset used was sourced solely from reviews of the Shopee and Tokopedia apps on the Google Play Store. This limits the generalizability of the results, as reviews from other platforms or social media channels were not included. Second, the aspect and sentiment annotation process was still carried out using a semi-manual approach that relied on keywords and simple labels. This method can introduce subjectivity and limitations in capturing the meaning of more complex sentences, such as reviews with mixed sentiments or the use of sarcastic language. Third, this study only compared four traditional machine learning algorithms—Naïve Bayes, SVM, Random Forest, and KNN—without including deep learning-based models such as CNN, LSTM, or Transformer (BERT). These models have been shown in several previous studies to provide superior results in sentiment analysis tasks [9], [28], [29], [30], [31], [32].

IV. CONCLUSION

The results show that all tested algorithms—Naïve Bayes, K-Nearest Neighbors (KNN), Random Forest, and Support Vector Machine (SVM)—have the ability to classify aspect-based sentiment, but with varying degrees of effectiveness. Naïve Bayes performs quite well on simple text datasets, but is less able to

capture complex semantic variations. KNN shows better results than Naïve Bayes, but its performance is affected by sensitivity to parameter selection and the presence of noisy data. Random Forest produces stable performance with high accuracy and is able to handle large data variations, although it requires longer computation time. Of all the tested algorithms, Support Vector Machine (SVM) proved to show the best performance with an accuracy of 89.3%, a precision of 88.7%, a recall of 87.9%, and an F1-Score of 88.3%. These results indicate that SVM is more effective in consistently classifying positive and negative reviews across the various aspects analyzed, including price, product quality, service, delivery, and application. With a clear separation margin on high-dimensional data, SVM is able to provide superior results compared to other algorithms. Thus, this study answers the main question: among the compared machine learning algorithms, SVM is the algorithm with the most optimal performance in aspect-based sentiment classification in e-commerce user reviews in Indonesia. These results provide a strong foundation for the application of SVM in sentiment analysis systems on e-commerce platforms, which can be used to improve service quality, develop marketing strategies, and improve user experience in a more targeted manner.

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