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Classification of E-Commerce Shipping Timeliness Using Supervised Learning Algorithm

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Abstract

Developments in the e-commerce sector have increased rapidly since the onset of COVID-19, which has changed consumers' shopping habits. The growth in the number of e-commerce consumers affects the demand for long-distance delivery of goods. The problem of late delivery of goods is one of the challenges that is often experienced, and this can affect the level of customer satisfaction. This study aims to analyze whether the delivery of goods has been carried out according to schedule or has experienced delays. By using e-commerce shipping datasets obtained through the website, this research applies five supervised learning algorithms in the classification process, namely Decision Tree, Naïve Bayes Classifier, K-Nearest Neighbors (K-NN), Random Forest, and Support Vector Machine (SVM). The evaluation results show that dataset sharing using the K-Fold Cross Validation technique provides the best performance at K=8. Support Vector Machine showed the highest level of accuracy of 66.35%, followed by precision of 69.31% and recall of 66.35%. In contrast, the Naïve Bayes Classifier algorithm recorded the lowest performance with accuracy 64.22%, 97.73% precision, and 42.67% recall. These results show that the SVM algorithm is better at classifying the timeliness of delivery compared to the other four algorithms.

Keyword: Classification, E-Commerce, Machine Learning, Naïve Bayes Classifier, Support Vector Machine

1. INTRODUCTION

The COVID-19 pandemic has drastically changed global consumer behavior. The social restrictions imposed in various countries led to a significant increase in the use of e-commerce services, causing a surge in online orders. This has made last-mile delivery a crucial factor in determining customer satisfaction [1][2]. This situation shows that the effectiveness and timeliness of delivery are among the main keys to the success of e-commerce operations during and after the crisis [3]. While demand has increased, it has also led to new challenges such as late deliveries, which have a direct impact on decreasing customer loyalty and trust [4]. Delayed delivery is a critical issue that has the potential to reduce customer satisfaction, harm brand image, and reduce efficiency in business operations [5].

In the last two decades, e-commerce has become an important pillar of global business strategy [1]. The peak of its growth acceleration occurred when the COVID-19 pandemic began to escalate at the end of 2019 [6], this change had a major impact on consumer habits, which increasingly rely on online shopping to fulfill their daily needs [7]. According to Amazon's 2020 sales data, the COVID-19 pandemic had a significant impact on the sales increase, which was recorded at $386.06 million, an increase of 37.6% compared to $280.52 million in 2019 [3]. With the significant growth in the e-commerce industry, the demand for last-mile parcel delivery has increased [1], [7].

Last-mile delivery is the final stage in the delivery process, where goods are delivered directly to the customer from the distribution center [7]. The process can be defined as the set of activities and steps required to deliver goods from an intermediate point in the distribution chain to the final destination [8]. This step is crucial in logistics services as it involves route planning, scheduling, and determining the required distribution capacity [2].

The growth in the number of customers making online purchases continues to increase, which has a direct impact on the distribution of goods [7]. This increase in demand also results in various challenges during the delivery process. One of the most common issues is late deliveries, which can lead to decreased customer satisfaction [4]. Delivery delays are influenced by several factors, such as the absence of customers when the goods are delivered, inaccuracies in delivery location information, traffic jam conditions, delivery mode, and product cost [5]. In contrast, on-time delivery has a significant impact on customer satisfaction, as it meets their expectations while enhancing the shopping experience [7]. Therefore, E-commerce companies need to understand the factors that cause delivery delays by analyzing the flexibility of delivery time, delivery volume, delivery method, and product price discounts [1].

Analysis of delivery delays and their contributing factors can be done using various relevant algorithms to improve efficiency and customer satisfaction [9]. In this study, five supervised machine learning algorithms were selected, namely Decision Tree, Naive Bayes Classifier, K-Nearest Neighbor (K-NN), Random Forest, and Support Vector Machine (SVM) [10]. The selection of the five algorithms is based on their ability to handle structured datasets with binary classification tasks, especially in the context of predicting customer satisfaction in the e-commerce logistics sector [11]. The five algorithms are based on the characteristics of algorithms commonly used in tabular data classification studies, as well as their ability to efficiently handle the combination of categorical and numerical attributes [12]. Algorithms such as Decision Tree and Naïve Bayes have high interpretability, making it easy to communicate prediction results to non-technical stakeholders in the industry [13]. Meanwhile, SVM and Random Forest excel in overcoming non-linearity and minimizing overfitting, making them suitable for comparative performance analysis [14].

Although supervised learning algorithms such as Decision Tree, Naïve Bayes, K-NN, Random Forest, and SVM have proven to be effective in handling structured data and are easy to interpret, they can also be used to analyze and analyze data [12], there is another approach that is gaining popularity in the classification field, which is deep learning. However, the application of these techniques in this study is considered suboptimal. Due to the limited size of the dataset, which is not sufficient for training, as well as the need for high computational resources and low interpretability, deep learning is not optimal [15]. Therefore, the classical approach with supervised learning is considered more appropriate for the context and scope of this research.

Research by Alsubari et al. (2022) showed that supervised learning algorithms such as Naïve Bayes (NB), Support Vector Machine (SVM), and Random Forest (RF) are effective in the classification of fake reviews on e-commerce datasets. In the study, RF recorded the highest accuracy and F1-score of 95%, followed by SVM with 93%, and NB with 88% [16]. Meanwhile, Vanhoenshoven et al. (2016) evaluated the performance of Decision Tree (DT) and K-Nearest Neighbors (K-NN) in detecting malicious URLs, where DT achieved an accuracy of 97.33%, and K-NN recorded 97.54%. These results corroborate that Decision Tree and K-NN are used in supervised learning to classify and analyze customer behavior in e-commerce [17].

Based on these data and problems, this study aims to analyze the on-time delivery patterns of e-commerce products, highlighting variables such as price discount, product weight, delivery method, and customer rating that are thought to affect delivery delays. Through a comparative approach of five supervised learning algorithms, this research is expected to identify the most accurate and efficient classification model in the context of e-commerce logistics, while providing a deeper understanding of its relationship with customer satisfaction.

2. MATERIAL AND METHOD

The purpose of the elements in the diagram is to structure and organize the data, to improve model accuracy and performance, and to minimize bias and error in the analysis of results. Research Methodology can see Figure 1.

2.1. Data Collecting

The data in this study uses e-commerce datasets obtained through the Kaggle website. This dataset consists of 10999 records with 12 attributes in the form of numerical and categorical data, including ID, Warehouse block, Mode of shipment, Customer care calls, Customer rating, Cost of the product, Prior purchases, Product importance, Gender, Discount offered, Weight in grams, and Reached on time.

2.2. Data Preprocessing

Once the data has been collected, the next step is to prepare it for use in analysis with machine learning models. This preprocessing stage includes filling in blanks, removing duplicates, checking to identify inconsistencies, cleaning the data, and correcting any errors found [18]. In this study, the data used was structured and free from missing values, so there was no need for further cleaning. The data transformation process is done by removing irrelevant attributes and converting categorical data into the numerical format.

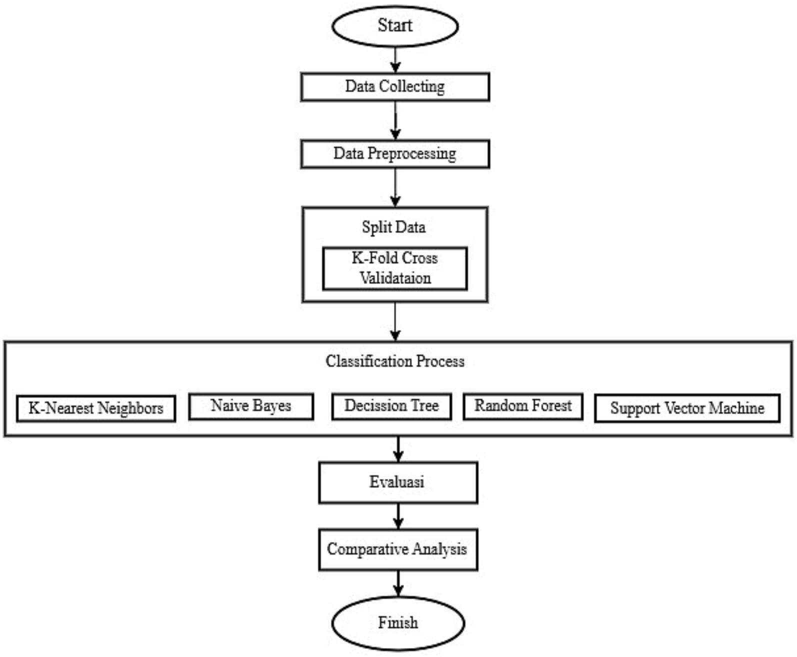

Figure 1. Research Methodology

2.3. K-Fold Cross Validation

Data is divided into 'k' folds using K-Fold Cross Validation, a machine learning model evaluation technique that uses each data point for testing and training in order to calculate the error rate [19]. With this approach, bias from a single split of training and testing data is minimized, leading to a more accurate assessment of model performance [20]. One of the most effective and frequently used techniques for validation and performance evaluation is the 10-fold cross-validation classification test [21]. There are several steps in the K-Fold Cross Validation procedure [20].

1. A dataset can be divided into k subsets of comparable size, referred to as "Folds."
2. Training and Testing, where the model performs k training iterations, with each iteration using k-1 folds for training and providing one fold for Testing.
3. To evaluate the model's overall performance, performance evaluation involves calculating the accuracy, precision, and recall of each iteration and then averaging the findings.

2.4. E-Commerce

In recent years, technological advancements have made e-commerce a top choice for consumers. The ability of businesses to attract customers and provide a pleasant shopping experience has driven the growth and importance of the sector [22]. Online shopping is growing in popularity because it is free of transportation costs, offers a wide range of products, and allows shopping anytime from home. Digital development and e-commerce have driven an increase in demand for long-distance parcel delivery [1]. Customer satisfaction has emerged as a crucial success factor in the e-commerce sector since it enables businesses to maintain their competitiveness, enhance their reputation, and keep clients [23].

2.5. Shipping

The growth of e-commerce is driving companies to build delivery channels to ensure the availability of contracted logistics slots. Despite offering convenience, challenges such as sub-optimal slots, fierce competition, and rising operational costs remain a major concern [24]. Shipping is expected to continue to play a significant role in the global economy, fostering the expansion of trade and e-commerce, despite these obstacles [25]. Understanding the relationship between logistics facility size and operational costs helps e-commerce platforms improve delivery efficiency [26]. Quality delivery services play a strategic role in enhancing customer experience, expanding market reach, and creating a competitive advantage, making it a key factor amid fierce competition [27].

2.6. Supervised Learning

Supervised learning is a machine learning technique that uses labeled data to teach computers input-output correlations, enabling accurate predictions on new data [28], [29]. With the primary objective of maximizing the model's performance for a given job, supervised learning is extensively utilized in applications like fraud detection and picture recognition [29]. Supervised learning uses labelled data for accurate predictions, with algorithms capable of learning patterns and making reliable predictions on new data [30], [31].

2.7. Classification

Classification is a supervised learning process where models predict new data categories using algorithms such as Naïve Bayes, K-Nearest Neighbor, Decision Tree, Random Forest, and SVM, and evaluate their performance with metrics such as Precision, Recall, and Confusion Matrix [30], [32]. Classification algorithms such as KNN, NBC, Decision Tree, and Random Forest process big data efficiently and provide accurate predictions for complex applications [32].

2.8. Confusion Matrix

When assessing the performance of classification models, the Confusion Matrix is a frequently used matrix that illustrates how well the machine learning model predicts the result [33]. The Confusion Matrix serves as an evaluation method for assessing classification performance based on true and false categories. This matrix includes accuracy, precision, and recall metrics, which are calculated based on four main outputs: recall, precision, accuracy, and error rate [18]. Based on Table 1, the confusion matrix diagram is displayed [34].

Table 1. Confusion Matrix

		Prediction	
		Positive	Negative
Actual	Positive	TP	FN
	Negative	FP	TN

The accuracy value can be computed using equation (1); precision and recall are calculated using equations (2) and (3), respectively [35].

$$\text{Accuracy} = \frac{\text{TP+TN}}{TP+TN+FP+FN} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{TP+FN} \tag{3}$$

2.9. Decision Tree

A decision tree is a type of machine learning technique used for classification and regression that resembles a tree. Internal nodes represent attribute tests, branches represent test outcomes, and leaf nodes represent final conclusions or class labels [32]. This algorithm excels in easy-to-understand interpretation and clear visualization, making it ideal for applications that require model transparency [13], [32]. Decision trees are known for their easy and intuitive interpretation, making them suitable for applications that require logical explanations, such as in the fields of mental health and education [13], [36]. In addition, the algorithm effectively handles categorical and continuous data without requiring complicated data distribution assumptions [37]. Information entropy describes the level of uncertainty or impurity in a data set, as described in equation 4.

$$\mathrm{E}ntropy(D) = -\sum_{k=1}^{m} P_k \log_2 P_k \tag{4}$$

D refers to the training data set with m number of samples, while Pk describes the probability of each class in the sample. The ratio of information gained serves to evaluate the difference in the level of uncertainty or information entropy between different classification methods.

2.10. Naïve Bayes Classifier

The Naive Bayes algorithm is a Bayes Theorem-based classification method that assumes independence between predictors to simplify calculations [38], [39]. The Naive Bayes algorithm calculates group probabilities based on a set of features, assuming independence between features. This method is simple yet effective, especially for categorical data such as text and spam detection data [29], [40]. The Naïve Bayes Classifier is known for its speed and efficiency in handling large datasets, especially for text classification, thanks to its simple probability calculation [20], [40]. The Naïve Bayes Classifier algorithm can be explained using equation 5.

$$P(a|y) = \frac{(P(y|a)P(a))}{P(y)} \quad (5)$$

The Naïve Bayes Classifier equation calculates the posterior probability P(a|y) as the result of the likelihood P(y|a) multiplied by the prior class probability P(a), divided by the prior predictor probability P(y). The observed data are used to calculate the class probabilities [38].

2.11. K-Nearest Neighbors (K-NN)

A nonparametric technique called K-Nearest Neighbors (K-NN) is used for both classification and regression. It classifies instances according to how similar they are to the 'k' nearest neighbors in the training data. The algorithm assigns a class based on the majority of labels among those neighbors [41]. The K-NN technique finds use in a number of domains, including anomaly detection, disease prediction, text categorization, and face recognition [42]. K-NN's benefits include its ease of use, adaptability, and efficiency in a range of categorization jobs such as pattern recognition and disease prediction, without requiring specific data distribution assumptions [42], [43].

This K-NN equation calculates the distance between two data points, d (i,j), by summing the squared difference of each feature for both points, then taking the square root. This notation considers all features (p) in the data, with $X_{ik}$and X_{jk} with the i-th and j-th data values in equation 6 as the kth feature value.

$$d(i,j) = \sqrt{\sum_{k=1}^{p}(X_{ik} - X_{jk})^2} \quad (6)$$

2.12. Random Forest

An ensemble technique known for its dependability in managing big datasets and reducing overfitting through random feature selection, Random Forest was first presented by Ho (1995) and improved by Breiman (2001) [44], [45]. Random Forest effectively handles data with many variables and is suitable for complex applications such as landslide susceptibility prediction and medical condition classification [44]. The Equation used in the Random Forest method can be seen in equation 7 [46].

$$\mathrm{H}(x) = \arg max\ \sum_{k=1}^{k} I(h_k(x) = c) \quad (7)$$

This Equation determines the final prediction H(x) of the Random Forest for input x. The arg max function selects the class c with the highest number of votes, where $h_k(x)$ is the class prediction of the kth treek_1, and I(·) is an indicator function that takes the value 1 if the kth tree chooses class c, or 0 otherwise. The summation is done for all trees in the forest, and the class with the most votes becomes the final prediction result.

2.13. Support Vector Machine

Support Vector Machine (SVM) is a machine learning approach for regression and classification that uses kernel functions to maximize the margin between classes using an ideal hyperplane. It works well with high-dimensional data [47], [48]. SVM identifies an optimal hyperplane that separates the classes of data, defined by support vectors, to maximize the margins and improve model generalization [47]. SVMs are known to efficiently handle complex classifications, especially on high-dimensional data, by utilizing the optimal hyperplane to maximize margins, even when the data is not linearly separable [19], [47].

SVM also has the advantage of clear visualization in separating data classes, making it useful for applications such as pattern recognition and satellite image classification [19], [49]. Equation 8 shows the SVM formulation to find the hyperplane with the largest margin [19].

$$min\frac{1}{2}||w||^2,\ y_1(w *\ x_1 + b) \geq 1 \quad (8)$$

This SVM equation minimizes an objective function $\frac{1}{2}||\boldsymbol{w}||^2$ to increase the margin between classes, where ||w|| is the norm of the weight vector w that determines the orientation of the hyperplane. The constraint $y_1(w * x_1 + b) \geq 1$ ensures that the data lies on the correct side of the hyperplane with a margin of at least 1.

3. RESULTS AND DISCUSSION

3.1. Initial Data

At this stage, the dataset represents the raw data as obtained from the original source, Kaggle, relating to product delivery in the e-commerce sector. The dataset used in this research consists of 10,999 entries and 12 attributes covering information related to products, customers, and shipments. This dataset is still in its raw form and will be used as the basis for analysis, with a preprocessing plan such as handling missing values, data type conversion, and normalization. Table 2 presents the details of each attribute, including its data type and description before preprocessing.

Table 2. Initial Data

No	Attribute Name	Data Type	Description
1	ID	Numerical	Unique identification number for each transaction
2	Warehouse_block	Categorical	Location of the warehouse where the product is stored (A, B, C, D, F)
3	Mode_of_Shipment	Categorical	Type of shipping method (Flight, Ship, Road)
4	Customer_care_calls	Numerical	Number of calls made by customers to customer service
5	Customer_rating	Numerical	Customer assessment of service (scale 1-5)
6	Cost_of_the_Product	Numerical	Product price in currency units (e.g. Rupiah or USD)
7	Prior_purchases	Numerical	Jumlah transaksi pembelian sebelumnya oleh pelanggan
8	Product_importance	Categorical	Number of previous purchase transactions by customers
9	Gender	Categorical	Customer gender (Male, Female)
10	Discount_offered	Numerical	Amount of discount given on products
11	Weight_in_gms	Numerical	Product weight in grams
12	Reached.on.Time_Y.N	Label (Target)	1 = On-time delivery, 0 = Late

3.2. Data Preprocessing

The first stage in the machine learning process is data transformation. In this stage, data is transformed by removing irrelevant attributes and converting categorical data to numerical. The purpose of data transformation is to avoid errors in modelling and make it easier for the model to understand the data. The attributes that were removed were ID and Gender, as they did not show a strong relationship with the label. In the meantime, a few categorical attributes were transformed into numerical format, including Warehouse Block, Mode of Shipment, and Product Importance. Table 3 displays the dataset that underwent the preprocessing step.

Table 3. Preprocessing Data Result

Werehouse_block	Mode_of_Shipment	…	Discount_offered	Weight_in_gms	0.on.Time_Y.N
3	0	…	44	1233	1
4	0	…	59	3088	1
0	0	…	48	3374	1
1	0	…	10	1177	1
2	0	…	46	2484	1
…	…	…	…	…	…
4	2	…	2	1210	0
3	2	…	6	1639	0

3.3. Implementation of the Classification Algorithm

This research implements classification algorithms and data analysis using the Python programming language. The purpose of testing these algorithms is to evaluate their accuracy in predicting product delivery timeliness. The five algorithms tested in this research include Decision Tree, Naïve Bayes, K-NN, Random Forest, and SVM.

The K-Fold Cross Validation method was used to conduct tests with different K values, specifically 2, 4, 6, 8, and 10. Accuracy, precision, and recall were some of the metrics used in the confusion matrix. Each algorithm was tested five times using various divisions of K, and the testing procedure was performed in stages. Based on the evaluation results of the five algorithms, a K-Fold division of 8 yielded the best performance, where each algorithm obtained the highest average accuracy when evaluated, as shown in Figure 2.

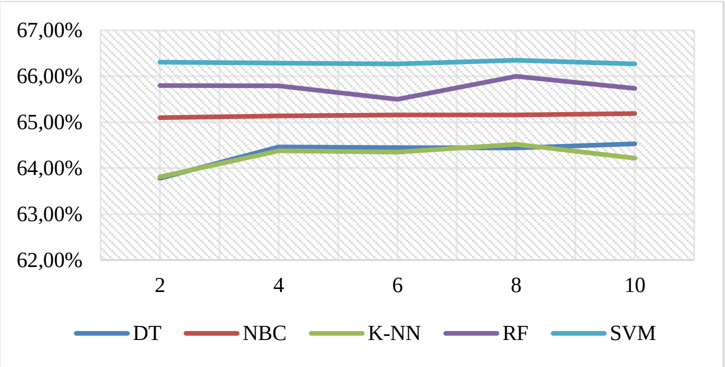

Figure 2. Accuracy Results Using K-Fold Cross Validation (K = 2 to K = 10)

Based on the diagram in Figure 2, it can be concluded that the best evaluation was obtained by applying K-Fold Cross Validation at K=8. The SVM algorithm showed the best performance among the five algorithms tested, as it managed to maintain a good balance on each metric used, by obtaining an accuracy of 66.35%. In the evaluation with K=2, the Decision Tree and K-NN algorithms showed accuracy below 64%, which is the lowest result compared to other K values. Meanwhile, the Naïve Bayes Classifier algorithm managed to maintain consistent accuracy at every multiple of K, although the improvement was not significant enough. Different results were obtained from the Random Forest algorithm, where the accuracy decreased significantly at K=6 with a value of 65.50%, but increased again at K=8 to 66%. Using K-Fold cross-validation with K=8, the assessment results of the five algorithms in determining the timeliness of e-commerce product delivery are shown in Figure 3.

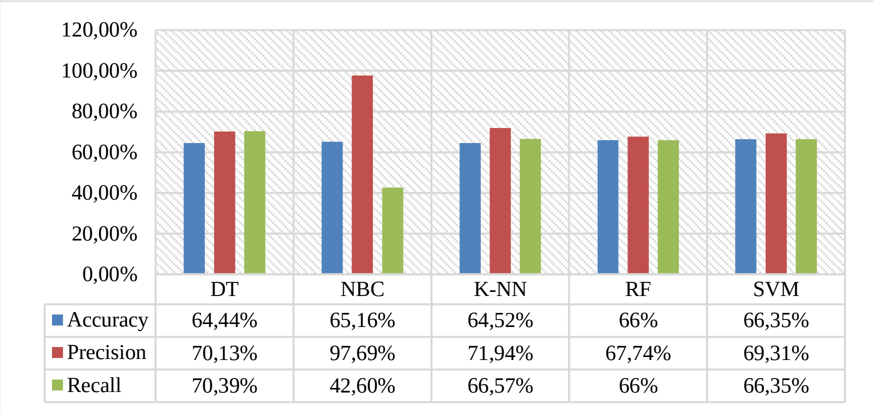

Figure 3. Comparison of Algorithm Classification Results

Figure 3 displays the classification evaluation results using the Decision Tree, Naïve Bayes Classifier, K-NN, Random Forest, and SVM algorithms. The SVM algorithm produces the best accuracy among the five algorithms, which is 66.35%, followed by precision of 69.31% and recall of 66.35%. The performance of the SVM algorithm shows a good balance between accuracy, precision, and recall. In contrast, the Naïve Bayes Classifier algorithm showed the lowest performance, with 64.22% accuracy, 97.73% precision, and 42.67% recall. This demonstrates how inconsistently the model classifies the data. Although highly accurate in predicting positive cases, the model is less effective in detecting most of the actual positive cases, as reflected by the low recall value. The low recall of Naive Bayes Classifier is due to the assumption of feature independence, which is not suitable for e-commerce data where features such as weight, shipping method, and discount are interdependent. To reduce the bias towards minority classes, a hybrid approach with ensemble or data balancing techniques, such as SMOTE can be used in the future. The Decision Tree algorithm shows quite good results with a precision of 70.13% and a recall of 70.38%, where both metrics have balanced values. However, the accuracy value of 64.44% is low when compared to the accuracy obtained by the Random Forest and SVM algorithms.

SVM is able to classify timeliness in a balanced manner, which minimizes prediction errors and ensures accurate detection of late deliveries. Despite the performance of the model, Random Forest feature analysis showed that discount offers were the main cause of delays, possibly due to high demand during promotions. These findings help in promotion planning and logistics improvement.

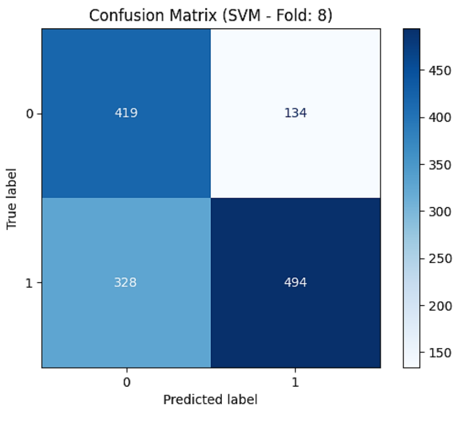

Figure 4. Confusion matrix of the Support Vector Machine (SVM)

Figure 4 shows the confusion matrix of the Support Vector Machine (SVM) algorithm with 8-Fold Cross Validation scheme. Based on the evaluation results, the Support Vector Machine (SVM) algorithm shows the best performance compared to the other four algorithms, with the highest accuracy of 66.35%. Confusion matrix in the 8-Fold Cross Validation scheme shows that SVM is able to classify most of the data correctly, namely 494 correct predictions for late delivery (True Positive) and 419 for on-time (True Negative). Although there are misclassifications, especially in late predictions, overall SVM has a good balance between accuracy and generalization ability, making it the most optimal algorithm in the context of e-commerce delivery timeliness prediction.

Based on the analysis, the SVM algorithm is chosen to classify the timeliness of e-commerce product delivery by providing a good balance, so as to reduce prediction errors and ensure accurate late delivery detection. Therefore, SVM is the right choice for this application.

4. DISCUSSION

The findings of this study show that the Support Vector Machine (SVM) algorithm provides the best performance in predicting the timeliness of e-commerce goods delivery, with an accuracy of 66.35%. The combination of using SVM and data division techniques using K-Fold Cross Validation (K=8) produces the most stable and accurate model. These results are in line with research by Akinola et al. (2024), who reported 88.3% accuracy using a similar approach, proving that SVM is able to handle high-dimensional data and recognize complex patterns in shipping attributes such as location, item type, and delivery time. In addition, Alsubari et al. (2022) also noted that SVM achieved an F1-score of 93% in review classification in the e-commerce domain, demonstrating the algorithm's consistent performance in text-based and numerical classification tasks [16].

Besides SVM, the Random Forest (RF) algorithm also showed competitive performance with 66% accuracy, only slightly lower than SVM. RF has the advantage of handling features that have non-linear relationships and producing models that are relatively easy to interpret. This finding was reinforced by Xie and Yu (2024), who showed that RF was effectively used in logistics cost prediction in the e-commerce sector [50], and by Vanhoenshoven et al. (2016), who recorded 97.3% accuracy in decision tree-based classification on a large-scale dataset [17]. RF is considered to be able to adjust to data variability and still maintain accuracy without significant overfitting.

Although SVM and Random Forest showed good results, some limitations need to be considered. One of the main limitations in this study is the lack of integration of external variables that may affect delivery, such as weather conditions, traffic disruptions, or seasonal factors. Future research is recommended to expand the data coverage to improve the validity of the prediction model. In addition, while SVM records the best performance, it tends to require higher training time on large datasets. In contrast, algorithms such as Naïve Bayes (NB) or K-Nearest Neighbors (K-NN) are superior in computational efficiency despite accuracy limitations. NB in this study has the lowest accuracy, which is consistent with the findings of Vanhoenshoven et al. (2016), which showed that NB tends to provide low recall values and is less reliable in recognizing minority classes. Therefore, model optimization through techniques such as feature selection, dimensionality reduction, or data balancing is recommended to improve training efficiency without compromising prediction quality.

5. CONCLUSION

This research aims to evaluate the effectiveness of various classification algorithms, namely Decision Tree, Naïve Bayes Classifier, K-NN, Random Forest, and SVM. These algorithms are applied to the e-commerce shipping dataset obtained from Kaggle. Five trials were conducted using the K-Fold Cross Validation technique to assess the best performance, the best assessment results were obtained on data sharing with K = 8. The accuracy of the SVM algorithm is the best at 66.35%, precision 69.31%, and recall 66.35%. With an accuracy of 66%, the Random Forest algorithm ranked second, followed by the Naïve Bayes Classifier with an accuracy of 65.16%. The K-NN algorithm obtained an accuracy of 64.52%, whereas the Decision Tree approach performed the worst in this modeling, with an accuracy of 64.44%. The findings of the modeling analysis indicate that the SVM technique is considered the best for categorizing e-commerce delivery timeliness data. Future research is recommended to explore additional classification algorithms, use more complex pre-processing techniques, and consider the use of deep learning or neural networks to handle greater data complexity and produce more accurate predictions.

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