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OPTIMIZING GOODS PLACEMENT IN LOGISTICS TRANSPORTATION USING MACHINE LEARNING ALGORITHMS BASED ON DELIVERY DATA

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ABSTRACT

This study addresses the challenge of predicting the optimal placement of goods for expeditionary transportation. Efficient placement is crucial to ensure that goods are transported in a manner that maximizes space and minimizes the risk of damage. This study aims to develop a prediction system using the K-Nearest Neighbor (KNN) method, which is based on expert data from expedition vehicles. To evaluate the effectiveness of the KNN method, the researcher compared it with the Support Vector Machine (SVM) method. By doing so, they sought to determine which method delivers more accurate predictions for the optimal placement of goods. The test results revealed that the KNN method outperformed SVM, achieving a higher accuracy of 95.97% compared to SVM's 92.85%. Additionally, KNN demonstrated a lower Root Mean Square Error (RMSE) of 0.18, indicating more precise predictions, while SVM had an RMSE of 0.271. These findings suggest that KNN is the more effective method for predicting the optimal placement of goods in expeditionary transportation.

Keywords*: classification, goods placement, k-nearest neighbor (KNN), support vector machine (SVM).*

I. INTRODUCTION

IN shipping and expedition services, determining the optimal position of goods within transportation means is crucial. Effective placement ensures that shipping processes are more efficient by aligning the positioning of goods with their weight, destination, and type. For companies, skilled workers significantly influence delivery performance [1]. Skilled workers can accurately estimate the optimal placement of goods, whereas new employees often lack the experience to perform this task effectively [2]. As a result, new employees in expedition services require tools or learning media to assist them in achieving optimal placement outcomes [3].

Optimal goods placement requires methods that ensure even distribution or strategic positioning [4]. Machine learning [5], logistic regression [6], and multiple logistic regression [7] are among the methods that can deliver optimal results for such tasks. One effective prediction method for achieving optimal placement is Weighted K-Nearest Neighbor (W-KNN). For example, Fan et al. utilized W-KNN to conduct predictive forecasting to optimize power load in the National Electricity Market in Australia [8]. Furthermore, W-KNN has been shown to effectively predict uncertainties related to fluctuations in electrical load distances [9], [10]. Another commonly used prediction method is the Support Vector Machine (SVM). In a study conducted by Fawzy et al., SVM and KNN were compared to predict gold prices over a certain period using time series data [11].

This study aims to classify a prediction system for the placement of goods in freight expedition transportation. By employing the K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) methods, the study compares their effectiveness using data on the placement of goods in expedition trucks. The results of these methods are evaluated to determine the most optimal approach for goods placement.

TABLE 1
RELATED WORK IN PREVIOUS RESEARCH

Reference	Topic	Method	Subject
[11]	Gold price prediction	SVM and KNN	Predicting gold prices based on historical data
[12]	Student Placement Opportunities	KNN, Logistic Regression, and KVM	Predicting a student's possible job placement
[13]	Rider behaviour	SVM, KNN, Discriminant Linear	Calculate driver behaviour when the traffic light is yellow
[14]	Effectiveness of the KNN algorithm	KNN, SVM	Effectiveness of the KNN algorithm for classification and regression
[15]	Evaluation and comparison of nonparametric classification algorithms	KNN, SVM, Random Forest, and Neural Network	Evaluation and comparison of classification algorithms based on various attributes
[16]	Classification of batik motifs	KNN	Classification of Lampung Batik motifs based on image samples in RGB format
[17]	Traffic classification	SVM	Machine learning-based network traffic classification in intelligent dynamic network management
[18]	Early detection and diagnosis of glaucoma disease	S-MSVM	High classification for detecting different stages of glaucoma
[19]	Classification of MRI images	SVM	Classification of brain MRI images for the diagnosis of brain tumors
[20]	Classification of body positions	SVM, KNN	Classification of body positioning based on sensor data on smartphones
Ours	Classification of goods placement	SVM & KNN	Classify the placement of goods for freight forwarding means

This study provides several key contributions: it optimizes the placement of goods in expedition transportation equipment, conducts a comparative analysis of method performance for goods placement, and validates prediction systems using freight forwarding datasets.

The structure of this paper is as follows: the Introduction highlights the significance of optimal goods placement in expedition logistics and the necessity of prediction methods to enhance efficiency. It introduces the KNN and SVM methods, which will be compared to identify the best classification method for goods placement. The Research Methods section explains the application of both methods, including dataset collection, preprocessing with data normalization, and evaluation metrics such as accuracy and Root Mean Squared Error (RMSE). The Results and Discussion section presents the findings, demonstrating that KNN outperforms SVM in terms of accuracy and error rates. Finally, the Conclusion confirms the superior performance of KNN and recommends further exploration and development.

This study addresses gaps in previous study, which have not thoroughly examined the effectiveness of KNN and SVM specifically in the logistics domain. This comparison is essential as prior studies offered limited insights into the optimal arrangement of goods in logistics transportation using machine learning techniques.

II. RESEARCH METHOD

Technology companies. Their results showed that among KNN, logistic regression, and SVM methods, the KNN algorithm achieved the highest accuracy: 78.57% for KNN, compared to 75% for logistic regression and 77.38% for SVM.

This study on goods placement refers to prior research summarized in Table 1. Fawzy et al. demonstrated the potential of SVM and KNN algorithms in time series forecasting, particularly for predicting gold prices [11]. Similarly, Giri et al. confirmed the effectiveness of KNN in predicting possible job placements for students based on various academic and non-academic attributes. The study highlighted KNN's high accuracy and its ability to manage multidimensional data complexity in the education domain [12].

Karri et al. examined the prediction of driver behavior at yellow traffic lights. Their findings indicated that both SVM and KNN performed well, with SVM exhibiting slightly superior accuracy and generalization in classifying "stop" or "continue" decisions based on vehicle dynamics [13]. Furthermore, Taunk et al. emphasized the versatility of KNN in various classification and regression tasks due to its simplicity, adaptability across domains, and capability to handle non-linear data without distribution assumptions [14].

According to Boateng et al., in evaluating classification algorithms, KNN is effective for datasets where the closest neighbors are highly informative, while SVM excels in handling noise and outliers

TABLE 2.
DATASET VARIABLE

No	Variable
1	Place
2	Province
3	Heavy
4	Product
5	Types of Goods

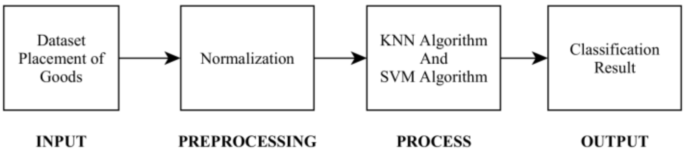

Figure 24. System Architecture

[15]. In the context of classifying goods placement on expeditionary vehicles, KNN may be more suitable for grouping goods based on physical similarity and delivery destination, whereas SVM is better equipped to address variability, such as unusual weight or non-standard shapes, ensuring optimal and safe loading.

Andrian et al. demonstrated that the KNN algorithm is highly effective in classifying Lampung Batik motifs based on RGB visual features, achieving high accuracy by leveraging pattern and color similarities [16]. J. Cao et al. showed that an improved SVM model significantly enhances accuracy in classifying complex and dynamic network traffic, particularly in identifying hidden patterns and managing unbalanced data [17].

Renukalatha et al. highlighted the effectiveness of the Simplified-Multiclass Support Vector Machine (S-MSVM) in classifying various stages of glaucoma with high accuracy, showcasing its ability to handle complex and multi-layered medical classification problems [18]. Similarly, Mishra et al. demonstrated that combining different wavelet transformations with SVMs is highly effective for classifying brain MRI images, emphasizing SVM's capability to integrate complex features across domains. A similar approach can be applied to goods placement on expeditionary vehicles, where SVM incorporates multiple variables for complex placement optimization [19].

Lastly, Yulita et al. found that in classifying body positions based on smartphone sensor data, SVM slightly outperforms KNN in overall accuracy, although KNN is better suited for handling rapid postural transitions [20].

According to Altay et al., Steel Fiber Reinforced Self-Compacting Concrete (SFRSCC) is a type of concrete that, due to its superior properties, has been the subject of extensive research. Their study aimed to predict the performance of new SFRSCC mixtures while adhering to early-stage design standards. To achieve this, the researchers employed two classification methods: Weighted-KNN (W-KNN) and Quadratic-SVM (Q-SVM). The results for slump-flow prediction showed that W-KNN achieved an accuracy of 76%, while Q-SVM achieved 84%. For V-Tunnel time, the accuracy values were 90% for W-KNN and 92% for Q-SVM. These findings demonstrate that Q-SVM outperforms W-KNN in predictive performance [21].

This study proposes datasets and methods for predicting the placement of goods on freight expedition transport vehicles, using the system design illustrated in Figure 1. The goods placement dataset undergoes normalization at the preprocessing stage. The normalized data is then processed using the KNN and SVM algorithms. The results of this process provide a comparative analysis of the two algorithms, identifying the best-performing method for predicting the placement of goods on transportation vehicles.

A. Method

The methodology consists of inputs, preprocessing, processes, and outputs. The input in this study comprises data obtained from the Indonesian Post Office in Malang City, collected between November 10, 2022, and November 17, 2022, using variables as presented in Table 2. The preprocessing stage involves normalizing the dataset. Datasets with diverse values are normalized to ensure a uniform value

TABLE 3.
ITEM PLACEMENT DATA NOVEMBER 10, 2022 – NOVEMBER 17, 2022

No	Place	Province	Weight	Type of Goods
1	Top Front (TF)	Outside Java	0.2	Parcel
2	Top Front (TF)	Outside Java	0.2	Parcel
3	Down Front (DF)	Outside Java	0.5	Parcel
4	Down Front (DF)	Outside Java	0.5	Parcel
5	Down Front (DF)	Outside Java	0.5	Parcel
6	Top Front (TF)	Outside Java	0.1	Parcel
7	Down Front (DF)	Outside Ava	0.3	Parcel
8	Down Front (DF)	Outside Java	0.6	Parcel
9	Down Center (DC)	Java	0.1	Parcel
10	Down Front (DF)	Outside Java	0.1	Parcel
		…….................................		
7021	Top Center (TC)	Java	0.1	Document
7022	Top Center (TC)	Java	0.3	Document
7023	Top Center (TC)	Java	0.4	Document
7024	Top Center (TC)	Java	0.1	Document
7025	Top Center (TC)	Java	1	Document
7026	Top Center (TC)	Java	0.04	Document
7027	Top Center (TC)	Java	0.13	Document
7028	Top Center (TC)	Java	0.12	Document
7029	Top Center (TC)	Java	0.1	Document
7030	Top Center (TC)	Java	0.2	Document

range, initially varied, into a range between 0 and 1. The normalization method applied is the min-max method, as shown in (1). Here, x' is the normalized data, x is the original data, *x_min* is the minimum value, and *x_max* is the maximum value [22]. This method adjusts the data range during preprocessing, converting the values to a consistent range of 0 to 1.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

$$\sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \tag{2}$$

$$y_i(w^T.\emptyset(x_i) + b) - 1 \leq 0 \tag{3}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - y'_i)^2}{n}} \tag{4}$$

The KNN method predicts values based on the similarity of data features with training data. KNN employs Neighborhood Classification for prediction and calculates distances using the Euclidean distance formula, as shown in (2). Euclidean distance represents the straight-line length between two points; the smaller the distance, the greater the similarity between the points [22]. In (2), *q* represents training data, *p* represents testing data, and *n* is the number of data dimensions or variables. SVM is a supervised learning method used to identify the optimal hyperplane that maximizes the margin between classes. The hyperplane function is given in (3). In (3), *w* is the weight vector derived from the input data, *x* is the input vector, *b* is the bias, and y_i is the class label, either +1 or -1. Hyperplane mapping plays a critical role in optimally separating classes in a higher-dimensional feature space [23]. The output of this study includes the accuracy and Root Mean Squared Error results obtained from testing the two methods. The method with the highest accuracy and the lowest error is considered the most effective.

B. Dataset

The input data for this study consists of freight delivery data from the Malang City Indonesian Post Office, collected between November 10, 2022, and November 17, 2022. The dataset contains 7,030 entries, randomly divided into 70% training data and 30% testing data. It includes several criteria, such as Province, Weight, Product, Type of Goods, and Place, as shown in Table 3.

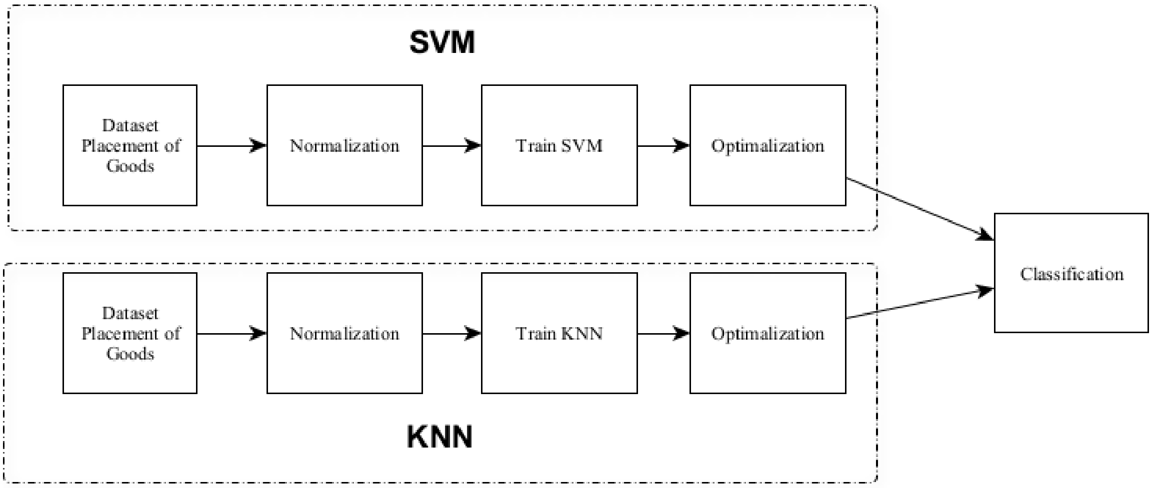

Figure 25. Block Diagram SVM & KNN

C. Evaluation

The evaluation of the two methods is based on accuracy and RMSE, calculated using (4). In (4), *n* represents the total number of observations, y_i is the actual value for the "*i*" observation, and y'_i is the predicted value for the "*i*" observation. $\sum$ spans all observations from 1 to n. *RMSE* is the square root of the average squared differences between the actual and predicted values. A smaller RMSE, closer to 0, indicates a more accurate prediction [24].

III. RESULT AND DISCUSSION

This chapter explains and analyzes the testing results and performance comparisons between the K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) methods for predicting the placement of goods on expedition vehicles. The accuracy and error rates of both methods are discussed in detail, with KNN demonstrating higher accuracy and lower error compared to SVM. The author also examines the performance differences between the two methods based on evaluation metrics, including accuracy and Root Mean Squared Error (RMSE). Additionally, this chapter explores the factors influencing the results and discusses the implications of these findings for optimizing goods placement in logistics operations.

Figure 2 illustrates the workflows of the two classification methods used in this study—Support Vector Machine (SVM) and K-Nearest Neighbor (KNN)—to determine goods placement. The steps outlined in Figure 2 are as follows.

1) Prepare item placement datasets: collect data for analysis and prediction.
2) Data normalization: transform raw data to a consistent scale to ensure processing accuracy by the model.
3) Model training:
   - SVM (Support Vector Machine): train the data using svm algorithms by identifying the optimal hyperplane for class separation.
   - KNN (K-Nearest Neighbor): train the data based on the proximity of data points within the feature space.
4) Model optimization: adjust models to enhance performance in terms of accuracy and efficiency.
5) Predict item placement: use the classification models of both methods (SVM and KNN) to predict goods placement.
6) Evaluation and comparison: compare the results of both methods to identify the most effective and accurate classification approach.
7) Show diagram blocks: show highlight process differences between the two algorithms and the significance of each step in achieving optimal prediction results.

At the final stage, both methods produce classification models that predict goods placement. The results are then compared to determine which method is more effective and accurate for classification

TABLE 4.
KNN PARAMETER VALUE

No	Parameter Name	Value
1	Hidden Layer	3
2	Training Cycles	200
3	Learning Rate	0.01
4	Momentum	0.9
5	Decay	True
6	Shuffle	True
7	Normalize	True
8	Error Epsilon	1.0E-4
9	Use Local Random Seed	False

TABLE 5.
KNN ACCURACY AND RMSE VALUES

	True TF	True DF	True TC	True DC	True TR	True DR	Class Precision (%)
Pred TF	67	0	0	0	0	0	100
Pred DF	3	165	0	0	0	0	98.10
Pred TC	0	0	**2332**	19	0	0	99.19
Pred DC	0	0	0	1806	0	0	100
Pred TR	0	0	0	0	287	0	100
Pred DR	0	0	0	0	0	252	100
Class Recall (%)	95.71	100	100	98.96	100	100	
Accuracy							99.55%
Precision							99.55%
Recall							99.11%
F1-Score							99.33%
RMSE							11.90%

TABLE 6.
SVM PARAMETER VALUE

No	Parameter name	Value
1	Kernel Type	Dot
2	Kernel Cache	200
3	C	0
4	Convergence Epsilon	0.001
5	Max Iterations	100000
6	Scale	True
7	L Pos	1.0
8	L Neg	1.0
9	Epsilon	0
10	Epsilon Plus	0
11	Epsilon Minus	0
12	Balance Cost	False
13	Quadratic Loss Pos	False
14	Quadratic Loss Neg	False

tasks. The block diagram serves to visualize the differences between the two algorithms and emphasizes the critical steps required to achieve optimal prediction outcomes.

The dataset is labeled according to the target variable, which in this case is the place. It is then normalized using the min-max method and converted into numerical format. The data is split into training and testing sets in a 70:30 ratio. The training data is analyzed using the SVM and KNN methods and compared against the testing data to calculate accuracy and RMSE. For KNN, the parameter values listed in Table 4 are used. These parameters are commonly applied in KNN settings for machine learning model training.

1) Hidden Layers: With three hidden layers, the neural network can identify more complex patterns in the data. However, too many hidden layers may lead to overfitting.
2) Training Cycles: The model undergoes 200 training cycles, meaning it processes the training data 200 times. This influences how well the model learns the data patterns.
3) Learning Rate: A learning rate of 0.01 results in small, incremental updates during training, promoting stable but slower convergence. Larger values could destabilize the model.
4) Momentum Parameter: A momentum value of 0.9 incorporates 90% of the previous gradient into the current update, helping to avoid local minima and accelerate convergence.
5) Decay Parameter: When set to True, the learning rate decreases as training progresses, enhancing stability and improving accuracy in later stages of training.

TABLE 7.
SVM ACCURACY AND RMSE VALUES

	True TF	True DF	True TC	True DC	True TR	True DR	Class Precision (%)
Pred TF	0	0	0	0	0	0	0
Pred DF	1	75	0	0	0	0	98.68
Pred TC	0	1	**1024**	9	0	0	99.03
Pred DC	28	0	0	737	0	115	83.75
Pred TR	0	0	0	0	118	0	100
Pred DR	0	0	1	0	0	0	0
Class Recall (%)	0	98.68	99.9	98.79	100	0	
Accuracy							92.65%
Precision							63.58%
Recall							66.23%
F1-Score							64.88%
RMSE							27.1%

6) Shuffling: Setting the shuffle parameter to True ensures the data is randomized during training, which prevents the model from learning specific data sequences and improves generalization.
7) Data Normalization: Normalization standardizes data to a similar scale, enabling more efficient and faster training by avoiding the dominance of features with larger scales.
8) Epsilon Error: An epsilon error value of 1.0×10−41.0 \times 10^{-4} means that if the error change becomes very small (less than 0.0001), training halts, indicating model convergence.
9) Random Seed: When the random seed is set to False, training results may vary across runs. Setting it to True ensures reproducible results by using consistent random seeding.

After testing, the KNN model achieved an accuracy of 99.55%, a precision of 99.55%, a recall of 99.11%, and an F1-Score of 99.33%, with an RMSE value of 11.9%, as shown in Table 5. The table provides an overview of KNN's performance in classifying data accurately, highlighting the model's effectiveness in recognizing each class based on precision and recall values. It also indicates the percentage of original data from each class that was correctly predicted.

Table 6 outlines the parameters used in the SVM model.

1) Kernel type: a linear kernel (dot product) is employed, which is effective for data that can be separated linearly. This kernel type often provides better interpretability and faster results compared to non-linear kernels.
2) Kernel cache: the kernel cache size is set at 200 mb to accelerate model training by minimizing the time required for repetitive kernel calculations, particularly for handling large datasets like freight data.
3) Parameter c: a value of 0 indicates no penalty is imposed for classification errors.
4) Epsilon convergence threshold: the epsilon value is set at 0.001 to ensure the model achieves stable predictions for goods placement.
5) Maximum iterations: the model training is capped at 100,000 iterations, providing ample opportunity to find the optimal solution, which is particularly important for large datasets such as freight data.
6) Scale parameter: scaled data enhances model performance and training speed, ensuring accurate predictions for goods placement.
7) L_Pos and L_Neg: there is no special emphasis on any single class, allowing fair treatment of all goods types during delivery classification.
8) Error tolerance: no tolerance is allowed for prediction errors, ensuring highly precise predictions critical for efficient logistics operations.
9) Quadratic loss: the quadratic loss parameter for positive and negative classes is set to False, meaning the model does not use quadratic loss for either class. Instead, it utilizes a linear loss function or another specified loss type.

The parameters used in the SVM model contribute to the development of an efficient and accurate goods placement prediction system for logistics. By employing a linear kernel and data scaling, the model effectively processes freight data from Pos Indonesia in Malang, facilitating improved decision-making in the logistics workflow. As referenced in Table 5, Table 7 presents the accuracy and RMSE values for the SVM model. After testing, the SVM model achieved an accuracy of 92.65%, a precision of 63.58%, a recall of 66.23%, and an F1-Score of 64.88%, with an RMSE value of 27.1%.

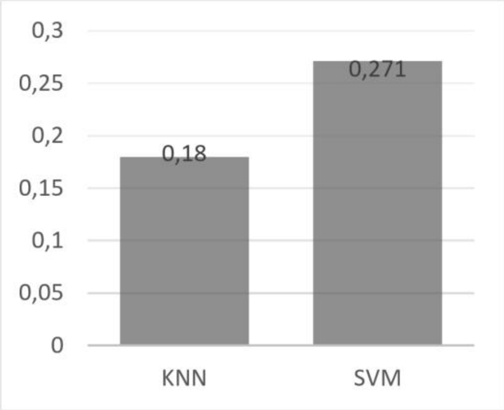

Figure 26. Error Result

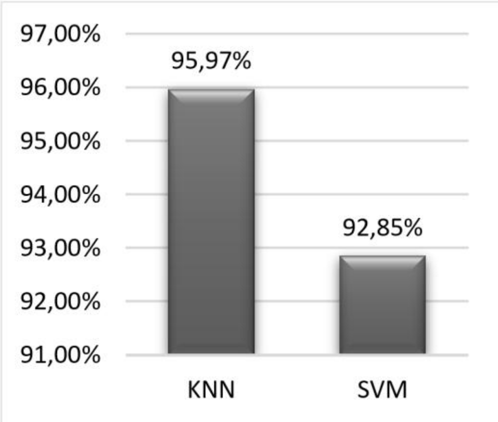

Figure 27. Accuracy Result

Based on the testing results, a comparison between the two classification methods—Support Vector Machine (SVM) and K-Nearest Neighbor (KNN)—demonstrates that KNN is more optimal than SVM. KNN achieved an accuracy of 95.97%, while SVM reached only 92.85%, as shown in Figure 3. The 3.12% difference in accuracy highlights the superiority of KNN in prediction accuracy.

In addition to accuracy, KNN outperforms SVM in terms of error scores. KNN achieved a Root Mean Square Error (RMSE) of 0.18, whereas SVM recorded a higher RMSE of 0.271, as shown in Figure 4. The lower RMSE of KNN indicates that this method produces predictions with smaller error rates. These results affirm that KNN is more reliable and consistent in predicting the placement of goods compared to SVM. The advantages of KNN in both accuracy and error scores suggest that it is better suited for classification applications in the datasets used.

IV. CONCLUSION

The comparison of classification methods reveals that K-Nearest Neighbor (KNN) outperforms Support Vector Machine (SVM) in both accuracy and error rates. KNN achieved a higher accuracy of 95.97% compared to SVM's 92.85%, with a 3.12% margin demonstrating KNN's superior predictive performance. Additionally, KNN's lower Root Mean Square Error (RMSE) of 0.18, compared to SVM's 0.271, underscores its ability to produce more precise predictions. These findings confirm that KNN is more reliable and better suited for classification tasks in the evaluated datasets.

The researchers recommend further development of this study to achieve even more optimal results. Future research could explore new techniques or alternative methods to enhance the performance of classification models. Additionally, the study results could be presented in visual forms that serve as practical guides for goods placement. Such visualizations would aid decision-making and improve the effectiveness of goods placement in real-world scenarios. To advance this research, future directions may include exploring hybrid models that combine the strengths of multiple algorithms, developing systems for real-time placement predictions, and testing more robust algorithms capable of handling complex and varied logistics scenarios. Examining larger datasets and incorporating deep learning techniques could also provide further insights for optimizing logistics efficiency.

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