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Prediction of Ship Time in Port Using Machine Learning Algorithm

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***Abstract*— Effective time management is crucial in the shipping business at ports, ensuring smooth operations from a ship's arrival to its departure. Delays in port can disrupt sailing schedules, leading to inefficiencies in logistics and increased operational costs. This study aims to predict the duration of a ship's stay in port, focusing on container and general cargo ships. Accurate predictions can help optimize scheduling and resource allocation. The research applies machine learning techniques, utilizing historical arrival and departure data from Tanjung Priok Port for 2022 and 2023. Four algorithms were evaluated: Random Forest, Linear Regression, K-Nearest Neighbors (KNN) Regression, and Support Vector Machine (SVM). Results indicate that Linear Regression provides the most accurate predictions, outperforming other models in terms of Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Additionally, its coefficient of determination (R^2) is closest to one, confirming its reliability for forecasting ship turnaround times.**

Keywords— machine learning, shipping, algorithm, maritime education.

I. INTRODUCTION

Maritime transportation is a crucial component of global trade, accounting for over 80% of the world's trade volume [1]. Containerized cargo represents approximately 60% of this trade, with the remainder handled as general cargo. Ports that provide container and general cargo services are crucial in supporting the supply chain and achieving economic growth strategies. Ports and terminals must serve ships efficiently and effectively, as this will impact their hinterland, meaning that good performance will affect the schedule of shipping routes and ensuring efficient handling and turnaround of ships [2]. The performance of a port is a crucial aspect for shipping companies operating both scheduled and regular (liner) services as well as unscheduled and irregular (trumper) services, because delays at the port of origin will affect the next port.

Tanjung Priok, Indonesia's busiest port, serves as a gateway for import and export activities, as well as inter-island cargo distribution throughout Indonesia. Tanjung Priok Port is the working area of the Tanjung Priok Port Authority and Harbor Office, which is responsible for monitoring and supervising the operations of the port. One of the platforms for carrying this out is through Inaportnet. The performance of the port, as seen from port operations and the duration of ships at the port that experience improved performance, will have a beneficial impact on stakeholders at the port, as this is an important aspect of port performance indicators [3] [4]. The World Bank Group in – The Container Port Performance Index 2023, A Comparable Assessment of Performance Based on Vessel Time in Port, states that Tanjung Priok Port has significantly risen in rank to number 23. The performance of Tanjung Priok Port was ranked 281 in 2022 and 124 in 2021.

In the UNTACD report for 2023, it is noted that bulk carriers spend three times longer in port compared to container ships, while for general cargo vessels, speed is not as critical. In mid-2022, the median time in port for container ships was approximately 0.77 days, which marked an increase from 0.8 days in the first half of 2022 [5]. Vessels entering ports in Indonesia must be notified by the ship operator, captain, agent, general agent, or sub-agent no later than 24 hours before the ship's arrival at the port to the Port Authority. This requirement is not only applicable in Indonesia but also in regional ports of other countries, where it must be communicated to the local authorities [6] [7]. The time a ship spends in the port is defined as the period from when the ship enters the port area until it leaves the port. In every port in Indonesia that is served by the Inaportnet system, each ship entering and exiting the port is recorded based on its arrival and departure times. Mathematically, the time a ship spends in the port is the difference between the departure time and the arrival time of the ship at the port.

Artificial Intelligence (AI) can be a solution in optimizing ports, managing port operations, reducing ship time in ports, cargo throughput, and overall efficiency at ports. AI can also reduce environmental impact at ports and optimize ship routes as well as logistics [8]. Machine Learning (ML) is a branch of artificial intelligence that enables computer programs to automatically learn and improve their capabilities from experience. Machine learning algorithms study a

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dataset, and then based on the patterns identified from that dataset, they make predictions on unseen data [9]. Machine learning algorithms can be categorized into two types: supervised learning algorithms and unsupervised learning algorithms. Supervised learning algorithms consist of two types: regression algorithms and classification algorithms [10].

The fundamental idea behind machine learning is to use statistical learning and optimization techniques to enable computers to scan information for patterns. Data mining is a tool used by machine learning approaches to find previous trends and provide guidance for future models. A decision process is a series of computations or other procedures that receives data and determines the type of pattern your algorithm is searching for. When available, an error function can be used to compare the quality of the question to known examples. The complete set of raw historical data is needed for machine learning. A model must first be trained using historical data, and then it must be trained using fresh parameters or new data sets, to produce an algorithm that detects trends or deviations. ML can be applied to predictions or classifications [11]. The more data there is, the more precise the machine learning prediction.

Machine learning is well suited for large-scale data analysis of daily port operations. By processing historical data quickly and in depth, ML processing algorithms help predict the length of time a ship will dock based on historical patterns and current conditions, which might take a very long time if done manually. Because they are able to learn from previous data and optimize the model based on discovered errors, machine learning (ML) models tend to make more accurate predictions [12]. In contrast, traditional methods may be less flexible to new data changes. The prediction process can be automated with machine learning, which is definitely more efficient than manual methods. This can help port management make faster and more proactive decisions about scheduling, resource allocation and improving operational efficiency.

There are several pieces of literature that analyze the turnaround time of ships in ports using machine learning, but none specifically focus on predictions. Research that has been conducted, such as predicting the time ships spend in port for liquid cargo vessels at the port of Mumbai, India, indicates that among the various machine learning algorithms used, the more accurate supervised model is random forest; however, the best results are achieved using the artificial neural network method [13]. This research introduces a novel approach by applying multiple machine learning algorithms—Random Forest (RF), Linear Regression (LR), K-Nearest Neighbors (KNN) Regression, and Support Vector Machine (SVM)—to predict ship turnaround time at Tanjung Priok Port. While some studies have applied machine learning for similar predictions in other ports by comparing the error metrics of each type of ship. This study focuses on Indonesian port operations, providing localized insights that have not been extensively explored in previous research. By leveraging historical ship arrival and departure records, this study aims to determine the most effective machine learning model for predicting ship turnaround time at Tanjung Priok Port. The findings of this research can contribute to better port management, optimized ship scheduling, and reduced operational inefficiencies.

Several studies have compared these algorithms in maritime applications. A study on Mumbai Port found that RF outperformed LR in predicting liquid cargo vessel turnaround time. Conversely, research on container ports in Europe indicated that LR achieved higher accuracy in predicting port congestion levels [14]. This study contributes to the literature by applying these models to Indonesian port data, specifically Tanjung Priok Port, and identifying the most suitable algorithm for predicting ship turnaround times. While previous studies have examined ML applications in maritime logistics, few have focused on ship turnaround time prediction in Indonesia. Most studies analyze global ports, whereas this research provides localized insights by utilizing Indonesian port data. Furthermore, existing literature often relies on single-algorithm approaches, whereas this study compares multiple ML techniques to determine the most accurate model. By doing so, this research offers a novel contribution to port management strategies and operational efficiency improvements at Tanjung Priok Port.

II. METHOD

A. *Data Sets*

The dataset used consists of data from the arrival and departure reports of ships (LK3) domestically, obtained from the Port Authority and Harbor Office of Tanjung Priok for the years 2022 and 2023. Based on this dataset, calculations can then be performed to determine the duration of ships at the port[15], with the ship category used for container ships and general cargo. Data of LK3 used is the daily data of the ship. From the data set, it is known that for container ships it is a type of liner operation, and for general cargo ships it is a mixture of liner and tramping.

B. *Model Selection*

Ship turnaround time is a key performance indicator for port efficiency, as it directly influences shipping schedules, trade costs, and logistics planning. Efficient port operations ensure that vessels spend minimal time docked, reducing operational expenses and improving cargo flow [16]. Studies have shown that container ships generally have shorter turnaround times compared to bulk carriers and general cargo vessels [17]. Delays in port operations lead to congestion, increased costs, and environmental impacts due to prolonged fuel consumption during idling [18]. Supervised learning algorithms have been widely used for predictive analytics in maritime studies. Four common algorithms include: Random Forest (RF) – A decision-tree-based model known for its robustness in handling large datasets. Prior research has found RF effective in predicting vessel arrival times when dealing with incomplete data [19]. Linear Regression (LR) – A statistical model that establishes relationships between input features and the target variable. Studies have shown that LR performs well in predicting port congestion trends [20]. K-Nearest Neighbors (KNN) Regression – A distance-based algorithm that assigns predictions based on the nearest training samples. While effective for small datasets, KNN tends to perform poorly with high-dimensional maritime data. Support Vector Machine (SVM) – A machine learning technique that maximizes the margin between different data points to improve predictive accuracy. However, SVM is computationally expensive for large-scale port datasets.

Supervised learning is a fundamental type of machine learning, which is based on the patterns that relate variables and labels from a dataset. Supervised learning algorithms take feature data as input and prediction values as output [21]. The chosen model from the two available types is the regression type, which includes algorithms such as random forest, linear regression, K-Nearest Neighbors (KNN), and SVM algorithms. (Support Vektor Machine). Due to time constraints, we decided not to use hyperparameter tuning in this research, in the future further experiments will include hyperparameters so that the algorithm results are more optimal.

The KNN algorithm is a method where the available data is stored and new data is categorized based on similarity, with predicted values obtained from the arithmetic mean of the target data [14]. Linear regression is a statistical analysis method that uses regression analysis to determine the quantitative relationship between two or more variables. The K-Nearest Neighbors (KNN) regression algorithm is based on the discovery of Euclidean distance between different data points and training dataset points to select one k-nearest value and form an average as a prediction [22]. Meanwhile, the support vector machine algorithm minimizes the error between actual predictions and predicted values by maximizing the distance between hyperplanes that contain the data.

From the four algorithms, the quality of the prediction results will be assessed using commonly used statistical measurements based on the results of a training model and a test prediction dataset, namely mean absolute error, mean squared error, and root mean squared error. Mean Absolute Error (MAE) is calculated based on the average of the absolute errors obtained from the subtraction of the actual values from the predicted values. Mean Squared Error (MSE) is similar to MAE, where the error of each data point is squared, and root mean squared error is the square root of MSE, as shown in Table 1, where n is the number of data points to be tested, Yi is the actual value of the i-th data point, and Ŷi is the predicted value of the i-th data point, along with the measurement of the coefficient of determination (r^2 score) to observe the relationship between predictions and actual values [23][14]. The method used to obtain that value is available in the sklearn.metric class in the Python programming language version 3.9.12.

TABLE 1.
METRIC MEASUREMENT

Description	Equation
Mean Absolute Error	$\frac{1}{n}\sum_{i=1}^{n}\lvert Yi - \hat{Y}i\rvert$
Mean Squared Error	$\frac{1}{n}\sum_{i=1}^{n}(Yi - \hat{Y}i)^2$
Root Mean Squared Error	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Yi - \hat{Y}i)^2}$

C. Data Processing

Data processing using machine learning algorithms requires a specific data format for training. Therefore, the data source must undergo separation, cleaning, and processing. The Excel data file will be analyzed by separating and cleaning unnecessary data so that we obtain the arrival and departure data of ships and the duration of time ships spend in the port. In machine learning algorithms, they can only operate with numerical data, so the first step involves converting the data into numbers. The second step is to divide the data into a training dataset of 80% and a test dataset of 20%. The final step is data scaling or normalization [24]. Data processing is carried out using the Python programming language to obtain metrics from the tested algorithms.

III. RESULTS AND DISCUSSION

The distribution of goods at Tanjung Priok Port is predominantly carried out using container ships compared to general cargo ships, according to the data analysis results at Tanjung Priok Port, as shown in Table 2. The average time that container ships spent at the port in May 2022 was still high, reaching 6 (six) days; similarly, in 2023, during the same month, it was at its peak. The length of time the ship is in port in that month is because the end of April 2022 and the beginning of May 2023 are the Eid holidays, many workers at the port are still on holiday. It is recommended that the container terminal should be more competitive to achieve operational efficiency [23]. The average time at the port for general cargo ships in July 2023 even reached 24 (twenty-four) days as indicated in Table 3. The port must improve its performance by serving more ships in a shorter time [25]. A comparison of the time spent at the port for container ships and general cargo ships shows that the average time for general cargo ships is longer than that for container ships, reaching 1.5 times longer in 2022, and in 2023, it increased to 2 times longer than that of container ships.

TABLE 2.
SHIP TIME IN PORT TYPE CONTAINER SHIPS

Month	2022			2023		
	Total Ships	Mean (days)	standard deviation	Total	Mean (days)	standard deviation
January	213	3.49	3.16	219	3.48	3.16
February	200	3.03	2.37	219	3.09	2.40
March	232	2.95	2.06	258	2.59	2.24
April	204	2.77	1.75	170	4.36	10.36
May	183	5.93	9.08	235	4.44	5.55
June	223	3.05	2.46	230	2.69	2.23
July	234	3.16	2.99	232	2.93	2.51
August	228	3.23	2.76	234	2.89	2.68
September	211	2.89	2.90	238	2.80	2.93
October	234	3.29	7.74	231	4.36	15.63
November	212	3.18	2.60	234	2.76	2.24
December	227	2.92	2.01	231	2.92	4.15
TOTAL/Mean	2374	3.32		2731	3.28	

TABLE 3.
SHIP TIME IN PORT TYPE GENERAL CARGO SHIPS

Month	2022			2023		
	Total Ships	Mean (days)	standard deviation	Total	Mean (days)	standard deviation
January	76	14.14	85.19	82	5.16	9.33
February	74	3.16	4.04	77	6.76	16.23
March	73	5.57	13.48	70	5.30	13.85
April	66	3.82	4.39	60	7.74	16.79
May	64	4.41	4.20	58	3.86	5.64
June	83	5.33	9.03	70	3.81	8.54
July	86	3.57	4.83	74	24.69	179.26
August	77	4.01	6.65	68	4.91	7.80
September	91	3.86	6.48	79	5.62	13.70
October	96	4.90	15.63	80	5.08	15.67
November	98	5.89	26.29	78	4.32	7.37
December	78	3.44	5.62	77	4.92	6.92
TOTAL/Mean	962	5.18		873	6.85	

Daily data based on the duration of time ships spend in port for container ships and general cargo ships, as shown in Figure 1 and Figure 2.

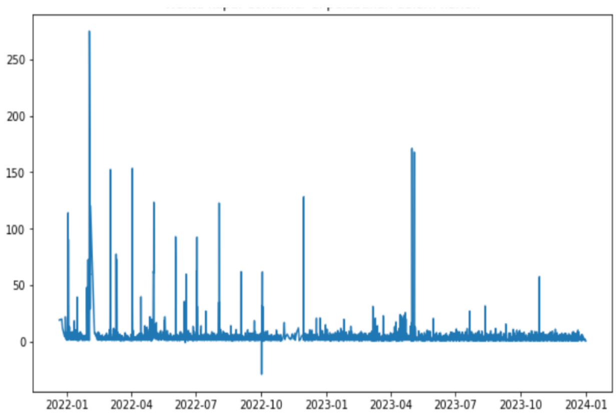


Figure 1a. Arrival time vs. duration at Port

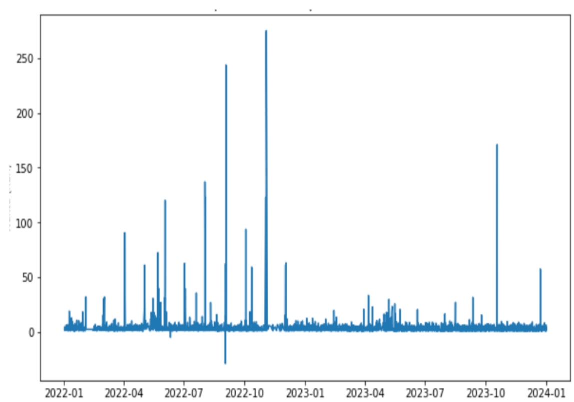


Figure 1b. Departure time Vs duration at port

Figure 1. Ship time at port for container ships

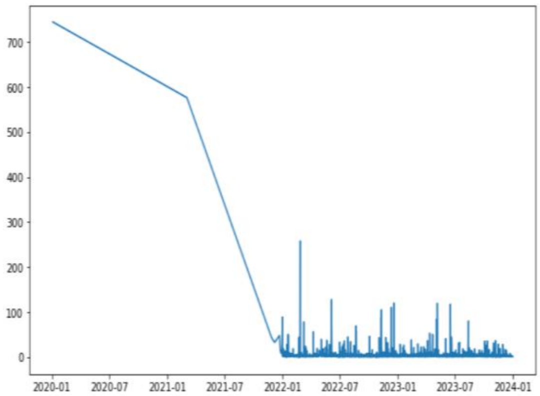


Figure 2a. Arrival time vs. duration at port

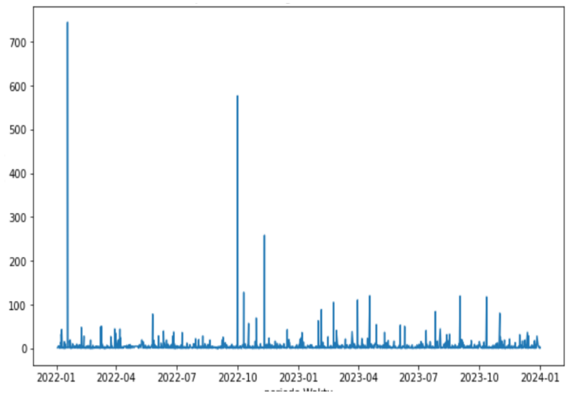


Figure 2b. departure time Vs duration at port

Figure 2. Ship time in port for general cargo ships

For container ships in 2022, there was an input error that resulted in negative port times, and the daily data was still unstable regarding the duration of ships in port. However, in 2023, there has been an improvement in the average time ships spend in port. For general cargo ships, there were several vessels with very long port stay times, even reaching hundreds of days in 2022, as shown in Table 2. There was a high standard deviation in January 2022; however, in 2023, there has been an improvement in the average data for the duration of ships at the port.

Machine learning has advantages in prediction accuracy [26], particularly in predicting ship arrival times at ports for container ships using the random forest algorithm, which is useful when we lose data or have an imbalanced dataset. The Mean Absolute Error (MAE) obtained is 0.989, and the Mean Squared Error (MSE) is 19.578. The graphical representation of the predicted and actual results is shown in Figure 3..

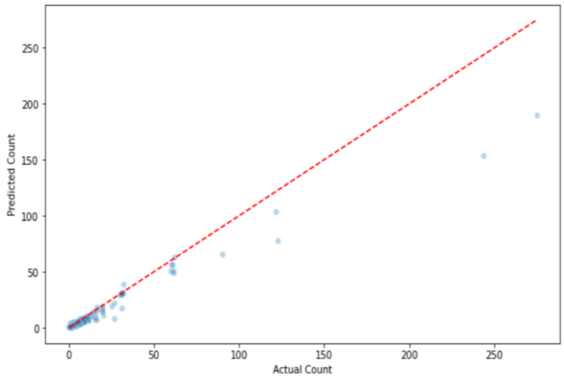


Figure 3. Random Forest Algorithm

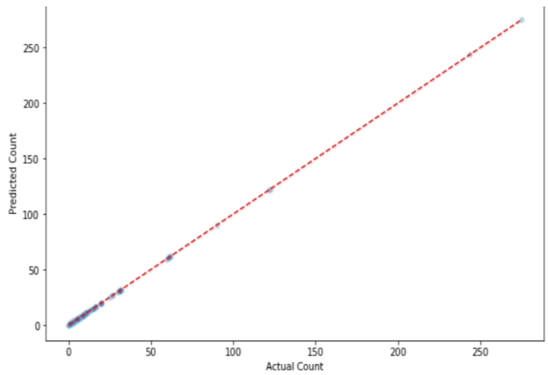


Figure 4. Linier Regression Algorithm

Using the Linear Regression algorithm, an MAE of 1.341e-12 and an MSE of 5.141e-24 were obtained, which are lower than those of the random forest algorithm. The linear regression graph is shown in Figure 4, where it can be seen that the predictions and actual values are very close to each other. The measurements using the K-Nearest Neighbors regression (KNN) algorithm resulted in an MAE of 1.104 and an MSE of 23.058, which are higher than those of the random forest, as shown in Figure 5. For the support vector machine (SVM) algorithm, the MAE value obtained was 2.998 and the MSE value was 178.775, which is greater than that of the KNN algorithm, with its regression graph presented in Figure 6.

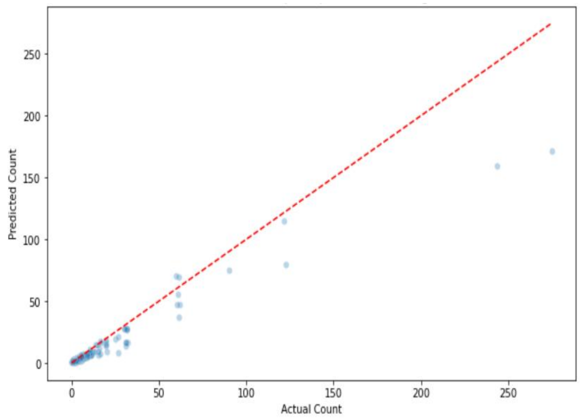


Figure 5. KNN Algorithm

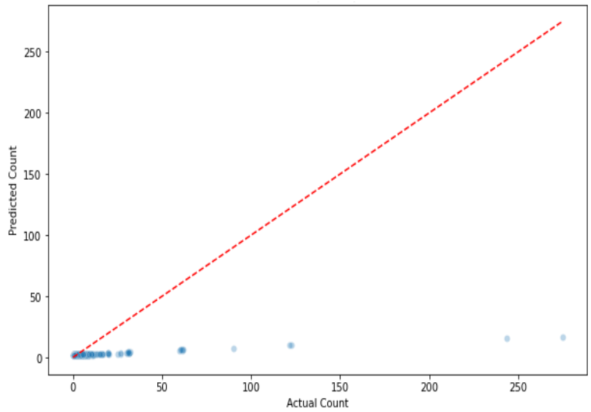
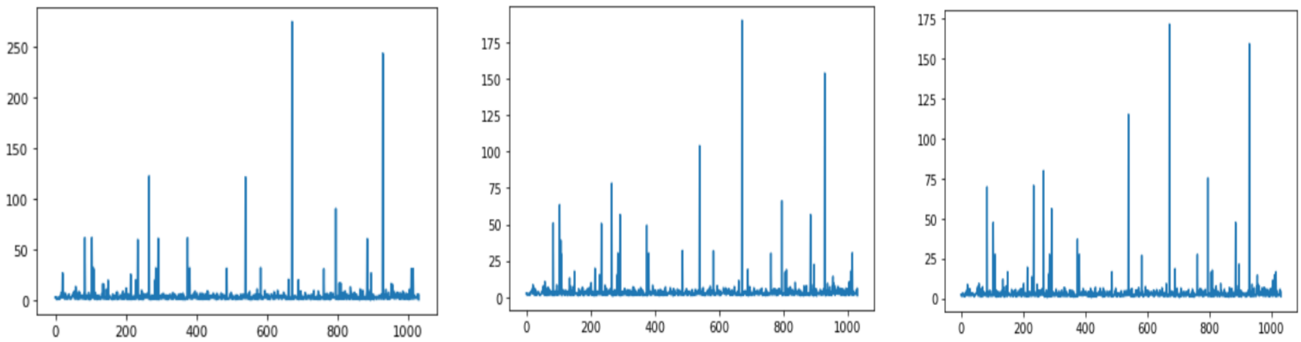


Figure 6. SVM Algorithm

From the calculations, it was found that the linear regression algorithm has the lowest value compared to the other three algorithms, as shown in Table 4, and the prediction graph of this algorithm can be seen in Figure 7. This indicates that the linear regression algorithm performed better in terms of accuracy or error rate when compared to the other algorithms analyzed. Consequently, it suggests that this method may be more reliable for the given data set. Furthermore, the consistent performance of the linear regression algorithm across various test scenarios highlights its robustness, making it a preferred choice for future predictive modeling tasks. This reliability not only enhances the validity of the results but also instills confidence in stakeholders regarding the decision-making process based on these predictions.



a. Linier Regression Algorithm
b. Random forest Algorithm
c. KNN Regression Algorithm

Figure 7. Predicting the duration of a ship's stay at the port using algorithms

TABLE 4.
MEASUREMENT METRICS FOR CONTAINER SHIPS

No	Algortihm	MAE	MSE	RMS	r^2
1	Random Forrest	0.989	19.578	4.425	0.899
2	Linier Regression	1.341 e-12	5.1349 e-24	2.267 e-12	1
3	KNN	1.104	23.058	4.802	0.882
4	SVM	2.998	178.775	13.371	0.086

In the prediction of the time a general cargo ship spends in port using the random forest algorithm, the MAE value obtained is 3.683 and the MSE value is 704.275. These values are higher than those for container ships, as general cargo is a combination of liner and tramping routes, as shown in Figure 8. Using the linear regression algorithm, the MAE value obtained is 1.079e-12 and the MSE is 4.045e-24, which are lower than those from the random forest algorithm, as illustrated in Figure 9.

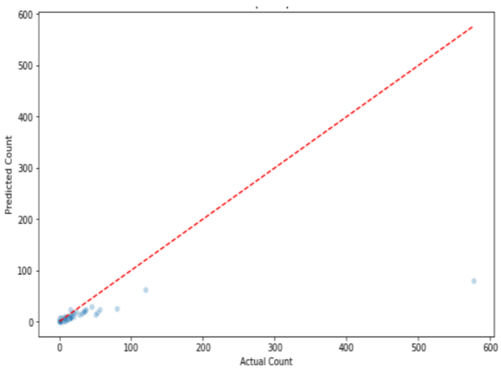


Figure 8. Random Forest Algorithm

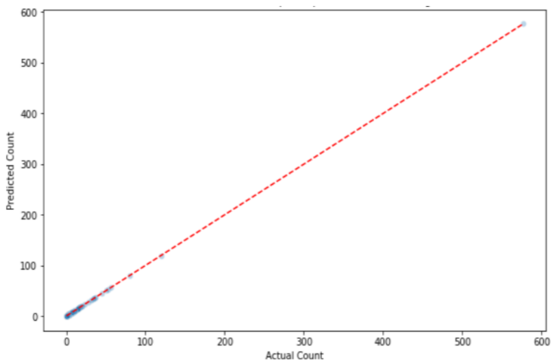


Figure 9. Linier Regression Algorithm

Measurements using the K-Nearest Neighbors regression (KNN) algorithm yielded an MAE of 3.725 and an MSE of 667.686. In terms of MSE, KNN is lower than random forest, as shown in Graph 10. With the SVM algorithm, an MAE of 5.257 and an MSE of 997.061 were obtained, with the graph illustrated in Figure 11. Similar to the container ship, the linear regression algorithm has a lower value than the three algorithms used to predict the ship's time at the port. The calculations show that the linear regression algorithm has the smallest value among the three other algorithms, as presented in Table 5, and the prediction graph from this algorithm can be seen in Figure 12.

TABLE 5.
MEASUREMENT METRICS FOR GENERAL CARGO SHIPS

No	Algorithm	MAE	MSE	RMS	r^2
1	Random Forrest	3.683	704.275	26.538	0.288
2	Linier Regression	1.079 e-12	4.045 e-24	2.011 e-12	1
3	KNN	3.725	667.686	25.839	0.325
4	SVM	5.257	997.061	31.576	-0,008

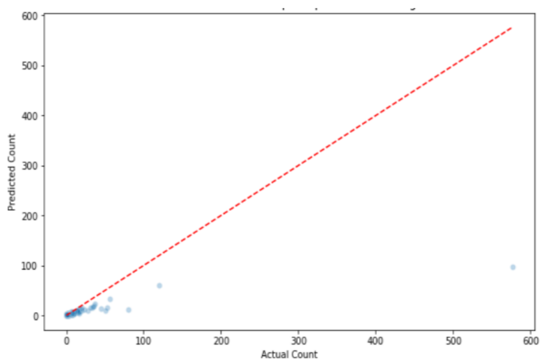


Figure 9. KNN Algorithm

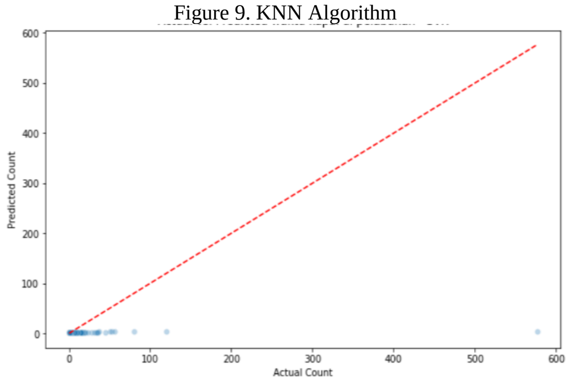
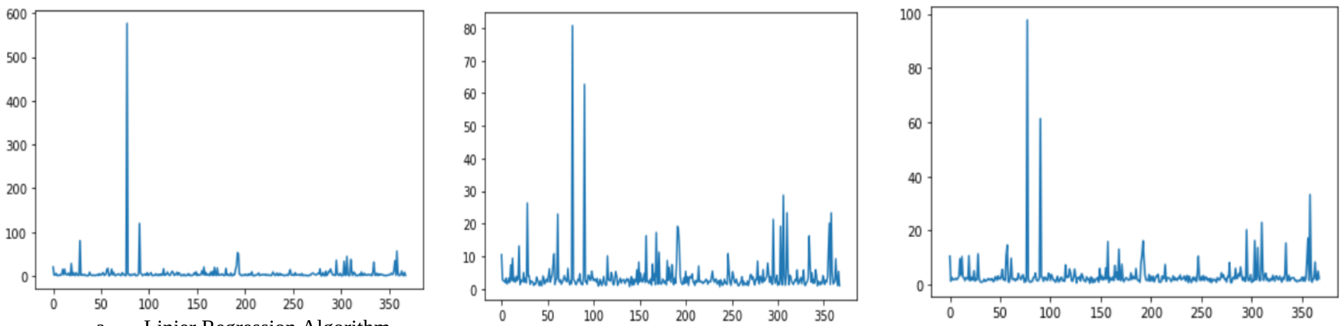


Figure 10. SVM Algorithm



a. Linier Regression Algorithm   b. Random forest Algorithm   c. KNN Regression Algorithm

Figure 12. predicting the duration of a ship's stay at the port using algorithms

Based on the results of each algorithm, container type ships have a better value than general cargo ships. This is due to the fact that on the container ship type all shipping is on a liner route, while on the general cargo ship type it is a mixture of liner and tramper. Likewise, from statistical data, the average monthly standard deviation of the length of time a ship is in port for general cargo ships is very varied and large, even reaching 179 days in 2023 and 85 days in 2022. From the results of the prediction of the length of time a ship will be in the port, it can be used if ship service is still low from the port, so if there is free time and the presence of the ship can be used for other ships, the ship's efficiency can also be maximized if the ship can enter at an empty time. Data from metric measurements that are suitable and more accurate can be used as reference material for predicting the length of time a ship will be in port so that it can be used as an assessment in order to increase port efficiency and performance. By implementing, reducing the ship's time at the port is not only for loading and unloading, goods clearance and truck rotation, also saves time, money and reduces trading costs but also reducing CO2 emissions from ships waiting in port [27] [5]. Of course, it is also an assessment to make green ports in ports even better because by knowing the predicted length time of the ship, exhaust gas emissions from the ship can be controlled, which contributes to the sustainability of port operations.

IV. CONCLUSION

The ship is at the port from the moment it arrives until it departs, which is a service process. Therefore, the longer the ship stays at the port, the more costs will be incurred by the ship owner, and it will affect the logistics schedule of goods. This study aimed to predict the duration of a ship's stay in port using machine learning algorithms, focusing on container and general cargo ships at Tanjung Priok Port. By analyzing historical ship arrival and departure data from 2022 and 2023, four machine learning models—Random Forest, Linear Regression, K-Nearest Neighbors (KNN) Regression, and Support Vector Machine (SVM)—were evaluated based on their predictive accuracy. The results indicate that Linear Regression performed the best, yielding the lowest Mean Absolute Error (MAE), Mean Squared

Error (MSE), and Root Mean Squared Error (RMSE) compared to the other algorithms. Additionally, its coefficient of determination (R^2) was closest to 1, confirming its reliability for predicting ship turnaround time. These findings demonstrate that Linear Regression is the most suitable model for forecasting ship stay duration at Tanjung Priok Port. The implementation of machine learning for port time prediction offers significant benefits for port authorities, shipping companies, and logistics operators by improving scheduling efficiency and resource management. Future research should explore hyperparameter tuning and additional features, such as weather conditions and berth availability, to further enhance predictive accuracy.

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