1st Proceeding of International Conference on Science and Technology UISU (ICST)
"Contribution of Engineering Disciplines to Achieving Sustainable Development Goals Research Realizing the Vision of Golden Indonesia 2045"
ISSN: 3063-7929 (Online)
DOI: https://doi.org/10.30743/icst

Regression Model Analysis in Forecasting Logistics Transportation Performance at Belawan Port Terminal

Ekoliyono Wahyu Sumantri[1*], Dedy Hartama[2], Lili Tanti[3]
[1]Master of Computer Science, Faculty of Engineering and Computer Science, Universitas Potensi Utama, Medan. Indonesia
[2]Department of Computer Science, Faculty of Engineering and Computer Science, Sekolah Tinggi Tunas Bangsa, Pematang Siantar. Indonesia
[3]Department of Computer Science, Faculty of Engineering and Computer Science, Universitas Potensi Utama, Medan. Indonesia
[*]Corresponding author: masterfelixcyber@gmail.com, dedyhartama@amiktunasbangsa.ac.id, lilitanti82@gmail.com

Abstract - This study analyzes the performance of three regression models: Gradient Boosting Regressor (GBR), AdaBoost Regressor (ABR), and Support Vector Regressor (SVR) in the context of predicting the departure time of logistics vehicles at PT. Pelabuhan Belawan. The results show that GBR is optimal at learning rates between 0.05 and 0.07, with high accuracy but prone to overfitting. ABR shows good stability at higher learning rates, while SVR is the most stable model, consistent across a range of epsilon values. Although GBR excels in accuracy, SVR provides the best balance between performance and generalization ability, with delta metrics that are almost unchanged. The analysis shows that logistics vehicles depart early more often than on time or late, reflecting the sensitivity of the model to aggressive learning rate changes. These findings recommend SVR with a learning rate of 0.1 as the optimal model for prediction applications that require stability.

Keywords: ***Regression Model; Predictive Modeling; Learning Rate; Stability; Logistics Transportation***

1. INTRODUCTION

A regression model is a statistical analysis tool used to predict the value of a variable based on a linear relationship with one or more independent variables [1]. The main advantage of using regression models in forecasting is its ability to provide accurate estimates and clear interpretations of the effects of independent variables on the dependent variable [2]. In addition, regression models are relatively easy to apply and can be adapted to various types of data, both continuous and categorical data [3]. In the context of logistics transportation forecasting, regression models can help solve problems by predicting shipping demand, determining precise arrival times, and optimizing shipping routes [4]. By analyzing historical data and variables such as freight volume, traffic conditions, and weather, regression models can provide useful insights to improve operational efficiency and reduce logistics costs.

As an important trade gateway in the region, Belawan Port Terminal plays a major role in facilitating the flow of goods and cargo to and from the region [5]. In the context of a continuously developing economy, efficient logistics transportation at Belawan Port Terminal is crucial to support sustainable economic growth [6]. Improved performance in logistics transportation not only speeds up the flow of goods, but also opens up opportunities for cost savings, increased productivity, and increased competitiveness of local companies [7]. Therefore, research on factors that influence logistics transportation performance at Belawan Port Terminal and efforts to improve it have a significant impact on operational efficiency and economic growth in the region.

Forecasting logistics transportation performance is an important step in overcoming the challenges faced in port terminal management [8]. With accurate forecasting, stakeholders can anticipate demand and goods movement patterns, allowing for more efficient inventory management [9]. This not only reduces the risk of stockouts or excess inventory, but also minimizes storage costs and improves customer service [10]. In addition, accurate forecasting also supports optimal delivery scheduling, ensuring goods arrive on time without unnecessary delays [11]. Route planning based on forecasting can reduce travel time and operational costs, as well as minimize the possibility of congestion and delays [12]. Finally, by leveraging accurate forecasting, resources such as transportation fleets and workforce can be optimized more effectively, resulting in significant operational efficiencies and cost savings [13]. Thus, forecasting logistics transportation performance is not only a predictive tool, but also a key element in a sustainable and efficient management strategy.

The use of regression models in forecasting, especially in the context of logistics transportation at port terminals, is a very relevant and effective strategy [14]. Regression models allow to understand and predict the complex relationships between various variables that influence logistics transport performance [15]. By using a regression model, an analysis can be carried out on how each variable contributes to logistics transportation performance, as well as the extent of its influence [16]. Thus, the use of regression models in forecasting logistics transportation performance at Belawan Port Terminal can help stakeholders to understand the complex dynamics that affect terminal operations, as well as make better and more informed decisions to improve efficiency and effectiveness in logistics transportation management.

Recent developments in regression models, such as Gradient Boosting Regression, AdaBoost Regression, and Support Vector Regression, provide significant progress in forecasting logistics transportation performance. [15], [17]. Gradient Boosting Regression has the advantage of overfitting and producing accurate predictions even in complex datasets. This method iteratively improves the model by considering previous errors, making it effective for handling data with complex patterns [18]. Meanwhile, Adaboost Regression combines several simple regression models into one powerful model [19]. Its advantage lies in its ability

ISSN: 3063-7929 (Online)
DOI: https://doi.org/10.30743/icst

to adjust the weights of each model based on its performance, making it suitable for dealing with imbalanced data problems or dealing with noise in the dataset [20]. On the other hand, Support Vector Regression offers flexibility in handling nonlinear relationships between input and output variables [21]. By utilizing kernel functions, the model built can adapt to complex data patterns and has good generalization capabilities [22].

The purpose of this study is to apply and compare regression models in forecasting logistics terminal density at Belawan Port, focusing on factors that have not been fully explored in previous studies. This study aims to address several existing gaps, such as the use of the Support Vector Regression (SVR) method and the evaluation of the effects of learning rate variations on regression models, which have not been studied in depth before. Using data on logistics trucks entering and leaving Belawan Port during the period 2022 to 2023, this study will apply standard evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared to provide a comprehensive assessment of model performance. This study is expected to provide valuable new insights for port terminal managers, logistics practitioners, and researchers in an effort to improve logistics transportation performance forecasting and operational effectiveness at Belawan Port Terminal.

2. METHOD

This study aims to predict how the performance of logistics transportation at the Belawan Port Terminal, especially in the process of loading goods onto ships from the warehouse of the shipping company. Based on the results of observations made on several shipping companies that use the services of the Belawan Port Terminal, the following is the process of loading the goods:

1. Collection of goods at the warehouse
   The process begins with the collection of goods at the shipping company's warehouse. These goods may have been prepared in advance or have just arrived from the factory or supplier.
2. Processing and Arrangement of Goods
   Once the items are collected, they are processed and arranged according to type, shipping destination, and other special instructions. The items are then labeled or marked for easier identification.
3. Transportation to the Port
   Once the goods are prepared, they are then transported to the port using various transportation methods, such as trucks.
4. Inspection and Documentation
   Before goods enter the port, trucks carrying goods must go through a security inspection and document check at the checkpoint, to ensure that the goods comply with regulations and that the required documents are complete.
5. Loading Goods into Container Terminal
   After going through the inspection and document check process, the goods are then transferred to the container terminal at the port. Here, trucks carrying goods arrive and unload goods from the shipping company's warehouse or storage facility to the container terminal. At the container terminal, the goods are then arranged using the transport equipment available at the terminal, such as cranes, cranes, or conveyors.
6. Return of Truck to Shipping Company
   After the loading process is complete and the goods have been loaded onto the ship, the trucks carrying the goods will leave the port empty or without cargo. These trucks will return to their respective shipping companies.
7. Maintenance and Preparation for Further Delivery
   Once the trucks are back to the shipping company, they will go through a maintenance process and prepare for the next shipment. This includes routine inspections, vehicle maintenance, refueling, and scheduling for the next shipment.

In this study, data collection was carried out in the form of truck activities entering and leaving the Belawan Port Terminal as a research dataset. Data was collected from the Belawan Port Terminal system database regarding the activities of expedition company trucks, which were taken from the period 2023 to 2024. The features of the dataset used in this study are as shown in Table 1.

Tabel 1. Features In Dataset

Fitur	Keterangan
Type	Is the type of vehicle used
Vehicle Brand	Represents the brand of vehicle used
Company	Is the name of the shipping company that owns the vehicle
Distance To Port	Distance from the location where the vehicle is located to the port
In	Vehicle arrival time to the port terminal, in date and time format

ISSN: 3063-7929 (Online)
DOI: https://doi.org/10.30743/icst

Out	Vehicle departure time from the port terminal, also in date and time format
Duration	Duration or length of time spent by the vehicle at the port terminal, calculated from the time of entry to the time of exit. This duration is displayed in the format hours: minutes: seconds

Model Design, this study uses three ensemble learning algorithms in model development, namely Gradient Boosting Regression, AdaBoost Regression, and Support Vector Regression, with the model work process flow as seen in Figure 1.

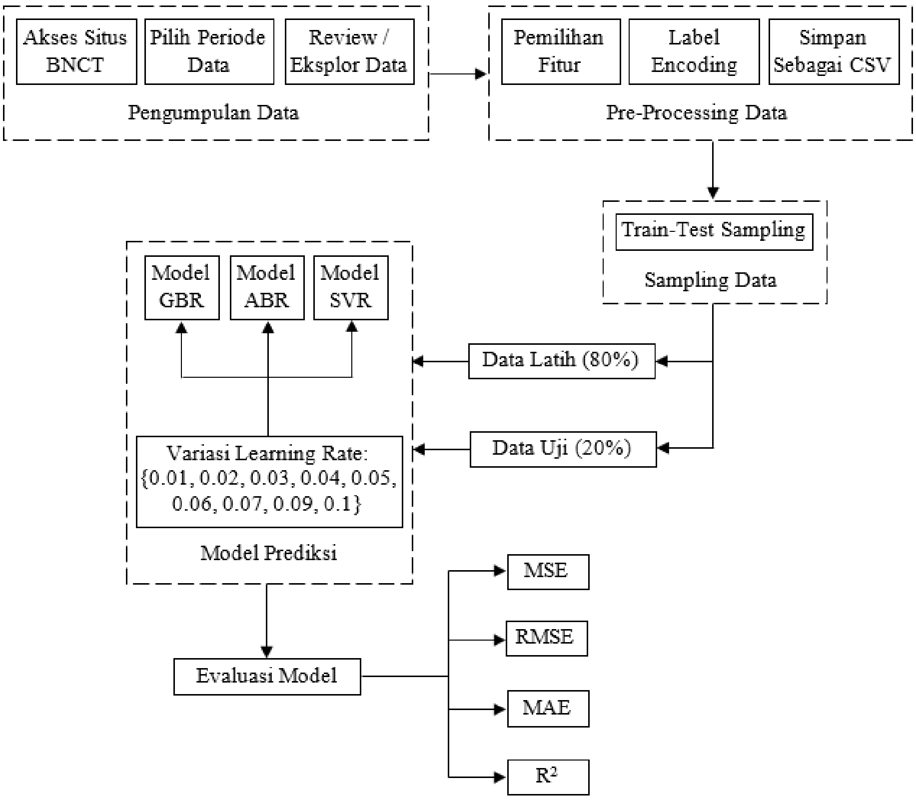

Figure 1. Model Work Process Flow

The following is an explanation of Figure 1 above:

1. Data Collection
   The data collection process begins by accessing the BNCT site at https://portal.bnct-id.com/sso/, where the selected data is the STID TRUCK ACTIVITY LIST for the period August 2023 to August 2024. After the data is obtained, the next step is to explore the data to sort and determine the features that will be used in the analysis. This exploration is important to ensure that only relevant features are used in the model, increasing the accuracy of predictions and the relevance of research results.
2. Data Pre-Processing
   The data pre-processing process begins by selecting important features, namely Type Number, Type, Vehicle Brand, Company, Distance to Port, Vehicle In, and Vehicle Out. To prepare the data for the machine learning model, label encoding is performed on categorical features such as Type, Vehicle Brand, and Company. Next, a new feature is added, namely Duration, which is calculated from the difference between Vehicle Out and Vehicle In. After the pre-processing is complete, the dataset is saved in CSV format for use in the next analysis stage.
3. Data Sampling
   The data sampling process is carried out using the train-test sampling method to divide the data into training data and test data. From a total of 141,786 data, a division with a ratio of 80:20 was carried out, resulting in 113,428 training data used to train the prediction model. Meanwhile, the remaining 28,358 data are used as test data to measure model performance and carry out an evaluation process to ensure prediction accuracy.
4. Prediction Model

ISSN: 3063-7929 (Online)
DOI: https://doi.org/10.30743/icst

This study designs a prediction model by comparing three regression algorithms: Gradient Boosting Regression, AdaBoost Regression, and Support Vector Regression. In the training and testing process, different variations of learning rates are used for each model, with values ranging from 0.01 to 0.1. The purpose of this variation is to evaluate how changes in learning rates affect the performance of each model in predicting logistics terminal density.

5. Model Evaluation
The model evaluation process was carried out using 28358 prepared test data. Each model, with a predetermined learning rate variation, was tested and evaluated using the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-Squared (R^2) metrics. The results of these tests were then compared to determine the most optimal model based on the best metrics. In addition, additional analysis was carried out to assess the effect of each learning rate on model performance using the resulting metrics.

3. RESULTS AND DISCUSSION

Using the prediction results of each GBR, ABR, and SVR model, an analysis of the performance of logistics transportation at Belawan Port was carried out. This analysis was carried out by observing the difference in the OUT value (logistics vehicle exit time in the dataset) with OUT_PREDICT (predicted logistics vehicle exit time). From the results of this calculation, a classification of logistics vehicle performance categories was carried out, such as early, on time, and delayed. This categorization was carried out using a time limit of 10 minutes, which means that if the model prediction results show a difference of less than 10 minutes from the actual time, then the performance of the logistics vehicle is said to be faster. If the difference is between the 10-minute limit, the performance of the logistics vehicle is stated to be on time, while if it exceeds the 10-minute time limit, the performance of the logistics vehicle is late. Tables 2 to 4 show the tabulation results of the number of logistics vehicles from the processed dataset, based on the predetermined categories.

Table 2. Performance Categories of GBR Model Logistics Vehicles

Learning		Train			Test	
Rate	Early	Ontime	Delayed	Early	Ontime	Delayed
0,01	55661	15	60654	14013	1	15069
0,02	56434	7	59889	14194	4	14885
0,03	57621	49	58660	14516	11	14556
0,04	57297	142	58891	14432	35	14616
0,05	56170	591	59569	14186	147	14750
0,06	56523	1809	57998	14150	489	14444
0,07	55220	4078	57032	13978	1067	14038
0,08	54277	6260	55793	13640	1522	13921
0,09	53382	6909	56039	13340	1745	13998
0,1	53049	7185	56096	13274	1699	14110

From Table 2 above, it can be seen that changes in learning rate have a significant effect on the distribution of Early, On-Time, and Delayed categories in predicting logistics vehicle performance. With increasing learning rate from 0.01 to 0.1, there is a change in the pattern of the number of vehicles categorized as Early, On-Time, and Delayed. At low learning rates (e.g. 0.01 to 0.03), the number of vehicles categorized as On-Time is relatively small, while the Early and Delayed categories dominate. However, as the learning rate increases, the number of On-Time vehicles increases significantly. This indicates that models with higher learning rates have the ability to better adjust predictions to actual values, although they do not always result in an increase in overall accuracy. From the average calculation, it can be concluded that overall, vehicles are more often categorized as Delayed with an average of 58,062.1 vehicles (49.91%) in the training data and 14,438.7 vehicles (49.64%) in the testing data. This shows that the model often predicts vehicle departure times later than their actual values. Meanwhile, the Early category has an average of 55,563.4 vehicles (47.76%) in the training data and 13,972.3 vehicles (48.04%) in the testing data. This shows that there are many predictions that tend to be faster than the actual value. The On-Time category, which is the best accuracy indicator, has an average of 2,704.5 vehicles (2.32%) in the training data and 672 vehicles (2.31%) in the testing data. This percentage is very low compared to the other two categories, indicating that the model is still not optimal enough in making truly timely predictions.

Table 3. ABR Model Logistics Vehicle Performance Categories

Learning		Train			Test	
Rate	Early	Ontime	Delayed	Early	Ontime	Delayed
0,01	54398	32	61900	13545	8	15530
0,02	54347	35	61948	13530	11	15542

ISSN: 3063-7929 (Online)
DOI: https://doi.org/10.30743/icst

0,03	54286	22	62022	13508	5	15570
0,04	54282	29	62019	13501	5	15577
0,05	54252	24	62054	13489	7	15587
0,06	54218	43	62069	13481	9	15593
0,07	55989	40	60301	13968	5	15110
0,08	57956	42	58332	14460	15	14608
0,09	57788	45	58497	14424	7	14652
0,1	58214	50	58066	14528	16	14539

Based on the results in Table 3, it can be seen that the model still shows the dominance of the Delayed category, with an average of 52.20% in the training data and 52.37% in the test data. This means that the model tends to predict vehicles leaving later than the actual time. At a learning rate of 0.01 - 0.06, the number of Early predictions is relatively stable at around 54,200-54,300 vehicles. However, starting from a learning rate of 0.07, the number of Early increases significantly to 58,214 at a learning rate of 0.1. This shows that with a higher learning rate, the model tends to be more aggressive in predicting departure times that are faster than the actual value.

The prediction of vehicles that are truly On-Time is very small compared to other categories. The average On-Time on the training data is only 0.0311% and on the test data only 0.0303%. This indicates that the model is still not accurate enough in placing predictions around the 10-minute time limit, so that vehicles are more categorized as Early or Delayed. At a learning rate of 0.01, the number of Delayed reached 61,900 in the training data and 15,530 in the test data. However, as the learning rate increases, this number decreases to 58,066 in the training data and 14,539 in the test data at a learning rate of 0.1. This shows that models with higher learning rates are increasingly likely to predict vehicles exiting faster than the actual time, so that the number of Delayed decreases and the number of Early increases. From the average prediction results, it is obtained that:

1. Early: 47.77% on training data and 47.60% on test data.
2. On-Time: 0.03% on training data and 0.03% on test data.
3. Delayed: 52.20% on training data and 52.37% on test data.

This percentage shows that the model with learning rate variation is still not effective enough in improving On-Time prediction. Most predictions fall into the Delayed category, although there is an increasing trend of Early when the learning rate is getting bigger. On-Time remains very small, indicating that the model is not yet capable of capturing vehicle departure patterns with high accuracy within a time span of ±10 minutes.

Table 4. SVR Model Logistic Vehicle Performance Category

Learning Rate	Train			Test		
	Early	Ontime	Delayed	Early	Ontime	Delayed
0,01	77103	22122	17105	19252	5607	4224
0,02	95545	9654	11131	23898	2415	2770
0,03	103402	4950	7978	25885	1233	1965
0,04	107363	3084	5883	26867	751	1465
0,05	109728	2086	4516	27456	488	1139
0,06	111342	1412	3576	27847	355	881
0,07	112424	1089	2817	28120	280	683
0,08	113286	719	2325	28329	201	553
0,09	113840	545	1945	28479	151	453
0,1	114245	451	1634	28590	115	378

At a low learning rate of 0.01, the model produces a fairly high number of Early predictions, reaching 77,103 out of a total of 116,330 data, which means that about 66.3% of the predictions assume the vehicle exits faster than the actual time. As the learning rate increases, the number of Early predictions increases, and at a learning rate of 0.1, Early predictions jump to 114,245, or 98.2% of the total. This increase in the number of Early predictions indicates that the model tends to be more optimistic, predicting the vehicle exits faster than it should, as the learning rate increases. This phenomenon shows that the model becomes more sensitive to the acceleration pattern of vehicles that exit early. On the other hand, the On-Time category experiences a significant decrease as the learning rate increases. At a learning rate of 0.01, the number of On-Time predictions is still quite high, at 22,122 (19.0%), but as the learning rate increases, the number of On-Time predictions decreases drastically, even at a learning rate of 0.1, the number is only 451, or about 0.39% of the total data. This indicates that models with higher learning rates tend to be more often wrong in predicting on-time vehicles, and categorize more vehicles in the Early or Delayed categories. On the other hand, the Delayed category also shows a fairly drastic decrease along with the increase in learning rate. At a learning rate of 0.01, the number of Delayed predictions is 17,105 (14.7%), but at a learning rate of 0.1, the number of Delayed predictions drops sharply to only 1,634 (1.4%). This illustrates that the model tends to avoid predicting late vehicles,

ISSN: 3063-7929 (Online)
DOI: https://doi.org/10.30743/icst

and more often assumes that vehicles will leave earlier (Early category). Overall, although a high learning rate can increase the number of Early predictions, this has the potential to harm the model's accuracy in predicting On-Time and Delayed, indicating that the model is biased towards predicting accelerated vehicle departure times. In terms of average performance, in the training data, the Early category tops with a percentage of 90.97%, while the On-Time category is only 3.96%, and Delayed is around 5.06%. In the test data, similar results are seen with Early reaching 91.02%, On-Time only 3.99%, and Delayed decreasing to 4.99%. This indicates that the model, although very good at predicting vehicles that exit early, is less able to accurately predict vehicles that exit on time or late. In general, the Early category (vehicles that exit earlier than the predicted time) dominates the prediction of logistics vehicle performance in the three tables presented, with a very high percentage, especially at higher learning rates. For example, at a learning rate of 0.1, the proportion of vehicles that exit earlier (Early) reaches 98.2% in the training data and 91.0% in the test data. This shows that the model tends to predict vehicles that are faster than the actual time, with a tendency towards optimism in the model. The model more often predicts that vehicles will exit earlier than what actually happens. However, in reality, the performance of logistics vehicles at PT. Pelabuhan Belawan shows that these vehicles more often exit earlier than the estimated time. This can be interpreted as indicating that logistics vehicles tend to start operations earlier than the scheduled time, although the model predictions can be too extreme in this regard. The Early category recorded significantly more results than the other categories, indicating that even though the actual time was ahead of schedule, vehicles departed earlier than predicted more often.

The On-Time category or vehicles that leave exactly at the predicted time, shows much smaller results compared to the Early category. For example, at a learning rate of 0.01, vehicles categorized as On-Time only reach around 19.0% of the total training data. Even at a higher learning rate, the percentage of vehicles leaving on time decreases drastically. At a learning rate of 0.1, vehicles leaving On-Time only record around 0.39% of the total training data. This illustrates that the model is not very sensitive in predicting vehicles leaving on time, preferring to categorize vehicles in the Early or Delayed categories. Practically, this means that logistics vehicles rarely leave on time based on the prediction model, and there is more tendency for vehicles to leave earlier or later than the specified time. This could be an indication that logistics at PT. Pelabuhan Belawan is more often affected by external factors that cause vehicles to leave earlier or later than predicted. The Delayed category, which indicates vehicles leaving later than predicted, appears with a fairly low number in all tests, but the number is higher at a lower learning rate. For example, at a learning rate of 0.01, the prediction of late vehicles reached 14.7% in the training data, but at a learning rate of 0.1, this figure dropped to only about 1.4%. This shows that late logistics vehicles are not very common in the model's predictions, with the model more likely to predict vehicles that leave early. In reality, although there are late vehicles, the model predicts too optimistically, and vehicles that are truly late are relatively few in the prediction compared to Early. Overall, the conclusion that can be drawn is that logistics vehicles at PT. Pelabuhan Belawan more often leave early (Early category) compared to on-time or late. This reflects the efficiency in the operation of logistics vehicles, but also shows that the prediction model with a high learning rate may be too optimistic in predicting vehicle departures earlier than the actual time. However, most of the predictions of vehicles that leave early may better reflect existing operational patterns, although improvements need to be made to the model to improve the balance between the Early, On-Time, and Delayed categories.

4. CONCLUSION

The GBR model shows significant performance improvement with higher learning rates, reaching optimal values between 0.05 and 0.07 with low error and perfect R-squared. The ABR model shows more stable improvement with higher learning rates, reaching optimal performance between 0.08 and 0.10. The SVR model is very stable to changes in epsilon, with near-perfect R-squared and low error across the tested epsilon range. SVR is the most stable and robust model, ideal for consistent predictions, while GBR is better suited for maximum accuracy, and ABR offers a balance between stability and high accuracy. GBR shows the best consistency at low learning rates, with small metric deltas especially for MAE. ABR shows good consistency at low learning rates for MAE, but is more stable at high learning rates for MSE and RMSE. SVR shows very high consistency across the epsilon range, with almost unchanged metric deltas, making it the most stable model against parameter variations. SVR is more robust to parameter changes than GBR and ABR, which are more affected by learning rate variations. Boosting-based models (GBR and ABR) are more sensitive to learning rate, while SVR is more stable to changes in epsilon. GBR performs best at high learning rates (0.06 to 0.1), with very low error and R-squared close to 1.00, but is at risk of overfitting. ABR performs more stable across the learning rate range, with consistent results and less tendency to overfit. SVR performs almost identically to ABR, with a slight advantage in prediction precision, especially at a learning rate of 0.1. GBR excels in accuracy but is prone to overfitting, while ABR and SVR are more stable and offer better generalization. Between the two, SVR with a learning rate of 0.1 is the optimal choice, as it provides the best balance between high performance and generalization capability, suitable for applications that require stability in prediction. The Support Vector Regressor (SVR) model is the most optimal based on its performance stability across a wide range of parameter variations. SVR shows almost unchanged delta MAE, MSE, and RMSE values despite variations in epsilon, with a very small delta MAE (0.0024–0.0026) and a consistent delta R-Squared at 0.0001. This indicates the consistency of SVR in producing stable predictions between training and testing data, as well as robustness to parameter changes. Gradient Boosting Regressor (GBR) shows larger fluctuations in delta MAE, MSE, and RMSE, especially at low to medium learning rates, indicating potential overfitting and sensitivity to changes in learning rate. AdaBoost Regressor (ABR) is more stable than GBR, but still shows spikes in delta MAE at certain learning rates, which reduces its consistency

ISSN: 3063-7929 (Online)
DOI: https://doi.org/10.30743/icst

compared to SVR. As the learning rate increases, the model tends to be more aggressive in predicting vehicles that depart early and reduces the number of predictions of vehicles that are late. This shows that although high learning rates can increase the model's sensitivity to vehicle acceleration trends, the model still has weaknesses in producing truly accurate predictions in the On-Time category. Logistics vehicles at PT. Pelabuhan Belawan more often depart ahead of schedule (Early category) than on time (On-Time) or late (Delayed). The prediction model also reflects this trend, but with a more extreme tendency towards Early predictions, especially at higher learning rates.

ACKNOWLEDGMENT

The authors would like to thank the Master of Computer Science Program for its support and sponsorship. And we also thank the research collaboration of Universitas Potensi Utama and Sekolah Tinggi Tunas Bangsa for supporting this research.

REFERENCES

[1] A. M. El-Habil, "An application on multinomial logistic regression model," *Pakistan J. Stat. Oper. Res.*, vol. 8, no. 2, 2012.

[2] W. Xu, H. Peng, X. Zeng, F. Zhou, X. Tian, and X. Peng, "A hybrid modelling method for time series forecasting based on a linear regression model and deep learning," *Appl. Intell.*, vol. 49, no. 8, pp. 3002–3015, Aug. 2019.

[3] M. Baak, R. Koopman, H. Snoek, and S. Klous, "A new correlation coefficient between categorical, ordinal and interval variables with Pearson characteristics," *Comput. Stat. Data Anal.*, vol. 152, 2020.

[4] L. Huang, G. Xie, W. Zhao, Y. Gu, and Y. Huang, "Regional logistics demand forecasting: a BP neural network approach," *Complex Intell. Syst.*, vol. 9, no. 3, pp. 2297–2312, 2023.

[5] S. Saragi, "Manajemen Konflik Terhadap Kasus Banjir Rop Akibat Reklamasi Pelabuhan Belawan," *Publik Reform J. Adm. …*, no. 2, pp. 83–92, 2023.

[6] N. Dhiwa, Humaira, Y. Junitasari, I. Asmana, Apsari, Nurftiani, S. Sahara, and E. Aulia, "Dampak Perubahan Teknologi Sistem Logistik di Pelabuhan," *J. Ilm. Wahana Pendidik.*, vol. 9, no. 14, pp. 273–289, 2023.

[7] V. K. Ayu, W. W. Yunanda, and F. Nulhakim, "Strategi Meningkatkan Sistem Keamanan Di Daerah Perbatasan Dengan Jaringan Logistik yang Terintegras," *J. Kewarganegaraan*, vol. 6, no. 1, pp. 1219–1233, 2022.

[8] C. P. Ping *et al.*, "Analisis Kinerja Logistik PT. Batara Indah Mulia Ke Luar Negeri," *J. Ilmu Komput. dan Bisnis*, vol. 13, no. 2, pp. 187–198, 2022.

[9] H. F. D. Siwu, "Permintaan Dan Penawaran Jasa Transportasi," *J. Pembang. Ekon. Dan Keuang. Drh.*, vol. 19, no. 6, pp. 114–122, 2019.

[10] D. Jenderal Penguatan Riset dan Pengembangan, D. Wistiasari, G. Hasan, K. Yanti Limanda, and N. Ohanna, "Peran Supply Chain Management Terhadap Customer Retention Pada Pt. Kimia Farma, Tbk. 1," *J. Ilm. Mhs. Ekon. Manaj. TERAKREDITASI SINTA*, vol. 4, no. 3, pp. 699–707, 2023.

[11] K. Kundori and P. Pranyoto, "Implementasi Kebijakan Transportasi Laut dalam Rangka Pengembangan Sistem Logistik Nasional," *Maj. Ilm. Bahari Jogja*, vol. 21, no. 1, pp. 52–60, 2023.

[12] A. I. Karim and M. A. Anshori, "Analisis Pemilihan Rute Perjalanan Dari Dan Menuju Pulau Pasaran Berdasarkan Waktu Perjalanan," *TAPAK (Teknologi Apl. Konstr. J. Progr. Stud. Tek. Sipil*, vol. 13, no. 1, p. 47, 2023.

[13] C. Rohyana and C. Wulandari, "Analisis Efisiensi Biaya Operasional Menggunakan Pendekatan Forecasting (Studi Kasus Pt Pos Indonesia Kantor Cabang Garut)," *L. J.*, vol. 4, no. 2, pp. 134–153, 2023.

[14] Zurkiyah and S. Asfiati, "Analisis Tingkat Pelayanan Dermaga Pelabuhan Penumpang Teluk Nibung Asahan, Tanjung Balai Sumatera Utara," *Semnastek Uisu*, pp. 248–252, 2021.

[15] H. K. Pambudi, P. G. A. Kusuma, F. Yulianti, and K. A. Julian, "Prediksi Status Pengiriman Barang Menggunakan Metode Machine Learning," *J. Ilm. Teknol. Infomasi Terap.*, vol. 6, no. 2, pp. 100–109, 2020.

[16] W. Kartikasari, D. Setiawan, and E. Fauziah, "Efektifitas Transportasi dan Lokasi Terhadap Distribusi Logistik di Wilayah Komando Armada I TNI-AL," *Rekayasa*, vol. 14, no. 2, pp. 183–190, 2021.

[17] K. Tsolaki, T. Vafeiadis, A. Nizamis, D. Ioannidis, and D. Tzovaras, "Utilizing machine learning on freight transportation and logistics applications: A review," *ICT Express*, vol. 9, no. 3, pp. 284–295, 2023.

[18] S. B. Nadkarni, G. S. Vijay, and R. C. Kamath, "Comparative Study of Random Forest and Gradient Boosting Algorithms to Predict Airfoil Self-Noise," *Eng. Proc.*, vol. 59, no. 1, 2023.

[19] Anwar Sanusi, Chrystia Aji Putra, and Fawwaz Ali Akbar, "Implementation of ADABOOST Algorithm on C50 for

ISSN: 3063-7929 (Online)
DOI: https://doi.org/10.30743/icst

Improving the Performance of Liver Disease Classification," *JEECS (Journal Electr. Eng. Comput. Sci.*, vol. 8, no. 2, pp. 93–102, 2023.

[20] C. Piao, N. Wang, and C. Yuan, "Rebalance Weights AdaBoost-SVM Model for Imbalanced Data," *Comput. Intell. Neurosci.*, vol. 2023, pp. 1–26, 2023.

[21] H. Muradi, A. Saefuddin, I. M. Sumertajaya, A. M. Soleh, and D. D. Domiri, "Support Vector Regression (Svr) Method for Paddy Growth Phase Modeling Using Sentinel-1 Image Data," *Media Stat.*, vol. 16, no. 1, pp. 25–36, 2023.

[22] Z. Liu, K. Zhao, X. Liu, and H. Xu, "Design and optimization of haze prediction model based on particle swarm optimization algorithm and graphics processor," *Sci. Rep.*, vol. 14, no. 1, pp. 1–16, 2024.