



Forecasting Demand for Motorbikes at Astra Motor Balikpapan Using Support Vector Regressor

Rifaldho Muhammad Rizki¹, Ramadhan Paninggalih², Syamsul Mujahidin³

^{1,2,3} Institute Kalimantan Technology, North Balikpapan, Indonesia

Correspondence: E-mail: ramadhanpaninggalih@lecturer.itk.ac.id

ABSTRACT

Forecasting requests for motorbikes is a critical aspect of Astra Motor Balikpapan's operations. The Support Vector Regression (SVR) model, a method commonly used in forecasting, is particularly useful when dealing with complex data that may contain outliers and when the data is limited. This research evaluates the performance of the SVR model in estimating requested motorbikes at Astra Motor Balikpapan for 3, 6, 9, and 12 months, and analyzes the impact of parameter changes in the model evaluation. The request data for Astra Motor Balikpapan motorbikes used for five years or 60 months, which are divided into two parts: training and test data. The SVR model was built with three Kernel types: linear, polynomial, and RBF kernels. The evaluation results demonstrate the SVR model's ability to predict request motorbike with Sufficient accuracy, with minor mark errors, including an average MAE of about 0.49, RMSE of about 0.58, and R^2 score of about 0.99. Parameter changes also affect model evaluation, as in the case of ADV motorbike with RBF kernel; adjustment of parameter C from 0.01 to 10 results in significant accuracy, decreasing MAE from 0.36 to 0.004. This study concludes that the SVR model is an effective method for predicting motorcycle requests, with practical implications for Astra Motor Balikpapan's operations.

ARTICLE INFO

Article History:

Submitted/Received 27 Jan 2024

First Revised 16 Feb 2024

Accepted 05 May 2024

First Available online 07 Jun 2024

Publication Date 07 Jun 2024

Keywords:

Forecasting,
motorcycle,
SVR,
MAE,
R2-Score

1. INTRODUCTION

Motorized two-wheel vehicles, more generally known as motorbikes, are popular transportation among the public. Every month, the number of motorbike users increases. According to data from the Central Statistics Agency (BPS) (BPS, 2021), in 2020, 115.29 million motorbikes were used, and the figure has been increasing since then. With the increasing public demand for motorbikes, companies that sell motorbikes only need a few answers to fulfill the need.

One company that provides motorbikes is Astra Motor Balikpapan. The current company faces very high demand, especially for automatic type motorbikes. His height request has resulted in a phenomenon indent, where consumers must order with pay in advance and wait for a certain period of time. This matter shows the necessity of the company's own system forecasting motorbike requests from the public.

Forecasting plays a vital role in planning production companies. One of the frequent methods used for forecasting is Support Vector Regression (SVR), which uses an algorithm learning machine. In the SVR method, data is divided into two categories: training data and testing data. Training data is used to build a model while testing data is used to test the model's performance.

SVR has several superiorities in forecasting requests, including its ability to overcome data with outliers and complexity and its suitability for datasets that are not too big. Research by Hendayanti et al. (2019) shows that SVR delivers good results, with a Mean Absolute Percentage Error (MAPE) error of 7.30 seconds using test data.

Access to deep SVR demonstrates various things, such as requesting blood (Rifqi et al., 2018) and price material principal (Astiningrum & Wijayaningrum, 2020). Therefore, research aims to test and evaluate deep SVR models to predict request motorbikes and identify whether parameter changes in the SVR model affect results evaluation. The implementation of the SVR method is expected to give a good evaluation in support of planning and retrieval decisions related to stock motorcycles.

2. METHODS

Support Vector Regression is a machine learning technique used for continuous regression analysis of data. The core of SVR involves the formation of a capable model to identify the optimal hyperplane for separating the input data into two parts: those above the hyperplane and those below it. A key role of SVR is to minimize data error forecasting during stage model training, making it a valuable tool in practical applications. SVR works with maps input data to in-room features with more dimensions—feature space. This is Then used to build a regression model. The optimal hyperplane is determined with minimized function-related objectives with hyperplane margins. The function objective used in SVR is a modified version of the function objective used in SVM (Support Vector Machine). The basics of SVR are explained in Equation 1.

$$y = w_1x_1 + w_2x_2 + \dots + w_nx_n + b \quad (1)$$

y is forecasting from target value, w is weight, x is input variables, and b is the bias.

SVR can be used to predict values numerically with high accuracy and coping overfitting problems (Drucker et al., 1996). SVR has been used in various applications, such as price stocks, weather forecasting, and medical data analysis. Draft basic SVR can be seen in **Figure 1**

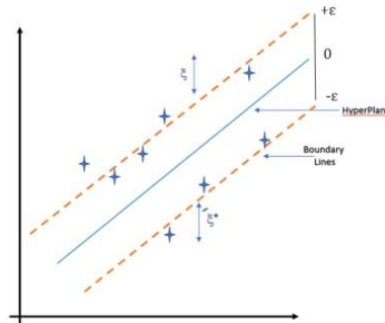


Figure 1. Basic Concepts of Support Vector Regression

In SVR, kernel functions are used to discover hyperplanes in higher dimensions by mapping data. This kernel function is effective for separating non-linear data. SVR employs several standard kernel types, such as linear, polynomial, and radial basis function (RBF) kernels. The kernel and parameters, found with parameter settings, are then used to construct a training model. The SVR stages, which are clearly depicted in **Figure 2**, provide a visual aid for understanding the process.

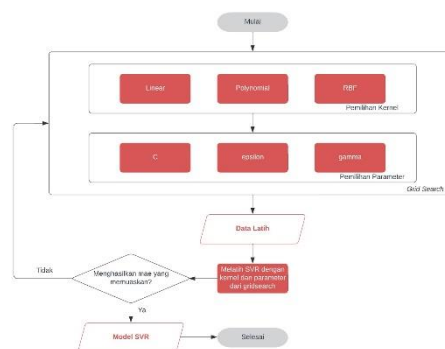


Figure 2. SVR Model Flow Chart

The parameters in the SVR are set with thoroughness and care using the Grid Search method. This technique ensures that the optimal kernel and parameters are found for the adjusted parameters covering C, epsilon, and gamma values, with the application of linear, polynomial, and radial basis functions (RBF) kernels. The process is performed using a moderate dataset, and the regulated aspects can be seen in **Table 1**.

Table 1. Initial Parameters in Grid Search

Parameter	Parameter Value			
C	0.01	0.1	1	10
Epsilon	0.001	0.01	0.1	1

Parameter	Parameter Value			
Gamma	0.0001	0.001	0.01	0.1
Degrees	2	3	4	

Furthermore, model evaluation is done. Evaluation is done to know how well both models work on the given data and when the model can be reliable for predicting results with high accuracy. Evaluation is always needed to determine whether the model will do a good job of forecasting new and future data (Amazon AWS, 2022).

In stage evaluation, the model is tested on validation data to see how well both models can work with that data. A number of method calculation evaluations were used in the study. These include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R² Score.

3. RESULTS AND DISCUSSION

The best kernel obtained from parameter settings using the Grid Search method is linear with parameter settings, as seen in **Table 2**.

Table 2. Linear Kernel Evaluation for Best Parameters

Motor Type	C	epsilon	gamma	MAE
ADV	10	0.001	0.0001	0.000745
Beat	10	0.001	0.0001	0.002369
Beat Street	10	0.001	0.0001	0.002816
Genio	10	0.001	0.0001	0.001081
PCX	10	0.001	0.0001	0.000569
Scoopy	10	0.001	0.0001	0.001964
Vario 125	10	0.001	0.0001	0.006069
Vario 160	10	0.001	0.0001	0.000758

An SVR model with a linear kernel with the above parameters was used for training. The training results obtained are as follows.

Table 3. Evaluation result Training

Motor Type	MAE	RMSE	R2 Score
ADV	0.045386	0.056241	0.999989
Beat	0.252657	0.295826	0.999990

Motor Type	MAE	RMSE	R2 Score
Beat Street	0.160351	0.189141	0.999964
Genio	0.122444	0.145473	0.999986
PCX	0.094895	0.112711	0.999976
Scoopy	0.396324	0.442584	0.999985
Vario 125	0.134062	0.160463	0.999976
Vario 160	0.172281	0.203769	0.999973

Table 3 shows that motorbikes with the most miniature MAE evaluation, 0.04, get results. This indicates a high level of accuracy in the forecasting model. On the other hand, motorbike-type Scoopy gets results with the most significant MAE evaluation, 0.39, which suggests a lower level of accuracy in the forecasting model for this motorbike type.

The SVR model was rigorously tested for forecasting, with evaluations conducted for 3, 6, 9, and 12 month schemes. The thoroughness of the testing process instills confidence in the validity of the results.

Table 4. Evaluation result Testing 3 Month Forecasting

Motor Type	MAE	RMSE	R2 Score
ADV	0.606612	0.74649	0.985336
Beat	13.99834	15.242884	0.586247
Beat Street	0.120967	0.135403	0.999928
Genio	4.781151	5.935944	0.370796
PCX	4.912672	6.520372	0.779333
Scoopy	0.330192	0.474631	0.999940
Vario 125	2.719629	3.344146	0.996442
Vario 160	0.923312	1.541264	0.999712

Table 4 shows the results of evaluation testing for 3-month forecasting. Motorcycle type BeAT Street gets the most miniature MAE evaluation, 0.12. Furthermore, motorbike type Beat gets the largest MAE evaluation, 13.99.

Table 5. Evaluation result Testing 6 Month Forecasting

Motor Type	MAE	RMSE	R2 Score
ADV	0.398814	0.554783	0.990348
Beat	1.060074	1.113449	0.999921
Beat Street	0.537099	0.679288	0.999917
Genio	1.353211	1.541543	0.997694
PCX	0.590557	0.711127	0.999767
Scoopy	2.349049	2.865574	0.999781
Vario 125	0.725771	0.808761	0.999659
Vario 160	1.190181	1.646409	0.999632

Table 5 shows the results of evaluation testing for 6-month forecasting. ADV-type motorbikes get the most miniature MAE evaluation, 0.39. Furthermore, motorbike-type Scoopy gets the largest MAE evaluation, 2.34.

Table 6. Evaluation result Testing 9 Month Forecasting

Motor Type	MAE	RMSE	R2 Score
ADV	0.056304	0.069546	0.999982
Beat	2.13786	2.528577	0.999664
Beat Street	0.599956	0.745371	0.999911
Genio	3.400063	4.318462	0.982527
PCX	0.972182	1.040565	0.999541
Scoopy	0.858448	1.004346	0.999975
Vario 125	0.730669	0.808591	0.999516
Vario 160	1.781991	2.015642	0.999325

Table 6 shows the results of evaluation testing for 9-month forecasting. ADV-type motorbikes get the results with the most miniature MAE evaluation, 0.05. Furthermore, Genio-type motorbikes get the largest MAE evaluation, 3.40.

Table 7. Evaluation result Testing 12 Month Forecasting

Motor Type	MAE	RMSE	R2 Score
ADV	0.054695	0.072615	0.999974
Beat	7.021085	7.95732	0.996647
Beat Street	0.74025	0.916357	0.999824
Genio	1.771243	2.270199	0.995733
PCX	1.05911	1.127849	0.999480
Scoopy	0.314699	0.378022	0.999996
Vario 125	0.497432	0.580983	0.999827
Vario 160	1.713348	1.953516	0.999280

Table 7 shows the results of evaluation testing for 12-month forecasting. ADV-type motorbikes get the results with the most miniature MAE evaluation, 0.05. Furthermore, motorbike type Beat gets the largest MAE evaluation, 7.02.

4. CONCLUSION

Based on the results, the evaluation uses three methods: MAE, RMSE, and R2 Score; the built SVR model can produce forecasting request motorbike with Good. This matter, shown by the evaluation of the results, shows that the SVR model works well in predicting request motorcycles. The SVR model's error value, which is also relatively small, provides a strong indication of its reliability. Parameter changes to the kernel have been made and determined in the study. This influences the evaluation of the results. This matter can be seen in the parameter setting process using the Grid Search method to find the most optimal parameters.

AUTHORS' NOTE

This writer states that there is no conflict of interest in this study. We accept thank you to Astra Motor Balikpapan for allowing us to do the study with data belonging to Astra Motor Balikpapan.

REFERENCES

- Amazon AWS, (2022). *Evaluating ML Models*. https://docs.aws.amazon.com/id_id/machine-learning/latest/dg/evaluating_models.html
- Astiningrum, M., Putri, IK, & Wijayaningrum, VN, (2020). Forecasting Prices of Basic Materials Using Support Vector Regression. *Proceedings of SENTIA*, 12(1), 77-82.

- Central Statistics Agency. (2021). *Developments Amount Vehicle Motorized by Type (Unit), 2019-2021*. <https://www.bps.go.id/indicator/17/57/1/besar-kendaraan-bermotor.html>
- Drucker, H., Burges, C.J.C., Kaufman, L., Smola, A., & Vapnik, V. (1996). Advances in Neural Information Processing Systems. *Support Vector Regression Machines*, 9, 155-161.
- Géron, A. (2019). *Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. 2nd ed. O'Reilly Media, Inc.
- Hendayanti, NPN, Suniantara, IKP, & Nurhidayati, M. (2019). Application of Support Vector Regression (SVR) in Predicting Amount Visit Traveler Domestic to Bali. *Journal of Variants*, 3(1), 43-50.
- Rifqi, MR, Setiawan, BD, & Bachtiar, FA. (2018). Support Vector Regression for Forecasting Blood Demand: Case Study of Blood Transfusion Unit Branch – PMI Malang City. *Journal Development Technology Information and Science Computer*, 2(10), 3332-3342.