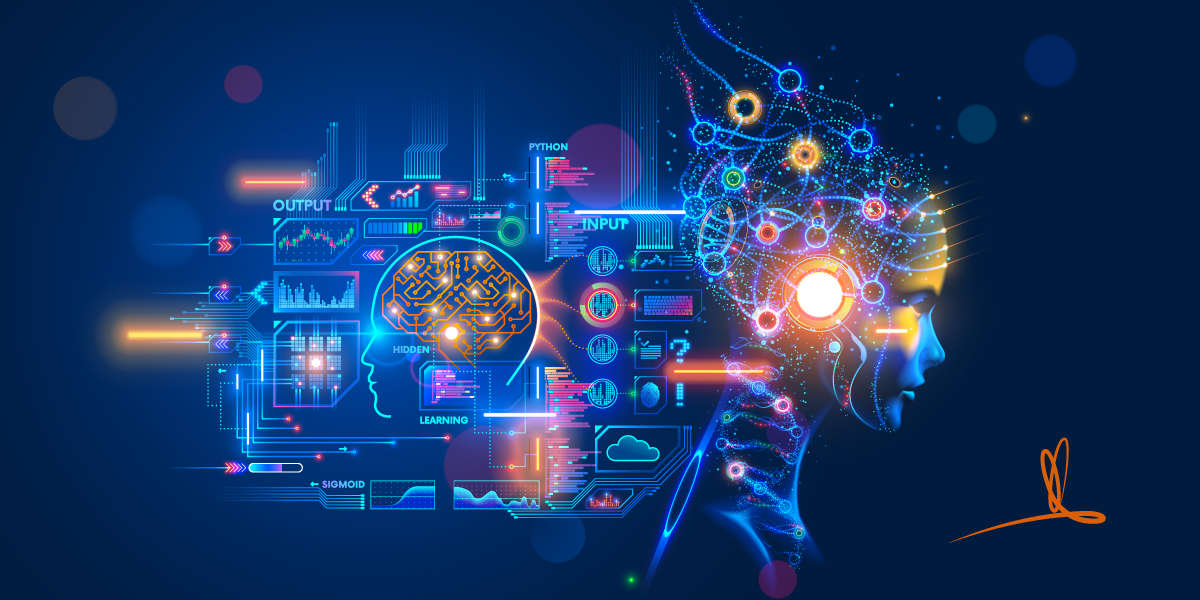
STAT 4011

Project 1

Prediction of Vehicle Carbon Dioxide Emissions by Statistical Learning Models



Group 1

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1. **Introduction**

As hotter summers and warmer winters become a common phenomenon, environmental protection has gained increasing global importance. Road transportation-related contamination, particularly from vehicles, is a main contributor to environmental deterioration. To reduce its impacts, characteristics of light-duty vehicles are identified to build a CO2 emissions prediction model.

The audience is assumed to have interest in statistics and machine learning, an application of artificial intelligence enabling systems to learn from experience without explicit programming. No prior knowledge is required.

The dataset consists of model-specific fuel consumption ratings and estimated carbon dioxide emissions for new light-duty vehicles for retail sale in Canada. Vehicle manufacturers use controlled experimental procedures to generate fuel consumption data. Afterwards, Environment and Climate Change Canada and Natural Resources Canada collates information to publish the Fuel Consumption Guide for audiences including car purchasers, manufacturers, and government bodies.

The aim of this paper is to shortlist a machine learning algorithm with the greatest predictive power of carbon dioxide emissions based on critical features, such that consumers can compare and purchase vehicles with longer lifetime and lower maintenance costs, saving money in the long run.

1. **Data**

The data used spans 7 years of compiled features and CO2 emissions of various light-duty vehicles. There are 7385 rows of observations and 12 columns in total. The columns include 11 features: Make, Model, Vehicle Class, Engine Size, Cylinders, Transmission, Fuel Type, Fuel Consumption City, Fuel Consumption Hwy, Fuel Consumption Comb (L/100 km), Fuel Consumption Comb (mpg), and 1 target variable: CO2 emissions. With a large sample size to features ratio, dimension reduction is not necessary. There are 5 non-numeric features which require further analysis to see if it can be manipulated or may otherwise be dropped. There are no null or missing values.

*Data Visualization*

As part of the data exploration, distributions and interactions of discrete and continuous variables and a correlation matrix is plotted and shown in the Appendix. Some notable insights:

* The top company is Ford
* Suv-small is the most common vehicle class
* Majority of vehicles have 8-16L/100km fuel consumption
* All features have a strong positive correlation with CO2 Emissions except for Fuel Consumption Combined which has a strong negative correlation with it
* Median engine size is 3L, while the mode is 2L. Usually, a larger engine is more powerful, accelerates faster, and has a higher speed, but it may burn more fuel and emit more CO2
* Data is centralized on 3 to 8 cylinders. The more cylinders, the less the horsepower and carbon emissions
* Regular (49%) and premium (43%) gasoline make up overwhelming majority of the data
* Strong positive relationship between Fuel Consumption Comb and CO2 Emission, though the data is split by two different slopes due to fuel type. Vehicles using ethanol emit less CO2

*Data Preprocessing*

Since linear regression and XGBoost require numerical values, one hot encoding is used to replace 5 categorical variables with 93 dummy variables. The “Model” column is dropped since there are 2053 unique values out of 7385. It would not provide much information besides the values in “Make” and would result in an overly complex model. Additionally, normalization is applied to avoid distortion of differences in range and to model the data accurately for linear regression and KNN. The new dataframe is shown in the Appendix.

1. **Methodology**

*Models*

Six algorithms are employed and compared to select one in terms of predictive power.

* Linear, Lasso, Ridge Regression

Linear regression is a simple and popular baseline model to evaluate the performances of more complex models. A linear relationship is assumed between input variables *x* and an output variable *y*. However, the model is not penalized for choice of weights. In order to prevent overfitting, two modifications, namely lasso, which penalizes the model for the sum of absolute values of the weights, and ridge, which penalizes for the sum of squared value of the weights, are used.

* K-Nearest Neighbors Algorithm

KNN is a supervised nonlinear learning algorithm. It provides an alternative if the true relationship is nonlinear and is also easy to interpret and scale to big data.The prediction of a new data point is the average of the *k* nearest data points’ response variable. “Nearest” is defined by Euclidean distance, which is the length of the difference of two vectors.

* Extreme Gradient Boosting

XGBoost, or Extreme Gradient Boosting, is an ensemble method that aims to aggregate weak learning models to form a stronger and more robust estimator (Zhang et al., 2018). At each iteration, the residual of the previous estimator is used to learn and optimize the loss function. A binary decision tree is selected as a basic learner, and regularization added to avoid overfitting. Extreme refers to pushing computational limits to achieve gains in accuracy and speed.

* Random Forest

Random forest is powerful and accurate on a variety of problems, including features with nonlinear relationships. It is constructed of numerous individual decision trees that run independently to represent a feature class prediction. Each tree gives a predicted value and the forest averages all predictions as output as an ensemble.

All hyperparameters (except in linear regression) are currently following the default setting.

*Performance Metrics*

Three metrics are used to consistently evaluate and compare model performance.

Root-mean-square error =

Mean absolute percentage error =

Mean absolute error =

10-fold cross validation is used to evaluate and compare model results. For each fold, 70% is used as a training set while the remaining 30% is used as a test set.

1. **Analysis**

*Comparison of Algorithms*

|  | Linear Regression | Lasso | Ridge | KNN | XGBoost | Random Forest |
| --- | --- | --- | --- | --- | --- | --- |
| RMSE | 5.3224 | 9.3545 | 5.302839 | 5.9344 | 3.5362 | 3.9224 |
| MAPE (%) | 2.9943 | 5.9765 | 3.011799 | 1.3808 | 0.9388 | 0.8339 |
| MAE | 1.2191 | 2.346942 | 1.221484 | 3.5064 | 2.3333 | 2.0493 |

Random forest has the best performance in terms of MAPE and MAE, whereas XGBoost performs best by RMSE. Hence, we will proceed with random forest as our prediction model.

*Parameter Tuning*

Hyperparameters are tuned to improve performance. GridSearchCV finds optimal parameters within a given range. Max\_depth refers to maximum tree depth and balances local learning and overfitting. Max\_features is the maximum number of features to consider at each split. N\_estimators is the number of trees in the forest to average over. A higher number will improve but slow down performance. The best result is achieved by max\_depth = 19, max\_estimators = 9, n\_estimators = 125.

1. **Results**

Random forest was the most accurate among six models. As shown in the Appendix, after parameter tuning of max\_depth, max\_estimators, and n\_estimators, the performance has deteriorated. Hence, it is suggested to use the default hyperparameters or test other parameter sets for tuning.

In terms of feature importance, combined fuel consumption (55% city + 45% highway) is the most relevant variable to accurately predicting CO2 emissions, and to a lesser extent engine size. This is expected as the more fuel required to travel a given distance, the more gasses would be emitted.

1. **Conclusion**

An effective model was proposed to predict carbon dioxide emissions of light-duty vehicles in this paper. Exploratory data analysis was performed for a thorough understanding of the dataset, as well as data preprocessing to improve accuracy. Four algorithms were used for model development including linear regression, KNN, XGBoost, and random forest. After assessing the root-mean-square error, mean absolute percentage error, and mean absolute error of each algorithm, random forest conclusively produces the best results. Combined fuel consumption and engine size are critical prediction features.

1. **Limitations and Suggestions**

Besides the three selected hyperparameters that were tuned for in random forest, others such as min\_samples\_split and min\_samples\_leaf can be explored to improve model performance.

Periodic model update is recommended as annual publications are provided by governments on the fuel consumption data. Revalidation ensures accurate forecasting and provides indication of whether model redevelopment would be appropriate.

Large engine size is correlated with higher CO2 emissions and are usually less efficient than small engines. One solution is to replace large engines with small turbocharged engines, generating more power and torque but limiting emissions.

Fuel consumptions and carbon emissions data are presented annually by vehicle manufacturers along with government departments. CO2 is the most important greenhouse gas, and accurate predictions and future research allow for significant mitigation and long-term planning through environmental purchases, policy setting, and fuel-efficient technological innovation.

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1. **Appendix**

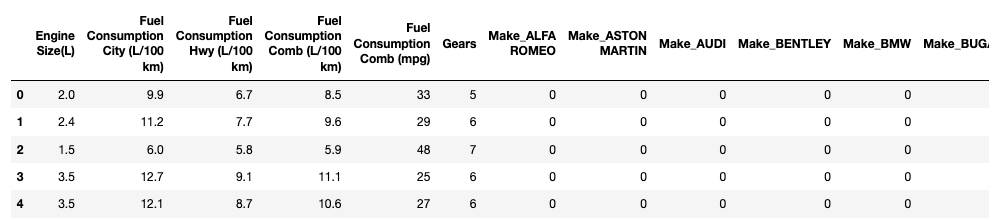
*Data Visualization*

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*Data Preprocessing*

New Dataset



*Model Performance*

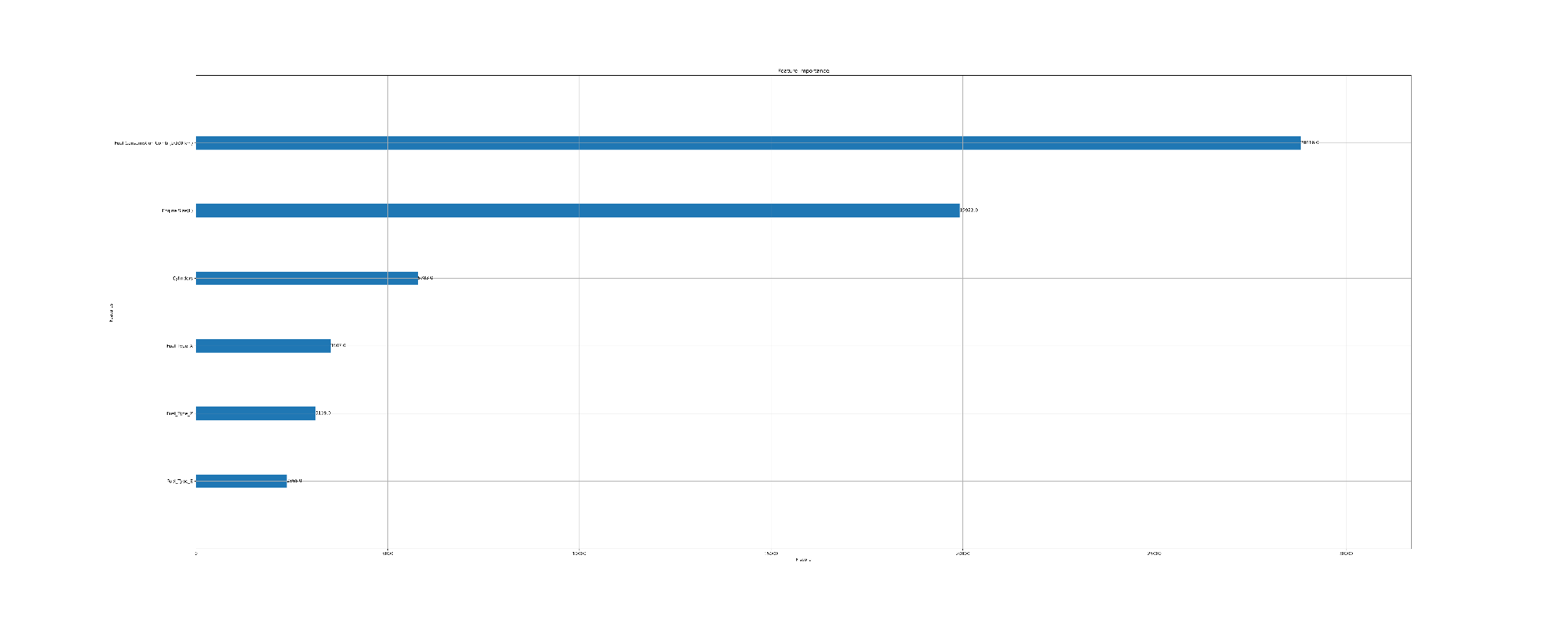
Linear Regression

|  | Linear regression | Ridge regression | Lasso regression |
| --- | --- | --- | --- |
| Before tuning | 0.9936 | 0.9753 | 0.9935 |
| After tuning | NA | 0.993477 | 0.9935 |

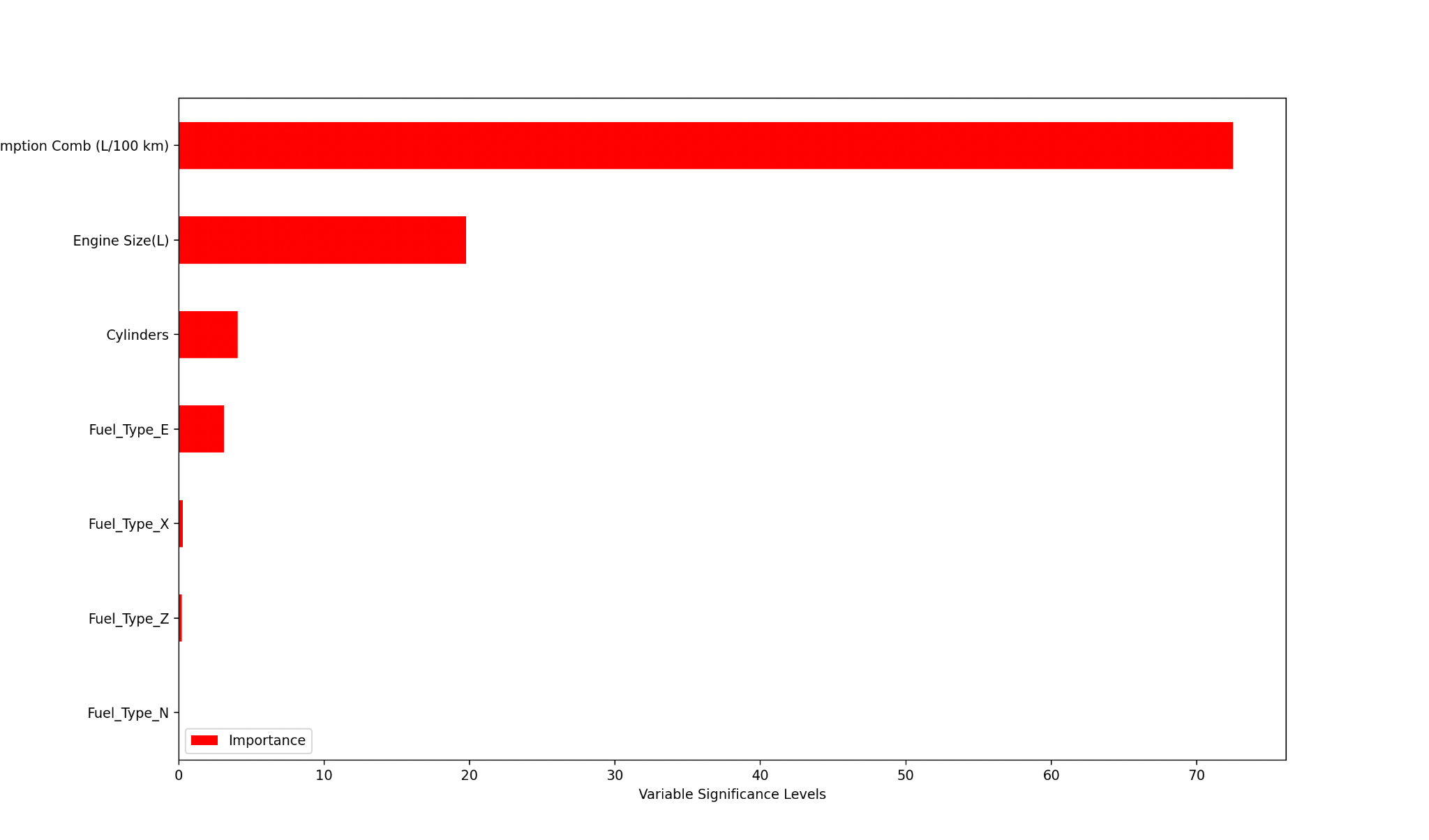
KNN

|  | Default, k=5 | Tuned, k=1 | Tuned with bagging(100 estimators) |
| --- | --- | --- | --- |
| RMSE | 11.421831 | 7.598125 | 4.815121 |
| MAPE | 7.228700 | 1.476974 | 1.199203 |
| MAE | 2.992004 | 3.169585 | 2.904765 |

XGBoost



Random Forest

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| RMSE | MAPE (%) | MAE |
| --- | --- | --- |
| 14.4933 | 4.0843 | 9.4356 |

*Random forest performance after tuning*