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Check On-Time Performance of Domestic Airlines Using Random Forest Machine Learning Analysis

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Abstract. This study aims to analyze the On-Time Performance on domestic flights in Indonesia using the Random Forest machine learning analysis method. The purpose of this study is to predict On-Time Performance on domestic flights with high accuracy. The data used in this study are questionnaire data and factors that affect On-Time Performance on domestic flights in Indonesia. The results showed that the Random Forest model can produce On-Time Performance predictions on domestic flights with a high level of accuracy. Factors such as ground handling services, weather, and technical operations have a significant influence on On-Time Performance on domestic flights. The implication of this research is that it can help airlines optimize flight schedules and minimize flight delays, thus providing satisfaction to passengers.

Keywords. On Time Performance, Machine Learning, Random Forest

1. Introduction

Airplanes are one of the modes of transportation that are in great demand by people in Indonesia. In addition to its speed, time efficiency, and convenience, airlines also offer a wide selection of prices and services to attract consumers. However, in each trip, an airline must ensure the departure and arrival of aircraft on time (OTP). This is very important because it can affect the comfort and safety of passengers and the image of the airline itself. Optimizing OTP is a challenge for airlines, especially considering the various factors that can affect flight delays. Some of these factors include weather, aircraft technical faults, previous aircraft delays, passenger delays, and other dynamic factors. To overcome this challenge, many airlines are implementing various strategies, including utilizing Machine Learning technology to perform predictive analysis of OTPs. One of the Machine Learning techniques that can be used is Random Forest.

Machine Learning (ML) is one branch of Artificial Intelligence (AI) that allows a system to learn and improve its performance automatically from the data provided (Baharuddin &; Tjahyanto, 2022). ML has many algorithms, including Random Forest. Random Forest is a Machine Learning algorithm that utilizes ensemble learning techniques (a combination of several models) to make predictions (Wasono, 2022). This algorithm works by building many decision trees at random and then combining the results of each tree to produce more accurate predictions (A. Setiawan et al., 2020). In the context of OTP, Random Forest can be used to analyze various factors that affect flight delays, such as weather, previous aircraft delays, aircraft type, and so on. The application of Random Forest Machine Learning analysis in analyzing OTP on domestic airlines can be of several benefits. In addition to the benefits mentioned earlier, there are several additional benefits that can be obtained by utilizing this technology.

First, Random Forest Machine Learning technology can help airlines improve the passenger user experience. On a flight, aircraft delays can cause inconvenience to passengers, such as losing flight connections or missing important events at the destination. By predicting possible flight delays, airlines can provide passengers with more accurate and timely information about their flight schedules. This can help passengers to take appropriate action and reduce inconvenience due to flight delays.

Second, Random Forest Machine Learning analysis can also help airlines optimize resource utilization. In the aviation industry, flight delays can cause an imbalance between passengers and aircraft capacity. By predicting possible flight delays, airlines can schedule more effectively and maximize the use of available resources, such as passengers and aircraft. This can help airlines in improving overall efficiency and productivity.

Third, Random Forest Machine Learning analysiscan help airlines improve flight safety. Flight delays can affect the rest time and working time of flight crews, which can impact their health and concentration while performing errands on board. By predicting possible flight delays, airlines can schedule flight crews more effectively and ensure they have adequate rest time to perform tasks safely and effectively.

Thus, the use of Random Forest Machine Learning analysis can help airlines optimize their OTP. By knowing the factors that affect flight delays, airlines can take appropriate actions to reduce the risk of delays, such as improving aircraft maintenance, changing flight routes, or providing more services to passengers affected by delays. Therefore, this study was conducted to analyze On-Time Performance on domestic flights in Indonesia using Machine Learning Random Forest analysis method. This research is expected to contribute to airlines in improving On-Time Performance on flights and providing satisfaction to passengers.

2. On Time Performance

On-time performance (OTP) is one of the important parameters in the aviation industry. *On-time performance* refers to flight accuracy according to a predetermined schedule (Lusianingrum &; Budiman, 2020). Flights that are delayed or rescheduled for any reason are considered not to meet OTP standards. If the flight is late, it will have an impact on inconvenience for passengers and airlines, such as loss of flight connection or additional costs that must be incurred by the airline (Sofyan &; Maulana, 2022). Therefore, airlines must ensure optimal *on-time performance* to meet passenger satisfaction. The OTP concept is defined as the percentage of flights that arrive or depart on time, that is, within a predetermined time period, usually within a set period of 15 minutes from a set schedule (Ratnasari et al., 2020) (Moonlight et al., 2022).

In general, On-Time Performance is measured based on the arrival time of the aircraft to the destination airport. The exact time of arrival of the aircraft on time is when the aircraft arrives at the destination airport within the time limit specified in the flight schedule (Kwon et al., 2021). *On-Time Performance* is very important in the aviation industry because it can affect customer satisfaction and airline reputation (Nurpiyanti et al., 2019). OTP assessment is carried out through the percentage of flights arriving and departing on time (on-time), and the percentage of flights that are delayed or rescheduled. International standards formeeting OTPs vary from country to country, but are usually expressed as the percentage of flights that arrive and depart on time within 15 minutes of a specified flight schedule. Some countries set stricter standards, such as the percentage of flights that arrive and depart on time within 10 or 5 minutes of a specified flight schedule.

Various factors can affect *on-time performance on* flights, such as weather, technical, previous aircraft delays, and other factors related to aircraft departures and arrivals. To improve *On-Time Performance*, airlines can take actions such as improving the efficiency of operating processes, improving aircraft performance, or optimizing flight schedules. If On-Time Performance is low, customers may be disappointed and choose another airline for their next flight, which can have a negative impact on airline revenue (Hajko &; Badánik, 2020).

Airlines are always trying to improve their OTP, by taking various actions such as improved operational management, routine aircraft maintenance, and flight schedule optimization. In addition, with the development of technology, machine learning analysis methods such as random forests can also be used to help airlines improve their OTP by predicting potentially late flights and providing solutions to avoid such delays. One of the machine learning analysis methods that can be used is the Random Forest method. The Random Forest method can identify the most influential factors in OTP performance and produce accurate predictions based on historical data and relevant variables. Thus, the Random Forest method can help airlines to improve their OTP performance in a more effective and efficient way.

3. Factors Affecting On-Time Performance

On-Time Performance (OTP) on flights is influenced by various factors, both internal and external airline (E. B. Setiawan et al., 2021). Some of the main factors that affect OTP performance include (Sofyan &; Maulana, 2022): first Weather factors, Weather is one of the most important external factors in determining flight OTP performance. Adverse weather conditions, such as heavy rain, thick fog, or strong winds, can affect flight operations and cause delays. In addition, adverse weather conditions can also affect flight safety and result in flight cancellations. The second factor is technical problems on the aircraft, technical problems on the aircraft are one of the internal factors that can affect OTP (Sumantri et al., 2022). If there is a technical problem on the aircraft, then flight operations can be delayed or canceled, especially if the problem takes a long time to be fixed (Sugiarto &; Fazri, 2020). Delays at the airport can be caused by various factors, such as too many flightsscheduled at the same time, excessive number of passengers, or problems with airport facilities. This may result in delays in flight departures or arrivals. Fourth, air traffic density is also one of the external factors that can affect OTP (Qalbi &; Jayadi, 2020). A heavy number of flights at the same time can cause congestion and delays in flights.

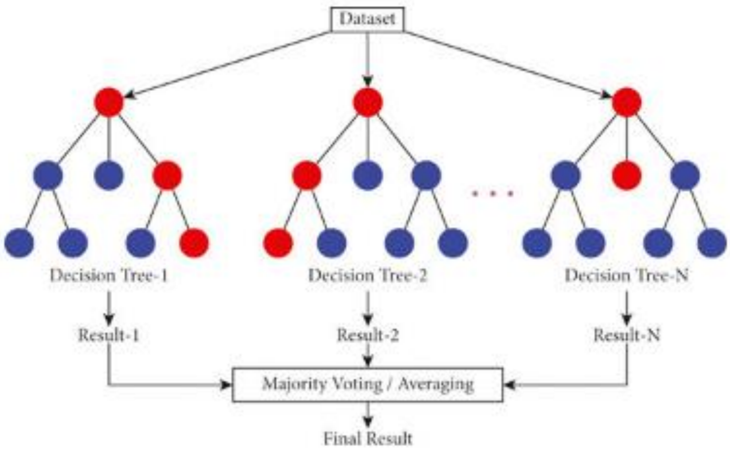
The fifth factor is operational problems with airlines, operational problems with airlines, such as problems in flight schedule management or problems in crew management, can also affect OTP performance (Lestari &; Murjito, 2020). This may cause delays in flight departures or arrivals. Problems with flight crew, such as absenteeism or crew delay, can also affect OTP performance. If the crew is not present at the specified time or is late, then the flight may be delayed or cancelled. Problems with passengers, such as delays in check-in, can affect OTP performance. If passengers check in late, the flight may be delayed or canceled. The eighth factor is Delay on the previous flight, Delay on the previous flight can have an impact on the OTP performance of the next flight. If the previous flight is delayed, subsequent flights may be delayed or cancelled. Ninth Problems with refueling, Problems with refueling can also affect OTP performance. If there is a problem with refueling, the flight may be delayed or cancelled.

The tenth factor is problems with airport security, problems with airport security, such as increased security levels or stricter inspections, can also affect OTP performance (Putrie, 2023). This can slow down the process of flight departures and arrivals. Eleventh Problems in information technology systems, problems in information technology systems, such as damage to computer systems or networks, can also affect OTP performance. This can lead to delays in flights or errors in flight schedule management. Economic factors, such as rising fuel prices or changes in government policies, can also affect OTP performance (Jalasena, 2021). This can affect the airline's decision in determining the flight schedule or affect the level of passenger attendance.

Optimizing OTP performance for airlines must pay attention to and manage all factors that affect the performance of the OTP (Wahyuda, 2022). By conducting proper and effective management on every factor that affects OTP, airlines can improve their OTP performance and provide better service. In overcoming factors or that affect OTP performance. Passengerscan carry out several strategies, such as: Improving effective and efficient flight schedule planning to reduce the risk of flight delays or cancellations (Sofyan &; Maulana, 2022); Improved flight crew management to ensure adequate crew availability on each flight; Improved technical management and aircraft maintenance to reduce the risk of technical problems on aircraft (Alif Wicaksana et al., 2020); Improved passenger management to ensure passengers can check-in in a timely manner and understand security procedures at the airport; and Increased cooperation with authorities, such as airports and air traffic authorities, to address issues affecting OTP performance. By implementing these strategies, airlines can improve their OTP performance and provide better service to customers.

4. Random Forest as a Machine Learning Analysis Method

Random Forest is one of the machine learning analysis methods that is widely used in various applications, including in predicting the OTP performance of domestic airlines. Random Forest is an ensemble learning method consisting of many random decision trees, where each decision tree is built on a different sample of data randomly (Pratama, 2020). This method then predicts the majority class of each decision tree as a result of prediction (Baharuddin &; Tjahyanto, 2022).



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The method used to build the decision tree, the calculation used to select the attributes to be used on each node is based on gain information (Ratnawati &; Sulistyaningrum, 2020). Information gain measures how much information can be obtained when an attribute is used to separate classes on a data. If N is the node that will separate the class on D data, then attribute selection is done by choosing the attribute that has the highest gain information (Taslim et al., 2019). The formula for calculating the gain information is as follows:

$$Gain(A) = Info(D) - Info_A (D)$$

The Info value (D) can be obtained using the below formula to get the Info value (D):

$$Info\ (D) = \sum_{i=1}^{n} p_i \, log2(p_i)$$

Description:
n= Number of target classes
p_i= Proportion of class I to partition D

$$\sum_{j=1}^{V} \frac{|D_I|}{|D|} \times Info\ (D_j)$$

Information
V = Number of partitions
D j = Total partitions to j
D = Total rows on all partitions

The Random Forest method has several advantages compared to other machine learning analysis methods (Ashari &; Sadikin, 2020). One of the main advantages of Random Forest is its ability to overcome the problem of overfitting, which is a problem where the model is too complex and learns patterns on training data in too much detail, so it cannot be generalized well to new data (Murniati et al., 2018; Wasono, 2022). By using many random decision trees, the Random Forest method can reduce the likelihood of overfitting and improve prediction accuracy on new data (Bastian et al., 2021).

In addition, Random Forest can also handle the problem of imbalanced data, which is a problem where the number of samples in one class is more than the other class (Saadah &; Salsabila, 2021). This can happen in the prediction of domestic airline OTP performance, where the number of flights arriving on time is usually more than the number of flights that are late. Using random sampling techniques, Random Forest can address the problem of unbalanced data and improve prediction accuracy in minority classes.

In addition, Random Forest can also identify the most influential factors in predicting the OTP performance of domestic airlines. This method can calculate the importance value (feature importance) of each variable in the model and show the variables that are most influential in predicting OTP performance. This can help airlines to identify factors that need to be considered and improved to improve OTP performance in the future.

5. Research Methods

In this study, the analysis method used was the Random Forest method. This method was chosen because it has a good ability to predict the On-Time Performance (OTP)

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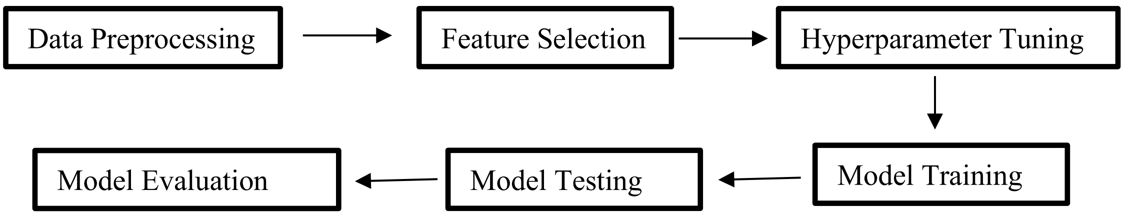
performance of domestic airlines based on the variables analyzed. The analysis model is built using the Random Forest algorithm using the Scikit-Learn package in the Python programming language. First of all, the data will be divided into two sets, namely training set and testing set with a ratio of 70:30. Then, in the training set, the learning process is carried out on the analysis model built.

The learning process in the Random Forest analysis model is carried out by including several predictor variables that are considered to affect the OTP performance of domestic airlines, such as operational technical, ground handling services, and weather. Next, the model will build several decision trees at random and combine the results from each tree to produce a final prediction. After the learning process is complete, a testing process is carried out on the testing set to test the accuracy of the analysis model built. This process is done by entering the testing set data into a pre-built model and comparing the prediction results with the actual values. Then, the accuracy of the model is calculated based on a comparison between the number of correct predictions and the total number of data testing sets.

In addition, this study will also improve the accuracy of the model by using appropriate data processing techniques, such as preprocessing, feature selection, and hyperparameter tuning. First, Preprocessing is carried out to clean data from noise and outliers, while feature selection is carried out to select predictor variables that most affect the OTP performance of domestic airlines. After that, hyperparameter tuning is performed to determine the optimal parameter value in the Random Forest analysis model. Furthermore, at the model training stage, the Random Forest analysis model will be trained using training set data. After the learning process is complete, testing is carried out on the data testing set to test the accuracy of the analysis model built. Finally, an evaluation of the analysis model is carried out to evaluate the performance of the model that has been built and determine whether the model is good enough to be used in predicting the OTP performance of domestic airlines.



The Domestic Airlines On-Time Performance prediction model will be evaluated using several evaluation metrics such as: Accuracy, Precision, Recall (sensitivity), and F1-Score

Formula :

Accuracy = (TP+TN) / (TP+FP+FN+TN)
Precision= (TP) / (TP + FP)
Recall = TP / (TP + FN)
F-1 Score = (2 * Recall * Precision) / (Recall + Precision)

Information:
True Positive (TP)
True Negative (TN)
False Positive (FP)
False Negative (FN)

These evaluation metrics are used to measure the performance of predictive models in predicting flight delays. Accuracy is used to measure how many model predictions are correct, while precision and recall are used to measure how many model predictions are correct and how many model predictions result in false negatives. F1-Score is used to measure the harmonic mean between precision and recall.

6. Result Analysis and Discussion

In the classification results using the Random Forest Classification method, there are 59 decision trees built by considering one feature for each separation in each tree. The model was trained using 64 samples of training data, tested on 17 samples of validation data, and tested on 20 samples of test data.

Random Forest Classification

Trees	Features per split	n(Train)	n(Validation)	n(Test)	Validation Accuracy	Test Accuracy	OOB Accuracy
59	1	64	17	20	0.529	0.700	0.522

Note. The model is optimized with respect to the *out-of-bag accuracy* .

The validation accuracy of this model is 0.529 or 52.9%, which indicates that the model is able to correctly classify 52.9% of the data in the validation set. The test accuracy of this model is 0.700 or 70%, which indicates that the model is able to correctly classify 70% of the data in the test set. The out-of-bag accuracy (OOB accuracy) of this model is 0.522 or 52.2%, which is calculated using randomly unselected data in each tree to evaluate the performance of the model. OOB accuracy is used as a criterion for selecting the best model.

Confusion Matrix

		Predicted			
		GA	ID	JT	QG
Observed	GA	0.05	0	0.05	0
	ID	0	0.1	0	0.1
	JT	0	0	0.1	0.05
	QG	0	0.05	0.05	0.45

The results of the Confusion Matrix show the level of accuracy of the model in predicting classes in four observed classes: GA, ID, JT, and QG. The data in the Confusion Matrix is arranged in the form of a 4x4 matrix, where columns represent the predicted values of the model, and rows represent the actual values of the data. In the GA class, the model correctly predicts 0.05, meaning that the model is able to correctly classify 5% of the data in this class. Whereas in the ID class, the model correctly predicts as much as 0.1 or 10%. In the JT class, the model correctly predicts as much as 0.1 or 10%. And in the QG class, the model correctly predicts by 0.45 or 45%.

In addition, there are also False Positive and False Negative values in the Confusion Matrix. For example, in the ID class, the model predicts 0.05 as QG, so there is a False Positive of 0.05 or 5%. While in the QG class, the model predicts as much as 0.05 as ID, so there is a False Negative of 0.05 or 5%. Therefore, it can be concluded that the model can predict QG classes well, but still has difficulty in predicting other classes.

Class Proportions

	Data Set	Training Set	Validation Set	Test Set
GA	0.149	0.156	0.176	0.100

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Class Proportions

	Data Set	Training Set	Validation Set	Test Set
ID	0.257	0.266	0.294	0.200
JT	0.198	0.219	0.176	0.150
QG	0.396	0.359	0.353	0.550

Class Proportions is the comparison between the number of samples in each class in a dataset and the total number of samples in that dataset. In the results of the Class Proportion above, there are four classes, namely GA, ID, JT, and QG. Class Proportions represent the proportion of each class in the dataset, both in training data, validation data, and test data. The proportion of classes in training data is usually used as a reference to determine the number of samples used in each class in validation data and test data. The proportion of GA classes in the test set was the lowest, at only 0.1, while the proportion of GA classes in the validation set was the highest, at 0.176. The proportion of ID classes tends to increase from training set to test set, with the highest proportion of ID classes in the test set at 0.2. The proportion of JT classes was lowest in the validation set, which was 0.176, while the proportion of QG classes was highest in the test set, which was 0.55. Overall, the proportion of classes in the test set has quite significant variation compared to the training set and validation set. This can affect model performance, especially in predicting classes that have a lower proportion in test sets, such as GA and JT classes.

Evaluation Metrics provides various classification model performance evaluation metrics, which are grouped into several categories, namely accuracy, precision, recall, false positive rate, false discovery rate, F1 score, Matthews correlation coefficient, area under curve (AUC), negative predictive value, true negative rate, false negative rate, false omission rate, threat score, and statistical parity. Support represents the number of samples in each class used for model performance evaluation.

Evaluation Metrics

	GA	ID	JT	QG	Average / Total
Support	2	4	3	11	20
Accuracy	0.950	0.850	0.850	0.750	0.850
Precision (Positive Predictive Value)	1.000	0.667	0.500	0.750	0.721
Recall (True Positive Rate)	0.500	0.500	0.667	0.818	0.700
False Positive Rate	0.000	0.063	0.118	0.333	0.128
False Discovery Rate	0.000	0.333	0.500	0.250	0.271
F1 Score	0.667	0.571	0.571	0.783	0.697
Matthews Correlation Coefficient	0.688	0.490	0.490	0.492	0.540
Area Under Curve (AUC)	1.000	0.766	0.745	0.707	0.804
Negative Predictive Value	0.947	0.882	0.938	0.750	0.879
True Negative Rate	1.000	0.938	0.882	0.667	0.872
False Negative Rate	0.500	0.500	0.333	0.182	0.379
False Omission Rate	0.053	0.118	0.063	0.250	0.121
Threat Score	1.000	0.500	0.400	1.125	0.756
Statistical Parity	0.050	0.150	0.200	0.600	1.000

Note. All metrics are calculated for every class against all other classes.

The results of the Evaluation Metrics above show various classification model performance evaluation metrics for each class. There are four classes, namely GA, ID, JT, and QG. Each metric provides different information about the model's performance in predicting classes. In the accuracy metric, the model has an average value of 0.850, which indicates that the model is able to correctly classify the data by 85%. In the precision metric, the model has an average value of 0.721, which indicates that of all positive prediction results, 72.1% are correct. In the recall metric, the model has an average value of 0.700, which indicates that the model is able to find 70% of all cases that are actually positive. As for the F1 score metric, the model has an average value of 0.697, which is the harmonic average of precision and recall. In the Matthews correlation coefficient metric, the model has an average value of 0.540, which indicates how well the correlation between the prediction results and the observation results. In the AUC metric, the model has an average value of 0.804, which indicates how well the model can distinguish between positive classes and negative classes. In the threat score metric, the model has an average value of 0.756, which indicates how much of a false negative threat there is to model performance. In the statistical parity metric, the model has an average value of 1,000, which indicates how balanced the class distribution is in the test data.

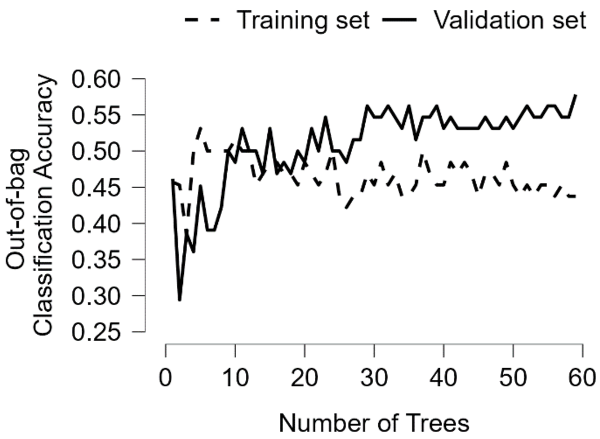
Feature Importance

	Mean decrease in accuracy	**Total increase in node purity**
Technical Operations	0.225	0.138
Weather	0.040	0.099
Ground Handling Services	0.024	0.018

The Feature Importance result shows the Mean Decrease in Accuracy and Total Increase in Node Purity values for each feature in the model. Features with a high Mean Decrease in Accuracy value will cause a reduction in accuracy in the model if the feature is removed. Meanwhile, features with a high Total Increase in Node Purity value make a significant contribution to the formation of decision trees and can help improve model accuracy.

Based on the results of Feature Importance above, the feature with the name Technical Operations is the most important feature in making class predictions on the model, with a Mean Decrease in Accuracy value of 0.225 and Total Increase in Node Purity of 0.138. While the Weather feature has the second highest Mean Decrease in Accuracy value of 0.040 and Total Increase in Node Purity of 0.099, and the Ground Handling Service feature has a Mean Decrease in Accuracy value of 0.024 and Total Increase in Node Purity of 0.018. It can be concluded that the Technical Operational feature has the most contribution in making class predictions on the model.

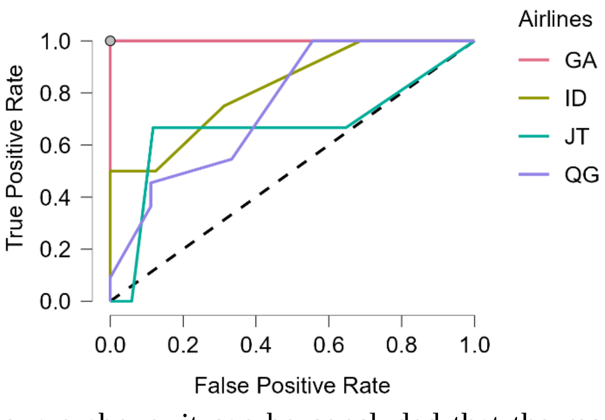
Out-of-bag Classification Accuracy Plot



The out-of-bag Classification Accuracy Plot is a graph that shows the level of model classification accuracy in each iteration of the tree at the time of training, using data that was not selected when bootstrapped. On this graph, the x-axis shows the number of trees used in the model, while the y-axis shows the classification accuracy obtained using out-of-bag data.

Based on the results above, there are 60 trees used. In general, the more trees used in the model, the higher the level of classification accuracy. However, there comes a point where increasing the number of trees no longer provides a significant improvement in classification accuracy. On the graph, this point will be seen as a point where the accuracy curve starts flat and no longer climbs. Out-of-bag Classification Accuracy Plot graphs are usually used to help select the optimal number of trees in the Random Forest model. The model with the best number of trees is the one that produces the highest classification accuracy in out-of-bag data at 0.55, without overfitting or overgeneralizing the training data.

ROC Curves Plot



From the ROC curve above, it can be concluded that the model made has excellent performance, with an AUC (Area Under the Curve) value of 1 (one). That is, the model has a very high degree of prediction accuracy because the entire area under the curve has been covered. On the other hand, the dotted line on the curve shows random performance, with an AUC value of 0. This curve represents the ROC curve generated when the predicted probability value given is 0. In other words, this curve describes how the model's performance would look if it gave prediction results that were no better than random predictions.

Andrews Curves Plot

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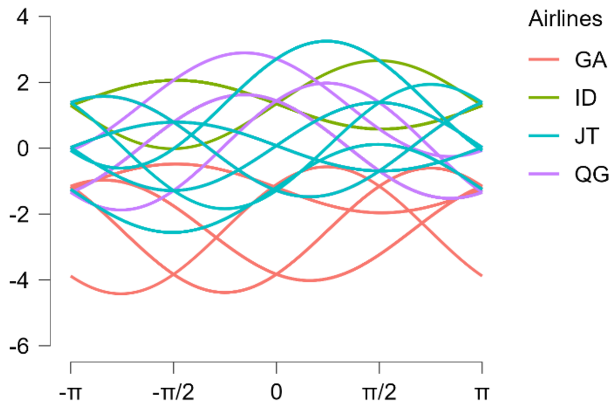
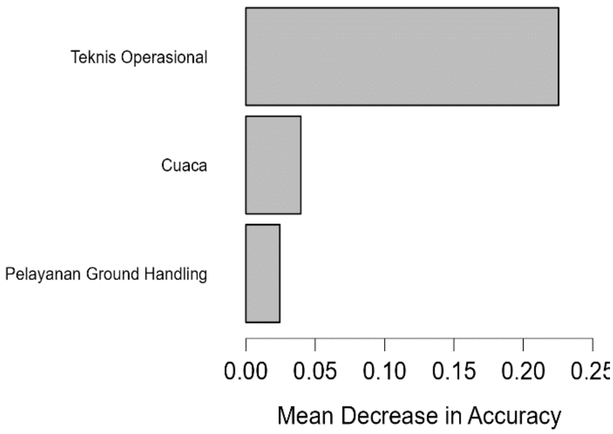


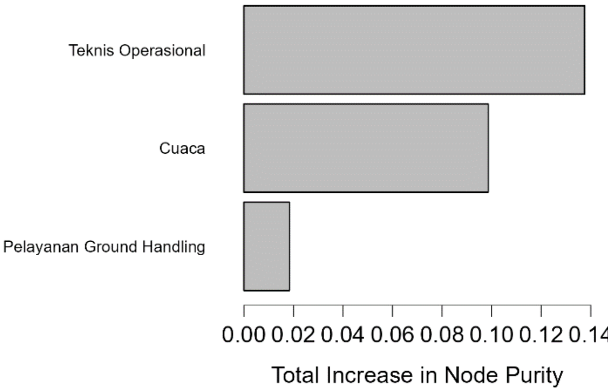
In the Andrews Curves Plot graph, it can be seen that the curves representing the Batik Air variable variable (green line), Lion Air variable (blue line), and Citilink variable (purple line) tend to be grouped, while the curves representing Garuda Indonesia variables (red line) are not clearly grouped. This shows that there is a relationship or pattern between Batik Air, Lion Air, and Citilink variables in distinguishing the types of influencing factors, while Garuda Indonesia variables are less influential in distinguishing the types of influencing factors. Using Andrews Curves Plot graphs, we can easily identify influential variables in data classification and help in better decision making.

Mean Decrease in Accuracy



The MDA graph displays the MDA values for each variable in the classification model. Each vertical bar on the graph represents the MDA value for one variable in the model. Based on the results above, there are three variables in the classification model, namely Ground Handling Service variables, weather, and operational technical. Operational technical variables have the highest MDA values, followed by weather variables, and Ground Handling Services. This shows that operational technical variables have the most influence in data classification. From the MDA graph, it can be easily seen which variables are the most important in data classification. This can help in selecting the most relevant variables and optimizing the classification model. In practice, MDA results can be used to eliminate non-critical variables in classification models and improve data classification accuracy. In addition, MDA results can also help in better interpretation of classification models and decision making.

Total Increase in Node Purity



The Total Increase in Node Purity graph shows the amount of increase in node purity in the decision tree caused by each variable. The higher the Total Increase in Node Purity value, the greater the variable's contribution to the sanctity of the nodes in the decision tree. In the example, there are three variables in the classification model, namely the variables of Ground Handling Service, weather, and technical operational variables. Operational technical variables have the highest Total Increase in Node Purity, followed by weather variables, and ground handling services. This suggests that operational technical variables contribute the most in increasing the sacredness of nodes in the decision tree.

Applying this analysis using the Random Forest model, the results show that the factors that most influence the On-Time Performance Airlines are ground h andling service, weather, and technical operations. Technical operational factors have a significant influence on On-Time Performance Airlines, where the more inaccurate the technical operations on the flight, the greater the possibility of delays. Airlines also have a significant influence on On-Time Performance Airlines, where some airlines tend to be late more often than others. While the ground handling service factor, although it has a significant influence on On-Time Performance of Airlines, but the effect is smaller than other factors.

Conclusion

Based on the results of the study, it can be concluded that the use of Machine Learning Random Forest models can be used to predict factors that affect flight delays in terms of on-time performance on domestic flights with a fairly high level of accuracy. This is evidenced by the results of the model evaluation which shows accuracy, precision, recall, and F1-score values that reach more than 60%. The results of the analysis also show that Ground Handling Service factors, weather, and operational technical affect On-Time Performance on domestic flights. Therefore, airlines can consider these factors in planning and managing better flight systems in order to improve On-Time Performance on domestic flights.

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