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Vol. x, No. x, April 2025, pp. x-x p-ISSN: 2614-8897
DOI: 10.33387/jiko e-ISSN: 2656-1948

# PERFORMANCE ANALYSIS OF MACHINE LEARNING MODEL COMBINATION FOR SPACESHIP TITANIC CLASSIFICATION USING VOTING CLASSIFIER

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The Spaceship Titanic dataset is fictional yet complex and challenging, containing a combination of numerical and categorical features as well as missing values. This study aims to evaluate the performance of three machine learning model scenarios in classifying passenger status, “Transported” or “not”. The three scenarios implemented include linear-like models, a combination of the Top 5 Diverse models, and tree-based/ensemble models, each using a voting classifier approach. The dataset was obtained from Kaggle and underwent several stages: data preprocessing, data splitting, model training, and evaluation. The evaluation result shows that the tree-based/ensemble scenario achieved the highest accuracy of 90.38%, followed by the combination of the Top 5 Diverse models at 87.31%, and the Linear-like model at 76.51%. Visualization using a confusion matrix, ROC Curve, and Feature importance analysis further supports that ensemble models are superior in detecting complex classification patterns. These findings recommend the use of tree-based/ensemble models as an optimal approach for classification tasks on a dataset like Spaceship Titanic.

**Keywords**: *Machine Learning, Spaceship Titanic, Classification, Ensemble, Voting Classifier, Confusion Matrix, ROC Curve, Feature Importance*



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## 1. INTRODUCTION

The Spaceship Titanic is a unique fictional data entity, inspired by a combination of two films: the 1997 Titanic and the Star Wars series. Spaceship Titanic represents an intergalactic spacecraft transporting thousands of passengers from various home planets, creating a complex and diverse dataset. While on the journey, some mysterious event occurs that causes some of them to become “transported” to an unknown dimension without any logical explanation or clear evidence.

The utilization of artificial intelligence (AI) and machine learning (ML) technologies has experienced significant advancements across various data sectors [1][2][3]. Machine learning algorithms such as Decision Tree, Random Forest, Logistic Regression, ExtraTreesClassifier, and Naïve Bayes are widely applied in disease prediction tasks because of their ability to learn patterns from data and make accurate classifications on unseen data [4][5]. The use of methods such as Random Forest, XGBoost, and SHAP allows for the interpretation of Feature Importance in data with class imbalance [6][7][8]. These techniques are relevant for understanding key predictors in an imbalanced dataset. Their ability to process, analyze, and extract patterns from data has made them essential tools in solving classification problems. Each classification algorithm has different strengths and weaknesses, making algorithm selection crucial in a supervised learning task. Evaluation metrics like accuracy, precision, and recall are essential to compare model performance [9][10].

The classification problem in this fictional dataset presents not only a technical challenge but also an opportunity to examine how machine learning can generalize on complex data, which includes mixed types, both numerical and categorical, and contains missing values, demanding careful preprocessing and imputation strategies. Addressing these issues effectively allows for better generalization and prediction capability of the model. To solve this, the combining of different models and dividing them into several scenarios offers a practical solution [11][12].

This study aims to analyze the performance of machine learning models across three combination scenarios: linear-like models, a combination of the Top 5 Diverse models, and tree-based/ensemble models. Ensemble learning is a machine learning paradigm where multiple base learners are strategically generated and combined to solve a particular classification problem [13]. This technique increases the overall performance of the model by reducing variance and bias [14][15]. Performance evaluation is conducted by measuring the accuracy of each combined model using a voting classifier technique, along with confusion matrices for all three scenarios. The voting classifier technique combines multiple classification algorithms to improve prediction accuracy [16].

It can be implemented using hard or soft voting, depending on whether the majority class or the average probability is used for final decision making [17][18]. It is also essential to consider that in many real-world machine learning problems, the presence distributions can complicate the classification process. Effective preprocessing, including missing value imputation, encoding, and feature scaling, is fundamental to ensuring the reliability of model training. The structure of each classification scenario plays a crucial role in final model performance. By identifying which combination scenario yields the best results, this research is expected to provide practical recommendations for selecting classification strategies on similar types of datasets.

## 2. RESEARCH METHOD

### 2.1 Research Stage

The Spaceship Titanic dataset consists of 8,693 rows and 14 columns. Key attributes in this dataset include PassengerId, HomePlanet, CryoSleep, Cabin, Destination, Age, VIP, RoomService, FoodCourt, ShoppingMall, Spa, VRDeck, Name, and Transported. The primary target column for classification is Transported (True/False). The initial stage of this study is data collection.

After the data had been collected, the preprocessing stage was carried out, which included removing empty records, imputing missing values, encoding categorical features, and normalizing numerical features. These preprocessing steps are crucial in preparing clean data for modeling and ensuring generalization across unseen datasets [19]. The next step involved splitting the dataset into 80% training data and 20% testing data. Subsequently, multiple models were grouped into three scenarios, each built using a voting classifier approach [20]. Model performance was then compared using accuracy metrics. Finally, results were further analyzed through a Confusion matrix, ROC curve visualization, and feature importance analysis.

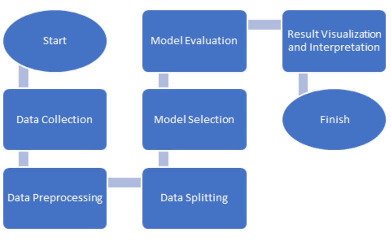


Figure 1. Stages of Research Methods

### 2.2 Model Performance Evaluation

The selection of classification methods was carried out by comparing three combinations of machine learning models across the following three different scenarios :

a. Linear-like: Logistic Regression, LinearSVC, SGDClassifier, RidgeClassifier, Perceptron.
b. Combination of the Top 5 Diverse Models: Logistic Regression, SVC, ExtraTreesClassifier, BaggingClassifier, KNeighborsClassifier.
c. Tree-Based/Ensemble: ExtraTreesClassifier, BaggingClassifier, AdaBoostClassifier, DecisionTreeClassifier, ExtraTreeClassifier.

These scenarios were combined using the Voting Classifier technique with hard and soft voting methods, where the final prediction is determined by the accuracy of all models within the given scenario [16][21]. Accuracy is one of the most commonly used evaluation metrics for classification model performance in machine learning. It measures the proportion of correct predictions (both positive and negative) compared to the total number of predictions made by the model.

Table 1. Model Types in Each Scenario

| Scenario | Type of Model Combination | Number of Models |
|---|---|---|
| Linear-like | Logistic Regression, LinearSVC, SGDClassifier, RidgeClassifier, Perceptron. | 5 |
| Combination of the Top 5 Diverse Models | Logistic Regression, SVC, ExtraTreesClassifier, BaggingClassifier, KNeighborsClassifier. | 5 |
| Tree-based/Ensemble | ExtraTreesClassifier, BaggingClassifier, AdaBoostClassifier, DecisionTreeClassifier, ExtraTreeClassifier. | 5 |

### 2.3 Model Performance Evaluation

To evaluate the model's performance in classifying passenger status in the Spaceship Titanic dataset, several evaluation methods were employed: accuracy score, voting classifier (soft and hard voting), ROC Curve with AUC, and feature importance interpretation.

1. Accuracy

Accuracy measures the proportion of correct predictions. It is defined as :

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} x\ 100\% \qquad (1)$$

Accuracy is a primary metric for comparing the performance of classification models across various scenarios, as it indicates how well the model recognizes patterns and generates correct predictions overall. The evaluation was carried out using the scikitlearn library, which included a confusion matrix and a classification report to reinforce the classification results of the best-performing model.

2. Voting Classifier

Each model scenario is implemented using a voting classifier, an ensemble method that combines multiple base classifiers to enhance prediction performance.

a. Soft voting

This method selects the final class based on the majority class predicted by all models :

$$P_{ensemble}(C_k) = \frac{1}{n}\sum_{i=1}^{n} P_i\,(C_k) \qquad (2)$$

b. Hard voting

This method averages the predicted class probabilities from all models and selects the class with the highest average probability :

$$P_{ensemble} = mode(C_1, C_2, \dots, C_n \qquad (3)$$

3. ROC Curve

The ROC (Receiver Operating Characteristic) Curve is used to assess the diagnostic ability of a classifier. It plots:

$$P_{ensemble} = mode(C_1, C_2, \dots, C_n \qquad (4)$$

4. Feature Importance

To interpret which input features most influence the classification result, feature importance is calculated for applicable models. For tree-based models (and models that support it), the importance of a feature is calculated using:

$$FI(f) = \sum_{t \in t_f} \frac{N_t}{N} \cdot \triangle_i\,(t) \qquad (5)$$

Higher importance values indicate that the feature plays a more significant role in improving the model's predictive performance.

## 3. RESULT AND DISCUSSION

### 3.1 Data Collection

The data used in this study was obtained from Kaggle under the title "Spaceship Titanic," consisting of 8,693 rows and 14 relevant features. These features include demographic information (such as age and home planet), cabin details, and entertainment and accommodation expenses on board the spacecraft.

Table 2. Description of the Spaceship Titanic Dataset

| Column | Data Type | Number of Nulls | Number of Unique Values |
|---|---|---|---|
| PassengerId | object | 0 | 2 |
| HomePlanet | object | 0 | 2 |
| CyroSleep | bool | 0 | 2 |
| Cabin | object | 0 | 2 |
| Destination | object | 0 | 2 |
| Age | int64 | 0 | 2 |
| VIP | bool | 0 | 2 |
| RoomService | float64 | 0 | 2 |
| FoodCourt | float64 | 0 | 2 |
| ShoppingMall | float64 | 0 | 2 |
| Spa | float64 | 0 | 2 |
| VRDeck | float64 | 0 | 2 |
| Name | object | 0 | 2 |
| Transported | bool | 0 | 2 |

### 3.2 Data Preprocessing

To evaluate the model's performance in classifying passenger status in the Spaceship Titanic dataset, several evaluation methods were employed: accuracy score, voting classifier (soft and hard voting), ROC Curve with AUC, and feature importance interpretation.

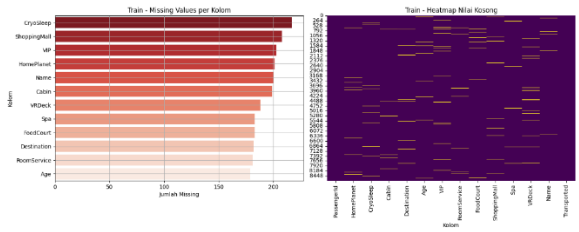

Figure 2. Missing Values and Heatmap – Train

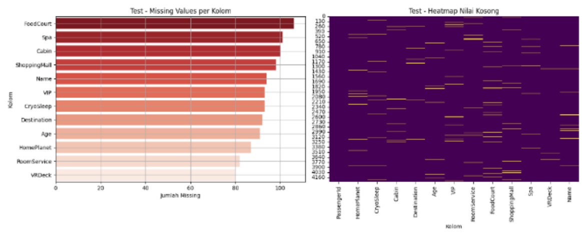

Figure 3. Missing Values and Heatmap – Test

### 3.3 Data Splitting

After the data preprocessing stage, the dataset will be split. However, before that, the data will first be evaluated in its unsplit form.

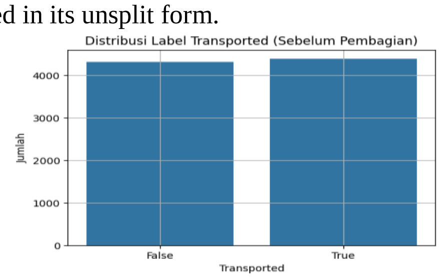


Figure 4. Distribution of the Transported (Before Splitting)

After the data preprocessing stage, the dataset will be split. However, before that, the data will first be evaluated in its unsplit form.

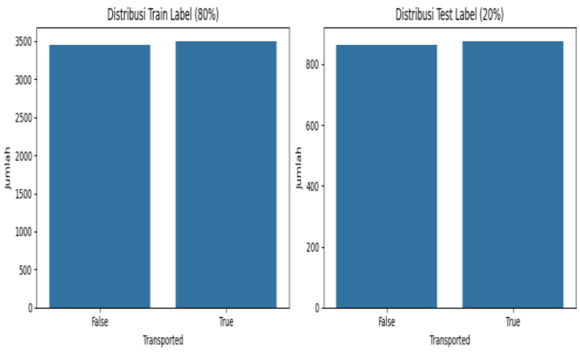


Figure 5. Distribution of the Transported (After Splitting)

### 3.4 Model Selection

After the data is split, the models are grouped into three combination scenarios as follows :

1. Linear-like: Logistic Regression, LinearSVC, SGDClassifier, RidgeClassifier, Perceptron
2. Combination of the Top 5 Diverse Models: Logistic Regression, SVC, ExtraTreesClassifier, BaggingClassifier, KNeighborsClassifier
3. Tree-based/ensemble: ExtraTreesClassifier, BaggingClassifier, AdaBoostClassifier, DecisionTreeClassifier, ExtraTreeClassifier

Each scenario is implemented using the Voting Classifier approach, incorporating both hard voting and soft voting methods, where classification decisions are based on the majority vote from all models within the scenario.

### 3.5 Model Evaluation

The performance evaluation is conducted using the accuracy metric, which is calculated based on predictions made on the test data. The evaluation results are presented in Table 3 below :

Table 3. Accuracy Results Of The Three Scenarios

| Scenario | Type of Model Combination | Type of Voting | Accuracy |
|---|---|---|---|
| Combination of the Top 5 Diverse Models | Combination of the Top 5 Diverse Models | Soft Voting | 87.31% |
| Linear-like | Linear-like | Hard Voting | 76.51% |
| Tree-based | Ensemble | Soft Voting | 90.38% |

Scenarios 1 and 3 use soft voting, while Scenario 2 uses hard voting because it consists of linear models, some of which do not support probability prediction (predict_proba), which is required for soft voting. The tree-based/ensemble scenario produced the best result, achieving an accuracy of 90.38%.

### 3.6 Result Visualization and Interpretation

After evaluating the models, the next step is to visualize the three scenarios using the confusion matrix, ROC curve, and feature importance. The results will indicate which scenario performs the best

1. Confusion Matrix

   The confusion matrix method is used to visualize the differences in results among the three scenarios.

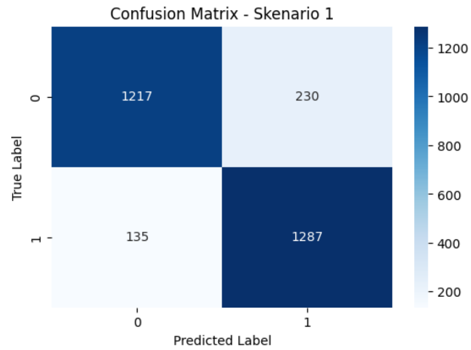


Figure 6. Confusion Matrix - Scenario 1

The results of Scenario 1 show that the model performs well in identifying both positive and negative classes, as indicated by the high number of True Positives (TP) and True Negatives (TN). In contrast, the number of False Positives (FP) and False Negatives (FN) remains relatively low. Although the accuracy is high, the model demonstrates a fairly balanced performance.

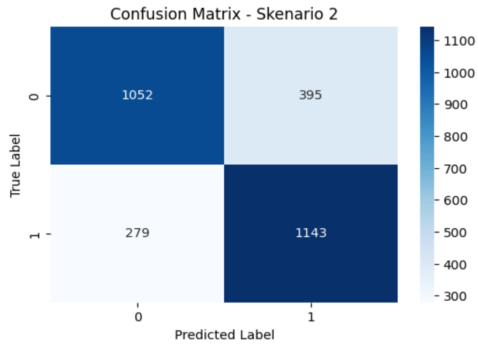


Figure 7. Confusion Matrix - Scenario 2

Each scenario is implemented using the Voting Classifier approach, incorporating both hard voting and soft voting methods, where classification decisions are based on the majority vote from all models within the scenario.

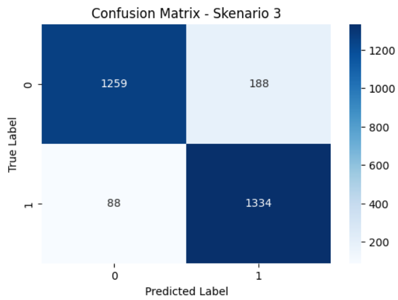


Figure 8. Confusion Matrix - Scenario 3

The results of Scenario 3 indicate that it outperforms the previous two scenarios, with the highest number of True Positives (TP) and True Negatives (TN), and the lowest number of False Positives (FP) and False Negatives (FN). This reflects excellent accuracy, precision, and recall, demonstrating that the tree-based ensemble model has better generalization capability compared to the other two scenarios.

2. ROC Curve (Receiver Operating Characteristic Curve)

   The method involves visualizing the three scenarios using the ROC Curve (Receiver Operating Characteristic Curve).

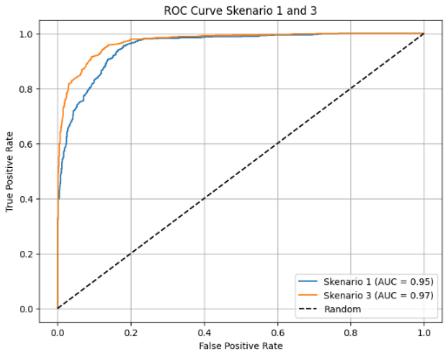


Figure 9. ROC Curve - Scenario 1 and 3

The ROC Curve results show that Scenario 3 achieved an AUC value of 0.97, higher than Scenario 1, which scored 0.95. This indicates that the model in Scenario 3 is better at distinguishing between positive and negative classes. Scenario 2 is not included in the ROC visualization because it consists of a Combination of the Top 5 Diverse models, such as LinearSVC, RidgeClassifier, Perceptron, and Logistic Regression. In Scenario 2, only a few models achieved high accuracy while others performed poorly, leading to inconsistency in generating probability scores. For this reason, Scenario 2 is also excluded from the following method, which is Feature Importance.

3. Feature Importance

   The following method is to visualize Scenarios 1 and 3 using Feature Importance.

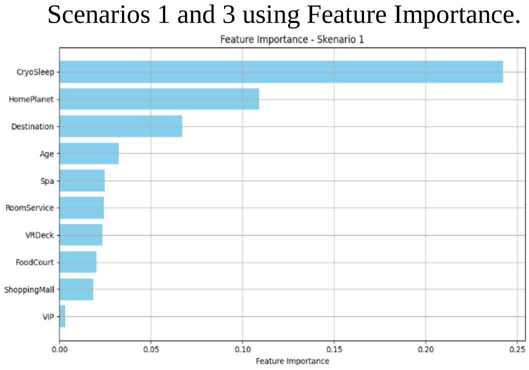


Figure 10. Feature Importance - Scenario 1

In Scenario 1, which uses linear-like models, the most dominant features significantly influence the classification results. However, features such as HomePlanet, Destination, and Age also make significant contributions, indicating that passengers' origin, destination, and age are relevant to the likelihood of being "Transported".

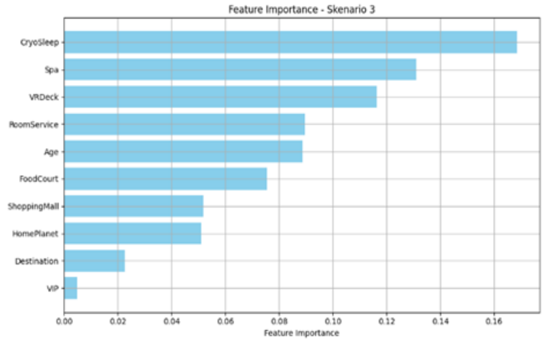


Figure 11. Feature Importance - Scenario 3

Scenario 3 shows that the CryoSleep feature has a greater influence. However, features such as Spa, VRDeck, and RoomService carry more weight compared to Scenario 1, as tree-based models are capable of capturing complex patterns and interactions between features. Both scenarios agree that CryoSleep is a key feature, but tree-based models emphasize the passenger's service usage, while linear models highlight the origin and destination of the journey.

After presenting all the visualization and interpretation results, the model in Scenario 3 is proven to deliver the best overall performance. The confusion matrix indicates high and balanced classification accuracy across classes, the ROC Curve shows the highest AUC, reflecting optimal detection capability, and the feature importance highlights the most relevant key variables. This makes the tree-based ensemble approach highly recommended for use on the Spaceship Titanic dataset, which is complex, contains a mix of numerical and categorical features, and includes missing values.

## 4. CONCLUSION

This study has evaluated three combinations of machine learning models on the Spaceship Titanic dataset, consisting of linear-like, combination of the Top 5 Diverse, and tree-based/ensemble models. The classification process was conducted using a voting classifier approach, along with stages of data preprocessing, data splitting, model training, and evaluation. The accuracy results show that the tree-based/ensemble achieved the highest performance with a score of 90.38%, followed by the Combination of the Top 5 Diverse at 87.31%, and the linear-like at 76.51%.

Visualization through the confusion matrix shows that the ensemble model is the most balanced in recognizing both target classes. At the same time, the other two scenarios still produce relatively high misclassification on one of the classes. The ROC Curve reinforces this finding with a higher AUC score for Scenario 3, indicating better model sensitivity. Additionally, the feature importance analysis reveals that CryoSleep is the dominant feature across all scenarios, with differing preferences for additional features between linear and ensemble models.

Based on the overall evaluation, the tree-based/ensemble model is the most optimal approach for handling classification tasks on the Spaceship Titanic dataset. This model excels not only in accuracy but also in prediction stability and the ability to capture complex patterns from both numerical and categorical features. These findings are expected to serve as a reference for selecting ensemble-based classification strategies for similar datasets in the future.

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