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SkyServe AI - Data-Driven Solution to Optimize Airline Food Loading Processes

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Abstract

Air transportation is one of the fundamental elements of the global transportation network and plays an important role in both commercial and passenger transportations. The increasing number of passengers every day is leading airlines to seek more efficient and sustainable solutions in operational processes. The food supply process is a critical factor in maintaining passenger comfort and service quality, especially on long-haul flights. The amount and variety of food offered during the flight requires effective planning in terms of both customer satisfaction and operational efficiency. This research presents a data-driven approach to optimize food loading processes in the airline transportation sector. The main objective of the project is to increase operational efficiency, reduce costs and minimize food waste by predicting the amount of food required for flights. In the study, variables such as flight route, number of passengers, flight duration and total demand are considered and the effects of these factors on food consumption are analyzed. In the model development process, machine learning algorithms were applied using real flight data. The data set taken to train the model includes detailed information about approximately 180,000 flights. This data is divided into two as training and test sets in order to improve the learning ability of the model and increase the prediction accuracy. In order to evaluate the prediction performance of the model, comparisons were made with the real consumption values at the end of the flight. The accuracy rate of the developed model shows that the model has a general prediction ability according to the initial findings. The study has the potential to contribute to the improvement of food loading processes of airline companies with data-driven decisions. Development steps such as expanding the data set, model optimization and error analysis are suggested for higher accuracy rates.

Keywords: Artificial Intelligence; Airline Catering Optimization; Food Supply Chain in Aviation; Machine Learning in Airline Operations.

1. INTRODUCTION

The airline industry constantly needs innovative approaches to increase operational efficiency and improve customer satisfaction. In this context, food stock management is one of the critical processes in the industry. Making accurate stock estimates is of great importance both in terms of reducing costs and contributing to sustainability goals. In order to overcome these challenges, the SkyServe AI project aims to offer an advanced solution for food stock estimates per flight by using artificial intelligence and data science technologies.

Since traditional methods do not sufficiently take into account dynamic factors such as seasonal changes and passenger profiles, there are serious problems in the accuracy of the estimates. These deficiencies cause problems such as food waste and customer dissatisfaction. Our research aims to provide a comprehensive machine learning-based model that supports data-driven decision-making processes in the airline industry. This model aims to estimate the ideal amount of food for each flight by combining a wide range of data sources such as flight duration, passenger age group data and food variety data. In a report published by American

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Airlines in 2019 [7], it was stated that food consumption estimates on flights often lead to waste and customer dissatisfaction. The company stated that it plans to predict food demand more precisely using data analysis and artificial intelligence.

Similarly, a study conducted by Airbus suggests that optimizing food stock management per flight can save an average of 100,000 USD per flight [8]. Such data reveals how critical the SkyServe AI project is for the airline industry and the practical necessity of the solution it has developed.

The study will not only increase operational efficiency but will also make significant contributions to the industry in terms of environmental sustainability and customer experience. Because food waste not only causes economic losses for airline companies but also creates negative impacts on the environment. In order to solve this problem, SkyServe AI aims to minimize food waste by stocking the right amount. This approach aims to reduce operational costs and achieve environmental sustainability goals in line with the United Nations (UN) Development Goals.

In terms of customer experience, insufficient food stock can negatively affect customer satisfaction during air travel. SkyServe AI aims to meet the needs of each passenger by accurately predicting the food demand on board, thus increasing customer satisfaction. This project will provide passengers with a more satisfying flight experience while also helping airline companies gain customer loyalty. The research project aims not only to provide solutions to existing problems, but also to demonstrate the potential of data science and artificial intelligence-based approaches in the airline transportation sector. The innovative solution offered by the project will pioneer the optimization of administrative processes in the sector and will also make valuable contributions to the literature in this field. Working on complex and dynamic data structures in the airline transportation sector, SkyServe AI aims to create a model that will serve as an example for other applications in this field.

The long-term goals of the study include demonstrating the applicability of artificial intelligence in a wider area in airline operations and providing support for sustainability-oriented operational processes. The developed model can be adapted not only to the airline sector but also to other transportation and shipping areas. Thus, it will provide solutions to similar problems in other transportation systems. SkyServe AI aims to create an innovation that will contribute to both internal and external sector applications by bringing together data science, artificial intelligence and sustainability principles. This comprehensive and innovative approach is considered as part of the digital transformation in the airline transportation sector and distinguishes our research from other solutions in the sector. The project not only improves current processes but also provides a solution for the future operational needs of the airline industry.

2. LITERATURE REVIEW

The 21st century, where digitalization has increased rapidly, has also brought with it a tremendous explosion in data production. Especially since the beginning of the 2000s, with the widespread use of the internet and mobile devices becoming indispensable in daily life, the rate of data production has increased exponentially. According to statistics, approximately 2.5 quintillion bytes of data are produced every day in the world (Statista, 2024). The increase in the use of social media platforms, the rise of e-commerce, and the widespread use of digital systems used in the healthcare sector are some of the most obvious reasons for this increase. For example, the transfer of information systems by hospitals to digital environments and the transition of student information management systems from paper-based forms to electronic systems by educational institutions are important steps that trigger big data production. This transformation has not only increased the volume of data, but also significantly expanded the variety of data.

This rapid increase in data is analyzed within the framework of a classification called the “5V Notation” in the literature. This notation; defines big data with criteria such as data volume, data variety, data processing speed, data accuracy and data value [1]. For example, financial transactions that need to be processed within seconds or situations requiring urgent intervention in the health sector clearly reveal the importance of data processing speed. Similarly, determining the accuracy of data coming from channels such as social media platforms is of critical importance in combating information pollution. Big data is evaluated not only with storage and access problems, but also with technical difficulties related to processing and interpreting this data. At this point, artificial intelligence and machine learning techniques stand out as effective tools in the analysis of big data. Artificial intelligence makes it possible to reach new information by extracting meaningful patterns and relationships from huge amounts of data. For example, the use of artificial intelligence in the health sector accelerates patient diagnoses and offers customized solutions in treatment processes. Machine learning algorithms, on the other hand, find applications in a wide range of areas from social media analysis to financial risk management. According to McKinsey's 2011 report [2], artificial intelligence applications have the potential to contribute $4.6 trillion to the global gross domestic product.

Big data analysis methods are fed by various disciplines and include areas such as statistics, data mining and machine learning [3]. While statistical methods allow for determining general trends by modeling data, data mining techniques aim to discover hidden patterns and relationships in large amounts of data. Machine learning, on the other hand, automates the processes of making predictions or making decisions on certain tasks by processing data through algorithms. For example, sub-branches such as neural networks, natural language processing (NLP) and image processing are among the artificial intelligence techniques frequently used for the analysis of big data [5].

The techniques mentioned above are used in every field where big data is available, depending on the variety of the problem. Education, finance, social media, and transportation are at the forefront of these fields. In addition, machine learning algorithms are also needed in the aviation field, where optimization is needed [4]. Route optimization, ticket pricing strategies, and passenger satisfaction analyzes in air transportation are effectively managed with big data and artificial intelligence. For example, machine learning algorithms used to minimize fuel consumption and reduce delays both reduce costs and contribute to environmental sustainability (IATA, 2023). In addition, the analysis of passenger behavior provides airline companies with important data to increase customer satisfaction. In this context, the combination of artificial intelligence with big data has not only provided operational efficiency but also transformed the customer-oriented service approach. Another important point is that the solutions in this field are compatible with the 12th article titled “Responsible Production and Consumption” within the 17 articles presented within the scope of the Sustainable Development Plan determined by the United Nations. The project developed within the scope of this study aims to develop a model to estimate food demand during flight.

Similar studies in the literature are presented below.

In the study "Evaluation of Machine Learning Algorithms for Customer Demand Prediction of In-Flight Meals" [13], the performances of various machine learning algorithms used to predict in-flight food demand were compared. However, one of the limitations of the study was the use of data collected only from short- and medium-haul flights.

This led to a narrow scope of the analyzed dataset and underrepresentation of food demand estimates across a wider range of flight distances. In addition, the study focused only on a basic feature such as flight duration. Factors such as demographic characteristics of flight passengers, flight time, and number of passengers were ignored. These deficiencies limit the accuracy of food demand prediction and reveal the need for a more comprehensive model.

In the study "In-Flight Sales Prediction Using Machine Learning" [16], the performances of LightGBM, Linear Regression, and Decision Tree models used to predict in-flight sales were compared. The study revealed that LightGBM showed superior performance due to its ability to better handle nonlinear relationships. However, one of the shortcomings of the study was the lack of qualitative data such as customer satisfaction. This lack of data limited the model's prediction accuracy. In addition, the focus of the study was based on predicting in-flight sales, and a solution that was applicable in a more niche area such as food stock prediction was not developed. These shortcomings narrowed the scope of application of the model and indicate that solutions that can address general operational optimization requirements should be developed more broadly.

In the study "Machine Learning for Sales Prediction in Big Mart" [14], algorithms such as Random Forest and Gradient Boosting were used to predict store sales. The study emphasized that data preprocessing, feature selection, and seasonal effects should be taken into account. The importance of extracting features from large data sets and incorporating them into the model was effectively emphasized. However, one of the biggest limitations of the study is the difficulties in processing large data sets and the inadequacy of integrating seasonal effects with features. In addition, the dataset used in the study focused on store sales, which prevented applications to narrower and more specific areas such as flight and food demand. These deficiencies reveal the need for more specialized and specific data models.

The study "Machine learning demand forecasting and supply chain performance" (Abadi & Javad, 2020) focused on demand forecasting, especially for perishable products. The study demonstrated the effectiveness of LSTM and CNN models in dealing with temporal data. In addition, it was emphasized that data augmentation methods are important in reducing data deficiencies. However, this study does not consider the requirements specific to the aircraft industry and focuses on demand forecasting in a wider range of products. It does not address the specific requirements for food demand forecasting in specific sectors such as air travel. In addition, studies on demand forecasting of perishable products are usually based on dynamics in other sectors, which may ignore the special conditions of the airline industry.

The studies presented above show that machine learning models can be used effectively in topics such as flight food demand forecasting or sales forecasting. For example, the "Evaluation of Machine Learning Algorithms for Customer Demand Prediction of In Flight Meals" study determined that flight duration has a significant impact on customer demand. The "In-Flight Sales Prediction Using Machine Learning" study emphasized that more complex algorithms such as LightGBM are superior in capturing nonlinear data relationships. The "Machine Learning for Sales Prediction in Big Mart" study drew attention to the fact that data preprocessing, seasonal changes, and feature selection are critical for forecasting models.

The methods and findings used in the relevant studies provided an important foundation for the SkyServe AI model and guided the project development process. The selection of the algorithms applied within the scope of this study was supported by the information obtained from the studies presented above, and an approach was adopted that expanded the scope of the project and increased its accuracy. By adapting the methods of these projects to its own context, this model managed to provide a more innovative and problem-oriented solution and developed a forecasting model focused on customer satisfaction.

The sub-problems of the study require addressing various factors in order to manage the food stock estimation process per flight correctly. First, it is necessary to model data such as passenger profile (such as age, gender, nationality) and flight duration. Such demographic information plays an important role in understanding the food preferences and consumption amounts of different passenger groups. In addition, external factors such as seasonal changes, special holidays and weather conditions can also affect the accuracy of the estimation model. These sub-problems reveal the necessity of data diversity for accurate and dynamic food stock estimation.

The limitations of the study are related to the accuracy and scope of the data used. Incomplete or incorrect existing data can negatively affect the success of the model. In addition, food demand variability can be affected not only by customer demographics, but also by cultural differences, airline food policies, and even unexpected situations during the flight. Therefore, the model cannot always be expected to work with 100% accuracy. In addition, while training a machine learning model relies on high-quality data and accurate algorithms, time and resources are required to do these processes correctly. Considering these limitations, the model's performance can be improved with richer data sets and advanced algorithms in the later stages of the project.

3. METHOD

This project provides a solution to food waste in the airline industry. The study was carried out with the support of expert academicians in the Software Engineering Department of a university in Istanbul. The main problem is the suggestions for waste caused by overproduction, more accurate estimation of food resources for certain flight numbers, and the availability of customer locations and departments.

3.1.1 Preparing a Data Set Appropriate for the Problem

During the preparation of the dataset, synthetic data similar to the data kept by airline companies were produced by taking the data obtained from Kaggle as a reference. This data includes flight information of customers, number of passengers and the number of food purchased on flights in the past. The dataset included flight duration, passenger types (e.g. Turkish male adult passenger, foreign female passenger) and product-based sales data.

3.1.2 Data Preprocessing

The following steps were taken to process the data and prepare it for analysis:

- Detection of missing and erroneous data and correction or removal with appropriate methods.
- Checking product IDs and selecting only real products.
- Combining data formats (e.g. date and time) and making them consistent.
- Analyzing anomalies in the data and reducing the impact of extreme values.

Sample process: During the coding phase, product IDs in the flights_product and stock_out files were matched and only data for existing products was included.

3.1.3 Cleaning and Consolidation of Data

The aim is to bring together data from multiple files to form a meaningful whole:

- Data cleaning: Incorrect entries and unnecessary columns were removed. For example, product IDs that do not exist in the stock_out file were cleaned from the data set.
- Data merging: All data was merged based on flight ID (Core_leg_isn). This process matched flight information with product sales and demand data.

Figure 1. Model Development Process. [Self Made].

3.1.4 Development of Machine Learning Model

In the modeling phase, a regression model was created that estimates food demand using customers' flight information:

● Independent variables: Passenger profiles, flight duration and other flight information.
● Dependent variables: Total demand for each product.
● Algorithm used: Random Forest Regressor, extended with MultiOutputRegressor to allow predictions for multiple products.

As in this code example written by us using the Random Forest library:

```
from sklearn.multioutput import MultiOutputRegressor
model = MultiOutputRegressor(RandomForestRegressor(n_estimators=100, random_state = 42))
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

Table 1. Model Code Example [Self Made].

● The model provided high accuracy in predicting total demand and error metrics were calculated separately for each product.

3.1.5 Data Analysis and Interpretation of Results

The model results were analyzed and the prediction accuracy was evaluated:

● R^2 scores were calculated separately for each product.
● The strengths and weaknesses of the model were determined by comparing the error rates.

3.1.6 Results

The average R^2 score of the model was above 0.85, providing high success in food demand prediction. These methods formed the basic building blocks of the solution proposed to reduce food stock waste by airline companies. The model results were designed to contribute to more efficient decisions to be taken by companies.

3.2 Linear Regression, Random Forest Regressor and LightGBM Regressor

3.2.1 Linear Regression

Linear Regression is a statistical method used to predict a continuous target variable. This algorithm tries to model the linear relationship between the independent variables (features) and the dependent variable (target).

For example, the values “number of passengers” and “flight duration” are independent variables and are represented by x in the graph; “amount of food” is expressed as Y and changes depending on the X variables. As a result of model training, the program develops an equation in the form of “y=mx + c”, where the ‘m’ and ‘c’ values are determined. When we enter the X value, the y value it will give us actually means the “estimation of the amount” we want.

To express it in the figure below; the drawn line is positioned as close as possible to all points. This line represents the general trend of the data points and expresses the model’s predictive ability. The distance of the data points to the line indicates the model’s error rate. The goal is to minimize this error.

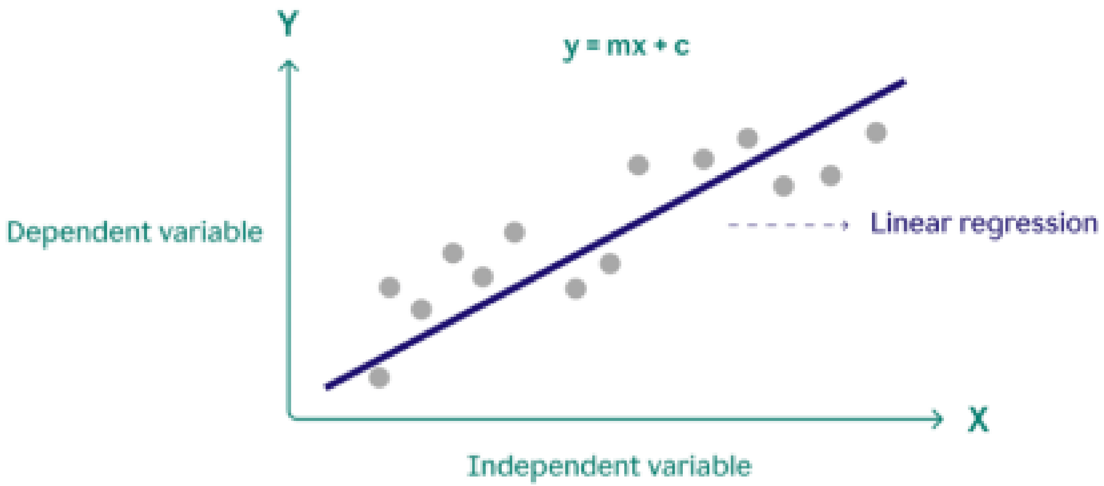

Figure 2. Linear Regression Graph Example [17].

Advantages of Linear Regression:
○ It is quite effective for linear relationships.
○ It has high interpretability.

Disadvantages of Linear Regression:
○ It cannot model non-linear relationships.
○ It is sensitive to outliers.

The table above shows how the Total Demand changes depending on the Flight Duration. Each blue dot represents a flight data, and the red line seen on the graph is the trend line created by the linear regression algorithm used to model the relationship between flight duration and total demand. This model shows that such a relationship can be analyzed, even if the amount and variety of data is limited. It is emphasized that much higher accuracy results can be obtained with more and more diverse data, as well as with correct modeling approaches. This study can be considered as a fundamental step in the transition to more complex models.

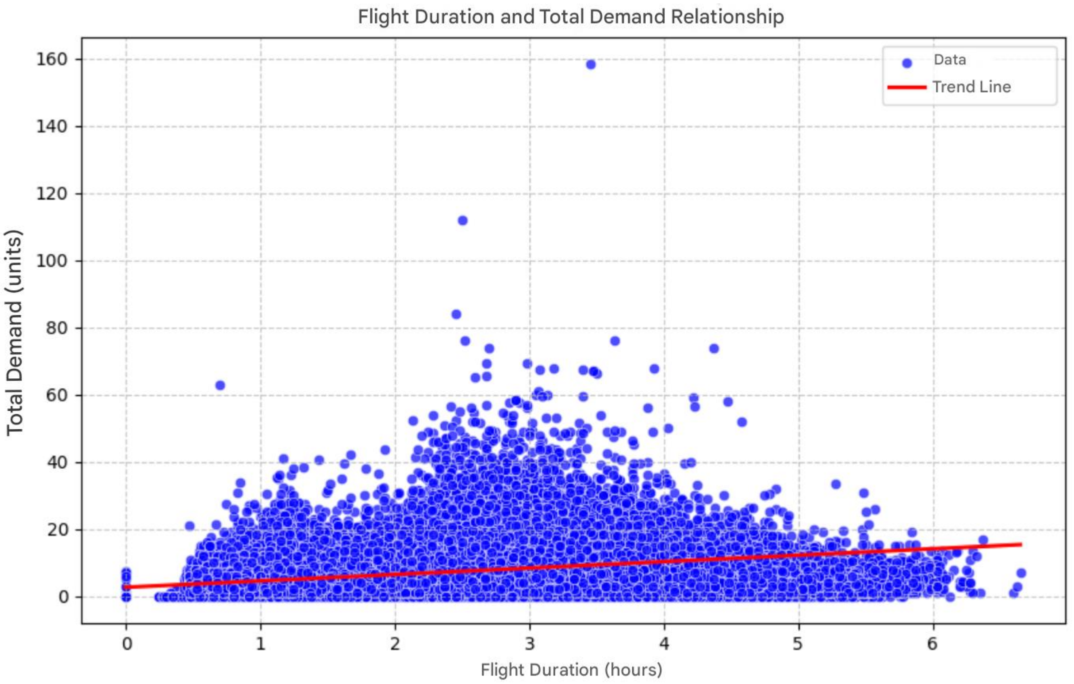

Figure 3. Flight Duration and Total Demand Relationship Graph [Self Made].

3.2.2 Random Forest Regressor

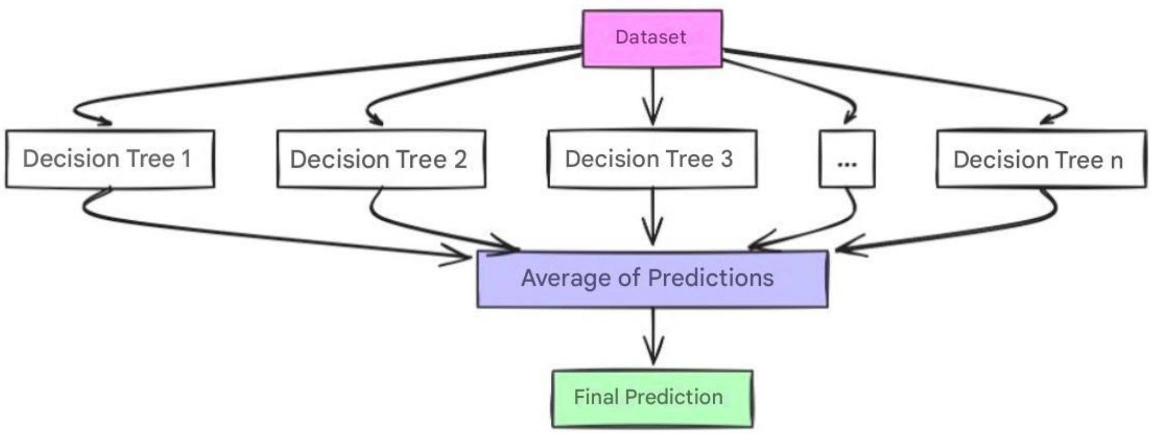

Figure 4. Random Forest Regressor Example [Self Made].

Random Forest Regressor is an ensemble learning method that makes predictions using multiple decision trees. This algorithm aims to make a more general prediction by "averaging" the decision trees. The basic working principles are as follows:

1. Random subsamples are selected from the dataset (Bootstrap method).
2. Decision trees are trained on each subsample. Each tree works with a specific subset of features.
3. In the prediction phase, the final prediction is obtained by averaging the predictions of all trees.

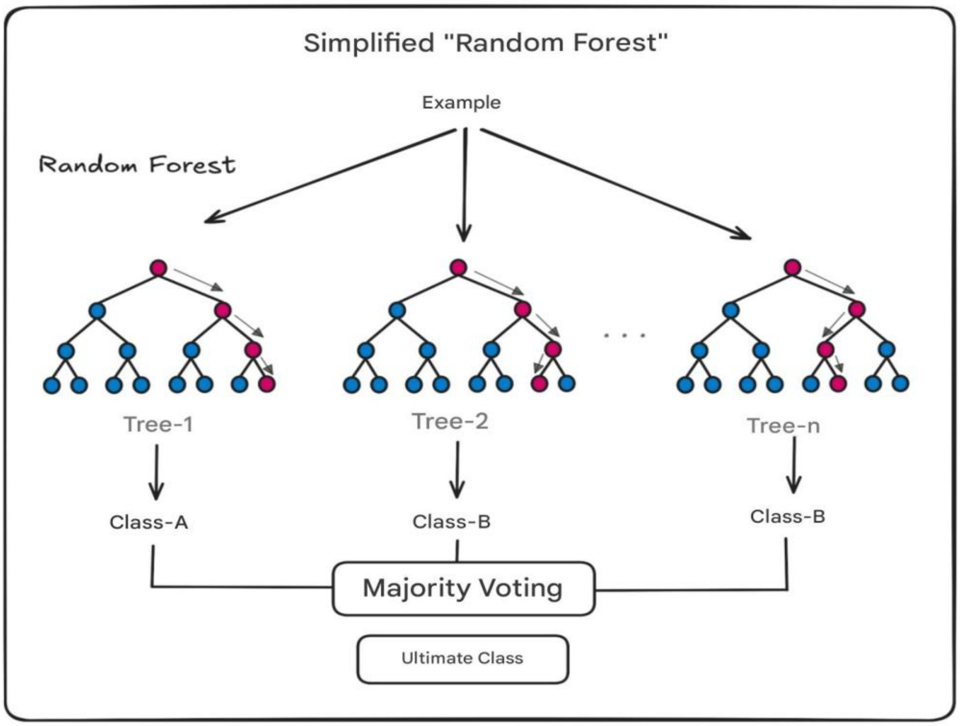

Figure 5. Connection Between Random Forest and Random Tree [18].

The basic idea behind Random Forest is to increase the overall performance by reducing the errors of different decision trees. Furthermore, the independence between trees strengthens the generalization ability.

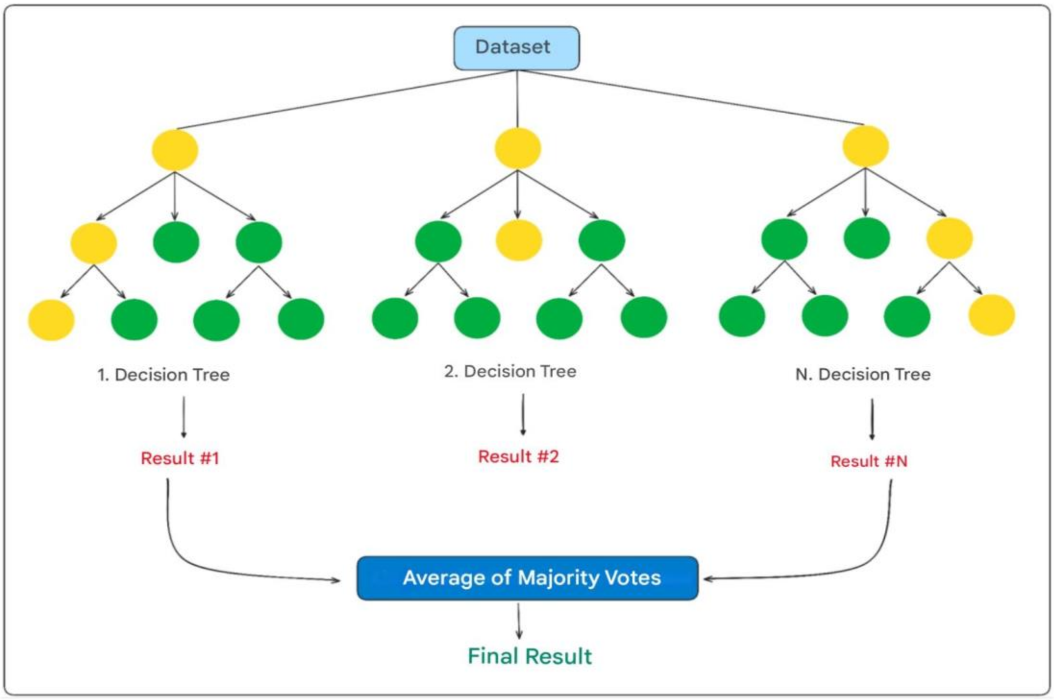

Figure 6. Random Forest Example [Self Made].

Advantages of Random Forest:
● Can model both linear and nonlinear relationships.
● Resistant to overfitting.
● Can be used to determine the importance of features.

Disadvantages of Random Forest:
● Can be slower and require more computational resources.
● Can sometimes be less effective on very large data sets.

Version	Algorithm	Data Used	R^2 Score	MAE	RMSE
Version 1	**LinearRegression()**	Total number of passengers, total demand	**0.02**	**20.5**	**25.1**
Version 2	**LinearRegression()**	Total number of passengers, flight duration, total demand	**0.06**	**18.3**	**22.7**
Version 3	**RandomForestRegressor()**	Total number of passengers; # Turkish male adults; # foreign male adults; # Turkish female adults; # foreign female adults; # Turkish child passengers; # foreign child passengers; # Turkish infant passengers; # foreign infant passengers; flight duration, total demand	**0.44**	**7.9**	**11.2**
Version 4	**LightGBMRegressor()**	Total number of passengers; # Turkish male adults; # foreign male adults; # Turkish female adults; # foreign female adults; # Turkish child passengers; # foreign child passengers; # Turkish infant passengers; # foreign infant passengers; flight duration, total demand	**0.85**	**2.28**	**3.35**

Figure 7. Versions and Algorithms Used Table [Self Made].

3.2.3. Random Forest vs Linear Regression

1. Model type:
○ Linear Regression: Suitable for linear relationships.
○ Random Forest: Can model both linear and non-linear relationships.

2. Performance:
○ Linear Regression: Effective on small data sets and linear relationships.
○ Random Forest: Generally performs better on large datasets and complex relationships.

3. Outliers:
○ Linear Regression: Sensitive to outliers.
○ Random Forest: More resilient to outliers.

4. Speed:
○ Linear Regression: Works faster.
○ Random Forest: Requires more computing power and time.

5. Interpretability:
○ Linear Regression: More easily interpretable.
○ Random Forest: More difficult to interpret, but offers the advantage of determining feature importance.

3.2.4. LightGBM

1.Model type:
○ LightGBM: Gradient-boosted decision trees optimized for speed and accuracy.

2.Performance:
○ LightGBM: Consistently achieves higher R^2 and lower error than both linear and random-forest models on large, complex datasets.

3.Outliers & missing data:
○ LightGBM: Naturally handles missing values and is robust to outliers via tree-based splits.

4.Speed & scalability:
○ LightGBM: Implements histogram-based learning and leaf-wise tree growth, delivering much faster training and inference on big data.

5.Interpretability & tuning:

○ LightGBM: Provides built-in feature-importance metrics and integrates seamlessly with SHAP for detailed model explanations, while offering extensive hyperparameter tuning options.

4. FINDINGS

In this section, a graph comparing the actual and estimated demand amounts is presented to better understand the analysis of the obtained data. The dataset used in this study is fully real, containing actual operational records from the airline transportation sector. In the graph, the blue dots represent the actual demand, and the orange crosses represent the estimated demand. As can be seen, while the actual demand values exhibit a wide distribution, the estimated demand is concentrated in a narrower range. This situation shows that the model is successful in capturing general trends but has difficulty representing sudden increases or extreme values in the demand amount. It is also noteworthy that the estimates are more accurate in low demand ranges, while deviations become more pronounced at high demand levels. These findings reveal that the performance of the model should be analyzed in more detail in data sets showing high variance.

In this study, more than 180,000 flight data belonging to the airline transportation sector were analyzed. The data set used includes information such as flight identity (ID), number of passengers, flight duration, food types and quantities for each flight. The model was trained on this comprehensive data set and gained the ability to make estimates. During the training process, the data set was divided into 80% training and 20% test data, and the performance of the model was evaluated based on this division.

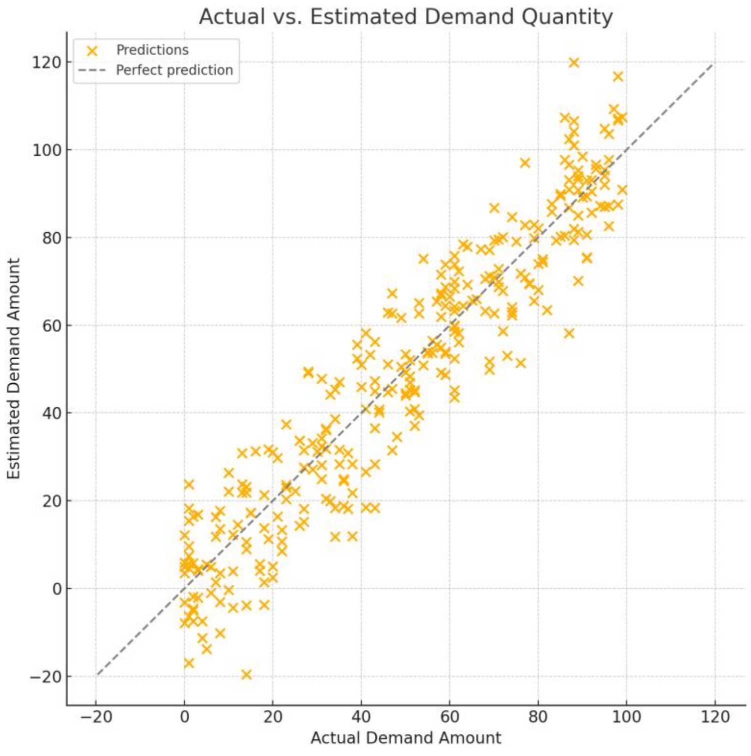

Figure 8. Actual vs. Estimated Demand Quantity Graph [Self Made].

The following basic findings were reached during the data analysis process:

1. Passengers with Similar Profiles: Similar food consumption was observed on flights with passengers of similar age and occupation ranges.
2. Occupancy Rate: Food consumption was found to be more predictable on flights with high occupancy rates, highlighting the impact of occupancy rates on food forecast accuracy.
3. Analysis of Model Outputs: The model's initial outputs were compared with consumption values to assess its accuracy. This benchmarking process provides a roadmap for improving the model's performance. The model's current predictive success can be improved with future optimizations.
4. Future Potential: The findings obtained during the study provide an important basis for improving data-driven decision-making processes in food stock management. The model is open to development to increase forecast accuracy and support operational efficiency.

4. CONCLUSION and DISCUSSION

The predictions of the developed model were compared with the food consumptions at the end of the flight, thus validating the learning mechanism of the model. However, a detailed analysis was not performed. The first results show that the model has a general prediction ability. These results can contribute to airline companies optimizing their food planning processes. However, in order to take the performance of the model to a higher level, detailed error analysis, performance metrics and additional data sources are planned to be integrated into the model.

In this study, a prediction model that can help airline companies optimize their food planning processes was developed and the first results were evaluated. The model made food consumption predictions based on flight data and the obtained predictions were compared with the consumption values realized after the flight. This process provided validation of the general prediction capacity of the model. In the first analyses, it was seen that the model has a certain prediction ability; However, the model can be improved by expanding the data set, model optimization and analyzing the errors.

The performance of the model is limited by the size and diversity of the existing data set. Although data from 180,000 flights have been studied, the features and algorithms used in the model need to be improved. In this context, it is planned to add additional features to the dataset such as customer preferences, seasonal factors and flight classes. Such an expansion can increase the model's prediction accuracy and make food consumption predictions more realistic. In addition, comparing the pre-flight predictions with the post-flight data and providing feedback to the model can strengthen the learning process and increase the model's adaptability.

The commercial applicability of the approach used in the study was considered. When the developed model is optimized correctly, it can help airlines reduce their costs and make their resource use more efficient. In particular, accurate estimation of food stock per flight can play a critical role in reducing waste. However, a more comprehensive testing process is needed before switching to commercial use. The accuracy rates of the model's predictions made with real flight data should be evaluated with detailed error analyses.

The initial findings obtained in line with the research question "How can we accurately estimate the food stock required per flight using customer data?" indicate a starting point. It has been understood that the prediction accuracy rates can be increased by using more data and optimizing the algorithms. In addition, the integration of a continuous learning mechanism can enable the model to update itself after each flight and make better predictions. This will contribute significantly not only to food planning but also to areas such as price performance and cost. As a result, this study offers an important solution to the food planning problem in the airline sector. However, more data analysis, model optimization and testing processes are needed for the model to be applied in the commercial field and to reach high accuracy rates. Future studies will guide us to achieve these goals.

Authors' Contributions

No	Full Name	ORCID ID	Author’s Contribution
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2	Emre Atlıer Olca	0000-0001-6812-5166	1, 2, 5
1- Study design, 2- Data collection, 3- Data analysis and interpretation, 4- Manuscript writing, 5- Critical revision			

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