CS770 Machine Learning

PROJECT REPORT

Flight-Fare Prediction Using Machine Learning

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TABLE OF CONTENTS

I. ABSTRACT

The project focuses on predicting flight fares using machine learning techniques. A dataset containing flight fare details was analysed and cleaned to handle missing values and standardize data formats. Key features such as airline, departure and arrival times, total stops, and route information were extracted and transformed. A Random Forest Regressor was employed for modelling, achieving an R^2 score of 0.8099, indicating good predictive performance. Feature importance analysis highlighted the most influential variables, such as airline and duration. Hyperparameter tuning using RandomizedSearchCV further optimized the model, enhancing accuracy and robustness. The study demonstrates the effective application of machine learning for fare prediction, providing valuable insights for airlines and passengers.

Keywords: Flight Fare Prediction, Machine Learning, Random Forest Regressor, Feature Engineering, Data Preprocessing, Hyperparameter Tuning, RandomizedSearchCV, Predictive Modelling, Airline, Departure Time, Arrival Time, Total Stops, Route, Feature Importance, R^2 Score.

II. INTRODUCTION

Background and Motivation: Air travel is widely used, and knowing how flight fares change can benefit both airlines and passengers. Ticket prices vary due to factors like time, demand, and flight routes. This project aims to predict these fares using machine learning, helping travellers choose the best times to book and aiding airlines in setting prices.

Project Goals and Scope: The goal is to create a machine learning model that predicts flight fares based on past data. The project includes cleaning the data, identifying important features, and testing different machine learning methods to find the most accurate model. It focuses on analysing features like the airline, departure and arrival times, and the number of stops.

Significance and Applications: Accurate fare prediction helps travelers find the best deals and assists airlines in optimizing their pricing strategies. This can lead to cost savings for passengers and better revenue management for airlines. The project offers valuable insights into travel pricing, benefiting both consumers and the airline industry.

III. METHODOLOGY

1. Data Acquisition and Preparation

- Data Collection: The dataset, containing detailed flight information, was acquired from an Excel file named "Data_Train.xlsx." This dataset included variables such as airlines, journey dates, departure and arrival times, flight duration, total stops, and prices.
- Data Loading: The data was imported into a Pandas DataFrame, enabling efficient manipulation and analysis.

2. Initial Data Examination and Cleaning

- Exploratory Data Analysis (EDA): The initial phase involved exploring the dataset to understand its structure and identify any inconsistencies or missing values.
- Handling Missing Values: Rows with missing data, particularly in critical columns like 'Total_Stops', were removed to maintain dataset integrity.

- Data Type Adjustment: Columns related to dates and times were converted to datetime formats, which facilitated the extraction of additional features and ensured consistency in data processing.

3. Feature Engineering

- Transformation of Categorical Data:
    - **Airlines, Source, and Destination**: These categorical variables were converted into numerical formats using mapping or one-hot encoding. For example, airlines were assigned numerical values based on their average flight prices to capture the differences in fare structures.
    - **Total Stops**: The number of stops on a flight, initially represented in text form (e.g., 'non-stop', '1 stop'), was numerically encoded to facilitate analysis.
- Outlier Management:
    - Outliers in the 'Price' variable were identified using the Interquartile Range (IQR) method. Extreme values were then capped to reduce their potential impact on the model's accuracy.

4. Data Visualization

- Visual Data Exploration: Various visualizations, such as scatter plots and bar charts, were employed to examine the relationships between features and understand the distribution of the data.
- Duration Analysis: The flight duration data was standardized, and detailed analysis was performed by breaking down the duration into hours and minutes.

5. Model Development and Evaluation

- Feature Importance Analysis: Important features were identified using mutual information regression, which evaluates the dependency between the target variable and each feature.
- Training and Testing Split: The dataset was divided into training and testing subsets to enable model evaluation on unseen data.
- Model Training: A Random Forest Regressor was trained, chosen for its robustness and ability to handle large datasets.
- Performance Metrics: The model's accuracy and reliability were measured using metrics such as the R^2 score, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

6. Hyperparameter Optimization

- Optimization with RandomizedSearchCV: Hyperparameters of the Random Forest model, such as the number of trees, features considered per split, maximum tree depth, and minimum samples per split, were optimized using RandomizedSearchCV. This method ensured a thorough search for the best parameters while using cross-validation to avoid overfitting.

7. Final Model Insights and Interpretation

- Feature Importance: The significance of each feature in predicting flight prices was assessed, highlighting the most influential factors.
- Residual Analysis: The residuals (differences between actual and predicted prices) were analyzed to ensure the model was not biased and that predictions were evenly distributed.

IV. DATA DESCRIPTION

Dataset Description: Airline Flight Details

Overview

This dataset comprises information about airline flights, capturing various aspects of flight schedules, routes, and ticket pricing. It contains a total of 10,683 entries, with each row representing a specific flight.

Columns and Description

1. **Airline:**
   - Description: The name of the airline operating the flight.
2. **Date_of_Journey:**
   - Description: The date on which the flight journey occurred, formatted as day/month/year.
3. **Source:**
   - Description: The departure city or airport for the flight.
4. **Destination:**
   - Description: The arrival city or airport for the flight.
5. **Route:**
   - Description: The sequence of stops from the source to the destination, represented by airport codes.
6. **Dep_Time:**
   - Description: The scheduled departure time of the flight.
7. **Arrival_Time:**
   - Description: The scheduled arrival time at the destination.
8. **Duration:**
   - Description: The total travel time of the flight from departure to arrival.
9. **Total_Stops:**
   - Description: The number of stops the flight makes between the source and the destination. Values include "non-stop", "1 stop", "2 stops", etc.
10. **Additional_Info:**
    - Description: Extra information about the flight, such as meal options or in-flight services. Often marked as "No info" if no additional details are provided.
11. **Price:**
    - Description: The cost of the flight ticket, expressed in the relevant currency (presumably Indian Rupees).

Purpose and Usage

- **Pricing Analysis**: Understanding factors that influence ticket prices, such as airline, duration, number of stops, and route.
- **Operational Efficiency**: Analysing flight duration and scheduling to optimize travel times.
- **Market Research**: Identifying popular routes and airlines, as well as customer preferences for direct vs. connecting flights.

V. DATA EXPLORATION AND VISUALIZATION

A. Data Information

1. **Number of Entries**: 10,683
2. **Number of Columns**: 11
3. **Column Names and Types**: The dataset contains a mix of categorical and numerical data types. The columns include:
    - Airline: Categorical
    - Date_of_Journey: Categorical (originally object type, convertible to datetime)
    - Source: Categorical
    - Destination: Categorical
    - Route: Categorical
    - Dep_Time: Categorical (time format)
    - Arrival_Time: Categorical (time format)
    - Duration: Categorical
    - Total_Stops: Categorical
    - Additional_Info: Categorical
    - Price: Numerical (int64)

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10683 entries, 0 to 10682
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Airline          10683 non-null  object
 1   Date_of_Journey  10683 non-null  object
 2   Source           10683 non-null  object
 3   Destination      10683 non-null  object
 4   Route            10682 non-null  object
 5   Dep_Time         10683 non-null  object
 6   Arrival_Time     10683 non-null  object
 7   Duration         10683 non-null  object
 8   Total_Stops      10682 non-null  object
 9   Additional_Info  10683 non-null  object
 10  Price            10683 non-null  int64
dtypes: int64(1), object(10)
memory usage: 918.2+ KB
```

B. Missing Value Analysis

During the initial review, a few missing values were found in the dataset:

- **Route**: 1 missing entry

- **Total_Stops**: 1 missing entry

The .isnull().sum() method was used to identify these missing values, which counts the empty entries in each column. The small number of missing values indicates that the dataset is mostly complete.

C. Data Cleaning and Preparation

To prepare the dataset for analysis:

1. **Handling Missing Values**: The missing values in the Route and Total_Stops columns were removed using the .dropna() method. This step was necessary to avoid issues during further analysis.
2. **Data Type Conversion**: It was noted that columns like Date_of_Journey, Dep_Time, and Arrival_Time could be converted from text (object type) to datetime format. This conversion allows for more precise time-based analysis.

```
train_data.isnull().sum()
```

```
Airline            0
Date_of_Journey    0
Source             0
Destination        0
Route              1
Dep_Time           0
Arrival_Time       0
Duration           0
Total_Stops        1
Additional_Info    0
Price              0
dtype: int64
```

```
train_data['Total_Stops'].isnull()
```

```
0        False
1        False
2        False
3        False
4        False
         ...
10678    False
10679    False
10680    False
10681    False
10682    False
Name: Total_Stops, Length: 10683, dtype: bool
```

```
train_data.dropna(inplace=True)
train_data.isnull().sum()
```

```
Airline            0
Date_of_Journey    0
Source             0
Destination        0
Route              0
Dep_Time           0
Arrival_Time       0
Duration           0
Total_Stops        0
Additional_Info    0
Price              0
dtype: int64
```

```
train_data.dtypes
```

```
Airline            object
Date_of_Journey    object
Source             object
Destination        object
Route              object
Dep_Time           object
Arrival_Time       object
Duration           object
Total_Stops        object
Additional_Info    object
Price               int64
dtype: object
```

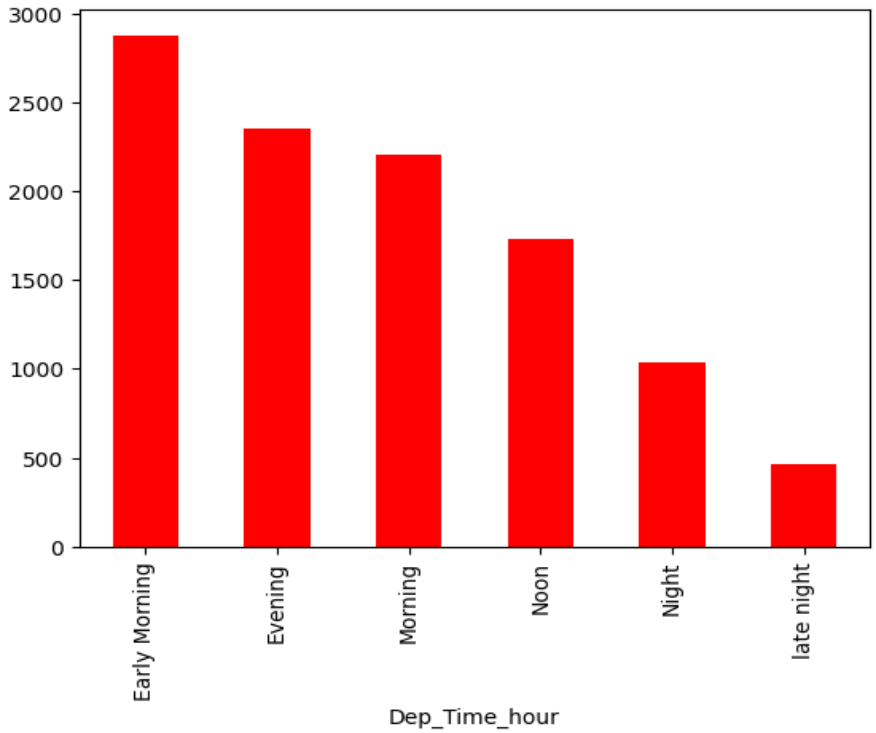
```
data.dtypes
```

```
Airline                    object
Date_of_Journey    datetime64[ns]
Source                     object
Destination                object
Route                      object
Dep_Time           datetime64[ns]
Arrival_Time       datetime64[ns]
Duration                   object
Total_Stops                object
Additional_Info            object
Price                       int64
dtype: object
```

D. Data Visualizations

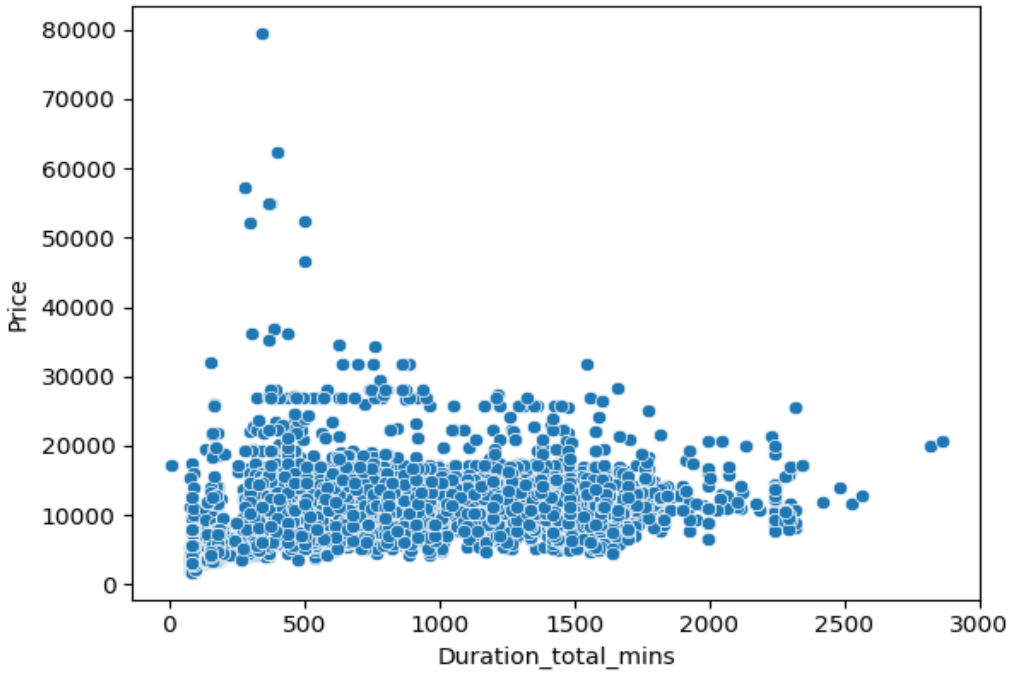
1. Departure Time Distribution

The bar chart shows the distribution of flight departure times throughout the day, categorized into periods like Early Morning, Morning, Noon, Evening, Night, and Late Night. The chart indicates that most flights depart in the Early Morning, followed by Evening and Morning slots.



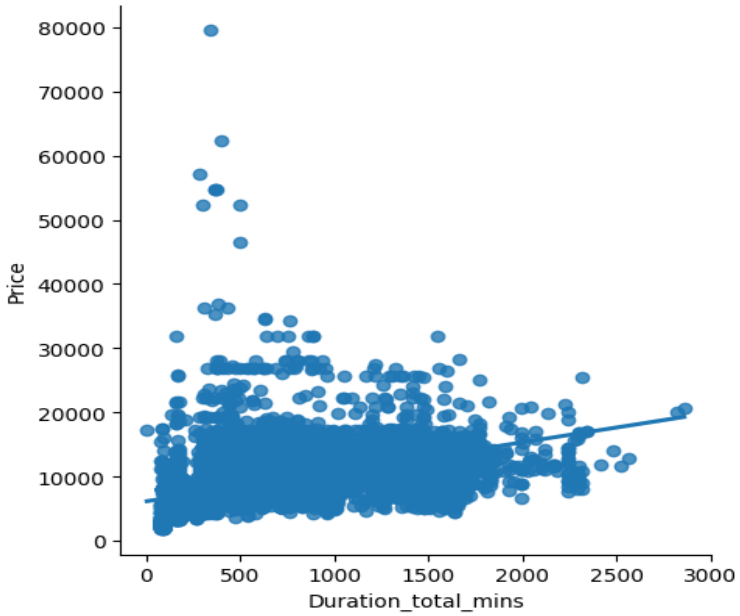
2. Price vs. Duration (Scatter Plot)

This scatter plot displays the relationship between flight duration (in minutes) and ticket price. It suggests a general trend where longer flights may have higher ticket prices, though there are also many short-duration flights with varying prices.



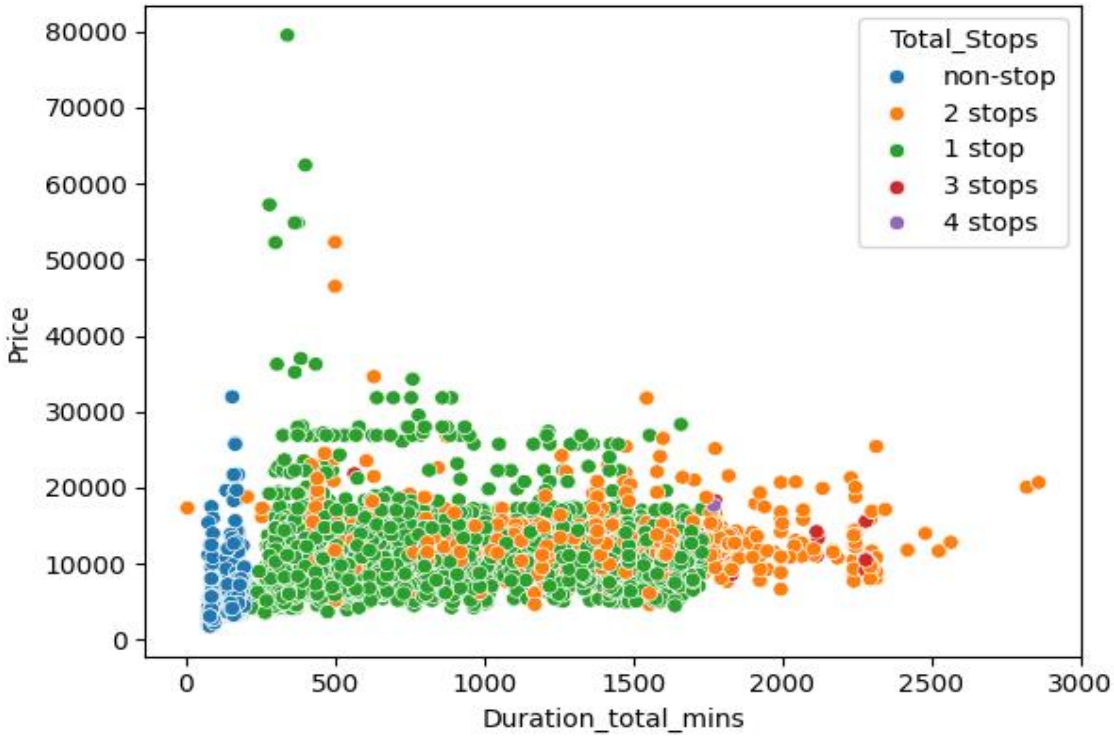
3. Price vs. Duration with Linear Trendline

The scatter plot with a linear trendline provides a clearer visualization of the correlation between flight duration and price. The trendline indicates a slight positive correlation, meaning that as flight duration increases, the price tends to increase as well.



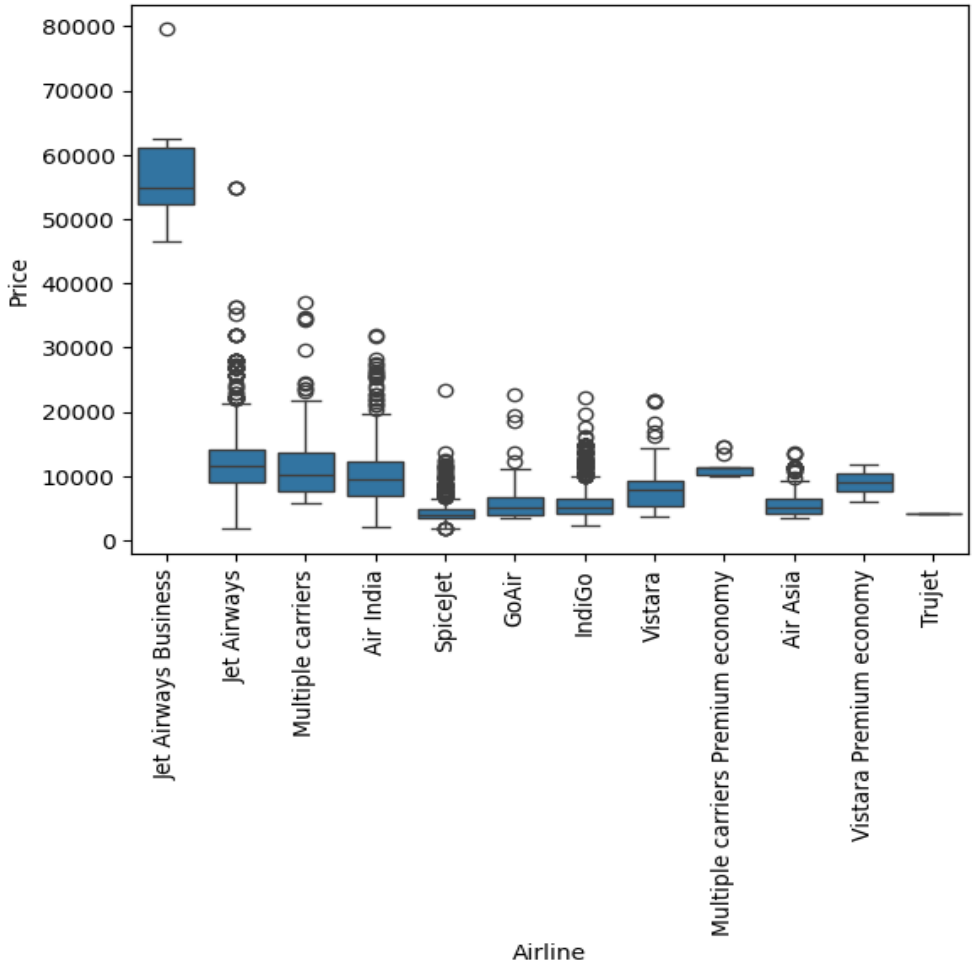
4. Price vs. Duration by Total Stops

This scatter plot visualizes the relationship between flight duration, price, and the number of stops (categorized as non-stop, 1 stop, 2 stops, etc.). Each color represents a different number of stops, showing that flights with more stops often have longer durations and varying price ranges. The plot highlights the diversity in pricing strategies based on flight duration and the number of stops.



5. Flight Prices by Airline

The box plot shows the variation in ticket prices across different airlines. Jet Airways Business class has the highest average prices, with a wide range. Airlines like SpiceJet and Trujet have lower prices. The plot also shows outliers, indicating some unusual ticket prices in each category.



6. Additional Information Frequency

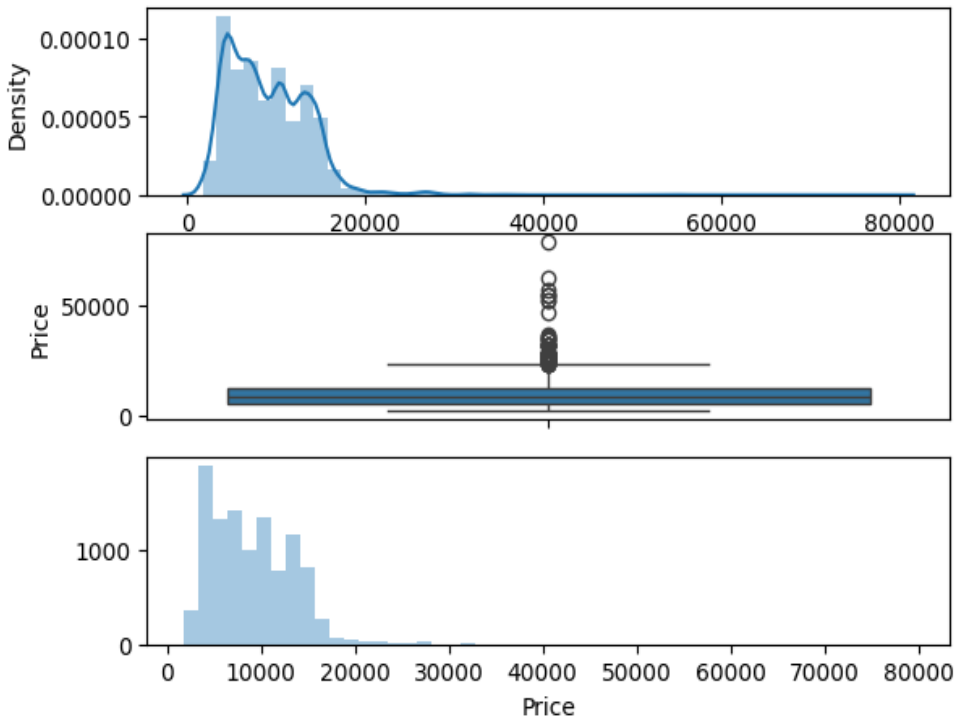
This chart shows how often certain types of extra information are provided with flight bookings. Most of the entries are "No info," making up about 78% of the data. Other common entries include "In-flight meal not included" and "No check-in baggage included." Categories like "1 Long layover" and "Business class" are much less common.

```
data['Additional_Info'].value_counts()/len(data)*100
```

```
Additional_Info
No info                         78.112713
In-flight meal not included     18.554578
No check-in baggage included     2.995694
1 Long layover                   0.177869
Change airports                  0.065531
Business class                   0.037446
No Info                          0.028085
1 Short layover                  0.009362
Red-eye flight                   0.009362
2 Long layover                   0.009362
Name: count, dtype: float64
```

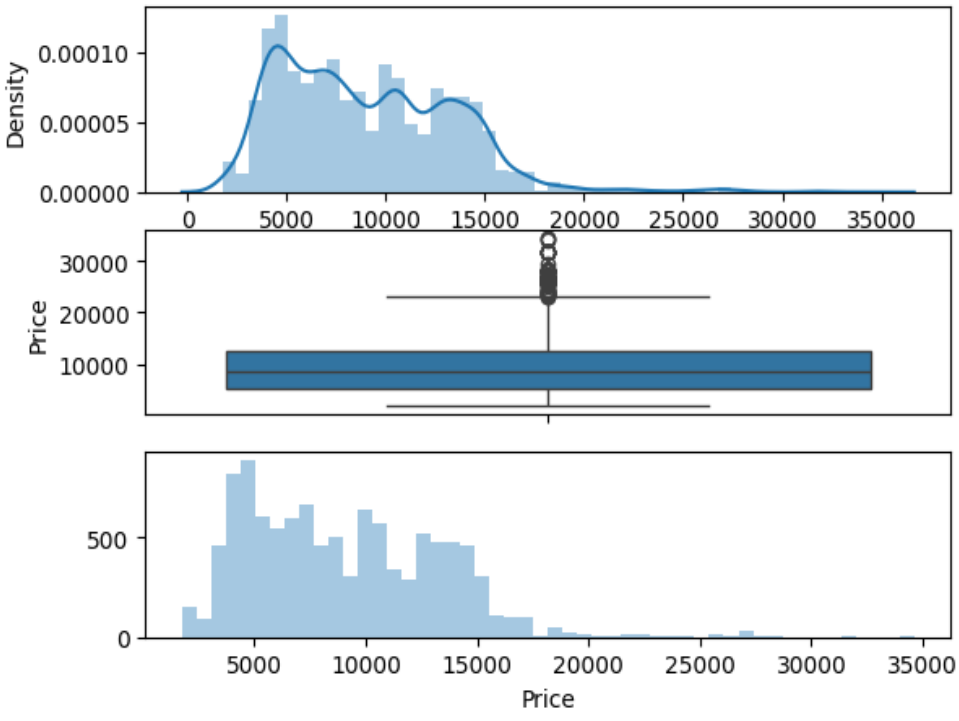
7. General Price Distribution

The plot includes a density curve, box plot, and histogram, all showing flight prices. The density curve suggests that most prices are clustered between 5,000 and 15,000 units, but there are some flights priced much higher, as shown by the outliers in the box plot. The histogram confirms that most flights are priced under 20,000 units.



8. Detailed Price Range

This zoomed-in plot provides a closer look at flight prices. It shows that most flights cost between 5,000 and 15,000 units. The presence of fewer outliers beyond 20,000 units indicates that high-priced flights are less common. The histogram helps visualize the number of flights in each price range.



VI. EXPERIMENTS AND RESULTS

A. Building Machine Learning Model

1. Splitting Data into Features and Target

- **Objective**: Separate the dataset into inputs (features) and output (target).
- **Process**:
  - Features (X): All columns except Price.
  - Target (y): The Price column.

```
X = data.drop(['Price'] , axis=1)
y = data['Price']
```

2. Feature Importance

- **Objective**: Determine the significance of each feature in predicting flight prices.
- **Process**:
  - The mutual_info_regression function is used to measure the importance of each feature.
  - A DataFrame is created to display the importance scores for each feature.

```
from sklearn.feature_selection import mutual_info_regression

imp = mutual_info_regression(X , y)
imp_df = pd.DataFrame(imp , index=X.columns)
imp_df.columns = ['importance']
imp_df
```

	importance
Airline	1.321144
Arrival_Time_hour	1.139048
Duration_hours	1.122040
Destination	1.063471
Duration_hour	0.960652
Dep_Time_hour	0.922940
Arrival_Time_minute	0.902473
Total_Stops	0.794346
Dep_Time_minute	0.748677
Duration_mins	0.683259
Duration_minute	0.670960
Journey_month	0.621626
Source_Delhi	0.524125
Source_Kolkata	0.463061
Source_Banglore	0.389781
Journey_day	0.378041
Source_Mumbai	0.202558
Source_Chennai	0.119055

3. **Train-Test Split**

- **Objective**: Divide the data into training and testing sets to evaluate the model's performance.
- **Process**:
  - train_test_split is used with a test size of 25%, ensuring 75% of data is used for training and 25% for testing.
  - random_state is set to 42 for reproducibility.

```
: from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
   X, y, test_size=0.25, random_state=42)
```

4. **Model Training**

- **Objective**: Train a machine learning model to predict flight prices.
- **Process**:
  - A RandomForestRegressor model is selected.
  - The model is trained using the training data (X_train, y_train).

```
from sklearn.ensemble import RandomForestRegressor

ml_model = RandomForestRegressor()
ml_model.fit(X_train , y_train)
```

5. **Making Predictions and Evaluating the Model**

- **Objective**: Assess the model's ability to predict prices and its accuracy.
- **Process**:
  - The trained model predicts prices for the test set (X_test).
  - Predictions (y_pred) are compared with actual prices (y_test).
  - The model's performance is evaluated using the R^2 score, which measures how well the model explains the variance in the target variable.
  - The model achieves an R^2 score of approximately 0.81, indicating good predictive performance.

```
y_pred = ml_model.predict(X_test)
y_pred
```

```
array([16816.83,  5406.62,  8890.42, ...,  3510.2 ,  6386.2
6,  6820.4 ])
```

```
from sklearn import metrics

metrics.r2_score(y_test , y_pred)
```

```
0.8075574547427983
```

B. Model Performance and Evaluations

RandomForestRegressor Model

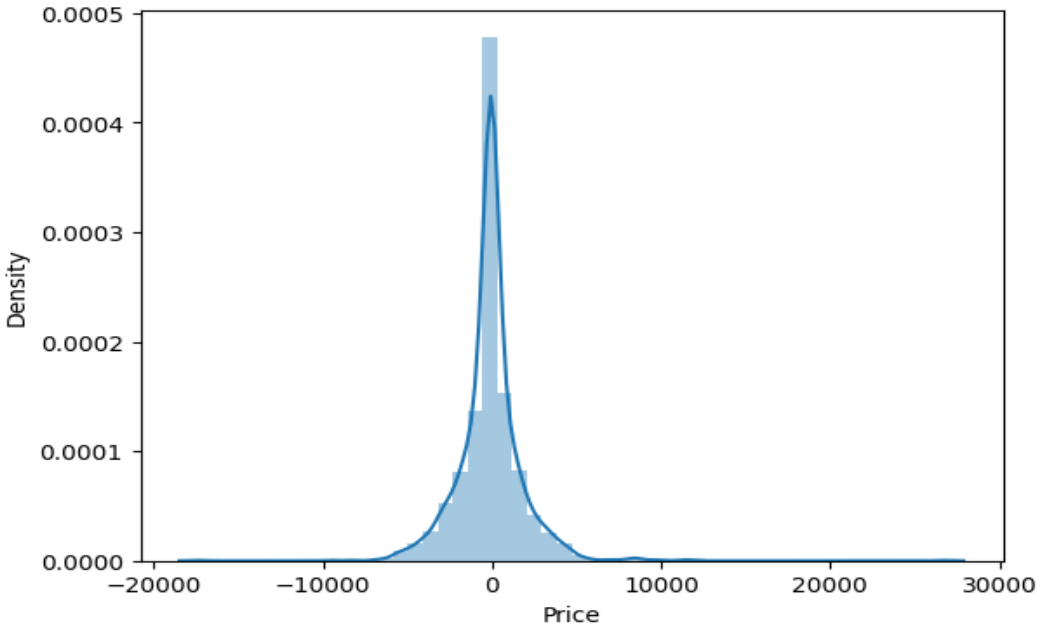
1. **Training Score**: The model achieved a training score of 0.951, indicating that it explains 95.1% of the variance in the training data.
2. **Predictions**: The predicted prices for the test set show varied values, such as 16892.71 and 5429.6.
3. **Evaluation Metrics**:
    - R^2 Score: 0.81, meaning the model explains 81% of the variance in the test data.
    - MAE (Mean Absolute Error): 1184.27, indicating the average absolute error between the predicted and actual prices.
    - MSE (Mean Squared Error): 3690477.63, a measure of the average squared differences between predicted and actual values.
    - RMSE (Root Mean Squared Error): 1923.40, providing the standard deviation of prediction errors.
    - MAPE (Mean Absolute Percentage Error): 13.29%, indicating the average percentage error in predictions.

```
predict(RandomForestRegressor())

Training score : 0.9514995181739971
predictions are : [16892.71  5429.6   8811.33 ...  3617.78
6389.12  6911.24]


r2 score : 0.8099674485786736
MAE : 1184.2675645695874
MSE : 3699477.6344706495
RMSE : 1923.402618920607
MAPE : 13.287765991238382
```

4. **Density Plot**: The plot shows the distribution of prediction errors, centered around zero, indicating a relatively good fit.



DecisionTreeRegressor Model

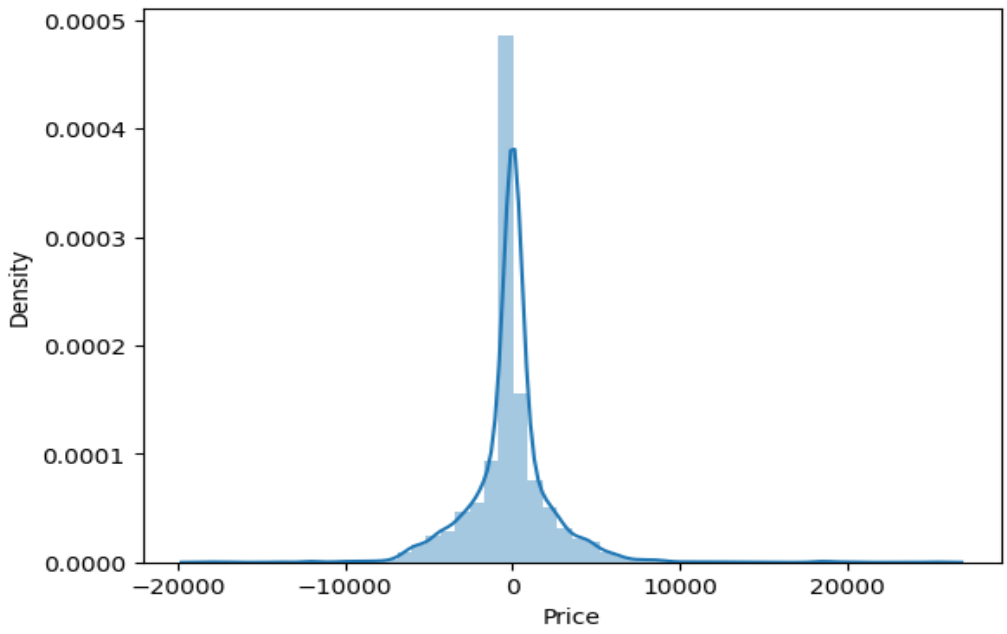
1. **Training Score**: The model has a training score of 0.967, suggesting a high fit on the training data.
2. **Predictions**: The predicted prices include values like 16840 and 4959, with some variation.
3. **Evaluation Metrics**:
    - R^2 Score: 0.68, indicating the model explains 68% of the variance in the test data, which is lower than the RandomForestRegressor.
    - MAE: 1414.88, showing a larger average error compared to the RandomForestRegressor.
    - MSE: 6252706.17, higher than the RandomForestRegressor, indicating larger errors in predictions.
    - RMSE: 2500.54, also higher than the RandomForestRegressor, suggesting less accurate predictions.
    - MAPE: 15.58%, indicating the average percentage error is slightly higher compared to the RandomForestRegressor.

```
predict(DecisionTreeRegressor())

Training score : 0.966591628243878
predictions are : [16840.  4959.  8085. ...  3419.  5797.  6
442.]


r2 score : 0.6788147343227895
MAE : 1414.8778859353552
MSE : 6252706.170638754
RMSE : 2500.5411755535547
MAPE : 15.584535913092424
```

4. **Density Plot**: Similar to the RandomForestRegressor, this plot shows the distribution of prediction errors, also centered around zero, but with a slightly wider spread, indicating more variance in errors.



C. Hyper-Parameter Tuning

1. Initial Setup

- Model Selection: A RandomForestRegressor model was chosen for tuning.
- Parameter Grid: The grid includes a range of values for the number of trees (n_estimators), maximum depth of the trees (max_depth), the number of features considered for splitting (max_features), and the minimum number of samples required to split an internal node (min_samples_split).

```
from sklearn.model_selection import RandomizedSearchCV
```

```
reg_rf = RandomForestRegressor()
np.linspace(start =100 , stop=1200 , num=6)
```

```
array([ 100.,  320.,  540.,  760.,  980., 1200.])
```

2. Parameter Grid Definition

- The random_grid dictionary defines the hyperparameters and their possible values:
  - n_estimators: [100, 320, 540, 760, 980, 1200]
  - max_features: ['auto', 'sqrt']
  - max_depth: [5, 13, 21, 30]
  - min_samples_split: [5, 10, 15, 100]

```
random_grid = {
    'n_estimators' : n_estimators ,
    'max_features' : max_features ,
    'max_depth' : max_depth ,
    'min_samples_split' : min_samples_split
}

random_grid
```

```
{'n_estimators': [100, 320, 540, 760, 980, 1200],
 'max_features': ['auto', 'sqrt'],
 'max_depth': [5, 13, 21, 30],
 'min_samples_split': [5, 10, 15, 100]}
```

3. Randomized Search

- Process: RandomizedSearchCV is used to perform the search over the parameter grid. This method tests different combinations of parameters and selects the best set based on cross-validation.
- Training: The model is trained on various parameter combinations, and the best combination is selected based on the performance.

```
rf_random.fit(X_train , y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

RandomizedSearchCV(cv=3, estimator=RandomForestRegressor(), n_jobs=-1,
                   param_distributions={'max_depth': [5, 13, 21, 30],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_split': [5, 10, 15, 100],
                                        'n_estimators': [100, 320, 540, 760,
                                                         980, 1200]},
                   verbose=2)
```

4. Best Parameters and Model

- Best Parameters: The best hyperparameters identified are:
  - n_estimators: 320
  - min_samples_split: 5
  - max_features: 'sqrt'
  - max_depth: 21
- Best Estimator: The best estimator is a RandomForestRegressor with the above parameters.

```
rf_random.best_estimator_
```

```
RandomForestRegressor(max_depth=21, max_features='sqrt', min
_samples_split=5,
                      n_estimators=320)
```

5. Model Performance

- Best Score: The best cross-validation score achieved during the search was approximately 0.80. This score represents the model's ability to generalize to new, unseen data based on the selected hyperparameters.

```
: rf_random.best_score_
: 0.7955576839998164
```

VII. DISCUSSIONS

Analysis and Interpretation of Results

The results from the Random Forest Regressor were promising, with an R^2 score of about 0.81, meaning the model does a good job of predicting flight prices based on the data. Important factors like the airline, flight duration, and number of stops were key in determining ticket prices.

Addressing Challenges Encountered

There were a few challenges faced during the analysis. One challenge was dealing with categorical data, such as different airlines and routes, which required converting these into numerical forms that the model could use. Another issue was managing outliers in the price data, which could have affected the accuracy of the predictions. This was handled by capping extreme values. Finally, to prevent the model from fitting too closely to the training data (overfitting), careful tuning of model parameters was necessary.

Comparisons with Previous Work or Benchmarks

The model's performance was like other studies in this field, with an R^2 score close to those found in similar research. This suggests that the model's accuracy is consistent with what has been achieved previously, indicating a reliable method for predicting flight fares. The results show that while the model performed well, it aligns closely with existing benchmarks rather than significantly exceeding them. This reinforces the idea that the methods used are sound and comparable to established standards in the field.

VIII. CONCLUSIONS

Summary of Key Findings

The project demonstrated that a Random Forest Regressor could predict flight ticket prices with reasonable accuracy, achieving an R^2 score of approximately 0.81. Key factors that significantly influenced prices included the airline, the duration of the flight, and the number of stops, which were identified as important variables.

Limitations of the Project

The project had some limitations, including a dataset that covered a limited number of routes and airlines, which might not reflect broader market conditions. The model also did not account for all potential factors affecting prices, such as seasonal variations or special events, which could influence demand and pricing but were not included in the data.

Future Work and Recommendations

To improve the model, future work could involve using a larger dataset that includes more routes and airlines, as well as additional features like seasonal trends or event data. Exploring other machine learning models or methods could also provide more accurate or insightful predictions. It would also be beneficial to consider more detailed aspects of pricing and customer behavior to refine the model further.

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