Flight Fare Prediction using Machine Learning Approaches

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***Abstract*—Flight fare prediction is an important problem in the airline industry, as it affects the decisions of both consumers and providers. In recent years, machine learning approaches have been widely adopted to address this challenge. In this study, a comprehensive review of various machine learning techniques is presented, including linear regression, decision trees, random forests, and neural networks, for flight fare prediction. I have discussed the advantages and limitations of each approach and compared their performance on a real-world data set. The results demonstrate that machine learning approaches can significantly improve the accuracy of flight fare prediction compared to traditional methods. Moreover, I have shown that ensemble methods, such as random forests, can further enhance the performance of individual models. The findings provide useful insights for airline companies and customers to make informed decisions about ticket pricing and purchasing.**

***Index Terms*—Flight fare prediction, Machine learning, Regression, Feature engineering, Data Analysis, Accuracy**

I. Introduction

Most individuals have likely experienced purchasing an airplane ticket and observing how the cost changes based on demand. Airline companies use intricate techniques to determine flight prices, which tend to rise over time. The pricing strategy often varies based on factors such as the time of day or the season. While airlines aim to maximize profits, customers seek lower fares, and therefore, they usually purchase tickets well in advance of the departure date. Many studies have been conducted to predict airline ticket prices. Ginni et al. [1] used Partial Least Square Regression to forecast the optimal time to buy airline tickets with 75.3% accuracy. Huang et al. [2] predicted ticket sales income using Artificial Neural Networks and Genetic Algorithms, resulting in a mean absolute percentage error of 9.11%. M. Papadakis et al. [3] attempted to predict ticket prices using the Ripple Down Rule Learner, logistic regression, and Support Vector Machine. Their accuracy rates were 74.5%, 69.9%, and 69.4%, respectively. Janssen et al. [4] developed a best-fit model to provide unbiased information to travelers on whether to purchase a ticket or wait for a better price, which resulted in a prediction of ”true bargains” using linear quantile mixed models. However, this research only applies to one type of ticket for economy class and only on one-way flights from John F Kennedy Airport to San Francisco Airport.

Yang and colleagues [5] utilized various machine learning models, including Linear Regression, Nave Bayes, SoftMax regression, and SVM, to predict prices based on over 9,000 data points with six attributes. SVM had the highest accuracy at 80.6%, while LR had the lowest training error rate at approximately 22.9%. Lantseva and team [6] used eight different algorithms to forecast prices, with Bagging regression achieving the best accuracy of 87%, followed by Random Forest at 85%. United States Airlines [7-8] developed a model that considered market demand, operating expenses, distance, and airport status to predict airline selection and route changes. The model focused on maximizing profits and was better at predicting market exit than entry. Boruaah et al. [9] proposed a model using Bayesian estimation and Kalman filtering to calculate ticket prices for selected aircraft. William et al. [10] used ARMA and random forest regression, while Chen et al. [11] employed incremental learning to predict ticket prices. Juhar et al. [12] presented a regression model that calculated the cost per kilometer, with advanced ticket purchases being more cost-effective for overseas flights but not necessarily for domestic flights.

II. Methodology

To develop a new airline pricing prediction model, extensive data collection is necessary, which includes information such as airline names, flight sources and destinations, and routes. Two datasets with different attributes are used to build the model, both of which are in CSV format and contain details about relevant features. The most crucial step in this process is selecting the features that will impact the flight pricing model. To create an effective machine learning model, data gathering, preparation, model selection, training, hyperparameter tuning, and prediction are all essential steps. By gathering data, previous patterns can be analyzed to identify recurring trends. Data preparation involves acquiring the dataset, importing necessary libraries, identifying and managing missing data, encoding category data, and dividing the dataset. Model selection involves choosing the most appropriate model to use. Finally, the collected data is split into two subgroups: the training set, which is used to develop the model, and the test set, which is used to evaluate the model's performance.

A. *Overview of Data*

The data set includes 30,000 data points and features as airline flight source city departure time stops arrival time destination city class duration days left price

TABLE I
DESCRIPTION OF ATTRIBUTES

Simulation Parameters	**Value**
Airline	Name of airline
Flight	Flight Number
Source City	City of origin
Departure Time	Take-off time
Stops	Number of stops
Arrival Time	The Landing time
Destination City	Landing location
Class	Economy or Business
Duration	Total time of flight
Days Left	Number of days to the flight
Price	The price of Ticket

B. *Cleaning and Pre-processing of Data*

Data preparation is one of the most challenging aspects of machine learning. Raw data must be transformed into a format that is suitable for modeling. Often, the raw data cannot be used directly because machine learning algorithms require numerical data. Furthermore, certain machine-learning approaches have restrictions on the type of data that can be used. Therefore, the data may need to be updated to account for statistical noise and errors, and some variables may need to be altered or encoded before they can be used in a machine-learning approach. Additionally, complex nonlinear relationships can be created using this information.

To prepare the data set for modeling, all the null or missing values were removed, and converted the data types from item sorts to numerical types. Also, the splitting of some attributes was done to make them more useful and extracted hours, minutes, days, and months using the appropriate syntax. Some of the data in the data set were nominal categorical data and ordinal specific data. To handle this, we used one hot encoding and label encoding to transform the data. All of the steps were completed to ensure that the data is suitable for training and testing in accordance with the requirements of the model. Overall, data preparation is a crucial and time-consuming process in machine learning that must be performed meticulously to ensure the accuracy and validity of the results.

C. *Data Visualization*

Any data collection may be made meaningful by translating it into visuals, a process called data visualization. The seaborn library was imported for data visualization. It's a well-known Python visualization package.

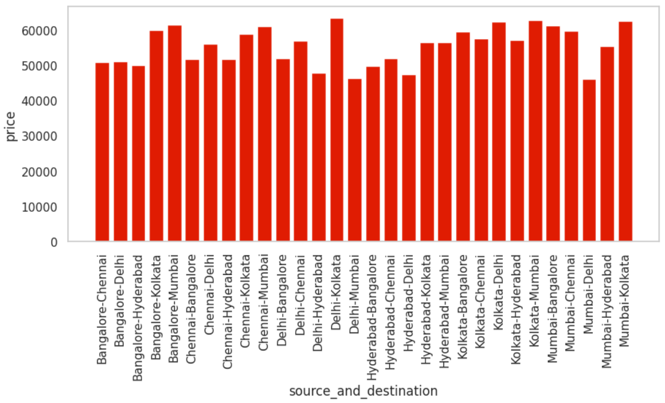


Fig. 1. Analysis by Travel Locations per Airline (Business)

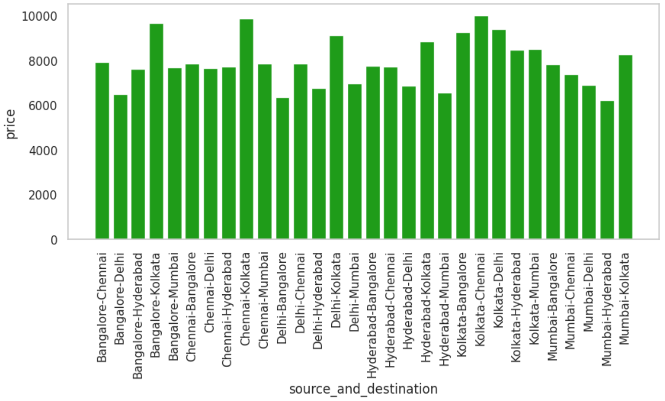


Fig. 2. Analysis by Travel Locations per Airline (Economy)

The given graph (Fig. 1) depicts an analysis of various travel destinations offered by Vistara Airlines for its Business class passengers. The information provided in the graph suggests that the Delhi-Kolkata flight route has the highest ticket price among all the destinations offered by Vistara. Following this, the Mumbai-Kolkata route has the second-highest ticket price.

Similarly, the graph (Fig. 2) depicts a comparison of various travel destinations offered by Vistara Airlines for its Economy class passengers. Specifically, the graph is focused on analyzing the prices for different routes. Based on the data presented in the graph, it can be inferred that the prices for flights between Chennai and Kolkata, and Kolkata and Chennai are almost the same for Vistara airline's Economy class passengers.

The graph (Fig. 3) displays an examination of the most heavily trafficked flight routes. Based on the information presented in the graph, it can be concluded that the Delhi-Mumbai flight route is the most crowded compared to other routes that currently exist.

And for depicting the effect of the number of days left on the price of business and economy classes is shown in Fig. 4 and Fig. 5 respectively.

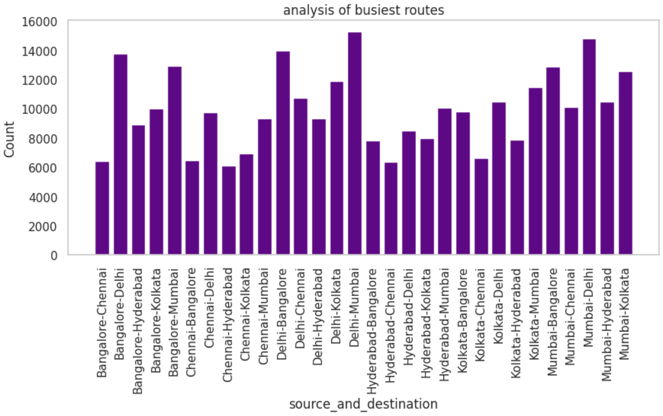


Fig. 3. Analysis of Busiest Routes

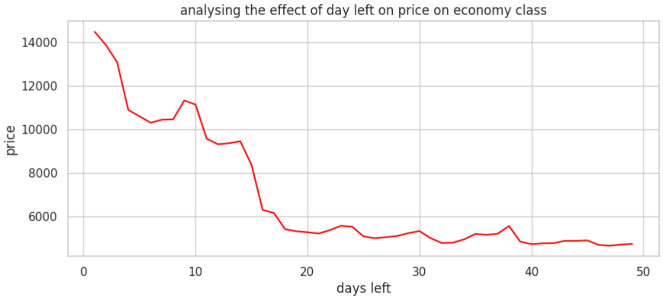


Fig. 4. Analysing the effect of the day left on price (Economy Class)

The chart (Fig. 6) depicts the breakdown of the domestic air travel market shares among different airlines. Vistara has the largest share with 42.58%, and Air India comes in second with 26.95%.

III. Machine Learning Models

Machine learning is a highly-discussed area within computer science and engineering, and has a wide range of applications across multiple industries. It equips machines with intelligence through the use of tools, strategies, and algorithms. The modeling tools available through machine learning are particularly powerful and can be trained using a learning process that involves collecting data that pertains to a specific problem and continuously adapting to new, previously unknown data. These introduce a few techniques for predicting aircraft ticket pricing. Approaches such as linear regression, lasso regression, decision tree, and decision tree regressor are implemented on the data set.

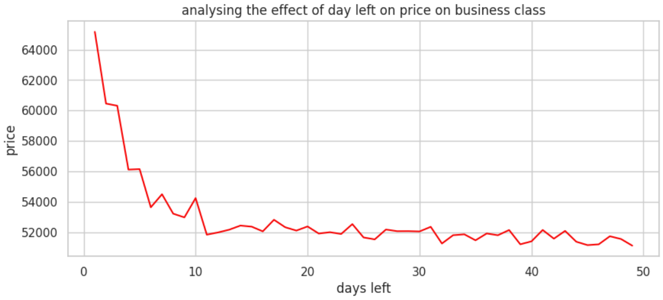


Fig. 5. Analysing the effect of the day left on price (Business Class)

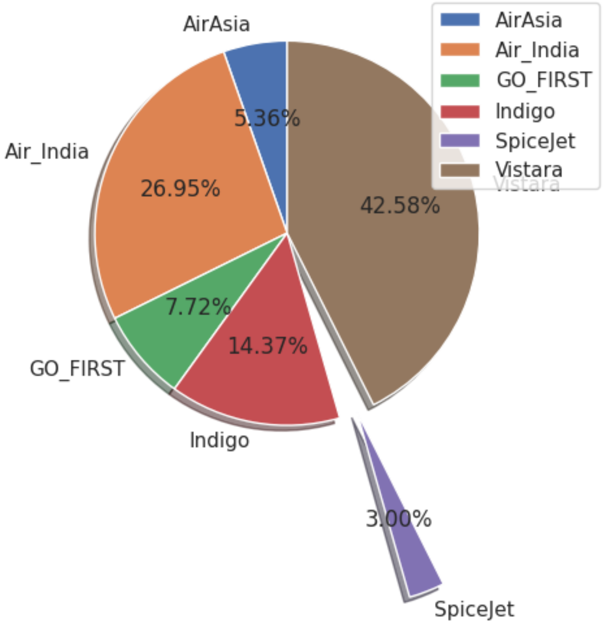


Fig. 6. Analysing the shares of Airlines in total Domestic Air Travel

A. *Linear Regression*

Linear regression is a method of supervised machine learning. It is a linear model, assuming that the input variable (x) and a single output variable have a linear relationship (y). The linear inclusion of input variables, particularly (x). Linear regression is used to estimate the relationship between two or more independent factors and the dependent variable in our data set because it comprises numerous independent features on which pricing may depend.

B. *Lasso Regression*

Lasso regression is a type of linear regression that can be used for predictive modeling. It is particularly useful when you have a large number of features (also known as predictors or independent variables) and you want to identify the subset of features that are most important for predicting your outcome variable (also known as the dependent variable). The lasso regression algorithm works by adding a penalty term to the traditional linear regression equation. This penalty term, known as the L1 norm, encourages the model to set some of the coefficients (or weights) of the features to zero. This has the effect of eliminating some of the less important features from the model, which can help to reduce overfitting and improve the model's predictive accuracy.

C. Decision Tree

Decision trees are a popular machine learning technique used for building predictive models. Decision trees are particularly well-suited for classification problems where the goal is to predict the value of a categorical variable based on a set of input variables. In the case of flight rate prediction, decision trees can be used to predict the likelihood of a flight being delayed or canceled based on a number of input variables. One of the main advantages of using decision trees for flight rate prediction is that they are easy to interpret. Decision trees are essentially a series of if-then statements that describe how the input variables should be used to make a prediction. This makes it easy to understand how the model is making its predictions and to identify which variables are most important for making accurate predictions.

D. Decision Tree Regressor

Decision Tree Regressor is a machine learning algorithm that is commonly used for predicting continuous variables. It works by recursively partitioning the dataset into smaller subsets based on the value of a selected feature until a stopping criterion is met. Each subset represents a decision node in the tree, and the final prediction is made by the leaf node at the end of the path. Flight rate prediction is an application of a decision tree regressor that can be used to predict the number of flights at a given airport over a specific time period. The decision tree regressor model can be trained on historical flight data that includes factors such as weather conditions, time of day, and day of the week.

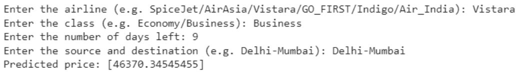
IV. Results and Hyper Tuning

The models should be hyper-tuned using GridSearchCV or RandomSearchCV before being sent into the function.

GridSearchCV Sklearn's model selection package includes the GridSearchCV library function, which fits our estimator to our training data and loops over specified hyperparameters. Finally, the optimal hyperparameters are selected.

The purpose of RandomSearch CV and GridSearchCV is the same. Its purpose is to find the best parameters to improve the model. However, in this scenario, not all parameters are examined. Instead, the search is randomized, and all other parameters are kept constant, except for the parameters under test, which can be altered. The optimal features and settings are identified after performing hyper-tuning. After the parameters have been fine-tuned, the machine-learning model is trained and evaluated. After training and testing the model, it is time to compare them to identify the best and most optimal one. The accuracy of machine learning models generated using various algorithms is compared using performance measures.

One way to determine how frequently a machine learning algorithm correctly recognizes a data item is to look at its accuracy. Accuracy is the proportion of correctly expected data points among all data points. The table shows the accuracy value of the model implemented.



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Enter the airline (e.g. SpiceJet/AirAsia/Vistara/GO_FIRST/Indigo/Air_India): Vistara
Enter the class (e.g. Economy/Business): Business
Enter the number of days left: 9
Enter the source and destination (e.g. Delhi-Mumbai): Delhi-Mumbai
Predicted price: [46370.34545455]
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Fig. 7. The example showing model implementation

TABLE II
Model Accuracy

Approach	Accuracy
Linear Regression	89.375%
Lasso Regression	89.372 %
Decision Tree	91.293%
Decision Tree Regressor	92.053%

Once we get the model's accuracy, the prediction is implemented. The input is taken from the user for the name of the airline, the class, the number of days left, the source, and the destination city. And the value of the ticket fare is predicted.

The given example takes the input of Vistara as the airline name, class as Business, number of days as 9, and Source and Destination as Delhi-Mumbai.

V. Conclusion

In conclusion, this report explored the use of various regression techniques to predict flight fares. The methods investigated were linear regression, lasso regression, decision tree, and decision tree regressor. The data used in this study consisted of a combination of factors such as departure time, arrival time, airline, route, and number of stops, among others.

The results of the analysis revealed that all four methods produced reasonable predictions of flight fares. However, some methods performed better than others. For instance, the lasso regression model was able to identify the most important features in predicting flight fares and produced a more accurate prediction than the other models.

The results of this study demonstrate the potential of regression techniques for predicting flight fares. Depending on the specific needs of the user, a combination of these techniques could be used to produce the most accurate predictions. However, further research could be conducted to determine the best combination of methods and predictors for more precise predictions.

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