ISSN (Online): 2583-7052

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 3(02), February 2024, pp. 1-15

Article Title: Applications for Predicting Airfare Prices based on Machine Learning Techniques and the Flask Web App

Applications for Predicting Airfare Prices based on Machine Learning Techniques and the Flask Web App

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ABSTRACT

The flight fare prediction model is meant to receive user inputs from the Flask web application, including departure and arrival cities, trip dates, and airline preferences. The flight price predictor estimates flight fares by comparing the previous prices of flights for the dates and destinations. This paper proposes an applications for predicting airfare prices based on machine learning techniques and the flask web app. This paper uses Machine Learning (ML) techniques, which provide a collection of data accurately and efficiently. Additionally, it is also used to forecast future requirements. The input dataset is initiated by a preprocessing technique, which helps clean the datasets, and the data exploration tries to explore the datasets. ML classification is the next step, which is conducted using the Gradient Boosting Algorithm (GBA). This technique is used in regression and classification tasks. Hyper-parameter tuning in gradient boosting is essential for the overall performance of the machine learning model. The last step in the Flask application is to connect to the database and display the flight price data to users. This paper provides excellent specificity and sensitivity for classifying flight prices. Further provides users with a better understanding of when to purchase tickets and how long they profitable. Overall, the proposed work is developed using the Python Jupyter software. The Specificity Comparison of GBA is 93.5% and Sensitivity Comparison of GBA is 92.5% respectively.

Keywords: ML, Airfare, GBA, Flask Web, Flight.

1 Introduction

In the world of contemporary travel, forecasting flight prices has grown more and more important as changes in ticket prices have a big influence on travel arrangements and expenditures. Travelers and airlines alike now have access to a comprehensive set of tools for forecasting and optimizing flight rates because to the numerous creative solutions that have arisen in response to this problem, using advances in machine learning techniques and web application development [1, 2]. The complexities of these applications is covered in detail in this introduction, along with an examination of their functions, approaches, and possible effects

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on the aviation sector [3, 4]. Many variables influence airfare pricing, including as demand, seasonality, fuel prices, and airline rivalry. Because of this, ticket costs are differ significantly depending on the route, the time of booking, and other factors. Accurately predicting flight costs has various advantages for airlines as well as travellers [5, 6].

Travellers are better manage their trip budgets and achieve the greatest rates by using the insightful information it offers on the ideal times to purchase flights. Additionally, by providing competitive pricing and customized promotions, airlines increase customer happiness, boost profitability, and optimize revenue management techniques with the use of airfare prediction. Massive data analysis and precise prediction-making are now possible to machine learning algorithms [7, 8]. Machine learning algorithms are use previous flight data to find patterns and trends in the context of predicting ticket pricing. This allows them to estimate future prices with a high degree of accuracy [9]. These algorithms cover a variety of approaches, such as ensemble methods, regression, and classification, each with specific benefits for assessing and forecasting ticket costs [10, 11].

Python web application developers have a lightweight and adaptable platform for creating web apps with the Flask web application framework. Because of its ease of use and expandability, Flask is a great option for creating flexible and dynamic web interfaces that forecast airline fares. Users input their travel choices, such as departure and arrival locations, trip dates, and airline preferences, and obtain real-time forecasts of flight rates catered to their particular itinerary by integrating machine learning models into Flask apps [12, 13]. Travel technology has advanced significantly with the use of machine learning techniques and Flask web apps to predict flight pricing. Travellers and airlines use these programs to forecast and optimize airfare pricing by utilizing advanced prediction algorithms and historical flight data. Machine learning techniques combined with Flask web apps have the ability to completely change how we book, plan, and travel as the market for effective and tailored travel solutions continues to rise [14, 15].

Manage irrelevant material from the dataset, enhance model efficiency using pre-processing approaches, analyze the trained model in terms of hyper-parameter tweaking, and utilize a special machine learning model to predict transportation costs.

2 Recent Works

Theofanis Kalampokas *et al* [2023] succinctly, innovative pricing policies and tactics from experts that support global competitiveness. The pricing of tickets is frequently changed by airline companies depending on a range of criteria, including their own proprietary rules and algorithms that look for the best possible price policy. Artificial Intelligence (AI) models are being used more and more for the latter job because of their various potentials in data generalization, compactness, and quick adaptation. Computationally expensive, particularly when tweaking hyperparameters. In its gradient iteration, the classical gradient-based

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optimization approach necessitates the computation-intensive design and assessment of many quantum circuits. All model domains are able to identify commonalities and extract patterns from the provided flight data, even with a limited collection of characteristics. It should be made clear that the flight data do not cover a full year since, mostly because of differences in demand, several airline firms did not offer the same flights for every destination throughout the year. Since there are no non-linear principles, the QMLP architecture maps input and quantum weight values to the output using classical activation functions, most frequently sigmoid.

Supriya V. Mahadevkar *et al* [2022] Recently, there has been a noticeable shift in computer applications from single data processing to machine learning due to the availability of vast amounts of data gathered from multiple sources, including the internet. Machine learning automates human assistance by using relevant data to build an algorithm; there are three main types of machine learning approaches: reinforcement learning, supervised learning, and unsupervised learning. Among the machine learning techniques commonly used in computer vision today are zero-shot learning, active learning, contrastive learning, self-supervised learning, life-long learning, semi-supervised learning, ensemble learning, sequential learning, and multi-view learning. Systematic reviews for every learning type are lacking. Learning ensemble learning is challenging, and each bad choice leads to a model that is less accurate at predicting the future than an individual model. The ensemble model requires a lot of time and storage space. Describe the challenges associated with different machine learning techniques, including processing high-quality data, datasets, and the accuracy of current systems. Numerous learning strategies rely on the way algorithms extract more complex information from the raw input by using multiple layers.

Shokoufeh Mirzaei *et al* [2019] elucidated since a protein's structure dictates its function, effective techniques for determining protein structure are necessary to enhance scientific and medical research. Computational predictions are extremely desirable because the experimental structure determination methods available today are somewhat expensive. In order to estimate the quality of protein structures that is, the degree of similarity between the predicted and experimental structures without requiring knowledge of the latter this study provides two machine-learning based scoring systems. ML technique as we think it has a great deal of potential to raise scores. Drawbacks as a performance metric: it is susceptible to the assignment of domain boundaries and quirks in the native structure that is discovered via experimentation. Unlike the d dataset, which is utilized in literature, which is chopped randomly, the dataset is divided taking into account protein targets and the models that go along with them. Meal and metrain, together with their corresponding costs, stand for the average median error of the training and validation sets, respectively, in the legend. The poor speed and high expense of experimental techniques to structure determination have been attributed to computational methods.

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Shabnam Mohamed Aslam *et al* [2021] It has been shown recently that, as artificial intelligence and human intelligence have advanced, the importance of flexible e-learning has grown. In order to work with students and produce better learning outcomes, they shift toward more tailored, adaptable learning as e-learning methods become less appealing and the calibre of online courses rises. Artificial Neural Networks and Deep Learning approaches have several underlying similarities. Measuring student accomplishment is challenging as it depends on a variety of factors. The supervised back propagation learning approach achieves a high stage in order to forecast the degree of information that students would possess after engaging in the online learning mode. A system of student evaluation with high accuracy. Big data challenges are addressed by convolution GRU models, XNN, semantic clustering, and ANN. To create an ML model using Bayesian judgments is the aim of the machine learning application of the Bayesian approach. The parameters are estimated using Bayes inferences in a straightforward manner. Reinforcement learning researchers are concentrating on problems that require management but are progressively being disregarded.

Haibo Wang *et al* [2022] proposed in machine learning is being used more and more to identify fraudulent transactions. Nevertheless, most application systems don't identify dishonest behavior in real time rather, they do it after the fact. Because there are far fewer spurious transactions than legitimate ones, the extremely unbalanced data makes fraud detection extremely difficult and necessitates approaches other than the conventional machine learning method. The outcome demonstrates that, when it comes to speed and accuracy using the bank loan dataset, the quantum augmented SVM has clearly surpassed the competition. These results have shown the value of classical machine learning techniques in non-time series data and the possibility of QML applications on time series based, highly unbalanced data. There are three key reasons why it is difficult to detect and avoid these events. First, there has been a significant surge in online transactions as a result of the advancement and widespread use of mobile technology. In order to build more accurate prediction models, we employ Least Absolute Shrinkage and Selection Operator to remove variables that either do not contribute to the prediction accuracy or are "noises" that lower it.

3 Proposed Work Explanation

This paper proposed and uses Python Jupyter software to create a Flask web application for machine learning-based flight price prediction. Initially, preparation is permitted for the supplied dataset. It include eliminating the null values from the input dataset and cleaning and analyzing it. Researching and thoroughly examining the observed data is the next step in the data exploration process, which comes after data pre-processing. The features in the data, which includes airways over a certain time period and arrival and departure times, are extracted using the feature extraction procedure.

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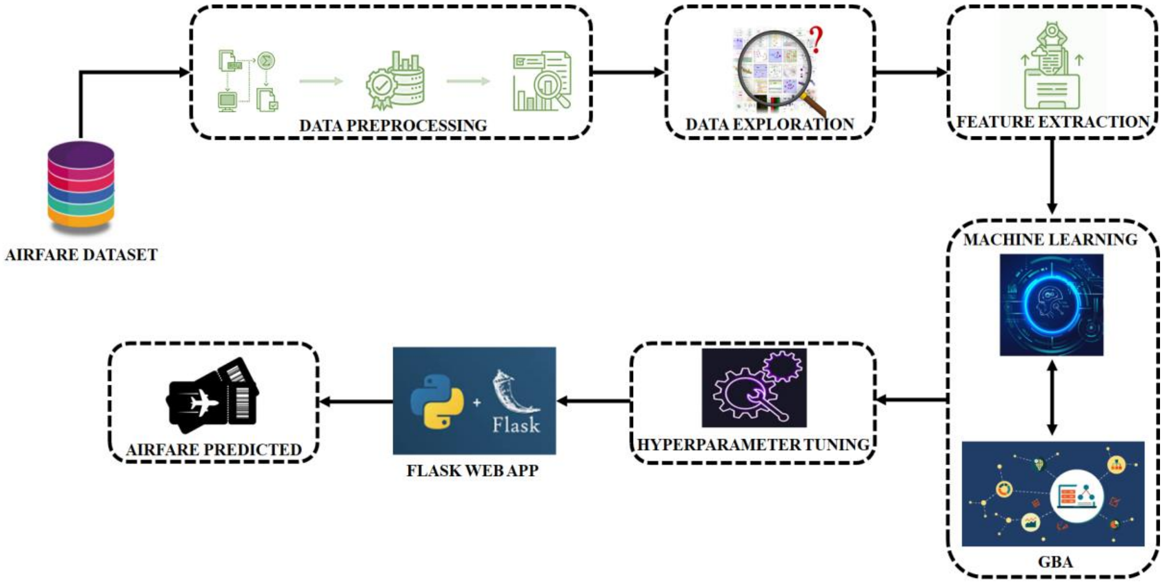

Figure 1: *Proposed block diagram*

The machine learning classifier approach, or gradient boosting algorithm, is the next phase in the process. It is a well-liked choice for many applications, including aircraft fare prediction, since it manage robustness, missing data, and feature significance analysis against overfitting. The last stage usually involves adjusting the hyperparameters to make the model more stable and effective. It also forecasts continuous numerical data, such airline tickets, with relative accuracy and accuracy. As the last stage, the output details are generated in the deployed web application. Finally, using the Flask web app, the user is shown the estimated fare via the online interface.

3.1 Data Preprocessing

Data preprocessing, which is a subset of data preparation, is any type of processing done on raw data to prepare it for another data processing step. It has always been an essential initial step in the process of data mining. To improve the quality of the data, preprocessing is essential. During preprocessing, the computer receives the gathered datasets as input and is trained appropriately. As a result, businesses and people spend a significant amount of effort cleansing and getting ready for modelling data. To prepare the raw data for analysis and model training, preprocessing include converting and cleaning it. Preprocessing procedures for flight price prediction involve dividing the dataset into training and testing sets, scaling numerical features, encoding categorical variables, and managing missing values.

3.2 Data Exploration

In order to better comprehend the nature of the data, data analysts employ data visualization and statistical tools to explain dataset characterizations, such as size, amount, and correctness.

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This process is known as data exploration. This method involves the use of both automatic and human data exploration software programs to visually examine and pinpoint connections between various data variables and the dataset's structure. It gives data analysts more insight into the raw data and helps them comprehend and visually spot links and abnormalities that they would miss otherwise. The goal of data exploration is to learn from and comprehend the dataset. It entails examining the properties of the dataset to find trends, correlations, and outliers. Data exploration in the context of predicting flight prices entail displaying price distributions, analysing the connections between various parameters (such as departure time, airline, origin, and destination), and spotting any abnormalities or inconsistencies.

3.2.1 Qualitative Statistics

Summaries that characterize the data's form, central tendency, and dispersion are provided by descriptive statistics. Measures like mean, median, standard deviation, and quartiles are examples of common descriptive statistics.

3.2.2 Data Display

A crucial component of data exploration is displaying the data visually using plots, graphs, and charts. Finding patterns, trends, and outliers is made easier with the use of visualization tools like heat maps, box plots, scatter plots, and histograms. In addition, they offer a graphic depiction of the correlations and patterns found in the data.

3.2.3 Data Cleaning

Finding and managing duplicates, outliers, missing values, and inconsistent datasets are common tasks associated with data exploration. To guarantee the accuracy and dependability of the analysis, these data cleansing procedures are required. Imputation of missing values, outlier removal, and inconsistent value resolution are a few examples of data cleaning procedures.

3.2.4 Evaluation of Features

Examining the connections between various characteristics or variables within the dataset is known as data exploration. Examining dependencies, correlations, or relationships between variables are all part of it. Finding significant factors, comprehending their impact on the target variable, and seeing any dependencies or interactions are all made easier with the aid of feature analysis.

3.3 Gradient Boosting Algorithm

Algorithms for machine learning do far more than merely forecast. Fitting data into models is not enough to increase the accuracy of machine learning outcomes. Better data processing strategies are necessary to handle growing and complicated amounts of data. One method used

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in groups is gradient boosting. Regression and classification problems are the main uses for it. It offers a forecast model made up mostly of decision trees and other inferior prediction models. The reason for the name "gradient boosting" is that the intended results are dependent on the gradient of the error compared to the prediction. Each new model generated in this way approaches the route that minimizes prediction error over all possible outcomes for each ML training example.

Depending on the target columns, there are primarily two methods of gradient boosting:

1. Gradient Boosting Regressor: This type of regression is used to continuous columns.
2. When the target columns include classification issues, the gradient boosting classifier is employed.

Gradient Boosting The foundation of machines is the Data Science idea of Boosting, which builds a model by trying to fix the errors made by a previous model. By following the Gradient Descent principles, it reduces errors. Consistently offers better prediction accuracy. With several hyper parameter tuning options and the ability to optimize on a variety of loss functions, the function fit is very flexible. Drawbacks with gradient boosting. Even though it withstand outliers, it is computationally expensive, especially when dealing with large datasets or deep trees. Gradient descent causes the overfitting problem when dealing with complex models or high learning rates. A machine learning algorithm that is a member of the gradient boosting technique family is called the Gradient Boosting Regressor. Regression problems, in which the objective is to predict continuous numerical values, are the main applications for it.

3.4 Hyperparameter Tuning

Hyperparameter tuning is the process of determining which hyperparameters are optimal for usage, and it is a crucial aspect of machine learning. Selecting the right Hyperparameter values is the aim of this procedure, which is essential to success. In decision trees and GBR, Hyperparameter tuning refers to modifying the parameters that aren't acquired by data-driven learning. It seeks to determine the ideal values for many factors, including feature selection techniques, number of trees, and tree depth. Hyperparameter tuning enhances system performance and enables model performance to be changed for best outcomes. These are also used to define the model's complexity and learning capability. The precise configuration options known as hyperparameters impact the learning and performance of a machine learning system. They have an impact on the behavior and functionality of the model and are specified by the user prior to training.

3.5 Methods for Hyperparameter Tuning

Manual Tuning: In this method, the user carefully chooses the Hyperparameter values based on their comprehension of the algorithm and the issue at hand. Nevertheless, the process of manual tuning laborious and it’s not yield the ideal values for the parameters.

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3.5.1 Grid Search

Creating a grid of potential Hyperparameter values and thoroughly assessing the model's performance for every conceivable set of parameters is known as grid search. It looks through every potential combination and chooses the one that yields the greatest results. Grid search is methodical, but when working with a lot of hyperparameters, it be computationally costly.

3.5.2 Random Search

Hyperparameter combinations are randomly selected from predetermined ranges using random search. Iterating through a certain number of times, it assesses the model's performance for every sampled combination. Given that random search does not examine every conceivable combination, it is less computationally costly than grid search. It frequently locates optimal Hyperparameter values more quickly.

3.5.3 Bayesian Optimization

Bayesian optimization models the algorithm's performance as a function of its hyperparameters using probabilistic models. Iteratively examining the Hyperparameter space, it modifies the model in response to performance observations. In big and complicated search spaces, Bayesian optimization performs better than grid search and random search.

3.6 Flask Web App

A Flask web application is one that is created with the Flask framework, a versatile and lightweight Python web framework. Flask offers tools, libraries, and functionality for managing HTTP requests, routing, and other tasks, making it possible for developers to construct online applications rapidly and effectively. The Flask application is connect to the database in this task and show users the flight fare information. Because Flask is flexible, integrating different functionality to create web apps is simple. A Python web framework called Flask makes it possible to create online apps. It incorporates the GBR algorithm, data exploration, and preprocessing into a Flask web application for predicting airline prices. Users enter pertinent data into the app's user interface, including the departure date, origin, destination, and other features. Next, the app is utilize the learned machine learning model to forecast the flight price after preprocessing the input data and, if desired, doing data exploration.

Types of Flask Web Apps

- Single-Page Applications (SPAs): This type of web application loads a single HTML page and uses JavaScript to refresh its content dynamically. While JavaScript frameworks like React or Vue.js are used to develop the frontend, Flask are utilized to provide the backend logic for managing requests and supplying data via APIs.

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- Multi-Page Applications, or MPAs: MPAs are a type of conventional web application made up of several HTML pages. With Flask, build MPAs by setting up routes for several pages and using templates to generate dynamic content on each one.

4 Results and Discussion

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	No info	3897
1	Air India	1/05/2019	Kolkata	Banglore	CCU → IXR → BBI → BLR	05:50	13:15	7h 25m	2 stops	No info	7662
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL → LKO → BOM → COK	09:25	04:25 10 Jun	19h	2 stops	No info	13882
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	1 stop	No info	6218
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	No info	13302

Figure 2: *Dataset*

Figure 2 shows the flight price forecast dataset. To build a Flask web application for ticket price prediction, you would typically require a dataset including historical flight data, including several factors like departure city, arrival city, departure time, airline, duration, and the associated airfare cost. To train a machine learning model that estimates flight costs, this dataset is employed.

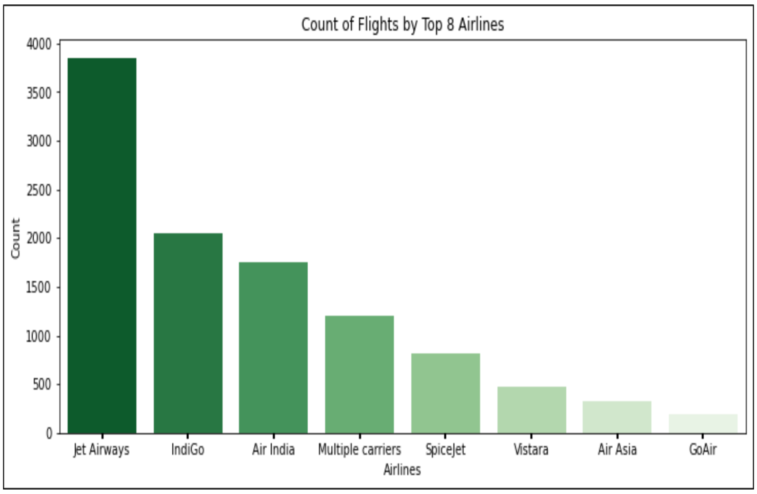

Figure 3: *Count of Flights*

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Every aircraft included in the dataset used to train the airfare prediction algorithm is counted in Figure 3. It displays the dataset's scope, or total size. Users determine the amount and representativeness or comprehensiveness of the dataset by examining this information.

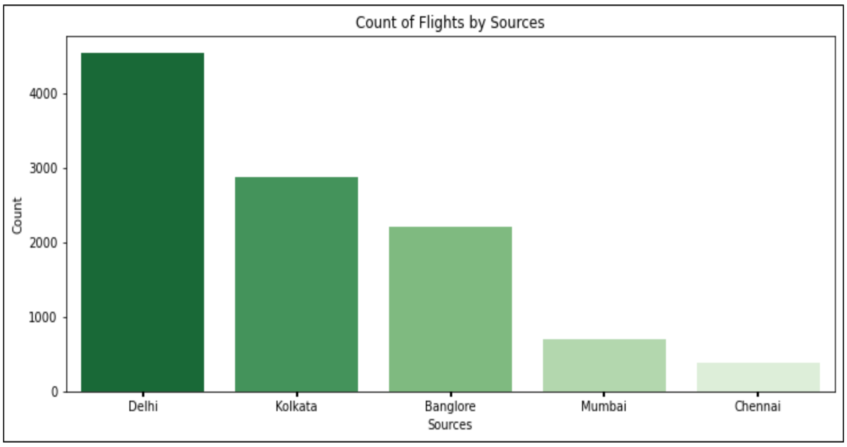

Figure 4: *Count of Flights by Sources*

Figure 4 shows the number of flights broken down by source. It gives an overview of the total number of flights, split down by origin or source. It displays the distribution of flights among various airports or cities of departure. The percentage of flights from each of these cities is shown.

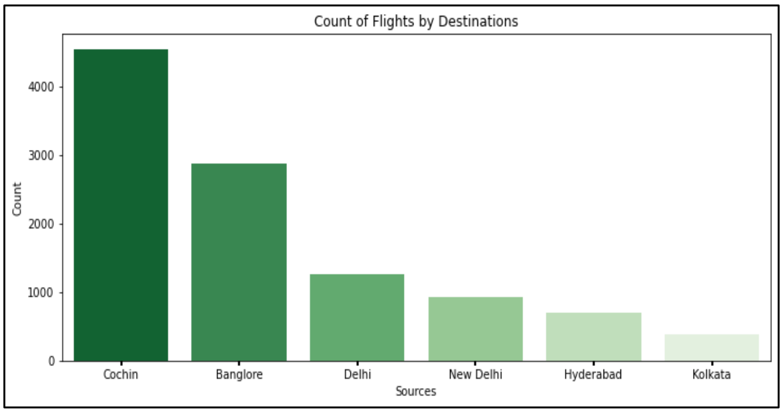

Figure 5: *Count of Flights by Destinations*

The number of flights by destination is displayed in Figure 5. The system would collect and examine the available data, classifying flights according to their destinations and calculating the total number of flights for each in order to produce a count of flights by destination. This information is shown either on a specific page or the system's home page.

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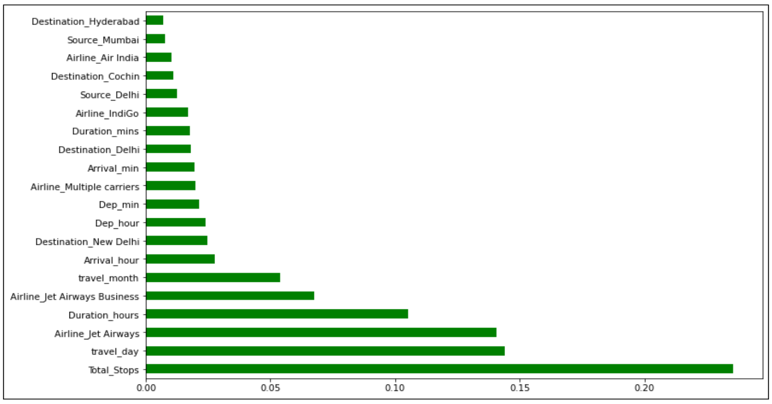

Figure 6: *Selected features*

The features that were chosen are displayed in Figure 6. A system that forecasts airfare take into account a number of variables, including flight class, airline carriers, and dates, locations of departure and arrival, and advance booking windows, among other aspects that influence pricing. These attributes are frequently entered into a prediction model to determine the cost of flights.

Table 1: *Parameter Values*

Parameters	MAE	MSE	RMSE
GBR	1567.85	4903894.00	2214.47
Hyper-Parameter Tuning GBA	1173.99	3232702.22	1797.97

Table 1 displays the final parameter loss values for the airfare forecast. It consists of the MAE, MSE, and RMSE loss values. It establishes the GBR settings and Hyperparameter adjustment.

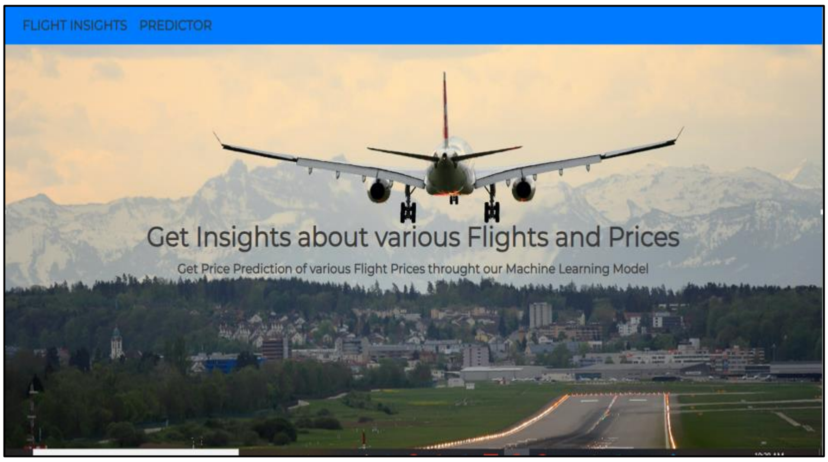

Figure 7: *Home Page*

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Figure 7 displays those home pages. Users are able to enter travel information on the home page, including arrival and departure dates and other pertinent data. After processing these inputs, the application would then offer estimates or suggestions for flight costs.

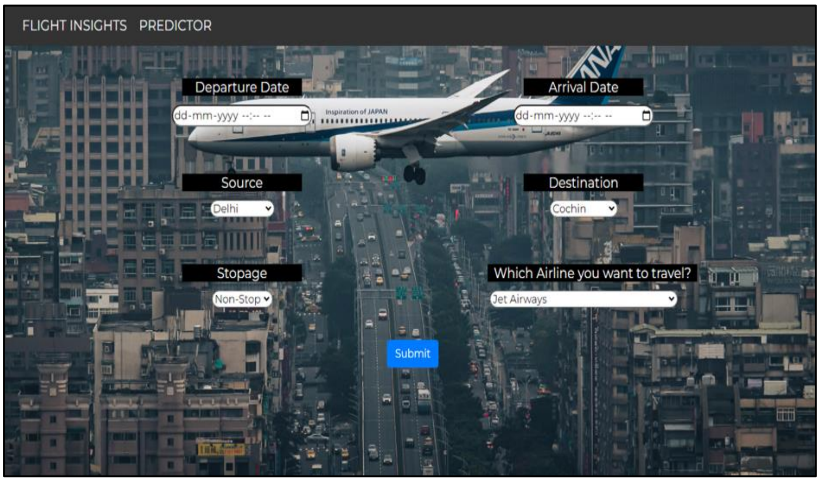

Figure 8: *Prediction page*

The page that is predicted for the flight is shown in Figure 8 Predictive modelling methods combined with historical data are typically used by flight price prediction systems to generate the projected price. The technology looks at past flight prices in addition to other flight-related information including dates, airline names, aircraft types, and arrival and departure locations.

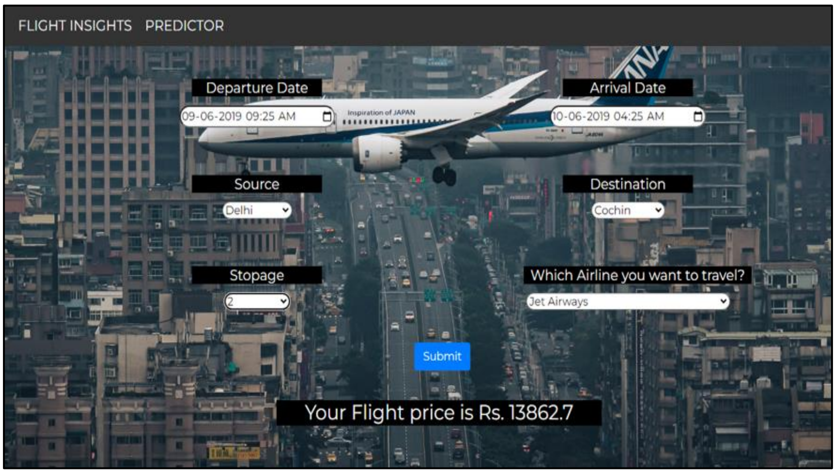

Figure 9: *Predicted price*

The projected cost of the flight is shown in Figure 9. The expected price is frequently shown in the output that the system generates or on the prediction page. Based on the information they

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provide, it estimates the cost of a flight for clients. The projected cost should not be taken as a guarantee of the final cost, as several factors including supply, demand, and market circumstances affect flight prices. Instead, it should be used as a broad guideline only.

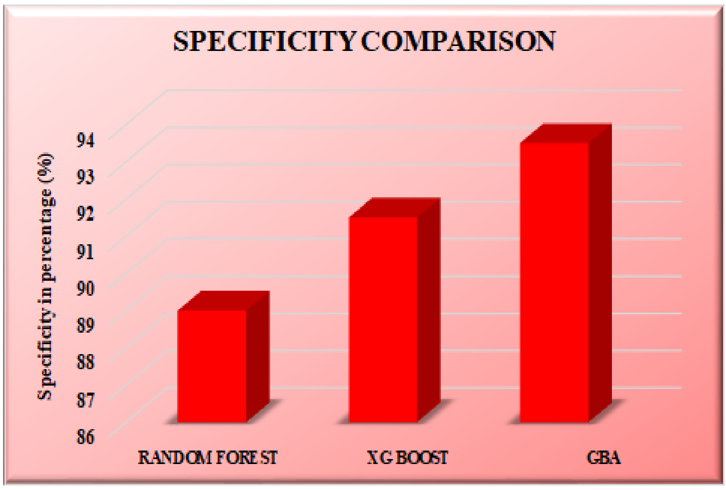

Figure 10: *Specificity Comparison*

The Specificity Comparison of the Classification values is presented in Figure 10, where the values for the Random Forest, XG Boost and GBA are, respectively, 89%, 91.5%, and 93.5%.

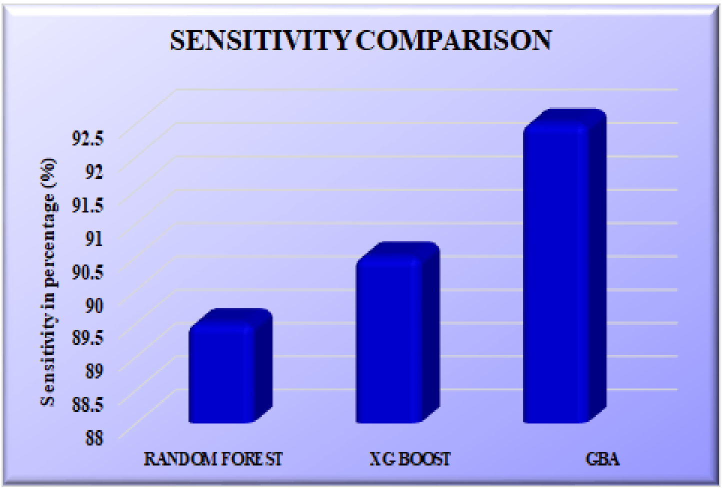

Figure 11: *Sensitivity Comparison*

Figure 11 presents the Sensitivity Comparison of the Classification values, which are, respectively, 89.5%, 90.5%, and 92.5% for the Random Forest, XG Boost and GBA.

ISSN (Online): 2583-7052

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5 Conclusion

This paper is put into action: a flask web application for machine learning-based flight price prediction. Preparation is initially allowed for the provided dataset. It comprises cleaning, analyzing, and deleting the null values from the input dataset. The following stage of the data exploration procedure involved investigating and carefully examining the observed data. The feature extraction process is used to extract the features from the data, which included arrival and departure times as well as airways throughout a certain time period. The collected data is analyzed to extract characteristics for use in machine learning (ML) models. The next step in the process the machine learning classifier approach, which works with the GBA algorithm.Due to its ability to handle missing data and provide crucial analysis against overfitting, it is a popular option for a variety of applications, including flight fare prediction. Usually, the final step is modifying the hyperparameters to improve the model's stability and performance. Additionally, it predicts continuous numerical data with a reasonable degree of accuracy, such airline fares. Lastly, the user view the estimated fare through the internet interface by utilizing the Flask web app. Python software is used to implement this paper. The Specificity Comparison of GBA is 93.5% and Sensitivity Comparison of GBA is 92.5% respectively.

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