Air Flight Ticket Price Prediction Using Flight Number As Reference*

*Note: Sub-titles are not captured in Xplore and should not be used

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***Abstract*—Many different fields have employed machine learning. We describe how machine learning can be used to solve the time-series problem. We use the airline ticket prediction problem as our specific problem. Based on data over more than 60 days period, we trained our models, getting the best model - which in our case is Random Forest and in case of classification it is Decision tree. These algorithms has the best performance over the observed 12 routes, which is in Regression case 94% closer to test values and 99% accurate in case of Classification .This predicting Machine learning model is more reliable than the random purchase strategy, and relatively small error of 6% over these routes for predicting price of tickets. Our findings demonstrate that utilizing these models and strategies to guide purchase policies can help both sides (buyer and Seller) when deciding what should be the purchase costs of the ticket, both for seller (Airline companies) buyer (Target Audience) before the departure of the flight. The suggested approach can also outperform a deployed commercial website offering comparable purchase policy advice.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

The typical buying plan for airline tickets is to acquire a ticket far in advance prior to the departure date in order to avoid the risks that costs may increase significantly before the flight's departure date. However, this is not always the case because occasionally, airlines will cut their pricing in an effort to increase sales. When determining ticket prices, airlines take into account a wide range of variables, including the month of travel, the number of seats on the plane, and whether or not it is a holiday. Some of the variables are buried, but others are clearly visible. The contrary is also true—airlines companies want to maintain a high level of overall income. In this case, buyers are looking for the ideal day to buy a ticket [?]. This project intends to use machine learning techniques to model the behavior of airline ticket prices over time. Airlines have complete discretion over when and how much to charge for tickets. If one buys a ticket at the cheapest price, then, he might be able to save money. Finding the best time to book a flight for the chosen destination and term is the difficult part which in our case is our main goal. Given historical pricing, and the current price of a Flight, our algorithms must determine if it is better to buy or wait for another day before the departure date.For the creation and evaluation of the model, we use historical data on the cost of individual aircraft routes with reference to Air-Line Numbers [?].

II. Related work

Some work has been done for determining optimal purchasing time for airline Tickets. Our work is especially inspired by Etzioni et al and Jun Lu.Etzioni in his research he achieve an accuracy to predict flight ticket with 61.8 percent in 2017 [?].Followed by his research Jun Lu in his research achieve an accuracy of 61.35% on prediction Flight ticket prices with edition to predict price of flight which are non-direct flight [?]. Recently a project carried out by the students in which they achieved an accuracy of 64% on predicting flight ticket prices. Two more research carried out in India with the name of Implementation of Flight Fare Prediction System Using Machine Learning 87.42%[2022] and Flight Price Prediction: A Case Study [2022] [?].These two researches use data sets which are city-to city flight-dependent. The most common approach in all the research is decision tree algorithms and its sub-sets like random forest,ada boost decision tree. In our case, unlike previous researches. We also considered such a situation in which flight numbers are known, which further leads to historical data of the flight on all possible routes through which the price of the ticket is predicted on the possible route which is entered by user. Due to the fact that we do not need to train our model with a big amount of data again, it can reduce computation time when we want to anticipate whether to buy or wait quickly.Unlike previous researches this model consisted of two task classification of flight-Numbers and. second is predicting price.

A. Methodology

Our issue is divided into two issues: the first is to create a function and train a model to anticipate future prices. The second is to allocate numbers to fight against flight names. At first, we applied the preprocessing procedures and produced a data Frame (1). Then, this data Frame goes through a testing and training process. In these two stages, 30% of the data was used for testing and 70% for training. An algorithm for machine learning is applied on the data Frame(1). This will result in a train model that can forecast future ticket prices [?].

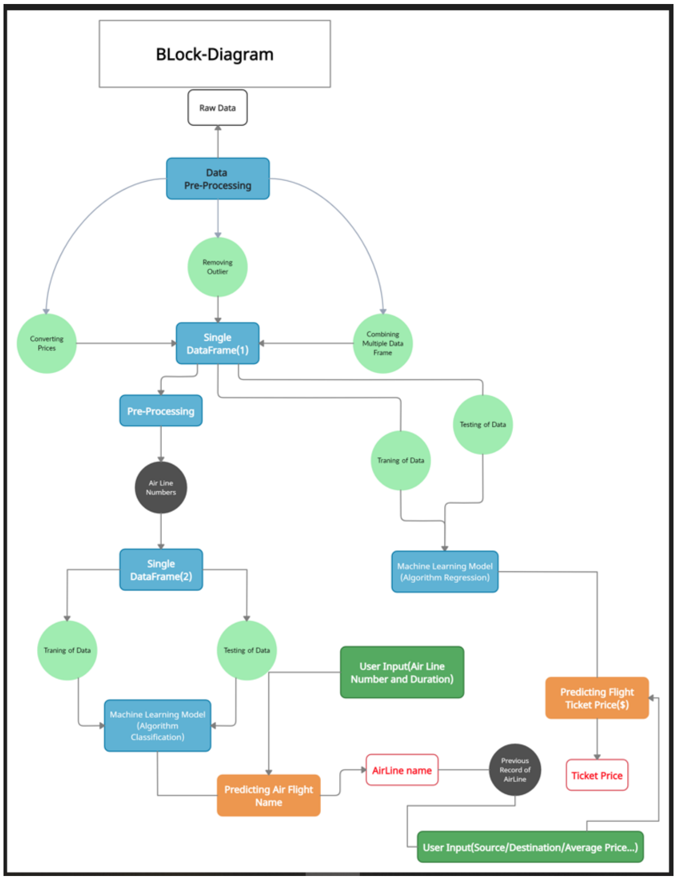

Fig. 1. Block Diagram

For our second part we lake a feature in our data set which could represent flight numbers. This custom made feature was not actually available in our data set when we performed our first task.So in our second task, which involved classifying Air flight numbers,we add a number next to each flight name to symbolise flights and flight with identical names has same numbers while also adding time conversion in minutes for each flight.These steps result in the development of a Data Frame (2).This data Frame(2) then send to training and test phase [**?**]. After that a machine learning algorithm is applied which can do classification of flight name when flight number is entered as shown in combine result section.This complete process can be viewed in fig:1.

III. Data Collection

This data set is available on GitHub.It consist of 55,365 rows, 7 columns and divided in 12 CVS files. The data for our analysis was collected as daily price quotes from a major airplane search web site between Feb, 2022 and April,2022 (60+ observe days)fig:2. A web crawler was used to query for each route and departure date pair, and the crawling was done every day at 10:00 AM.

IV. Experimental Results

Our routs consist of 4 destination and their total trips are shown in table:1.We found that the ticket price for flights

1	Airline	Source	Destinatio	Duration	Total stop	Price	Date
2	Lufthansa	PAR	RUH	9h 10m	1 stop	1,575Â SAI	2/1/2022
3	SAUDIA	PAR	RUH	5h 50m	nonstop	2,168Â SAI	2/1/2022
4	Ryanair, fl	PAR	RUH	38h 05m	3 stops	1,069Â SAI	2/1/2022
5	Lufthansa	PAR	RUH	9h 10m	1 stop	1,544Â SAI	2/1/2022
6	Lufthansa	PAR	RUH	10h 10m	1 stop	1,544Â SAI	2/1/2022
7	Egypt Air	PAR	RUH	10h 50m	1 stop	1,599Â SAI	2/1/2022
8	Transavia	PAR	RUH	10h 55m	1 stop	1,720Â SAI	2/1/2022
9	Turkish Air	PAR	RUH	9h 05m	1 stop	1,811Â SAI	2/1/2022
10	Turkish Air	PAR	RUH	11h 55m	1 stop	1,811Â SAI	2/1/2022
11	Turkish Air	PAR	RUH	16h 40m	1 stop	1,811Â SAI	2/1/2022
12	Air Europa	PAR	RUH	10h 55m	1 stop	1,960Â SAI	2/1/2022
13	British Airv	PAR	RUH	9h 00m	1 stop	2,018Â SAI	2/1/2022
14	Iberia Expr	PAR	RUH	13h 00m	1 stop	1,854Â SAI	2/1/2022
15	Transavia	PAR	RUH	10h 10m	1 stop	1,997Â SAI	2/1/2022
16	British Airv	PAR	RUH	10h 10m	1 stop	2,018Â SAI	2/1/2022
17	British Airv	PAR	RUH	13h 35m	1 stop	2,018Â SAI	2/1/2022
18	Iberia, SAL	PAR	RUH	10h 45m	1 stop	2,024Â SAI	2/1/2022
19	Etihad Airv	PAR	RUH	11h 00m	1 stop	2,098Â SAI	2/1/2022
20	Emirates	PAR	RUH	10h 00m	1 stop	2,300Â SAI	2/1/2022
21	Emirates	PAR	RUH	14h 25m	1 stop	2,300Â SAI	2/1/2022
22	Emirates	PAR	RUH	15h 35m	1 stop	2,300Â SAI	2/1/2022
23	Emirates	PAR	RUH	16h 25m	1 stop	2,300Â SAI	2/1/2022
24	Emirates	PAR	RUH	19h 15m	1 stop	2,300Â SAI	2/1/2022
25	SAUDIA	PAR	RUH	10h 00m	1 stop	2,344Â SAI	2/1/2022
26	SAUDIA	PAR	RUH	12h 55m	1 stop	2,344Â SAI	2/1/2022
27	SAUDIA	PAR	RUH	13h 55m	1 stop	2,344Â SAI	2/1/2022
28	SAUDIA	PAR	RUH	14h 55m	1 stop	2,344Â SAI	2/1/2022
29	SAUDIA	PAR	RUH	15h 55m	1 stop	2,344Â SAI	2/1/2022

Fig. 2. Features

can vary significantly over time.Prices may differ from direct routes as compared to multi routes.In this table,we can have an overall glance at total trips from Paris to New York so on fig:3.These total trips consist of nonstop flight to up the flight consist of 3 stops

PAR	SVO	NYC	RUH
14881	4202	5334	7279
2403	2235	1905	553
7327	3314	3205	2725
22208	97511	10444	10557

TABLE I
12 Routes

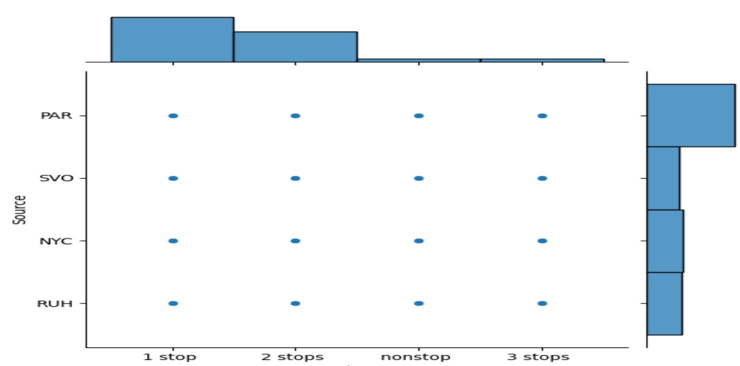

Fig. 3. Frequency OF Stops

A. Prepossessing

This data set is available on GitHub.It consist of 55,365 rows, 7 columns and divided in 12 CVS files. The data for our analysis was collected as daily price quotes from a major airplane search web site between Feb, 2022 and April,2022 (60+ observe days)fig:2. A web crawler was used to query for each route and departure date pair, and the crawling was done every day at 10:00 AM.

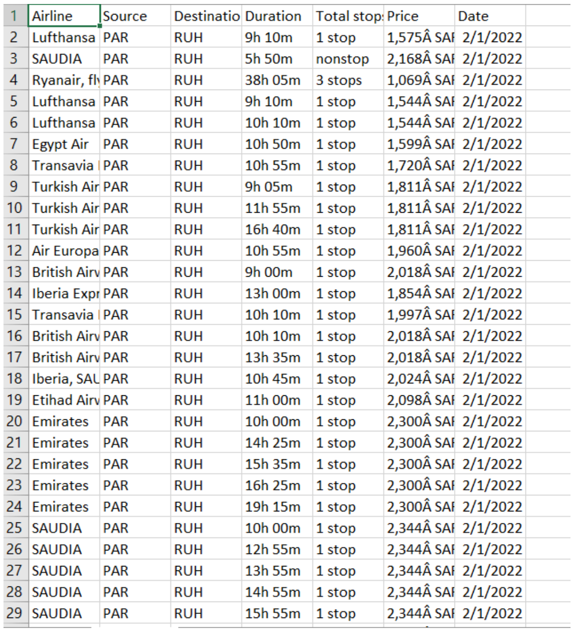

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Fig. 4. Features

V. Experimental Results

Our routs consist of 4 destination and their total trips are shown in table:1.We found that the ticket price for flights can vary significantly over time.Prices may differ from direct routes as compared to multi routes.In this table,we can have an overall glance at total trips from Paris to New York so on fig:3.These total trips consist of nonstop flight to up the flight consist of 3 stops

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TABLE II
12 Routes

A. Identifying Outliers IQR Method

We can use the IQR method of identifying outliers to set up a "fence" outside of Q1 and Q3. Any values that fall outside of this fence are considered outliers. To build this fence we take 1.5 times the IQR and then subtract this value from Q1 and add this value to Q3. This gives us the minimum and maximum fence posts that we compare each observation to. Any observations that are more than 1.5 IQR below Q1 or more than 1.5 IQR above Q3 are considered outliers.Now after all the above process our data look like fig:4.

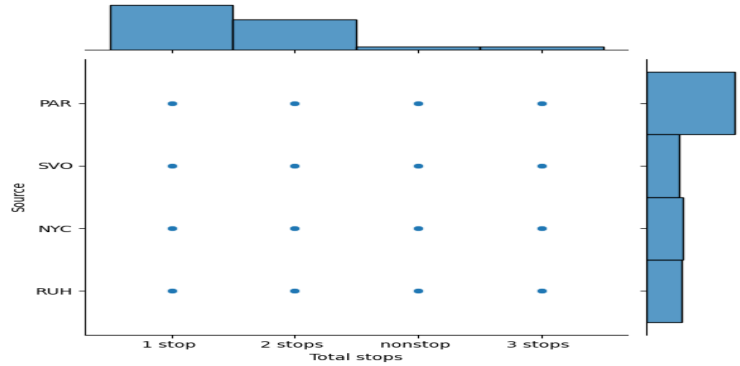


Fig. 5. Frequency OF Stops

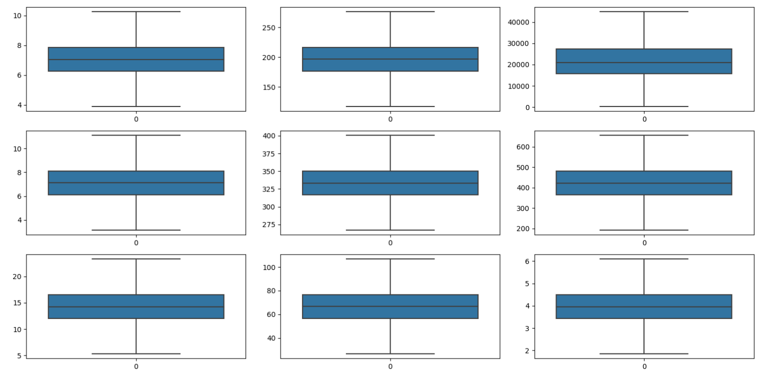


Fig. 6. Outliers

B. Regression Algorithms

Regression is a subset of Supervised Learning. It learns a model based on a training data-set to make predictions about unknown or future data. The description 'supervised' comes from the fact that the target output value is already defined and part of the training data.In our case our label data was number of stops and their ticket price at that time [?].We want to predict the prices accordingly against our label data.Best performance in case for prediction prices of ticket were given by Decision Tree and its sub types.Overall highest performance was give by Random Forest observed in the table:2.

No1	Decision Tree	Random Forest	Extra DT	Bagging DT	AdaBoost DT	KNN
MSE $\$^2$	43195	39727	39673	40313	148130	57967
MAE $	61.11	61.87	59.7	62.4	242.7	75.3
RMSE $	207.8	199.3	199.1	200.7	384.8	240.7

TABLE III
Error Expectation on Average

1) Results :

2) MAE MSE RMSE: The Mean absolute error represents the average of the absolute difference between the actual and predicted values in the data set. It measures the average of the residuals in the data set.

$$MAE = \frac{\sum_{i=1}^{D} |x_i - y_i|}{N}$$

Mean Squared Error represents the average of the squared difference between the original and predicted values in the data set. It measures the variance of the residuals.

$$MSE = \sum_{i=1}^{D} (x_i - y_i)^2$$

Root Mean Squared Error is the square root of Mean Squared error. It measures the standard deviation of residuals.

$$RMSE = \sqrt{MSE}$$

Variance between Test value and predict are shown in table:3.

No1	Decision Tree	Random Forest	Extra DT	Bagging DT	AdaBoost DT	KNN
Variance%	94.06	94.55	94.54	94.45	79.72	92.04

TABLE IV
PREDICTED RESEMBLANCE TO TEST POINT

3) Training and Testing Accuracy: In addition to measuring error we also measure accuracy in terms of X-train against X-test and Y-train vs Y-test as shown in table:4.

No1	Decision Tree	Random Forest	Extra DT	Bagging DT	AdaBoost DT	KNN
X-Train vs Y-Train %	96.42	96.42	96.42	96.4[illegible]	96.41	96.40
X-Test vs Y-Test %	94.53	94.50	94.49	94.5[illegible]	94.56	94.52

TABLE V
X-TRAIN VS X-TEST AND Y-TRAIN VS Y-TEST

C. Classification Algorithms

On the basis of training data, the Classification algorithm is a Supervised Learning technique that is used to categorise new observations. In classification, a programmer makes use of the data set or observations that are provided to learn how to categorise fresh observations into various classes or groups. For instance, cat or dog, yes or no, 0 or 1, spam or not spam, etc. Targets, labels, or categories can all be used to describe classes.In our case Decision Tree preform with 99% accuracy predicting flight name on the bases of flight reference which then lead to the flight history and results are shown in table:5.

No1	Decision Tree	Random Forest	Extra DT	Bagging DT	Ac DT
Accuracy%	99	98	98	99	27

TABLE VI
PREDICT OF FLIGHT NAME

1) Results:

2) Accuracy: The accuracy of our algorithm demonstrates how accurate the values we would expect to see if we had entered the flight number to locate the flight name and its historical information.In initial stage the accuracy of algorithm was about 97% we add duration which we converted in prepossessing step in minutes using pandas direct command.This step is done to to achieve an accuracy of 99%.Their relationship is shown infig:5.

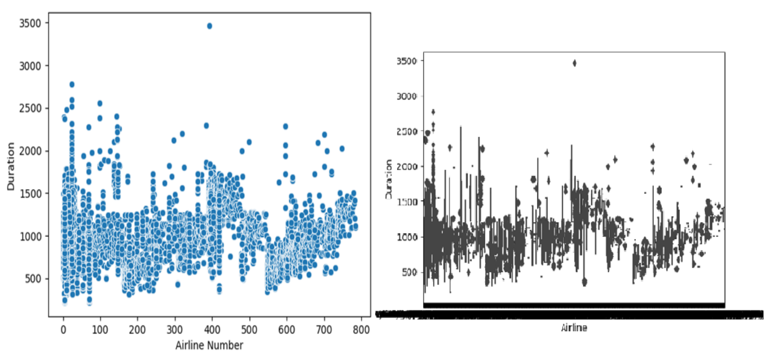


Fig. 7. Duration Against Flight

VI. Data and information visualization

Anyone can better understand data by displaying it visually and meaningfully through information visualisation. Common information visualisation examples include dashboards and scatter plots. Information visualisation enables people to efficiently and effectively derive meaning from abstract data by providing an overview and important relationships.

A. Visualization in Regression

So from the fig:6 we can visualize how price increase specially when When we plot the average price rise against the actual cost of an airline ticket, we can see how prices are rising. Second, we see in our plot of price vs duration that prices rise in a logical order as travel times to a certain destination lengthen [**?**].

1) Random Forest: A group of decision trees is called a random forest. This means that a Random Forest is made up of several trees that were built in a particular "random" manner.

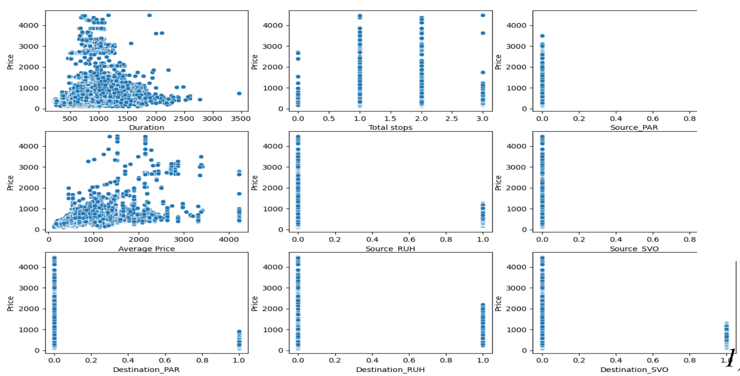


Fig. 8. Regression

B. Visualization in Classification

So from the fig:7 we can visualize the relationship between airline number and other features.So through visualization we can add features who are more depended on airline number and select those features to solve classification problem.In the experiment we added duration and flight number to predict flight name with an accuracy of 99%.

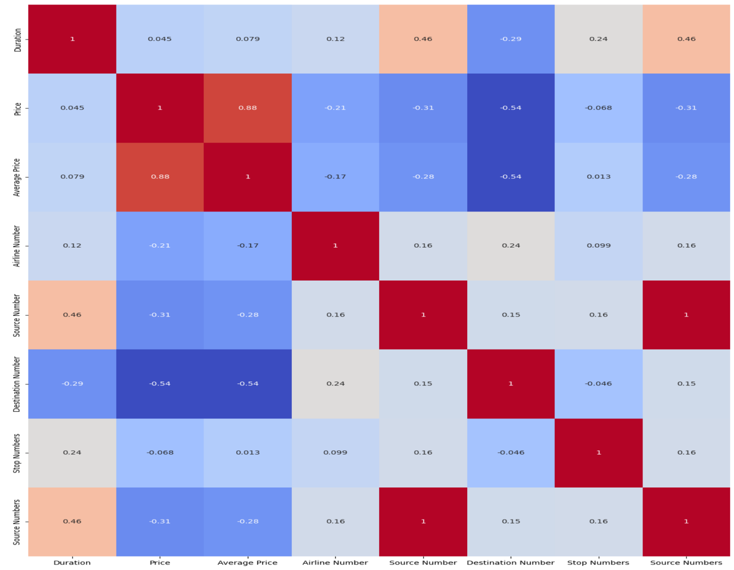


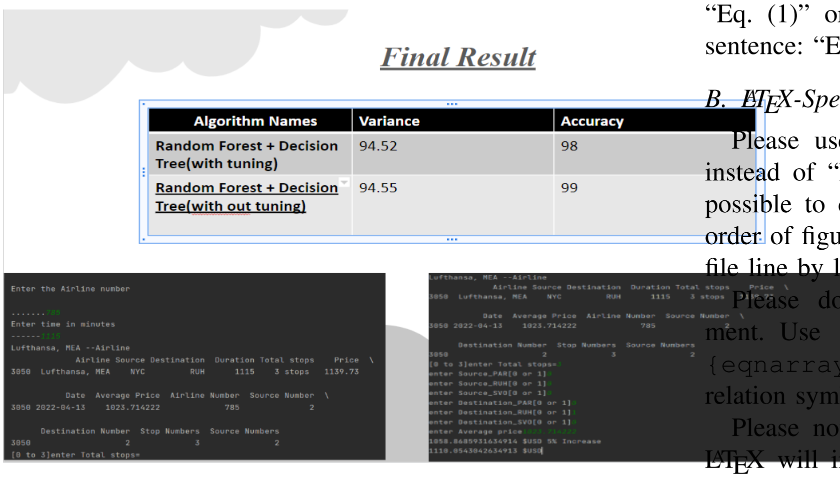
Fig. 9. Classification

1) Decision Tree: The most effective and well-liked technique for categorization and prediction is the decision tree. A decision tree is a type of tree structure that resembles a flowchart, where each internal node represents a test on an attribute, each branch an outcome of result, and each leaf node (terminal node) a class label. A separate sample of rows are used to build each tree, and a different sample of characteristics are chosen for splitting at each node. Each tree provides a unique prediction on its own. A single outcome is then produced by averaging these predictions [**?**] [**?**].

$$Gini = 1 - \sum_{i=1}^{c}(p)^2$$

VII. Combine Result

After selecting the best algorithm for Regression and Classification.We join both algorithms predicting models in such a way that, after entering the flight number, our classification predicts flight name and its destination up to 5 historical records of the same flight present in the data set up to 5, days if records exist.After the record history is displayed, we input the requirement defined by the user which in the end results in flight ticket prediction .We choose Random Forest(Regression) and Decision tree(Classification) machine learning models to predict price and flight name as shown in fig:8.



Algorithm Names	Variance	Accuracy
Random Forest + Decision Tree(with tuning)	94.52	98
Random Forest + Decision Tree(with out tuning)	94.55	99

Fig. 10. Final Result

VIII. Conclusion

In this study, we performed our ML-Models using the raw flight data from airline tickets that is available on GitHub, which spans over 60 days of historical flight data written in 12 CVS flies for 12 routes. We have used decision tree algorithm and its subsets for ticket price prediction with addition to the categorization of flight number, we have removed outliers using the IQR approach. Overall, decision tree algorithms and our experiment demonstrate that the most optimum score is achieved by decision tree, with a 99.9% accuracy rate, is used to classify flight numbers which results in predicting flight name. Secondly the best method for forecasting ticket prices is done using random forest algorithms, with an MAE of 61.8$ and a result variance of 94.55% compared to test data which means or results are 94.55% accurate.

A. Equations

Number equations consecutively. To make your equations more compact, you may use the solidus (/), the exp function, or appropriate exponents. Italicize Roman symbols for quantities and variables, but not Greek symbols. Use a long dash rather than a hyphen for a minus sign. Punctuate equations with commas or periods when they are part of a sentence, as in:

$$a + b = \gamma \tag{1}$$

Be sure that the symbols in your equation have been defined before or immediately following the equation. Use “(1)”, not “Eq. (1)” or “equation (1)”, except at the beginning of a sentence: “Equation (1) is . . .”

B. LaTeX-Specific Advice

Please use “soft” (e.g., `\eqref{Eq}`) cross references instead of “hard” references (e.g., `(1)`). That will make it possible to combine sections, add equations, or change the order of figures or citations without having to go through the file line by line.

Please don’t use the `{eqnarray}` equation environment. Use `{align}` or `{IEEEeqnarray}` instead. The `{eqnarray}` environment leaves unsightly spaces around relation symbols.

Please note that the `{subequations}` environment in LaTeX will increment the main equation counter even when there are no equation numbers displayed. If you forget that, you might write an article in which the equation numbers skip from (17) to (20), causing the copy editors to wonder if you’ve discovered a new method of counting.

BibTeX does not work by magic. It doesn’t get the bibliographic data from thin air but from .bib files. If you use BibTeX to produce a bibliography you must send the .bib files.

LaTeX can’t read your mind. If you assign the same label to a subsubsection and a table, you might find that Table I has been cross referenced as Table IV-B3.

LaTeX does not have precognitive abilities. If you put a `\label` command before the command that updates the counter it’s supposed to be using, the label will pick up the last counter to be cross referenced instead. In particular, a `\label` command should not go before the caption of a figure or a table.

Do not use `\nonumber` inside the `{array}` environment. It will not stop equation numbers inside `{array}` (there won’t be any anyway) and it might stop a wanted equation number in the surrounding equation.

C. Some Common Mistakes

- The word “data” is plural, not singular.
- The subscript for the permeability of vacuum μ_0, and other common scientific constants, is zero with subscript formatting, not a lowercase letter “o”.
- In American English, commas, semicolons, periods, question and exclamation marks are located within quotation marks only when a complete thought or name is cited,

such as a title or full quotation. When quotation marks are used, instead of a bold or italic typeface, to highlight a word or phrase, punctuation should appear outside of the quotation marks. A parenthetical phrase or statement at the end of a sentence is punctuated outside of the closing parenthesis (like this). (A parenthetical sentence is punctuated within the parentheses.)
- A graph within a graph is an "inset", not an "insert". The word alternatively is preferred to the word "alternately" (unless you really mean something that alternates).
- Do not use the word "essentially" to mean "approximately" or "effectively".
- In your paper title, if the words "that uses" can accurately replace the word "using", capitalize the "u"; if not, keep using lower-cased.
- Be aware of the different meanings of the homophones "affect" and "effect", "complement" and "compliment", "discreet" and "discrete", "principal" and "principle".
- Do not confuse "imply" and "infer".
- The prefix "non" is not a word; it should be joined to the word it modifies, usually without a hyphen.
- There is no period after the "et" in the Latin abbreviation "et al.".
- The abbreviation "i.e." means "that is", and the abbreviation "e.g." means "for example".

An excellent style manual for science writers is [7].

D. Authors and Affiliations

The class file is designed for, but not limited to, six authors. A minimum of one author is required for all conference articles. Author names should be listed starting from left to right and then moving down to the next line. This is the author sequence that will be used in future citations and by indexing services. Names should not be listed in columns nor group by affiliation. Please keep your affiliations as succinct as possible (for example, do not differentiate among departments of the same organization).

E. Identify the Headings

Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads.

Component heads identify the different components of your paper and are not topically subordinate to each other. Examples include Acknowledgments and References and, for these, the correct style to use is "Heading 5". Use "figure caption" for your Figure captions, and "table head" for your table title. Run-in heads, such as "Abstract", will require you to apply a style (in this case, italic) in addition to the style provided by the drop down menu to differentiate the head from the text.

Text heads organize the topics on a relational, hierarchical basis. For example, the paper title is the primary text head because all subsequent material relates and elaborates on this one topic. If there are two or more sub-topics, the next level head (uppercase Roman numerals) should be used and, conversely, if there are not at least two sub-topics, then no subheads should be introduced.

F. Figures and Tables

a) Positioning Figures and Tables: Place figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation "Fig. 11", even at the beginning of a sentence.

TABLE VII
TABLE TYPE STYLES

Table Head	**Table Column Head**		
	Table column subhead	***Subhead***	***Subhead***
copy	More table copy[a]		

[a]Sample of a Table footnote.

Fig. 11. Example of a figure caption.

Figure Labels: Use 8 point Times New Roman for Figure labels. Use words rather than symbols or abbreviations when writing Figure axis labels to avoid confusing the reader. As an example, write the quantity "Magnetization", or "Magnetization, M", not just "M". If including units in the label, present them within parentheses. Do not label axes only with units. In the example, write "Magnetization (A/m)" or "Magnetization {A[m(1)]}", not just "A/m". Do not label axes with a ratio of quantities and units. For example, write "Temperature (K)", not "Temperature/K".

ACKNOWLEDGMENT

The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression "one of us (R. B. G.) thanks . . .". Instead, try "R. B. G. thanks. . .". Put sponsor acknowledgments in the unnumbered footnote on the first page.

REFERENCES

Please number citations consecutively within brackets [1]. The sentence punctuation follows the bracket [2]. Refer simply to the reference number, as in [3]—do not use "Ref. [3]" or "reference [3]" except at the beginning of a sentence: "Reference [3] was the first . . ."

Number footnotes separately in superscripts. Place the actual footnote at the bottom of the column in which it was cited. Do not put footnotes in the abstract or reference list. Use letters for table footnotes.

Unless there are six authors or more give all authors' names; do not use "et al.". Papers that have not been published, even if they have been submitted for publication, should be cited as "unpublished" [4]. Papers that have been accepted for publication should be cited as "in press" [5]. Capitalize only the first word in a paper title, except for proper nouns and element symbols.

For papers published in translation journals, please give the English citation first, followed by the original foreign-language citation [6].

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