International Journal of Informatics and Information System ISSN 2579-7069
Vol. 4, No. 1, March 2021, pp. 82-94

Predicting Airline Passenger Satisfaction with Classification Algorithms

B.Herawan Hayadi [1,*], Jin-Mook Kim [2], Khodijah Hulliyah [3], Husni Teja Sukmana [4]

[1] Informatics Program, Faculty of Engineering, Universitas Prof. Dr. Hazairin, SH., Bengkulu, Indonesia.
[2] Division of IT Education, Sunmoon University, South Korea
[3] International Islamic University Malaysia, Malaysia
[4] Universitas Islam Negeri Syarif Hidayatullah, Indonesia
[1] b.herawan.hayadi@gmail.com*; [2] calf0425@sunmoon.ac.kr; [3] khodijah2@yahoo.com; [4] husniteja@uinjkt.ac.id
* corresponding author

(Received February 16, 2021 Revised February 22, 2021 Accepted February 27, 2021, Available online March 1, 2021)

Abstract

Airline businesses around the world have been destroyed by Covid-19 as most international air travel has been banned. Almost all airlines around the world suffer losses, due to being prohibited from carrying out aviation transportation activities which are their biggest source of income. In fact, several airlines such as Thai Airways have filed for bankruptcy. Nonetheless, after the storm ends, demand for air travel is expected to spike as people return for holidays abroad. The research is aimed at analyzing the competition in the aviation industry and what factors are the keys to its success. This study uses several classification models such as KNN, Logistic Regression, Gaussian NB, Decision Trees and Random Forest which will later be compared. The results of this study get the Random Forest Algorithm using a threshold of 0.7 to get an accuracy of 99% and an important factor in getting customer satisfaction is the Inflight Wi-Fi Service.

Keywords: Classification, Airlane, Satisfaction, Predicting, Random Forest

1. Introduction

Today, the service industry has become the most important segment of the world economy [1]. In the US, the service industry constitutes about 60% of annual GDP and nearly 70% of new jobs, leading the expansion of service industries worldwide [2]. Thus, many researchers have studied service quality and tried to identify the factors that influence customer satisfaction and loyalty in various industries to improve service performance [2-6]. However, there is quite a lot of research on the service quality of the aviation industry, even though the airline industry has traditionally had a high level of competition, a situation that has made airlines trying hard to find ways to improve the quality of their services to gain a competitive advantage.

Airline services that are most direct to customers are in-flight services by flight attendants & facilities on the plane, because passengers tend to evaluate airlines based on their level of satisfaction with in-flight services [7]. Therefore, improving the quality of in-flight service is one of the determining factors for the success of an airline company, more specifically, in-flight food service is a major determinant of in-flight service. There are several important previous studies that have attempted to identify service quality factors in the aviation industry [8-11] . However, empirical studies on the importance of in-flight service quality are still limited. The purpose of this study was to determine the importance of in-flight service quality, with a focus on food and beverage services in airline airlines to increase customer satisfaction and loyalty.

In this paper, the research will begin, we present a brief literature review on general service quality and airline services. Then, we present a research methodology process using several classification algorithms to analyze the most important factors / features of the dataset & perform comparisons of the accuracy of each algorithm used.

2. Review of relevant literature

2.1. Service Quality

Satisfaction is a direct response to consumption, while service quality is defined as the customer's overall impression of the service provided [12, 13]. Service quality is influenced by expected service and perceived service. If the service is received as expected, the quality of service is satisfactory, but if the service received exceeds their expectations, customers will be happy, and will consider the quality of service to be very good and vice versa [14]. So, improving service quality is highly dependent on the airline's ability to consistently meet the needs and desires of passengers. Airlines can benefit while achieving a competitive advantage by doing their best to create and maintain quality service, which can lead to customer satisfaction. This in turn will provide various advantages for airlines by, for example: (1) building a strong relationship between the airline and its passengers, (2) providing a good basis for repurchase activities, (3) encouraging passenger loyalty, (4) making recommendations word of mouth that will promote the airline, (5) creating a good corporate reputation in the minds of passengers, and, finally, (6) by promoting the increase in airline profits [15, 16]. Therefore, airlines must recognize the strategic importance of quality: continuous quality improvement is not expensive in the long run; on the contrary, it is an investment that will generate greater returns.

2.2. Airline Companies Services

It is important to conceptualize the characteristics of an airline's service in order to estimate them accurately. Airline service is a concept that represents all types of services provided by airlines. In clarifying and applying the concept of airline service, Chang [8] refers to airline jobs as service storage based on the model proposed by Davis (1999), which identifies four types of service companies with two task dimensions as shown in Table 1.

Table. 1. Four types of service business

Service Work & Provider	Routinized	Knowledge
Integrated	Service Factory	Service Shop
Decoupled	Service Store	Service Complex

The services provided by airlines have fixed and flexible characteristics [6, 17]. The characteristics remain subject to seat size, cargo storage, aircraft type and aircraft maintenance. The flexible features of airline services include in-flight meal services which have both tangible and intangible services from departure to arrival such as services by flight attendants. Airline customers tend to be loyal to certain airline companies due to the nature of the airline's services. as a mileage program. Even customers who are not satisfied with the quality of service can continue to use certain airlines rather than switch to other airlines [18]. Apart from the perception of service quality, transaction and switching cost factors also have a significant effect on service loyalty [19]. Recognition of the quality of airline services is much more difficult compared to other service companies such as financial institutions whose work processes consist of separate but interrelated matters. the task of one organization. However, airline services are carried out concurrently with various processes by multiple entities such as TSA, airport authorities, catering companies, etc. [6, 8, 20-22]. Therefore, it requires smooth coordination of various activities by many organizations to improve the quality of airline services.

3. Method

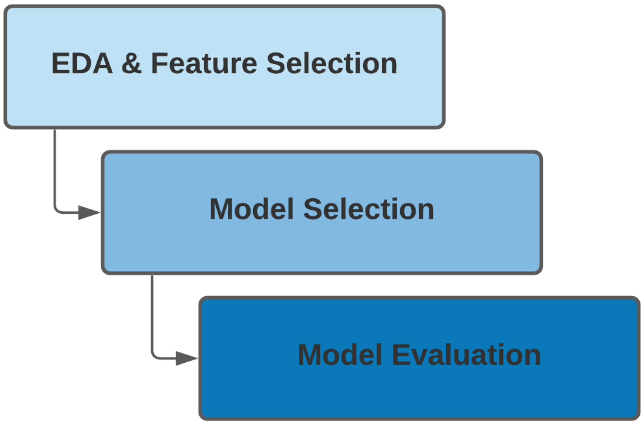


Fig. 1. Methodology Process

Before determining and building the model to be used it is very important to know which dataset we are using, our dataset contains around 130,000 survey entries and passenger / flight details from US airlines. In total, there are 21 feature columns and 1 class target column. Of all its features, 14 are survey entries where passengers rate the flight experience on a scale of 1 to 5. However, there are also some survey entries with a score of 0, which we conclude as unfilled survey questions. After deleting this survey entry and some NaN (Not a Number) values, the resulting data set for modeling has about 70,000 entries. Also some columns and other entries have been renamed for clarity. Finally, we have a cleaned data set as shown below:

	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink
0	70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	460	3	4	3	1	5
1	5047	Male	disloyal Customer	25	Business travel	Business	235	3	2	3	3	1
2	110028	Female	Loyal Customer	26	Business travel	Business	1142	2	2	2	2	5
3	24026	Female	Loyal Customer	25	Business travel	Business	562	2	5	5	5	2
4	119299	Male	Loyal Customer	61	Business travel	Business	214	3	3	3	3	4
...	...	...	...	...	...	...	...	...	...	...	...	...
129875	78463	Male	disloyal Customer	34	Business travel	Business	526	3	3	3	1	4
129876	71167	Male	Loyal Customer	23	Business travel	Business	646	4	4	4	4	4
129877	37675	Female	Loyal Customer	17	Personal Travel	Eco	828	2	5	1	5	2
129878	90086	Male	Loyal Customer	14	Business travel	Business	1127	3	3	3	3	4
129879	34799	Female	Loyal Customer	42	Personal Travel	Eco	264	2	5	2	5	4

	Online boarding	Seat comfort	Inflight entertainment	On-board service	Leg room service	Baggage handling	Checkin service	Inflight service	Cleanliness	Departure Delay in Minutes	Arrival Delay in Minutes	Satisfaction
0	3	5	5	4	3	4	4	5	5	25	18.0	neutral or dissatisfied
1	3	1	1	1	5	3	1	4	1	1	6.0	neutral or dissatisfied
2	5	5	5	4	3	4	4	4	5	0	0.0	satisfied
3	2	2	2	2	5	3	1	4	2	11	9.0	neutral or dissatisfied
4	5	5	3	3	4	4	3	3	3	0	0.0	satisfied
...	...	...	...	...	...	...	...	...	...	...	...	...
129875	3	4	4	3	2	4	4	5	4	0	0.0	neutral or dissatisfied
129876	4	4	4	4	5	5	5	5	4	0	0.0	satisfied
129877	1	2	2	4	3	4	5	4	2	0	0.0	neutral or dissatisfied
129878	4	4	4	3	2	5	4	5	4	0	0.0	satisfied
129879	2	2	1	1	2	1	1	1	1	0	0.0	neutral or dissatisfied

Fig. 2. Dataset after Cleaning

As seen in Figure 2 above, data can be categorized as usable for modeling. However, it would be unpleasant if we did not do a simple analysis of the data such as knowing the Amount, Average, Largest Value, Minimum Value, Quartile, and Standard Deviation. We may not always use this analysis for modeling, but it would be great if the reader could understand how the dataset we are using is deeper, this will also help readers get an idea of the results that will be produced later. The results of the analysis for each feature are attached in Figure 3 below.

	id	Age	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink	Online boarding	Seat comfort
count	129487.000000	129487.000000	129487.000000	129487.000000	129487.000000	129487.000000	129487.000000	129487.000000	129487.000000	129487.000000
mean	64958.335169	39.428761	1190.210662	2.728544	3.057349	2.756786	2.976909	3.204685	3.252720	3.441589
std	37489.781165	15.117597	997.560954	1.329235	1.526787	1.401662	1.278506	1.329905	1.350651	1.319168
min	1.000000	7.000000	31.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	32494.500000	27.000000	414.000000	2.000000	2.000000	2.000000	2.000000	2.000000	2.000000	2.000000
50%	64972.000000	40.000000	844.000000	3.000000	3.000000	3.000000	3.000000	3.000000	3.000000	4.000000
75%	97415.500000	51.000000	1744.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	5.000000
max	129880.000000	85.000000	4983.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000

Inflight entertainment	On-board service	Leg room service	Baggage handling	Checkin service	Inflight service	Cleanliness	Departure Delay in Minutes	Arrival Delay in Minutes
129487.000000	129487.000000	129487.000000	129487.000000	129487.000000	129487.000000	129487.000000	129487.000000	129487.000000
3.358067	3.383204	3.351078	3.631886	3.306239	3.642373	3.286222	14.643385	15.091129
1.334149	1.287032	1.316132	1.180082	1.266146	1.176614	1.313624	37.932867	38.465650
0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2.000000	2.000000	2.000000	3.000000	3.000000	3.000000	2.000000	0.000000	0.000000
4.000000	4.000000	4.000000	4.000000	3.000000	4.000000	3.000000	0.000000	0.000000
4.000000	4.000000	4.000000	5.000000	4.000000	5.000000	4.000000	12.000000	13.000000
5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	1592.000000	1584.000000

Fig. 3. Dataset Analysis

After conducting the analysis, we can clearly see how the data we have from a statistical point of view, but there are some drawbacks, namely that there are some features and data in features that are suitable but not suitable for making several models. So the next thing we're going to do is adjust the feature name and content to make it easier to build the model. The changes we have made are like:

- Changes in the structure of some features in the dataset.
- Removing the ID column at the beginning of the dataset
- Data transformation in the class Satisfaction or satisfaction with, satisfied: 1, neutral or dissatisfied: 0.
- Remove Departure Delay In Minutes & Arrival Delay In Minutes features.
- Data transformation on class feature (Ticket type) with, Eco: Economy, Eco Plus: Economy, & Business: Business.

	Satisfaction	Gender	Customer Type	Age	Type Of Travel	Class	Flight Distance	Inflight Wifi Service	Departure/Arrival Time Convenience	Ease Of Online Booking	Gate Location	Food And Drink	Online Boarding	Seat Comfort	Inflight Entertainment	On-board Service	Leg Room	Baggage Handling	Checkin Service	Inflight Service	Cleanliness	Total Delay
0	0	Male	Returning Customer	13	Personal Travel	Economy	460	3	4	3	1	5	3	5	5	4	3	4	4	5	5	43.0
1	0	Male	First-time Customer	25	Business travel	Business	235	3	2	3	3	1	3	1	1	1	5	3	1	4	1	7.0
2	0	Female	Returning Customer	25	Business travel	Business	562	2	5	5	5	2	2	2	2	2	5	3	1	4	2	20.0
3	1	Male	Returning Customer	61	Business travel	Business	214	3	3	3	3	4	5	5	3	3	4	4	3	3	3	0.0
4	0	Female	Returning Customer	26	Personal Travel	Economy	1180	3	4	2	1	1	2	1	1	3	4	4	4	4	1	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
69061	0	Female	First-time Customer	36	Business travel	Economy	432	1	5	1	3	4	1	4	4	5	2	5	2	3	4	0.0
69062	0	Male	First-time Customer	34	Business travel	Business	526	3	3	3	1	4	3	4	4	3	2	4	4	5	4	0.0
69063	0	Female	Returning Customer	17	Personal Travel	Economy	828	2	5	1	5	2	1	2	2	4	3	4	5	4	2	0.0
69064	1	Male	Returning Customer	14	Business travel	Business	1127	3	3	3	3	4	4	4	4	3	2	5	4	5	4	0.0
69065	0	Female	Returning Customer	42	Personal Travel	Economy	264	2	5	2	5	4	2	2	1	1	2	1	1	1	1	0.0

Fig. 4. Final Dataset Structure

After making some of these changes, for example changing the Satisfaction column to binary, with this we can make a clear comparison of the amount of data. Comparisons that are owned for each data in the satisfaction column are attached in the figure below. Namely, 0 = 0.564257 1 = 0.435743 The result of sharing the data that is owned is quite balanced and makes sense. with this the model selection process can be carried out.

```
0    0.564257
1    0.435743
Name: Satisfaction, dtype: float64
```

Fig. 5. Data Comparison between positive & negative class

3.1. EDA & Feature Selection

In order to visualize, we first need to understand the business problem, and also identify the important features for modeling. Find out the proportion of classes in the target, and separate them by Trip Type and Customer Type (To understand satisfaction trends - useful later in model evaluation). Identify the significance of features for the model through visualization of KDE plots, LASSO lines, and heat maps. After careful evaluation and selection, we decided to delete 'Gender', 'Total Delay', 'Flight Distance', 'Age', 'Gate Location' and 'Departure / Arrival Time Convenience'

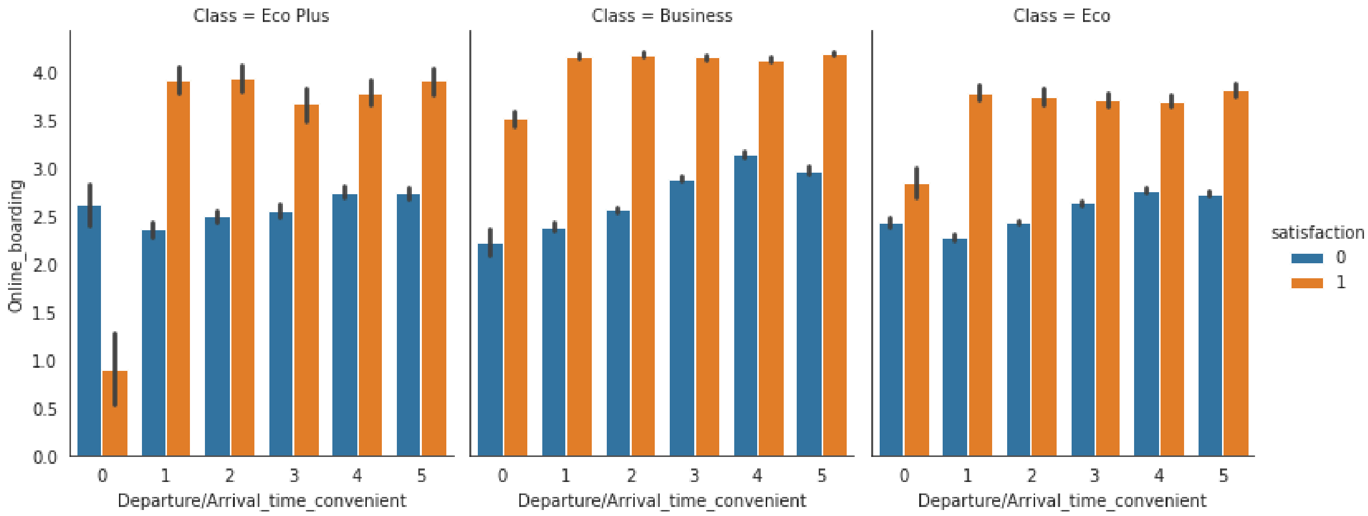


Fig. 5. EDA of target classes

The target class is quite balanced with 56.4% of passengers reporting Neutral / Dissatisfied (negative class: 0) and 43.6% reporting Satisfied (positive class: 1). The high number of entries in the negative class is not surprising as 'Neutral / Dissatisfied' does not necessarily mean dissatisfaction. This also includes passengers who feel indifferent to the flight experience. When we further divided the satisfaction class according to customer type, we saw that first-time customers had a lower satisfaction ratio. In addition, when we segmented the satisfaction classes by trip type, it was seen that customers who took personal trips (holidays) had a much lower satisfaction ratio. In both cases, higher experience expectations may play a role in decreased satisfaction.

Also, we aim to remove features that don't contribute to our predictive modeling. It includes features that don't contribute to target class differences as well as highly correlated features, which can cause multi-collinearity issues. As much as possible, we want to maintain features that include survey entries, so that we can identify areas of flight satisfaction. For this purpose, we apply Kernel Density Estimation (KDE) plots, heat map correlation and LASSO regression for feature selection. We found that:

- KDE plot: The 'Gate Location' feature appears to contain missing '2' and '4' scores, suggesting an anomaly as it is unlikely that passengers will enter these scores. In the 'Gender' feature, the distribution of satisfaction is roughly identical for both indicating that it is poorly correlated with the target, and has therefore been removed.
- Correlation Heatmap: 'Age', 'Departure / Arrival Time Convenience', 'Gate Location' and 'Total Delay' features have a low correlation of 0.15 downwards with the target.

- LASSO Regression Plot: The least important feature has a linear coefficient that decreases to zero at the earliest as the alpha hyper parameter increases. From the plot, we identified that the features are 'Food and Drink', 'Ease of Online Booking', 'Age', 'Flight Distance', 'Total Delay' and 'Gate Location'

After considering various conditions & possibilities, we decided to remove the features "Gender", "Age", "Gate location", "Total Delay", "Flight Distance" and "Departure / Arrival Time Convenience". Finally we only have 15 features which contain most of the survey categories and customer types / classes.

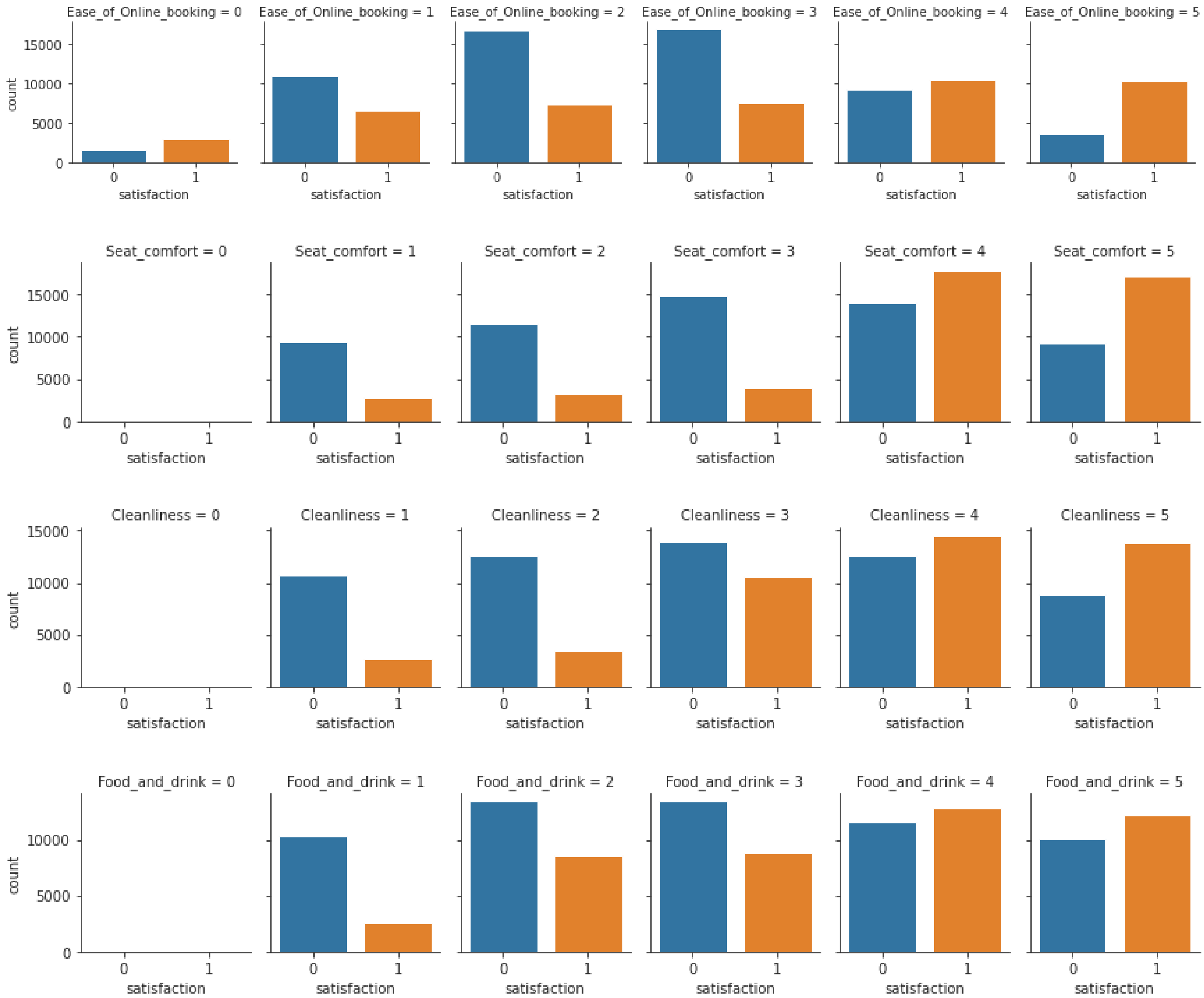


Fig. 6. KDE Plots of Features split by target classes

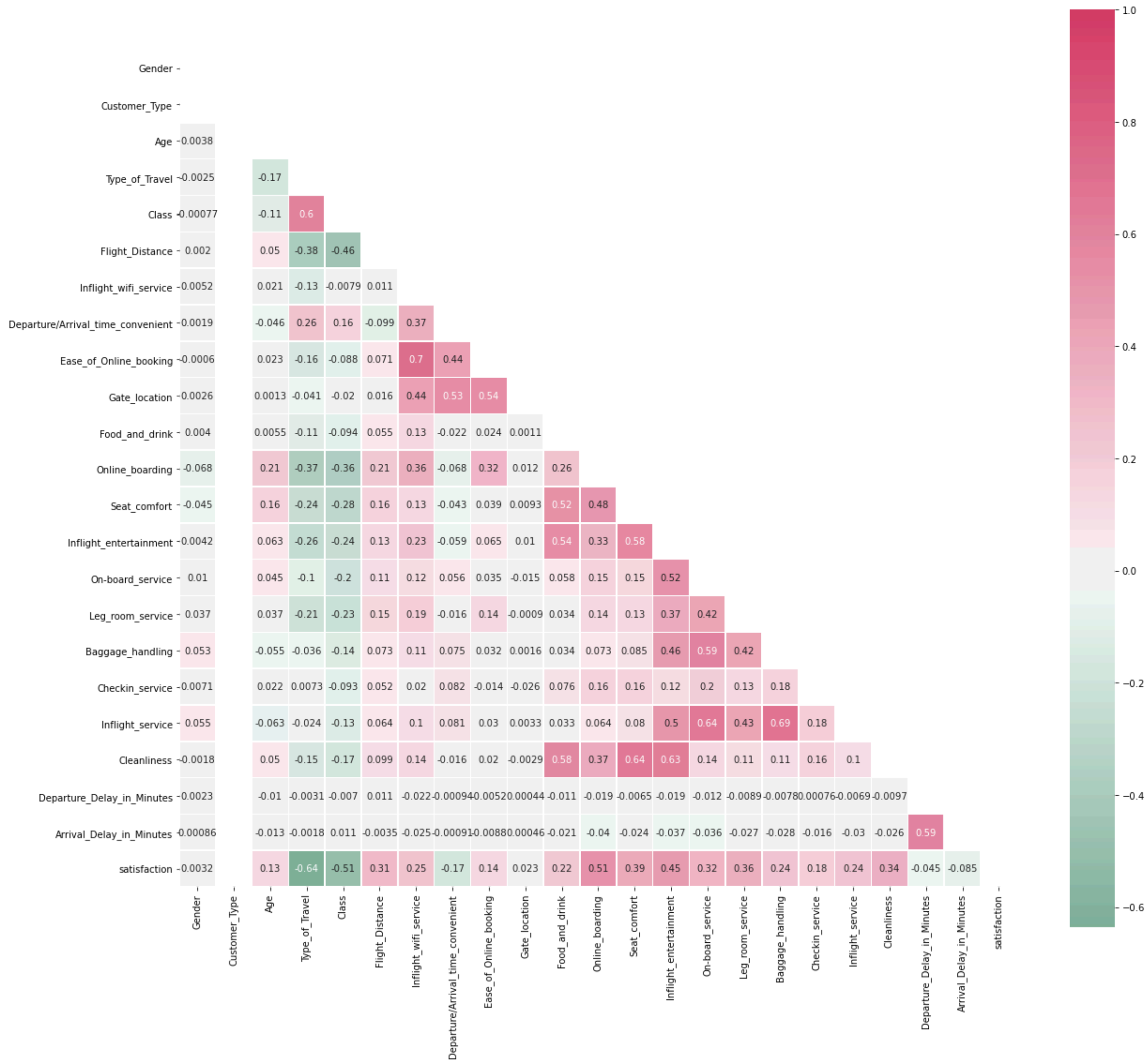


Fig. 7. Correlation Heat Map

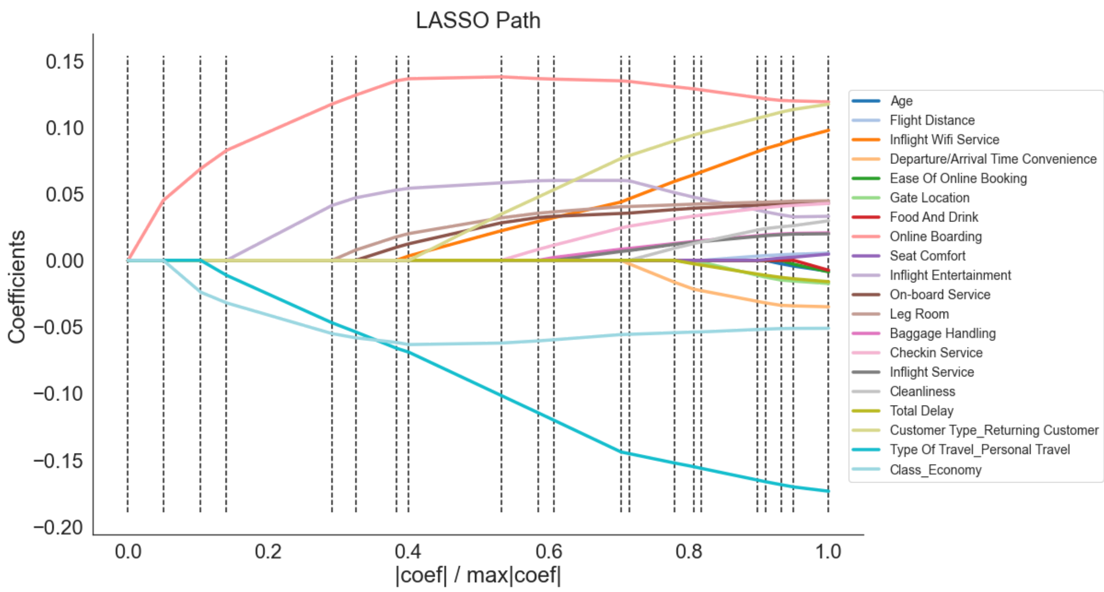


Fig. 8. Plot of LASSO Regression

Before we identified which classification model was the most predictive of the data set, we divided the data into 80% for 5-fold cross validation and 20% as a test kit for the final evaluation of the selected model. Then, we performed 5-fold cross-validation across various classification models to identify their hyper-optimal parameters.

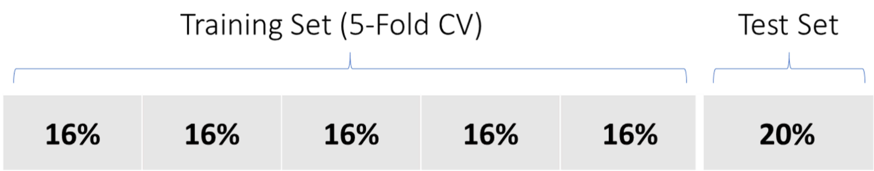
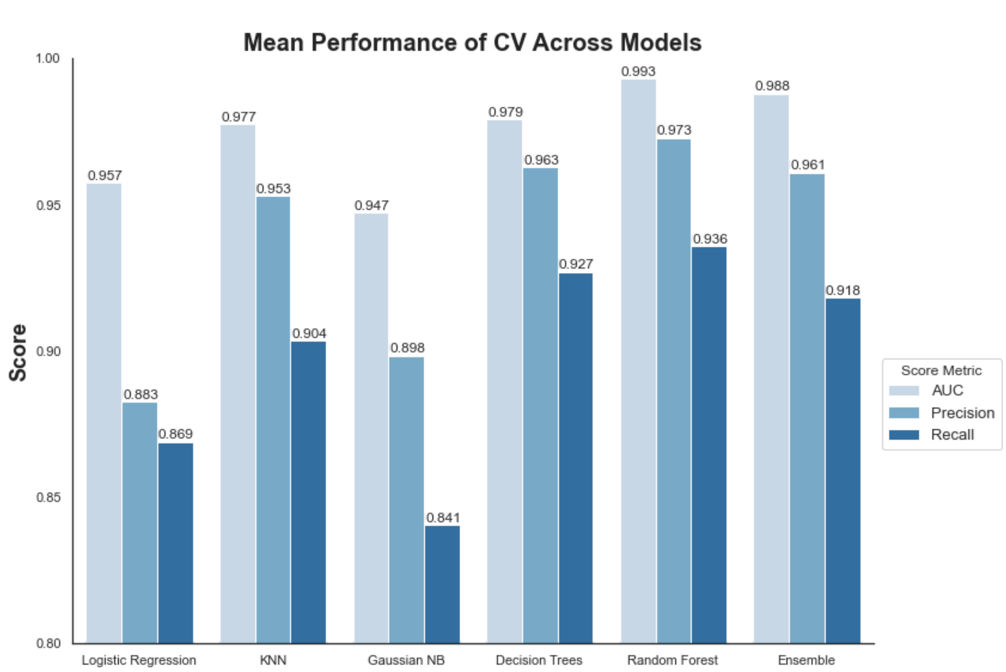


Fig. 9. Splitting of data set into Test Set (20%) and Training-Validation Set (80%)

By running the GridSearchCV algorithm on Scikit-Learn, the optimum hyper models and parameters are:

- k-Nearest (k = 7)
- Logistics Regression (C = 0,04)
- Decision Tree (Max Depth= 12)
- Random Forest (Max Depth= 17)

Apart from that, we also include Gaussian Naive Bayes and the Ensemble method (taking all models by voting) in the cross validation process. After assessing all models considered on AUC, Precision and Recall, the Random Forest model was identified as the best performing one with AUC 0.99, Precision 0.97, and Recall 0.94.



	Model	Scoring	Score
0	Logistic Regression	AUC	0.957475
1	Logistic Regression	Precision	0.882574
2	Logistic Regression	Recall	0.868921
3	KNN	AUC	0.977434
4	KNN	Precision	0.952958
5	KNN	Recall	0.903554
6	Gaussian NB	AUC	0.947164
7	Gaussian NB	Precision	0.898347
8	Gaussian NB	Recall	0.840534
9	Decision Trees	AUC	0.979282
10	Decision Trees	Precision	0.963492
11	Decision Trees	Recall	0.927137
12	Random Forest	AUC	0.992917
13	Random Forest	Precision	0.972766
14	Random Forest	Recall	0.935849
15	Ensemble	AUC	0.987846
16	Ensemble	Precision	0.961036
17	Ensemble	Recall	0.917993

Fig. 10. Mean scores of cross-validation for all classification models

Next, let's understand the meaning of some of these valuation metrics, which will allow us to identify which valuation metrics are most relevant to our business problem.

- Recall: The ratio of the number of positive classes correctly predicted by the model to the actual total number of positive classes. For example, this metric will be important for models predicting cancer in patients, because it is critical to catch as many positive cases as possible.
- Precision: The ratio of the number of positive classes that the model correctly predicted to the total number of positive classes predicted. For example, this metric is relevant to the spam filter model, as it is very important to catch only real spam cases and reduce the number of false positives.

Under this paradigm, having high precision will be more important for our business matters. In order to correctly identify the important factors that lead to customer satisfaction, the prediction of the positive class model, 'Satisfied' must be very reliable. Since the Precision-Recall interchanges the probability threshold adjustment, we next perform Simple Validation using the Random Forest Model to decide the optimal probability threshold.

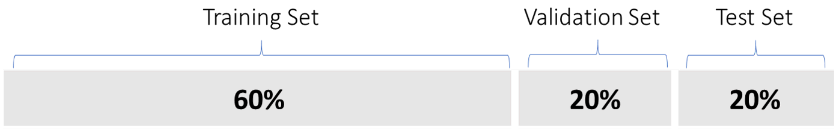
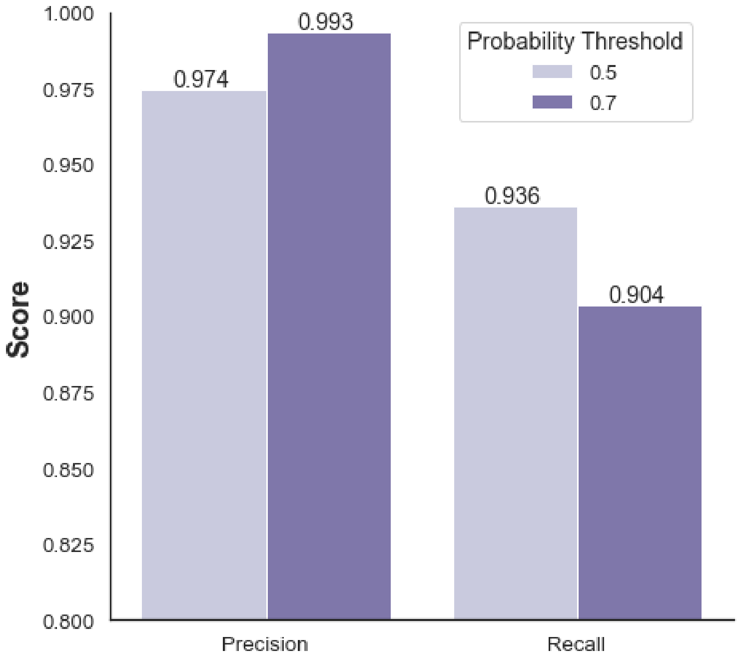


Fig. 11. Simple Validation: Re-training the Random Forest on training set, and scoring on the validation



	Scoring	Threshold	Score
0	Precision	0.5	0.974476
1	Precision	0.7	0.993353
2	Recall	0.5	0.936335
3	Recall	0.7	0.903746

Fig. 12. Precision and Recall scores of Random Forest with different threshold

The Random Forest's default probability threshold is 0.5. After setting it to 0.7, the Precision has increased from 0.97 to 0.99, without sacrificing big on Gain. Since this is in line with the objectives of our model, we chose our final model to be a Random Forest (Max Depth = 17) with a probability threshold of 0.7.

4. Results and Model Evaluation

Finally, after we build the model & retrain the selected model on 80% of the data set (Training + Set Validation), then evaluate the predictions on the remaining 20% of the data set (Set Testing). The final evaluation of model performance gives AUC 0.993, Recall 91.2% and Accuracy of 99.1%.

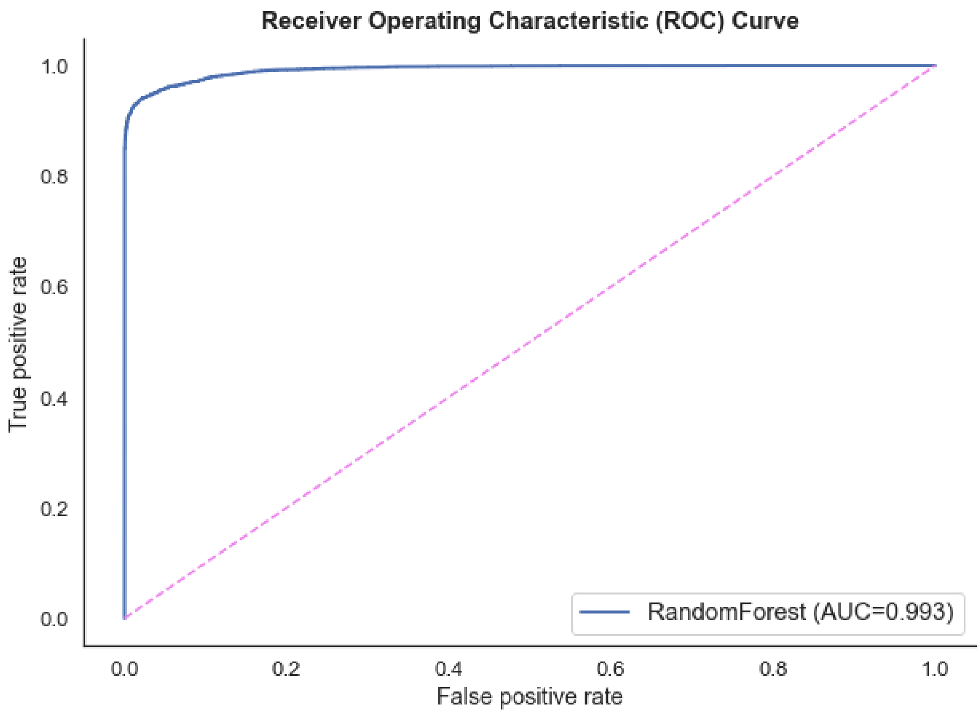


Fig. 13. The ROC curve on final evaluation of Random Forest model on Test Set

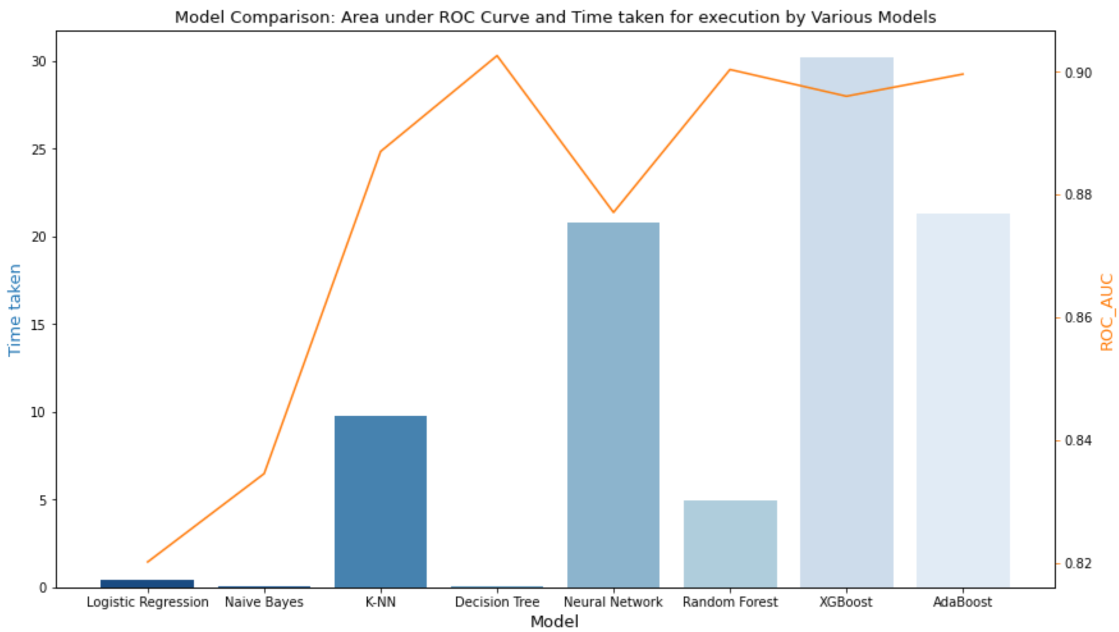
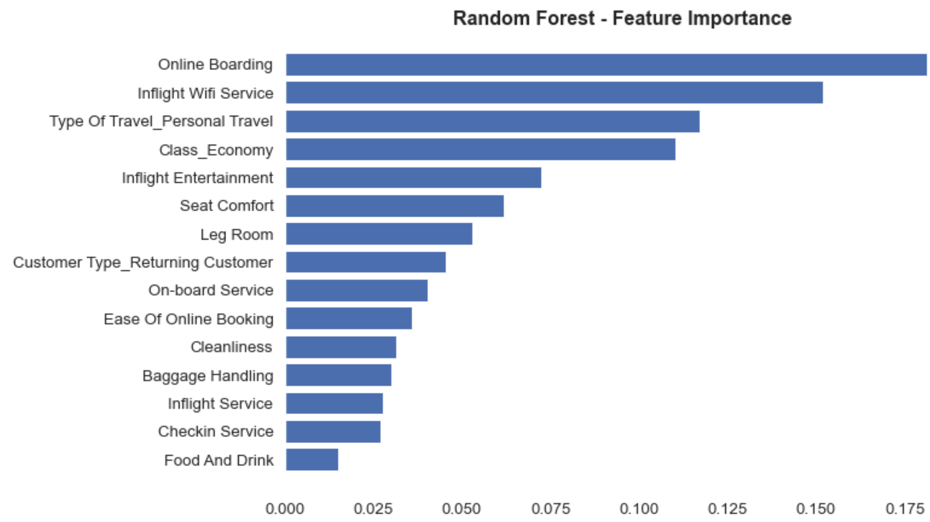


Fig. 14. The confusion matrix on final evaluation of the model



	features	importance
2	Food And Drink	0.015048
9	Checkin Service	0.026856
10	Inflight Service	0.027592
8	Baggage Handling	0.030065
11	Cleanliness	0.031272
1	Ease Of Online Booking	0.035996
6	On-board Service	0.040355
12	Customer Type_Returning Customer	0.045322
7	Leg Room	0.052875
4	Seat Comfort	0.061945
5	Inflight Entertainment	0.072244
14	Class_Economy	0.110338
13	Type Of Travel_Personal Travel	0.116912
0	Inflight Wifi Service	0.151804
3	Online Boarding	0.181375

Fig. 15. Feature Importance

As you can see in Figure 14, the accuracy obtained is 99.1%, meaning that when the model predicts passenger satisfaction, the model is sure that the prediction is 99.1% accurate and correct. Let's see how this high precision can be applied to the business problems we face and described earlier in the method.

4.1. Business Problem

As previously indicated in the EDA, first-time customers have higher expectations and are thus less likely to be satisfied. However, capturing customer satisfaction the first time is important as it ensures a higher probability of returning to the airline for the journey. Using this model, we can explore the important factors that lead to first-time customer satisfaction.

A. Private Travel in Economy Class - First Time Customer

For economy customers on a personal journey, when we started by assigning all categories to the average rating (rating: 3), the model was not sure that the customer would be satisfied. However, if we upgrade the In-Flight Wifi Service rating to excellent (rating: 5), with other categories having average performance, the model is confident that the customer will be satisfied. Interestingly, if we downgrade the In-Flight Wi-Fi Service while setting the rest of the category to very good, the model is still not sure that the customer will be satisfied.

	Predicted Satisfaction	Inflight Wifi Service	Ease Of Online Booking	Food And Drink	Online Boarding	Seat Comfort	Inflight Entertainment	On-board Service	Leg Room	Baggage Handling	Checkin Service	Inflight Service	Cleanliness	Customer Type_Returning Customer	Type Of Travel_Personal Travel	Class_Economy
0	Neutral/Dissatisfied	3	3	3	3	3	3	3	3	3	3	3	3	0	1	1
1	Satisfied	5	3	3	3	3	3	3	3	3	3	3	3	0	1	1
2	Neutral/Dissatisfied	4	5	5	5	5	5	5	5	5	5	5	5	0	1	1
3	Neutral/Dissatisfied	3	5	5	5	5	5	5	5	5	5	5	5	0	1	1

Fig. 16. simulation of first-time customer satisfaction on personal travel in economy class

B. Business Travel in Business Class - First Time Customer

For business customers who go on business trips, the model predicts that they will be more easily satisfied. With a lower In-Flight Wi-Fi Service rating while the rest of the category is set to a very good rating, this model is confident that business customers will be satisfied. However, as I continued to downgrade in other categories, this model only believes that customers will be satisfied if I at least set the Ease of Online Ordering rating to very good (rating: 5).

	Predicted Satisfaction	Inflight Wifi Service	Ease Of Online Booking	Food And Drink	Online Boarding	Seat Comfort	Inflight Entertainment	On-board Service	Leg Room	Baggage Handling	Checkin Service	Inflight Service	Cleanliness	Customer Type_Returning Customer	Type Of Travel_Personal Travel	Class_Economy
0	Neutral/Dissatisfied	3	3	3	3	3	3	3	3	3	3	3	3	0	0	0
1	Satisfied	5	3	3	3	3	3	3	3	3	3	3	3	0	0	0
2	Satisfied	3	5	5	5	5	5	5	5	5	5	5	5	0	0	0
3	Neutral/Dissatisfied	3	4	4	4	4	4	4	4	4	4	4	4	0	0	0
4	Satisfied	3	5	4	4	4	4	4	4	4	4	4	4	0	0	0
5	Neutral/Dissatisfied	3	4	5	5	5	5	5	5	5	5	5	5	0	0	0

Fig. 17. simulation of first-time customer satisfaction on business travel in business class

5. Conclusion

We have created a very precise classification model for airlines to identify critical bottlenecks to improve passenger satisfaction. From several simulations, we recommend that airlines should focus on improving the In-flight Wi-Fi Service experience. For example, airlines could develop better software to allow easier access to in-flight wi-fi, or lower costs for accessing in-flight wi-fi so that more economy class customers can enjoy the service. In addition, airlines must also focus on the Ease of Online Booking, because business passengers prioritize convenience and comfort in their travels. Finally, we hope that this model can become a reference for airlines and can be used for business value.

References

[1] J. Choi, H. Seol, S. Lee, H. Cho, and Y. Park, "Customer satisfaction factors of mobile commerce in Korea," Internet Res., vol. 18, no. 3, pp. 313–335, 2008, doi: 10.1108/10662240810883335.

[2] B. K. Behn and R. A. Riley, "Using Nonfinancial Information to Predict Financial Performance: The Case of the U.S. Airline Industry," J. Accounting, Audit. Financ., vol. 14, no. 1, pp. 29–56, 1999, doi: 10.1177/0148558X9901400102.

[3] K. Singaravelu and V. P. Amuthanayaki, "A Study on Service Quality and Passenger Satisfaction on Indian Airlines," J. Commer. Trade, vol. 12, no. 2, 2017, doi: 10.26703/jct.v12i2-16.

[4] R. Hussain, A. Al Nasser, and Y. K. Hussain, "Service quality and customer satisfaction of a UAE-based airline: An empirical investigation," J. Air Transp. Manag., vol. 42, pp. 167–175, 2015, doi: 10.1016/j.jairtraman.2014.10.001.

[5] D. Martín-Consuegra, A. Molina, and Á. Esteban, "An integrated model of price, satisfaction and loyalty: An empirical analysis in the service sector," J. Prod. Brand Manag., vol. 16, no. 7, pp. 459–468, 2007, doi: 10.1108/10610420710834913.

[6] T. Hariguna, W. M. Baihaqi, and A. Nurwanti, "Sentiment Analysis of Product Reviews as A Customer Recommendation Using the Naive Bayes Classifier Algorithm," IJIIS Int. J. Informatics Inf. Syst., vol. 2, no. 2, pp. 48–55, 2019, doi: 10.47738/ijiis.v2i2.13.

[7] C. F. Chen, "Investigating structural relationships between service quality, perceived value, satisfaction, and behavioral intentions for air passengers: Evidence from Taiwan," Transp. Res. Part A Policy Pract., vol. 42, no. 4, pp. 709–717, 2008, doi: 10.1016/j.tra.2008.01.007.

[8] S. Tiernan, D. L. Rhoades, and B. Waguespack, "Airline service quality: Exploratory analysis of consumer perceptions and operational performance in the USA and EU," Manag. Serv. Qual. An Int. J., vol. 18, no. 3, pp. 212–224, 2008, doi: 10.1108/09604520810871847.

[9] J. Kandampully and D. Suhartanto, "Customer loyalty in the hotel industry: The role of customer satisfaction and image," Int. J. Contemp. Hosp. Manag., vol. 12, no. 6, pp. 346–351, 2000, doi: 10.1108/09596110010342559.

[10] J. W. Park, R. Robertson, and C. L. Wu, "The effect of airline service quality on passengers' behavioural intentions: A Korean case study," J. Air Transp. Manag., vol. 10, no. 6, pp. 435–439, 2004, doi: 10.1016/j.jairtraman.2004.06.001.

[11] A. Shahin and M. Zairi, "Kano model: A dynamic approach for classifying and prioritising requirements of airline travellers with three case studies on international airlines," Total Qual. Manag. Bus. Excell., vol. 20, no. 9, pp. 1003–1028, 2009, doi: 10.1080/14783360903181867.

[12] G. C. Saha and Theingi, "Service quality, satisfaction, and behavioural intentions: A study of low-cost airline carriers in Thailand," Manag. Serv. Qual., vol. 19, no. 3, pp. 350–372, 2009, doi: 10.1108/09604520910955348.

[13] N. Adler and J. Berechman, "Measuring airport quality from the airlines' viewpoint: An application of data envelopment analysis," Transp. Policy, vol. 8, no. 3, pp. 171–181, 2001, doi: 10.1016/S0967-070X(01)00011-7.

[14] M. A. Jones and J. Suh, “Transaction-specific satisfaction and overall satisfaction: an empirical analysis,” J. Serv. Mark., vol. 14, no. 2, pp. 147–159, 2000, doi: 10.1108/08876040010371555.

[15] C. Gan, “An empirical analysis of customer satisfaction in international air travel,” Innov. Mark., vol. 4, no. 2, pp. 49–62, 2008.

[16] M. Söderlund, “Customer satisfaction and its consequences on customer behaviour revisited: The impact of different levels of satisfaction on word-of-mouth, feedback to the supplier and loyalty,” Int. J. Serv. Ind. Manag., vol. 9, no. 2, pp. 169–188, 1998, doi: 10.1108/09564239810210532.

[17] E. Lacic, D. Kowald, and E. Lex, “High enough? Explaining and predicting traveler satisfaction using airline reviews,” HT 2016 - Proc. 27th ACM Conf. Hypertext Soc. Media, pp. 249–254, 2016, doi: 10.1145/2914586.2914629.

[18] P. Zahir Irani, S. Mohamed Fadel Bukhari, A. Ghoneim, C. Dennis, and B. Jamjoom, “The antecedents of travellers’ e-satisfaction and intention to buy airline tickets online: A conceptual model,” J. Enterp. Inf. Manag., vol. 26, no. 6, pp. 624–641, 2013, doi: 10.1108/JEIM-07-2013-0040.

[19] L. Y. Leong, T. S. Hew, V. H. Lee, and K. B. Ooi, “An SEM-artificial-neural-network analysis of the relationships between SERVPERF, customer satisfaction and loyalty among low-cost and full-service airline,” Expert Syst. Appl., vol. 42, no. 19, pp. 6620–6634, 2015, doi: 10.1016/j.eswa.2015.04.043.

[20] N. Gures, S. Arslan, and S. Yucel Tun, “Customer Expectation, Satisfaction and Loyalty Relationship in Turkish Airline Industry,” Int. J. Mark. Stud., vol. 6, no. 1, pp. 66–74, 2014, doi: 10.5539/ijms.v6n1p66.

[21] N. Elkhani, S. Soltani, and M. H. M. Jamshidi, “Examining a hybrid model for e-satisfaction and e-loyalty to e-ticketing on airline websites,” J. Air Transp. Manag., vol. 37, pp. 36–44, 2014, doi: 10.1016/j.jairtraman.2014.01.006.

[22] H. Han, K. S. Lee, B. L. Chua, S. Lee, and W. Kim, “Role of airline food quality, price reasonableness, image, satisfaction, and attachment in building re-flying intention,” Int. J. Hosp. Manag., vol. 80, no. January, pp. 91–100, 2019, doi: 10.1016/j.ijhm.2019.01.013.

[23] H. J. Ban and H. S. Kim, “Understanding customer experience and satisfaction through airline passengers’ online review,” Sustain., vol. 11, no. 15, 2019, doi: 10.3390/su11154066.