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Analyzing Airline Services and Communication Systems by Designing Machine Learning Model to Predict Passenger Satisfaction

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Abstract

This research explores the methods of assessing airline passenger satisfaction through surveys and analyzing factors that are strongly linked to whether a passenger is satisfied or dissatisfied. The aim is also to investigate if it is possible to predict passenger satisfaction levels. The dataset used in this study comes from a Kaggle dataset titled "Airline Passenger Satisfaction," which includes 223,690 records with 23 measurement variables and 1 response variable. It identifies three key factors critical to airline service improvement: delays, online boarding, and class. Airlines can enhance their service offerings by focusing on these areas as air travel activities pick up. Specifically, online boarding is highlighted as a significant factor in reducing the need for manual check-ins and waiting in queues, thereby providing a faster and more efficient process. Furthermore, the study's analysis of categorical data and its correlation with satisfaction levels yields important insights into customer preferences within the airline industry. The differentiation between loyal and disloyal customers, as visualized in the study, shows that many loyal customers are dissatisfied. This points to the fact that loyal customers, despite their overall satisfaction, have faced varying levels of service quality.

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INTRODUCTION

Flight delays pose significant challenges for airlines, resulting in both economic losses and inconvenience for passengers worldwide [1],[2]. These delays cost airlines billions of dollars annually and inconvenience travelers substantially [3]. To address these issues, airlines' recognition is growing that improving on-time departures and aircraft turnaround times is crucial.

In response to a prolonged period of decreasing prices, airlines are now exploring ways to differentiate themselves through enhanced quality and service offerings [4]. This shift highlights the need to reduce boarding time and increase overall aircraft efficiency to ensure timely departures. However, amidst these efforts, there is a concern that some airlines may overlook the importance of prioritizing service quality and customer satisfaction.

A study investigating the impact of service quality and satisfaction on passenger behavior sheds light on this matter [5]. The findings reveal that service quality significantly influences customer satisfaction, and both factors play a crucial role in determining passenger behavior, including word-of-mouth recommendations, repeat purchase intentions, and feedback. Notably, the reliability of flight

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schedules emerges as a key factor affecting customer satisfaction.

Airlines grapple with the challenges of flight delays. There is a dual focus on operational efficiency and enhancing service quality to meet passengers' evolving expectations. Balancing these priorities is essential for the sustained success of airlines in an increasingly competitive industry.

Trust is crucial in the marketing relationship between consumers and service providers. While acknowledging the pivotal role of trust, this study refines and expands existing literature by dynamically modeling the processes of trust building and reduction. It introduces several dimensions of trust, such as operational competence, operational benevolence, and problem-solving orientation, providing detailed insights [6],[7]. This understanding illustrates the complexity of factors affecting passenger loyalty and underscores the need to involve psychological aspects and employee service.

Furthermore, it is revealed that airline passengers have different expectations regarding service quality based on their nationality, as well as varying perceptions of airline service quality [8] and influencing customer satisfaction that is positively related to loyalty [9], [10].

As a reaffirmation, loyalty is measured based on behavioral intent [11], [12]. Overall, a deep understanding of the interaction between trust, loyalty, and satisfaction is key for companies in managing relationships with their customers in the competitive aviation industry.

Passenger Service and Communication encompasses vital dimensions and service items, focusing on reliability, assurance, safety, and customer complaint handling. Passengers prioritize reliability and safety, while comfort and seat cleanliness have increased in recent years [13], [14]. This technological integration is poised to reshape the landscape of passenger experience and communication.

On the other hand, passengers utilize social media platforms like Twitter to communicate their complaints, categorizing tweets into positive, negative, and neutral classes [15], [16]. This highlights the evolving landscape of customer feedback channels, emphasizing the need for airlines to engage with passengers on these platforms actively.

Research endeavors, such as Zheng's exploration of deep learning approaches for passenger profiling in aviation security, highlight the importance of addressing privacy concerns in technological advancements [17] and enhancing service quality [18]. This emphasizes the operational aspects that contribute to overall passenger satisfaction.

Studies of airline service quality find that passengers prioritize physical aspects over empathy. Key criteria involve the consistency of crew politeness, safety, seat comfort, and cleanliness, as well as crew responsiveness [19], service and customer relationship management [20] and satisfaction levels, passenger perceived value, and, presumably, commercial sustainability [21]. This reinforces the strategic imperative for airlines to align their services with passenger expectations for sustained success.

Implementing a machine learning (ML)-based approach in the aviation industry, particularly within airlines, has become a strategic key to optimizing services and passenger experiences. The integration of ML enables airlines to automatically analyze and understand passenger behavior patterns, map individual preferences, and enhance operational efficiency.

As ML technology continues to evolve, the relationship between the aviation industry and machine learning is becoming increasingly intertwined, creating new opportunities for innovation and efficiency improvements throughout the value chain. In this context, collaboration between ML experts and aviation industry professionals is crucial to optimizing the benefits of this technology and achieving better goals in delivering high-quality services to passengers [22] and alternative attributes and decision-maker characteristics [23].

The Python programming language and its rich ecosystem are crucial in implementing various ML algorithms in this context. This provision addresses the growing need for statistical data analysis in software and web development industries and non-computer science fields such as biology or physics [24].

This research is on how to know airline passenger satisfaction through a survey. What factors are highly correlated to a satisfied (or dissatisfied) passenger, and can we predict passenger satisfaction?

METHOD

Here, we are using a dataset about airline services. The dataset contains an Airline Satisfaction Passenger survey from the Kaggle website. This analysis aims to get an insight into what factors are highly correlated to a satisfied (or dissatisfied) passenger and whether the data can predict passenger satisfaction.

Selection of Research Variables

The Dataset contains an Airline Satisfaction Passenger survey from Kaggle dataset https://www.kaggle.com/teejmahal20/airline-passenger-satisfaction. Kaggle took data from US Airlines passengers in 2018 by satisfaction survey Passenger Satisfaction with data totaling 223,690 records and consisting of 19-23 measuring variables and one response variable that can detailed on https://github.com/RodzanIskandar/Airline_Passenger_satisfaction/blame/main/Train%20Feature%20Engineering.csv and selected featured below.

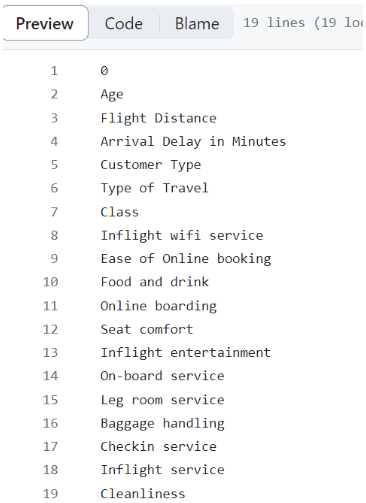

Figure 1. Train Featured Data Set.

Based on dataset above, we use the dataset to train feature engineering such as ID, Gender, Customer Type, Age Type of Travel, Class, Flight Distance, Inflight Wi-Fi service, Departure/Arrival time convenient, Ease of Online booking, Gate location, Food and drink, Online boarding, Seat comfort, Inflight entertainment, On-board service, Leg room service, Baggage handling, Check-in service, Inflight service, Cleanliness, Departure Delay in Minutes, Arrival Delay in Minutes, Satisfaction.

This analysis aims to get insight into what factors are highly correlated to a satisfied (or dissatisfied) passenger and whether the data can predict passenger satisfaction. From the Data Analysis result, airline passenger satisfaction is dominant by the older people between the ages of 40-60 for business travel using business class within long flying range distance, which is supported and reinforced by good services scores for older people like seat comfort, on-board service, and leg room. Also, in machine learning modeling, the model got 96% precision in predicting passenger satisfaction using the support vector classifier.

The following are the variables from the data that will be used:

1. Gender: Gender of the passengers (Female, Male)
2. Customer Type: The customer type (Loyal customer, disloyal customer)
3. Age: The actual age of the passengers
4. Type of Travel: Purpose of the flight of the passengers (Personal Travel, Business Travel)
5. Class: Travel class in the plane of the passengers (Business, Eco, Eco Plus)
6. Flight distance: The flight distance of this journey
7. Inflight Wi-Fi service: Satisfaction level of the inflight Wi-Fi service (0:Not Applicable;1-5)
8. Departure/Arrival time convenient: Satisfaction level of Departure/Arrival time convenient
9. Ease of Online booking: Satisfaction level of online booking
10. Gate location: Satisfaction level of Gate location
11. Food and drink: Satisfaction level of Food and drink
12. Online boarding: Satisfaction level of online boarding
13. Seat comfort: Satisfaction level of Seat comfort
14. Inflight entertainment: Satisfaction level of inflight entertainment
15. On-board service: Satisfaction level of On-board service
16. Legroom service: Satisfaction level of legroom service
17. Baggage handling: Satisfaction level of baggage handling

18. Check-in service: Satisfaction level of Check-in service
19. Inflight service: Satisfaction level of inflight service
20. Cleanliness: Satisfaction level of Cleanliness
21. Departure Delay in Minutes: Minutes delayed when departure
22. Arrival Delay in Minutes: Minutes delayed when Arrival
23. Satisfaction: Airline satisfaction level (Satisfaction, neutral or dissatisfaction)

This dataset contains an airline passenger satisfaction survey. What factors are highly correlated to a satisfied (or dissatisfied) passenger? Can we predict passenger satisfaction?

Machine learning involves using algorithms to enable computers to learn and make predictions or decisions without being explicitly programmed for a particular task. There are various machine learning algorithms, each designed for specific tasks. We chose a model of algorithm-supervised learning (random forests) by classification model to Predict a categorical outcome. Here is a general outline of the machine-learning process:

Preprocessing Data

Before the data is used for the classification analysis stage, the dataset must do data preprocessing, which will include cleaning incomplete data (missing values), data transformation, and data conversion to be used at the classification stage [22].

Split Data Training and Testing

At this stage, the dataset will be divided into two parts, namely training data and test data, with four different percentage divisions to compare the accuracy results so that the results will be optimal.

Table 1. The Split Percent (%) and Total (Data)

Split Percent (%)		Total (Data)	
Data Training	**Data Test**	**Data Training**	**Data Test**
....	....	....	....
....	....	....	....
....	....	....	....
....	....	....	....

Data Collection

To understand the data, we do some data analysis as follows:

Table 2. Selected and Trained Data

Train Feature Engineering data	Selected_ feature data	Testing data	Training data
• Entertainment, • On-board service, • Legroom service, • Baggage handling, • Check-in service, • Inflight service, • Cleanliness, • Departure Delay in Minutes, • Arrival Delay in Minutes, • Satisfaction	• Age • Flight Distance • Arrival Delay in Minutes • Customer Type • Type of Travel • Class • Inflight Wi-Fi service • Ease of Online booking • Food and drink • Online boarding • Seat comfort • Inflight entertainment • On-board service • Legroom service • Baggage handling • Check-in service • Inflight service • Cleanliness	• id, • Gender, • Customer Type, • Age, • Type of Travel, • Class, • Flight Distance, • Inflight Wi-Fi service, • Departure/ Arrival time convenient , • Ease of Online booking, • Gate location, • Food and drink, • Online boarding, • Seat comfort, • Inflight entertainment, • On-board service, • Legroom service, • Baggage handling, • Check-in service, • Inflight service, • Cleanliness , • Departure Delay in Minutes, • Arrival Delay in Minutes,	• id, • Gender, • Customer Type, • Age, • Type of Travel, • Class, • Flight Distance, • Inflight Wi-Fi service, • Departure/ Arrival time convenient , • Ease of Online booking, • Gate location, • Food and drink, • Online boarding, • Seat comfort, • Inflight entertainment, • On-board service, • Legroom service, • Baggage handling, • Check-in service, • Inflight service, • Cleanliness , • Departure Delay in Minutes,

	• Satisfaction	• Arrival Delay in Minutes, • satisfaction

RESULTS AND DISCUSSION

The result of Split Data Training and Testing

At this stage, the dataset will be divided into training and test data with four different percentage divisions: 96%-4%, 91%-9%, 86%-14%, and 81%-19%.

Table 3. The Result Split Percent (%) and Total (Data)

Split Percent (%)		Total (Data)	
Data Training	**Data Test**	**Data Training**	**Data Test**
96%	4%	214742	8948
91%	9%	203558	20132
86%	14%	192373	31317
81%	19%	181188	42502

Exploratory Data Analysis

To understand the data, we do some Data Analysis as follows:

1. Imbalance checks within the satisfied and not satisfied dataset.
2. Not Available data analysis.
3. Discrete Numeric Columns and Continuous Numeric Columns Analysis.
4. Categorical columns analysis.
5. Correlation between columns analysis.

The relation of Satisfaction Passenger Satisfaction can be looked at in the Graph below:

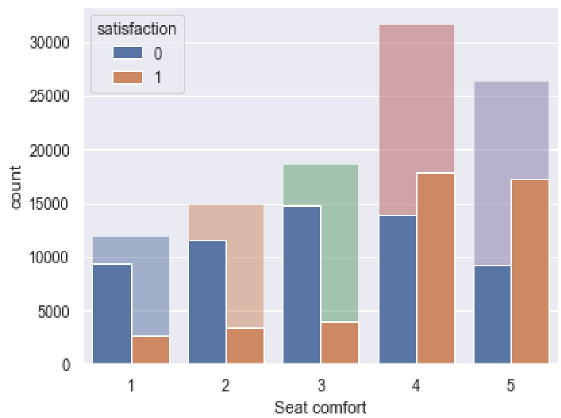

Figure 2. Passenger Satisfaction is based on the seat (Airline) comfort and number of passengers.

Figure 2 shows passenger satisfaction with the seat comfort of US Airplane. The numbers show that the passenger is more un-satisfaction passenger than satisfaction.

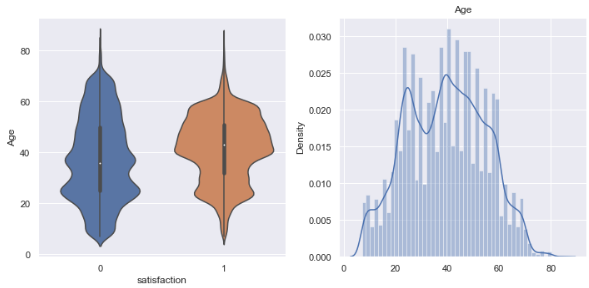

Figure 3. The Passenger Satisfaction based on Age and Density

Figure 3 shows passenger satisfaction with US Airplane. The numbers show that satisfied passengers are primarily by age 40 and un-satisfaction passengers are older than 20.

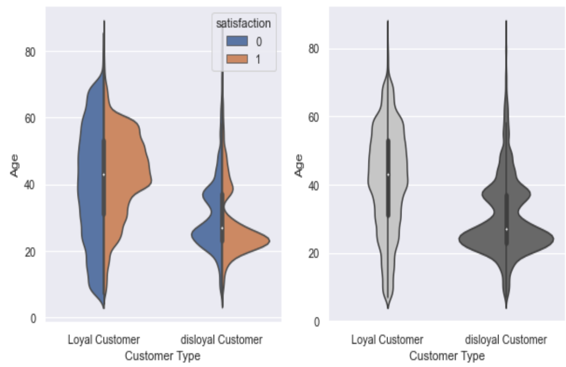

Figure 4. Passenger satisfaction is based on Loyal – Disloyal customers and their age.

Figure 4 shows loyal passenger satisfaction with US Airplane. The numbers show the satisfaction of loyal passengers mostly by age 40 and satisfaction of disloyal passengers primarily by elders older than 20.

So, from Figures 2, 3, and 4 above, we focus on examining the relationship between categorical data columns and satisfaction levels. Aiming to delve into customer satisfaction concerning these categorical variables.

Feature Engineering

1. Fill the NA columns with the median of NA_columns.
2. Transform the 0 value (Not Applicable) with the modus of the columns.
3. Transform not normally distributed data to normally distributed.

4. Encode string categorical column into numeric ordered by the sum of satisfaction within one category in each column.
5. Scale the dataset using MinMAxScaler'.

Feature Selection

In the Feature Selection, we use filter methods to get the essential features of the model. 1) We drop 'Departure Delay in Minutes' based on f-score in continuous columns because it's too correlated with 'Arrival Delay in Minutes'; 2) In Categorical columns, we are using chi-squared as a score function.

Machine Learning Modeling

1. Split the dataset to 96% training and 4% test.
2. Compare the classification models in the default setting and pick the top 3 performances using the precision score in classification problems.
3. Check the performance of the best models using confusion_matrix and ROC_AUC.
4. Check the model fitting
5. Hyperparameter tuning the model using GridSearchCV and RandomizedSearchCV
6. Compare the two default models and models after tuning as the final recap.

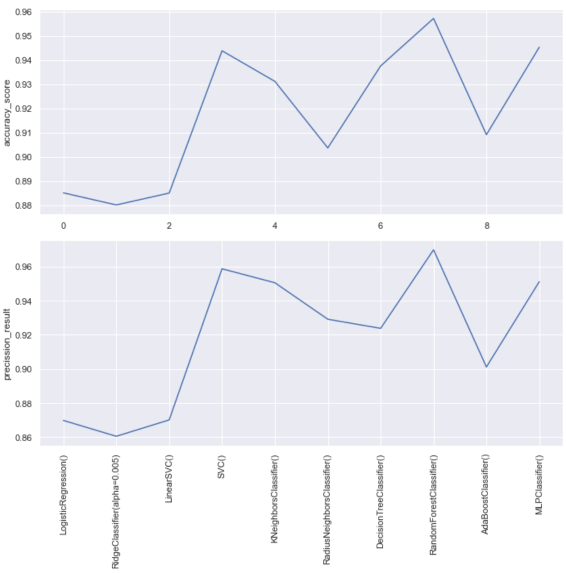

Figure 5. Precision and Accuracy Data

Figure 5 shows that Precision is concerned with the correctness of positive predictions, specifically the fraction of true positive predictions among all positive predictions. It is relevant in situations where false positives are costly or undesirable. Of all the instances predicted as positive, 6 numbers are positive.

Accuracy looks at the overall correctness of predictions, considering both true positives and true negatives. It is a broader measure and is suitable when the classes are balanced. Of all the instances, how many were correctly predicted, 6 of 10 class. They are SVC() – MLPClassifier().

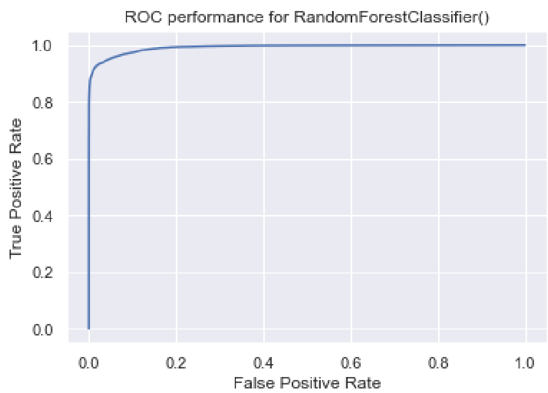

Figure 6. True and False positive rate

Figure 6 shows about Receiver Operating Characteristic (ROC) Performance. The ROC curve is used to understand how well a model can distinguish between two different classes. Typically, one class is referred to as the True Positive Rate (TPR) or Sensitivity, while the other is the False Positive Rate (FPR). In the ROC curve, the X-axis typically represents FPR, while the Y-axis represents TPR. The curve represents the relationship between TPR and FPR at various threshold values used to classify instances.

ROC visualizes the model's performance in classifying two classes and provides further insight into the trade-off between sensitivity (positive identification) and specificity (negative identification). The closer the ROC curve is to the top-left corner, the better the model performance.

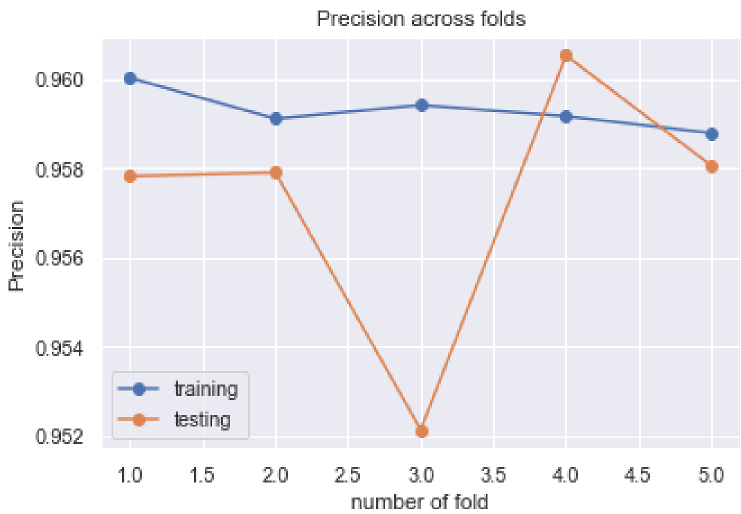

Figure 7. The training and testing data

Figure 7 shows that separating data into training and testing sets is common in developing machine learning models to ensure their good performance on unseen data. Precision across folds involves calculating the precision metric for each fold during cross-validation, contributing to a comprehensive assessment of the model's precision performance across the entire dataset. There are some folds by 3.0 and 4.0.

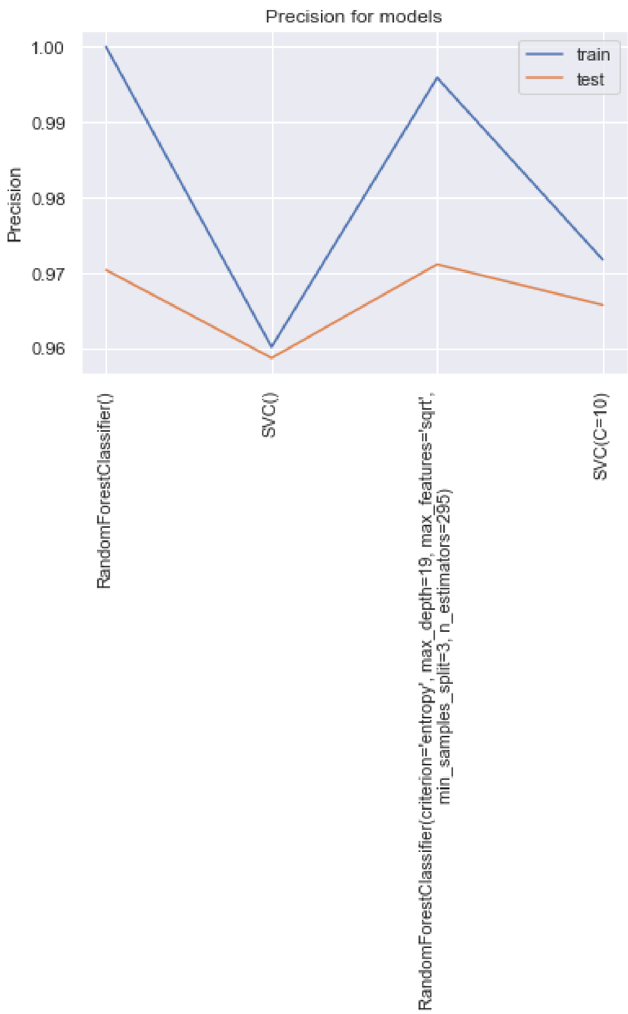

Figure 8. The precision testing and training data

Figure 8 shows a high precision value, indicating that it is likely to be correct when the model predicts a positive outcome.

So, the visualization of customer types reveals a significant difference between loyal and disloyal customers. While a majority of loyal customers appear satisfied, there is also a noticeable portion that is dissatisfied. We speculate that many loyal customers have been faithful airline users, experiencing excellent and subpar services.

Analysis of the type of travel indicates that customers traveling for business tend to be more satisfied than those traveling for personal reasons. This may be attributed to the fact that, during business travel, the company manages passenger belongings, reducing passenger concerns and increasing satisfaction levels. Visualization of class types shows that passengers in economy class exhibit a higher dissatisfaction rate than those in business class. This underscores the importance of the class in influencing customer satisfaction.

Three crucial factors identified in airline service are delay, online boarding, and class. Thus, airlines can improve these three aspects, preparing to welcome customers with better services as air travel activities resume. Online boarding, as one of the key factors, reduces the need for passengers to manually check in and stand in queues, providing a faster and more efficient experience. Class types also play a vital role. Passengers with higher budgets and frequent long-distance travelers will likely choose business or premium economy class for enhanced comfort and facilities.

The research results from training data and datasets indicate that with a 96% training and 4% testing data split, the accuracy reaches 81.466%. Although this distribution may influence accuracy values, the results suggest that airlines must minimize flight delays to improve customer satisfaction, especially for long-haul flights.

To enhance services and passenger satisfaction, airlines can leverage the information from machine learning models applied to passenger satisfaction datasets. We recommended here are some actionable insights that airlines can consider: 1) Identify Key Factors Influencing Satisfaction; 2) Personalized Service Offerings; 3) Real-Time Feedback Analysis; 4) Operational Efficiency; 5) Predictive Maintenance; 6) Enhance Communication Strategies; 7) Staff Training Programs; 8) Benchmarking Against Competitors; 9) Continuous Improvement Cycle; 10) Promotional Strategies.

In conclusion, leveraging machine learning insights from passenger satisfaction datasets empowers airlines to make informed decisions for enhancing services. By implementing these actionable insights, airlines can improve passenger satisfaction and stay competitive in the dynamic aviation industry.

CONCLUSION

The analysis of categorical data and its correlation with satisfaction levels provides valuable insights into customer preferences within the airline industry. Visualizing customer types highlights a significant distinction between loyal and disloyal customers, with a notable portion of loyal customers expressing dissatisfaction. This suggests that loyal customers have encountered varying service qualities despite their overall satisfaction.

Leveraging machine learning insights from passenger satisfaction datasets empowers airlines to make informed decisions for enhancing services. By implementing these actionable insights, airlines can improve passenger satisfaction and stay competitive in the dynamic aviation industry.

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