UNDERSTANDING PASSENGER SATISFACTION THROUGH AIRLINE SERVICE QUALITY : A STRUCTURAL EQUATION MODELLING PERSPECTIVE

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ABSTRACT

Customer satisfaction plays a vital role in the airline industry, as it strongly influences customer loyalty, brand image, and long-term business success. This project aims to analyze airline customer satisfaction by combining Structural Equation Modeling (SEM) with machine learning techniques. Customer opinion data, along with service quality indicators and demographic details, is used to identify the key factors that affect overall passenger satisfaction. A hybrid analytical approach is applied to predict and classify satisfaction levels effectively. The results show that the proposed hybrid model significantly improves prediction accuracy. Among the machine learning techniques used, the Random Forest classifier performs the best, achieving an accuracy of 92%, making it suitable for handling complex and high-dimensional airline data. Other models such as Logistic Regression, Support Vector Machine (SVM), and Decision Tree also produce reliable results, offering a comparative view of their classification performance.

The integration of SEM and machine learning provides a balanced framework that supports both interpretability and accuracy. SEM helps in analyzing hidden factors such as emotional satisfaction, perceived value, and customer loyalty, while machine learning models capture complex relationships among service attributes. The study identifies important satisfaction drivers including in-flight service quality, staff behavior, ease of booking, and on-time performance. Feature selection and feature engineering further enhance model efficiency and reliability. This study also contributes to improving data-driven decision-making in airline service management. By combining structured survey data with unstructured customer reviews, the proposed model offers deeper insights into passenger behavior, preferences, and concerns. Additionally, the use of sentiment analysis strengthens real-time prediction and service optimization . Overall, the findings demonstrate that the hybrid SEM–machine learning approach is effective in analyzing and forecasting airline customer satisfaction. The results provide useful recommendations for airline management to improve customer retention, operational performance, and personalized service offerings. The proposed framework can also be extended to related sectors such as hospitality and transportation, supporting the development of smart and customer-focused business analytics systems.

Keywords – Random Forest, SVR, Logistic Regression, Decision Trees, MLP, Airlines, Customer Satisfaction.

1.Introdution

Customer satisfaction is very important in the airline industry because it directly affects customer loyalty and business profits. Passenger satisfaction depends on many factors such as service quality, travel experience, and personal characteristics. Although airlines collect large amounts of customer feedback, it is difficult to obtain useful information without proper analytical methods.
Structural Equation Modeling (SEM) is an effective technique used to analyze both measurable and non-measurable factors like service quality, passenger experience, and emotional satisfaction. These factors cannot be measured directly but have a strong impact on customer satisfaction. In practical applications, combining SEM with machine learning methods improves prediction accuracy and classification results. SEM includes measurement models and structural models that help study relationships between observed and hidden variables at the same time. This allows researchers to understand how different service attributes influence customer satisfaction, perceived value, and loyalty. Unlike traditional statistical methods, SEM can identify indirect relationships and mediating effects, giving a clearer picture of passenger behavior.

SEM is especially useful for evaluating airline service quality by identifying key dimensions such as reliability, responsiveness, assurance, empathy, and physical facilities. These dimensions help explain how passengers form their overall opinion about airline services. The analysis obtained through SEM helps airlines make better strategic decisions, improve service quality, introduce innovations, and enhance customer experience. The main objective of this study is to improve the prediction of airline customer satisfaction by integrating SEM with machine learning techniques. The dataset used includes service ratings, customer demographics, and passenger reviews. Four machine learning models—Random Forest, Logistic Regression, Support Vector Machine (SVM), and Decision Tree—are used to compare classification performance. Among these models, Random Forest provides the highest accuracy of 92%.

The results show that combining SEM with supervised machine learning techniques produces more accurate, reliable, and understandable results for predicting airline customer satisfaction.

2. Literature Review .

The study of airline service quality and its effect on customer satisfaction has received sustained attention from researchers due to the dynamic and highly competitive nature of the aviation industry. As passengers are offered multiple airline choices, service quality has become a critical factor influencing satisfaction, loyalty, and long-term business success. Airline service quality is generally considered a multidimensional concept that includes operational reliability, employee behavior, safety standards, comfort, punctuality, and overall service efficiency. Customer satisfaction emerges when passengers perceive that the delivered service meets or exceeds their expectations. Several studies highlight the importance of employee performance in shaping passenger perceptions.

Choi et al. [1] identified cabin crew appearance, attitude, and emotional engagement as key contributors to passenger satisfaction and loyalty. Their research emphasized that courteous behavior and effective communication by flight attendants significantly enhance the perceived quality of airline services. Similarly, Chow and Fung [2] investigated airline services within the Chinese aviation market and concluded that customer satisfaction directly contributes to improved financial performance and competitive strength, reinforcing the strategic role of service quality.

Customer perception and corporate image have also been widely examined in airline research. Cintamur [3] analyzed the relationship between service quality and corporate reputation, finding that consistent service excellence encourages repeat travel behavior and positive word-of-mouth. In the airline sector, where services are largely intangible, reputation acts as a powerful decision-making factor for passengers. Cohen's statistical framework [4] has played a foundational role in service quality research by providing reliable quantitative methods for measuring and validating research outcomes.Operational efficiency is another essential element influencing passenger satisfaction. Barros et al. [5] explored airport-level service performance and demonstrated that check-in efficiency, transfer processes, and ground services significantly affect the overall travel experience. Additionally, aviation authority reports and industry statistics [6] supply essential operational data that enable researchers to analyze service trends, passenger flow, and performance indicators across the airline industry.With the advancement of analytical techniques, recent studies have adopted sophisticated modeling approaches to better understand passenger behavior. Ding et al.

[7] proposed a hybrid model combining Structural Equation Modelling (SEM) and Neural Networks, demonstrating that integrating behavioral models with machine learning techniques improves prediction accuracy for customer satisfaction and loyalty. Ekiz et al. [8] further applied SEM in airline service studies and confirmed strong causal relationships between service quality dimensions, customer satisfaction, and behavioral intentions. Ensuring methodological accuracy has become a priority in service quality research. Faul et al. [9] introduced G*Power as an effective tool for calculating sample size and statistical power, improving the reliability of empirical studies. Fornell and Larcker [10] established widely accepted criteria for assessing construct validity and reliability in SEM models, which remain essential for service quality analysis. Gallarza et al. [11] extended this research by demonstrating that service quality and perceived value jointly influence customer loyalty, particularly in competitive airline markets. Theoretical models have also evolved to capture airline-specific service characteristics.

Grönroos [12] introduced a service quality framework that distinguishes between technical quality, representing service outcomes, and functional quality, representing service delivery processes. Both dimensions are critical in evaluating airline performance. Hair et al. [13] provided comprehensive guidelines for multivariate analysis and SEM applications, making their work a key methodological reference in airline and service quality research. More recent studies have expanded airline service quality research by incorporating psychological and behavioral perspectives. Hameed et al. [14] identified a strong link between service satisfaction, customer trust, and sustainable behavior, highlighting the growing relevance of ethical and environmental considerations in airline operations. Additionally , Hapsari et al. [15] demonstrated that customer engagement and trust act as mediating variables between service quality and passenger loyalty, emphasizing the importance of emotional connections in fostering long-term relationships.

3. **Methodology**

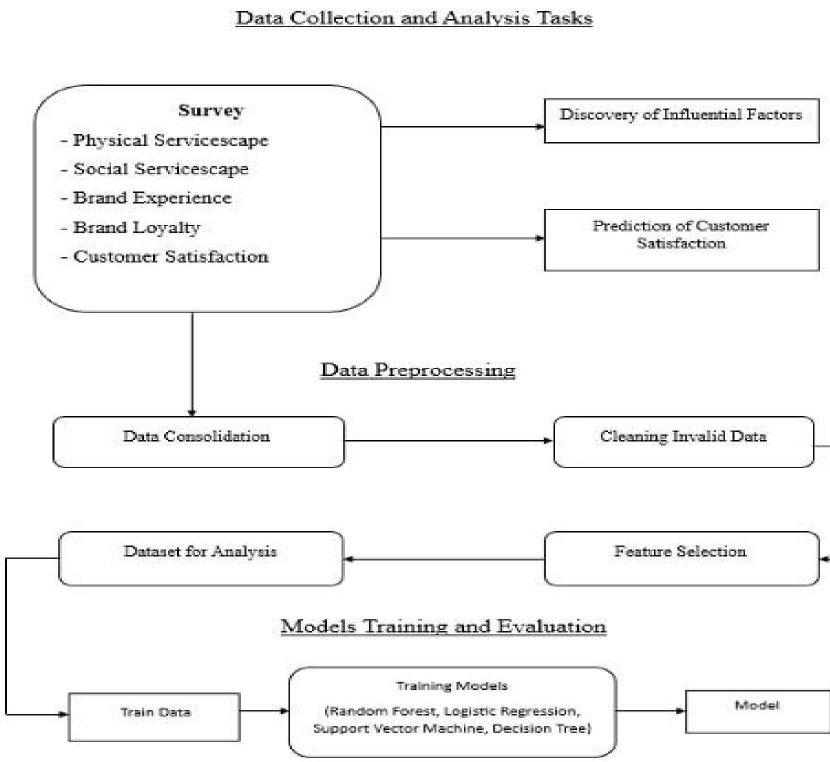

Figure.3.1: Project architecture of Understanding Passenger Satisfaction Through Airline Service Quality : A Structural Equation Modelling Perspective**.**

The project architecture illustrates the systematic procedure adopted in this study to analyze airline customer satisfaction, beginning from data input and ending with final prediction and interpretation. The overall methodology follows a structured, data-driven approach that integrates survey-based data collection, preprocessing techniques, and model-based analysis to identify key factors influencing customer satisfaction in the airline industry. The initial stage of the methodology focuses on data collection and analysis tasks. Customer feedback is gathered primarily through structured surveys designed to capture passengers' perceptions across several service dimensions. These dimensions include physical service scape (such as comfort, cleanliness, and seating arrangement), social service scape (staff behavior and interpersonal interactions), brand experience, brand loyalty, and overall customer satisfaction. The collected responses serve as the foundation for identifying influential service attributes and understanding their impact on customer satisfaction levels.

Following data collection, the study proceeds to the data preprocessing phase, which ensures the quality and reliability of the dataset. This stage involves data consolidation, where information from multiple sources such as survey responses, online reviews, and operational airline data is combined into a single dataset. Data cleaning is then performed to remove incomplete responses, inconsistencies, and outliers that could negatively affect analysis results. Feature selection techniques are applied to identify the most significant variables influencing customer satisfaction, such as flight punctuality, in-flight services, baggage handling efficiency, and ticket pricing. Once the dataset is prepared, it moves to the model training and evaluation phase. The cleaned and processed data is divided into training and testing sets to ensure unbiased evaluation. Various machine learning models are trained using the prepared dataset, including Decision Tree, Random Forest, Support Vector Machine, and Logistic Regression algorithms. These models are employed to analyze customer satisfaction patterns, predict satisfaction levels, and identify potential dissatisfaction or churn risks. Model performance is evaluated using appropriate metrics, and the best-performing model is selected for final analysis.

3.2 Use Case Diagram

The use case diagram illustrates the complete process used to evaluate customer satisfaction in the airline industry by involving three primary stakeholders: the Customer, the Manager, and the Data Analyst. Each stakeholder has a clearly defined role that contributes to collecting customer opinions, analyzing service performance, and implementing improvements. Customers initiate the process by interacting with the airline system to search for available flights, make reservations, monitor flight status, and share feedback after their journey. This feedback reflects the customer's experience and satisfaction level, serving as an essential input for understanding service quality and identifying problem areas. Customer responses provide valuable insights into expectations, preferences, and service gaps. Once the feedback is received, the Manager becomes responsible for reviewing and responding to customer concerns. The manager examines complaints and suggestions, prepares improvement strategies, and ensures that corrective actions are carried out.

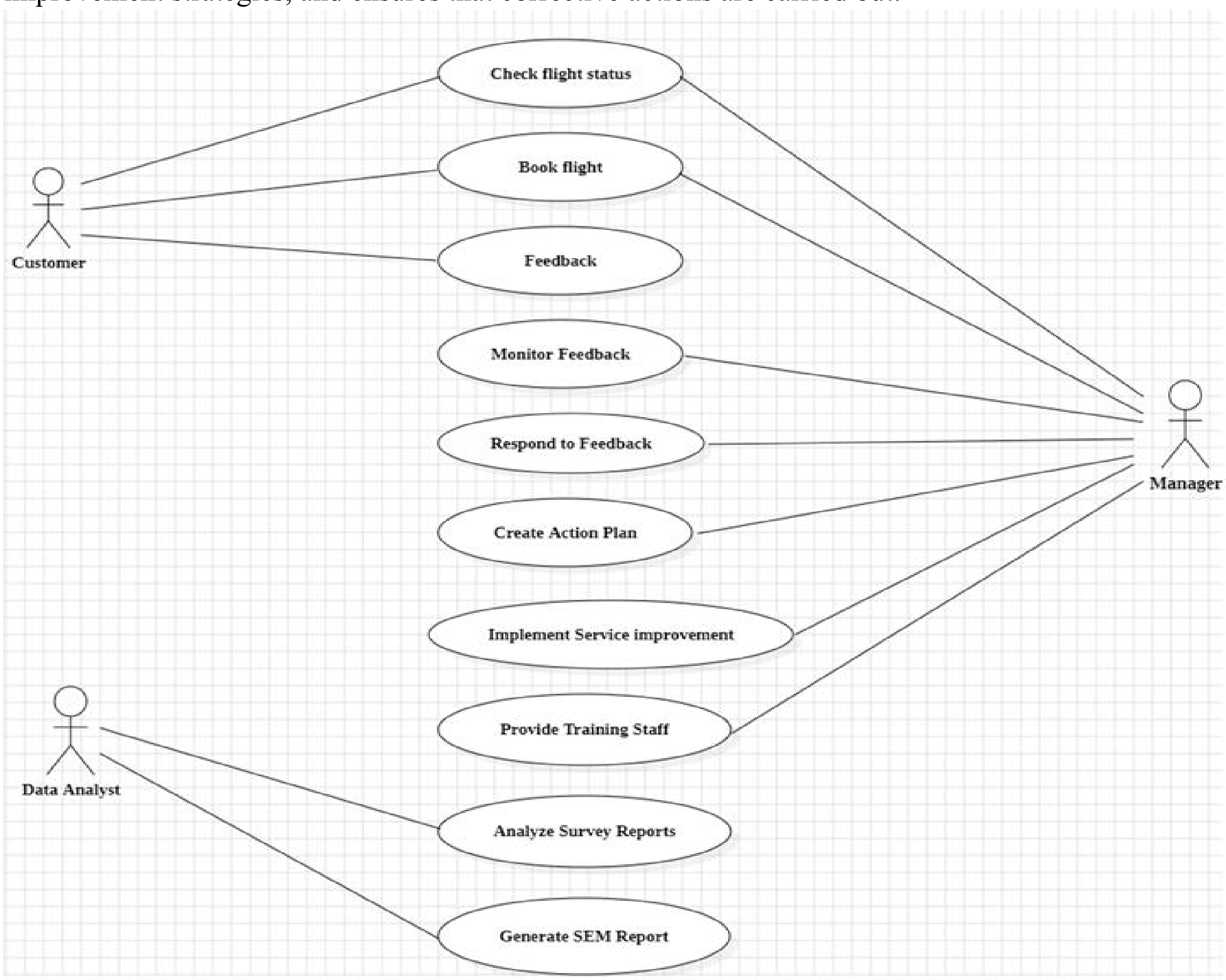

Figure.3.2: Use Case Diagram for Understanding Passenger Satisfaction Through Airline Service Quality : A Structural Equation Modelling Perspective**.**

The Data Analyst is responsible for processing and interpreting customer satisfaction data. This includes analyzing survey responses, identifying trends, and determining the factors that most strongly influence customer satisfaction. Structural Equation Modeling (SEM) is used to study the relationships between service quality variables and overall satisfaction. SEM offers a systematic, data-driven approach that improves accuracy and supports better decision-making compared to traditional analysis techniques.

3.3 Class Diagram

The class diagram represents how three main components—Customer, Manager, and Data Analyst—interact within an airline customer satisfaction system. Each class defines specific attributes and functions that describe its role in the system.

The Customer class stores basic details such as customer ID, name, and email, and allows customers to book flights, check flight status, cancel bookings, and provide feedback. These actions reflect how customers interact with airline services. The Manager class includes manager-related information and supports activities such as reviewing reports, implementing service improvements, managing flight operations, and sharing necessary details with customers. Managers play an important role in converting customer feedback into service enhancements.

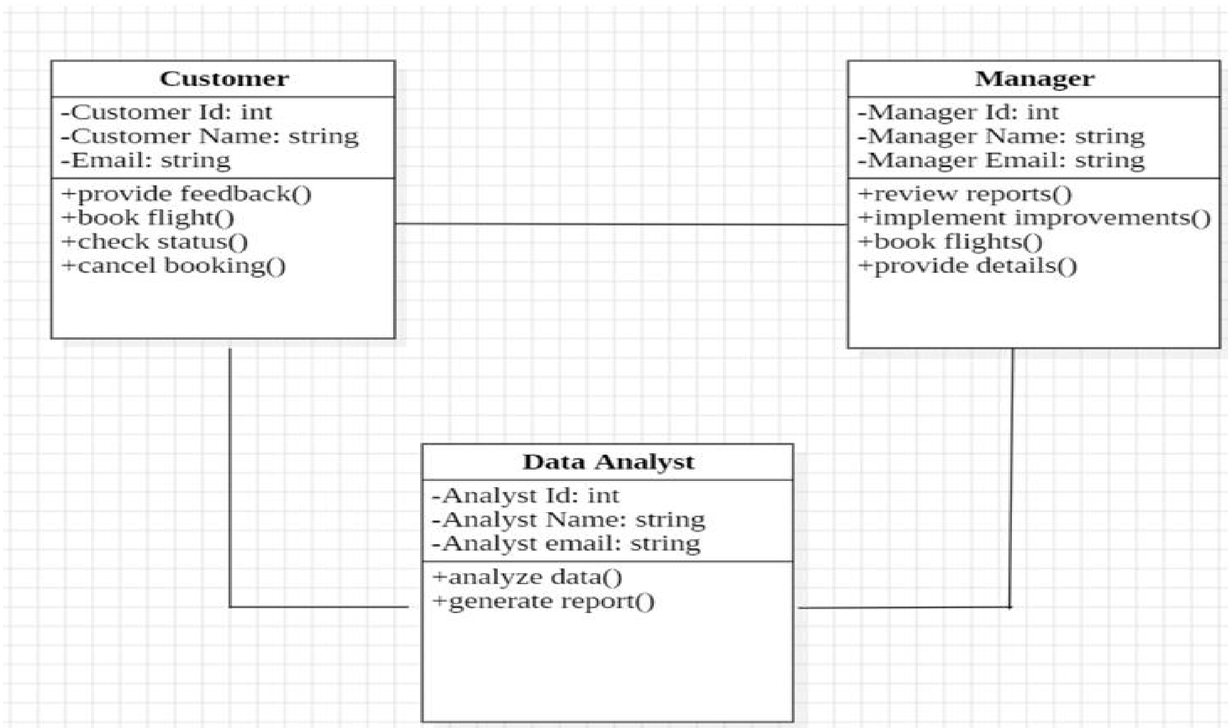

Figure .3.3: Class Diagram for Understanding Passenger Satisfaction Through Airline Service Quality : A Structural Equation Modelling Perspective**.**

The Data Analyst class focuses on analyzing customer satisfaction data and generating reports. By examining feedback and performance data, the analyst provides valuable insights that help managers make informed decisions. Overall, the class diagram clearly shows how customer feedback is collected, analyzed, and used to improve airline services through a well-structured and efficient process.

3.4 Sequence Diagram

The sequence diagram explains how the Customer, Manager, and Data Analyst interact during flight booking, feedback handling, and data analysis. The process begins when the customer logs into the system. The manager verifies the login details and grants access to the customer.

After successful login, the customer requests flight booking. The manager checks flight availability and status before confirming the booking, and the system notifies the customer once the booking is completed.

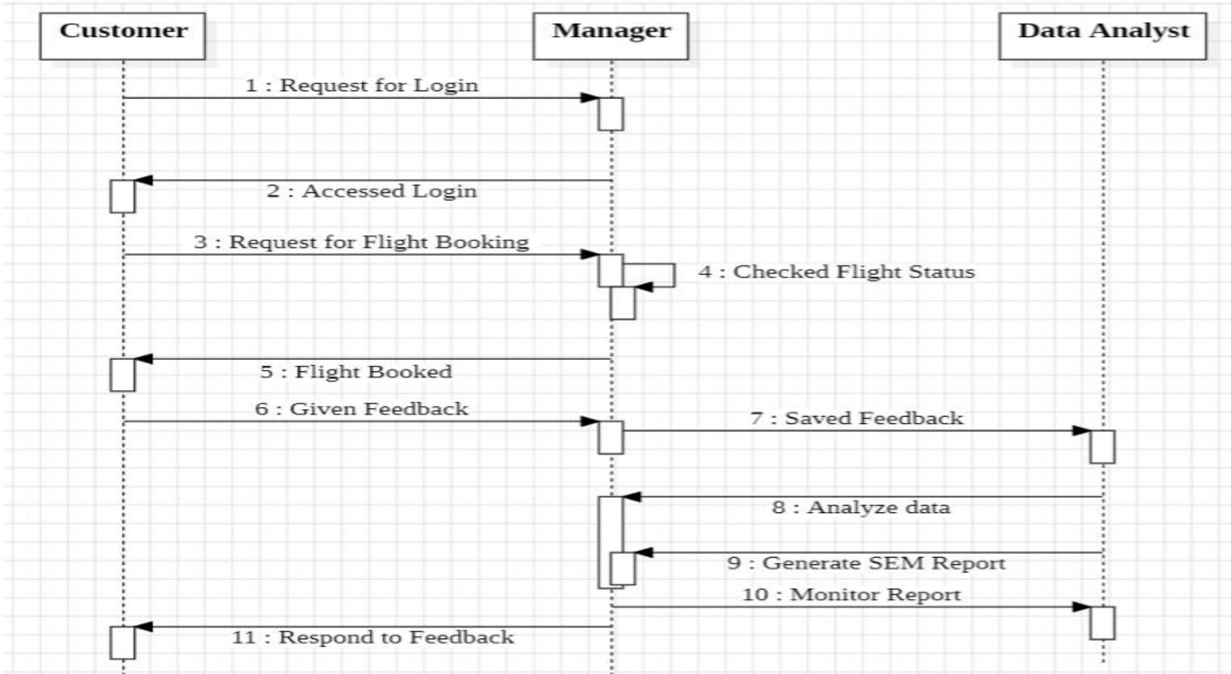

Figure.3.4: Sequence Diagram for Understanding Passenger Satisfaction Through Airline Service Quality: A Structural Equation Modelling Perspective**.**

Once the journey is over, the customer submits feedback, which is collected and stored by the manager. This feedback is then shared with the data analyst for detailed evaluation. The data analyst analyzes the feedback data and generates a report using Structural Equation Modeling (SEM).Based on the report findings, the manager takes appropriate actions and responds to the customer. This sequence diagram highlights a clear and organized flow of operations, ensuring effective feedback analysis, improved service quality, and data-driven decision-making

4. Implementation

4.1 Random Forest

The Random Forest algorithm is used as an important part of the customer satisfaction prediction system. Random Forest is selected because it can handle large and complex data effectively and provide reliable predictions. It helps in identifying the key factors that influence customer satisfaction by learning from multiple service-related attributes. During the training phase, the Random Forest model is trained using customer feedback data. The algorithm builds several decision trees using different subsets of the data. Each tree makes its own prediction, and the final result is obtained by combining the outputs of all trees. This approach helps reduce errors and improves prediction accuracy. It also minimizes overfitting, making the model more reliable for real-world data.

One of the major advantages of Random Forest is its ability to identify important features that affect customer satisfaction. This helps in understanding which airline services, such as punctuality, comfort, or service quality, have the greatest impact on passenger experience. In the prediction phase, the trained model is used to analyze new customer feedback. Based on the input attributes, the model predicts whether the customer is satisfied or dissatisfied. These predictions help airlines recognize problem areas early and take corrective actions to improve services.

4.2 Logistic Regression

Logistic Regression is applied in this study to classify airline passengers as satisfied or dissatisfied based on their service experience. It works by estimating the probability of customer satisfaction using various airline service attributes such as seating comfort, staff behavior, in-flight facilities, and punctuality. During model training, Logistic Regression learns the relationship between service factors and customer satisfaction by adjusting feature weights to minimize prediction errors.

This allows the model to highlight which service elements have the strongest influence on passenger satisfaction. One of the key advantages of this method is its transparency, as it clearly shows how each attribute contributes to the final outcome.4.3 Decision TreesIn the testing phase, the trained model evaluates new customer feedback and calculates a satisfaction probability. Passengers whose probability value exceeds a defined threshold are categorized as satisfied, while the rest are marked as dissatisfied. This structured classification process helps airlines monitor service quality, identify improvement areas, and make informed decisions to enhance the overall travel experience.

4.3 Decision Trees

Decision Trees are used in this study to evaluate airline customer satisfaction due to their simple and transparent decision-making process. The model categorizes passengers as satisfied or dissatisfied by examining key airline service factors such as seating comfort, staff support, baggage services, and ticket cost.

During training, the Decision Tree learns from customer feedback by repeatedly splitting the data based on the most influential attributes. At each level of the tree, the model selects the best condition to separate the data, allowing a clear understanding of how different service features affect passenger satisfaction.

In the testing phase, new customer inputs are processed through the learned decision rules until a final classification is reached. This method enables airlines to easily interpret results, identify service weaknesses, and apply focused improvements to enhance customer satisfaction and overall service performance.

4.4 Support Vector Machine

In this study, the Support Vector Machine (SVM) approach is applied to evaluate airline customer satisfaction due to its reliability in handling large and complex datasets. SVM works by separating satisfied and dissatisfied passengers using airline service parameters such as flight punctuality, seating quality, staff responsiveness, baggage handling, and in-flight services. During model training, SVM identifies the most effective separating boundary, known as the hyperplane, which clearly divides customer satisfaction levels. The model aims to maximize the distance between the closest data points of each class, thereby improving prediction accuracy.

When passenger satisfaction patterns are not linearly separable, kernel techniques allow SVM to transform the data into a higher-dimensional space, enabling better classification. In the testing phase, the trained SVM model processes new passenger feedback and assigns satisfaction labels based on learned patterns. This method helps airlines detect service strengths and weaknesses, understand customer expectations, and implement targeted improvements.

4.5 Dataset Description

The airline customer satisfaction dataset used in this study offers comprehensive insights into passenger travel experiences by covering a wide range of personal, travel-related, and service quality factors. It includes demographic information such as age, gender, and customer category, which helps differentiate between first-time passengers and loyal travelers. The dataset also contains detailed travel information, including the purpose of travel (business or personal), travel class (Economy, Business, or First Class), and flight distance. These variables support a deeper analysis of how different passenger groups perceive airline services and how satisfaction levels vary across travel types.

Service quality evaluation forms a core part of the dataset. Passengers provide ratings on a scale of 1 to 5 for multiple service aspects such as seat comfort, in-flight WiFi, food and beverage quality, cleanliness, entertainment facilities, cabin crew service, legroom space, baggage handling, and check-in services. In addition, convenience-related factors such as online booking ease, boarding efficiency, gate location, and schedule convenience are recorded. These ratings help identify which services positively or negatively influence customer satisfaction.

4.6 Performance Metrics

Accuracy.

Accuracy is an important measure used to check how well a model predicts airline customer satisfaction. It shows the percentage of customers whose satisfaction level (satisfied or dissatisfied) is predicted correctly. A higher accuracy means the model is more reliable and useful for improving service quality. In Structural Equation Modeling (SEM), accuracy is reflected through model fit values, while in machine learning it is calculated using classification results. Generally, an accuracy above 85% indicates a strong predictive model. However, accuracy alone is not enough, so it is usually evaluated along with precision, recall, and F1-score.

Formula:

Accuracy = (Correct Predictions / Total Predictions) × 100

Classification Report

A classification report gives a detailed view of how well the model performs for each category, such as satisfied and dissatisfied customers. It includes important measures like precision, recall, and F1-score, which help understand the model’s strengths and weaknesses.

Precision

Precision shows how many of the customers predicted as dissatisfied are actually dissatisfied. High precision means the model makes fewer incorrect dissatisfaction predictions, helping airlines focus only on real service problems. This is especially useful when dissatisfied customers are fewer than satisfied ones.

Formula:

Precision = True Positives / (True Positives + False Positives) × 100

Recall

Recall measures how well the model identifies all truly dissatisfied customers. A high recall value means the model successfully detects most unhappy passengers, allowing airlines to respond quickly and reduce customer loss.

Formula:

Recall = True Positives / (True Positives + False Negatives) × 100

F1-Score

The F1-score combines precision and recall into a single value. It helps balance the trade-off between identifying unhappy customers correctly and avoiding false alarms. This metric is very useful when the dataset is unbalanced, meaning satisfied customers are much more than dissatisfied ones.

Formula:
F1 = 2 × (Precision × Recall) / (Precision + Recall)F1 = 2 × (Precision × Recall) / (Precision + Recall)

4.7 Confusion Matrix

A confusion matrix is a simple but powerful method used to evaluate how well a classification model predicts airline customer satisfaction. It compares the model's predicted results with the actual feedback given by customers and shows how accurately the model separates satisfied and dissatisfied passengers.

The confusion matrix is made up of four main parts:

True Positives (TP): Customers who are satisfied and correctly predicted as satisfied.

False Positives (FP): Customers who are dissatisfied but wrongly predicted as satisfied.

True Negatives (TN): Customers who are dissatisfied and correctly identified as dissatisfied.

False Negatives (FN): Customers who are satisfied but wrongly predicted as dissatisfied.

These values help airlines understand how reliable their prediction model is. A model with a high number of true positives and true negatives shows strong performance and can support better decision-making related to service improvement and marketing planning. However, a large number of errors can weaken the usefulness of the model. If there are many false positives, airlines may miss serious service issues because unhappy customers appear satisfied in the results. On the other hand, too many false negatives may cause airlines to waste time and resources trying to fix problems that do not actually exist.

Therefore, the confusion matrix is an important tool for improving classification models. By reducing misclassifications, airlines can gain clearer insights into customer opinions, enhance service quality, personalize customer experiences, and take timely actions to maintain high levels of customer satisfaction..

5. Results

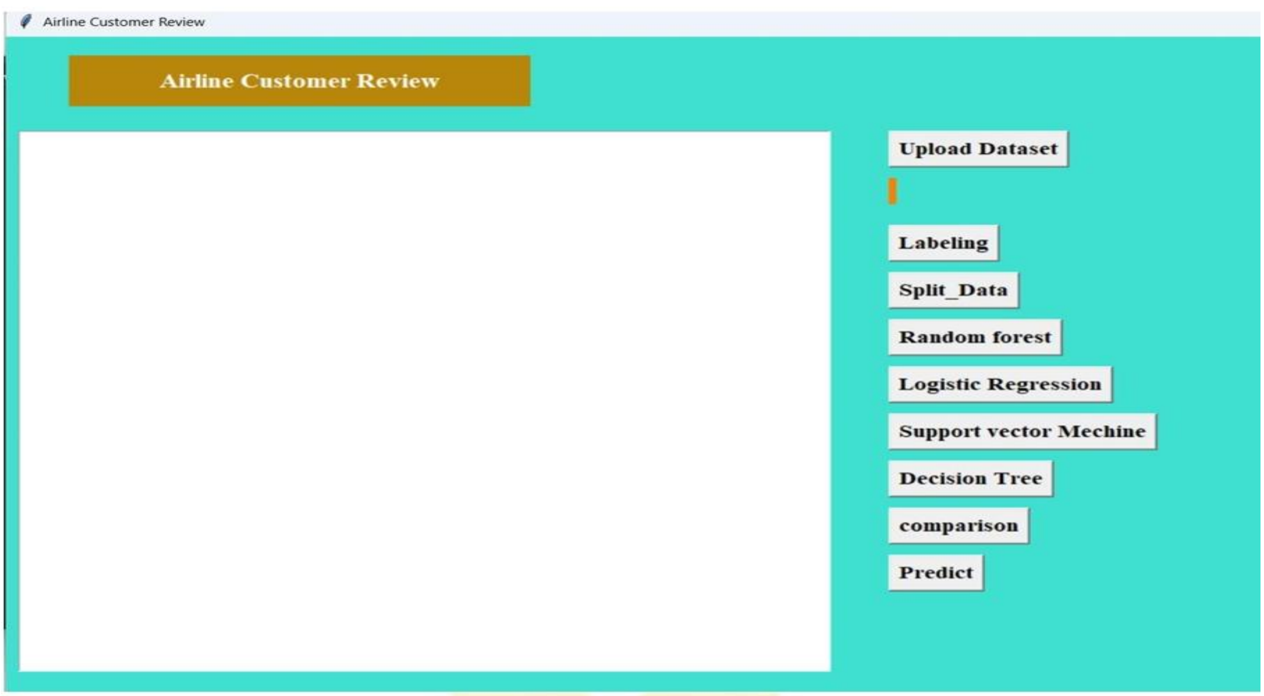

Figure.5.1: home page

Figure.5.2: Dataset uploaded page

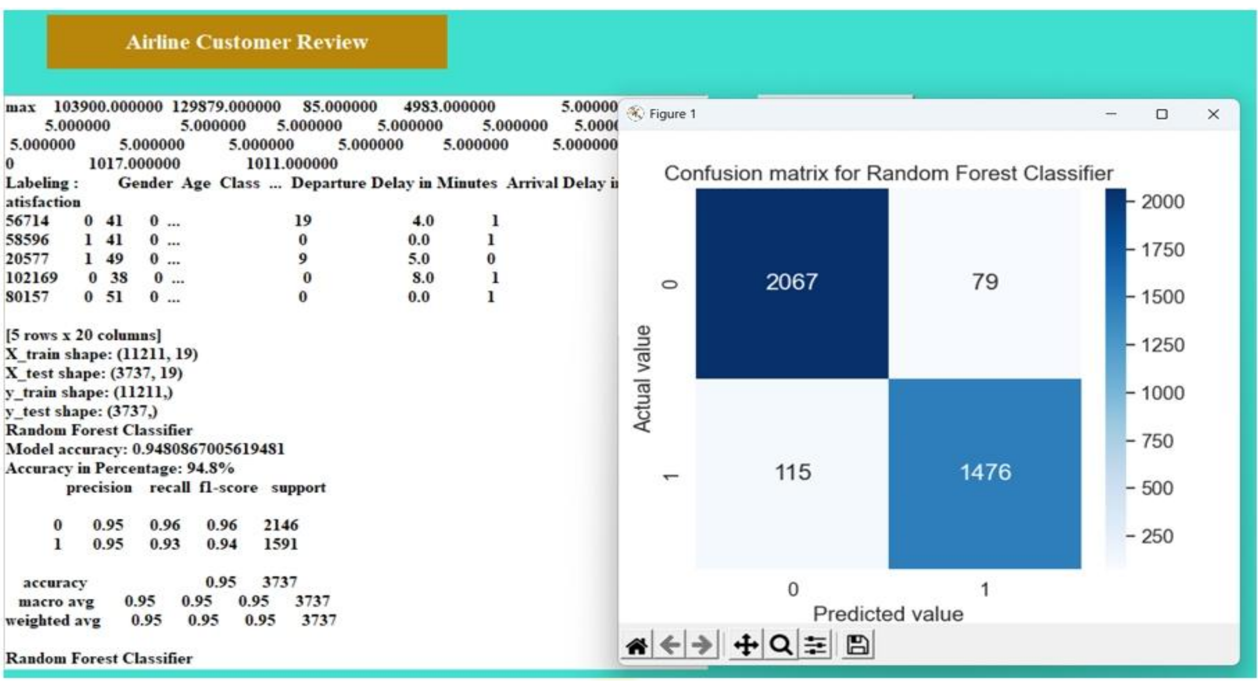

Figure.5.3: Random Forest Algorithm Page

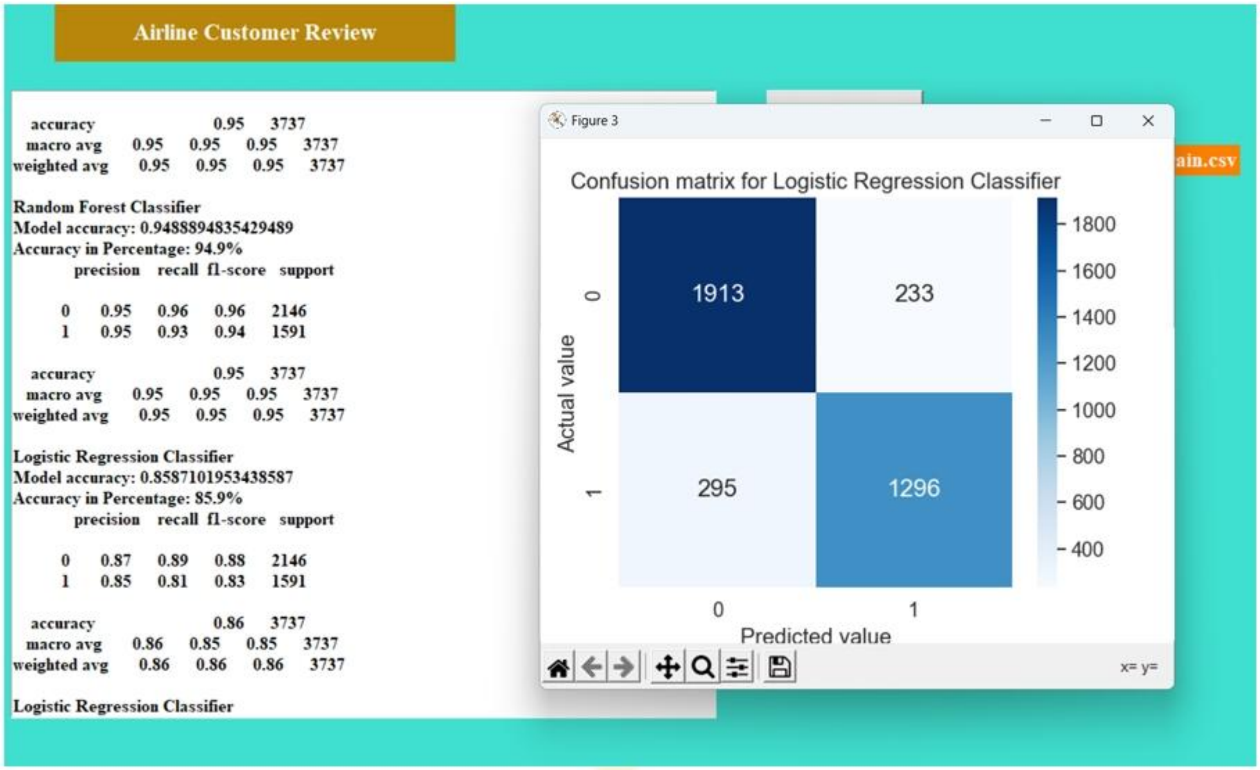

Figure.5.4: Logistic Regression Classifier Algorithm Page

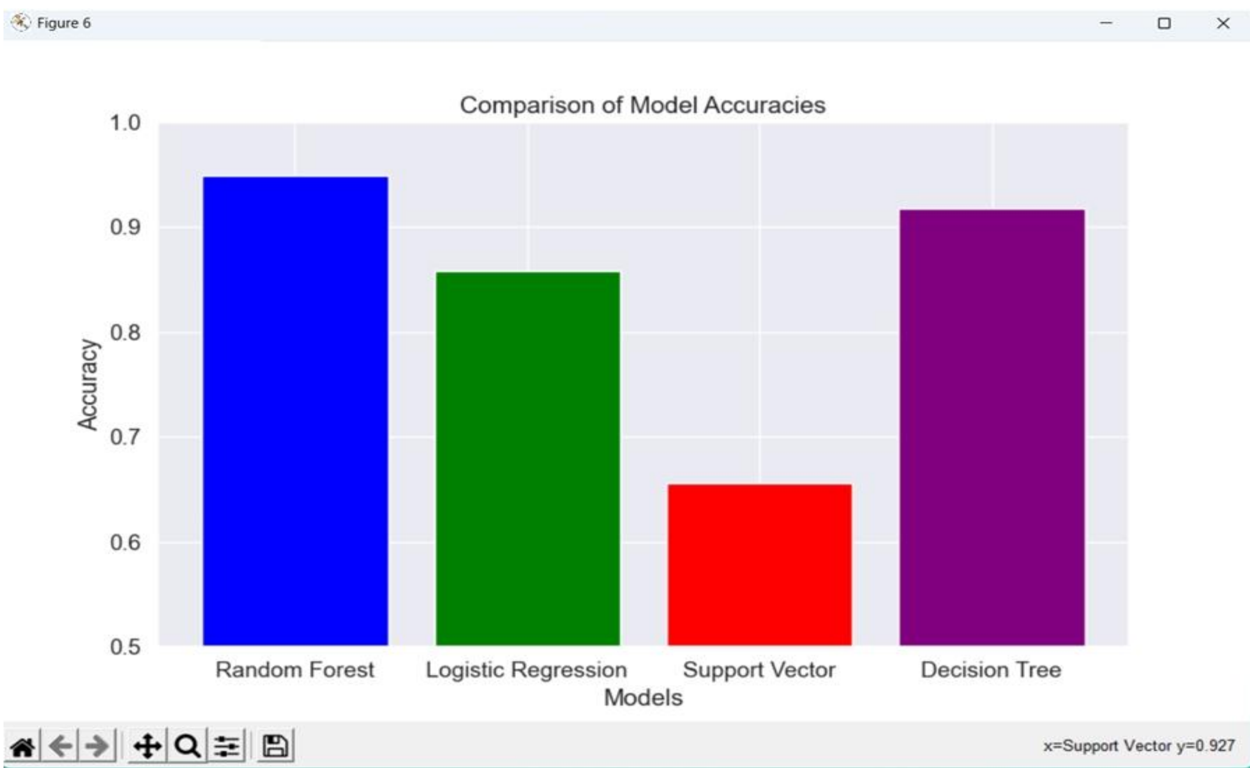

Figure.5.5: Comparison of Algorithms Page

6. Conclusion

This study used Structural Equation Modeling (SEM) to analyze airline customer satisfaction and identify the main factors influencing passenger loyalty and perceptions. The model combined statistical techniques to evaluate how service quality, in-flight experience, support services, and pricing affect satisfaction.

The findings show that SEM helps airlines understand customer expectations, recognize service gaps, and implement targeted improvements. The framework is reliable across different customer groups and can be further enhanced in future studies using real-time feedback and advanced data analysis.

7. Future Enhancement.

The proposed model for evaluating airline customer satisfaction can be further improved by expanding the type and source of data used in the analysis. Collecting live feedback through mobile platforms, digital check-ins, and post-travel surveys can help airlines track passenger opinions more effectively and take timely action. In future work, combining Structural Equation Modeling with artificial intelligence and machine learning can strengthen predictive capability. These tools can process large and complex datasets, uncover hidden trends in passenger behavior, and support more accurate forecasting of customer satisfaction and loyalty.

Another enhancement involves analyzing customer emotions and opinions expressed on social media and online review platforms. Sentiment analysis can provide a richer understanding of passenger experiences that goes beyond traditional numerical ratings, offering airlines deeper insights into customer feelings and expectations. Future research can also include external influences such as economic shifts, operational disruptions, and technological advancements in aviation services. Considering these elements will make the model more realistic and responsive to real-world conditions.

Additionally, conducting studies across different regions and cultures can help airlines understand varying passenger expectations and adapt their services accordingly. Finally, regular updates to the measurement framework, validation methods, and data collection processes will ensure the model remains accurate, reliable, and relevant in a constantly evolving airline industry.

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