Predictive Models with XAI: A Comparative Study of Enhancing Airline Customer Satisfaction

Cloë C. E. van Geest
x00204826@mytudublin.ie
Technological University Dublin
Dublin, Ireland

Yong Wan Yit
x00205680@mytudublin.ie
Technological University Dublin
Dublin, Ireland

Zaur T. Gouliev
x00205702@mytudublin.ie
Technological University Dublin
Dublin, Ireland

Keith Quille
keith.quille@tudublin.ie
Technological University Dublin
Dublin, Ireland

ABSTRACT

In today's airline industry, it is crucial to keep customer happy and satisfied. Airlines are always looking for ways to improve their services and relationships with passengers so they can make necessary improvements. The primary objective of this study is to predict customer satisfaction based on various parameters and identify areas in which the airline can enhance its services to generate more satisfied customers. The models were trained on an Airlines Customer Satisfaction dataset, provided by IIT Roorkee in 2020 containing 129,880 rows and 24 columns, including the target variable "satisfaction". The study employed two different approaches to make predictions: a Blackbox approach using a deep neural network which obtained an overall accuracy of 92% and a Glassbox approach using a decision tree which reached 94% accuracy. Both approaches were evaluated by standard measures such as accuracy, loss, precision, recall, f1-score, and confusion matrices. In addition, LIME and SHAP approach were applied to the models to retrieve further insights into the predictions and feature importance. The results indicated that XAI explains the Blackbox approach well. The Glassbox approach, as it is explainable on its own, does not require XAI. Therefore, after comparing the models' accuracy and level of explainability, researchers recommend the use of the Glassbox approaches for airline customer satisfaction.

CCS CONCEPTS

• Computing methodologies → Artificial intelligence; **Neural networks**; **Model development and analysis**; **• Human-centered computing → Human computer interaction (HCI)**.

KEYWORDS

Deep Learning, XAI, Glassbox model, Blackbox model, Airline Customer Satisfaction

HCAIep '23, December 14–15, 2023, Dublin, Ireland

ACM ISBN 979-8-4007-1646-1/23/12.
https://doi.org/10.1145/3633083.3633189

ACM Reference Format:
Cloë C. E. van Geest, Yong Wan Yit, Zaur T. Gouliev, and Keith Quille. 2023. Predictive Models with XAI: A Comparative Study of Enhancing Airline Customer Satisfaction. In *Human Centered AI Education and Practice Conference 2023 (HCAIep '23), December 14–15, 2023, Dublin, Ireland*. ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3633083.3633189

1 INTRODUCTION

In today's highly competitive airline industry, ensuring customer satisfaction is paramount to the success and sustainability of any airline company [1]. Airlines continuously strive to improve their services and build strong relationships with passengers, as happy and satisfied customers are more likely to become loyal, repeat travelers and advocates for the airline. As a result, airlines are constantly seeking innovative ways to enhance the passenger experience and identify areas where improvements can be made. The ability to accurately predict customer satisfaction is a critical aspect of this endeavor, and the integration of artificial intelligence (AI) and machine learning techniques has emerged as a powerful tool to achieve this objective.

The primary aim of this study is to leverage explainable AI to forecast customer satisfaction within the airline industry. This is a challenging task due to the multifaceted nature of passenger preferences and the myriad factors that can influence satisfaction levels. Airlines have access to a wealth of data, ranging from passenger demographics and flight details to in-flight services and post-flight feedback. Harnessing this complex dataset to discern patterns and predict passenger satisfaction is a formidable undertaking.

To tackle this challenge, the study adopts two main approaches: Glassbox and Blackbox. Glassbox methods, exemplified by decision tree classifiers, offer clear and interpretable insights into the decision-making process. In this context, decision trees provide a visual representation of decision points based on specific features, making it easier to grasp which factors are most influential in predicting customer satisfaction. Conversely, the Blackbox approach, represented by deep neural networks, capitalizes on their ability to handle complex patterns within extensive datasets. While these models can achieve remarkable accuracy, they often lack transparency, making it difficult to understand the reasoning behind their predictions. To address this issue, the study incorporates explainability techniques like LIME (Local Interpretable Model-agnostic

Explanations)[2] and SHAP(Shapley Additive Explanations)[3], because previous research by [4] suggests these XAI methods are reliable in predicting time-based travel and features associated with it. LIME creates interpretable models at the local level to clarify individual predictions, while SHAP assigns contribution scores to each feature, unveiling both local and global feature importance within the Blackbox model.

The ability to predict customer satisfaction accurately can inform airlines about the specific aspects of their services that require improvement, allowing for targeted enhancements. Moreover, it can aid in resource allocation, helping airlines allocate their budget to areas that will have the greatest impact on passenger satisfaction, thereby optimizing operational efficiency. As previous research has shown, passenger satisfaction is a multifaceted concept influenced by a multitude of factors [5]. These factors can include, but are not limited to, the quality of in-flight services, seat comfort, punctuality, baggage handling, and overall customer service interactions. Consequently, predicting satisfaction accurately necessitates the consideration of a wide array of variables and their interactions. This complexity is where AI and machine learning models excel, as they can handle large volumes of data and detect subtle patterns that might elude traditional statistical methods.

We will be utilizing 2 approaches, the first of these will be the Blackbox approach which is a deep neural network and the Glassbox approach, which will employ a decision tree model. These models will be trained and tested on a large customer satisfaction dataset, further explained in our section 3. Our hypothesis was that the Blackbox approaches would perform much better than the Glassbox approaches due to the complexity of the problem and the multifaceted explanations for predicting why customers could be satisfied in their flights which is a very human-centered problem.

However, it is crucial to delve deeper into the evaluation of these models, considering standard performance metrics such as accuracy, loss, precision, recall, f1-score, and confusion matrices. These metrics offer a more nuanced understanding of model performance, helping to identify potential strengths and weaknesses. Additionally, the study employed XAI techniques, including LIME [2] and SHAP [3], to shed light on the rationale behind the model's predictions and ascertain the importance of different features in influencing satisfaction levels.

2 LITERATURE REVIEW

Customer satisfaction has been used in predicting customer satisfaction in a number of fields, and the level of accuracy demonstrated by AI systems has been well documented, for example Christian Eckert et al [6] and Soyoung Oh et al [7] looked at predicting customer satisfaction in the hospitably and insurance sector and yielded high results. They both noted that using AI technologies such as deep learning can be powerful tools in predicting customer satisfaction. In previous research [8], variables such as gender, age, type of travel, gate location, inflight entertainment, legroom were used in order to develop a predictive model of satisfaction, and in a similar fashion, we have also decided to stick with this approach and develop our model in similar features, in their paper inflight Wi-Fi was the best predictor of a customer satisfaction.

Airline customer satisfaction is a critical factor in the aviation industry, as it directly influences passenger loyalty, repeat business, and overall profitability. In recent years, the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques has gained significant attention in predicting and understanding the factors that influence customer satisfaction in the airline industry. This literature review aims to provide an overview of key research in this domain, highlighting trends, methodologies, and findings.

Predictive modeling is a fundamental approach to understanding and forecasting airline customer satisfaction. Several studies have utilized AI and ML algorithms to build predictive models. For instance, a study employed statistical techniques to predict passenger satisfaction levels based on various flight-related features, achieving an accuracy rate of 90% [9]. The key findings of the study indicated that overall service quality is highly related to both passenger satisfaction and loyalty.

Feature selection and engineering play a crucial role in developing accurate predictive models. Research has explored the identification of influential features, such as seat comfort, inflight entertainment, and flight delay [10]. These features are often used to train models for customer satisfaction prediction. Another study [11] looked solely at the different factors of in-flight service quality and suggested that it had an impact on airline customer satisfaction.

In addition to the existing body of research, recent studies have explored innovative ways to enhance predictive models and the understanding of customer satisfaction within the airline industry. Soleymani et al. [12] conducted an in-depth analysis of how the sentiment analysis of passenger reviews on social media platforms can be harnessed to augment predictive models. Their work highlighted the power of harnessing unstructured data to gain insights into passenger sentiment, ultimately contributing to more robust predictive models.

Moreover, cutting-edge approaches such as deep learning have gained traction in this research domain. Wu et al. [13] utilized deep neural networks to delve into the latent patterns of passenger behavior and preferences, enabling more accurate predictions of customer satisfaction. The study emphasizes the growing role of deep learning techniques in uncovering hidden insights within vast datasets, which is particularly valuable for airline customer satisfaction prediction.

3 METHODOLOGY

3.1 Data Description and Preprocessing

The dataset used in this study, provided by IIT Roorkee in 2020 [14], encompasses a substantial number of observations and variables, making it an ideal candidate for AI-based predictive modeling. With 129487 rows and 23 columns, including the critical target variable "satisfaction," this dataset offers a comprehensive overview of passenger experiences, providing ample data for model training and validation. The dataset itself is fairly balanced, with an equal measurement of 49.3% of our dataset is male, and 50.7% and in terms satisfied is 54.7% and unsatisfied is 44.3%.

The dataset comprises several key variables, each playing a crucial role in understanding and predicting customer satisfaction within the airline industry. The primary focus of our predictive model is the "Satisfaction" variable, which serves as the target variable. It categorizes customers into two groups, indicating whether they are satisfied or dissatisfied with the airline's services.

To provide a comprehensive perspective, various other predictor variables are included as listed below.

- Gender: Identifies customer gender (Male/Female).
- Customer Type: Classifies as "Loyal" or "Disloyal" based on previous interactions.
- Age: Provides insights into passenger age distribution.
- Type of Travel: Categorizes as "Business" or "Personal" travel.
- Class: Indicates service class (Economy, Eco Plus, Business).
- Flight Distance: Quantifies flight distance in miles.
- Seat Comfort: Customer's perception of seat comfort (scale: 0-5).
- Departure/Arrival Satisfaction with flight times (scale: 0-5).
- Food and Drink: Satisfaction with onboard services (scale: 0-5).
- Gate Location: Satisfaction with assigned gate location (scale: 0-5).
- Inflight WiFi Service: Quality and satisfaction with inflight WiFi (scale: 0-5).
- Inflight Entertainment: Satisfaction with onboard entertainment (scale: 0-5).
- Online Support: Satisfaction with online support (scale: 0-5).
- Ease of Online Booking: Convenience of online booking process (scale: 0-5).
- On-board Service: Satisfaction with general on-board services (scale: 0-5).
- Leg Room Service: Satisfaction with legroom space (scale: 0-5).
- Baggage Handling: Satisfaction with baggage handling (scale: 0-5).
- Check-in Service: Satisfaction with check-in service (scale: 0-5).
- Cleanliness: Satisfaction with aircraft cleanliness (scale: 0-5).
- Online Boarding: Satisfaction with online boarding process (scale: 0-5).
- Departure Arrival Delay in Minutes: Quantifies flight delay in minutes.

Furthermore, several variables gauge specific aspects of the customer experience, each rated on a scale from 0 to 5 (see Figure 1), with 0 being 'Not Applicable', 1 being 'Least Satisfied', and 5 being 'Most Satisfied'.

Additionally, two variables, "Departure Delay in Minutes" and "Arrival Delay in Minutes", quantify the delay in minutes experienced during the departure and arrival phases of the flight, respectively. This comprehensive set of variables provides a rich source of information for our predictive model, enabling us to analyze and understand the factors influencing customer satisfaction in the airline industry.

3.2 Model Development

In the process of model development, we constructed a deep neural network using TensorFlow and Keras to predict customer satisfaction within the airline industry. This model was designed with

Figure 1: Spider graph of variables rated from 0 to 5

several hidden layers, each comprising a varying number of neurons activated by the rectified linear unit (ReLU) function. The choice of the ReLU activation function helps the model capture complex patterns within the data.

The model architecture consisted of an input layer with 22 features, which corresponded to various factors influencing customer satisfaction, such as gender, customer type, age, class, flight distance, and several aspects of the customer experience rated on a scale from 0 to 5. The subsequent hidden layers contained 1000, 500, 100, 50, and 10 neurons, respectively, gradually reducing the dimensionality of the data representation. Our rationale and justification for using this particular configuration of hyper-parameters was based on several experimentation that was aimed at getting the best accuracy and reducing the loss function in this particular dataset.

To facilitate binary classification (satisfied or dissatisfied), we employed a sigmoid activation function in the output layer. The model was trained using binary cross-entropy loss and optimized with the Adam optimizer. During training, we ran the model for 100 epochs, utilizing a batch size of 1000 and assessing its performance on a validation dataset.

4 RESULTS

In this section, the evaluation metrics that have been used for this research are as follows:

- Accuracy: This measures the proportion of true results (both true positives and true negatives) among the total number of cases examined.
- Precision: Precision is the ratio of correctly predicted positive observations to the total predicted positives. It's a measure of a classifier's exactness. A low precision indicates a high number of false positives.

- Recall (Sensitivity): This measures the ratio of correctly predicted positive observations to the all observations in actual class. It is a measure of a classifier's completeness.
- F1-score: This is the harmonic mean of Precision and Recall and gives a balance between the two.

As we see in Table 1, we employed a Glassbox approach which was a decision tree algorithm. Our configuration was on a base level and included all nodes which yielded results of 94% accuracy. This had results that were almost on par with the Blackbox approach, with an accuracy of 92%. This high accuracy demonstrates the model's capability to effectively predict customer satisfaction based on the provided dataset, thereby offering valuable insights for improving airline services and enhancing customer experiences.

In comparing the performance metrics of the Blackbox and Glassbox models, it is evident that the Blackbox model exhibits a very high precision of 96.89%, signifying its exceptional accuracy in correctly identifying positive cases and minimizing false positives. On the other hand, the Glassbox model, while slightly lower with a precision of 95%, still maintains a commendable level of accuracy. Moving to recall, the Blackbox model demonstrates a rate of 88.63%, indicating its ability to reasonably detect positive cases but with some instances of misses. In contrast, the Glassbox model outperforms with a higher recall of 94%, suggesting its superior capability in identifying true positives compared to the Blackbox model. Finally, when considering the F1-score, the Blackbox model achieves a high score of 0.9257, highlighting a good balance between precision and recall. While the F1-score for the Glassbox model is not explicitly provided, given its high precision and recall values, it can be inferred to be around 0.945, showcasing an impressive equilibrium between precision and recall.

The Glassbox model appears to be more balanced and effective across all metrics, with higher accuracy, recall, and a comparable F1-score. The Blackbox model, while having a slightly higher precision, falls behind in other metrics. The choice between these models would depend on the specific requirements of the task at hand – for instance, if avoiding false positives is critical, the Blackbox model might be preferable despite its slightly lower overall performance.

Table 1: Model Evaluation Metrics

Model	Accuracy	Precision	Recall	F1-score
Blackbox	0.922	0.9689	0.8863	0.9257
Glassbox	0.94	0.95	0.94	0.95

In the "Model Loss" graph in Figure 2, both training and test loss start high and decrease sharply in the first few epochs, indicating that the Blackbox model is learning quickly. After the initial drop, the loss continues to decrease gradually, suggesting the model is improving its performance over time. The test loss shows some spikes, which could indicate moments when the model didn't generalize well to new data but overall it's decreasing, which is good. The "Model Accuracy" graph in Figure 2 shows an increase in accuracy for both training and test data over epochs. The accuracy increases rapidly at first and then plateaus, which is typical as the Blackbox model begins to converge to its best performance. The training and test lines are close together, which is a good sign that the model is not overfitting significantly (i.e., not just memorizing the training data but generalizing well to new, unseen data).

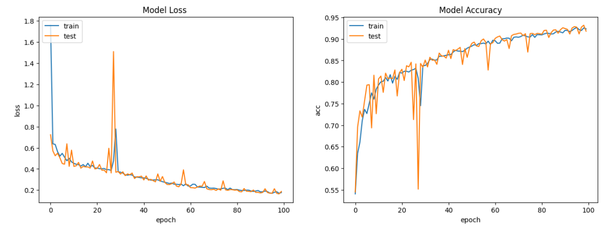

Figure 2: Model Loss and Model Accuracy

Table 2 represents a confusion matrix of the Blackbox model, which is a performance measurement for classification problems. In this context, the classification task involves predicting whether instances belong to a positive or negative class. The confusion matrix is structured as follows: (I) True Negatives (TN): The model correctly predicted negative outcomes. Here, there are 45,191 cases, (II) False Positives (FP): The model incorrectly predicted positive outcomes when they were actually negative. In this case, there are 1,617 instances. (III) False Negatives (FN): The model incorrectly predicted negative outcomes when they were actually positive. This occurred 6,458 times. (IV) True Positives (TP): The model correctly predicted positive outcomes. There are 50,323 cases of this.

Table 2: Confusion Matrix

	Predicted Negative	Predicted Positive
Actual Negative	45191	1617
Actual Positive	6458	50323

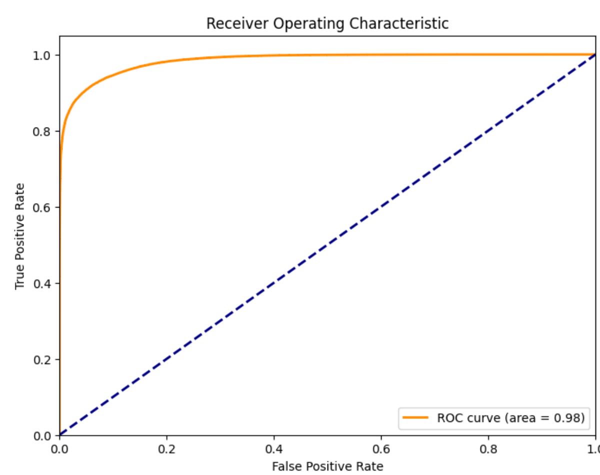

Figure 3: AUC

Lastly, figure 3 shows the area under the curve. This indicates the Blackbox model's ability to distinguish between the satisfied and unsatisfied class. The area is very large, at 0.98, signifying strong class differentiation.

5 XAI

In this project, we employed two XAI techniques, namely LIME [2] and SHAP [3], to gain deeper insights into the predictions made by our Blackbox approach. As mentioned in the section 1 of this paper, these XAI methods were shown to be reliable in predicting time-based travel [4]. These XAI approaches were instrumental in shedding light on the factors driving customer satisfaction within the airline industry. The LIME methods, shown in Figure 4, includes three different partial graphs for the two classes (with blue representing the unsatisfied class, and orange representing the satisfied class). The first part shows the prediction itself, the middle is showing the top 10 features affecting the model's prediction, and the third partial graph is listing the weights of various features. The SHAP method (Figure 5) is showing the weight for each feature in a single graph, where blue represents to unsatisfied and the pink represents to satisfied class.

5.1 Blackbox

Both LIME and SHAP analyses consistently pointed to "Seat Comfort" and "Inflight Entertainment" as the most significant contributors to predicting customer satisfaction. These two factors held the largest weights for both satisfied and dissatisfied classes, indicating their pivotal role in shaping passenger experiences. A negative rating for "Seat Comfort" or the absence of "Inflight Entertainment" had a substantial adverse impact, while positive ratings for these factors had a considerably positive influence on satisfaction. For instance, the SHAP analysis revealed that, for class 0 (dissatisfied), "Seat Comfort" had an average impact of 0.13 across the presented cases, while "Inflight Entertainment" had an even more substantial impact at 0.8 (see Figure 5). These findings align with common intuition, as these aspects are known to greatly affect the overall comfort of a flight.

Interestingly, the XAI analyses also highlighted the significance of the "Gender" variable, ranking it among the top five contributing factors for both satisfied and dissatisfied classes. Further research may be necessary to fully comprehend how gender influences customer satisfaction within the airline context (will be discussed in section 6).

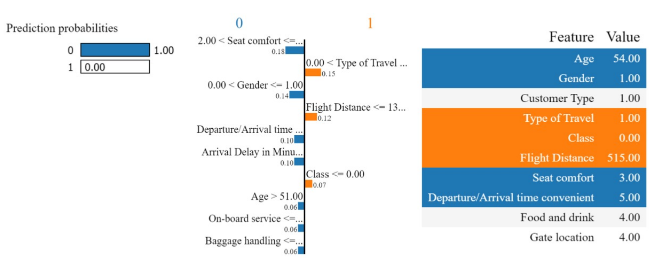

Figure 4: Lime Output of False Predictions

We also find, to our surprise, the model assigns considerable importance to the "Gender" variable, ranking it among the top five contributing factors for both satisfied and dissatisfied passengers. This unexpected finding underscores the need for further research to comprehensively understand how gender intersects with customer satisfaction in the airline industry.

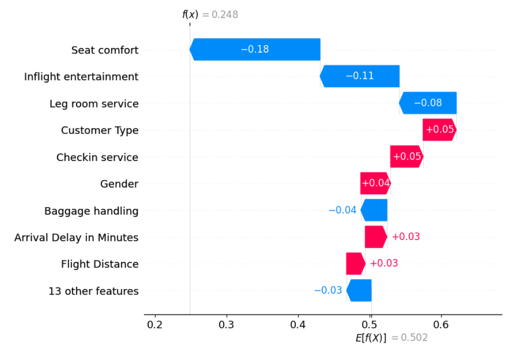

Figure 5: Shap Output for True Predictions

Upon scrutinizing correct and incorrect predictions, discerning clear-cut trends becomes a challenging endeavor. It appears that both correct and incorrect predictions draw upon a similar set of factors. Nevertheless, a noteworthy distinction arises in the weight attributed to the "Arrival Delay in Minutes" variable in the context of incorrect predictions. It becomes evident that the model assigns greater weight to this variable in cases where predictions falter. This observation raises the possibility that the model's performance could improve by re-calibrating the significance accorded to "Arrival Delay in Minutes," suggesting that fine-tuning this aspect of the model might enhance prediction accuracy.

5.2 Glassbox

Our Glassbox approach consisted of using decision tree graph, the results were as good as using the Blackbox approach. Our figure below shows that the Decision Tree classifier output with first three layers provides a high level of explainability. As shown in Figure 6, when "Inflight Entertainment" is above a value of 3.5, customers are predicted as satisfied. When this is lower, "Seat Comfort" comes into play. In the second layer, we see that if "Seat Comfort" is high, the customers are still predicted as satisfied. However, if "Seat Comfort" is low, customers have a high chance of being predicted as unsatisfied. Although there is some minor differences between Blackbox and Glassbox explanations, both of the approaches still show that "Seat Comfort" and "Inflight Entertainment" have the highest weights for the models' predictions.

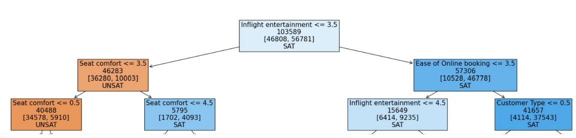

Figure 6: Decision Tree Graph Output with Nodes = 3

6 FUTURE WORK

One of the intriguing findings of this study is the significant role that gender plays in influencing customer satisfaction. While it is apparent that gender is among the top contributing factors in both satisfied and dissatisfied classes, further in-depth analysis is warranted. Future studies could explore the nuanced ways in which gender interacts with other variables to impact satisfaction. Understanding whether there are gender-specific preferences or concerns could lead to more targeted strategies for enhancing passenger experiences.

The predictive model developed in this study is based on historical data, rendering it static. However, the airline industry is dynamic and subject to constant changes in customer preferences, market conditions, and external events (e.g., pandemics). Future work should focus on creating dynamic models capable of adapting to these fluctuations in real-time. Incorporating streaming data and continuous learning algorithms would enable the model to provide more accurate and up-to-date predictions.

Personalization is becoming a cornerstone of the airline industry's efforts to enhance customer satisfaction. Airlines are increasingly recognizing the value of tailoring the passenger experience based on individual preferences. Future research can explore ways to further enhance personalization by incorporating additional customer-specific data, such as travel history, social media sentiment, or loyalty program participation. These personalized approaches can result in more satisfied and loyal customers.

To gain a more comprehensive understanding of the factors influencing customer satisfaction, future research could consider adopting a multi-model approach. This approach involves combining multiple models, including interpretable models and deep learning models, to leverage their respective strengths. Ensemble methods and hybrid models could be investigated to achieve improved predictive accuracy and interpretability.

7 CONCLUSION

One intriguing finding from this research is that, while XAI techniques are effective in elucidating the decision-making process of Blackbox approaches, the Glassbox approach achieves a similar level of accuracy. This observation has significant implications for the practical application of predictive models in the airline industry.

In summary, this research project employed deep learning techniques and Explainable AI (XAI) to analyze factors influencing airline customer satisfaction. Our objectives were to build a predictive model for categorizing satisfaction levels and to understand how the model makes decisions. We conducted data preprocessing, feature selection, and built a neural network model using Keras. We also explored a Decision Tree Classifier for explainability. Model evaluation showed high accuracy and provided insights through metrics and a confusion matrix. It is noteworthy to mention that our results only reflect the dataset that we used, and any changes to this dataset could effect our models results. One argument for using Blackbox approaches would be that the higher the complexity of the dataset, it could be warranted to use this approach.

Interpreting the model's predictions was a key focus of our study. The Decision Tree model provided valuable, interpretable insights into the pivotal factors influencing customer satisfaction, elucidating feature thresholds' effects on predictions. Our recommendation would be to use Decision-Trees on this dataset due to its low complexity. SHAP values enriched our understanding by elucidating the individual feature contributions to each prediction, while LIME explanations offered human-readable insights into the rationale behind specific predictions.

Interpreting model predictions was a focus, and the Decision Tree, SHAP, and LIME techniques were utilized. Key findings highlighted the significance of features like "Inflight Entertainment" and "Seat Comfort" in influencing satisfaction. The model excelled in predicting dissatisfaction.

REFERENCES

[1] Awadh, M. A. (2023). Assessing the Quality of Sustainable Airline Services Utilizing the Multicriteria Decision-Making Approach. Sustainability, 15(9), 1-19.
[2] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016, August). " Why should i trust you?" Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining (pp. 1135-1144).
[3] Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. Advances in neural information processing systems, 30.
[4] Ahmed, I. et al. (2021) Travel time prediction and explanation with spatio-temporal features: A comparative study, MDPI.
[5] Ban, H.-J. and Kim, H.-S. (2019) Understanding customer experience and satisfaction through airline passengers' online review, MDPI.
[6] Managing customer satisfaction: digital applications for insurance companies. Published: 07 February 2022, volume 47, pages569–602 (2022). Christian Eckert, Christof Neunsinger & Katrin Osterrieder
[7] Deep learning model based on expectation-confirmation theory to predict customer satisfaction in hospitality service. Soyoung Oh, Honggeun Ji, Jina Kim, Eunil Park & Angel P. del Pobil Information Technology & Tourism volume 24, pages109–126 (2022)Cite this article
[8] PREDICTING AIRLINE PASSENGER SATISFACTION WITH CLASSIFICATION ALGORITHMS, B.Herawan Hayadi, Jin-Mook Kim, Khodijah Hulliyah, Husni Teja Sukmana, International Journal of Informatics and Information Systems Vol. 4, No. 1, March 2021, pp. 82-94
[9] Khatib, F. (1998) An investigation of airline service quality, passenger satisfaction and loyalty: The case of Royal Jordanian airline, Academia.edu.
[10] Park, S.-H. et al. (2022) A deep learning approach to analyze airline customer propensities: The case of South Korea, MDPI.
[11] An, M. and Noh, Y. (2009) 'Airline Customer Satisfaction and loyalty: Impact of in-flight service quality', Service Business, 3(3), pp. 293–307. doi:10.1007/s11628-009-0068-4.
[12] Soleymani, M., Garcia, D., Jou, B., Schuller, B., Chang, S. F., and Pantic, M. (2017). A survey of multimodal sentiment analysis. Image and Vision Computing, 65, 3-14.
[13] Wu, J.-L., Lu, M. and Wang, C.-Y. (2023) Forecasting Metro Rail Transit passenger flow with multiple-attention deep neural networks and surrounding vehicle detection devices. Applied Intelligence, 53(15), pp. 18531–18546. doi:10.1007/s10489-023-04483-x.
[14] ITT Roorkee. (2020). Airlines Costumer Satisfaction. Kaggle. url: https://www.kaggle.com/datasets/sjleshrac/airlines-customer-satisfaction/data