An India Based Airline Recommendation System Using Sentiment Analysis and Machine Learning Techniques

Anusiya. L[1] Dr.R.Porkodi[2]
[1]PG Student [2]Professor & Head
[1,2]Department of Computer Science & Engineering
[1,2]Bharathiar University, Coimbatore, India

Abstract — The Fast Growth of the Aviation Industry in India, this has led to more travel alternatives, making airline choice a complex one for passengers. Passengers have to take several factors into account such as ticket price, journey time, and overall service quality while deciding upon an airline. Currently, there are many airlines Flight booking websites mainly concentrate on integer filters such as cost and stops, often failing to incorporate qualitative areas like customer satisfaction with passengers, among others perception. Further, this proposed Airline Customer Offer Recommendation system using Machine Learning and applying Sentiment Analysis to assist in passenger decision making informed travel decisions. The system combines "structured flight data with unstructured customer" reviews to develop sentiment-based airline recommendations. Natural Language Processing techniques applied to retrieve sentiment polarity from passenger reviews, which is then aggregated at the airline level to show the level of service provided. Many machine learning classifiers, including Logistic Regression, Support Vector Machine, Random Forest, Naive Bayes, XGBoost algorithms are implemented and evaluated. To improve robustness, ensemble models are also developed. Experimental results demonstrate that incorporating sentiment-based features significantly enhances recommendation accuracy and reliability. The proposed system provides balanced, data-driven, and user-centric airline suggestions, improving overall passenger decision confidence.

Keywords: Airline Recommendation System, Machine Learning, Sentiment Analysis, Passenger Satisfaction

I. INTRODUCTION

The Indian air transportation industry is reportedly experiencing a “rapid” significant expansion over the past years, hence increasing competition between airlines, with a growing diversity range of options available to passengers. As a result, airline choice is no longer influenced by factors such as for example: the price of a ticket or the duration of the trip, but is increasingly influenced by qualitative factors including service quality, punctuality, cabin

Comfort, and Overall Travel Experience. Notwithstanding shift, existing air travel booking systems continue to depend on primitive filtering techniques and "remain largely unaware of the experience of passengers in the" decision making process. Due to these drawbacks, airline recommendation systems have appeared as a data-driven approach for helping tourists choose suitable airlines. Conventional approaches such as collaborative filtering and content based filtering, have demonstrated effectiveness of personalization. Hybrid models have thus been investigated to improve robustness, accuracy, and scalability by combining multiple learning strategies. Although more recent studies have included natural language processing, and sentiment analysis to derive information from customer reviews.

Furthermore, challenges such as class imbalance in review datasets and the absence of practical deployment frameworks continue to hinder real-world applicability.

By leveraging ensemble-based machine learning models and sentiment aggregation techniques, the proposed approach aims to provide accurate, interpretable, and passenger-centric airline recommendations that better reflect both operational performance and customer experience.

II. RELATED WORK

Airline recommendation and passenger satisfaction analysis have attracted significant research attention due to the increasing availability of aviation data and the need for personalized decision support systems. Kan et al. [1] proposed a personalized flight recommender system using link prediction techniques on aviation network data. Their approach effectively captured relationships between flights, routes, and airlines, improving recommendation accuracy. However, the study primarily focused on network-level associations and did not deeply incorporate passenger satisfaction indicators such as reviews or sentiment.

Delay prediction and recommendation systems have also been explored to enhance passenger experience. Sirisati et al. [2] developed a machine learning–based aviation delay prediction and recommendation framework that analyzed operational and historical flight data. Their work demonstrated the usefulness of predictive analytics in supporting travel decisions, though it mainly emphasized operational efficiency rather than customer-centric satisfaction measures.

Passenger satisfaction and service quality remain critical factors influencing airline choice. Shah et al. [3] investigated the impact of airline service quality on passengers’ behavioral intentions, identifying satisfaction as a key mediating factor. Their findings confirmed that service attributes significantly influence customer loyalty and future travel decisions. Similarly, Jain et al. [4] utilized customer-generated feedback data to predict airline recommendations, highlighting the importance of online reviews in understanding passenger preferences.

The role of online ratings and customer satisfaction was further examined by Sudhakar and Gunasekar [5], who analyzed how digital feedback reflects passengers’ perceptions of airline services. Their study emphasized that online ratings serve as reliable indicators of service quality and satisfaction, reinforcing the relevance of review-based analytics in airline recommendation systems.

Recent research has increasingly integrated sentiment analysis with machine learning models to enhance satisfaction prediction. Murugesan et al. [6] applied VADER sentiment analysis combined with machine learning techniques to forecast airline passenger satisfaction. Their results showed improved predictive performance when textual sentiment information was incorporated alongside numerical ratings.

Advancements in deep learning have further improved airline review analysis. Syed et al. [7] proposed a deep transfer learning–based framework for processing airline reviews, focusing on abstractive summarization and sentiment classification. Their approach demonstrated strong performance in extracting meaningful insights from large-scale textual data, supporting more accurate satisfaction assessment.

Machine learning models have also been employed to identify key factors influencing passenger satisfaction. Li [8] analyzed airline customer satisfaction using multiple machine learning techniques and found that pricing, service quality, and flight reliability play dominant roles in shaping passenger perceptions. This work supports the use of data-driven models for understanding complex satisfaction patterns.

Sentiment analysis using deep learning has gained popularity for processing customer feedback. Samir et al. [9] developed a deep learning–based sentiment analysis model to classify airline customer feedback, achieving high accuracy in detecting positive and negative sentiments. Their study highlighted the effectiveness of neural networks in handling unstructured airline review data.

A broader understanding of sentiment-driven decision-making was presented in the systematic review by [10], which examined how airlines leverage emotional and sentiment data for strategic decision-making. The review emphasized the growing importance of sentiment analytics in improving customer experience and competitive advantage within the aviation industry.

Customer satisfaction benchmarking has also been studied using multi-criteria decision-making techniques. İnan [11] applied an entropy–grey relational analysis approach to compare airline companies based on customer satisfaction levels. The study provided a structured method for evaluating airline performance, offering insights that complement machine learning–based satisfaction prediction models.

III. METHODOLOGY OF THE PROPOSED SYSTEM

The proposed Airline Recommendation System (ARS) is designed to provide personalized and data-driven airline suggestions by integrating structured flight information with unstructured passenger review data. The overall workflow of the system is illustrated in Fig. 1, which outlines the major stages from data collection to recommendation generation.

A. Data Collection

Two publicly available datasets obtained from Kaggle were used in this study:

1) Flight Price Prediction Dataset:

This dataset contains structured flight attributes such as airline name, source and destination cities, departure and arrival times, number of stops, travel class, flight duration, and ticket price. These features form the quantitative foundation for analysing flight performance and pricing patterns.

2) Indian Airlines Customer Reviews Dataset:

This dataset consists of passenger reviews and numerical ratings reflecting service quality, punctuality, cleanliness, crew behaviour, and overall travel experience. It provides qualitative insights into passenger satisfaction.

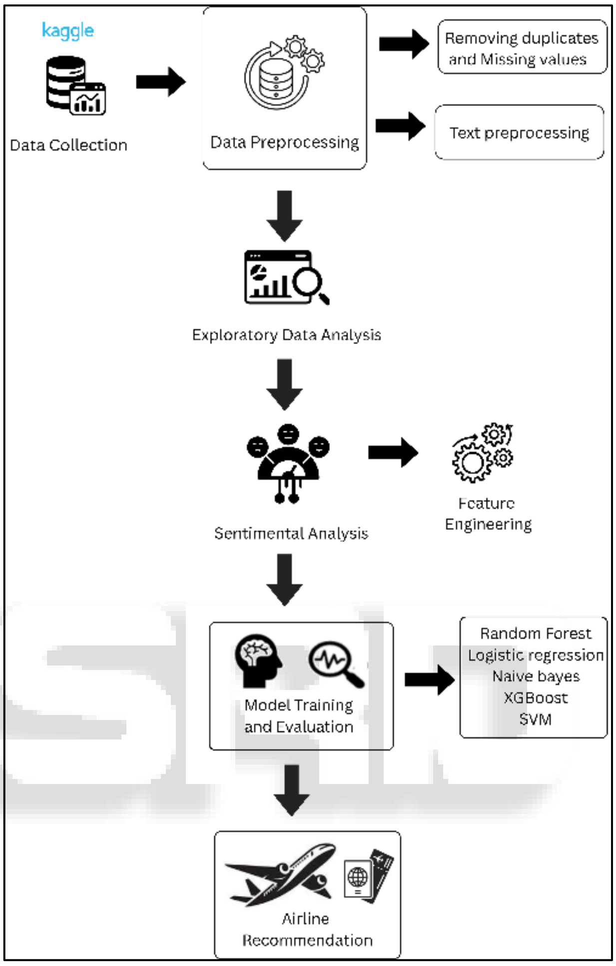

Fig. 1: ARS architecture

Both datasets were merged using the airline name as a common key, allowing the system to capture both operational and experiential aspects of airline performance.

B. Data Preprocessing

Data preprocessing was performed to ensure consistency and reliability. The flight dataset was verified for missing and duplicate values and was found to be complete. The customer review dataset contained incomplete and duplicate records, which were removed during cleaning.

For textual review data, Natural Language Processing can be applied. Processing (NLP) techniques were applied, including tokenization, removing stop words, The process involves stop word removal, stemming/Lem steps added to the normalization of text and the accuracy of sentiment extraction. The cleaned review data were then combined with the flight is to merge the above datasets to form a unified dataset containing both numerical and sentiment-based features.

C. Sentiment Analysis and Aggregation

A sentiment polarity score was assigned to each review showing positive, neutral, or negative sentiments. To obtain an interpretable measure of airline reputation, an aggregated sentiment score was These were calculated for each airline by averaging the sentiment scores of all related reviews. This collective sentiment value was introduced as a further factor present in the flights data set. the machine learning models to be considered perceived service quality as compared to traditional flights attributes such as price and duration.

D. Feature Engineering

Categorical variables such as airline name, source city, destination city, and travel class were converted into numerical form using label encoding. Continuous variables, including ticket price and flight duration, were retained in their original scales.

Correlation analysis was performed to identify and eliminate redundant features, ensuring minimal multicollinearity and improved model generalization. The final feature set effectively represents cost efficiency, operational performance, and passenger sentiment.

E. Model Development and Class Balancing

Five supervised machine learning models were implemented to predict passenger satisfaction and support airline recommendation:

- Logistic Regression
- Support Vector Machine
- Random Forest
- Naive Bayes
- XGBoost

To address class imbalance in sentiment categories, the Synthetic Minority Oversampling Technique (SMOTE) was applied to balance the training data. This ensured that all sentiment classes were equally represented during model learning, improving fairness and predictive stability.

F. Ensemble Modelling

To enhance robustness and reduce model-specific bias, two ensemble models were developed using majority voting. The first ensemble combined Support Vector Machine, Naive Bayes, and XGBoost to leverage diverse learning behaviours. The second ensemble integrated Logistic Regression and Random Forest to balance interpretability and non-linear modelling capability. Ensemble learning improved consistency and generalization across varying flight and sentiment conditions.

G. Recommendation Generation

Airline recommendations were generated using a utility-based ranking approach that integrates sentiment score, ticket price, and flight duration. Airlines with higher sentiment scores, lower prices, and shorter durations were ranked higher in the recommendation list. This approach ensures that the final recommendations are not solely cost-driven but also reflect passenger satisfaction and service quality.

IV. Results and Discussion

The proposed Airline Recommendation System was assessed with five supervised machine learning algorithms classifiers: Logistic Regression (LR), Naive Bayes (NB), Support Vector Machine (SVM), Random Forest (RF), and XGBoost (XGB). The dataset was split into training sets and test sets with an 80:20 ratio The model was then split to evaluate model generalization. Passenger sentiment classification tasks were conducted with three categories: Positive, Neutral, and Negative. The model's performance was tested by Accuracy metric Precision, Recall, y F1-score metrics for multi-class classification problems. These metrics provide a balanced view of classification effectiveness and robustness.

A. Model Performance Evaluation

Model	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression (LR)	86.72	0.88	0.87	0.87
Naive Bayes (NB)	83.21	0.86	0.85	0.85
Support Vector Machine (SVM)	88.44	0.89	0.88	0.88
Random Forest (RF)	85.63	0.84	0.83	0.83
XGBoost (XGB)	87.95	0.88	0.87	0.87

Table 1: Performance Comparison of Machine Learning Models

Table 1 presents a comparative performance analysis of the five classifiers. Among the evaluated models, the Support Vector Machine achieved the highest accuracy of 88.44%, followed closely by XGBoost (87.95%) and Logistic Regression (86.72%). Naive Bayes and Random Forest recorded comparatively lower accuracies but demonstrated stable performance across sentiment classes.

The superior performance of SVM can be attributed to its ability to handle high-dimensional feature spaces effectively, making it well-suited for sentiment-based text features. Logistic Regression provided reliable and interpretable results, serving as a strong baseline model. XGBoost benefited from gradient boosting mechanisms, enabling it to capture complex feature interactions, though minor overfitting tendencies were observed for majority sentiment classes.

Random Forest demonstrated reasonable recall for negative sentiment but showed reduced generalization due to class imbalance effects. Naive Bayes, while computationally efficient, struggled with capturing contextual dependencies in text data, leading to comparatively lower performance.

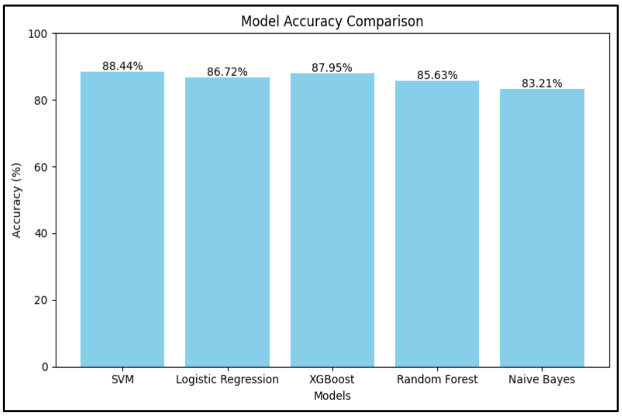

Fig. 2: Model Comparison

As shown in Fig. 2, SVM and XGBoost show better performance compared to the other models. Naive Bayes and Random Forest perform relatively lower, indicating variation in classification effectiveness among the models.

B. Ensemble Model Analysis

This would improve the stability of the predictions and reduce the individual model bias; two ensemble models are combined using majority voting. The ensemble for this purpose, the algorithms to be used in this study are the combination of SVM, Naive Bayes, and XGBoost. delivered the most consistent results across all sentiment classes. In this regard, the second ensemble combines Logistic Regression and Random Forest, was provided It is a trade-off between interpretability and nonlinear relationship.

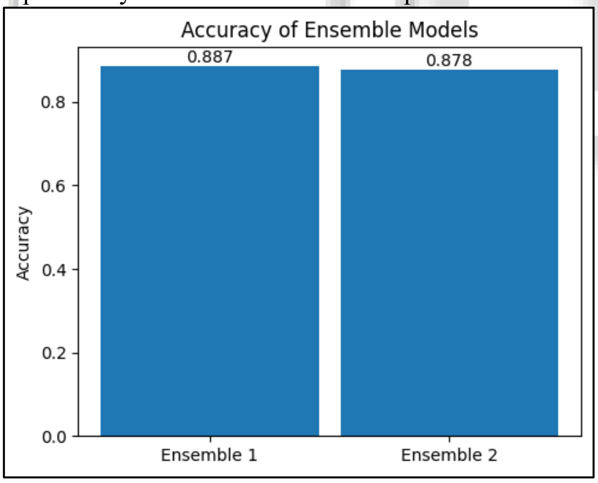

Fig. 3: Ensemble models

Fig 3, presents the final accuracy of the proposed ensemble models. Ensemble 1 outperforms Ensemble 2, highlighting the advantage of combining multiple complementary classifiers to enhance overall prediction accuracy.

Overall, ensemble learning improved robustness and reduced variance in performance, which confirms its effectiveness for sentiment-aware airline recommender systems.

C. Recommendation Analysis

A utility-based scoring function is used for recommendation, where airline quality is maximized while ticket price and travel duration are jointly minimized, as defined by

$$U \propto \frac{Quality^{1.0}}{(Price)^{1.0} \times (Duration)^{1.0}}$$

The recommendation process used utility based ranking system that combines aggregated Sentiment score, Ticket price, Flight duration. Airlines The reason for this seems to be that the stocks they purchased had duration trade-offs were ranked higher in the recommendation list. This method ensures that recommendations are not only driven by the need to cut costs but also reflect the level of passenger satisfaction. Empirical evidence shows that the combination insights into sentiment with structured flight data provides much more relevant and useful airline recommendations. The proposed system outperforms traditional price selection methods through balancing affordability, efficiency, and customer experience.

V. CONCLUSION AND FUTURE WORK

This study presented a Machine Learning–based Airline Recommendation System that integrates structured flight information with sentiment-derived insights from passenger reviews. By combining quantitative flight attributes, like price and Duration with qualitative indicators of service quality is proposed, whereby the system gives balanced and user-centric airline recommendations are made possible by the use of Natural Language Processing enabled effective the extraction of passenger sentiment, which was aggregated at the airline level to represent overall service perception. Various supervised machine learning models were are evaluated, including Logistic Regression, Naïve Bayes, Support Vector Machine, Random Forest, and XGBoost. Of the five algorithms tested, the Support Vector Machine (SVM) had the best accuracy of 88.44%, followed closely by Logistic Regression and XGBoost. Ensemble-based approaches Further improved the stability of prediction and reduced model bias, showing the efficiency of Multimodal integration in sentiment-aware Recommendation systems This fact is confirmed by the experimental results shown in Figure 4, where the addition of passenger sentiment alongside operational flight Data greatly enriches recommendation. accuracy and interpretability as compared to traditional cost-based approaches.

The emphasis of future work may lie in real-time everything ranging from flight data, weather conditions to seat availability to support dynamic recommendations. Advanced deep learning models like Bi-LSTM or BERT can be explored for enhancing sentiment classification. accuracy. Moreover, the deployment of the system on a cloud-based platform with integrated user feedback. Would enable scalability and continuous model.

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