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AIRLINE DATA ANALYTICS USING MACHINE LEARNING

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ABSTRACT

In this paper, we describe the formatting guidelines for IJOURNALS Journal Submission. The aviation industry is a multifaceted ecosystem where operational efficiency, cost-effectiveness, and customer satisfaction are paramount. This document presents an integrated framework designed to address three critical aspects of airline management: flight delay prediction, fare price estimation, and customer satisfaction enhancement. Through the strategic application of advanced data analytics and machine learning, this comprehensive framework aims to streamline airline operations, optimize pricing strategies, and elevate the overall passenger experience

Keywords: Flight, Delay, Prediction, Airline, Analytics, Airfare, Passenger satisfaction, Flask, Stream lit, Airport,

INTRODUCTION

The integrated framework acknowledges the multifaceted demands of the aviation industry, providing airlines with a strategic advantage amidst relentless market fluctuations. By empowering airlines with a holistic toolset, the framework enables them to navigate uncertainties with resilience and adaptability. The synergy of accurate delay predictions, dynamic pricing strategies, and customer-centric approaches positions airlines to not only survive but thrive in the competitive landscape.

1. LITERATURE SURVEY

The literature surrounding personalized recommendations in various industries, particularly e-commerce, push notifications, and movie recommendations, has seen considerable success with Collaborative Filtering (CF) methods. The implementation of CF techniques has significantly enhanced user experience and engagement. Moreover, the proliferation of mobile internet technology has enabled the collection, analysis, and utilization of vast amounts of travel scenario data, prompting a surge in context-sensitive mobile recommendation research.

2. PROBLEM DEFINATION

The aviation industry grapples with diverse challenges affecting operational efficiency, revenue management, and customer satisfaction. To tackle these issues, we propose an integrated approach harnessing data analytics and machine learning. Our primary objectives include the development of robust predictive models for flight delays, leveraging historical data, weather patterns, and air traffic trends.

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2.1 Limitations of existing system

Existing airline data analytics systems face limitations in predictive accuracy for flight delays, often due to challenges in incorporating real-time data on dynamic factors like weather and air traffic. Customer satisfaction analysis is hindered by inadequate data sources and methodologies, relying mainly on post-flight surveys. Integration challenges and data silos further complicate operations, limiting the ability to gain a comprehensive understanding of airline operations. Overcoming these limitations is essential for developing more robust.

2.2 Proposed system

The proposed advanced airline data analytics system addresses inherent limitations in existing frameworks by introducing a comprehensive and adaptive solution. At its core, dynamic flight delay prediction models utilize advanced machine learning algorithms to continuously analyze real-time data streams, enhancing prediction accuracy and enabling proactive measures to minimize disruptions. Complementing this, an adaptive fare price estimation mechanism responds to market dynamics and competitor strategies, maximizing revenue and maintaining competitiveness.

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3. FIGURES

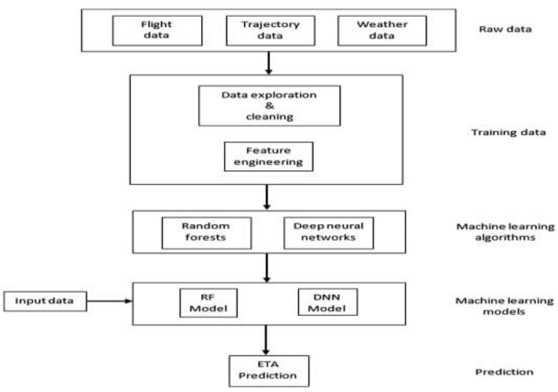

Figure 1: SYSTEM ARCHITECTURE

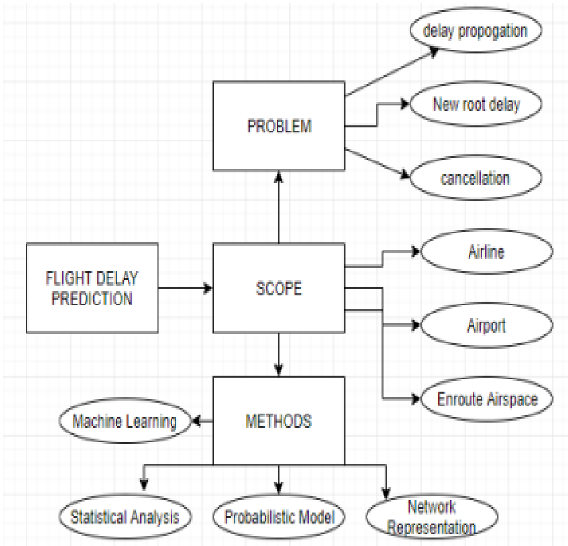

Figure 2 TAXONOMY OF FLIGHT DELAY PREDICTION PROBLEM

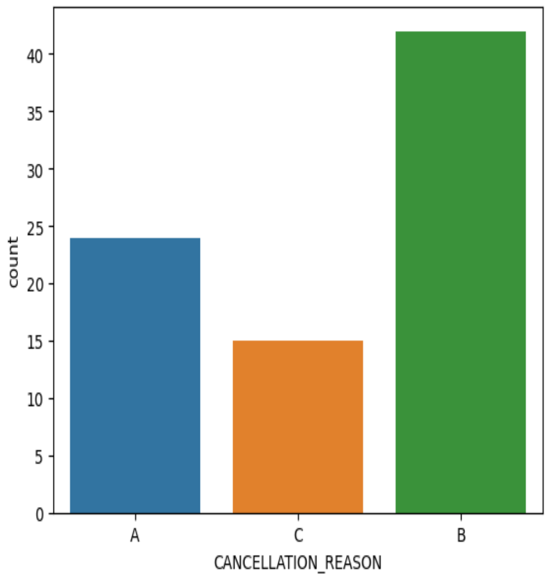

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Fig. 4.3 Cancellation of flight

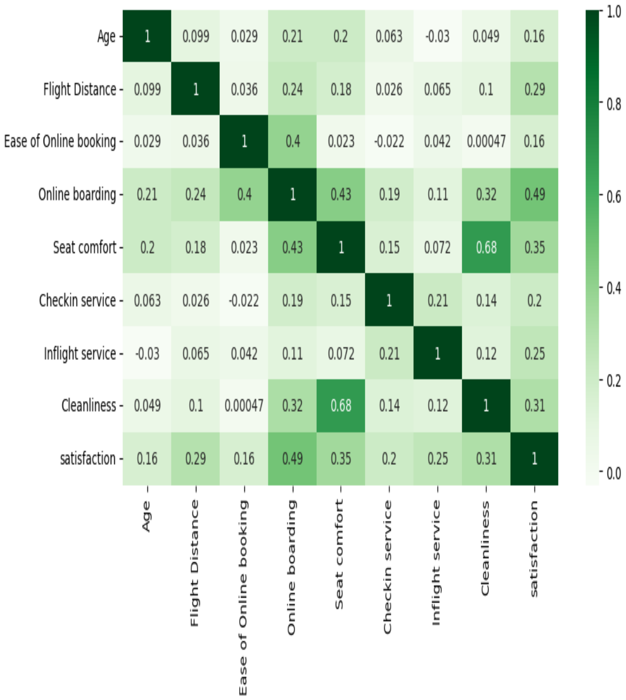

Fig. 4.4 Relationship of fare

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4. MODULES

4.1 Flight Delay Prediction

In examining the performance metrics of the Random Forest Regressor and Gradient Boosting Regressor models for departure delay prediction, we discern significant insights into their efficacy. The Random Forest Regressor model showcased an impressive R-squared (R2) score of 0.9264 on the test data, indicative of its ability to elucidate approximately 92.64% of the variance in the target variable.

4.2 Airfare Price Prediction

In the process of building a flight price prediction model, a systematic approach was followed, encompassing various stages from data loading to model evaluation. Initially, the dataset was loaded, and thorough checks for missing values were conducted to ensure data integrity. Exploratory data analysis (EDA) was then performed to gain insights into the structure and distribution of the data, providing a foundation for subsequent preprocessing steps.

4.3 Air Passenger Satisfaction

The classification report provides a comprehensive overview of the performance of a classification model. In this case, the precision, recall, and F1-score metrics were calculated for each class. Class 0, representing one category, achieved a precision of 0.79, a recall of 0.79, and an F1-score of 0.79. Similarly, class 1 exhibited precision, recall, and F1-score values of 0.77, indicating reasonably balanced performance across the classes. The support values indicate the number of instances for each class, with 105 instances for class 0 and 95 instances for class 1, suggesting a relatively balanced dataset.

5. ACKNOWLEDGMENTS

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