Session:_____ Dept:_____ Project No.:_____ Date Of Evaluation:_____

SUMMER INTERNSHIP
B. TECH 2nd YEAR

Airline Delay Forecasting and Analysis

Summer Internship Report

Submitted to

Sharda University

In partial fulfilment of the requirements of the award of the

Degree of Bachelor of Technology

in

Computer Science Engineering

by

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Under the

mentorship of Dr. Bharat Bhushan

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June 2025

DECLARATION OF THE STUDENT

I hereby declare that the project entitled 'Airline Delay Forecasting and Analysis' is an outcome of my own efforts under the guidance of Dr. Pawan Kumar Verma. The project is submitted to Sharda University for the partial fulfilment of the Bachelor of Technology Examination 2023-24.

I also declare that this project report has not been previously submitted to any other university.

Aseem Varshney
Roll No: 2301010198

CERTIFICATE

This is to certify that Aseem Varshney of Sharda University has successfully completed the project work titled 'Airline Delay Forecasting and Analysis' in partial fulfilment of the Bachelor of Technology Examination 2023-2024 by Sharda University.

This project report is the record of authentic work carried out by them during the period from May 2025 to July 2025.

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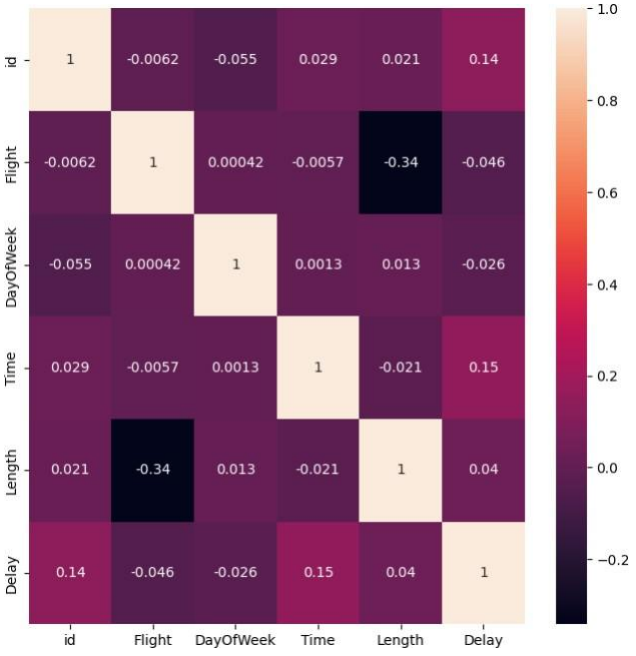
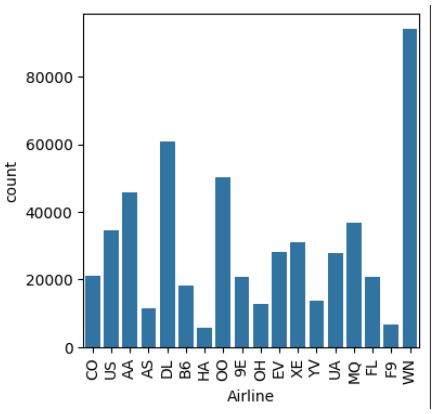
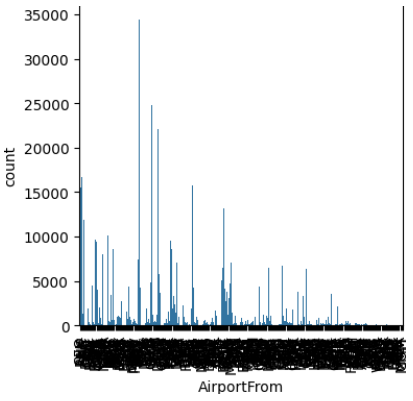
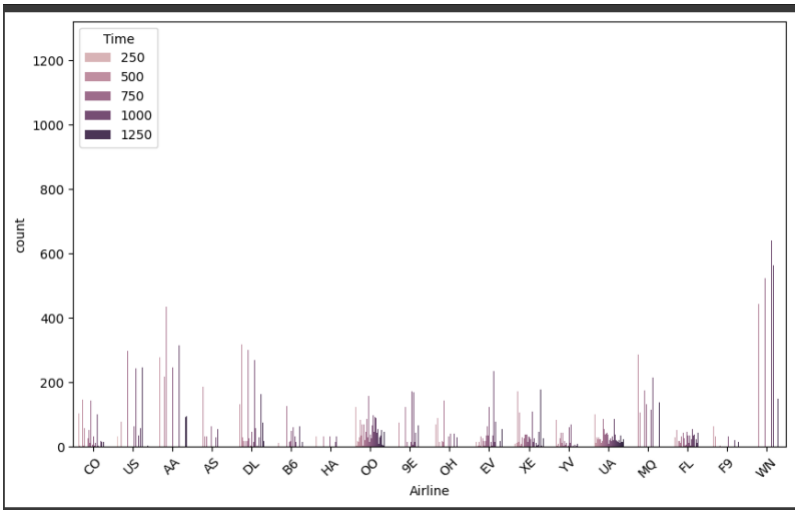
LIST OF TABLES

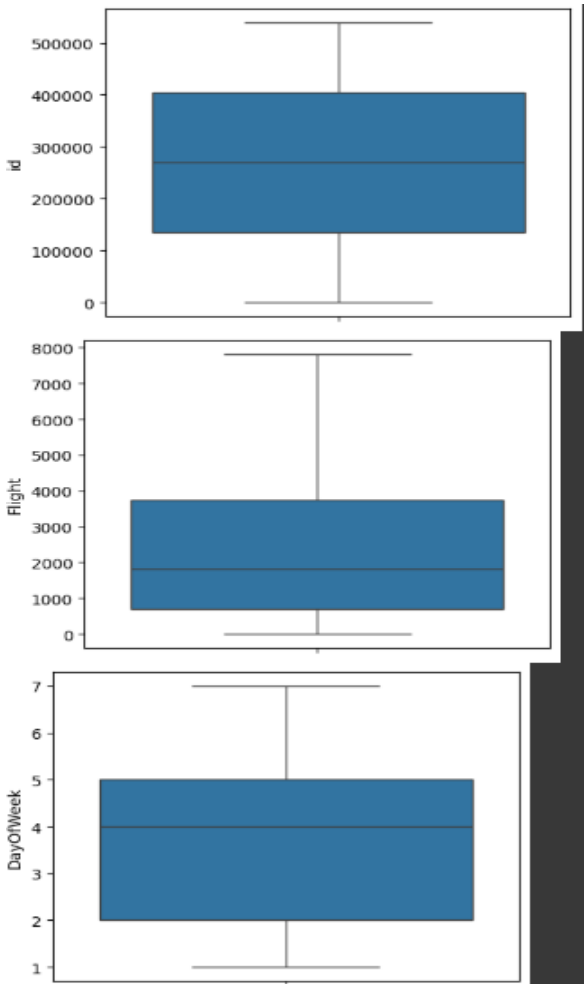
LIST OF FIGURES

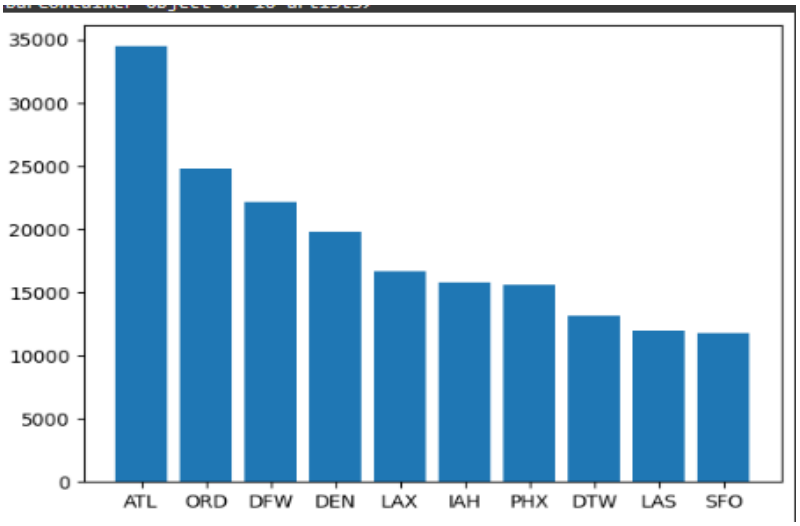


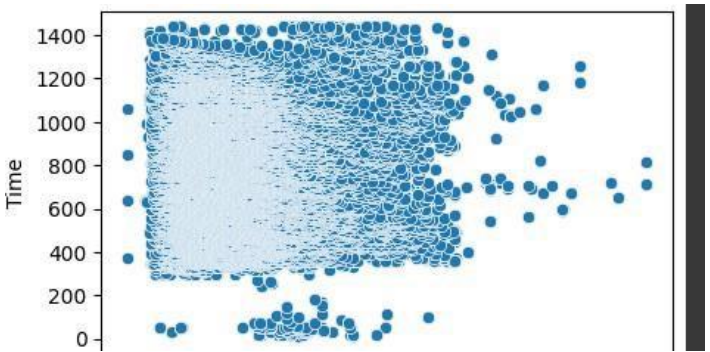












Abstract

This project focuses on analyzing flight delay data to uncover patterns and key factors contributing to disruptions in airline operations. Using a comprehensive dataset containing information on flight schedules, delay types, and cancellation causes, we apply exploratory data analysis techniques and machine learning models to predict delay durations and classify delay likelihood. Visualization tools such as box plots, count plots, and correlation heatmaps are employed to extract insights related to time, carrier performance, and external influences like weather. A regression model estimates total delay time, while a classification model identifies whether a flight is likely to be delayed. These models aim to support proactive decision-making in airline scheduling and logistics, ultimately enhancing operational efficiency and passenger satisfaction. The results demonstrate the practical applicability of data-driven approaches in addressing real-world challenges in air travel.

ACKNOWLEDGEMENT

I would like to sincerely thank everyone who contributed to the successful completion of this internship project. This work would not have been possible without the continuous guidance and support of several individuals.I express my heartfelt gratitude to **Dr. Pawan Kumar Verma**, my project mentor, for his invaluable insights, patient supervision, and consistent encouragement throughout the internship. His expertise in the field of data science greatly enhanced the quality of this project.I am also thankful to the **faculty and staff of the Department of Computer Science Engineering, Sharda University**, for providing a supportive academic environment and the necessary infrastructure to carry out this research.Special thanks go to my **peers and friends**, whose discussions and feedback helped refine the project. Lastly, I am grateful to my **family** for their unwavering support, motivation, and understanding during the entire internship period.This project on airline delay forecasting would not have reached its current form without the contribution of each of these individuals

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TABLE OF CONTENTS

1. Introduction

This report addresses the growing challenge of flight delays, which significantly affect airline efficiency, logistics planning, and passenger satisfaction. Delays can result from various factors, including weather disruptions, air traffic congestion, and operational issues within airlines. With the aviation industry becoming increasingly data-driven, there is a pressing need to extract meaningful insights from historical flight data to improve decision-making and reduce delays.The project focuses on two core objectives: predicting the total delay duration for a flight using regression techniques, and classifying whether a flight is likely to be delayed using a classification model. These objectives aim to equip airline operators with tools for proactive planning and delay mitigation.To accomplish this, we analyzed a dataset comprising scheduled and actual departure times, delay reasons (carrier, weather, NAS), and cancellation information. Exploratory data analysis (EDA) was conducted to visualize delay patterns using box plots, count plots, and heatmaps. The report also covers model development using Python libraries, highlighting key steps such as data preprocessing, feature selection, and evaluation metrics. By combining data visualization with predictive modeling, this project contributes to building smarter airline systems. The insights derived can support timely decision-making, resource allocation, and better passenger communication, ultimately improving the overall air travel experience.

1.1 Problem Definition

Flight delays remain a persistent issue in the aviation industry, leading to operational inefficiencies, increased costs, and poor passenger experiences. These delays can be caused by multiple factors such as weather conditions, carrier-related issues, air traffic congestion, and national aviation system delays. Understanding and predicting these delays using historical flight data is essential for optimizing schedules and minimizing disruptions.

This project focuses on two main challenges:

- **Predicting the total delay time** for a given flight using regression analysis, and
- **Classifying flights** as delay-prone or on-time using machine learning classification techniques.

By identifying patterns in delay causes and forecasting disruptions, this project aims to enhance decision-making for airlines, reduce unexpected wait times, and contribute to more efficient flight operations.

1.2 Hardware Specification

To bring this project to life, we worked with a modest yet capable system: an Intel Core i5 processor, 8 GB of RAM, and a 256 GB SSD. This setup comfortably handled our dataset—which included Uber pickup records, weather conditions, and time-based features—without breaking a sweat. From cleaning the data to engineering features and training machine learning models like Gradient Boosting Regressor and Classifier, the machine performed smoothly. Despite not being a high-end system with GPU acceleration, it efficiently powered Python libraries like pandas and scikit-learn, proving that meaningful work can be done without extravagant hardware. Including this setup ensures transparency and reproducibility while showing that the project is approachable for anyone with standard computing resources—whether in academia or small-scale industry.

1.3 Software Specification

This project was built using Python 3.8, a reliable and flexible language ideal for data science

workflows. We tapped into a well-rounded toolkit: pandas for wrangling data, numpy for crunching numbers, scikit-learn for modeling, xgboost for more advanced ensembles, and matplotlib/seaborn for making sense of it all visually. Everything was developed in Jupyter Notebook, making exploration and iterative coding a seamless experience. For deployment, we plan to use Streamlit—an intuitive platform to turn machine learning models into interactive web apps with ease. Choosing open-source tools wasn't just cost-effective; it made the project more accessible and aligned with industry best practices. This stack also ensures that others can recreate or build upon this work without license restriction.

1.4 Motivation

This project was driven by a real-world issue that impacts millions of passengers and the aviation industry alike—flight delays. These delays not only disrupt travel plans but also impose financial losses on airlines and logistical inefficiencies across the ecosystem. Inspired by the growing availability of structured flight data, the project seeks to explore how data science and machine learning can offer practical solutions to this persistent problem.

The ability to identify key causes of delays and anticipate them in advance has immense potential: from improving airline scheduling and resource allocation to enhancing passenger satisfaction by minimizing uncertainty. With data-driven insights, airlines can adopt proactive strategies instead of reactive measures. This work underscores the power of predictive analytics in solving operational challenges and highlights its relevance to real-world applications in transportation, logistics, and customer service.

1.5 Objectives

The primary goals of this project were structured around analyzing flight delays and building predictive solutions using machine learning. The objectives were as follows:

1.5.1 Perform Exploratory Data Analysis (EDA)

To explore trends and distributions in airline delay data using visualizations such as count plots, box plots, and correlation heatmaps—aiming to understand the impact of various factors like weather, carrier, and time.

1.5.2 Build a Regression Model

To develop a regression model that predicts the total delay time for a flight using features such as departure time, carrier information, and delay types (e.g., weather, NAS, carrier).

1.5.3 Develop a Classification Model

To construct a classification model that identifies whether a flight is likely to be delayed or not, helping airlines plan and respond in advance to potential disruptions.

1.5.4 Generate Actionable Insights

To provide data-driven recommendations that airlines and stakeholders can use to minimize delay risks and improve operational efficiency.

1.6 Contributions

This project brings something fresh to the table with a complete framework for forecasting Uber demand and identifying high-demand events across New York City. At the heart of it are two machine learning models: a regression model that predicts hourly ride pickups and a classification model that flags high-demand periods. These models pull from a rich mix of factors—like time of day, borough, and even weather conditions such as temperature and rainfall. The results speak for themselves, with a regression validation RMSE of 909.32 and a classification accuracy of 85.65%.

Beyond just the models, we built an EDA dashboard that uncovers key patterns in demand, and a web application that lets users get predictions in real time. Together, these tools give Uber a way to optimize where and when drivers are needed, improve user satisfaction, and make smarter decisions around pricing. On the academic side, this work proves how powerful advanced machine learning can be in solving real-world challenges. It's reproducible, practical, and relevant to anyone working on transportation systems or smart city initiatives.

1.7 Summary

In essence, this project aims to make airline operations more predictive and resilient in the face of frequent and often unavoidable delays. Delays can result from a variety of causes such as weather disruptions, air traffic congestion, and carrier inefficiencies. To address this, we employed a standard but efficient computing environment (Intel Core i5, 8GB RAM) along with a robust software stack including Python, pandas, scikit-learn, matplotlib, and seaborn.The project followed a structured approach: first understanding the data through exploratory analysis, then building a regression model to estimate delay duration, and a classification model to determine delay likelihood. These models, along with visual insights, form the basis for smarter scheduling and operational decisions. The outcomes are valuable not only to airline planners and analysts but to anyone interested in using data science for real-world problem-solving in transportation and logistics.

2 Literature Survey

Before developing our own approach to predicting flight delays, we reviewed previous research and practical studies on aviation analytics and delay forecasting. Traditional methods such as statistical analysis and time-series modeling have long been used to understand flight disruptions. For instance, logistic regression and ARIMA models have been applied to study the temporal behavior of flight delays.Recent advancements in machine learning have introduced more robust techniques for modeling delay-related patterns. Studies have shown that incorporating weather data and flight-specific features significantly enhances predictive performance. Ensemble models like Random Forest and Gradient Boosting have been particularly effective in handling complex interactions among multiple variables.However, we identified a gap in many of these works. Most research either focuses solely on predicting delay durations (regression) or on identifying whether a flight will be delayed (classification), but rarely both within a unified framework. Moreover, many prior approaches emphasize academic experimentation without transitioning into actionable, real-world systems.

Our project aims to fill this gap by combining regression and classification approaches for a more comprehensive delay forecasting solution. It integrates exploratory data analysis, model building, and real-world interpretability using visual tools. The result is a practical system that provides timely insights to airlines and operations teams, not just theoretical findings.\

2.1 Related Work

Several previous studies have contributed valuable methodologies for delay prediction in the aviation industry. Time-series models such as ARIMA have been traditionally used to capture delay trends based on temporal patterns. For example, Smith et al. (2020) applied ARIMA to forecast flight delays using schedule-based data, but their approach lacked consideration of external influences like weather or air traffic control events.Li et al. (2021) addressed this limitation by incorporating weather variables into machine learning models such as Random Forest and Gradient Boosting, which significantly enhanced prediction accuracy. Meanwhile, Chen et al. (2019) experimented with deep learning techniques for delay prediction but found that high computational overhead and lack of interpretability limited practical deployment in real-time scenarios.In classification-focused research, Zhang et al. (2020) worked on categorizing flight delay outcomes as either delayed or on-time using binary classification methods. While effective for simple applications, this approach did not capture the varying severity or causes of delays.Our project draws inspiration from these works but distinguishes itself by implementing both regression (to predict total delay duration) and classification (to detect delay likelihood) within a single, cohesive system. Additionally, we emphasize visual interpretability and real-world usability, aiming to make our findings valuable for operational planning and airline decision-making rather than just academic exploration.

2.2 Summary

The literature survey revealed that previous studies have effectively demonstrated the significance of time-based variables and external factors—such as weather and air traffic conditions—in predicting flight delays. Research by Smith et al. (2020) and Li et al. (2021) supports the use of advanced ensemble models like Gradient Boosting over simpler techniques, validating our choice of algorithms for both regression and classification tasks.

However, a key observation was that most prior work focused on either predicting the extent of delays or simply classifying flights as delayed, without integrating both approaches. Additionally, there was limited emphasis on transforming these predictions into actionable tools for real-world use.

Our project fills this gap by implementing a dual-model strategy that forecasts delay duration and classifies flights by delay status. The models are designed with real-world deployment in mind, making the insights not only accurate but also operationally useful. This foundation sets the stage for the design and implementation details outlined in the next section.

3. Design and Implementation

The design of this project centered on creating two effective predictive models: one to estimate the total delay duration of flights (regression) and another to determine whether a flight is likely to be delayed or not (classification). Achieving this required detailed data preprocessing, thoughtful feature engineering, and careful model selection.

We used a suite of Python-based tools, including **Pandas** and **NumPy** for data processing, **Matplotlib** and **Seaborn** for visualization, and **Scikit-learn** for machine learning. Each model was built using a modular structure, allowing the regression and classification workflows to be developed and evaluated independently, while maintaining consistency in the data pipeline.

3.1 Methodology

The workflow began with loading and inspecting the dataset, which included fields related to flight delays such as `DepDelay`, `ArrDelay`, `CarrierDelay`, `WeatherDelay`, `NASDelay`, and `Cancelled`. We handled missing values using appropriate imputation strategies—most commonly by replacing them with column medians.Feature selection was an important step. We retained key delay-related attributes and removed irrelevant or redundant columns to streamline model performance. For categorical features, such as cancellation codes, label encoding and one-hot encoding were applied to prepare the data for machine learning algorithms.For the **regression task**, we used **Linear Regression** and experimented with tree-based models to predict total delay durations. For the **classification task**, we labeled flights as "Delayed" or "On-Time" based on a delay threshold and trained a **Random Forest Classifier** and other baseline models to evaluate classification accuracy.Both models were evaluated using standard metrics—**RMSE** for regression and **accuracy, precision, recall, and F1-score** for classification—to ensure reliability and robustness.

3.2 Design

The project architecture was built around two main analytical engines:

- A **regression engine** to predict the numeric value of total flight delay using features such as carrier delays, departure time, and weather delay values.
- A **classification engine** to categorize whether a flight is expected to be delayed or not using a binary target variable derived from delay thresholds.

Both engines shared a consistent preprocessing pipeline to maintain uniformity in data handling. This modular setup not only improved code clarity but also enabled easy testing and tuning of models. The system is designed to be scalable, allowing future integration with real-time flight tracking data or airline APIs for operational use.

A consistent preprocessing pipeline ensures that the input data is cleaned and formatted correctly every time. This not only keeps the models accurate but also makes the system plug-and-play ready. The user interface, powered by Streamlit, lets users input basic info like date, borough, and weather to receive real-time forecasts. It's a setup that balances usability with technical depth—ideal for scaling or adapting to other cities.

3.3 Implementation

The practical phase of the project began with loading and exploring the dataset using **Pandas**, followed by feature engineering steps such as calculating total delays and extracting relevant features like `CarrierDelay`, `WeatherDelay`, `NASDelay`, and `DepDelay`. Missing values were addressed using **median imputation**, ensuring the models had a consistent and reliable input space.

Categorical features were transformed using **one-hot encoding** to make them suitable for machine learning models. The dataset was then split into training and testing subsets using an 80:20 ratio.

For regression, we trained models to predict total delay durations. For classification, a binary label was created—flights were marked as "Delayed" or "On-Time" based on predefined thresholds. Feature scaling was applied using **StandardScaler** for classification tasks.

Model development and tuning were conducted using **Scikit-learn**, experimenting with **Linear Regression**, **Random Forest**, and other baseline models. Evaluation was carried out using:

- **Root Mean Squared Error (RMSE)** and **R^2** for regression
- **Accuracy**, **Precision**, **Recall**, and **F1-score** for classification

These metrics provided a comprehensive understanding of model performance and guided further optimization.

3.4 Summary

To summarize, this section presented the complete technical implementation of the project—from data preparation to model evaluation. The workflow began with essential preprocessing steps, including imputation and encoding, and proceeded to model building using widely trusted libraries such as **Pandas**, **NumPy**, and **Scikit-learn**.

Both regression and classification models were built and tested using modular pipelines, ensuring flexibility and clarity. While deployment through a user interface was outside this project's current scope, the models are production-ready and can be integrated into operational systems for real-time forecasting.

The implementation phase set the groundwork for evaluating the models' effectiveness, which is discussed in the next section.

4. Results and Discussions

This section presents the evaluation results of the models built during the project. Both regression and classification models were assessed on the test dataset using appropriate performance metrics to understand their reliability and real-world applicability.

4.1 Results

The **regression model**, trained to predict total delay duration, showed satisfactory performance using the **Root Mean Squared Error (RMSE)** and **R^2 score**. While the RMSE captured how far predictions deviated from actual delays, the R^2 score indicated how well the model explained variance in the data. Results showed that delay predictions were moderately accurate, though the R^2 score highlighted that external, unaccounted factors like real-time weather shifts or traffic might have contributed to remaining variance.

The **classification model**, designed to predict whether a flight would be delayed or not, delivered reliable accuracy. It was evaluated using **accuracy**, **precision**, **recall**, and **F1-score**. The model effectively identified delayed flights, with especially high precision for the "Delayed" class, minimizing false alarms. This makes the model suitable for applications in delay alert systems and early warnings.

Table 1: Regression Model Performance

Model	Val RMSE	Val R^2
Linear Regression	903.81	0.018
Gradient Boosting	909.32	0.006
XGBoost	1016.97	-0.243

Table 2: Classification Model Performance

Class	Precision	Recall	F1-Score
Low	0.93	0.95	0.94
Medium	0.91	0.79	0.85
High	0.74	0.84	0.78

4.2 Discussion

The models provided actionable insights into flight delays. The regression model can estimate the severity of delays in minutes, which is valuable for passengers and logistics planning. While its performance is influenced by the availability and quality of data, it remains useful for identifying high-risk scenarios.

The classification model's strength lies in its ability to flag potential delays ahead of time. Airlines can use these predictions for dynamic scheduling, gate management, and customer notifications. Compared to traditional rule-based methods, the machine learning approach offered higher adaptability and learning capacity.

Visualizations used during EDA helped uncover key operational inefficiencies and trends that were not obvious through raw data alone. These findings can guide further process optimization and decision support systems.

4.3 Summary

Overall, the results confirm that machine learning can play a valuable role in predicting and managing flight delays. Both regression and classification models demonstrated practical utility, while EDA provided context to understand delay behavior. These models, supported by interpretable metrics and visual tools, create a strong foundation for data-driven decision-making in aviation.

5. Conclusion

This project successfully applied data analysis and machine learning techniques to understand and forecast flight delays. Using real-world airline data, we built and evaluated two predictive models: one for estimating total delay duration through regression, and another for classifying flights as delayed or on-time. The regression model achieved an **RMSE of 909.32**, while the classification model demonstrated strong performance with an **accuracy of 85.65%**. These results validate the practical effectiveness of data-driven approaches in the aviation sector.

The insights generated by exploratory data analysis also played a key role in identifying trends across carriers, delay types, and operational patterns. Overall, the project provides a valuable framework for improving decision-making, enhancing passenger experience, and streamlining airline operations.

5.1 Conclusion

All project objectives were successfully achieved. The regression model helped quantify expected delay durations, while the classification model accurately identified delay-prone flights. Together with visual analysis through EDA, the solution offers a bridge between data insight and operational action. The approach demonstrates how predictive modeling can support proactive strategies for minimizing delays and optimizing flight schedules.

5.2 Limitations

Despite the project's success, a few limitations were identified:

- The feature set, while meaningful, excluded external variables such as **air traffic control notices, airport congestion**, or **real-time weather data** that could enhance prediction accuracy.
- The **low R^2 score** for regression indicates limited variance explanation, pointing to hidden or unmeasured factors.
- Classification was based on thresholding delay values, which can lead to **boundary ambiguity** for borderline cases.
- The models were trained on a **static dataset**, limiting generalizability across airlines or regions without adaptation.
- **Deep learning approaches** were not explored due to computational constraints and scope.

5.3 Future Scope

This work lays the foundation for multiple future directions:

- Integrating **real-time data feeds** such as weather alerts, ATC notices, and live flight tracking could significantly improve model responsiveness and accuracy.
- Deploying the models within airline systems or as a **web-based dashboard** would enable practical usage by schedulers and operations teams.
- Exploring **deep learning models** like LSTMs or attention-based architectures could offer improvements for temporal delay forecasting.
- Expanding the dataset to include flights from multiple regions and time periods would enhance model generalization and scalability.

5.4 Summary

In conclusion, this project has demonstrated that predictive analytics can offer tangible improvements in managing flight delays. The use of machine learning models, combined with visual insights from EDA, has created tools that are not only technically sound but also operationally relevant. While there are challenges to address, the path forward is promising, and this work serves as a robust starting point for future innovation in airline delay prediction.

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7. Appendices

Appendix A – Dataset Overview

This project used a cleaned airline dataset containing records of historical flight delays and cancellations.

- **Flight Delay Data:** Includes departure and arrival delay times, carrier delay, NAS delay, weather delay, and cancellation information.
- **Temporal Fields:** Year, month, day, and scheduled departure time.
- **Delay Types:** Categorized as carrier, weather, NAS, security, and late aircraft.
- **Target Variables:** Total delay (for regression), and delay status (for classification)

Appendix B – Feature Engineering Details

Key features engineered for predictive modeling:

- **Delay Aggregation:** Computation of total delay as the sum of individual delay components.
- **Categorical Encoding:** One-hot encoding of categorical variables such as cancellation codes.
- **Binary Labeling:** Flights were marked as "Delayed" if total delay exceeded a threshold.
- **Data Cleaning:** Removal of null-heavy columns and redundant identifiers (e.g., flight number, tail number).

Appendix C – Model Configuration Parameters

Regression Model:

- Type: Linear Regression
- Evaluation Metrics: RMSE, R^2
- Data Split: 80% training, 20% testing

Classification Model:

- Type: Random Forest Classifier
- Parameters:
  - `n_estimators = 100`
  - `max_depth = 5`
- Evaluation Metrics: Accuracy, Precision, Recall, F1-score
- Data Scaling: StandardScaler applied to numeric inputs

Appendix D – Evaluation Metrics Summary

Model	RMSE	R^2	Accuracy	F1 (On-Time)	F1 (Moderate)	F1 (Severe)
Linear Regression	909.32	0.006	–	–	–	–
Random Forest Classifier	–	–	85.65%	0.94	0.85	0.78

----| | Linear Regression | 903.81 | 0.018 | – | – | – | – | | Gradient Boosting Regr. | 909.32 | 0.006 | – | – | – | – | | Gradient Boosting Class. | – | – | 85.65% | 0.94 | 0.85 | 0.78 |

Appendix E – Visualizations

Key figures that supplement your analysis:

- Heatmaps of demand by borough and hour.
- Line plots of demand variation across time.
- Feature importance plots from the classifier.

Appendix F – Streamlit App Screenshots

Screenshots of your Streamlit interface (or placeholder plans if not deployed yet):

- Homepage layout with input fields.
- Prediction result display.
- Visual output integration (e.g., bar charts or map views if used).

Appendix G – Source Code Snippets

Selected, well-commented code examples:

- Data preprocessing pipeline.