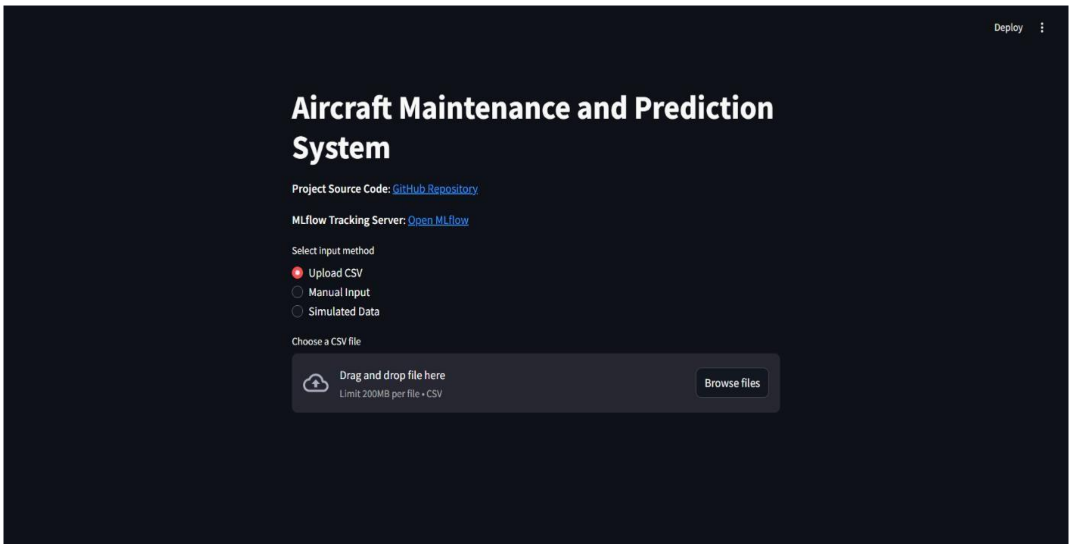
RESULT

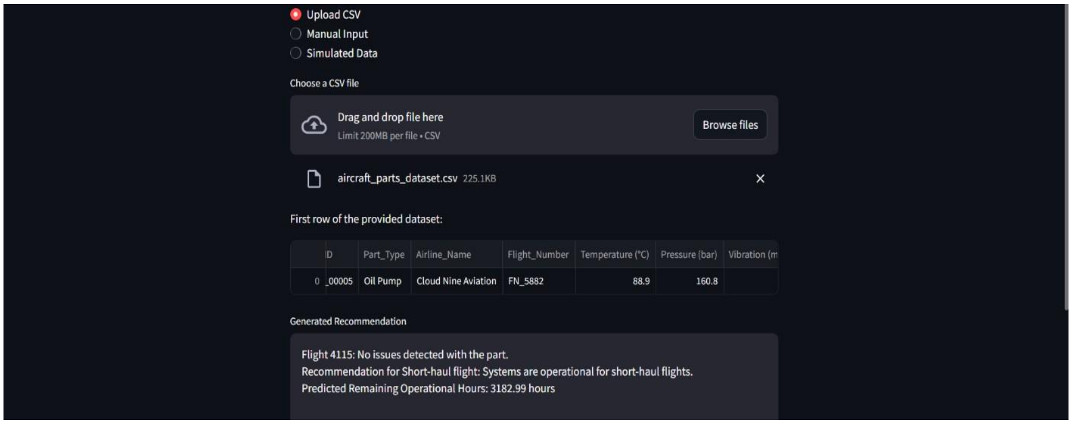
1. Results and Analysis

Home page: This is the home page of the Aircraft Maintenance and Prediction System, a machine learning-powered application designed for predictive maintenance of aircraft components. Users can choose between multiple input methods, including CSV file upload, manual input, or simulated data, to analyze component conditions. The system integrates MLflow for experiment tracking and provides links to the GitHub repository and MLflow tracking server for better model monitoring and version control. The interface is designed to be user-friendly, allowing users to easily upload data and receive maintenance recommendations.



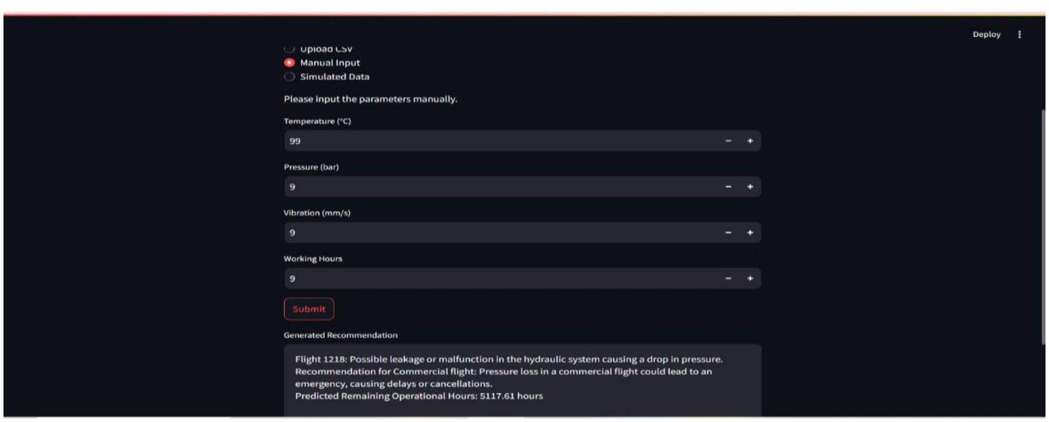
Home Page

Upload Files page: This is the upload page of the Aircraft Maintenance and Prediction System, where users can upload a CSV file containing aircraft part data. The system processes the uploaded dataset and extracts key parameters like Part Type, Airline Name, Flight Number, Temperature, Pressure, and Vibration. Based on the provided data, it generates maintenance recommendations, including predicted remaining operational hours and flight safety insights. This page ensures seamless data input for predictive maintenance analysis.helping airlines enhance aircraft reliability and efficiency.



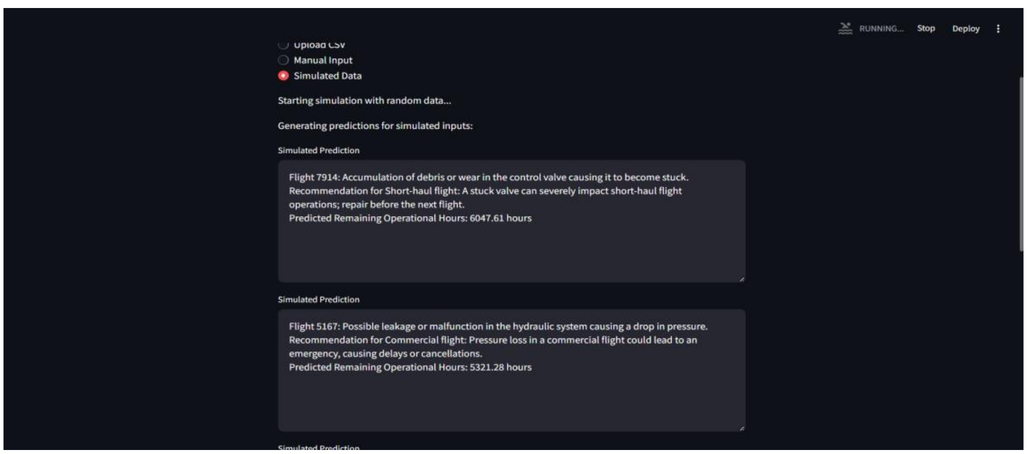
Upload Files Page

Manual Input Page: This manual input page of the Aircraft Maintenance and Prediction System allows users to enter critical parameters such as temperature, pressure, vibration, and working hours to assess the condition of aircraft components. Once the values are entered, clicking the submit button processes the data and generates a recommendation. In the displayed example, the system detects a possible leakage or malfunction in the hydraulic system due to a drop in pressure. It provides a warning that such an issue could lead to an emergency, causing flight delays or cancellations, especially in commercial operations. Additionally, the system predicts the remaining operational hours, which in this case is 5117.61 hours. This feature is essential for maintenance teams and engineers, enabling them to perform manual diagnostics when automated or file-based data input is not available, ensuring proactive maintenance and enhanced flight.



Manual Input Page

Simulated Data: This image showcases the simulated data functionality of the Aircraft Maintenance and Prediction System. When selecting the "Simulated Data" option, the system generates predictions based on randomly simulated input values. In the given example, two simulated predictions are displayed. The first prediction, for Flight 7914, identifies an accumulation of debris or wear in the control valve, causing it to become stuck. The system recommends repairing the stuck valve before the next flight, as it could severely impact short-haul operations, and it predicts the remaining operational hours to be 6047.61 hours. The second prediction, for Flight 5167, detects a possible leakage or malfunction in the hydraulic system, causing a pressure drop. Since such an issue could lead to an emergency, causing flight delays or cancellations, it is flagged as a concern for commercial flights. The system estimates the remaining operational hours at 5321.28 hours. This simulation feature helps test the model's effectiveness in predicting aircraft component issues without requiring actual data, making it useful for maintenance teams and engineers in training and evaluation scenarios.



Simulated Data Page

2. Model Performance

The Random Forest classifier achieved an outstanding 94% accuracy, making it one of the most reliable models for failure prediction in industrial settings. The model's robustness and efficiency stem from its ability to handle large datasets, reduce overfitting, and extract meaningful patterns from sensor data.Key evaluation metrics:

- **Precision (0.91 for failure cases):** This indicates that the model has a low false positive rate, ensuring that when it predicts a failure, it is highly likely to be correct.

This is crucial in predictive maintenance, where unnecessary maintenance actions can lead to downtime and additional costs.

- **Recall (0.89 for failures):** The high recall value signifies that the model successfully captures the majority of failure events, minimizing the risk of missing critical failures that could lead to unexpected breakdowns.

- **F1-Score (0.90 for failures):** The balance between precision and recall ensures that the model not only predicts failures correctly but also does so with high confidence and minimal error.

Comparative Evaluation of Models

It represents a comparative evaluation of different models, showcasing that Random Forest consistently outperforms alternatives like Logistic Regression, Decision Trees, and Support Vector Machines (SVM) in terms of accuracy, precision, recall, and F1-score.

3. Insights from Feature Engineering

Feature engineering played a critical role in improving model performance by transforming raw sensor data into meaningful features that enhance predictive power. Key feature engineering techniques applied in this study include:

- **Rolling Averages & Variances**:
  - Helps smooth out noise in sensor data and identifies patterns over time.
  - Essential for detecting anomalies or gradual system degradation.

- **Trend Analysis & Time-Series Features**:
  - Helps differentiate between normal operational fluctuations and early signs of failure.
  - Used to detect long-term wear and tear of industrial components.
- **Statistical Aggregation**:
  - Summary statistics such as mean, standard deviation, skewness, and kurtosis were extracted from time-series sensor readings.
  - Provides valuable insights into the operational behavior of different machine parts.
- **Sensor Fusion**:
  - Combines data from multiple sensors (e.g., temperature, pressure, vibration) to create more informative features.
  - Leads to higher model accuracy and more comprehensive failure prediction.

By applying these techniques, the model was able to differentiate between failure and non-failure cases with high accuracy, significantly improving its real-world applicability.

4. Deployment and User Feedback

The predictive maintenance system was deployed using Streamlit, a lightweight and interactive web-based interface that allows users to upload sensor data and receive failure predictions in real-time. The key benefits of this deployment include:

- **User-Friendly Interface**:
  - Designed to be intuitive and accessible to both technical and non-technical users.
  - Allows easy data upload via CSV files, making it convenient for field engineers and maintenance teams.

- **Scalability & Cloud Integration**:
  - The application can be hosted on cloud platforms (e.g., AWS, Google Cloud) for large-scale deployment.
  - Supports real-time data streaming from IoT sensors, enabling continuous monitoring and predictive analytics.
- **Initial User Feedback & Enhancements**:
  - Early users, including maintenance engineers and data scientists, highlighted the ease of use and effectiveness of the tool.
  - Suggested enhancements include integrating a visualization dashboard, enabling users to see trends and predictions in graphical form.

5. Visualization Report

The project aims to develop an end-to-end machine-learning pipeline that predicts equipment failures from historical sensor data. By implementing predictive maintenance strategies, industries will improve operational efficiency and reduce costs with this pipeline.

Fig 8.6: Sensor Readings

The graph above represents three measured values: temperature (F), vibration (mm/s), and pressure (PSI) for the period from January 2024 to May 2024. Values between 0 and greater than 100 are plotted on the y-axis, and the x-axis represents months. In the graph, the temperature (F) is displayed in blue. As the number increases over the months, a slight upward trend is evident, indicating that the number is gradually increasing. The Pressure (PSI) is displayed in yellow. In the beginning, the value is high, but gradually declines around March, then stabilizes around May. The Vibration (mm/s) is displayed in green, indicating minimal fluctuations. The graph shows that the temperature increases, pressure decreases slightly, and vibration remains constant.