

AircraftHealthML: Aircraft Health Monitoring Service

Predictive Maintenance and aircraft health monitoring powered by ML for real time analysis



Introduction to AircraftHealthML



Overview of AircraftHealthML

AircraftHealthML is our solution for integrated aircraft health monitoring, predicting maintenance needs, and component interaction analysis through the use of Machine Learning and utilizing historical data

Objectives of the Project

- Predict potential failures
- Analyze cascading faults
- Optimize maintenance strategies in aviation systems, ensuring safety and efficiency

This leads to: Reduced maintenance cost and increased operational Efficiency and Safety in the industry





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Project Motivation and Importance



Challenges in Aircraft Health Monitoring

- low quality data
- complexity of aircraft (avionics) systems
- need for real-time analysis
- delayed maintenance is caused leading to potential catastrophic failures if not addressed effectively early on.

Importance of Predictive Maintenance

- Enhances safety
- reduces unexpected downtimes
- reduces maintenance costs
- increasing aircraft availability
- increases operational efficiency.





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Key Features and Technologies

Integrated Health Monitoring

Real-time integrated health monitoring that continuously assessing aircraft conditions using onboard electronics like sensor data, and flight logs.



Predictive Maintenance

The system employs predictive maintenance strategies to forecast potential failures prior to occurrence unlike current Reactive alternatives.



Component Interaction Analysis

Analyzes interactions between different aircraft systems to identify cascading faults and optimize maintenance strategy



Machine Learning Models

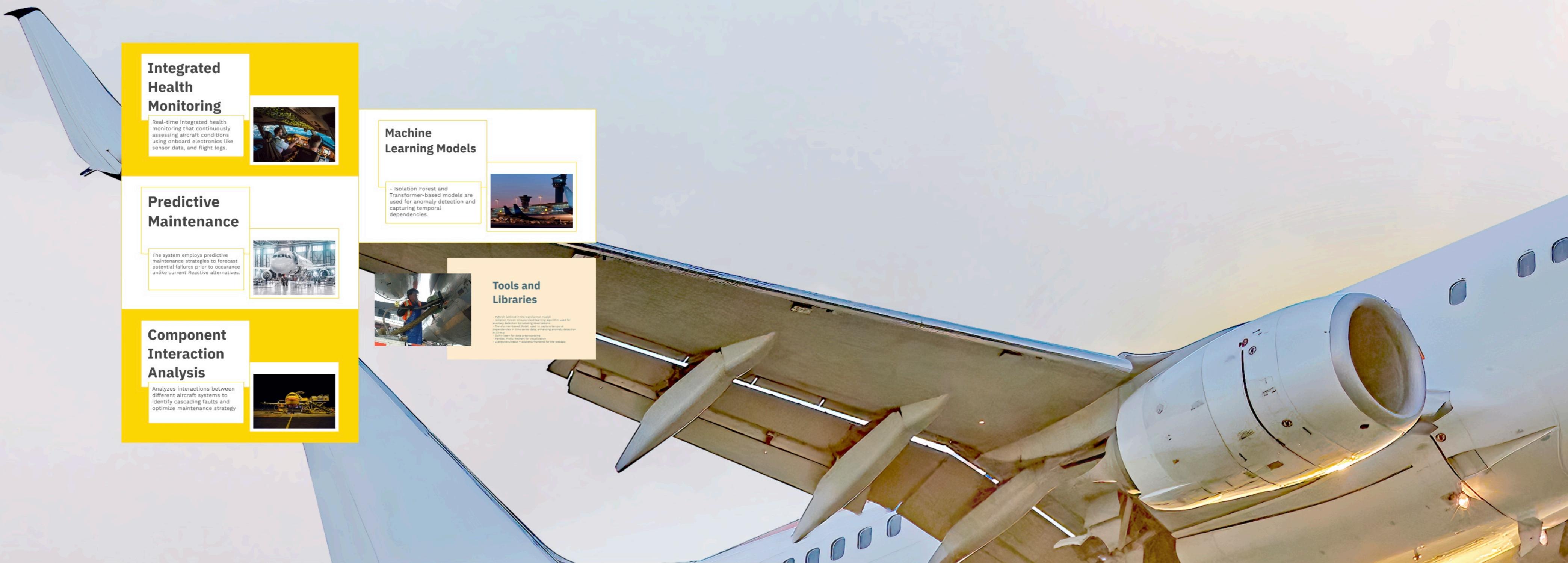
- Isolation Forest and Transformer-based models are used for anomaly detection and capturing temporal dependencies.



Tools and Libraries

Dyverse Library in the transformer model
PyTorch Lightning in the transformer model
PyTorch Lightning - PyTorch's circumvent learning algorithm used for distributed training and parallelism
Transformer-based model used to extract temporal dependencies from historical data for anomaly detection accuracy
Scikit-learn for data preprocessing
Pandas, Matplotlib for visualization
Django/python - Backend framework for the webapp





Integrated Health Monitoring

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Component Interaction Analysis

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Tools and Libraries

- PyTorch (utilized in the transformer model)
- Isolation Forest: Unsupervised learning algorithm used for anomaly detection by isolating observations.
- Transformer-based Model: used to capture temporal dependencies in time series data, enhancing anomaly detection accuracy.
- Scikit-learn for data preprocessing
- Pandas, Plotly, Rechart for visualization
- DjangoRest/React = Backend/frontend for the webapp

Machine Learning Models

- Isolation Forest and Transformer-based models are used for anomaly detection and capturing temporal dependencies.





System Architecture and Results

Data Preprocessing

- Data Ingestion: Involves collecting data from sensors, flight logs, and other relevant sources.
- Preprocessing: Includes steps like data cleaning, normalization, and feature extraction to prepare data for modeling.
- Model Training: Train models on historical "cleaned" data, enabling them to detect anomalies in new data.
- Anomaly Detection: Applies trained models to incoming data to identify potential anomalies in real-time.
- Result Visualization: Uses Plotly to create interactive charts and graphs that help users understand and analyze detection results.

System Architecture Overview



Data Ingestion: Collecting data from sensors, flight logs (from the datasets) and other relevant sources.
Preprocessing: Includes steps like data cleaning, normalization, and feature extraction to prepare data for modeling.
Model Training: Training Random Forest and Transformer Models on historical data, enabling them to detect anomalies and make predictions.
Anomaly Detection: Detects potential anomalies in real-time based on historical model training data.
Result Visualization: Creates charts and graphs using plotly that help users understand and analyze results.



Datasets

ADAPT Dataset: Contains time series data from various sensors (temperature, pressure, and vibration) collected at regular intervals. It is used for real-time anomaly detection insights on aircraft performance over time.

NGAFID Dataset: Contains data from various sensors (temperature, pressure, and vibration) recorded during flight time, it offers a comprehensive view of flight operations and conditions.

Web Application Integration



Result Visualizations

ADAPT Anomaly Scores: Visualized using a bar chart, with anomalies highlighted in red for easy identification.

NGAFID Anomaly Scores: This aspect uses a scatter plot, highlighting anomalies in real-time across multiple flights.

Flight Performance: The main monitoring key metrics such as take anomalies, detection rate, and health score for both datasets.

Use Cases and Future Work



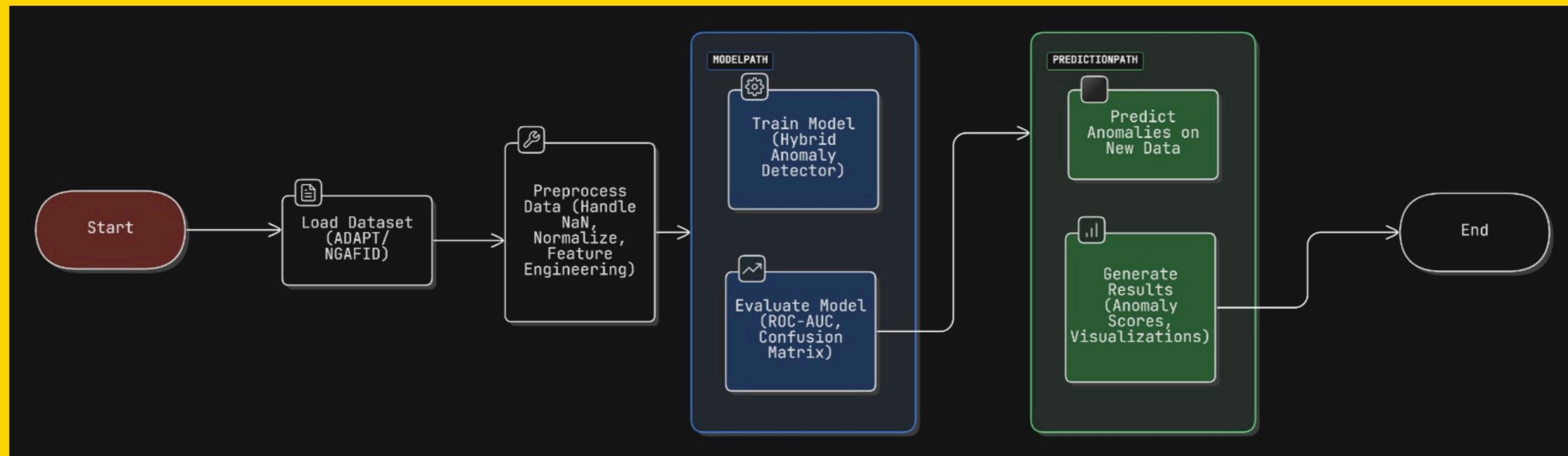
Frequently Asked Question

How does AircraftHealthML handle real-time data processing?
By leveraging data pipelines and scalable ML models where it continuously monitors incoming data streams, processes them in real-time, and updating the anomaly detection results in real-time, ensuring early identification of potential issues calling for immediate action or response.

What datasets are used in AircraftHealthML, and how are they integrated?
The system utilizes two primary datasets: the ADAPT dataset for time series data and the NGAFID dataset to track flight performance. These are integrated through a hybrid anomaly detection approach, combining the strengths of both datasets to provide comprehensive monitoring and analysis including data preprocessing, feature extraction, and model training to ensure accurate and reliable anomaly detection.

How does the web application enhance the usability of AircraftHealthML?
The web application enhances the usability by providing an interactive interface for users to visualize and analyze anomaly detection results in real-time. It offers real-time visualization of anomaly scores, detailed summaries, and interactive charts that help users quickly identify and understand potential issues.

System Architecture Overview



Data Ingestion: Collecting data from sensors, flight logs (from the datasets)

Preprocessing: Includes steps like data cleaning, normalization, and feature extraction to prepare data for modeling.

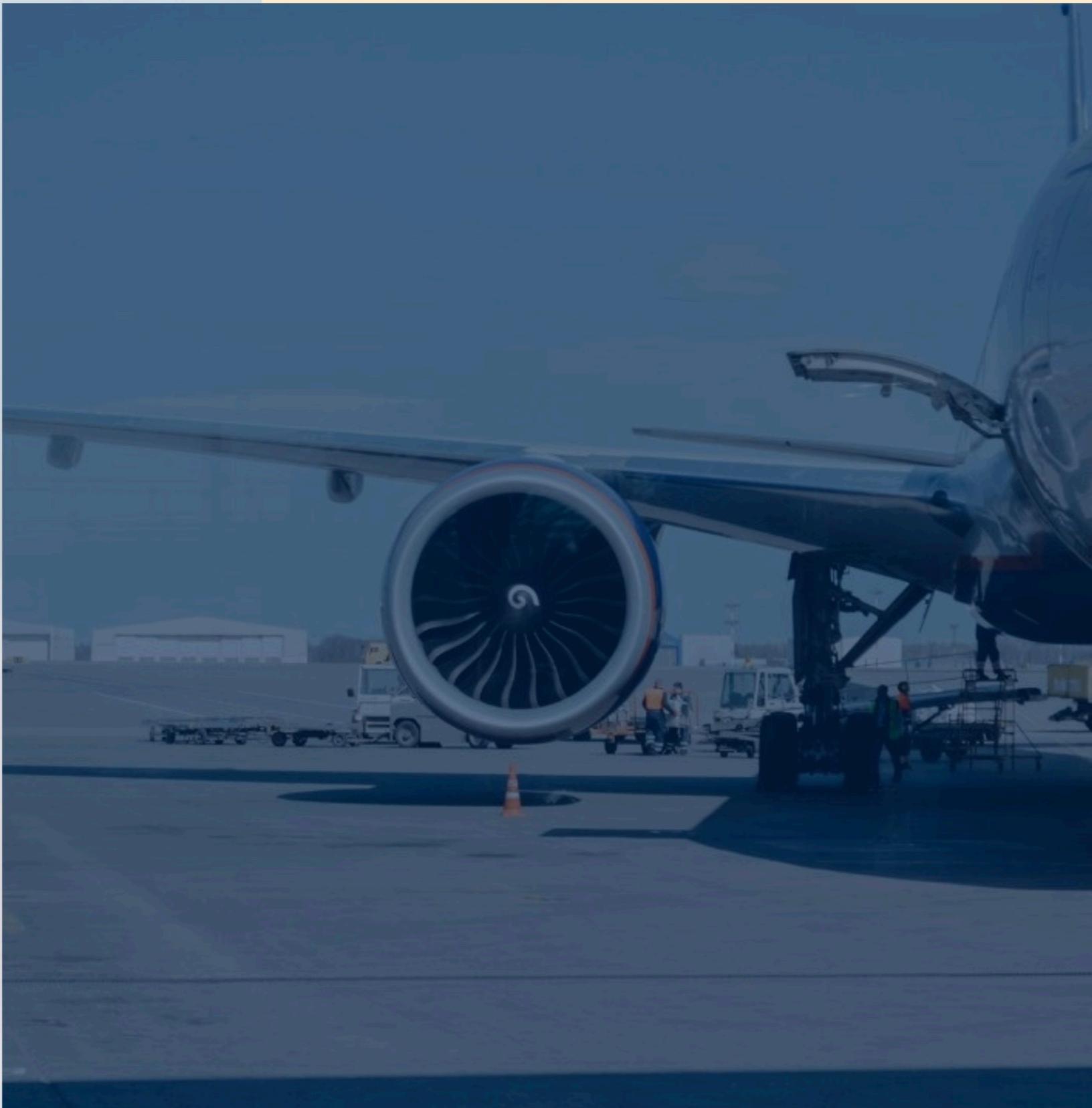
Model Training: Training Random Forest and Transformer Models on historical data, enabling them to detect anomalies and make predictions.

Anomaly Detection: Identifies potential anomalies in real-time based on historical model training data.

Result Visualization: Creates charts and graphs using plotly that help users understand and analyze results.

Data Preprocessing

- Data Ingestion: Involves collecting data from sensors, flight logs, and other relevant sources.
- Preprocessing: data cleaning, normalization, and feature extraction to prepare data for modeling.
- Model Training: train models on historical "cleaned" data, enabling them to detect anomalies in new data.
- Anomaly Detection: Applies trained models to incoming data to identify potential anomalies in real-time.
- Result Visualization: Uses Plotly to create interactive charts and graphs that help users understand and analyze detection results.



Datasets

ADAPT Dataset: Contains time series data from various sensors(temperature, pressure, and vibration) collected at regular intervals/periods, provided detailed technical insights on aircraft performance over time.

NGAFID Dataset: Contains flight data (altitude, speed, and engine performance) recorded during flight time. It offers a comprehensive view of flight operations and conditions.



Result Visualizations

ADAPT Anomaly Scores: Visualized using a line chart, with anomalies highlighted in red for easy identification.

NGAFID Anomaly Scores: Displayed using a scatter plot, with different colors representing normal and anomalous flights.

Summary Visualization: The Bar chart summarizing key metrics such as total anomalies, detection rate, and health score for both datasets.

Web Application Integration

Integration with a web application brings a user friendly GUI to our real-time system.

Key features include:
displaying health metrics
and model visualizations



Use Cases and Future Work

Real-world applications include predictive maintenance modeling and operational efficiency enhancements.

Future improvements will come through:

- improving model by training on higher quality dataset.
- Integrating real-time processing from real/simulated sensors
- integrating additional datasets for advanced analytics and anomaly detection capabilities.



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