Sri Sri University

Predictive Maintenance for Aircraft Engines & Aviation Safety

HIGH-LEVEL DESIGN

Predictive Maintenance

Baccalaureus Technologiae

Faculty Of Engineering & Technology

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1. Introduction

1.1. Scope of the Document

This document outlines the methodology, implementation, and evaluation of predictive maintenance strategies for aircraft engines using machine learning techniques. It delves into the process of leveraging sensor data to forecast potential failures, thereby enabling proactive maintenance practices.

1.2. Intended Audience

Engineers, data scientists, aviation professionals, and stakeholders involved in aircraft maintenance and operations form the primary audience for this document. It caters to individuals seeking insights into predictive maintenance methodologies and their application in the aviation industry.

1.3. System Overview

The system overview provides a high-level understanding of the predictive maintenance framework. It elucidates the data acquisition process, model development pipeline, and the ultimate goal of minimizing aircraft downtime through pre-emptive maintenance actions.

Objectives:

The primary objective of the predictive maintenance framework is to leverage machine learning techniques to forecast potential failures in aircraft engines based on sensor data. By proactively identifying maintenance needs, the framework aims to minimize downtime, optimize maintenance schedules, and enhance operational efficiency in aviation operations.

Components:

The predictive maintenance framework comprises several interconnected components, each serving a specific role in the overall workflow:

- Data Acquisition
- Data Preprocessing
- Model Development
- Model Evaluation
- Deployment and Monitoring

Operational Workflow:

The operational workflow of the predictive maintenance framework follows a cyclical process, iterating through stages of data acquisition, preprocessing, model development, evaluation, deployment, and monitoring. This iterative approach allows for continuous improvement and refinement of predictive models based on feedback from operational data and maintenance outcomes.

2. System Design

2.1. Application Design

The application design delineates the architecture and functionalities of the predictive maintenance system. It outlines the modules responsible for data preprocessing, model training, evaluation, and result visualization.

2.2. Process Flow

Process flow elucidates the sequence of steps involved in predictive maintenance, starting from data ingestion to model deployment. It highlights the iterative nature of model development, wherein insights gained from exploratory data analysis inform feature engineering and model selection.

Model Evaluations:

After training the models, they were evaluated using the test dataset to assess their performance in predicting aircraft engine failures. The following evaluation metrics were calculated:

```
Sigmoid Accuracy: 97.62%
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      4392
           1       0.94      0.89      0.92       766

    accuracy                           0.98      5158
   macro avg       0.96      0.94      0.95      5158
weighted avg       0.98      0.98      0.98      5158

[[4350   42]
 [  81  685]]
```

```
Hyperbolic Accuracy: 91.84%
              precision    recall  f1-score   support

           0       0.95      0.95      0.95      9087
           1       0.83      0.82      0.83      2852

    accuracy                           0.92     11939
   macro avg       0.89      0.89      0.89     11939
weighted avg       0.92      0.92      0.92     11939

[[8614  473]
 [ 501 2351]]
```

```
Logistic Regression Accuracy: 99.53%
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      4392
           1       0.97      1.00      0.98       766

    accuracy                           1.00      5158
   macro avg       0.99      1.00      0.99      5158
weighted avg       1.00      1.00      1.00      5158

[[4369   23]
 [   1  765]]
```

```
K Nearest Neighbors Accuracy: 98.41%
              precision    recall  f1-score   support

           0       1.00      0.98      0.99      4392
           1       0.90      1.00      0.95       766

    accuracy                           0.98      5158
   macro avg       0.95      0.99      0.97      5158
weighted avg       0.99      0.98      0.98      5158

[[4311   81]
 [   1  765]]
```

```
SVM Accuracy: 97.10%
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      9087
           1       1.00      1.00      1.00      2852

    accuracy                           1.00     11939
   macro avg       1.00      1.00      1.00     11939
weighted avg       1.00      1.00      1.00     11939

[[9087    0]
 [   0 2852]]
```

```
Random Forest Accuracy: 95.12%
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      9087
           1       1.00      1.00      1.00      2852

    accuracy                           1.00     11939
   macro avg       1.00      1.00      1.00     11939
weighted avg       1.00      1.00      1.00     11939

[[9087    0]
 [   0 2852]]
```

```
GaussianNB Accuracy: 93.16%
              precision    recall  f1-score   support

           0       1.00      0.92      0.96      4392
           1       0.69      0.99      0.81       766

    accuracy                           0.93      5158
   macro avg       0.84      0.96      0.88      5158
weighted avg       0.95      0.93      0.94      5158

[[4047  345]
 [   8  758]]
```

```
Decision Tree Accuracy: 94.88%
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      9087
           1       1.00      1.00      1.00      2852

    accuracy                           1.00     11939
   macro avg       1.00      1.00      1.00     11939
weighted avg       1.00      1.00      1.00     11939

[[9087    0]
 [   0 2852]]
```

2.3. Information Flow

Information flow diagrams depict the movement of data and insights across different stages of the predictive maintenance pipeline. It elucidates how raw sensor data is transformed into actionable insights through data processing and machine learning algorithms.

2.4. Components Design

Components design outlines the building blocks of the predictive maintenance system, including data preprocessing modules, machine learning algorithms, and evaluation metrics. It emphasizes modularity and extensibility to accommodate future enhancements.

2.5. Key Design Considerations

Key design considerations encompass scalability, interpretability, and reliability of machine learning models. It addresses challenges such as model drift, data quality, and computational resource constraints, ensuring robust performance in real-world deployment scenarios.

2.6. API Catalogue

The API catalogue provides documentation for accessing functionalities exposed by the predictive maintenance system. It facilitates seamless integration with existing infrastructure and enables interoperability with external applications.

3. Data Design

3.1. Data Model

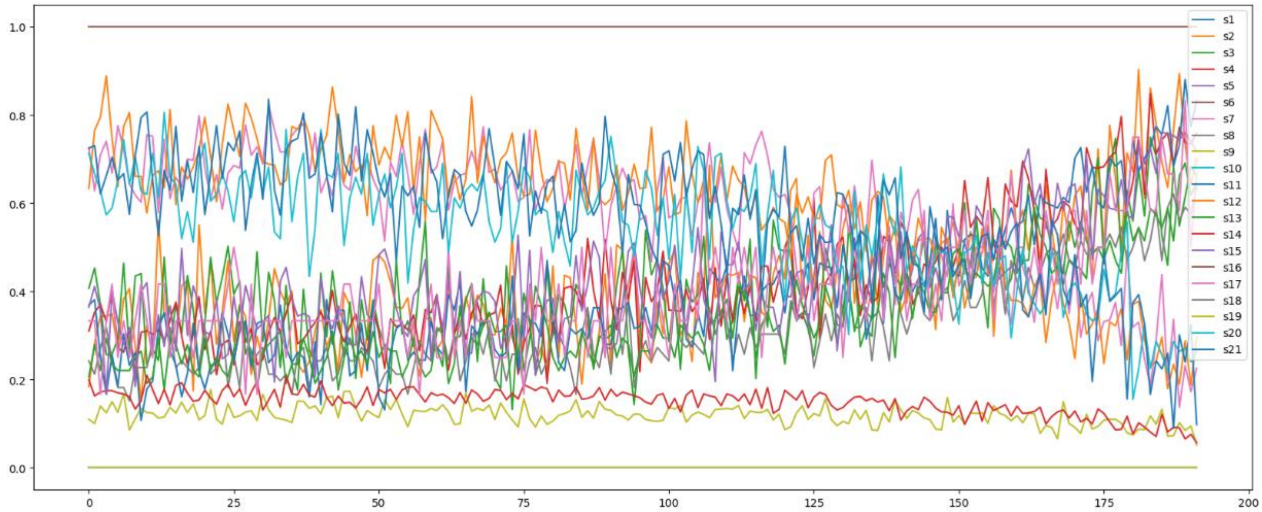
The data model defines the structure and semantics of the sensor data collected from aircraft engines. It specifies the attributes, data types, and relationships necessary for training machine learning models.

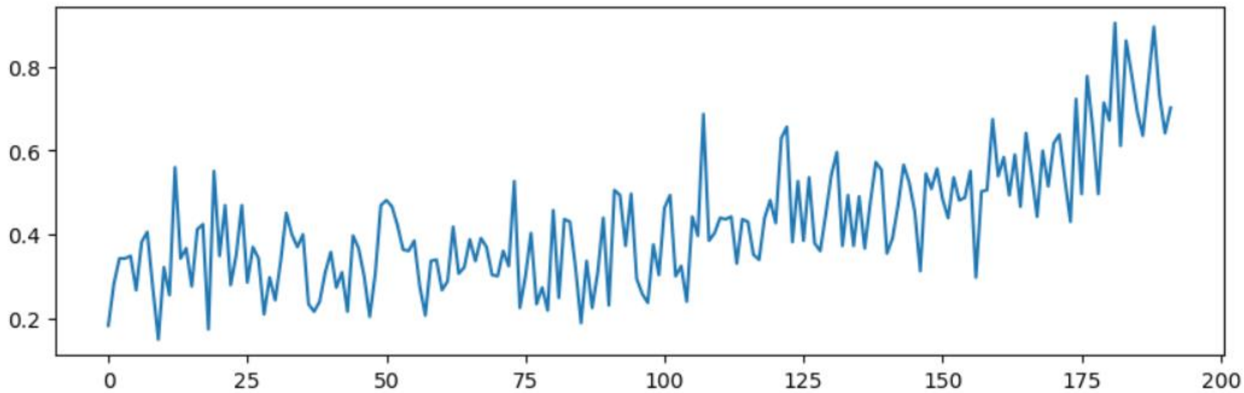
3.2. Data Access Mechanism

Data access mechanisms encompass data loading, preprocessing pipelines, and train-test splitting strategies. It ensures efficient data retrieval and manipulation while preserving data integrity and privacy.

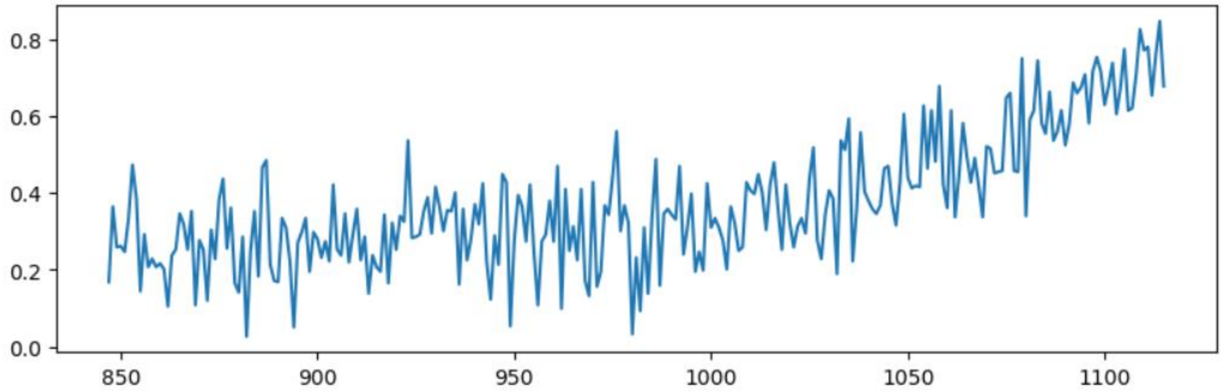
Exploratory Data Analysis (EDA)

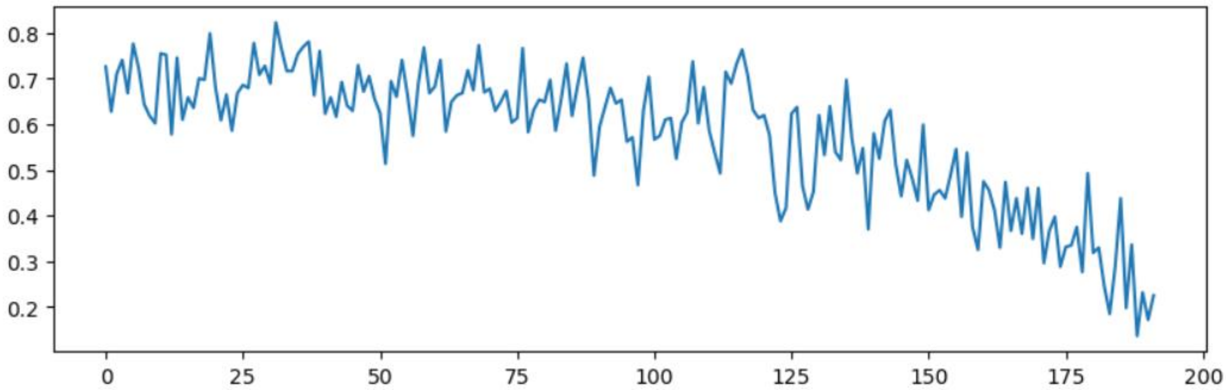
To gain insights into the dataset and understand its characteristics, an exploratory data analysis (EDA) was conducted. The EDA aimed to uncover patterns, distributions, and anomalies within the data, informing subsequent preprocessing steps and model development.





1. Sensor 1 values increase when the cycle of number incrceases.
2. Sensor 6 values decrease when the cycle of number increases.
3. Most other sensors exhibit either an increasing or decreasing trend.





3.3. Data Retention Policies

Data retention policies govern the storage and archival of historical sensor data for future analysis and model retraining. It addresses compliance requirements and data governance considerations to safeguard sensitive information.

3.4. Data Migration

Data migration strategies facilitate the seamless transfer of data between storage systems and environments. It ensures compatibility and consistency across different platforms and data processing frameworks.

4. Interfaces

4.1. User Interfaces

User interfaces provide interactive dashboards and visualizations for monitoring model performance and maintenance alerts. It enhances user experience and facilitates decision-making by presenting actionable insights in an intuitive manner.

4.2. Application Interfaces

Application interfaces enable communication between different modules within the predictive maintenance system. It defines protocols and data formats for exchanging information, ensuring interoperability and extensibility.

5. State and Session Management

5.1. State Management

State management mechanisms maintain the integrity and consistency of application state during model training and evaluation. It handles data persistence, session tracking, and concurrency control to support concurrent access from multiple users.

5.2. Session Management

Session management ensures secure authentication and authorization for users accessing the predictive maintenance system. It safeguards against unauthorized access and protects sensitive data from security breaches.

6. Caching

6.1. Cache Design

Cache design optimizes data access and processing speed by storing frequently accessed data and computation results. It minimizes latency and improves system performance, especially for repetitive tasks such as feature extraction and model inference.

6.2. Cache Implementation

Cache implementation involves selecting appropriate caching algorithms and integrating them into data processing pipelines. It considers factors such as cache eviction policies, expiration times, and cache coherence to maximize cache efficiency.

7. Non-Functional Requirements

7.1. Security Aspects

Security aspects encompass data encryption, access control, and secure communication protocols to protect sensitive information from unauthorized access and data breaches. It adheres to industry standards and regulatory requirements to ensure compliance and mitigate security risks.

7.2. Performance Aspects

Performance aspects focus on optimizing model accuracy, latency, and resource utilization. It involves benchmarking different machine learning algorithms, tuning hyperparameters, and optimizing computational workflows to meet performance targets and scalability requirements.

The performance of various machine learning models in predicting aircraft engine failures was compared based on their accuracy. Table presents the accuracy scores of different models, provides a Tabular representation of the accuracy comparison.

	Model	Accuracy
0	AeroSense Sigmoid	95.368121
1	AeroSense Hyperbolic	91.841863
2	Logistic Regression	98.601223
3	K-Nearest Neighbour	99.279672
4	Support Vector Machine	97.102547
5	Gaussian Naive Bayes	80.350113
6	Decision Tree	94.875211
7	Random Forest	95.120438

8. References

- Kaggle
- PawRepository
- Govt. Documents