Aircraft Risk Prediction Using Machine Learning and Explainable AI

Abstract

Aircraft operational safety depends on continuous monitoring of engine and mechanical parameters. This study presents a machine learning–based framework for predicting operational risk using sensor-generated data. The model analyzes four primary parameters: root mean square vibration (vibration_rms), rotational speed (RPM), engine temperature, and acoustic intensity (acoustic_db).

A Random Forest classifier was implemented to detect risky operating conditions. To enhance transparency and interpretability, SHAP (SHapley Additive exPlanations) was integrated to explain feature contributions at both global and local levels. Experimental results demonstrate that vibration_rms is the most influential parameter affecting risk classification.

Introduction

Modern aircraft engines operate under extreme mechanical and thermal stress conditions. Continuous monitoring of engine health is essential to prevent catastrophic failures and ensure passenger safety.

Sensor systems embedded in aircraft engines generate real-time data such as:

- Vibration levels
- Rotational speed (RPM)
- Temperature readings
- Acoustic intensity

Abnormal patterns in these parameters often indicate mechanical imbalance, bearing wear, combustion instability, or structural stress.

Traditional threshold-based monitoring systems may fail to capture complex nonlinear relationships among parameters. Therefore, machine learning techniques provide a more adaptive and intelligent alternative.

The objectives of this study are:

1. Develop a predictive model for aircraft operational risk.
2. Validate dataset integrity before model training.
3. Evaluate model performance using standard classification metrics.
4. Apply Explainable AI techniques to interpret predictions.
5. Assess fairness and bias across operational groups.

1. System Architecture

The overall system workflow consists of the following stages / modules:

1. Sensor Data Collection
2. Data Validation
3. Exploratory Data Analysis
4. Model Training
5. Model Evaluation
6. Explainability Analysis
7. Bias and Fairness Assessment

Architecture Flow:

Sensor Data → Validation → EDA → Model Training → Evaluation → SHAP →Fairness Check

This modular pipeline ensures reliability and interpretability at each stage.

2. Dataset Description

A synthetic dataset was constructed using ideal operational ranges referenced from aviation standards and publicly available engineering resources.

2.1 Features Used

1. **vibration_rms :** Root Mean Square vibration amplitude representing mechanical oscillations.

   Mathematical Definition: $\boldsymbol{RMS} = \sqrt{(\boldsymbol{1/n} * \boldsymbol{\Sigma}(\boldsymbol{x}_i^2))}$

2. **rpm :** Rotations per minute of engine shaft.
3. **Temperature :** Engine operating temperature in degrees Celsius.
4. **acoustic_db :** Noise intensity in decibels.

2.2 Target Variable

Risk is the target variable in our data

- 0 = Safe
- 1 = Risk

The target variable was generated based on logical threshold interactions between vibration, temperature, and acoustic behaviour.

3. Data Validation

Before training the model, rigorous validation was performed using the Great Expectations framework.

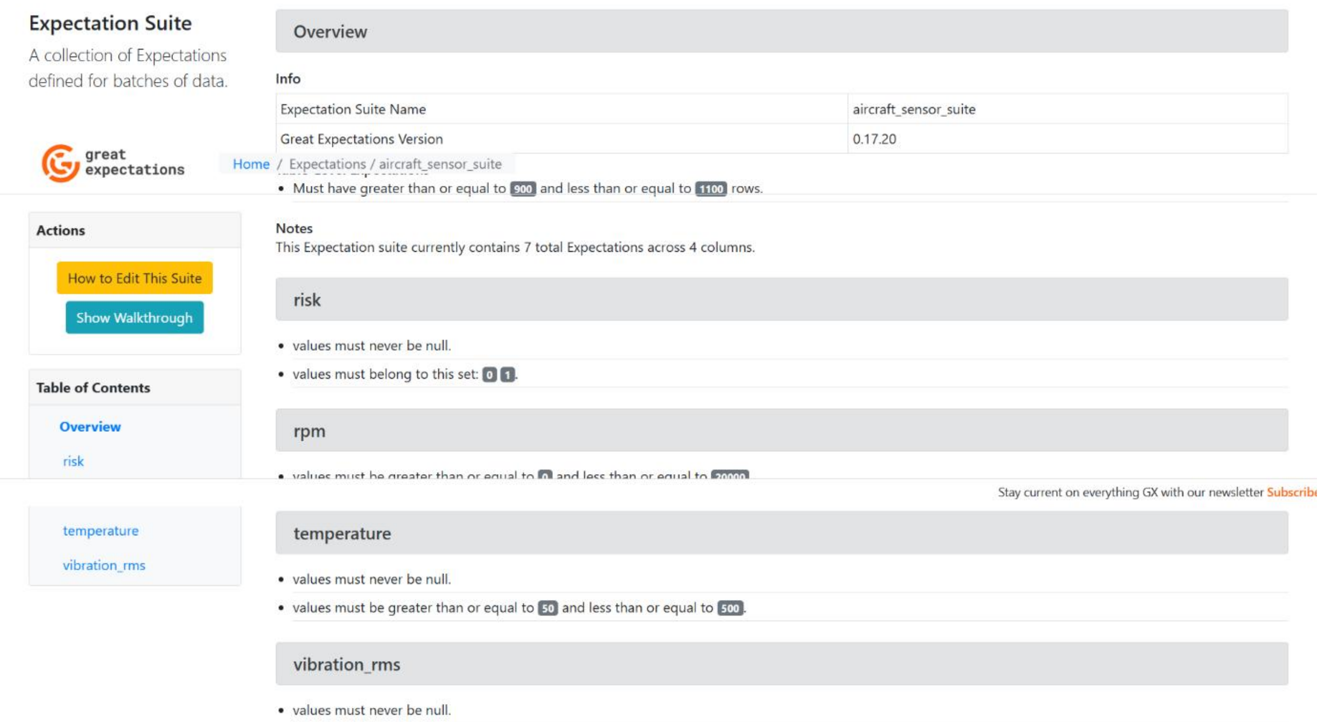
Validation checks included:

- Null value detection
- Data type verification
- Range validation
- Schema enforcement
- Logical consistency checks

The validation confirmed:

- No missing values
- All sensor readings within realistic operational limits
- Proper binary encoding of target variable
- No schema violations

Ensuring high data quality prevents model bias and unreliable predictions.



4. Exploratory Data Analysis

EDA was conducted to understand:

- Feature distributions
- Correlation between variables
- Class balance
- Outlier presence

4.1 Distribution Analysis

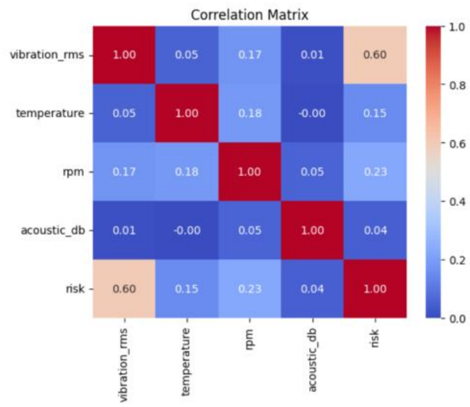
Vibration levels in risky conditions showed higher variance and higher mean values.

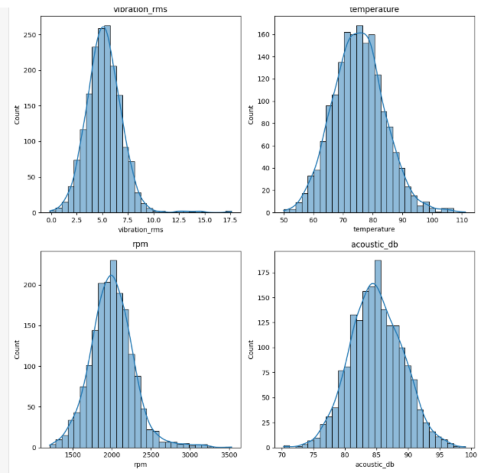
4.2 Correlation Analysis

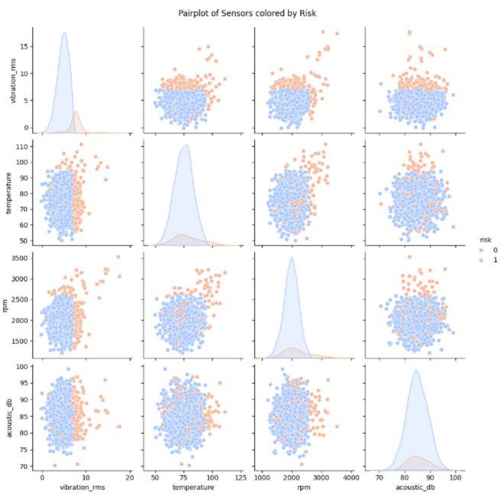
Correlation matrix revealed:

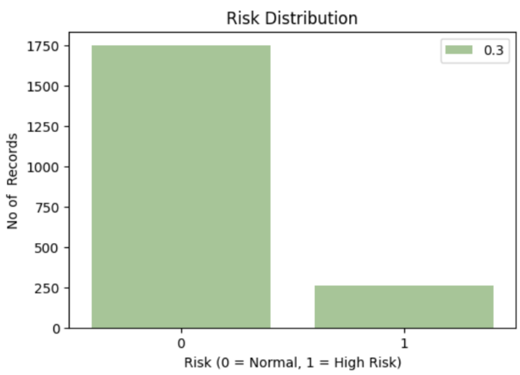
- Strong positive correlation between vibration_rms and risk
- Moderate correlation between temperature and risk
- Weak correlation between RPM and risk

This suggests vibration plays a dominant role in predicting failure conditions.









5. Model Selection

A Random Forest classifier was selected because:

- Handles nonlinear relationships
- Reduces overfitting via ensemble averaging
- Robust to noise
- Works well with tabular sensor data
- Provides built-in feature importance

Random Forest constructs multiple decision trees and aggregates predictions via majority voting.

6. Model Training

The dataset was split into:

- 80% Training set
- 20% Testing set

Hyperparameters tuned included:

- Number of estimators
- Maximum tree depth
- Minimum samples per leaf

Cross-validation was applied to improve generalization performance.

7. Model Evaluation

The model was evaluated using:

1. **Accuracy:** (TP + TN) / Total
2. **Precision:** TP / (TP + FP)
3. **Recall:** TP / (TP + FN)
4. **F1-Score:** 2 × (Precision × Recall) / (Precision + Recall)

Confusion matrix analysis helped identify:

- False positives (safe predicted as risky)
- False negatives (risky predicted as safe)

In aviation safety, minimizing false negatives is critical.

```
                 --- Report ---
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       292
           1       1.00      0.95      0.98       107

    accuracy                           0.99       399
   macro avg       0.99      0.98      0.98       399
weighted avg       0.99      0.99      0.99       399
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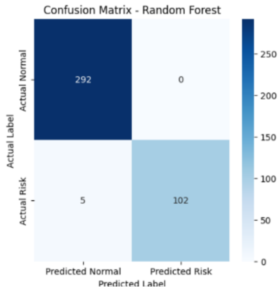


8. Explainability Analysis (SHAP)

Machine learning models often function as black boxes. To ensure transparency, SHAP was applied.

SHAP is based on cooperative game theory and calculates Shapley values, which represent each feature’s contribution to a prediction.

SHAP Advantages:

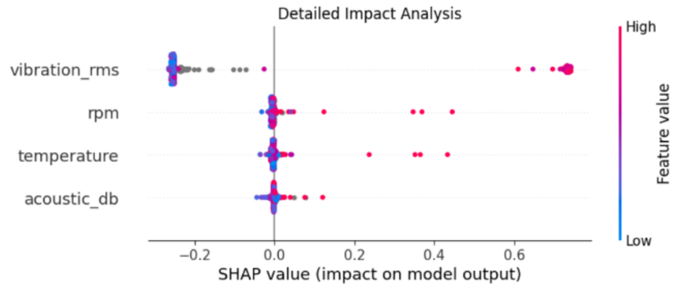
- Local interpretability (individual prediction explanation)
- Global interpretability (overall feature importance)
- Consistency and fairness in attribution

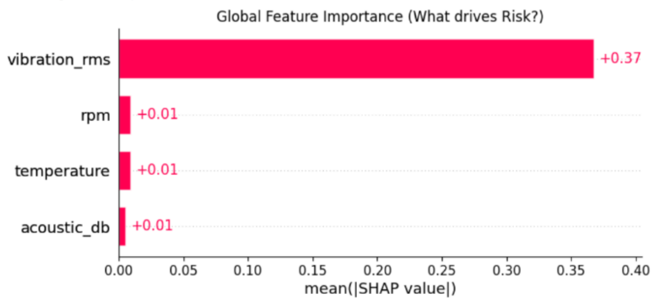
Global SHAP results indicated:

vibration_rms > temperature > acoustic_db > rpm

High vibration values strongly increase predicted risk probability.

This confirms engineering expectations, enhancing trust in the model.





9. Bias and Fairness Analysis

To evaluate fairness, data was grouped by RPM ranges:

- Low RPM
- Medium RPM
- High RPM

Performance metrics were compared across groups.

Findings:

- No extreme disparity in accuracy
- Slight variation in recall across RPM groups
- No systematic bias detected

Fairness assessment is essential in safety-critical systems to prevent unequal risk detection.

10. Conclusion

This study presents a robust and interpretable machine learning framework for aircraft operational risk prediction.

Key Contributions:

- Reliable data validation using Great Expectations
- Strong predictive performance using Random Forest
- Transparent model interpretation using SHAP
- Fairness evaluation across operational groups

The integration of Explainable AI ensures that predictions are not only accurate but also understandable, which is essential in aviation safety systems.

Full Forms

These are the list of abbreviations - full forms which are used in this document

Abbreviation	Full Form
ML	Machine Learning
AI	Artificial Intelligence
XAI	Explainable Artificial Intelligence
RF	Random Forest
SHAP	SHapley Additive exPlanations
RMS	Root Mean Square
RPM	Rotations Per Minute
EDA	Exploratory Data Analysis
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
dB	Decibel