PROMOTION ESILV 2026

ESILV DE VINCI ENGINEERING SCHOOL X DAVINCI HIVE

HACKATHON DATA & AI – DAVINCI HIVE

UAV ANOMALY DETECTION USING MACHINE LEARNING

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EQUIPE 24

07/11/2025

SOMMAIRE

Context & Problem

Context

- Growing use of UAVs → higher risk of mechanical failures
- Faulty propellers can cause unstable flights or crashes
- Goal: detect abnormal flight behaviors before failure occurs

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Context & Problem

Problem statement

- Challenge: identify flight anomalies using onboard sensor data
- Required: a model that distinguishes normal vs faulty trajectories
- Key difficulty: subtle differences in motion dynamics

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Objectives & Dataset

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Project Objectives

- Build a predictive model to detect anomalies
- Evaluate and compare ML algorithms
- Provide insights for predictive maintenance and UAV safety

Objectives & Dataset

02

Dataset Description

- Dataset: DronePropA (KFUPM, Saudi Arabia)
- 130 flight sequences, both healthy & faulty
  few but high quality data but
- Features: position, velocity, acceleration, orientation, thrust, battery
- Sampling frequency: 1 kHz
- files naming convention : F0_SV0_SP1_t1_D1_R1

Objectives & Dataset

02

Fault Types & Trajectories

Fault categories

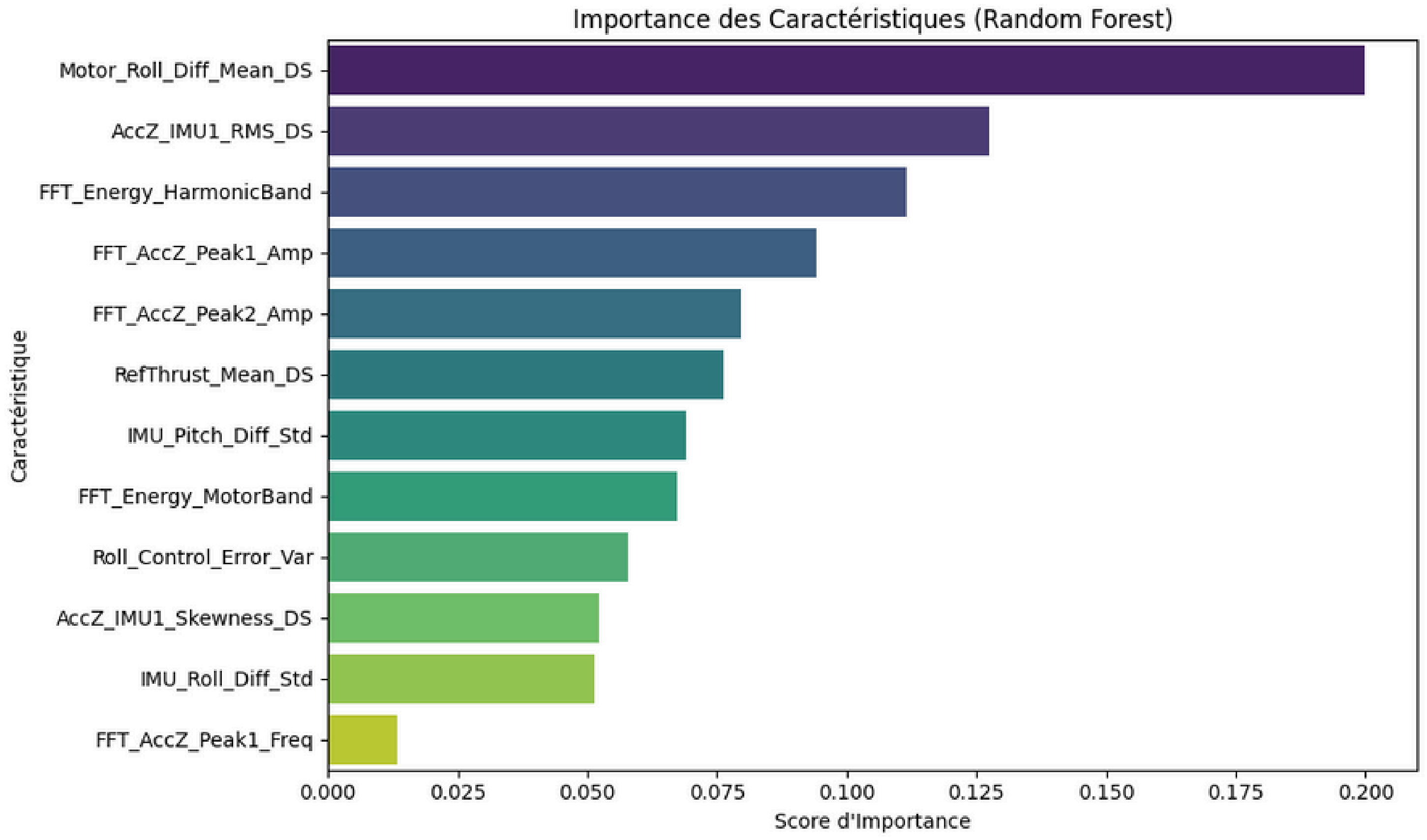
- Edge cuts · Cracks · Surface cuts
- 3 severity levels × 2 flight speeds

Trajectories tested:

- Diagonal · Square · Vertical ascent · Step ascent · Yawing motion
- Suggestion: include trajectory plot or images of propeller damage

Methodology

Data Preprocessing



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- Data cleaning & transformation
- Feature extraction & engineering from motion variables (from commander_data & QDrone_data datasets)
- Feature importance analysis :
  - Compensation effort of the autopilot
  - Overall vibration amplitude
  - Power of the secondary vibrations (harmonics)
- Tools: Python, pandas, scikit-learn, scipy, numpy

Methodology

Modeling Approach

Algorithms tested

- Random Forest (Classification)
- Isolation Forest (Anomaly detection)
- K-Means (Clustering)
- LSTM (Time Series Classification)

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Prediction on 4 classes to improve accuracy on the limited dataset

Final choice after testing → Random Forest

Results & Demonstration

Evaluation Metrics

- **Accuracy : 0.73 ➔ 73% of flights correctly classified**
- **Macro F1-Score : 0.71 ➔ balanced performance across 4 classes**
- **Balanced training set (F0S:40, F1S:30, F2S:30, F3S:30)**
- **Strong robustness despite small test set (7–10 samples/class)**

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Results & Demonstration

Class Performance :

F0S (Healthy): F1 = 0.90
F2S (Crack): Recall = 0.88
F3S/F1S: Moderate recall (~0.55)

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Top features:

Motor Imbalance Compensation

Harmonic Vibration Energy

Overall Vibration Amplitude

Conclusion & Further Analysis

Strengths

- F0S Reliability: The model performs excellently in identifying healthy drones (F1-Score = 0.90).
- F2S Detection: The signature of crack-type faults (F2S) is very well captured (Recall = 0.88).

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Weakness (Confusion)

The model shows significant confusion between fault types F1S, F2S, and F3S, as reflected by the moderate F1-Scores for these classes (0.62–0.70). This confusion is likely due to the fact that low-severity defects across these three groups exhibit very similar dynamic signatures.

Further Analysis

Next Steps

- **Hyperparameter Optimization:**
    - Tune max_depth and n_estimators to improve Precision and Recall for F1S, F2S, and F3S.
    - Goal: capture finer feature variations without overfitting.

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- **Cascade Diagnostic Approach:**
    - Step 1: Detect fault type (F1S, F2S, F3S).
    - Step 2: Predict fault severity level (SV1, SV2, SV3) using specialized models.
    - Goal: achieve higher accuracy and more detailed fault diagnosis.

THANK YOU FOR LISTENING !