



UAV & CO.

# PITCH DECK

## DRONE UAV PRESENTATION

### TEAM 25

Ryan JABBOUR - A5 DIA3

Charles DE PUYBAUDET - A5 DIA3

Alexis DUCROUX - A5 DIA3

Terence FERNANDES - A5 DIA3

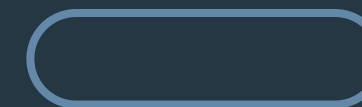
Arthur PUISSILIEUX - A5 DIA5

Lucas MIAKINEN - A5 DIA5



# OBJECTIVE

- Build an anomaly-detection & predictive-maintenance pipeline for commercial drones using the DronePropA dataset.
- Detect faults, identify probable origin, and assess severity to guide maintenance actions.
- Expected impact: improved availability, safety and lifespan of drones.



# OUR DATASET



## Files Format

MATLAB (.mat) files loadable  
via scipy.io



## Volume of the Dataset

130 files, 3 main categories,  
include healthy (F0) and 3 fault  
types (F1, F2, F3).



## Goals and Deliverables

- GitHub repo
- Pitch deck (.pdf)
- Demo video ( $\leq 5$  min)



# DATA PIPELINE



Ingest .mat files → normalized Pandas DataFrames.



Per-flight cleaning (null values...).



Feature extraction (statistical summaries per signal).



Scaling, dimensionality reduction (PCA for EDA).



Supervised models (Random Forest + hyperparameter search).



Evaluation, feature importance.

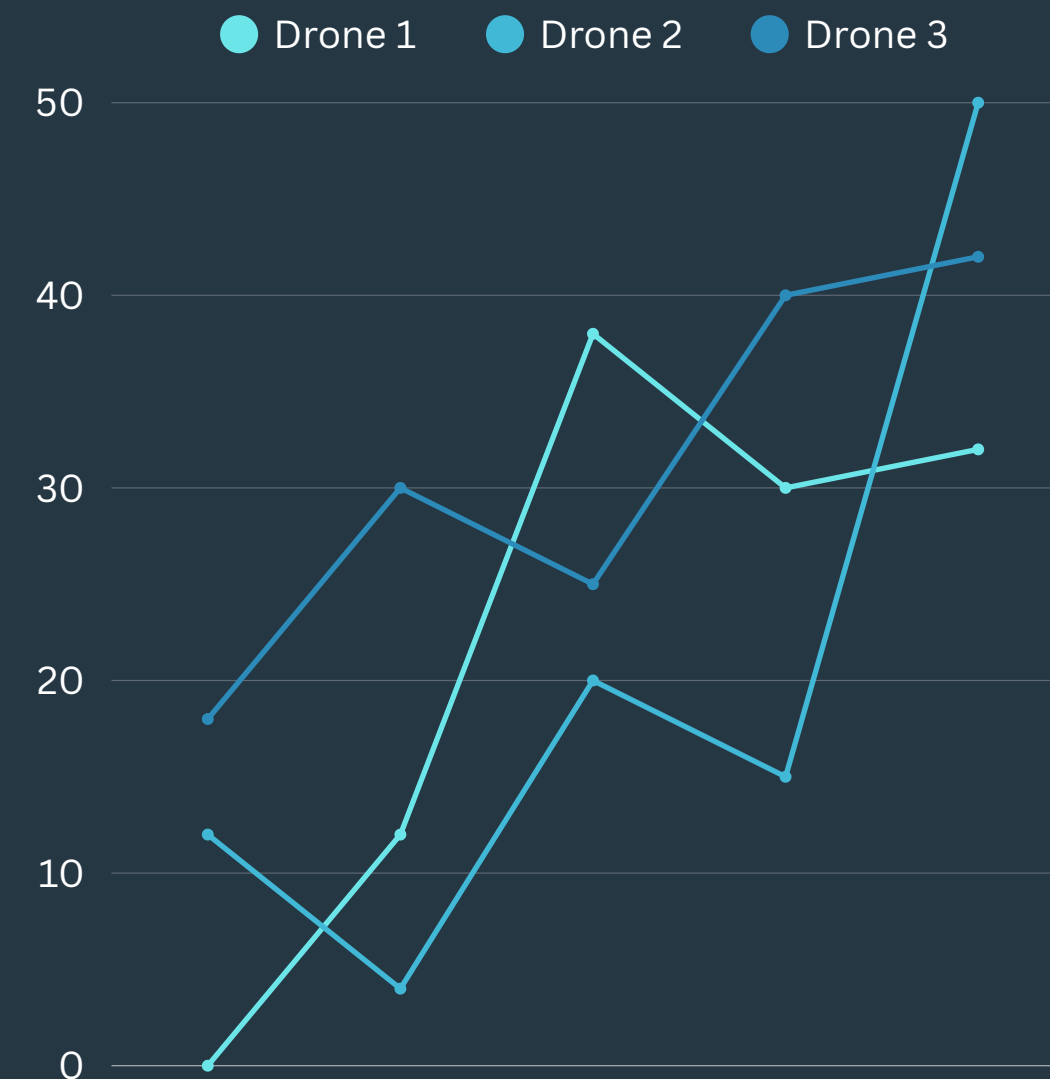


# FEATURE ENGINEERING

Total features  $\approx 114 \times 11 = 1254$  per flight

Per-flight statistical features per signal (114 signals):

- mean, median, std, min, max
- q25, q75, IQR
- skewness, kurtosis
- range





# EXPLORATORY DATA ANALYSIS (EDA)



## PCA Analysis

Visual separation of fault groups confirms feature relevance



## Class Balance

Fault classes moderately imbalanced



## Flight Statistics

Average duration ~45s, sampled at 1 kHz.





# MODELING APPROACH



## Baseline Model



Random Forest  
Classifier :  
interpretable, fast,  
robust.



## Optimization



RandomizedSearch  
CV with 50  
iterations, 5-fold CV



## Targets Modeled



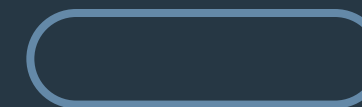
Fault Group,  
Severity, and  
Speed



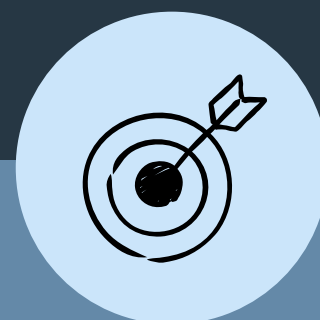
## Metrics Used



Accuracy, F1-score,  
confusion  
matrices, CV  
mean  $\pm$  std.



# MODELS RESULTS



## Modèle 1 – Fault Detection :

Accuracy test : **84.6%**

Accuracy cross-validation : **82.6%  $\pm$  3.8%**

Détection parfaite (100%) des pannes sévères (F3)

Aucun cas critique manqué



## Modèle 2 – Severity Assessment :

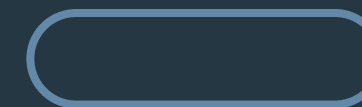
Accuracy test : **83.0%**

Accuracy cross-validation : **80.0%  $\pm$  3.2%**

Détection parfaite (100%) des sévérités critiques (SV3)

Stabilité exceptionnelle (variance CV la plus faible)





# NEXT STEPS & EXTENSIONS

## Alternative

01.

Extract advanced temporal features and test deep learning models (CNN/LSTM)

## Improvement

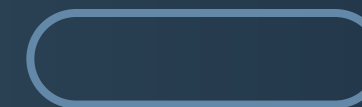
02.

Implement online monitoring dashboard s (alerts, thresholds...)





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# THANK YOU

FOR YOUR ATTENTION