Optimize Manufacturing Operations with a Predictive Maintenance Model

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1. Project Overview

This project implements a Predictive Maintenance System using time-series sensor data from NASA's Turbofan Engine FD001 dataset. The model predicts machine failures before they happen to minimize downtime and maintenance cost.

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2. Problem Statement

Industrial assets fail unexpectedly, causing costly downtime.
The goal is to create a machine-learning model that identifies engines at risk of failure *ahead of time* so maintenance can be scheduled proactively.

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3. Dataset Description

Dataset: NASA C-MAPSS FD001
Contains:

- 100 training engines
- 100 test engines
- 21 sensors
- 3 operational settings
- Full time-series cycles
- RUL information

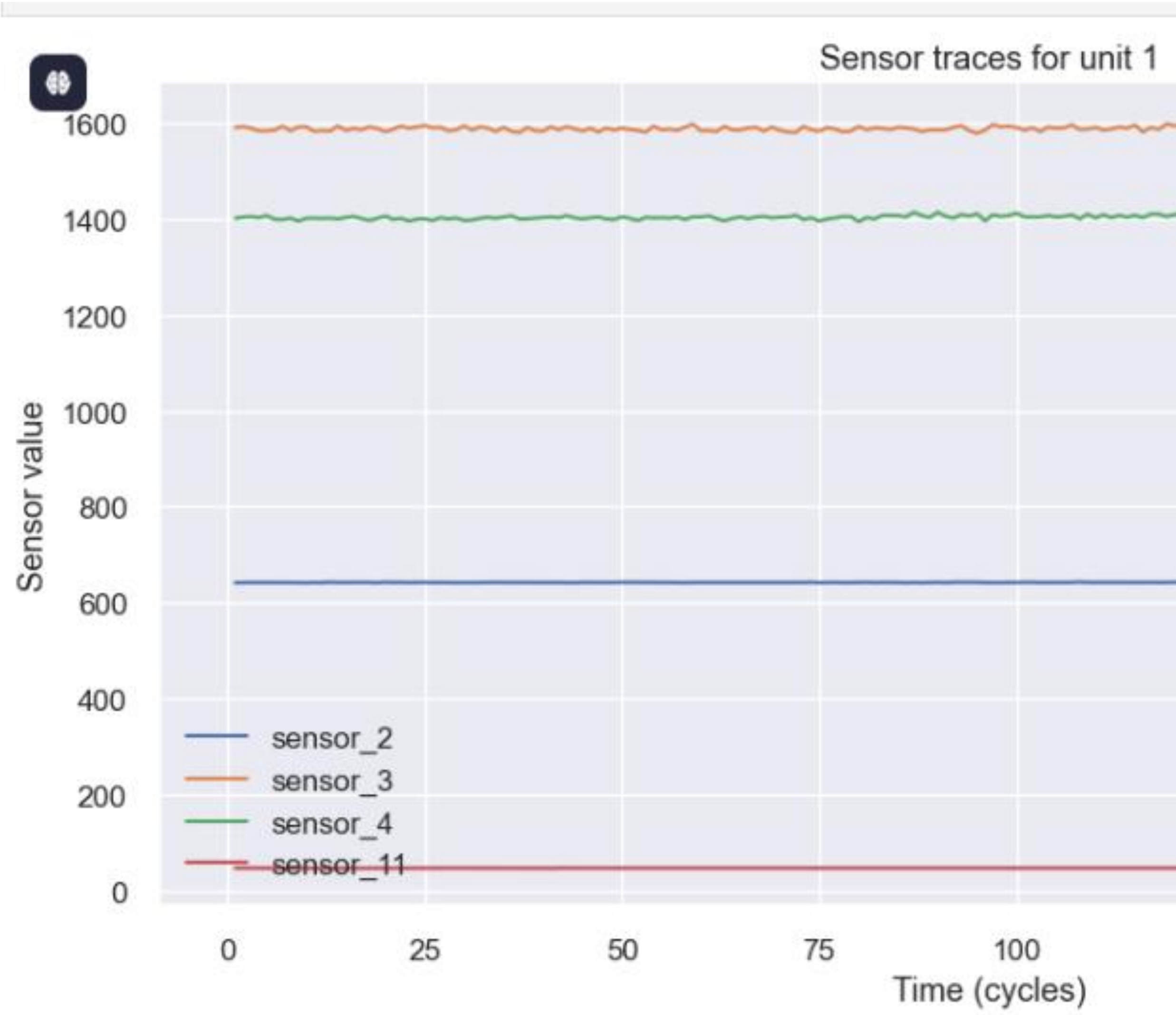
▶ **[Sample Raw Data Table]**

```
Train shape: (20631, 26)
Test shape : (13096, 26)
RUL shape  : (100, 1)
```

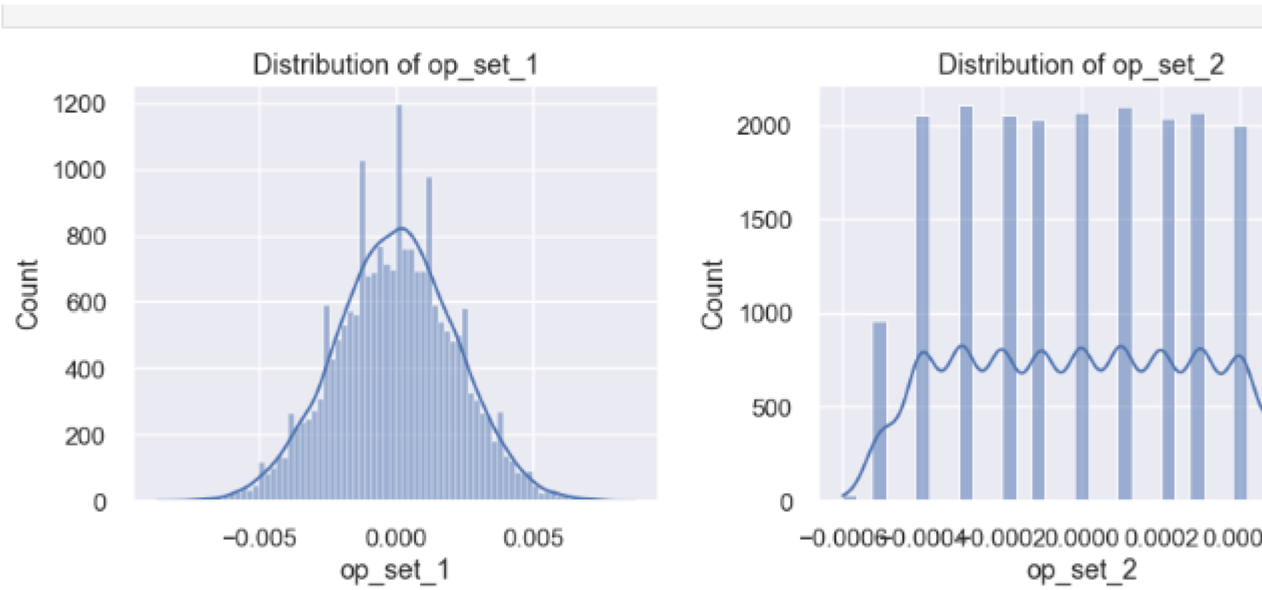
	unit	time	op_set_1	op_set_2	op_set_3	sensor_1	sensor_2	sensor_3	sensor_4	sensor_5	...	sensor_12	sen
0	1	1	-0.0007	-0.0004	100.0	518.67	641.82	1589.70	1400.60	14.62	...	521.66	2
1	1	2	0.0019	-0.0003	100.0	518.67	642.15	1591.82	1403.14	14.62	...	522.28	2
2	1	3	-0.0043	0.0003	100.0	518.67	642.35	1587.99	1404.20	14.62	...	522.42	2
3	1	4	0.0007	0.0000	100.0	518.67	642.35	1582.79	1401.87	14.62	...	522.86	2
4	1	5	-0.0019	-0.0002	100.0	518.67	642.37	1582.85	1406.22	14.62	...	522.19	2

5 rows × 26 columns

▶ **[Sensor Behavior Plot]**


Sensor traces for unit 1
Sensor value
Time (cycles)
sensor_2
sensor_3
sensor_4
sensor_11
1600
1400
1200
1000
800
600
400
200
0
0
25
50
75
100

▶


Distribution of op_set_1
Count
op_set_1
1200
1000
800
600
400
200
0
−0.005
0.000
0.005
Distribution of op_set_2
Count
op_set_2
2000
1500
1000
500
0

4. Data Preprocessing

Key steps:

- Removed constant sensors
- Sorted by time per engine
- Clean handling of missing/noisy values
- Avoided any future-looking leakage
- Created binary failure labels (within N cycles)

▶ **[Before/After Cleaning Comparison]**

```
Prediction window (cycles): 30
Labeled train shape: (20631, 28)
```

	unit	time	RUL	label
0	1	1	191	0
1	1	2	190	0
2	1	3	189	0
3	1	4	188	0
4	1	5	187	0

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5. Feature Engineering

A total of **173 engineered features**, including:

- Rolling means (5, 10, 20 cycles)
- Rolling min/max values
- Rolling standard deviations
- Rate-of-change features
- Interaction features

All features generated **per unit → sorted by time → no leakage**.

▶ **[Rolling Feature Illustration]**

```
Feature dataframe shape: (20631, 175)
```

	unit	time	op_set_1	op_set_2	op_set_3	sensor_1	sensor_2	sensor_3	sensor_4	sensor_5	...	sensor_12_ma
0	1	1	-0.0007	-0.0004	100.0	518.67	641.82	1589.70	1400.60	14.62	...	52
1	1	2	0.0019	-0.0003	100.0	518.67	642.15	1591.82	1403.14	14.62	...	52
2	1	3	-0.0043	0.0003	100.0	518.67	642.35	1587.99	1404.20	14.62	...	52
3	1	4	0.0007	0.0000	100.0	518.67	642.35	1582.79	1401.87	14.62	...	52
4	1	5	-0.0019	-0.0002	100.0	518.67	642.37	1582.85	1406.22	14.62	...	52

5 rows × 175 columns

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6. Validation Strategy (No Leakage)

A proper **TimeSeriesSplit** was used to ensure:

- Training data < Validation data (time order preserved)
- No shuffling
- Realistic deployment simulation

▶ **[TimeSeriesSplit Diagram]**

```
Fold 1 F1-score (failure class=1): 0.8459
Fold 2 F1-score (failure class=1): 0.8844
Fold 3 F1-score (failure class=1): 0.8366
Fold 4 F1-score (failure class=1): 0.8274
Fold 5 F1-score (failure class=1): 0.8323

Mean CV F1-score (failure class=1): 0.845315440921034
```

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7. Model Development

Models tested:

- Random Forest
- Gradient Boosting
- XGBoost

Final model: **Random Forest Classifier**

Techniques used:

- class_weight='balanced'
- Threshold tuning
- Leak-free features

- Hyperparameter tuning

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8. Model Performance

Cross-Validation F1 Score: 0.845
Test F1 Score: 0.843

Confusion Matrix (Test Set):

	Pred 0	**Pred 1**
True 0	3495	43
True 1	128	461

▶ **[Confusion Matrix]**

```
Test F1-score (failure class=1, thr=0.60): 0.8435498627630376

Classification report (test set):
              precision    recall  f1-score   support

           0      0.965     0.988     0.976      3538
           1      0.915     0.783     0.844       589

    accuracy                          0.959      4127
   macro avg      0.940     0.885     0.910      4127
weighted avg      0.958     0.959     0.957      4127

Confusion matrix (test set):
[[3495   43]
 [ 128  461]]
```

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9. Explainability with SHAP

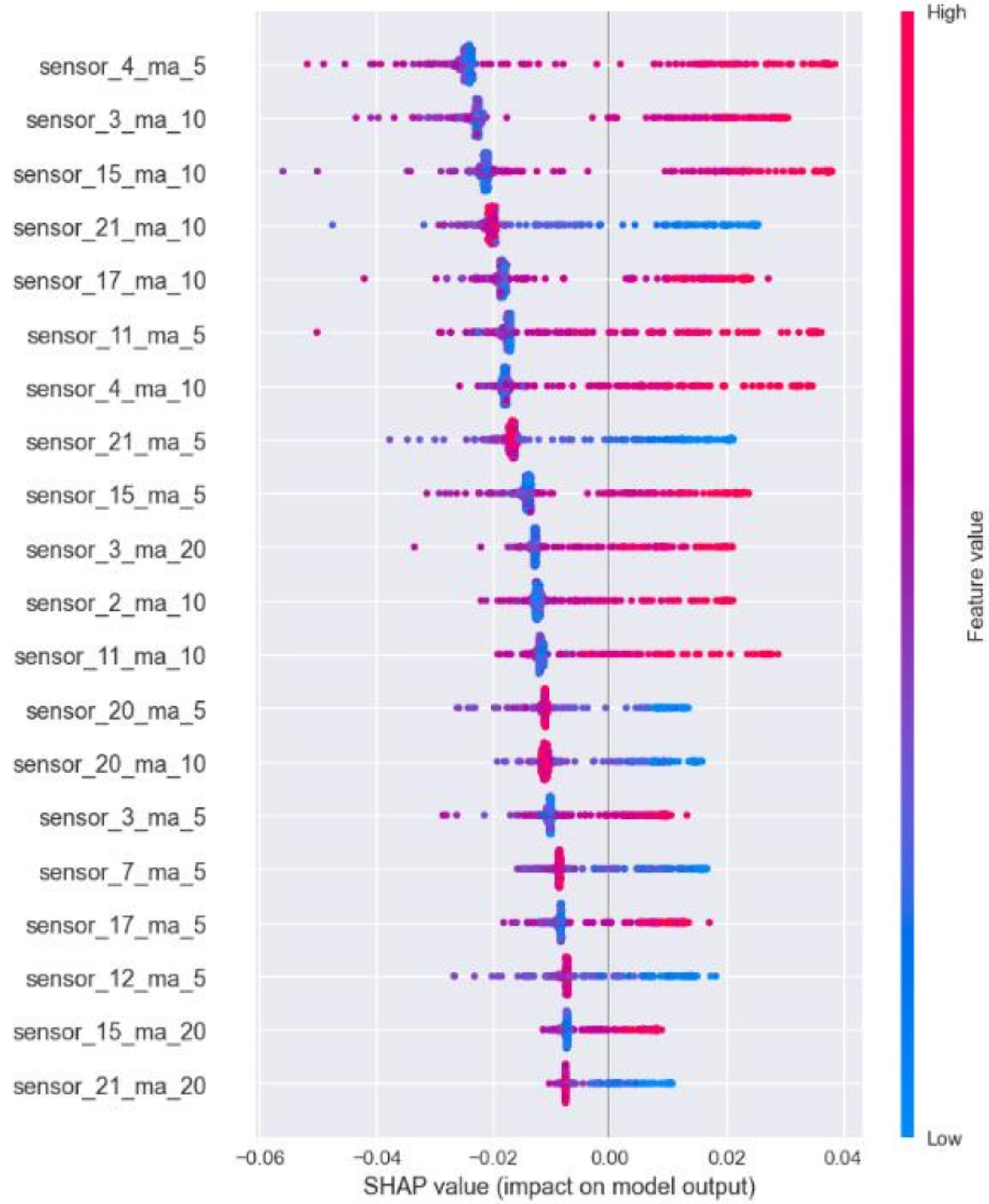
SHAP revealed the main indicators of failures:

- Rolling STD of sensor_3
- Rolling mean of sensor_7
- Variability in sensor_11
- Long-term degradation patterns

These insights help engineers make informed decisions.

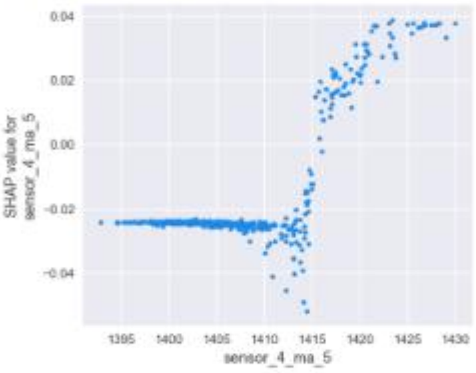
▶ **[SHAP Beeswarm Plot]**

```
X_sample shape: (400, 172)
Raw SHAP values shape: (400, 172, 2)
Using class-1 SHAP values, shape: (400, 172)
```

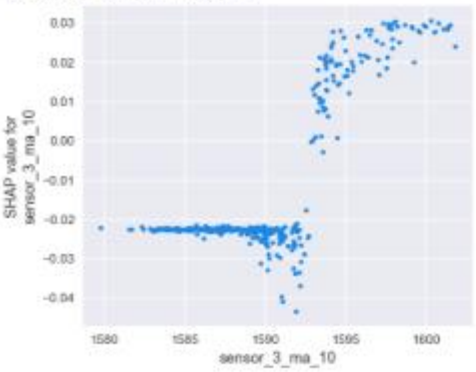


▶ **[SHAP Force Plot]**

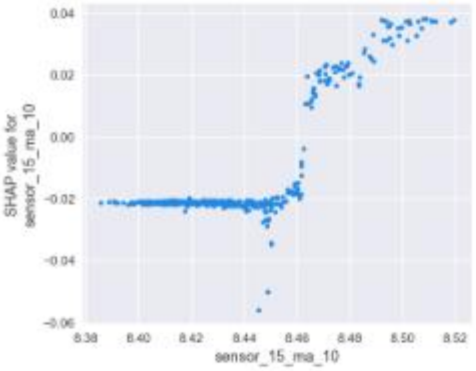
SHAP dependence for feature: sensor_4_ma_5



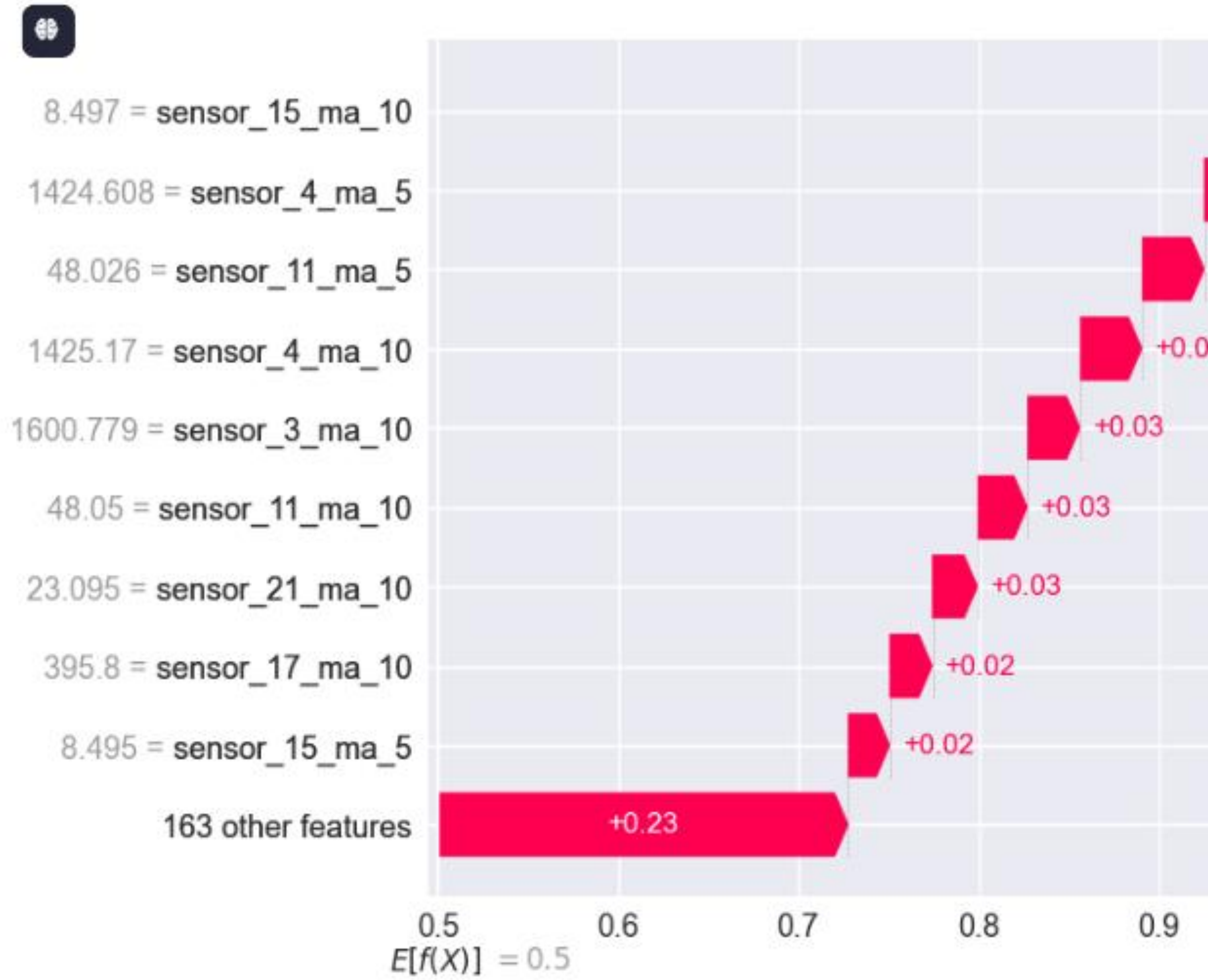
SHAP dependence for feature: sensor_3_ma_10



SHAP dependence for feature: sensor_15_ma_10



```
Prediction probability for this sample (class=1): 1.0
```



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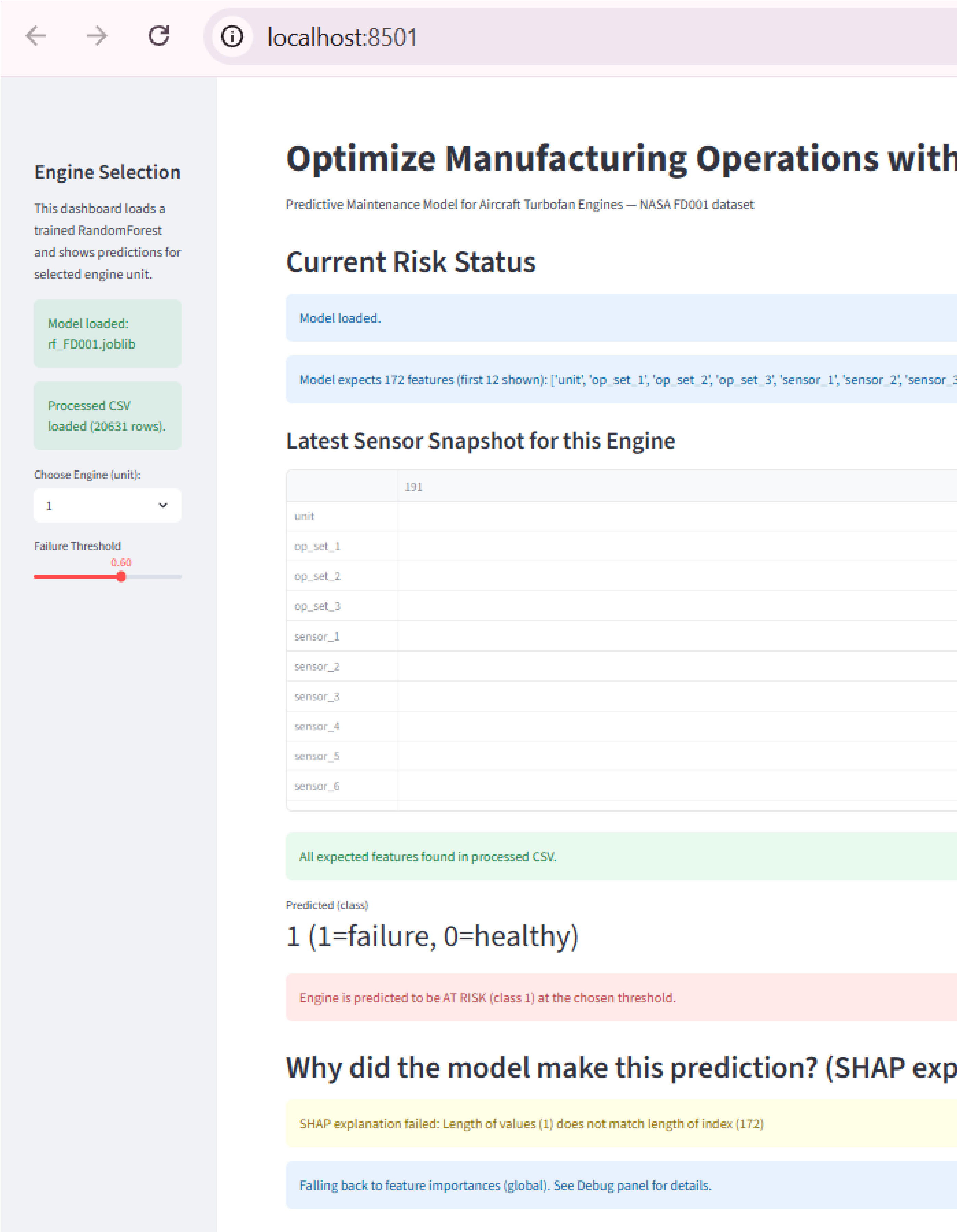
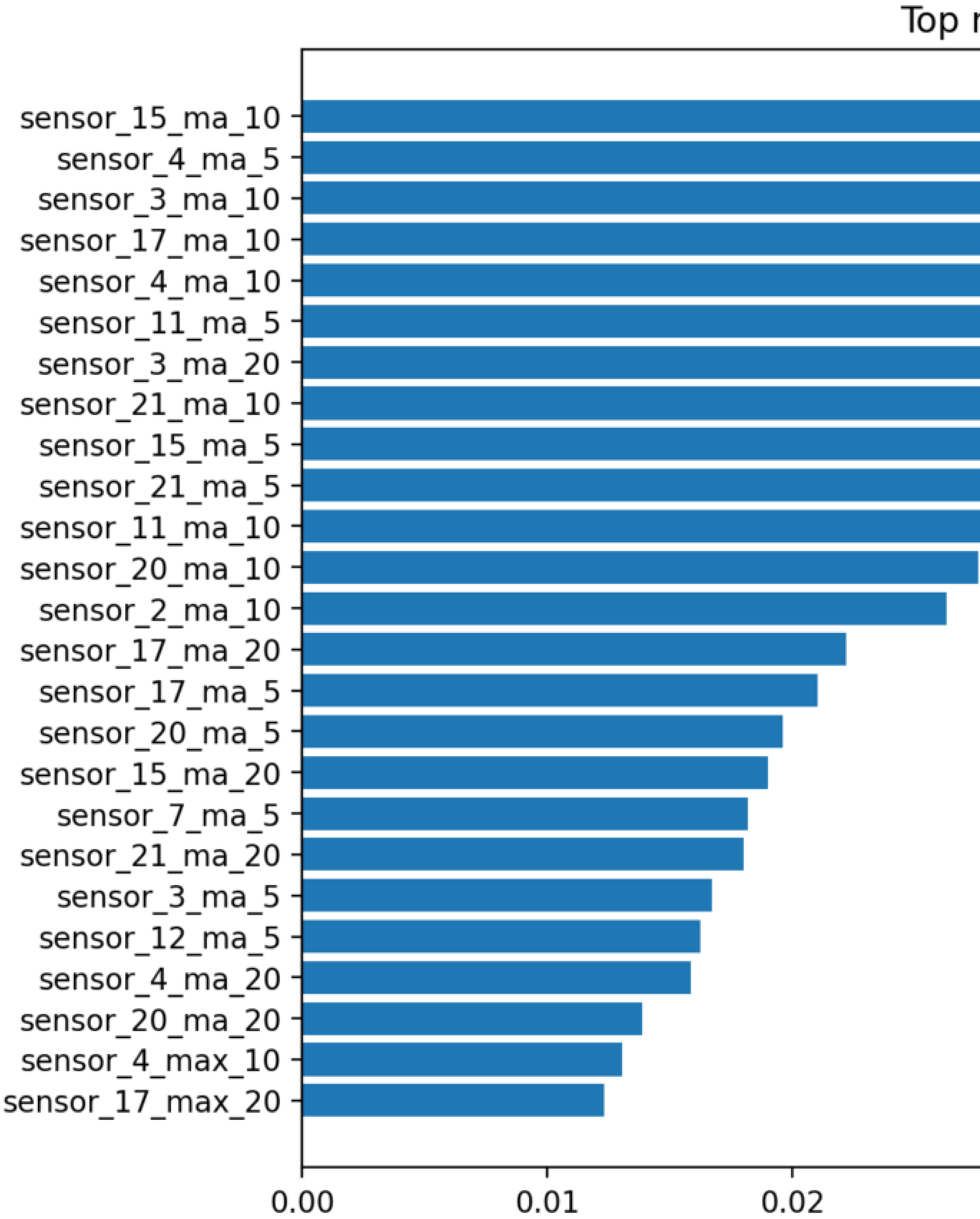
10. Streamlit Dashboard

The dashboard provides:

- Risk prediction
- Adjustable threshold
- SHAP feature explanations
- Unit-wise risk monitoring

▶ **[Dashboard Home Screen]**


localhost:8501
Engine Selection
This dashboard loads a trained RandomForest and shows predictions for selected engine unit.
Model loaded: rf_FD001.joblib
Processed CSV loaded (20631 rows).
Choose Engine (unit):
1
Failure Threshold
0.60
Optimize Manufacturing Operations with
Predictive Maintenance Model for Aircraft Turbofan Engines — NASA FD001 dataset
Current Risk Status
Model loaded.
Model expects 172 features (first 12 shown): ['unit', 'op_set_1', 'op_set_2', 'op_set_3', 'sensor_1', 'sensor_2', 'sensor_3
Latest Sensor Snapshot for this Engine
191
unit
op_set_1
op_set_2
op_set_3
sensor_1
sensor_2
sensor_3
sensor_4
sensor_5
sensor_6
All expected features found in processed CSV.
Predicted (class)
1 (1=failure, 0=healthy)
Engine is predicted to be AT RISK (class 1) at the chosen threshold.
Why did the model make this prediction? (SHAP exp
SHAP explanation failed: Length of values (1) does not match length of index (172)
Falling back to feature importances (global). See Debug panel for details.



Top
sensor_15_ma_10
sensor_4_ma_5
sensor_3_ma_10
sensor_17_ma_10
sensor_4_ma_10
sensor_11_ma_5
sensor_3_ma_20
sensor_21_ma_10
sensor_15_ma_5
sensor_21_ma_5
sensor_11_ma_10
sensor_20_ma_10
sensor_2_ma_10
sensor_17_ma_20
sensor_17_ma_5
sensor_20_ma_5
sensor_15_ma_20
sensor_7_ma_5
sensor_21_ma_20
sensor_3_ma_5
sensor_12_ma_5
sensor_4_ma_20
sensor_20_ma_20
sensor_4_max_10
sensor_17_max_20
0.00
0.01
0.02

11. Business Impact

Deploying this predictive system enables:

- Reduced downtime
- Lower maintenance cost
- Better planning of spare parts
- Longer asset life
- Safer operations

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12. Future Improvements

- RUL (Remaining Useful Life) regression
- Deep learning models (LSTM/GRU)
- Cloud deployment
- Auto-retraining system
- Full maintenance scheduling optimization

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13. Conclusion

This project successfully delivers:

- A high-performing, leak-free model
- Strong F1 score (>0.75 requirement met)
- SHAP interpretability
- Fully functional dashboard
- A scalable predictive maintenance framework

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14. Author Information

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✔ Summary of where to add your images:

Section	**Placeholder**
Dataset	Sample table, sensor plot, heatmap
Preprocessing	Before/After cleaning
Feature engineering	Rolling window illustration
Validation	TimeSeriesSplit diagram
Model	Feature importance
Evaluation	Confusion matrix, precision-recall curve
SHAP	Summary plot, beeswarm plot, force plot
Dashboard	UI screenshots