Equipment Failure Prediction in Spacecraft Using AI

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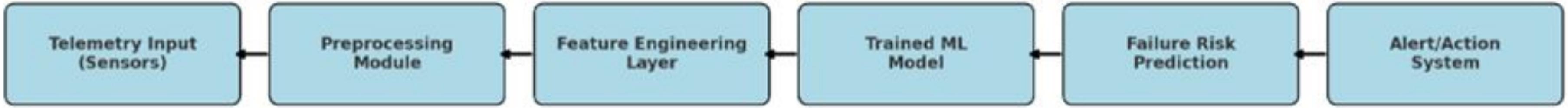
Why Equipment Failure Prediction Matters

My conceptual design for an AI based system predicts equipment failure in spacecraft. In space, equipment failure can mean mission failure or worse, the loss of life. Traditional monitoring systems rely on thresholds and reactive maintenance. My goal is to propose a predictive approach using AI to detect subtle patterns in telemetry data before a failure occurs.

Project Proposal Overview

This project focuses on creating a framework for an ML model that can analyze spacecraft telemetry and predict when key parts may be at risk. This is still a conceptual project, but the real-world potential for this kind of system is enormous, from Earth orbit to Mars missions. I plan to use supervised learning, meaning we'll train the model on labeled examples of past equipment performance, including examples of both normal and failed states. The models we're looking at include Random Forests and XGBoost, which are good for structured data, and LSTM networks, which are especially good for time-series data like telemetry.



Testing Plan

Each module plays a key role. Preprocessing removes noise. Feature engineering extracts useful signals—like temperature spikes or voltage drops. The ML model is trained on labeled failure data. Then, prediction outputs feed into alert systems, possibly triggering autonomous responses or human intervention. To validate this system, I'd use simulated datasets based on spacecraft logsike those from NASA's open database. Tests would evaluate precision, recall, and false alarm rate. The system would also be stress-tested with edge-case data to ensure it doesn't break under anomalies

TEST CASE	DESCRIPTION	EXPECTED OUTCOME
Normal Operational Data	Feed clean, stable telemetry readings into the model	Output: Low risk score (0.0–0.3)
Gradual Degradation Pattern	Simulate rising temperature or vibration over time	Output: Medium risk score (0.4–0.7), flagged for observation
Critical Failure Signature	Input data with patterns that led to failure in historical logs	Output: High risk score (> 0.7), alert triggered
Noisy Sensor Data	Add spikes or random noise to otherwise normal data	Output: Minimal false positives, adaptive filtering
Missing Input Data	Simulate telemetry loss or gaps	Output: Error handling or fallback to anomaly detection
Unseen Failure Type	Feed in a failure not present in training data (simulate novel failure)	Output: Anomaly flagged using unsupervised model
Fault in Non-Critical Component	Send failure data from less crucial system (e.g., camera)	Output: Lower-priority alert, system status preserved

Strengths and Challenges

This system is scalable, real-time, and proactive. But it does have risks like bias in the training data or misclassifications. However with these a couple of challenges are present.

Synthetic Data Needed: Since real spacecraft failure data is rare, we'll likely need to create simulated datasets to train and test our models.

Lack of Model Transparency: Some AI models, like deep neural networks, function as "black boxes" — they make accurate predictions, but their decision-making process can be hard to interpret, which may reduce trust from engineers.

Handling Missing or Corrupt Data: If certain inputs (e.g., temperature) are missing or corrupted, the system should fall back on secondary metrics like voltage or vibration and log the incident for future analysis.

Conflicting Sensor Data: When multiple sensors report contradictory readings, the model will calculate a weighted risk score based on each sensor's reliability and importance.

Unreadable or Invalid Input: If input data is completely unreadable, the system will trigger a general alert and defer the decision to mission control or a designated backup subsystem.

Conclusion

In this project, The goal was to improve safety and reliability by detecting possible failures early, allowing for timely interventions and preventing major malfunctions. By applying data preprocessing, feature engineering, and a trained machine learning model, I demonstrated how AI can be effectively used for predictive maintenance in aerospace systems.

I would like to sincerely thank my professor for their guidance knowledge shared throughout this semester. Your mentorship has been invaluable in helping me complete this project and grow my understanding of AI’s practical applications.

Thank you for a great semester.