

# ASTRA HACKATHON 2025



## TEAM-SPACEX

### A3. Satellite Health Monitoring Dashboard

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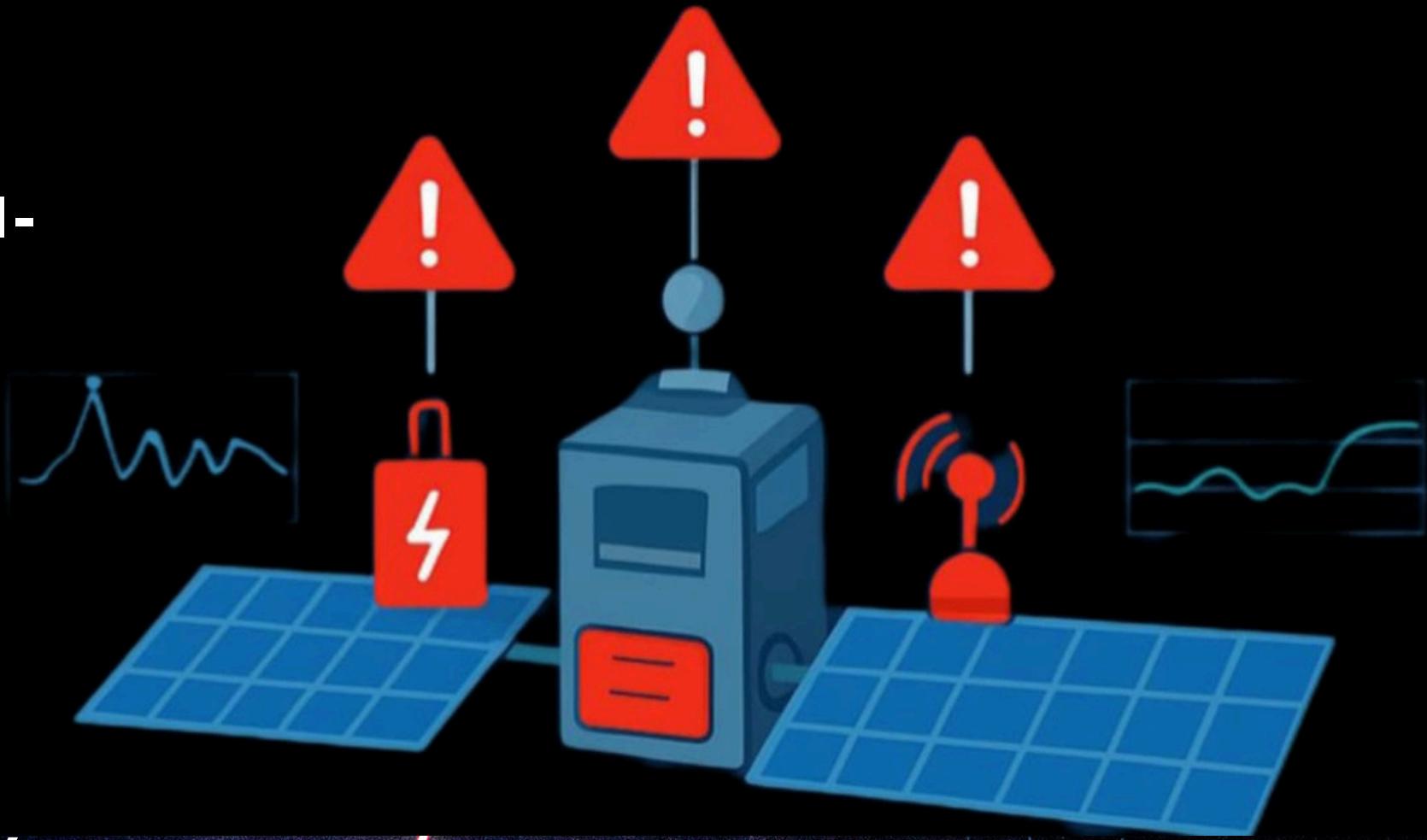
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# PROBLEM STATEMENT

- Satellites are prone to failures in critical subsystems like battery, thermal control, and communication.
- Anomalies often go unnoticed due to lack of real-time monitoring and advanced analysis.
- Failures lead to mission loss, high repair costs, and communication disruptions.
- Early detection and prediction are essential to prevent failures and ensure mission success.
- A smart monitoring system is required to identify anomalies, forecast risks, and guide corrective actions.



# APPROACH AND METHODOLOGY

## 1. Data Collection & Integration

- Gather real-time telemetry (power, thermal, communication subsystems).
- Include external factors like space weather.

## 2. Preprocessing & Rule-Based Monitoring

- Apply threshold checks (e.g., battery <20%).
- Filter normal variations vs. critical anomalies.

## 3. Machine Learning-Based Anomaly Detection

- Use supervised & unsupervised ML models.
- Detect hidden patterns and deviations beyond fixed rules.

## 4. Digital Twin Simulation

- Build a virtual replica of the satellite.
- Run “what-if” scenarios to predict failures & responses.

## 5. Contextual Anomaly Analysis

- Factor in orbit position, eclipse/shadow periods, and comms windows.
- Reduce false alarms with environment-aware filtering.

## 6. Decision Support System

- Risk-based categorization: Low, Medium, High.
- Suggest corrective actions (safe mode, backup switch, load shedding).

## 7. Visualization Dashboard

- Real-time health indicators with anomaly alerts.
- Intuitive UI for operators to act quickly.

# TOOLS USED

**Programming & ML:** Python, TensorFlow / Scikit-learn

**Data Processing:** Pandas, NumPy, Apache Kafka (for real-time streaming)

**Simulation :** MATLAB / Simulink, Digital Twin frameworks

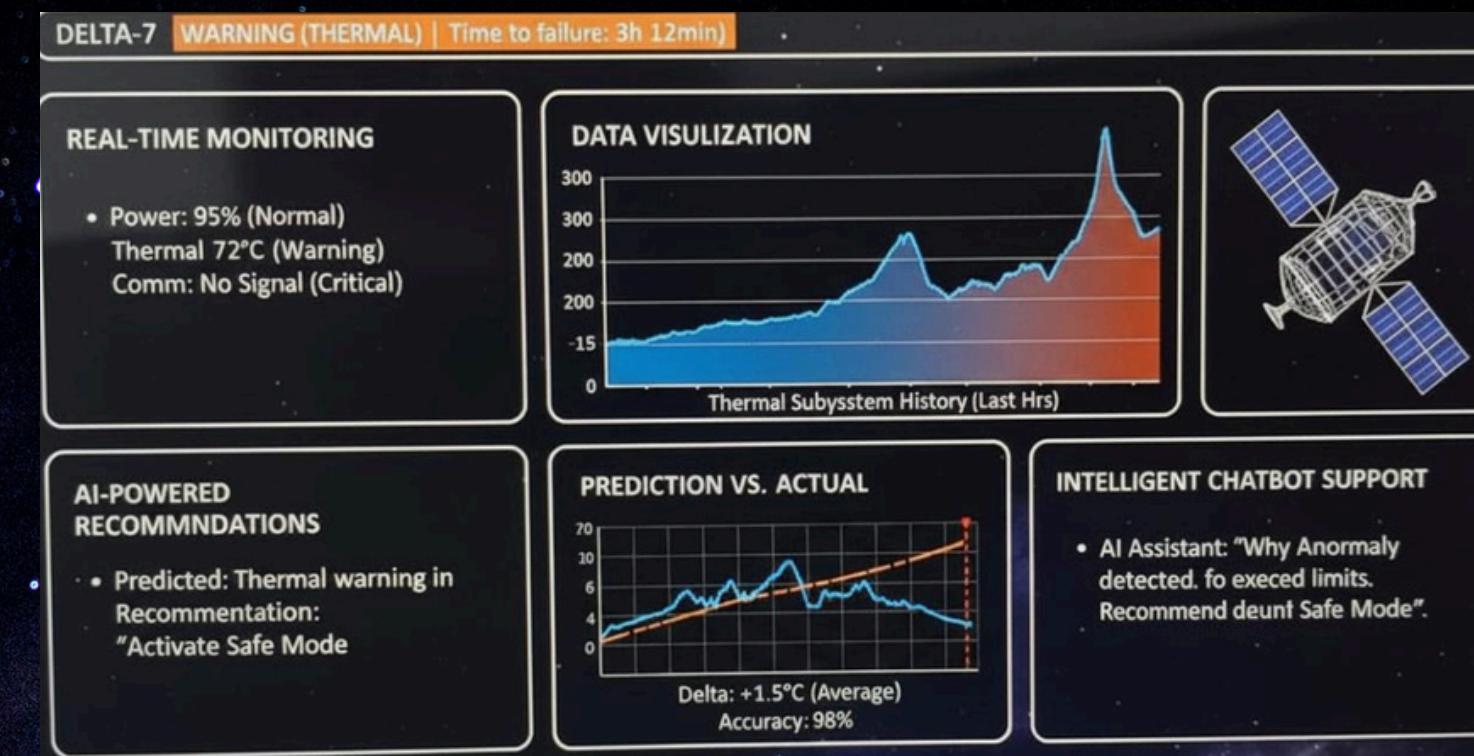
**Visualization:** Power BI / Grafana / Custom Web Dashboard

**Cloud & Deployment:** AWS / Azure / Google Cloud for scalable processingSpace

**Weather Data:** NASA APIs, NOAA Space Weather Prediction Center

# DASHBOARD AND EVALUATION

- **Real-time Monitoring:** Present live data with color-coded alerts and a simple health summary. This provides operators with an immediate snapshot of the satellite's status.
- **AI-Powered Recommendations:** Our system doesn't just show a problem; it suggests a solution. For example, it might predict a "Failure in 3h 12min" and recommend "Activate Safe Mode." This turns data into an action plan.
- **Intelligent Chatbot Support:** The AI chatbot can provide operators with quick, on-demand information and guidance, acting as an intelligent co-pilot.
- **Data Visualization:** Users can analyze historical telemetry data with interactive graphs and charts, aiding in deeper analysis and troubleshooting.
- **Evaluation Metrics:** Highlight the key benefits. Our system is designed for **low false positives** (for reliability), **scalability** (to handle multiple satellites), and **proven effectiveness** in identifying critical anomalies.



# CHALLENGES AND OUTCOMES

- Managing high-volume, real-time telemetry data led to the challenge of complexity, and the outcome is a streamlined data pipeline for faster processing.
- Differentiating genuine anomalies from normal variations was a challenge, resulting in the outcome of accurate anomaly detection using ML models.
- Integrating unpredictable space weather created a challenge, with the outcome of proactive risk prediction through external data feeds.
- Achieving real-time, low-latency alerts was a challenge, and the outcome is timely decision support for operators.
- Scaling the system for multiple satellites was a challenge, and the outcome is a cloud-based, scalable architecture.
- Building trust in AI recommendations posed a challenge, leading to the outcome of reliable, validated alerts supported by digital twin simulations.

## RESULTS AND SCOPE

- Early anomaly detection → prevents mission failures and saves costs.
- AI-driven decision support → improves operator response and reliability.
- Digital twin validation → ensures accurate predictions and trusted alerts.
- Scalable design → supports multiple satellites and future constellations.
- Adaptability → extendable to deep-space missions and evolving telemetry models.
- Future integration → potential for autonomous mission planning and AI-based control.
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**FOR YOUR ATTENTION**

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