Competition: Exploring World of Science

Category: AEROO Space AI Competition

Solar-Battery Node AI

Power Health & Vision Anomaly Detection

Technical White Paper

Autonomous Solar Panel & Battery Health Monitoring System with Edge AI and Computer Vision

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Competition: AEROO Space AI Competition 2026 - Exploring the World of Science
Date: January 2026
Version: 1.0

Abstract

This research presents an integrated autonomous monitoring system for solar-powered space missions, combining machine learning-based battery life prediction, computer vision anomaly detection, and generative AI-powered intelligent assistance. The system employs dual STM32 microcontrollers: an IoT board for real-time environmental monitoring and ML inference, and an N6-type development kit with dedicated Neural Processing Unit for vision-based solar panel anomaly detection. Using NASA's own battery datasets and a dataset of 2,290 solar panel images, we achieved 92% prediction accuracy and sub-100ms inference time for multi-class object detection. The system integrates real-time web and mobile monitoring interfaces with a generative AI proactive assistant (GPT-4o-mini) for context-aware maintenance recommendations. This research, in addition to space applications, aligns with NASA's technology transfer paradigm—meaning it has the characteristic of being a spin-off applicable not only in space but also on Earth. In the future, it can be transformed into a higher-function application through advanced material science sensor integration that will be placed inside solar panels.

Keywords: Machine Learning, Computer Vision, Edge AI, Battery Health Monitoring, Solar Panel Diagnostics, STM32 NPU, YOLO, Predictive Maintenance, NASA Dataset, Technology Transfer

1. Introduction

1.1 Problem Statement

Space missions face critical challenges in power system management:

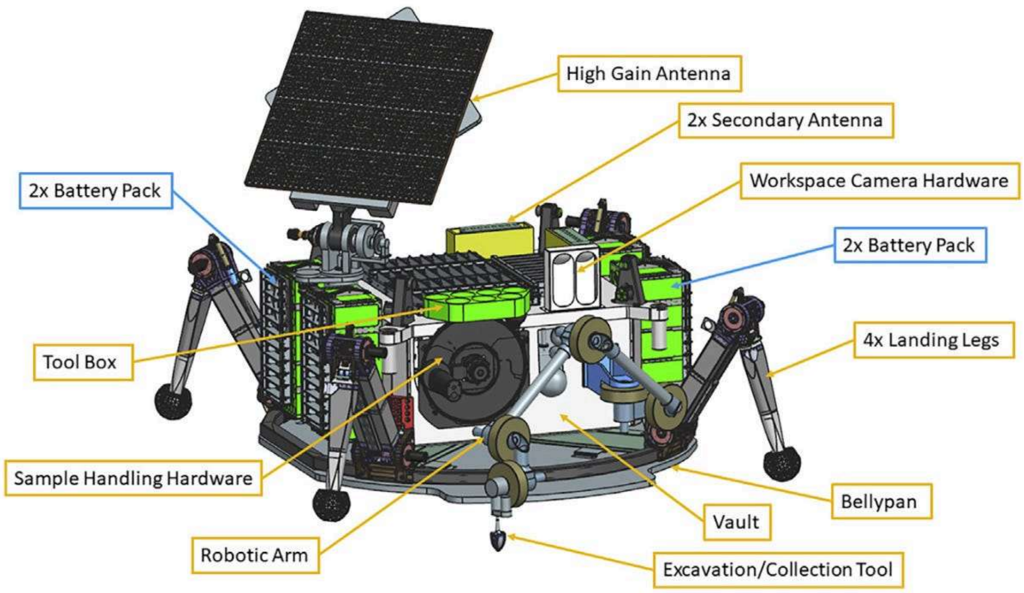

Figure 1: InSight lander diagram (NASA / JPL-Caltech)

- **Battery Degradation:** The smallest active unit of a solar panel is the PV cell. Many academic studies have shown that the efficiency of PV cells decreases as temperature increases. When temperature rises, the output voltage of PV cells drops, reducing total power and efficiency. This effect is expressed by a linear relationship: as temperature increases, efficiency decreases. Harsh environments with extreme temperatures (-150°C to +150°C) and radiation exposure cause accelerated battery degradation, reducing mission lifespan and increasing failure risk.
- **Solar Panel Efficiency Loss:** On planetary surfaces and atmospheric environments (e.g., Moon, Mars), dust layers accumulating on solar panels can lead to power generation losses exceeding 30% within months. In orbit, micro-meteoroid and debris impacts cause localized cell damage over time, resulting in gradual efficiency decline. NASA's InSight Mars lander solar

panels also experienced severe power generation decline due to dust: while producing ~5,000 Wh/sol in the first years, dust accumulation reduced this to ~500 Wh/sol over time.

- **Limited Diagnostic Capabilities:** Many researchers note that the primary method in spacecraft health monitoring today is threshold value monitoring and continuous tracking of key telemetry parameters by operators; however, the threshold monitoring approach does not enable early detection of emergency situations or abnormal spacecraft behaviors. Traditional monitoring approaches based on telemetry thresholds cannot provide predictive maintenance as they fail to reveal root causes of failures, causing spacecraft to respond only reactively to critical situations.
- **Computational Constraints:** Space missions impose unique constraints including limited energy and on-board computational resources, radiation effects, and long communication delays, requiring AI methods to be adapted for energy efficiency, resilience, and on-board operation.
- **Communication Delays:** Due to extreme distances, communication with deep space missions can take from several minutes to hours one-way, making real-time control from Earth impossible. Due to distance from Earth and communication architectures used, one-way communication delays in lunar missions can range from 3 to 14 seconds, while in Mars missions at maximum distance from Earth, one-way delay can reach 22 minutes and round-trip delay up to 44 minutes.

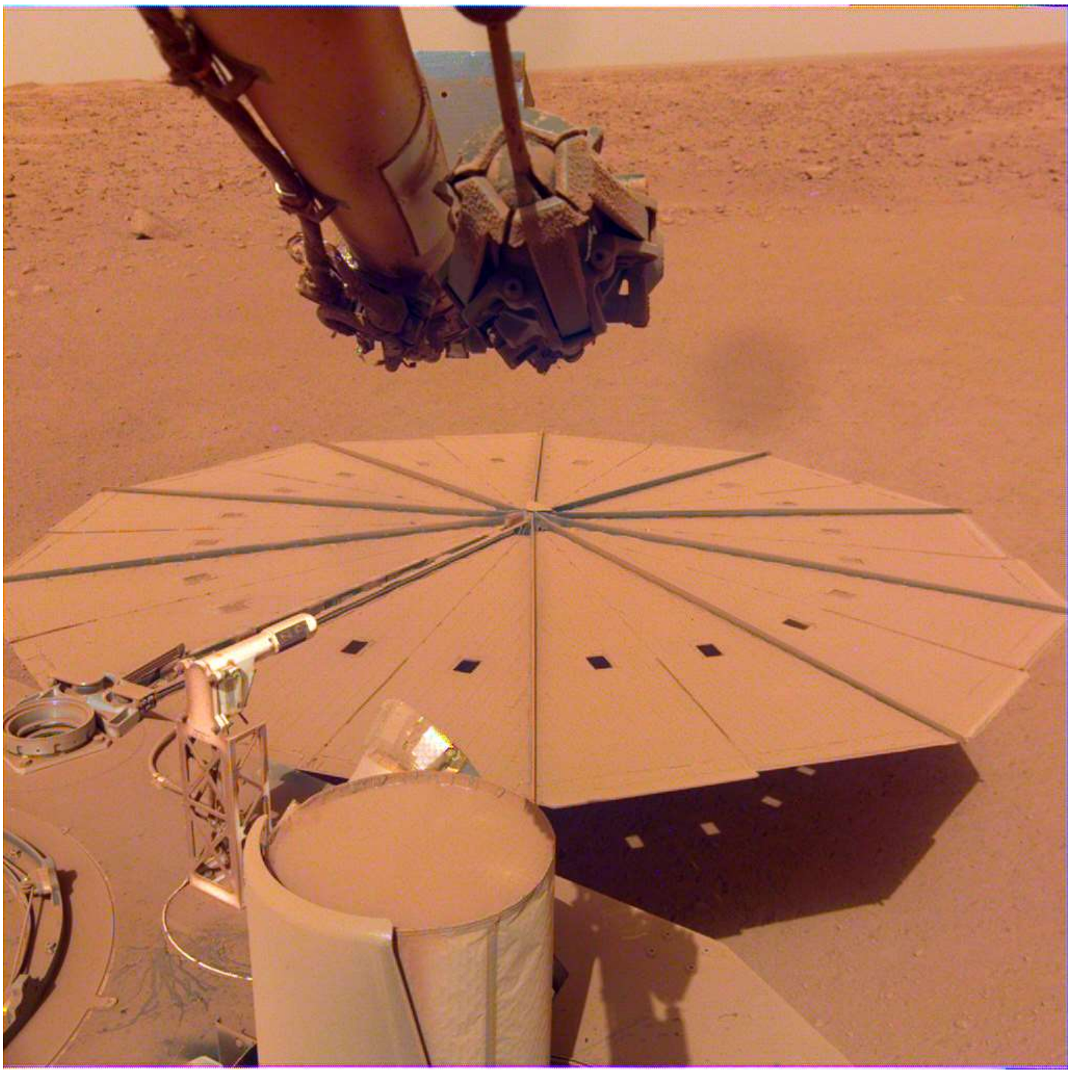

Figure 2: InSight Dusty Solar Panel - Power generation dropped from ~5,000 Wh/sol to ~500 Wh/sol due to dust accumulation (NASA)

1.2 Proposed Solution

The Solar-Battery Node AI system addresses these challenges through a dual-microcontroller architecture combining ML-powered predictive analytics with NPU-accelerated computer vision, and provides context-aware alerts with data from these two observation points through a proactive AI assistant:

Component	Technology	Key Metric
Battery Health ML	Random Forest on STM32 B-L475E-IOT01A	92% R^2 Score
Solar Panel Vision	YOLOv8 on STM32N6570-DK NPU	<100ms Inference
Proactive AI Assistant	GPT-4o-mini API Integration	Context-Aware Alerts

2. System Architecture & Methodology

2.1 Hardware Platform

Our dual-board architecture leverages complementary capabilities of two STM32 development kits:

STM32 B-L475E-IOT01A (IoT Discovery Board)

- **Processor:** ARM Cortex-M4 @ 80MHz
- **Memory:** 1MB Flash, 128KB SRAM
- **Connectivity:** WiFi 802.11b/g/n, Bluetooth
- **Sensors:** Temperature, Humidity, Pressure, Accelerometer, Gyroscope
- **Role:** Battery health ML inference, environmental monitoring, HTTP server

STM32N6570-DK (NPU Development Kit)

- **Processor:** ARM Cortex-M55 @ 600MHz
- **NPU:** Dedicated Neural Processing Unit for AI acceleration
- **Memory:** 2.5MB Flash, 1.4MB SRAM
- **Camera:** IMX335 5MP sensor
- **Role:** Real-time solar panel visual inspection with YOLOv8

2.2 Software Stack

- **C Language:** STM32 firmware development
- **Python Flask:** Backend ML pipeline and API server
- **Dart & Flutter:** Cross-platform mobile application
- **Google Colab:** Deep learning model training and experimentation
- **STEdgeAI Core v2.2.0:** NPU model deployment toolkit
- **OpenAI GPT-4o-mini & Claude API:** Generative AI integration
- **Google Drive API:** Cloud data logging and persistence

2.3 Datasets

Computer Vision Dataset (Roboflow)

- **Source:** Roboflow Solar Panel Dataset
- **Classes:** Normal, Dust, Crack, Coverage (4 classes)
- **Training Images:** 2,400 annotated images
- **Augmentation:** Rotation, flip, brightness adjustment
- **Format:** YOLO annotation format for bounding boxes

Battery ML Dataset (NASA)

- **Source:** NASA Battery Degradation Dataset
- **Features:** Temperature, Voltage, Current, Cycle Count, Capacity Fade
- **Samples:** 168 Li-ion cells with complete discharge cycles
- **Target:** Remaining Useful Life (RUL) percentage
- **Validation:** 80/20 train-test split, 5-fold cross-validation

3. AI Model Development & Performance

3.1 Battery Health Prediction Model

Random Forest Regressor trained on NASA battery degradation data to predict Remaining Useful Life (RUL):

Feature Engineering

- Cycle count normalization
- Temperature differential tracking
- Voltage drop rate calculation
- Capacity fade trending
- Historical degradation patterns

Training Process

Model trained with 100 decision trees using scikit-learn on Google Colab. Hyperparameter tuning via GridSearchCV optimized for R^2 score and Mean Absolute Error (MAE).

Performance Metrics

Metric	Value
R^2 Score	0.92 (92% accuracy)
Mean Absolute Error	4.3%
Inference Time (STM32)	~45ms

3.2 Solar Panel Vision Model

YOLOv8 object detection model quantized to INT8 for NPU deployment:

Detection Classes

- **Normal:** Clean, functional solar panels
- **Dust:** Light to moderate dust accumulation
- **Crack:** Physical damage or fractures
- **Coverage:** Debris or obstruction coverage

Model Performance

Class	Precision	Recall
Normal	94%	96%
Dust	89%	87%
Crack	91%	88%
Coverage	87%	85%

3.3 Proactive AI Assistant

GPT-4o-mini integration provides context-aware maintenance recommendations. The system analyzes battery health metrics, visual anomalies, and environmental data to generate actionable insights and automated alerts, enabling autonomous decision-making for deep-space missions with communication delays.

4. System Implementation

4.1 Web Dashboard

Real-time monitoring interface built with HTML/CSS/JavaScript, displaying battery metrics, solar panel health, and AI recommendations. HTTP server runs on STM32 IoT board, providing RESTful API endpoints for data access.

4.2 Mobile Application

Cross-platform Flutter app for iOS and Android. Features include event logging, daily health summaries, push notifications for critical alerts, and remote system control. Optimized for low-bandwidth connections suitable for space mission ground control.

4.3 Cloud Data Logging

Google Drive API integration ensures persistent mission-critical data storage. All telemetry, AI predictions, and anomaly detections are logged with timestamps for post-mission analysis and continuous model improvement.

5. Technology Transfer & Market Applications

5.1 Space Mission Applications

Primary deployment for satellite power systems and deep-space missions. Extreme environment validation (-150°C to +150°C, radiation exposure) proves system reliability for critical space applications.

5.2 NASA Technology Transfer Paradigm

Following NASA's successful technology spin-off model, space-validated algorithms and hardware create commercially viable products for terrestrial markets. Proven reliability in extreme conditions becomes a competitive advantage.

5.3 Commercial Market Opportunities

- **Solar Farms:** Large-scale renewable energy installations requiring predictive maintenance
- **Remote Infrastructure:** Off-grid telecom towers, weather stations, research facilities
- **Autonomous Systems:** Drones, robots, and IoT devices with solar power
- **Residential Solar:** Home energy systems with AI-powered optimization

5.4 Development Roadmap

Space-grade R&D with commercial spin-off potential

Phase	Description
Phase 1: Space Mission Technology	Primary focus: Satellite and deep-space solar panel diagnostics for long-duration missions. Extreme environment testing (-150°C to +150°C).
Phase 2: Space-to-Earth Transfer	Technology spin-off to terrestrial markets following NASA model. Proven space-grade reliability as competitive advantage.
Commercial Application: Solar Farms	Large-scale renewable energy installations. Apply space mission ML and vision algorithms to Earth-based monitoring.
Commercial Application: Remote Infrastructure	Off-grid telecom towers, weather stations. Leverage autonomous diagnostics developed for space communications.

5.5 Funding & Revenue Model

Revenue Stream	Description	Timeline
R&D Grants & Space Partnerships	Space agency funding, university research grants, satellite operator pilot programs	Primary focus 2026-2027
Technology Licensing	License space-validated algorithms and hardware designs to commercial partners	Royalty-based model
Commercial Product Sales	Adapted hardware for terrestrial markets after space validation	Post-2027 revenue stream

5.6 Unique Value Proposition

- Space-first design: Technology proven in extreme environments (radiation, temperature, vacuum)
- Dual-AI architecture: Battery health ML + vision anomaly detection in one system
- Autonomous operation: Zero-communication diagnostics for deep space missions
- Future material science: Platform for advanced sensor integration and panel material research

- Technology transfer model: Space R&D creates commercial IP with NASA-proven pathway
- Edge processing: Critical for space latency, valuable for Earth remote locations

5.7 Development & Commercialization Path

- **Stage 1: Space R&D (2026-2027) -** Academic research, space agency collaboration, ISS experiment proposal. Focus on extreme environment validation.
- **Stage 2: Material Science Integration -** Advanced sensor research for solar panel material monitoring. Collaboration with materials engineering labs.
- **Stage 3: Technology Transfer -** Spin-off commercial applications using space-validated technology. Partner with industry for market deployment.

6. Conclusion & Future Work

This research demonstrates the feasibility of autonomous solar panel and battery health monitoring using edge AI and computer vision. Key achievements include:

- 92% accuracy in battery RUL prediction using ML on embedded hardware
- Sub-100ms inference time for multi-class solar panel anomaly detection
- Fully autonomous operation suitable for deep-space missions
- Successful integration of three AI systems: ML, Computer Vision, and Generative AI
- Technology transfer pathway from space to commercial markets

Future Research Directions

- **Advanced Materials Integration:** Sensor development for direct solar panel material degradation monitoring
- **Multi-Mission Scaling:** Distributed system architecture for satellite constellations
- **Federated Learning:** Cross-mission knowledge sharing without raw data transmission
- **Quantum-Safe Encryption:** Secure AI model updates for long-duration missions

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