Research Proposal

AI in Spacecraft Health Maintenance

Section 1 : Title of Research Proposal

Optimization of AI Models for Real-time Anomaly Detection in Spacecraft Telemetry Under Resource Constraints

Section 2 : Summary :

Space missions depend significantly on real-time telemetry data to assess the health and performance of spacecraft. Given the intricate and crucial nature of these missions, any irregularity in the telemetry data can lead to serious repercussions, potentially threatening the success of the mission. Conventional anomaly detection methods usually necessitate extensive analysis on the ground, which may not be practical for deep space missions due to communication delays and restricted bandwidth. Furthermore, in human space missions where rapid decisions are required, AI tools can assist astronauts in analyzing and drawing relevant conclusions from onboard telemetry data. Additionally, the computational resources available on spacecraft are limited, creating hurdles for implementing advanced anomaly detection algorithms. Consequently, there is an urgent need to create an AI model that can effectively monitor telemetry data, identify anomalies in real-time, and function within the strict limitations of onboard computational capabilities.

Problem Statements :

- Currently, ISRO uses rule-based threshold monitoring (e.g., an alert if battery voltage < 3.6V)
- This leads to false alarms or misses slow-developing failures (e.g., gradual temperature rise).
- AI can learn patterns in telemetry data and predict failures before they occur, and prevent minor errors from leading to catastrophic ones, increasing chances of mission success

Section 3 : Objectives

- Develop an AI-based anomaly detection system optimized for real-time telemetry monitoring onboard spacecraft, specifically addressing the challenges of computational constraints in space mission environments.
- Reduce computational complexity and model size while maintaining high detection accuracy, focusing on lightweight AI programming techniques such as pruning, quantization, and knowledge distillation.
- Enhance spacecraft autonomy by minimizing reliance on ground-based monitoring and enabling real-time decision-making despite limited onboard resources.
- Implement and test the AI model on embedded hardware, simulating the resource-constrained environments typical in space missions.
- Contribute to ISRO's advancements in autonomous spacecraft operations, ensuring more efficient, safe, and sustainable space missions, especially in deep-space and human spaceflight missions.

Section 4 : Major Scientific fields of interest

1. Limitations of ISRO's Current Approach

ISRO currently relies on predefined thresholds and expert-driven analysis for telemetry monitoring. This has three major limitations:

1. Limited Prediction Capabilities: Cannot foresee failures in advance, leading to reactive maintenance rather than proactive intervention.
2. Data Overload: Continuous telemetry transmission overloads ground-based data processing centers.
3. Lack of Real-Time Autonomy: Reliance on Earth-based monitoring increases decision-making delays, which is problematic for deep-space missions like Chandrayaan, Mangalyaan, and future Gaganyaan missions.
4. In past missions, unexpected temperature fluctuations in spacecraft components have led to system malfunctions.

A lightweight AI model could predict temperature anomalies in advance and suggest corrective actions, preventing component damage.

2. Review of Current Work in the Field

1. NASA's Health Monitoring AI

- NASA has implemented Deep Learning for telemetry data analysis in its Remote Agent Experiment (RAX).

- Uses Long Short-Term Memory (LSTM) networks to predict failures in spacecraft power systems and attitude control.
- Limitation: Requires high computational resources, making it unsuitable for real-time onboard execution.
- Citations - Douglas E. Bernard1 , Gregory A. Dorais3 , Chuck Fry3 , Edward B. Gamble Jr. 1 , Bob Kanefsky3 , James Kurien3 , William Millar3 , Nicola Muscettola2 , P. Pandurang Nayak4 , Barney Pell4 , Kanna Rajan3 , Nicolas Rouquette1 , Benjamin Smith1 , Brian C. Williams5 1 Jet Propulsion Laboratory, California Institute of Technology 4800 Oak Grove Drive Pasadena, CA 91109 818-354-2597 douglas.e.bernard@jpl.nasa.gov, 2, 3, 4, 5 NASA Ames Research Center, MS 269-2 Moffett Field, CA 94035 2 Recom Technologies @ Ames 3 Caelum Research @ Ames 4 RIACS @ Ames 650-604-4756 nayak@ptolemy.arc.nasa.gov

2. ESA's Phi-Sat-1 AI System

- Deployed an Intel Movidius Myriad 2 VPU-based AI for cloud detection in Earth observation.
- Demonstrated that AI can run efficiently on low-power hardware, reducing the need to transmit unnecessary data.
- Citations -G. Giuffrida et al., "The Φ-Sat-1 Mission: The First On-Board Deep Neural Network Demonstrator for Satellite Earth Observation," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-14, 2022, Art no. 5517414, doi: 10.1109/TGRS.2021.3125567. keywords: {Artificial intelligence;Satellites;Cloud computing;Space vehicles;Hyperspectral imaging;Orbits;Earth;Φ-Sat-1;artificial intelligence (AI);earth observation (EO);hyperspectral;microsatellite;nanosatellite;on-the edge;satellite camera;segmentation network;synthetic dataset},

3. D-Orbit's RaVAEn Model

- Uses Variational Autoencoders (VAE) to compress telemetry data onboard satellites.
- Reduces data transmission costs by over 60%, improving bandwidth efficiency.

4. AIKO's Onboard AI:

- AIKO, an Italian space company, developed an AI-powered health monitoring system capable of identifying anomalies, classifying them, and taking immediate corrective actions without ground intervention.
- Citations - Ciardi, R., Giuffrida, G., Benelli, G., Cardenio, C., Maderna, R. (2023). GPU@SAT: A General-Purpose Programmable

Accelerator for on Board Data Processing and Satellite Autonomy. In: Ieracitano, C., Mammone, N., Di Clemente, M., Mahmud, M., Furfaro, R., Morabito, F.C. (eds) The Use of Artificial Intelligence for Space Applications. AII 2022. Studies in Computational Intelligence, vol 1088. Springer, Cham. https://doi.org/10.1007/978-3-031-25755-1_3

5. Private Sector: SpaceX and Blue Origin

- SpaceX has experimented with neural networks for Falcon 9 telemetry analysis
- Blue Origin integrates edge AI models for real-time monitoring of launch vehicle parameters.

3. Key takeaways of the Proposed research

Key Innovations

1. Use of Pruned and Quantized LSTM Networks
   - Reduces model size and computation needs.
2. Deployment on Low-Power Edge AI Hardware
   - Uses FPGAs or Intel Movidius VPUs instead of GPUs.
3. Adaptive Learning System
   - Ground-based AI periodically updates onboard models to improve accuracy.

Expected Impact for ISRO

- Early Failure Prediction → Reduces spacecraft downtime.
- Lower Bandwidth Needs → Optimized telemetry transmission.
- Autonomous Decision Making → Reduces manual intervention.

Section 5 : Approach

1. System Architecture :

The system consists of two key components:

A. Onboard AI (Edge Processing)

- **Objective:** Detect real-time anomalies using a lightweight LSTM model optimized for low-power hardware.
- **Hardware:** Runs on an FPGA, Movidius VPU, or ARM Cortex AI chip.

- **AI Model:** Compressed LSTM model trained to predict future telemetry values based on historical data.
- **Data Processing:**
  - Continuously receives real-time telemetry data from sensors.
  - Predicts next telemetry values based on past trends.
  - If predicted vs actual deviation exceeds threshold, flag as anomaly.
- **Action:**
  - If anomaly is critical → **Immediate alert to ground station**.
  - If anomaly is minor → **Store data for periodic analysis**.
- **NOTE** - Alternatively, a Lightweight recurrent network may be used since these are designed specifically for constrained environments with lower computational needs., however these are also known to sacrifice some accuracy for efficiency.

B. Ground-Based AI (Deep Analysis & Model Updating)

- **Objective:** Analyze telemetry patterns in-depth and send improved AI model updates to spacecraft.
- **Hardware:** High-performance server-based GPUs (e.g., NVIDIA A100).
- **AI Model:** Full-sized LSTM trained on large datasets from multiple past missions.
- **Data Processing:**
  - Receives flagged anomalies from onboard AI.
  - Reanalyzes data using more complex ML models (e.g., Transformer-based forecasting).
  - Sends periodic model updates to the spacecraft for better anomaly detection.

2. AI Model Selection and Optimization :

The AI model must be both **accurate and lightweight** for real-time use.

Step 1: Choosing a Base Model

- Since spacecraft telemetry is **time-series data**, a **Long Short-Term Memory (LSTM) network** is a great fit because it:
  - Learns long-term dependencies in telemetry.
  - Works well with fluctuating sensor readings.
  - Can predict future values for proactive issue detection.

Step 2 : Optimizing the LSTM for Spacecraft Hardware

Optimization Technique	Purpose	Expected Improvement
Pruning	Remove unimportant neurons	50% smaller model
Quantization (FP32 → INT8)	Convert floating-point to integer	75% lower memory use
Knowledge Distillation	Train a small model from a large one	Maintain accuracy with 90% fewer computations
Onboard Edge Computing	Deploy on FPGA/Movidius instead of CPU	10x faster inference

Step 3: Model Deployment Strategy

- **Onboard LSTM Model :** 10% of full AI size, running on FPGA.
- **Ground-Based LSTM :** Full model for deeper anomaly analysis.
- **Model Updates :** Every 3 months, the ground station trains an improved model and uploads it to the spacecraft.

3. Data Processing Pipeline :

A. Onboard Processing Flow

1. **Telemetry Sensors Collect Data**
    - Example: Battery voltage, temperature, current, pressure, radiation levels.
2. **Preprocessing**
    - Normalize values (0-1 range).
    - Remove outliers using statistical filters.
3. **LSTM Model Predicts Next Values**
    - Given the past 10 minutes of telemetry, predict the next 5 minutes.
4. **Anomaly Detection Algorithm**
    - If predicted value deviates from actual by 3σ, flag as anomaly.
5. **Decision Making**

    - If critical anomaly, send an immediate alert to the ground station.
    - If non-critical, log the data and continue monitoring.

B. Ground Processing Flow

1. Receives Flagged Anomalies from spacecraft.
2. Performs Detailed ML Analysis using full-scale LSTM & transformers.
3. Updates AI Model and Sends to Spacecraft every 3 months.

4. Hardware Selection :

Hardware	Use case	Power Consumption	AI Performance
FPGA (Xilinx Zynq)	Real-time AI on satellites	< 5W	Medium
Intel Movidius VPU	Image + telemetry processing	1 - 2W	High
ARM Cortex AI chip	Lightweight telemetry AI	0.5 - 1W	Low

Recommendation:

- Use FPGA for onboard inference (balance of speed + power efficiency).
- Use Intel Movidius VPU if ISRO wants to add image processing (e.g., Phi-Sat-1).
- Use ARM Cortex AI chip for low-power CubeSats & SmallSats.

5. Example workflow :

- **Data Collection**
    - Spacecraft sensors record battery voltage, temperature, pressure, power usage, etc.
    - Data is fed into an LSTM-based AI model onboard.
- **AI Anomaly Detection** (Onboard)
    - AI compares real-time telemetry values with expected trends.
    - If deviation > threshold, an alert is generated.
- **Prediction & Action**
    - AI predicts future failures (e.g., battery overheating in 6 hours).

  - Preemptive action: The system may suggest reducing power usage or switching to backup batteries.
- **Data Transmission**
  - Only important telemetry data is sent to ground stations, reducing communication bandwidth.

6. Work plan :

A time period of 2 years will be divided into 4 phases, which will then be further subdivided into subphases.

1. **Phase 1 (Months 1-4):** Data Collection and Preprocessing -
    a. Data comprehension and understanding (Month 1 - 2) - Learning to understand and work with Telemetry Data provided by ISRO.
    b. Clean, preprocess, and organize the data for training AI models.
2. **Phase 2 (Months 5-10):** Algorithm Development -
    a. Model Comprehension (Month 5 - 7) - Experimenting with Various AI models such as Random Forest, Support Vector Machines, and Neural Networks for fault detection and prediction.
    b. Model Implementation (month 8 - 10)
3. **Phase 3 (Months 11-16):** Model Testing and Refinement
    a. Validate models through simulation and adjust parameters to improve accuracy. (Month 11-13)
    b. Fine tuning models based on results from the Simulations. (Month 14 - 16)
4. **Phase 4 (Months 17-24):** Deployment and Integration
    a. Integrate the system with spacecraft telemetry.
    b. Test the model in real-time conditions and refine based on performance.

Gantt Chart - Project_ISRO

7. Hardware Requirements

- Microcontroller or Microprocessor: Space-qualified, low-power processor with AI/ML acceleration capabilities (e.g., NVIDIA Jetson, Xilinx Zynq, or radiation-hardened processors).
- Sensors: To monitor key subsystems (temperature, pressure, voltage, etc.).
- Memory and Storage: Use radiation-hardened memory for data logging and model storage.
- Communication Interfaces: Ensure reliable data transfer to ground stations or other spacecraft.

Section 6 : Data reduction and analysis

- During Phase 1, the data collection phase, historical data from power sensors and thermal systems is required, to process it and begin AI development later down the road.
- To effectively train the model, we need historical telemetry logs that contain both nominal (normal operation) and anomalous (faulty) data.
- Core Telemetry Parameters -

Subsystem	**Telemetry Parameter**	**Importance**
Power System	Battery voltage, current, state-of-charge (SOC), solar panel output, power consumption	Detects power failures, low battery, or solar panel degradation.
Thermal Control	Component temperatures, heat dissipation rate, heater status	Predicts overheating or thermal regulation failure.
Propulsion System	Fuel levels, pressure, thrust levels, valve status	Detects leaks, engine malfunctions.
Communication	Signal strength, antenna status, transmission power	Identifies signal dropouts or antenna misalignment.
Attitude Control	Gyroscope readings, accelerometer data, magnetometer data	Detects spacecraft orientation issues.
Radiation Sensors	Radiation levels (cosmic rays, solar storms)	Predicts radiation-induced anomalies.

- **Anomaly Labels (Supervised Learning)**

  Ideally, historical data should have **labeled anomalies**, such as:
  - **Battery degradation event** (e.g., sudden voltage drop).
  - **Overheating of payload electronics** (e.g., thermal sensor spike).
  - **Telemetry dropout** (e.g., missing data packets).

  If labels are unavailable, we can use **unsupervised learning** (e.g., autoencoders, clustering) to detect deviations from normal telemetry patterns.

Section 7 : Available Institutional facilities :

Section 8 : Fund requirement :

Budget Requirement (INR, Estimated):

Item	Year 1 (INR)	Year 2 (INR)	Total (INR)
Salary (Research Assistants, Engineers)	2,40,000	2,40,000	5,00,000
Equipment (Embedded systems, sensors, computing hardware)			
Consumables (Data storage, software licenses)			
Contingencies			
Travel (ISRO meetings, conferences)			
Other Expenses (Cloud computing, AI software tools)			
Sub Total			
Institute Overhead (20%)			
Total Budget			

Section 9 : References and additional Citations

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