Paper ID: 102622
student

23rd IAA SYMPOSIUM ON SPACE DEBRIS (A6)
Interactive Presentations - 23rd IAA SYMPOSIUM ON SPACE DEBRIS (IP)

Author: Mr. Gourav Mohanan
Dayananda Sagar University, India

Ms. S V Shrigandha
Dr. Ambedkar Institute Of Technology, India
Ms. Esra Şahin
Bursa Technical University, Türkiye

FEDERATED LEARNING FOR SPACE SITUATIONAL AWARENESS LIGHTWEIGHT AI MODELS FOR REAL-TIME FAULT DETECTION IN SATELLITES

Abstract

With the increasing congestion of Earth's orbit and the growing threat of space debris, ensuring the health and functionality of satellites is more critical than ever. Traditional satellite fault detection systems rely on centralized data processing, requiring frequent communication with ground stations. However, this approach is impractical for small satellites due to their limited computational resources, power constraints, and bandwidth restrictions. This paper proposes a novel federated learning (FL)-based framework for real-time fault detection in satellites, leveraging lightweight AI models to enhance autonomy while minimizing communication overhead.

Federated learning allows satellites to collaboratively train AI models without sharing raw telemetry data, preserving data privacy and reducing latency. This decentralized approach enables satellites to continuously learn and refine anomaly detection models in orbit, improving their ability to identify system malfunctions before they escalate into mission-threatening failures. The proposed system utilizes efficient machine learning techniques such as Decision Trees, Logistic Regression, and TinyML frameworks (e.g., TensorFlow Lite), ensuring compatibility with low-power satellite processors.

To validate this approach, we integrate publicly available satellite telemetry datasets from NASA and ESA with simulation tools like MATLAB, Scikit-learn, and CubeSat simulators. Our study evaluates model accuracy, computational efficiency, and communication costs, demonstrating that lightweight AI models deployed in a federated learning environment can detect faults with high precision while significantly reducing dependency on ground-based diagnostics. Additionally, we explore the role of AI-driven robotic assistance, including robotic arms for high-risk maintenance tasks, in improving satellite resilience and reducing human intervention in space operations.

By integrating real-time fault detection with AI-powered robotic assistants, this research contributes to enhancing space situational awareness (SSA) and mitigating space debris. Early fault detection helps prevent in-orbit failures, reducing the likelihood of debris generation. Furthermore, as AI-enabled federated systems evolve, they can optimize satellite swarm intelligence, enabling autonomous decision-making for collision avoidance and predictive maintenance.

This paper presents a scalable, efficient, and privacy-preserving AI framework for satellite health monitoring, addressing the pressing challenge of maintaining sustainable satellite operations in an increasingly crowded orbital environment. The findings suggest that federated learning, combined with lightweight AI models, offers a transformative approach to space-based fault detection, ensuring the longevity and reliability of future satellite networks. Future research will focus on optimizing federated models for deep-space missions, multi-agent collaboration, and extending AI capabilities for autonomous satellite