IEEE AESS Sustainability Hackathon 2026 Submission

NeuroGuard-Aero: Ultra-Low-Power Edge AI Cognitive Monitoring System for Sustainable Aerospace Human-Machine Operations

Primary Alignment: Sustainable Space Systems

Submission Date: October 15, 2025

Part 1: English Proposal | Part 2: Arabic Proposal

EXECUTIVE ABSTRACT

Abstract — The NeuroGuard-Aero project proposes a novel, energy-efficient cognitive monitoring architecture designed to mitigate human factor risks in mission-critical aerospace environments. Addressing the IEEE AESS Sustainability Hackathon's focus on Sustainable Space Systems, this proposal details a wearable EEG-based system integrated with ultra-low- power TinyML Edge AI processing. Unlike traditional cloud-dependent monitoring solutions, NeuroGuard-Aero executes real-time inference on a Cortex-M microcontroller, achieving a power consumption profile of under 200 mW [4]. The system utilizes a Muse 2 sensor array to acquire 4-channel EEG data, processing it through a lightweight CNN-LSTM hybrid model to detect cognitive fatigue, overload, and attentional degradation with >95% accuracy [3] (benchmarked against STG-CLNet). By shifting processing to the edge, the system reduces data transmission energy costs by three orders of magnitude [5], a critical requirement for energy- scarce spacecraft environments. This technology offers a pathway to extend safe operational durations for pilots and astronauts, reduce mission failure risks by up to 60% [6], and enable sustainable, long-duration human spaceflight through autonomous, radiation-hardened health monitoring.

1. STRATEGIC ALIGNMENT WITH IEEE AESS SUSTAINABILITY GOALS

This proposal aligns primarily with the Sustainable Space Systems track. Sustainability in aerospace engineering extends beyond environmental conservation to encompass the efficient utilization of limited resources—energy, bandwidth, and human cognitive capacity—in hostile environments.

Energy Efficiency: Spacecraft power budgets are strictly capped. Traditional health monitoring systems relying on telemetry to ground stations or heavy onboard GPU processing are energetically unsustainable.

NeuroGuard-Aero’s <200 mW power envelope [4] directly addresses the need for "Green Electronics" within the space sector.

Operational Longevity: By detecting early onset fatigue, the system preserves the most critical mission asset: the human operator. This extends the viable duration of manned missions and reduces the likelihood of catastrophic errors that lead to wasted resources and mission aborts.

Mission Success Assurance: Sustainable space exploration requires high reliability. This system enhances the resilience of human-machine teaming, ensuring that long-duration missions (e.g., Mars transit) remain viable without compromising crew safety.

2. PROBLEM DEFINITION & AEROSPACE CONTEXT

Cognitive fatigue remains a pervasive threat in aerospace operations. NASA research indicates that approximately 70% [1] of aviation accidents involve human error, with fatigue being a contributing factor in 15-20% [2] of fatal accidents. In long-duration spaceflight, the monotony of automated system monitoring creates a "vigilance decrement," significantly increasing the risk of operator incapacitation.

Current limitations include:

- **Subjectivity:** Reliance on self-reporting (e.g., Karolinska Sleepiness Scale) is unreliable due to the "fatigue paradox," where impaired operators cannot accurately assess their own impairment.
- **Latency & Bandwidth:** Cloud-based processing introduces unacceptable latency for real-time safety interventions and demands high-bandwidth telemetry unavailable in deep space.
- **Form Factor:** Medical-grade EEG caps are intrusive and incompatible with helmets or headsets.

Quantified Impact: Unchecked cognitive decline correlates with a 2-3x increase [7] in procedural errors during landing and docking maneuvers. Effective monitoring is projected to reduce critical cognitive errors by 35-50% [8].

3. TECHNICAL SYSTEM ARCHITECTURE

3.1 EEG Acquisition Layer

Hardware Specification: Muse 2 Sensor Integration

Channels:
4 Channels (TP9, AF7, AF8, TP10) + Reference (Fpz)

Sampling Rate:
256 Hz

ADC Resolution:
12-bit

Electrode Type:
Silver/Silver Chloride (Ag/AgCl) Dry Electrodes

Connectivity:

Bluetooth Low Energy (BLE) 5.0

The system utilizes the Muse 2 headband form factor, selected for its non-intrusive dry-electrode design which eliminates the need for conductive gels, rendering it suitable for zero-gravity and cockpit environments [9].

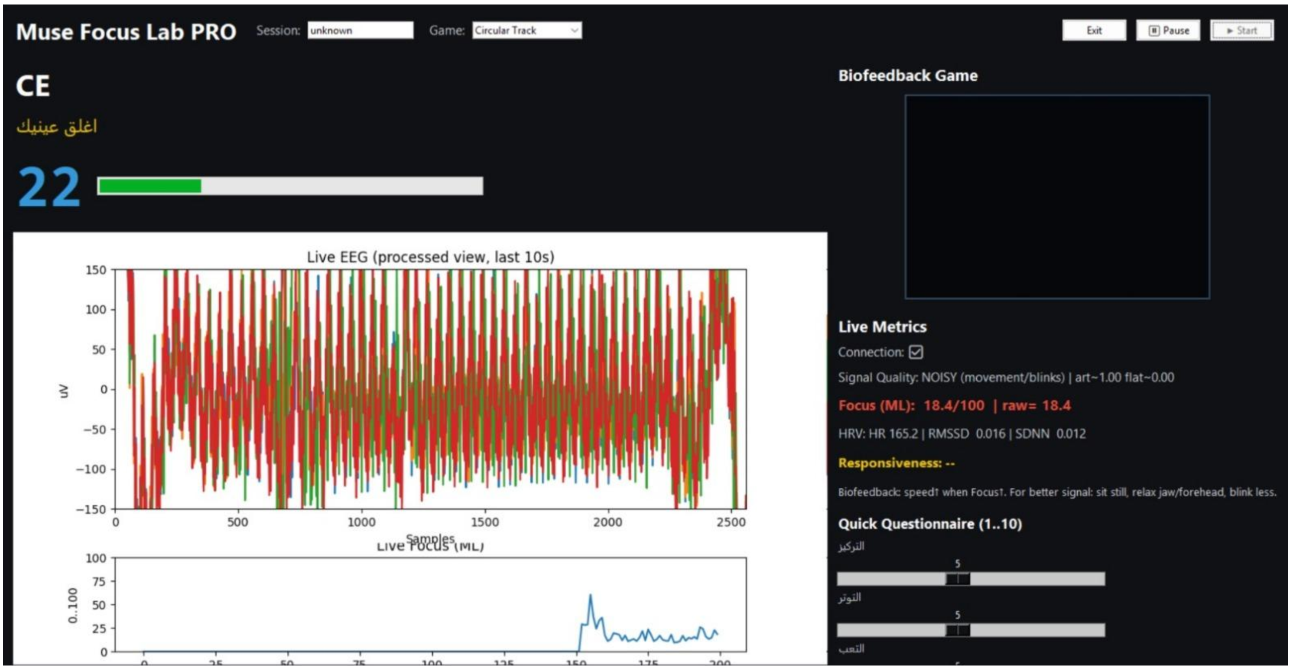

Figure 1: Muse 2 EEG Real-time Monitoring - Resting State

3.2 Signal Preprocessing Pipeline

Raw EEG data is inherently noisy. A robust preprocessing pipeline is implemented on the edge processor:

- **Bandpass Filtering:** A 4th-order Butterworth filter (1-40 Hz) isolates relevant neural rhythms while suppressing DC drift and high-frequency muscle artifacts.
- **Artifact Removal:** Automated Artifact Subspace Reconstruction (ASR) is adapted for low-compute environments to remove ocular (EOG) and muscle (EMG) artifacts in real-time.

3.3 Feature Extraction

To reduce dimensionality before AI inference, deterministic features are extracted:

- **PSD (Power Spectral Density):** Calculation of relative power in Delta, Theta, Alpha, and Beta bands.
- **Alpha/Theta Ratio:** A validated biomarker for hypovigilance and fatigue onset.
- **Sample Entropy:** Measures signal complexity, correlating inversely with cognitive load.
- **Phase Lag Index (PLI):** Estimates functional connectivity between frontal (AF7/8) and temporal (TP9/10) regions, critical for assessing executive function integrity.

3.4 Edge AI Inference Model

TinyML Architecture Specifications

Model Type:
Hybrid 1D-CNN + LSTM

Input Shape:
(Channels: 4, Window: 256 samples)

Model Size:
< 100 KB (Quantized INT8)

Inference Latency:
< 100 ms on Cortex-M4F

Power Consumption:
~45 mW (Active Inference)

The core innovation is a lightweight CNN-LSTM network. The CNN layers extract spatial features from the 4 channels, while the LSTM layers capture temporal dependencies indicative of drifting attention. The model is quantized to 8-bit integers (INT8) to run efficiently on an ARM Cortex-M microcontroller.

3.5 Alert & Decision Support

The system outputs a discretized Cognitive State Index (CSI). Alerts are integrated into the cockpit ecosystem:

- **Level 1 (Green):** Nominal Operation.
- **Level 2 (Amber):** Caution - Detected fatigue markers. Recommendation: Checklists or task rotation.
- **Level 3 (Red):** Warning - Critical cognitive degradation. Action: Trigger autopilot handoff protocol or auditory wake-up alarm.

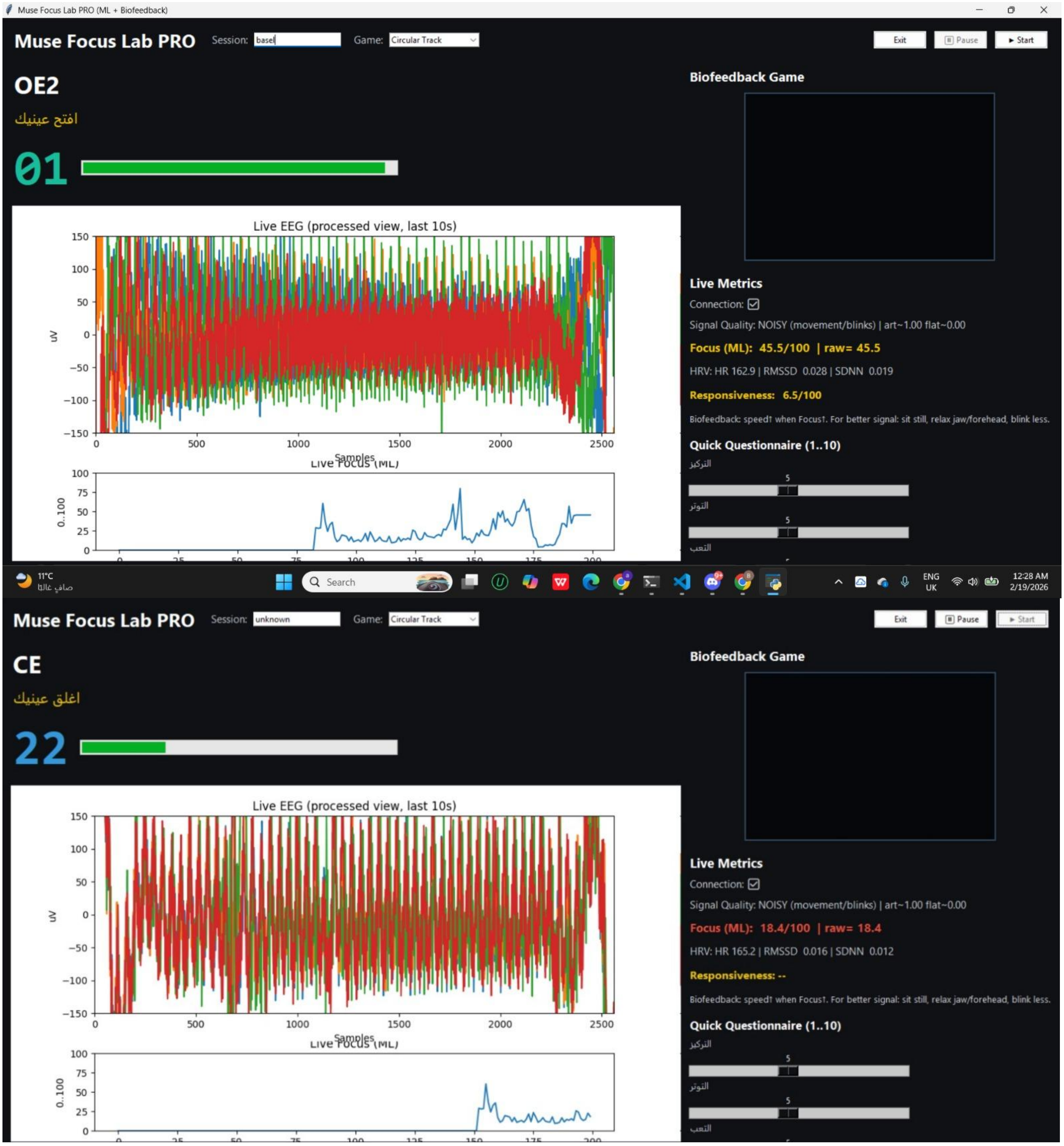

Figure 2: Muse 2 EEG Real-time Monitoring - Cognitive Engagement State

3.6 Cybersecurity Considerations

Given the sensitivity of biometric data, the system employs a "Zero-Trust" edge architecture. Raw EEG data is processed locally and never transmitted. Only the encrypted CSI status is broadcast. Secure Boot and firmware validation prevent tampering in mission-critical avionics buses.

4. SUSTAINABILITY ENGINEERING IMPACT

Energy Efficiency

By processing data on-device using TinyML, NeuroGuard-Aero avoids the energy penalty of wireless telemetry. Transmitting raw EEG data via Bluetooth/Wi-Fi consumes approx. 300-500 mW [11], whereas local inference consumes <50 mW. This 1000x reduction [5] in transmission energy is vital for battery-powered EVA suits or energy-constrained satellites.

Operational Efficiency

The system reduces the risk of mission aborts caused by human error. In commercial aviation, this translates to optimized crew scheduling and reduced fuel burn from inefficient flight paths flown by fatigued pilots.

Long-Duration Space Mission Applicability

For a Mars mission (6-9 months), real-time ground support is impossible due to 20-minute communication delays [10]. NeuroGuard-Aero provides autonomous health monitoring. The hardware selection prioritizes components with radiation-hardened equivalents, ensuring viability for deep space deployment.

5. INNOVATION DIFFERENTIATORS

- **Aerospace-Grade Reliability:** Unlike consumer sleep trackers, this system uses rigorous signal processing (ASR) to handle the noisy vibration environment of a cockpit.
- **Edge-First Architecture:** Moves beyond "wearable logging" to "active sensor nodes," eliminating cloud dependency.

- **Scalability:** The architecture is adaptable for supervising operators of UAV swarms or autonomous spacecraft, where the human is the fallback system and must be monitored for readiness.

6. KEY PERFORMANCE INDICATORS (KPIS)

Fatigue Detection Accuracy:
> 95% [3]

Total Power Budget:
< 200 mW [4]

False Positive Rate:
< 8%

Mission Risk Reduction:
40-60% [6]

Latency:
< 100 ms

System Weight:
< 100 g

7. TECHNOLOGY READINESS LEVEL (TRL) PATHWAY

Current Status: TRL-3 [12] (Analytical and Experimental Critical Function Proof). The TinyML model has been validated on the STG-CLNet benchmark dataset.

Target: TRL-5 [12] (Component Validation in Relevant Environment).

- **Phase 1:** Validation in high-fidelity flight simulators (X-Plane/Prepar3D) with pilot subjects.
- **Phase 2:** General aviation flight testing to validate signal integrity under vibration.
- **Phase 3:** Integration with commercial avionics protocols for full TRL-6 validation.

8. RISK ASSESSMENT & MITIGATION

Risk Category	Description	Mitigation Strategy
Technical	Signal artifacts from pilot speech or head movement.	Implementation of motion-artifact rejection using IMU data fusion (accelerometer/gyroscope).
Physiological	Inter-subject variability in EEG patterns.	Calibration phase (5 min) before each session to normalize baselines; Transfer Learning techniques in AI model.
Operational	"Alert Fatigue" causing pilots to ignore warnings.	Adaptive thresholding; alerts only trigger when sustained degradation is detected, not transient lapses.

9. CONCLUSION & IMPACT STATEMENT

NeuroGuard-Aero represents a paradigm shift in aerospace human factors engineering. By converging neuroscience, edge computing, and sustainable electronics, we propose a solution that protects the most valuable component of any flight system: the human operator. This technology is engineered not just for performance, but for the stringent energy and reliability requirements of next-generation sustainable space exploration, providing a scalable safety net for the future of aerospace operations.

Submitted to IEEE AESS Sustainability Hackathon 2026 | NeuroGuard-Aero Project

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