

A Machine Learning Framework for Anomaly Detection and Fault Classification in Deep-Space ECLSS

Cyclic Processes

1. Introduction & Background

The future of human space exploration hinges on autonomous systems capable of supporting crew operations during long-duration missions to the Moon, Mars, and beyond. Deep space habitats (DSHs) present unique operational challenges that distinguish them from spacecraft in low Earth orbit. Communication delays between Earth and deep space destinations can range from several minutes to over twenty minutes, fundamentally limiting real-time ground support for critical decision-making (Ibrahim et al., 2026). Consequently, DSHs require substantially higher levels of Earth-independence when responding to anomalies, particularly in safety-critical systems such as the Environmental Control and Life Support System (ECLSS).

The ECLSS maintains habitable conditions by regulating atmospheric composition, pressure, temperature, and humidity. Given the life-sustaining nature of these functions, even minor faults, such as sensor drift, valve malfunctions, or leaks can escalate into crew-threatening situations if not detected promptly (Gratius et al., 2024). Traditional ECLSS monitoring relies on predefined fault thresholds and human supervision from ground control, methodologies impractical in deep space environments. NASA explicitly requires that DSHs detect and resolve critical anomalies autonomously while permitting onboard subject matter expert involvement when necessary (Ibrahim et al., 2026).

Recent research increasingly employs data-driven machine learning approaches to enable autonomous health management in aerospace systems. Prognostics and Health Management (PHM) frameworks integrate diagnostic and prognostic capabilities to assess system health and predict component degradation (Li et al., 2017; Nguyen et al., 2019). In aerospace applications, PHM systems have demonstrated substantial benefits; UH-60 helicopter implementation increased fully mission capable status from 65% to 87% while reducing unscheduled maintenance (Nguyen et al., 2019). Systematic PHM architectures enable integration through standardized interfaces such as the Open System Architecture for Condition-Based Maintenance (Li et al., 2017).

Ibrahim et al. (2026) developed a pioneering generative machine learning framework for anomaly response in cyclical ECLSS processes on deep space habitats. Their approach addresses three critical limitations of traditional ML models:

static structures that cannot adapt to changing conditions, reliance on manual dataset curation for retraining, and insufficient training data due to novelty of DSH operations and rarity of fault events. The framework employs a Variational Autoencoder (VAE) trained on nominal operational data for anomaly detection, monitoring reconstruction error to identify deviations from expected behavior. A Support Vector Machine (SVM) classifier trained on latent-space features enables fault diagnosis, categorizing operating conditions into baseline states and specific fault types such as leaks, valve stiction, and vacuum anomalies. Experimental validation using Simulation Testbed for Exploration Vehicle ECLSS data demonstrated detection false negative rates and false positive rates below 10% with correct classification rates exceeding 90% (Ibrahim et al., 2026).

Complementary research has explored digital twin technologies for ECLSS autonomy. Glaessgen and Stargel (2012) introduced the digital twin paradigm for NASA vehicles, integrating ultra-high-fidelity simulation with onboard vehicle health management systems and historical fleet data. Digital twins create virtual representations of physical systems, continuously updated with sensor data to maintain synchronized state representations. For deep space applications, digital twins support uncertainty quantification in safety-critical predictions and facilitate autonomous decision-making during communication blackout periods (Gratius et al., 2024).

Broader ML research in aerospace fault detection demonstrates the effectiveness of various architectures. Hundman et al. (2018) developed LSTM-based anomaly detection systems for spacecraft telemetry achieving performance suitable for operational deployment on the Soil Moisture Active Passive satellite and Mars Science Laboratory rover. Deep variational autoencoders effectively reduce dimensionality while preserving fault-relevant features, with reconstruction error-based detection rates exceeding 99% for process faults (San Martin et al., 2019). These advances underscore the potential of generative models to capture complex temporal dependencies in sensor data streams characteristic of life support systems.

This project aims to validate whether a VAE-SVM machine learning framework can autonomously detect and classify ECLSS faults using synthetically generated sensor data, achieving performance comparable to Ibrahim et al. (2026) ($FNR/FPR < 10\%$, $CCR > 90\%$). Success would demonstrate the feasibility of autonomous fault management for deep-space habitats operating under communication constraints.

2. Dataset Discussion

A major challenge in developing machine learning models for spacecraft health monitoring is the scarcity of real operational data, especially for safety-critical subsystems such as the Environmental Control and Life Support System (ECLSS). Real ECLSS fault data from NASA testbeds or ISS operations is rarely released publicly, both for export-control reasons and because genuine failures in life-support hardware are intentionally rare. This creates a fundamental limitation: supervised machine learning models require representative examples of nominal and faulty behavior, yet those examples are extremely difficult to obtain in practice. Given these constraints, the present project uses synthetically generated ECLSS sensor data designed to mimic the physical behavior of a CO₂ removal subsystem. Synthetic data is widely accepted in aerospace ML research when real data is inaccessible or insufficient, and the approach aligns directly with the structure described in Ibrahim et al. (2026), where anomaly detection was performed on cycle-level sensor profiles. Importantly, synthetic data allows full control over fault characteristics, sensor noise, and cycle variability, conditions that are crucial for reproducible experimentation in a course-level project. Each dataset sample represents one complete adsorption–desorption cycle, the natural operating pattern of a CO₂ scrubber.

Three sensor streams are simulated:

1. O₂ concentration (%),
2. CO₂ concentration (%), and
3. Cabin pressure (psi).

Nominal cycles are generated using smooth periodic patterns, consistent with cyclical gas-exchange processes, combined with Gaussian sensor noise to reflect real measurement variability. Fault conditions are introduced by applying structured physical perturbations to the baseline signal: 1. CO₂ Leak: CO₂ levels are gradually elevated after mid-cycle, 2. Valve Stiction: Cabin pressure recovers more slowly, mimicking restricted airflow, and 3. Vacuum Anomaly: A sharp, localized pressure drop is imposed in the middle of the cycle.

These manipulations produce distinct, interpretable fault signatures that resemble real ECLSS anomalies without requiring proprietary NASA data. To reflect realistic operational diversity, multiple cycles per condition are created by varying noise realizations and minor dynamic fluctuations. This produces a compact but representative dataset well-suited for training a Variational Autoencoder on nominal cycles and evaluating fault classification using an SVM.

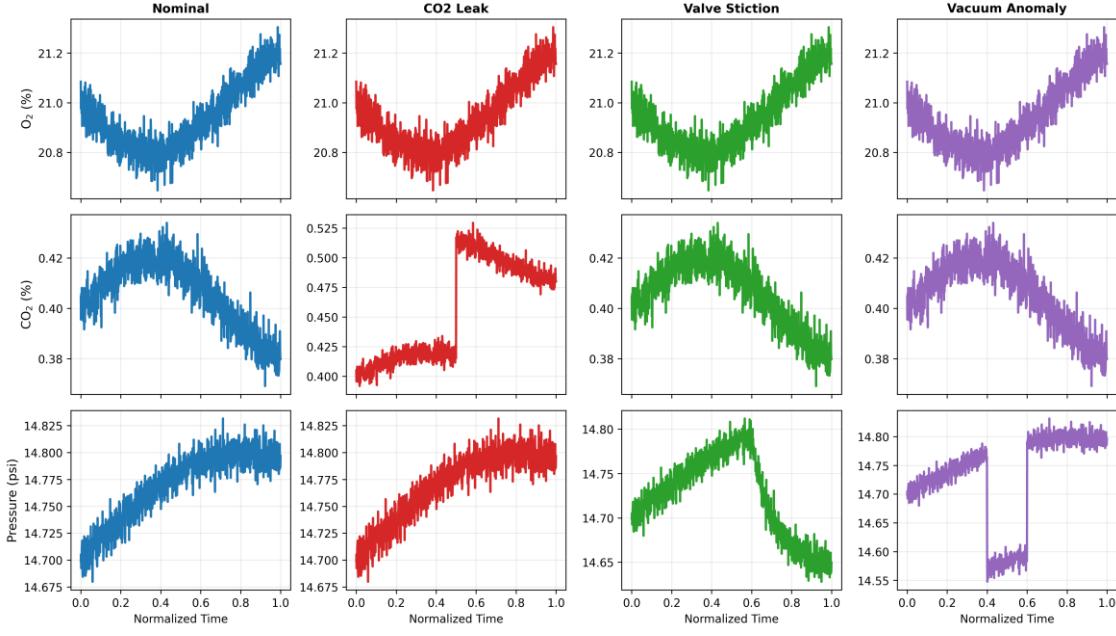


Figure 1. Simulated ECLSS sensor profiles across nominal and fault conditions for 1 cycle.

Figure 1 displays one representative cycle from each operating condition to illustrate the characteristic fault signatures. The complete dataset comprises 40 cycles total: 10 replicate cycles per operating condition, each containing 1000 timesteps and 3 sensor channels. Each cycle contains 1000 timesteps across three sensor channels, yielding a dataset of dimensions 40×3000 when flattened for model input.

3. Procedures

The system begins with synthetic cycle simulation, followed by data cleaning and cycle structuring. A VAE learns nominal behavior, producing both reconstruction-error anomaly scores and latent-space representations. An SVM classifier predicts fault labels while anomaly thresholds provide independent detection. Final evaluation metrics reflect system performance and mission-relevance.

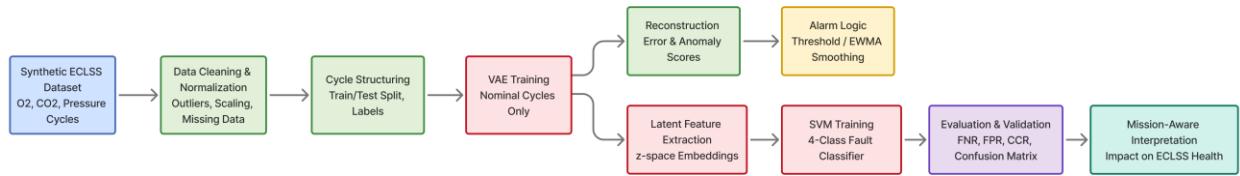


Figure 1. End-to-end pipeline for ECLSS anomaly detection and fault classification.

Figure 2 illustrates that the overall workflow begins with a synthetic ECLSS dataset consisting of multivariate cycles of O₂, CO₂, and cabin pressure. The dataset split follows the unsupervised anomaly detection paradigm: the VAE is

trained exclusively on 10 nominal baseline cycles to learn healthy system behavior. For fault classification, the SVM utilizes 32 labeled cycles for training (8 per condition) and 8 cycles for testing (2 per condition), ensuring balanced representation across all operating states. These signals are first cleaned and normalized to remove obvious outliers, handle missing values, and place all variables on a comparable scale. The cleaned data are then structured into cycles and split into training and testing sets, with only nominal cycles allocated for representation learning. A Variational Autoencoder (VAE) is trained on these nominal cycles to learn a compact latent representation of healthy ECLSS behavior. During inference, the VAE produces both reconstruction errors and latent-space embeddings for each cycle. Reconstruction error is converted into anomaly scores and passed through an alarm logic layer (e.g., fixed threshold or EWMA smoothing) to decide whether a cycle is flagged as off-nominal. In parallel, latent features are used to train a Support Vector Machine (SVM) to classify cycles into four operational classes: nominal, CO₂ leak, valve stiction, and vacuum anomaly. Finally, detection and classification performance are evaluated using FNR, FPR, and CCR, along with confusion matrices and plots. The framework aims to achieve (1) anomaly detection with FNR and FPR below 10%, (2) fault classification with CCR exceeding 90%, and (3) clear separation of operating conditions in VAE latent space, demonstrating autonomous ECLSS health monitoring capability.

4. Validation Process

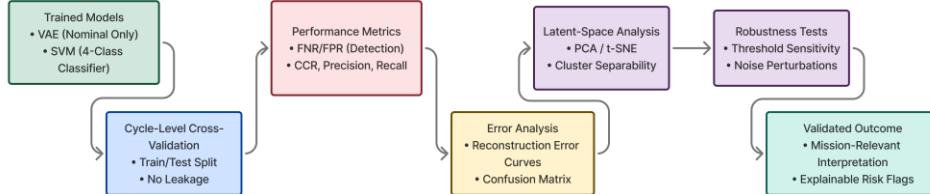


Figure 2. Validation process for the ECLSS anomaly detection and fault classification model.

The trained VAE and SVM models undergo cycle-level cross-validation to prevent data leakage. Detection performance is evaluated using reconstruction-error metrics (FNR/FPR), while classification performance is assessed using CCR, precision, recall, and confusion matrices. Latent-space visualizations (PCA/t-SNE) confirm cluster separability across nominal and fault conditions. Robustness is further tested through threshold-sensitivity and noise-perturbation analysis. Together, these steps produce a validated, mission-relevant model capable of generating interpretable and transferable risk indicators for deep-space ECLSS operations.

5. References:

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