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Anomaly Detection and Fault Prediction in Spacecraft Sensors

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Abstract
This paper presents a hybrid machine learning and deep learning framework for spacecraft sensor anomaly detection and fault prediction using NASA SMAP and MSL telemetry datasets. The framework combines Random Forest, Support Vector Machine (SVM), and LSTM Autoencoder models to improve anomaly detection accuracy and predictive maintenance capabilities. Experimental evaluation demonstrates strong classification performance, high ROCAUC values, and effective real-time monitoring through a dashboard-driven architecture.
Keywords: *Spacecraft telemetry, anomaly detection, fault prediction, predictive maintenance, Random Forest, SVM, LSTM Autoencoder, NASA SMAP, MSL.*

1. Introduction
Modern spacecraft rely on numerous subsystems such as power management, thermal control, propulsion, communication, and attitude-control systems. These subsystems continuously generate telemetry data describing the operational state of the spacecraft. Monitoring these telemetry streams is essential for ensuring mission success and preventing catastrophic failures. Traditional spacecraft monitoring systems employ threshold based fault detection techniques in which predefined limits are assigned to telemetry parameters. Although such approaches are computationally efficient, they often fail to identify hidden fault patterns, nonlinear dependencies, and previously unseen anomalies. Furthermore, increasing mission complexity and telemetry volume make manual monitoring impractical. Recent advances in Machine Learning and Deep Learning have enabled intelligent health-monitoring systems capable of learning operational patterns directly from telemetry data. Machine learning algorithms such as Random Forest and Support Vector Machine have demonstrated excellent performance in classification tasks, while deep learning models such as Long Short-Term Memory networks effectively capture temporal dependencies present in sequential telemetry data. This research proposes a hybrid framework that combines supervised and unsupervised learning techniques for spacecraft anomaly detection and fault prediction. The framework utilizes Random Forest and SVM models to predict fault conditions and employs an LSTM Autoencoder to identify anomalous behavior. Experimental results demonstrate the effectiveness of the proposed system in improving spacecraft health monitoring and predictive maintenance [1-5].

2. Related Work
Early research in spacecraft fault diagnosis focused on probabilistic and statistical learning techniques. In 2015, Dynamic Bayesian Networks (DBN) were introduced for fault detection, identification, and recovery in autonomous spacecraft, enabling uncertainty handling and improving onboard decision-making, although the approach required expert-driven model construction and high computational resources. In 2017, anomaly detection methods evolved through Principal Component Analysis (PCA), which used T^2 and SPE statistics to identify abnormal telemetry behaviour in spacecraft attitude control systems. During the same period, Deep Neural Networks (DNN) combined with Denoising Autoencoders were proposed for spacecraft power system diagnosis, improving feature extraction and classification accuracy but

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increasing dependency on large training datasets. Research during 2020 shifted toward machine learning–based prediction and diagnosis approaches. Support Vector Machine (SVM) methods were introduced for in-orbit satellite sensor fault prediction and showed strong performance with limited training samples. Improved Decision Tree models combined with telemetry data compression reduced communication overhead while maintaining diagnosis accuracy. Additionally, machine learning approaches integrating Random Forest, Artificial Neural Networks, and SVM demonstrated improved health monitoring and fault identification for satellite avionics systems, although most approaches relied heavily on labelled datasets and parameter tuning. The year 2021 emphasized predictive maintenance and sequence-based learning methods. Growing Recurrent Neural Networks (RNN) integrated with Long Short-Term Memory (LSTM) models enabled fault prognosis and Remaining Useful Life estimation for aerospace systems. Lightweight machine learning approaches combining PCA, KNN, and Bayesian classifiers improved onboard deployment efficiency for high-dimensional spacecraft telemetry. Another study proposed a data-driven aero-engine degradation prognostic framework integrating Fuzzy C-Means clustering, Deep Forest Classifier, and LSTM to estimate degradation behaviour and predict system lifespan with improved accuracy. Research in 2022 focused on handling complex telemetry dependencies and missing data conditions. Graph Convolutional Recurrent Autoencoders combined with adversarial learning were introduced for spacecraft anomaly detection and effectively captured temporal and spatial telemetry relationships under incomplete data conditions. Another study proposed multivariate anomaly detection using sparse decomposition techniques that preserved correlations among mixed telemetry variables while separating anomalies from normal operational patterns, improving detection robustness but increasing computational cost. In 2023, deep learning and hybrid anomaly detection approaches became dominant. Multiple studies combined LSTM Autoencoders, Isolation Forest, PCA, Random Forest, and Reinforcement Learning for satellite power system anomaly detection and diagnosis. A Bayesian-based anomaly detection framework with adaptive feature weighting was introduced to process mixed telemetry variables under multiple operating conditions and support incremental learning. Another work presented an unsupervised LSTM-based anomaly detection framework with dynamic thresholding for spacecraft telemetry, improving long-range dependency learning and reducing false alarms. Additionally, lightweight machine learning models for onboard deployment were reviewed to support real-time satellite monitoring. Research in 2024 emphasized intelligent information fusion and practical telemetry anomaly detection. CNN–RNN architectures with attention mechanisms were proposed for multisource aerospace fault diagnosis, improving decision-making across air-ground-space systems. Similarity-based anomaly detection methods integrated Euclidean, Cosine, Pearson, and Dynamic Time Warping (DTW) metrics with Isolation Forest to automatically identify abnormal spacecraft telemetry behaviour. These approaches improved anomaly recognition capability but remained sensitive to seasonal telemetry variations. Recent work in 2025 introduced advanced deep learning frameworks for robust spacecraft anomaly detection. Bidirectional Long Short-Term Memory (BiLSTM) combined with dynamic thresholding enabled anomaly detection by leveraging both historical and future telemetry information, improving identification of continuous anomaly segments. Another study proposed an unsupervised anomaly detection framework integrating Rolling Mean statistical analysis and Autoencoder-based reconstruction for spacecraft telemetry monitoring. The approach achieved superior precision, recall, and F1-score while reducing training complexity. Furthermore, lightweight machine learning techniques for real-time onboard monitoring were highlighted as practical solutions for future satellite missions [6-10].

3. Problem Statement

Spacecraft telemetry datasets present a number of significant analytical challenges. The sensor measurements collected are high-dimensional, often involve complex temporal dependencies between different telemetry parameters, and frequently contain noisy or missing values. Compounding these issues is the severe class imbalance between normal operational data and anomalous events, since anomalies are by nature rare compared to routine telemetry. Furthermore, spacecraft continuously generate large-scale telemetry streams, requiring systems that can process substantial volumes of data efficiently and in a timely manner. Traditional monitoring systems, which rely heavily on manually defined thresholds and expert knowledge, struggle to keep pace with these complexities. Such systems are often unable to detect subtle anomalies before they escalate into failures, and they tend to generate excessive false alarms, reducing operator trust and increasing the burden of manual review. Given these limitations, there is a clear need for an intelligent framework capable of detecting anomalous spacecraft behaviour in real time, predicting faults before system failure occurs, and processing large-scale telemetry datasets efficiently. Such a framework should also aim to reduce false alarms while maintaining high detection rates, ultimately supporting predictive maintenance and informed mission decision-making [11-15].

4. Proposed Methodology

The proposed framework consists of six major stages that work together to enable intelligent spacecraft anomaly detection and fault prediction. The first stage, data acquisition, makes use of the NASA SMAP (Soil Moisture Active Passive) and MSL (Mars Science Laboratory) telemetry datasets for model development and evaluation, as these datasets contain multivariate telemetry measurements collected from various spacecraft subsystems. The second stage, data preprocessing, prepares the raw telemetry for analysis through a combination of missing value handling, data normalization, noise reduction, sliding window generation, and feature extraction. Together, these operations improve data quality and enhance overall model performance. The third stage employs a Random Forest algorithm for fault prediction. As an ensemble learning method consisting of multiple decision trees, Random Forest allows each tree to independently predict the spacecraft state, with the final prediction determined through majority voting. This approach offers several advantages, including high classification accuracy, resistance to overfitting, and the ability to handle nonlinear data effectively. The fourth stage uses a Support Vector Machine (SVM) for fault prediction. SVM constructs an optimal decision boundary that maximizes separation between classes, and an RBF kernel is used to model the nonlinear relationships present in telemetry data. The advantages of this method include strong generalization, effective classification in high dimensional spaces, and robust performance even on limited datasets Shown in Figure 1.

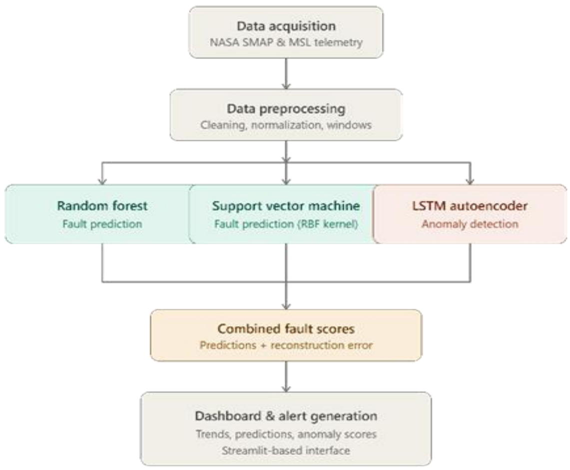

Figure 1 **System Architecture**

The fifth stage introduces an LSTM Autoencoder for anomaly detection. This model is trained exclusively on normal telemetry sequences, with the encoder compressing the telemetry data into a latent representation and the decoder reconstructing the original sequence from it. The final stage involves dashboard and alert generation. A Streamlit-based dashboard visualizes telemetry trends, fault predictions, anomaly scores, and alert notifications, thereby improving operational awareness and supporting real-time decision-making [16-20].

5. Results and Discussion

The pre-trained models in this project were trained on telemetry channel P-1 (a 25-sensor channel from the SMAP spacecraft). The performance metrics below are calculated for the three models: Random Forest (supervised classifier) SVM (supervised classifier with RBF kernel) LSTM Autoencoder (unsupervised anomaly detector, where a fault/anomaly is predicted if the reconstruction error exceeds the threshold of ‘1.001987’) Shown in Table 1 and 2.

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- **Holdout Test Partition (20% holdout split):** These metrics are computed on the unseen 20% holdout split of sliding windows from the `P-1` test set:
- **Full Test Set (100% of Channel P-1 Test Sequence):** These metrics represent the performance across the entire test sequence of `P-1`:

Table 1 **Evaluation Metrics of Testing Dataset**

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	99.47%	98.61%	95.30%	96.93%	0.9996
SVM (RBF)	99.70%	98.00%	98.66%	98.33%	0.9988
LSTM Autoencoder	35.42%	12.01%	100.00%	21.44%	0.9958

Table 2 **Evaluation Metrics of Complete Dataset**

Model	Accuracy	Precision	Recall	F1	ROC-AUC
Random Forest	99.83%	99.60%	98.54%	99.06%	0.9996
SVM	99.87%	98.94%	99.60%	99.27%	0.9988
LSTM Autoencoder	35.71%	12.13%	99.87%	21.63%	0.9949

Conclusion

This paper presented a hybrid machine learning and deep learning framework for spacecraft anomaly detection and fault prediction. The proposed system successfully analysed NASA telemetry datasets, predicted spacecraft faults, detected anomalies, and generated actionable alerts. Experimental results demonstrated high classification performance, with Random Forest and SVM achieving accuracy greater than 99% and the LSTM Autoencoder achieving a ROC-AUC score above 0.99.

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