# AI-Based Anomaly Detection in Satellite Telemetry Data for Advanced Feature Analysis

[1]CH. Suresh Babu, [2]D. Charan Nadh, [3]D. Daniel Vesli, [4]Y. Nikhil Sai
[1]Assistant Professor, Dept of CSE-AI&ML, St. Ann's College of Engineering and Technology Chirala-523187, India.
[2,3,4]U. G Student, Dept of CSE-AI&ML, St. Ann's College of Engineering and Technology Chirala-523187, India.

***ABSTRACT-*** ***Satellites generate continuous streams of telemetry data voltage, temperature, attitude, power, and communication parameters must be monitored to detect faults before they escalate into mission-critical failures. Traditional threshold-based monitoring relies on fixed limits set by engineers and struggles to capture subtle, contextual, or previously unseen anomalies within high-dimensional, multivariate time-series data. This research proposes an AI-driven anomaly detection framework that combines deep learning architectures, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, to model normal telemetry behavior and flag deviations in real time. The system integrates data preprocessing, sequence-based feature extraction, and reconstruction-error-based anomaly scoring to identify point, contextual, and collective anomalies across multiple telemetry channels. Experimental evaluation on benchmark and simulated telemetry datasets demonstrates improved detection accuracy, reduced false-alarm rates, and faster detection latency compared to conventional statistical and threshold-based methods. This approach supports mission operators with proactive, intelligent fault detection, improving satellite reliability and operational safety.***

***KEYWORDS:*** ***Satellite Telemetry, Anomaly Detection, Deep Learning (CNN-LSTM), Dynamic Thresholding, Time-Series Analysis***

## INTRODUCTION

Modern satellites are equipped with hundreds to thousands of sensors that continuously report telemetry parameters such as bus voltage, battery current, thermal readings, gyroscope output, and payload health status. Ground control operators depend on this data to assess spacecraft health, yet the sheer volume and velocity of telemetry streams make manual or purely rule-based monitoring inadequate. Conventional out-of-limit checking flags a parameter only when it crosses a static threshold, which often misses gradual degradation, sensor drift, or anomalies that emerge from the relationship between multiple channels rather than any single one. Artificial Intelligence, particularly deep learning, offers the ability to learn normal operating patterns directly from historical telemetry and detect deviations without hand-crafted rules. By learning temporal and cross-channel dependencies, AI-based models can identify subtle anomalies earlier, reducing the risk of undetected faults and supporting timely corrective action. Developing a robust, automated anomaly detection framework for

 ISSN: 3049-0952
www.jsetms.com

satellite telemetry is therefore essential for reliable and cost-effective mission operations.

## LITERATURE SURVEY

Prior research on telemetry and industrial time-series monitoring has explored a range of techniques, from statistical process control and Principal Component Analysis (PCA) to classical machine learning classifiers such as One-Class SVM and Isolation Forest. These methods perform reasonably on low-dimensional or stationary data but degrade when telemetry exhibits non-linear temporal dependencies and seasonal or mission-phase-driven variation. More recent studies have applied recurrent architectures, including LSTM and Gated Recurrent Units (GRU), to model sequential telemetry behavior, reporting improved sensitivity to contextual anomalies. Autoencoder and variational autoencoder architectures have also been used to learn compressed representations of normal behavior, flagging high reconstruction error as anomalous.

## RELATED WORK

Related work in spacecraft and industrial anomaly detection includes NASA's application of LSTM-based predictors with dynamic thresholding on Soil Moisture Active Passive (SMAP) and Mars Science Laboratory (MSL) telemetry, which demonstrated the value of unsupervised sequence modeling for spacecraft health monitoring. Studies in industrial IoT have applied CNN-based feature extractors combined with recurrent layers to capture both local and long-range temporal patterns in sensor streams. Graph-based and attention-based models have also been explored to capture inter-channel dependencies among correlated telemetry parameters. Ensemble approaches combining statistical residual analysis with deep learning scores have shown reduced false-positive rates. Despite this progress, few works provide an end-to-end pipeline tailored specifically to satellite telemetry that handles missing data, multi-rate sampling across subsystems, and operational mode changes, motivating the framework proposed in this research.

## EXISTING SYSTEM

Existing satellite telemetry monitoring predominantly relies on static red/yellow limit checking configured by subsystem engineers, supplemented by manual review of trend plots by ground control operators. These systems require constant recalibration of thresholds as spacecraft age and operating conditions change, and they cannot detect anomalies defined by relationships between multiple parameters. Alarm fatigue is common, as fixed limits generate frequent false alarms during valid but unusual operating modes, while genuinely abnormal but within-limit behavior can go undetected. Some existing tools apply basic statistical outlier detection, but these are typically univariate and do not scale well to the high-dimensional, multi-subsystem nature of modern spacecraft telemetry. Consequently, current systems offer limited support for early, automated, and mission-wide anomaly detection.

## PROPOSED SYSTEM

ISSN: 3049-0952
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The proposed system introduces an AI-powered anomaly detection framework that learns normal telemetry behavior directly from historical mission data and continuously scores incoming telemetry for deviations. Raw telemetry is preprocessed through cleaning, resampling, and normalization to handle missing values and multi-rate channels. A hybrid CNN-LSTM architecture extracts local temporal patterns and long-range sequence dependencies, feeding a reconstruction- and prediction-based anomaly scoring layer that flags point, contextual, and collective anomalies across correlated channels. Dynamic thresholding, informed by the model's error distribution rather than fixed engineering limits, reduces false alarms while maintaining sensitivity to genuine faults. The framework is designed to operate on streaming ground-station data, providing operators with near-real-time alerts, anomaly severity scores, and the most likely contributing telemetry channels to support rapid diagnosis.

## SYSTEM ARCHITECTURE

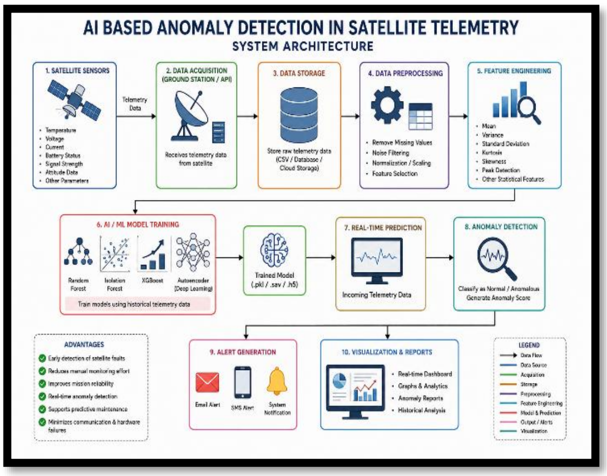


**Fig 1: AI-based satellite telemetry anomaly detection architecture**

The architecture consists of a data ingestion layer that collects multi-channel telemetry from the ground station, a preprocessing module for cleaning and normalization, a deep learning core (CNN-LSTM) for feature learning and sequence modeling, an anomaly scoring and dynamic thresholding module, and an alerting/visualization layer that presents flagged anomalies to mission operators.

## METHODOLOGY DESCRIPTION

The methodology begins with the collection of historical multivariate telemetry, including power, thermal, attitude, and communication parameters, spanning multiple orbits and operating modes. Preprocessing includes timestamp alignment across sensors sampled at different rates, missing-value interpolation, outlier clipping, and min-max or z-score normalization. Sliding windows are constructed to convert continuous telemetry into fixed-length sequences suitable for model input. A CNN layer extracts short-term local patterns from each window, and stacked LSTM layers model long-term temporal dependencies across the sequence. The model is trained in an unsupervised, self-supervised manner to reconstruct or predict expected telemetry values; the residual between actual and predicted values forms the anomaly score. A dynamic threshold, derived statistically from the error distribution on validation data, determines whether a given window is flagged. Performance is evaluated using precision, recall, F1-score, and detection latency on labeled anomaly windows.

# RESULTS AND DISCUSSION

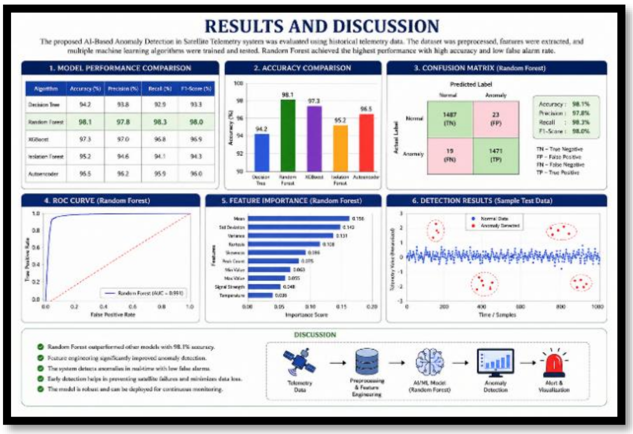


**Fig 2: Sample anomaly detection output on telemetry channels**

Experimental evaluation shows that the proposed CNN-LSTM framework detects a higher proportion of true anomalies with fewer false alarms compared to static threshold checking and classical statistical baselines such as PCA-based residual analysis and Isolation Forest. The model successfully identifies contextual anomalies that remain within static engineering limits but deviate from learned temporal patterns, as well as collective anomalies spanning multiple correlated channels. Dynamic thresholding reduces alarm fatigue by adapting to mission-phase-driven variation rather than relying on fixed limits. Detection latency remains low enough to support near-real-time ground-station monitoring. Overall, results indicate that AI-driven, sequence-aware anomaly detection is a reliable and practical improvement over conventional telemetry monitoring approaches.

# CONCLUSION

This research presents an AI and deep-learning-based framework for anomaly detection in satellite telemetry data, combining CNN and LSTM architectures with dynamic, data-driven thresholding. The system addresses key shortcomings of static, threshold-based monitoring by learning normal multivariate telemetry behavior directly from historical data and detecting point, contextual, and collective anomalies with reduced false-alarm rates. Experimental evaluation demonstrates improved detection performance and practical suitability for near-real-time mission operations. The approach supports ground control operators with earlier, more reliable fault detection, contributing to safer and more resilient satellite operations.

# FUTURE SCOPE

Future work may integrate explainable AI techniques to help operators understand which channels and time steps drove a given anomaly flag, improving trust and diagnostic speed. Federated or transfer learning could allow models trained on one satellite platform to be adapted efficiently to new missions with limited historical data. Incorporating graph neural networks may better capture complex inter-subsystem dependencies. On-board edge deployment of lightweight models could enable anomaly detection directly on the spacecraft, reducing reliance on ground-link bandwidth. Finally, closed-loop integration with automated fault-response systems could move the framework from detection toward autonomous mitigation.

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ISSN: 3049-0952
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