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AI-Based Spacecraft Health Monitoring System: A Machine Learning Approach for Telemetry-Based Health Classification

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Abstract: Spacecraft continuously generate telemetry data from onboard sensors and subsystems to support monitoring of health, performance, and operational status. Manual observation of large volumes of telemetry can be difficult and may delay recognition of abnormal conditions. This paper presents an AI-Based Spacecraft Health Monitoring System developed during a research internship at Acceleron Aerospace. The proposed prototype combines ESP8266-based sensor acquisition, synthetic telemetry generation, Python-based data processing, a Random Forest machine learning classifier, and an interactive Streamlit dashboard. The dataset contains temperature, humidity, light, three-axis acceleration, and three-axis gyroscope measurements, with spacecraft health classified into HEALTHY, WARNING, and CRITICAL states. A balanced synthetic dataset of 3,000 samples was generated and divided into training and testing subsets. The trained model was integrated into the monitoring application to provide rapid health classification and graphical telemetry visualization. The work demonstrates a modular foundation for AI-assisted spacecraft monitoring and can be extended toward real telemetry, anomaly detection, fault diagnosis, predictive maintenance, and intelligent alerting.

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1. Introduction

Modern spacecraft are complex engineering systems containing interconnected power, thermal, communication, propulsion, navigation, sensing, and onboard-computing subsystems. These subsystems continuously produce telemetry that describes the operating condition of the vehicle. Telemetry may include environmental measurements, motion parameters, electrical quantities, processor status, communication quality, and other engineering values. Continuous analysis of these measurements is important for mission safety, operational awareness, and early recognition of abnormal behavior.

Traditional health monitoring relies heavily on mission-control engineers who observe telemetry and respond when values cross expected limits or when unusual patterns become visible. As the number of monitored parameters increases, purely manual observation becomes time-consuming and can make early detection more difficult. Artificial Intelligence and Machine Learning provide a data-driven alternative by learning relationships among multiple telemetry parameters and producing automated health assessments.

Public academic research also faces a practical limitation: real spacecraft telemetry is often unavailable because of mission confidentiality, security, or proprietary restrictions. Therefore, this work adopts a simulation and prototype-based approach. A synthetic telemetry dataset is used for model development, while an ESP8266-based prototype demonstrates sensor acquisition and transmission. The resulting system combines data generation, preprocessing, machine learning, and visualization into a single modular monitoring framework.

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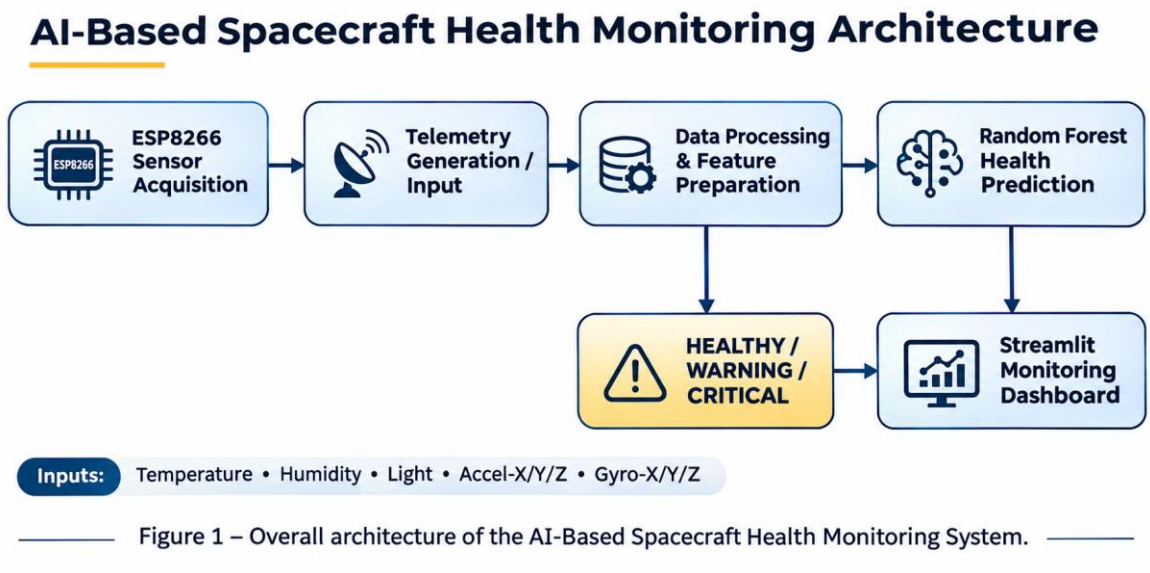


Figure 1 – Overall architecture of the AI-Based Spacecraft Health Monitoring System.

2. Objectives

- To generate a structured synthetic spacecraft telemetry dataset using Python.
- To preprocess telemetry parameters for Machine Learning.
- To develop a Random Forest classification model for spacecraft health assessment.
- To classify spacecraft conditions into HEALTHY, WARNING, and CRITICAL states.
- To demonstrate telemetry acquisition using an ESP8266-based hardware prototype.
- To develop an interactive Streamlit dashboard for telemetry visualization and health prediction.
- To provide a scalable software foundation that can later accept real spacecraft telemetry.

3. Research Methodology

The methodology follows a prototype-oriented systems integration approach. The first stage is telemetry generation or acquisition, followed by data organization and feature preparation. The prepared dataset is then used to train and test a supervised Machine Learning classifier. The trained model is saved and loaded by the monitoring application, where incoming telemetry is converted into a health prediction. Finally, the prediction and telemetry trends are presented through an interactive dashboard.

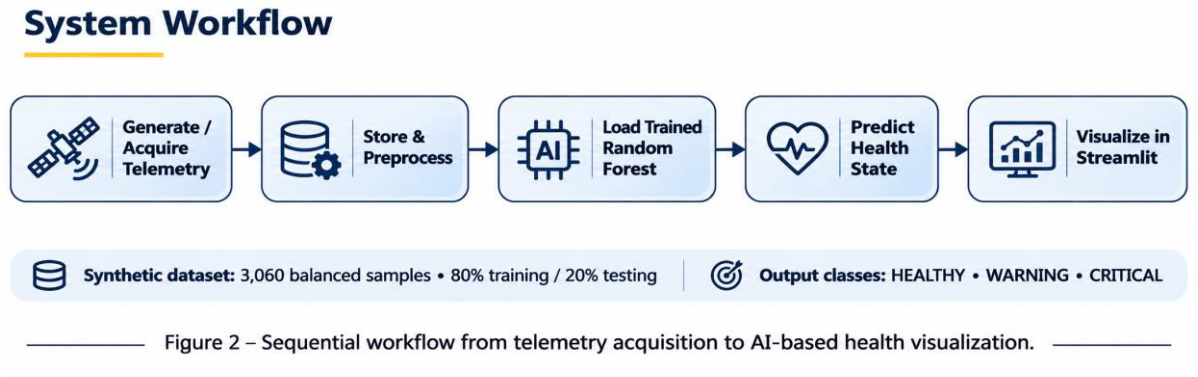


Figure 2 – Sequential workflow from telemetry acquisition to AI-based health visualization.

3.1 Telemetry Acquisition and Dataset Generation

The project uses two complementary telemetry sources. Synthetic telemetry is generated in Python for repeatable Machine Learning development, while the ESP8266 prototype demonstrates live sensor-based acquisition. The prototype uses a DHT11 sensor for temperature and humidity, an HW-072 light sensor module, and an MPU-6500 module for three-axis acceleration and gyroscope measurements. Acquired measurements can be transmitted to a computer through serial communication and recorded for analysis.

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Because real spacecraft telemetry is not readily available for academic development, a balanced synthetic dataset containing 3,000 samples was created. The dataset contains 1,000 samples for each of the three health classes. The input parameters are Temperature, Humidity, Light, Accel-X, Accel-Y, Accel-Z, Gyro-X, Gyro-Y, and Gyro-Z, while Health is the target classification label.

Parameter	Role	Type
Temperature	Spacecraft/environmental thermal condition	Input
Humidity	Environmental condition	Input
Light	Light detection status	Input
Accel-X/Y/Z	Three-axis motion/acceleration	Input
Gyro-X/Y/Z	Three-axis angular motion	Input
Health	HEALTHY / WARNING / CRITICAL	Target

3.2 Machine Learning Methodology

The Machine Learning component uses a Random Forest classifier implemented with Scikit-learn. Random Forest is an ensemble method that combines multiple decision trees to obtain a classification decision. It was selected because it can handle multiple input parameters, model nonlinear relationships, provide rapid predictions, and offer robust performance for the prototype telemetry classification task.

The generated dataset is divided into 80% training data and 20% testing data. The model learns the relationship between the telemetry features and the three health classes. After training, the model is serialized with Joblib so that the dashboard can load the trained model without repeating the training process.

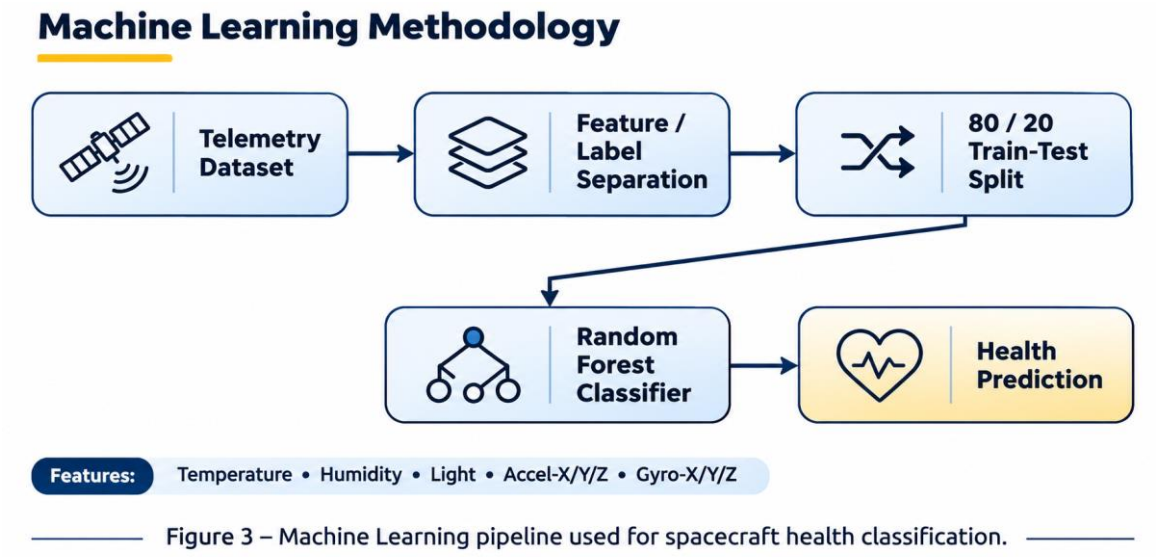


Figure 3 – Machine Learning pipeline used for spacecraft health classification.

4.System Design and Architecture

The system is organized into four principal modules: (1) telemetry generation and acquisition, (2) data processing, (3) Machine Learning health prediction, and (4) interactive dashboard visualization. This modular organization separates data collection from prediction and presentation, making the prototype easier to maintain and extend.

4.1 Telemetry Generator and Acquisition Module

This module creates synthetic telemetry for training and testing and also supports sensor-based acquisition through the ESP8266 prototype. The collected measurements can be transferred to the monitoring computer through serial communication and stored in CSV format.

4.2 Data Processing Module

The processing stage organizes telemetry records and separates input features from the Health target. The feature set consists of temperature, humidity, light, acceleration, and gyroscope measurements. The resulting structured data is passed to the trained classifier.

4.3 Health Prediction Module

The Random Forest model receives the prepared telemetry vector and predicts one of three operational states: HEALTHY, WARNING, or CRITICAL. The trained model is stored using Joblib and loaded by the monitoring application for rapid inference.

4.4 Interactive Dashboard Module

The Streamlit dashboard provides a user-friendly visualization layer. It can display telemetry values, interactive graphs, health predictions, and status information. The dashboard is intended as an operator-oriented prototype showing how AI-assisted spacecraft monitoring can be presented in an accessible form.

5.Results and Discussion

The developed workflow successfully generated synthetic spacecraft telemetry, trained a Random Forest classifier, loaded the trained model, produced health classifications, and presented the results through the Streamlit dashboard. The three-class design provides a simple operational interpretation: HEALTHY represents normal simulated operation, WARNING represents an intermediate abnormal condition, and CRITICAL represents a severe simulated condition.

Representative records demonstrate how combinations of environmental and motion parameters are associated with different health labels. For example, the project report includes sample telemetry records covering normal, warning, and critical operating conditions. The complete prototype therefore demonstrates an end-to-end flow from telemetry generation and acquisition through Machine Learning inference to visual monitoring.

Health State	**Interpretation**	**Dashboard Output**
HEALTHY	Simulated normal operating condition	Normal status
WARNING	Simulated abnormal/intermediate condition	Warning status
CRITICAL	Simulated severe abnormal condition	Critical status

An important result of the project is architectural rather than flight-performance validation: the prototype establishes that embedded telemetry acquisition, synthetic data generation, supervised classification, model persistence, and dashboard visualization can be integrated into a single software framework. Because the training data are synthetic, the results should be interpreted as a proof of concept rather than a flight-qualified health-monitoring performance evaluation.

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6.Software and Hardware Technologies

Technology / Component	Purpose
Python	Core programming and backend implementation
Pandas	Telemetry data handling and preprocessing
NumPy	Numerical operations and synthetic data generation
Scikit-learn	Random Forest Machine Learning model
Joblib	Saving and loading the trained model
Plotly	Interactive telemetry graphs
Streamlit	Monitoring dashboard
ESP8266	Prototype telemetry acquisition
DHT11 / HW-072 / MPU-6500	Temperature, humidity, light, acceleration and gyroscope sensing

7.Limitations

- The dataset is synthetic and may not fully represent real spacecraft mission conditions.
- The current telemetry set is limited compared with the large number of engineering parameters monitored on real spacecraft.
- The HEALTHY, WARNING, and CRITICAL labels are generated from predefined simulated conditions.
- The Random Forest model is static and does not currently perform continuous online learning.
- Full integration with real spacecraft communication and telemetry systems has not been implemented.
- The prototype predicts overall health but does not identify the exact subsystem responsible for a fault or recommend corrective action.

8.Future Scope

- Integration with real spacecraft telemetry and additional engineering sensors.
- Use of LSTM, GRU, or Transformer-based models for time-dependent telemetry.
- Anomaly detection using methods such as Isolation Forest and Autoencoders.
- Continuous telemetry streaming using MQTT, WebSocket, or REST APIs.
- Cloud deployment for remote monitoring and telemetry storage.
- Digital-twin integration for comparison of simulated and real telemetry.
- Intelligent alerting for automatic notification of abnormal conditions.
- Extension toward fault diagnosis and predictive maintenance.

9.Conclusion

This research internship project demonstrates a complete prototype for AI-assisted spacecraft health monitoring using telemetry data, embedded sensing, Machine Learning, and interactive visualization. A synthetic dataset of 3,000 balanced samples was generated, a Random Forest classifier was trained to distinguish HEALTHY, WARNING, and CRITICAL conditions, and the trained model was integrated with a Streamlit dashboard.

The work provides a practical foundation for further aerospace-oriented research. Although it is not a flight-qualified monitoring system and currently relies on synthetic telemetry, its modular architecture can be extended toward real-time telemetry, anomaly detection, fault diagnosis, digital twins, intelligent alerts, and predictive maintenance.

10. Project Repository / Project Demonstration Video

GitHub Repository: https://github.com/D555hruv/Acceleron-Aerospace_Spacecraft-Health-Monitor

The repository includes the following major components:

- app.py – Streamlit-based spacecraft health monitoring dashboard
- generate_dataset.py – Synthetic spacecraft telemetry dataset generation
- train_model.py – Random Forest Machine Learning model training
- training_dataset.csv – Generated telemetry dataset
- health_model.pkl – Saved trained Machine Learning model
- requirements.txt – Required Python libraries
- README.md – Project description, setup instructions, and usage information
- data/ – Dataset-related files
- models/ – Trained Machine Learning model
- reports/ – Project documentation and reports

The repository provides a reproducible reference for understanding the implementation of the proposed spacecraft health-monitoring framework.

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12. Conflict of Interest

The author declares no competing conflict of interest.

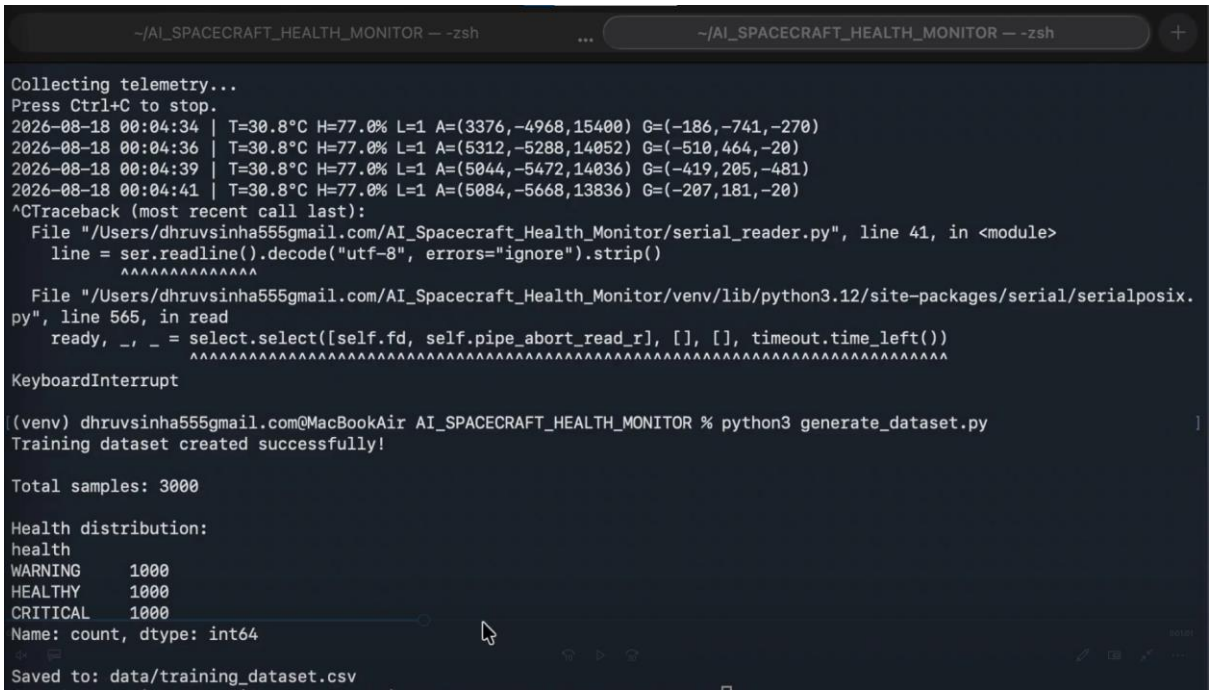
13. Funding

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14. Appendix


~/AI_SPACECRAFT_HEALTH_MONITOR — -zsh
~/AI_SPACECRAFT_HEALTH_MONITOR — -zsh
Collecting telemetry...
Press Ctrl+C to stop.
2026-08-18 00:04:34 | T=30.8°C H=77.0% L=1 A=(3376,-4968,15400) G=(-186,-741,-270)
2026-08-18 00:04:36 | T=30.8°C H=77.0% L=1 A=(5312,-5288,14052) G=(-510,464,-20)
2026-08-18 00:04:39 | T=30.8°C H=77.0% L=1 A=(5044,-5472,14036) G=(-419,205,-481)
2026-08-18 00:04:41 | T=30.8°C H=77.0% L=1 A=(5084,-5668,13836) G=(-207,181,-20)
^CTraceback (most recent call last):
File "/Users/dhruvsinha555gmail.com/AI_Spacecraft_Health_Monitor/serial_reader.py", line 41, in <module>
line = ser.readline().decode("utf-8", errors="ignore").strip()
^^^^^^^^^^^^^^
File "/Users/dhruvsinha555gmail.com/AI_Spacecraft_Health_Monitor/venv/lib/python3.12/site-packages/serial/serialposix.py", line 565, in read
ready, _, _ = select.select([self.fd, self.pipe_abort_read_r], [], [], timeout.time_left())
^^^^^^^^^^^^^^

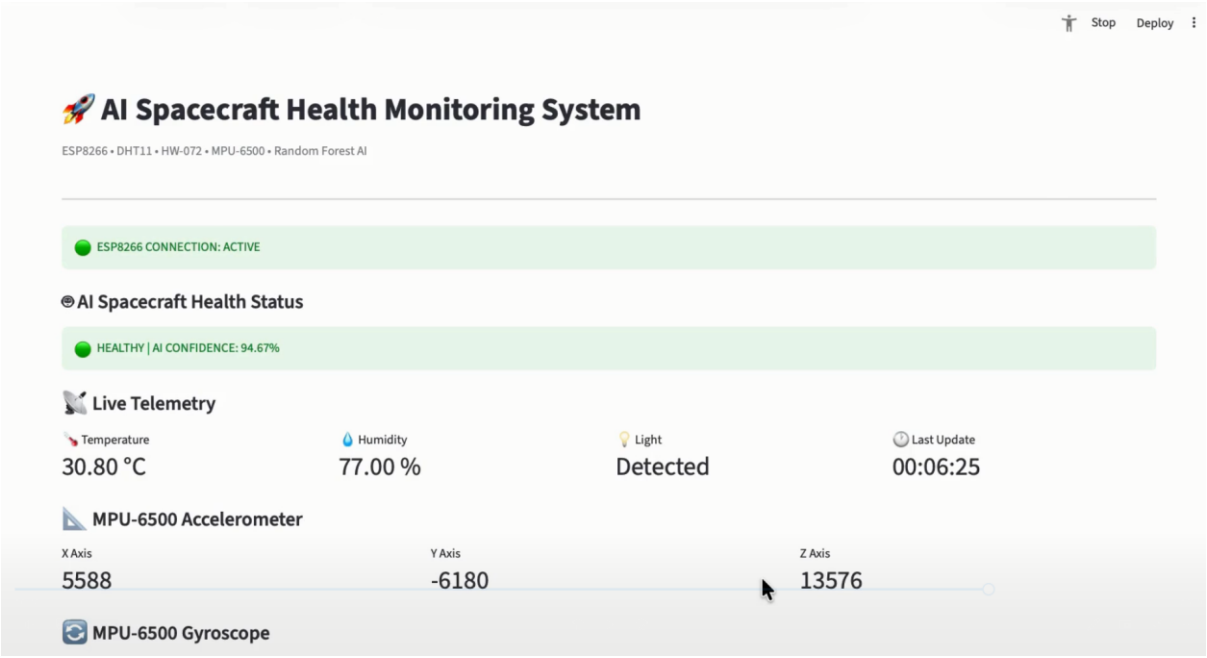


Figure-6: Dashboard to Monitor Spacecraft Health

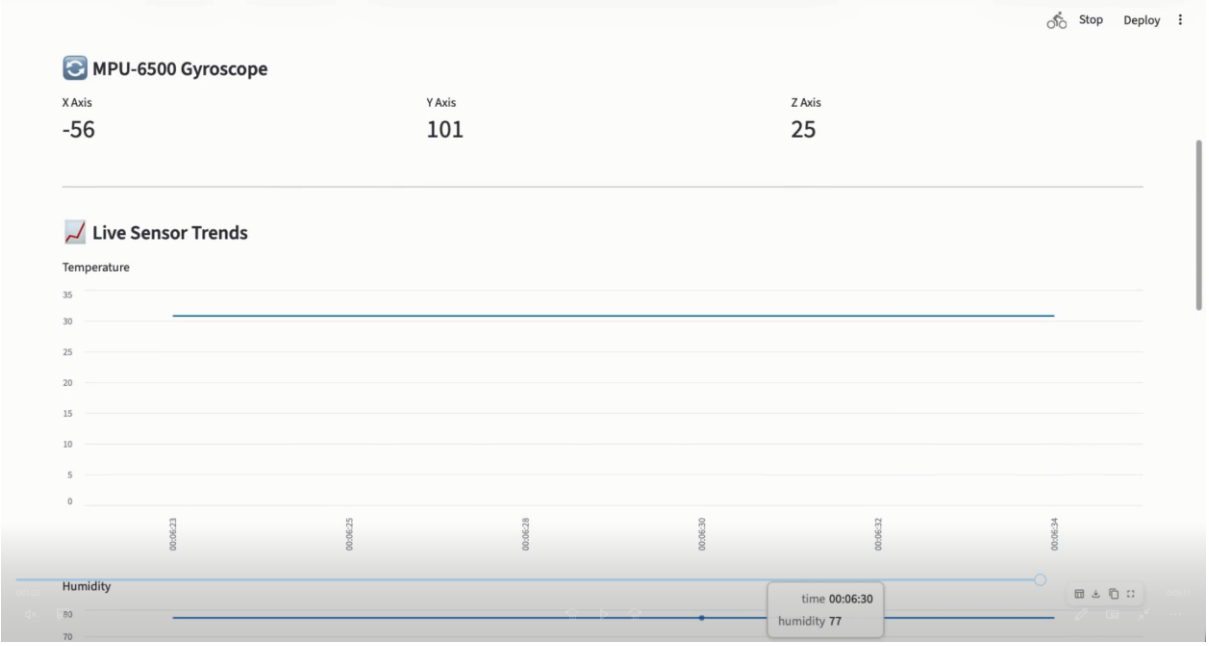


Figure-7: Live Sensor Trends

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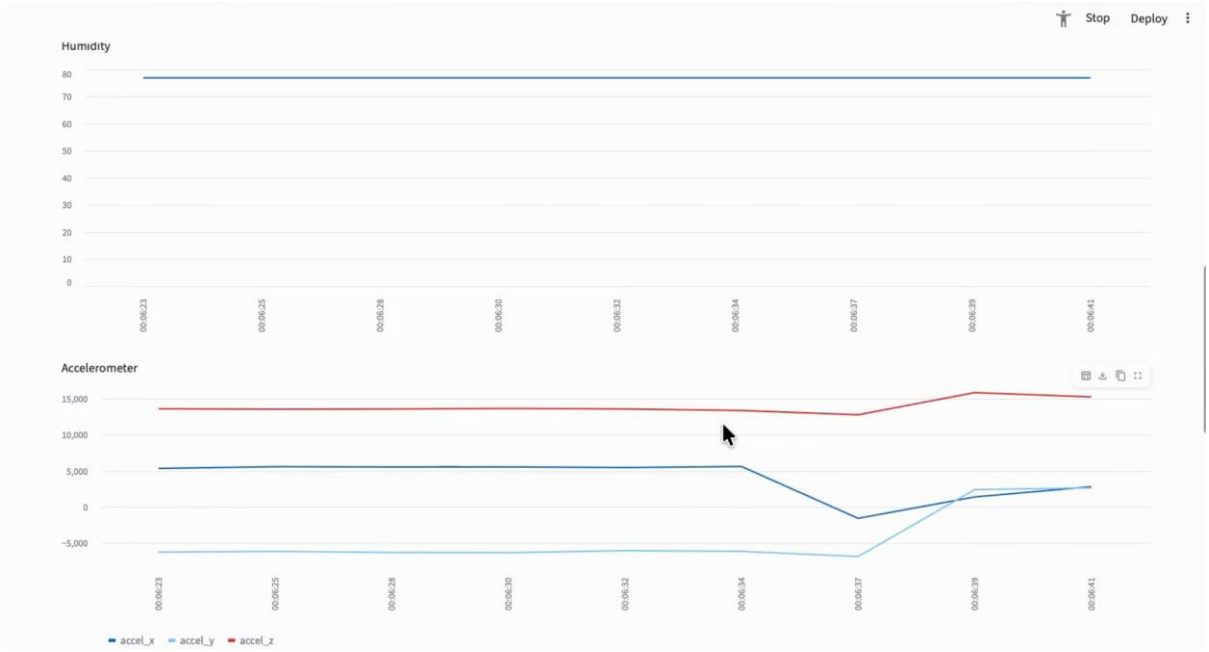
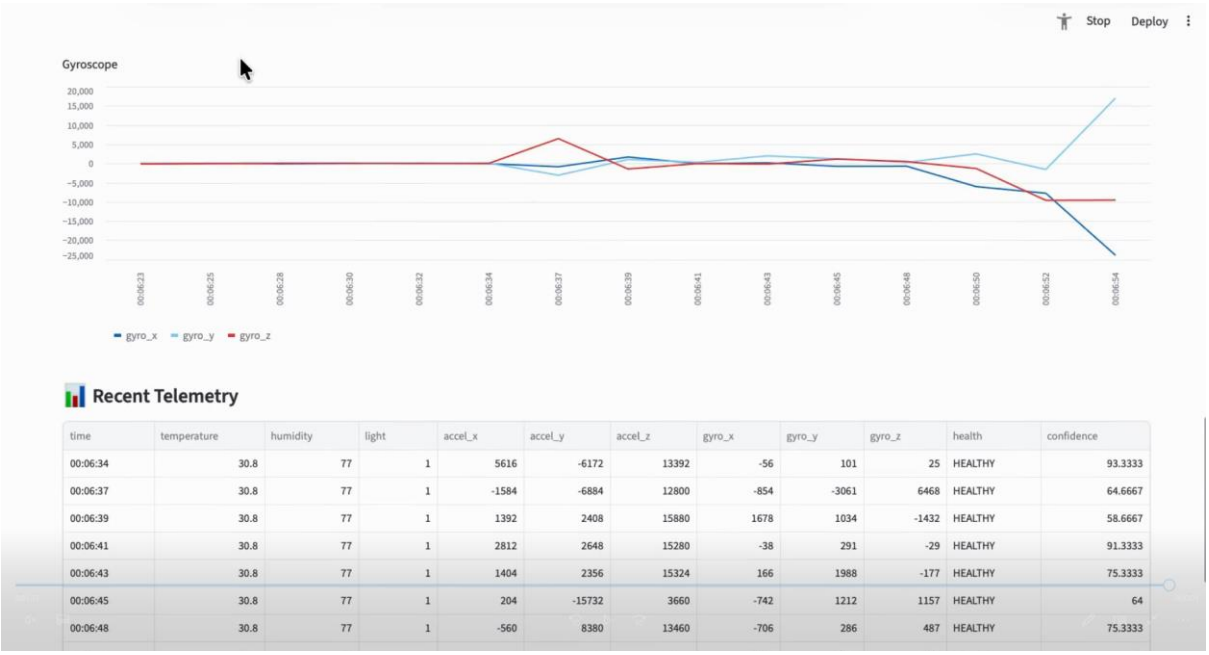


Figure-8: Humidity and Accelerometer Data



time	temperature	humidity	light	accel_x	accel_y	accel_z	gyro_x	gyro_y	gyro_z	health	confidence
00:06:34	30.8	77	1	5616	-6172	13392	-56	101	25	HEALTHY	93.3333
00:06:37	30.8	77	1	-1584	-6884	12800	-854	-3061	6468	HEALTHY	64.6667
00:06:39	30.8	77	1	1392	2408	15880	1678	1034	-1432	HEALTHY	58.6667
00:06:41	30.8	77	1	2812	2648	15280	-38	291	-29	HEALTHY	91.3333
00:06:43	30.8	77	1	1404	2356	15324	166	1988	-177	HEALTHY	75.3333
00:06:45	30.8	77	1	204	-15732	3660	-742	1212	1157	HEALTHY	64
00:06:48	30.8	77	1	-560	8380	13460	-706	286	487	HEALTHY	75.3333

Figure-8: Gyroscope and Telemetry Data

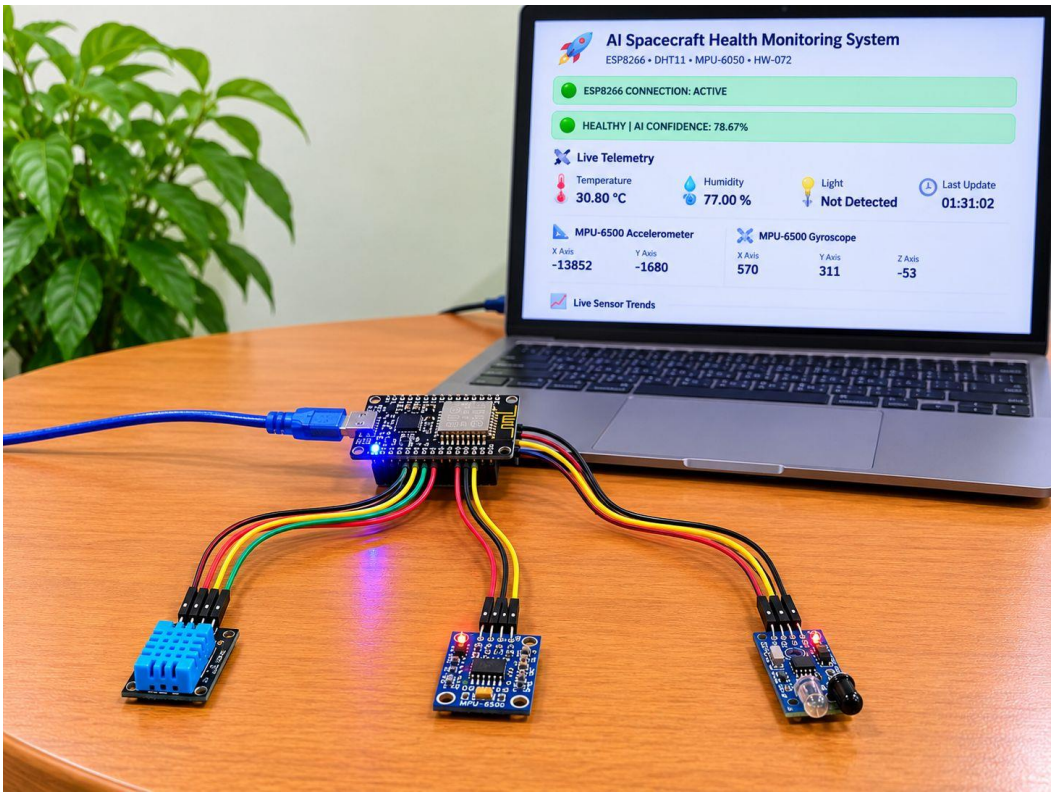


Figure-8: Hardware Setup

15. Author Biography

Dhruv Sinha is an engineering researcher affiliated with the Department of Electrical and Electronics Engineering, Gaya College of Engineering, Gaya, Bihar, India. His academic interests include electrical and electronic systems, embedded technologies, and emerging engineering applications. He is interested in exploring interdisciplinary approaches to technological development and research, with an emphasis on applying engineering principles to practical and innovative solutions.