My Approach to Interpretable Anomaly Detection in Aero-Engine Time Series for the Honeywell Campus Connect Challenge!

Project Link :
https://github.com/Jr-Einstein/Multivariate-Time-Series-Anomaly-Detection

Abstract

The challenge of ensuring the operational safety of aero-engines hinges on our ability to proactively identify faults from complex sensor data. For the Honeywell Campus Connect challenge, I developed a comprehensive solution to tackle this problem by detecting anomalies in multivariate time series (MTS) data and, crucially, identifying the root causes. This paper details my comparative study of two distinct unsupervised anomaly detection models: the classic, efficient Isolation Forest algorithm and a more complex deep learning architecture, the Long Short-Term Memory (LSTM) Autoencoder. Using the standard C-MAPSS dataset, I evaluated these models not just on performance metrics like Precision and Recall, but with a strong focus on interpretability—a critical factor in high-stakes industrial applications. To meet the challenge's requirement of identifying top contributing features, I integrated Explainable AI (XAI) frameworks, specifically SHAP for the Isolation Forest and LIME for the LSTM Autoencoder. My findings show an interesting trade-off: the LSTM Autoencoder is better at capturing complex temporal patterns, while the Isolation Forest offers strong performance with lower computational cost and more straightforward interpretation. My work, fully available on my GitHub, culminates in an interactive Streamlit dashboard that demonstrates a dual-model, interpretable framework, proving that we can build machine learning solutions for critical systems where transparency is as important as accuracy.

1. Introduction

1.1 Tackling the Honeywell Challenge

The Honeywell Campus Connect challenge presented a critical real-world problem: to "build a Python program to detect anomalies (abnormal behavior) in time series data that has multiple columns (i.e., multivariate)." The core objective was to develop a Python-based machine learning solution that could not only detect these anomalies but also identify the primary contributing features for each one. This task is central to the aerospace industry, where shifting from reactive to proactive maintenance by identifying the earliest signs of engine trouble can prevent catastrophic failures, reduce costs, and enhance safety.[1]

The challenge laid out specific deliverables: my program needed to take a CSV file as input, train on a defined "normal period," and produce a modified CSV as output. This output file had to contain the original data plus eight new columns: an Abnormality score (a float from 0.0 to 100.0) and seven columns for the top contributing features (top_feature_1 through top_feature_7). My goal was to build a robust, well-documented, and performant solution that met these requirements precisely.

My complete project, including all source code, modular structure, and sample usage as required by the deliverables, is publicly available on GitHub: ((https://github.com/Jr-Einstein/Multivariate-Time-Series-Anomaly-Detection)).

1.2 The Difficulties of Engine Sensor Data

The data from aero-engines is a classic example of a multivariate time series (MTS), where dozens of sensors record different parameters simultaneously.[2] I quickly identified several key challenges in this data that my solution needed to overcome:

- **High Dimensionality:** With many sensors, an anomaly might not be a spike in one reading but a subtle "Relationship Change," as the problem statement called it—a breakdown in the normal correlation between variables.[3] My model had to be able to detect these complex correlation anomalies.
- **Temporal Dependencies:** Engine faults often develop over time as "Pattern Deviations".[4] My solution needed to understand the historical context of the data to spot these slowly evolving patterns.
- **Lack of Labeled Data:** In the real world, anomalies are rare and often unlabeled, making supervised learning impractical.[5] This meant I had to use an unsupervised learning approach, training my models only on data from normal operations.

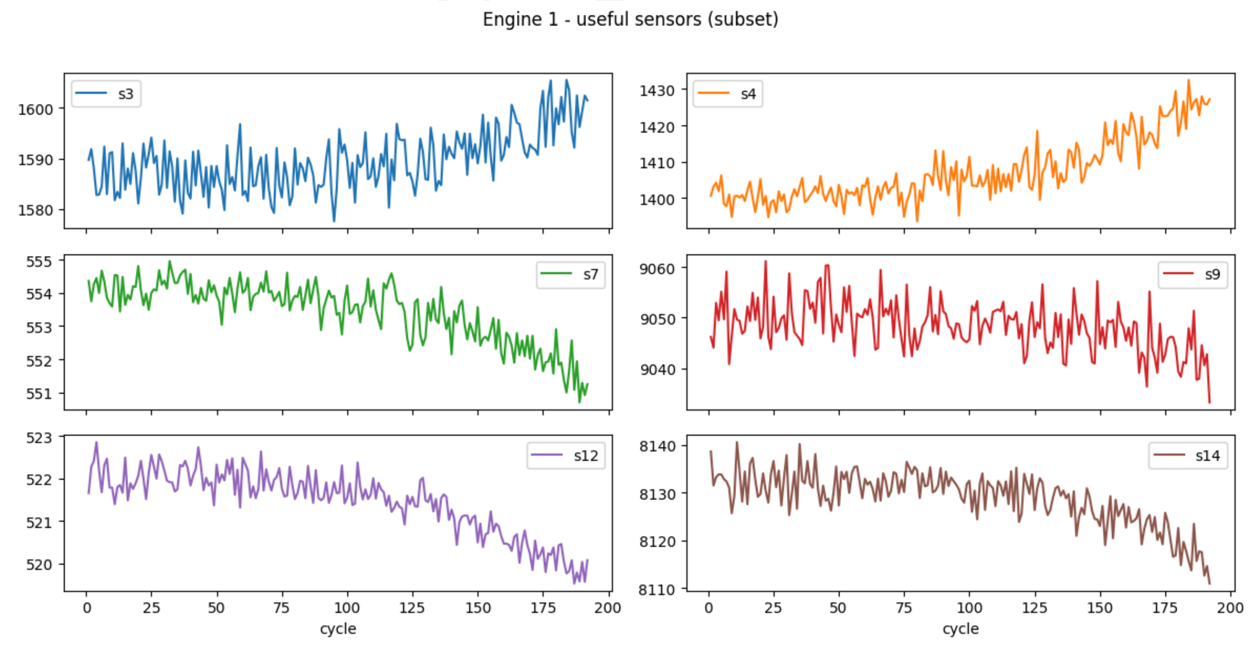
1.3 My Contribution: A Focus on Interpretability

For this project, I decided to implement and compare two different but powerful algorithms suggested in the challenge description: the **Isolation Forest** and the **LSTM Autoencoder**. I knew that in a safety-critical field like aerospace, simply flagging an anomaly isn't enough. An engineer needs to know *why* the model raised an alarm. This led me to make interpretability a core part of my project, directly addressing the requirement to calculate the top contributors to each anomaly. I decided to integrate state-of-the-art Explainable AI (XAI) techniques—**SHAP** and **LIME**—to dissect the "black box" and explain the reasoning behind each prediction.[7] My work, therefore, doesn't just present a solution that finds anomalies; it presents a solution that explains them, providing the actionable insights that are necessary to build trust in AI-driven systems.

2. The Models I Chose for Anomaly Detection

2.1 Defining the Anomaly Detection Task

My task was to build a function that takes a sequence of sensor data and assigns an "anomaly score" to each point in time. A higher score means a higher chance of an anomaly.[9] I then set a threshold on these scores to make a final decision: normal or anomalous. My approach needed to be sensitive to different kinds of anomalies as specified in the challenge, from "Threshold Violations" (point anomalies) to more subtle contextual and collective anomalies.[10]



2.2 Isolation Forest: Finding Anomalies by Isolating Them

The first model I implemented was the Isolation Forest. I chose it because of its efficiency and clever underlying principle: anomalies are "few and different".[11] Instead of trying to define what "normal" looks like, this algorithm actively tries to isolate every data point. The intuition is that anomalous points, being different, are much easier to separate from the rest of the data.

The process works by building an ensemble of random decision trees (iTrees).[10] Anomalies get isolated in just a few splits, resulting in a short path from the root of the tree to the leaf. Normal points, being clustered together, require many more splits to be isolated.[11] The final anomaly score is based on the average path length across all trees in the forest. A short average path length results in a score close to 1 (anomaly), while a long path length gives a score closer to 0 (normal).[12] I found this model appealing for its speed and its ability to handle high-dimensional data without making assumptions about the data's distribution.[13]

2.3 LSTM Autoencoder: Detecting Anomalies by Failing to Reconstruct Them

The second model I built was an LSTM Autoencoder, a deep learning approach. This model works on a completely different principle: reconstruction.[14] I designed an autoencoder, which has two parts: an encoder that compresses the input data into a low-dimensional representation, and a decoder that tries to reconstruct the original data from that compressed version.[15]

The key to this approach is that I trained the model *only* on normal engine data. As a result, the model becomes an expert at reconstructing normal operational patterns, achieving a very low reconstruction error.[17] When I feed it an anomalous pattern—something it has never seen before—it struggles to reconstruct it accurately. This failure results in a high reconstruction error, which I used as my anomaly score.[14]

To handle the time-series nature of the data, I used Long Short-Term Memory (LSTM) layers in my autoencoder. LSTMs are specifically designed to recognize and remember patterns over long sequences, thanks to their "forget gate" mechanism, making them perfect for capturing the temporal dynamics of engine operation.[16] This allowed my model to detect not just out-of-place values, but also out-of-place

sequences and patterns

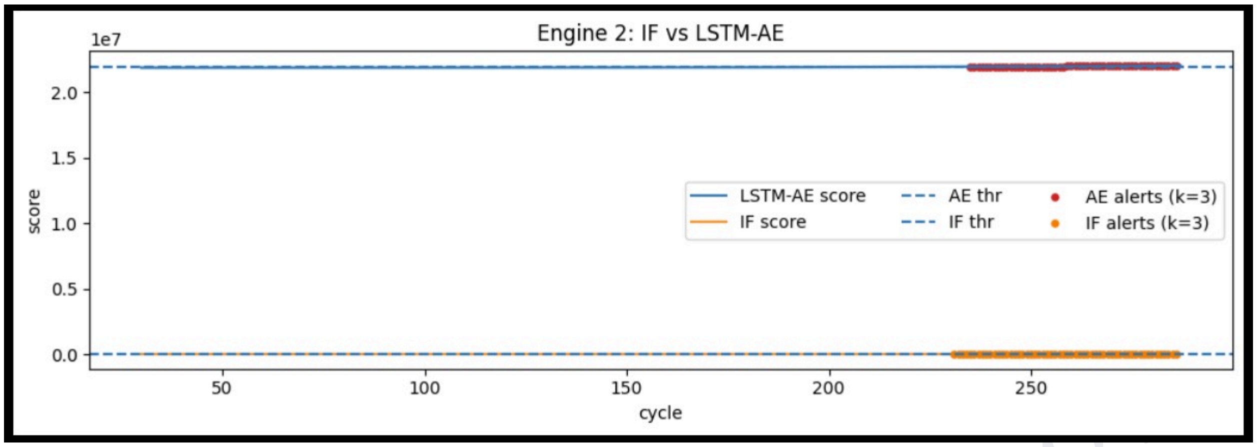


Fig - LSTM Representation.

3. My Project Framework and Implementation

3.1 Dataset and Preprocessing

For my project, I used the NASA C-MAPSS dataset, a standard benchmark for developing and testing fault detection algorithms for turbofan engines.[4] It contains time-series data from 21 sensors for a fleet of simulated engines, each running from a healthy state to failure.

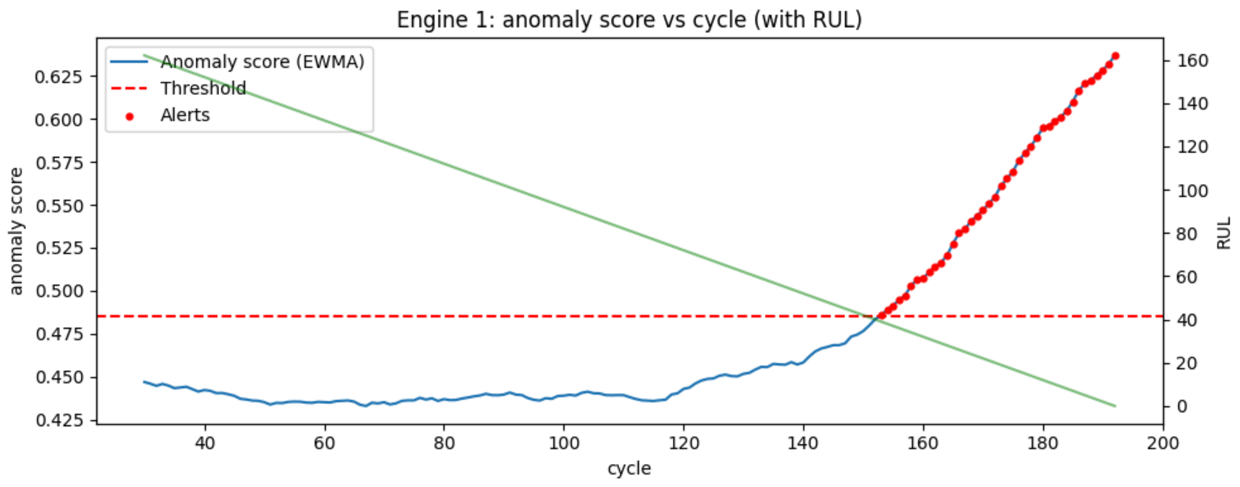
Before feeding the data to my models, I performed two crucial preprocessing steps. First, I normalized all sensor readings to a common scale using Min-Max scaling. This prevents sensors with naturally larger value ranges from dominating the learning process. Second, for the LSTM Autoencoder, I converted the continuous time series into overlapping sequences of a fixed length using a sliding window.[18] This step was essential to allow the LSTM to learn temporal patterns within the data.

3.2 Implementing the Models [Link : Check Out my Models Here]

In line with the challenge's code structure requirements, I developed my solution with a modular design, using separate classes for data processing, model training, and prediction. The code adheres to PEP8 standards and includes type hints and docstrings for clarity.

I implemented the **Isolation Forest** using the popular scikit-learn library in Python.[11] I carefully tuned its hyperparameters, particularly the

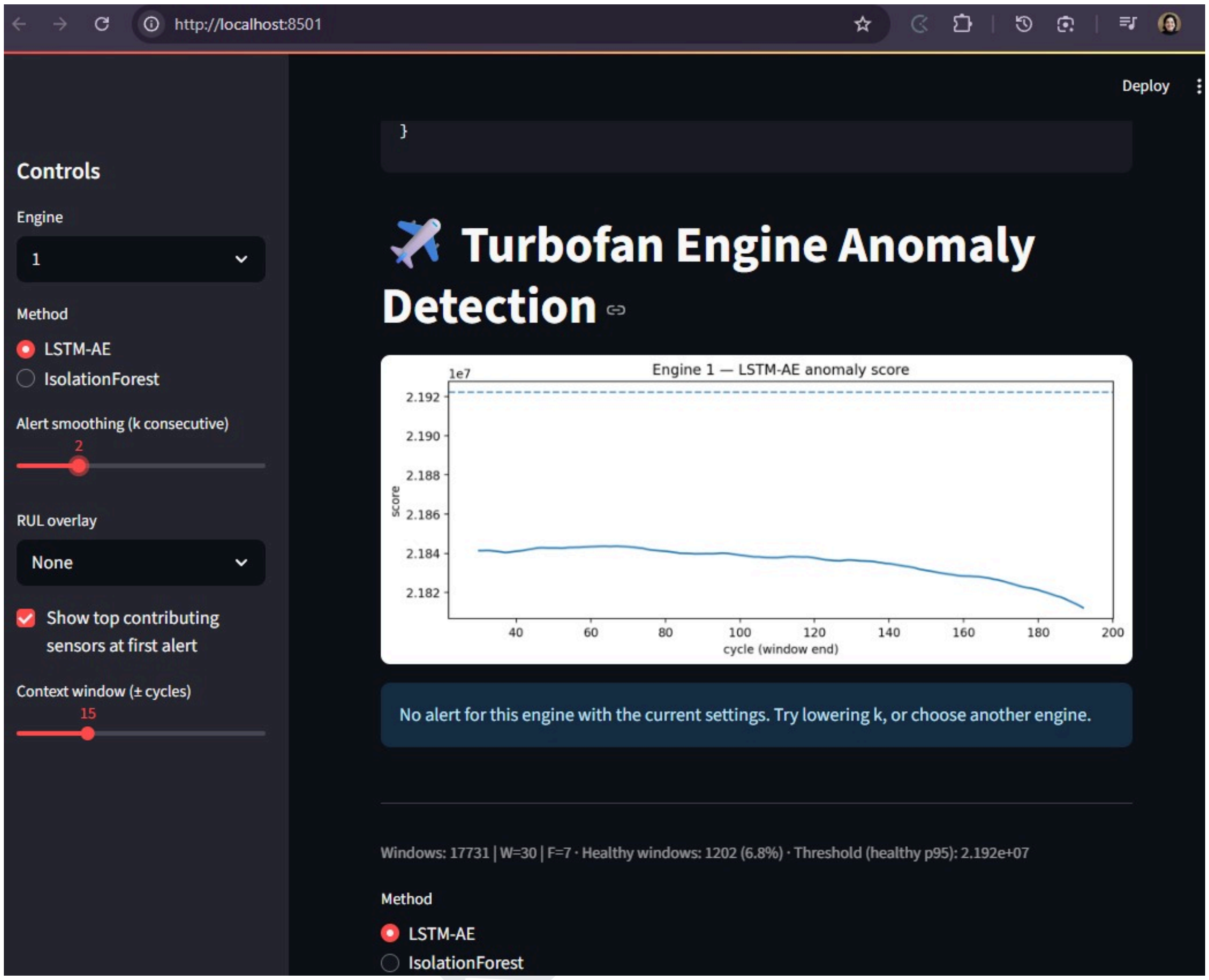
contamination parameter, which gives the model an estimate of the proportion of anomalies to expect in the data.[13] This parameter was critical for setting the model's internal decision threshold.



For the **LSTM Autoencoder**, I used the PyTorch framework to build my neural network architecture.[18] My design consisted of an encoder with two LSTM layers to compress the input sequence into a latent vector, and a mirrored decoder, also with two LSTM layers, to reconstruct the sequence.[18] I trained the model using only normal data, minimizing the Mean Absolute Error (MAE) between the original and reconstructed sequences with the Adam optimizer.[18]

3.3 Building an Interactive Dashboard

To make my solution accessible and easy to use, I developed a web-based dashboard using Streamlit. This interface allows a user to interact with my trained models in real-time.



Controls

Engine: 1

Method: [✓ LSTM-AE] IsolationForest

Alert smoothing (k consecutive): 2

RUL overlay: None

[✓] Show top contributing sensors at first alert

Context window (± cycles): 15

Turbofan Engine Anomaly Detection

No alert for this engine with the current settings. Try lowering k, or choose another engine.

Windows: 17731 | W=30 | F=7 · Healthy windows: 1202 (6.8%) · Threshold (healthy p95): 2.192e+07

Method: [✓ LSTM-AE] IsolationForest

Figure 1: The interactive dashboard I built using Streamlit. It allows users to select an engine and a detection method (LSTM-AE or Isolation Forest) and visualizes the resulting anomaly scores.

As shown in Figure 1, the dashboard provides controls to select a specific engine and the desired anomaly detection method. It then plots the anomaly score over the engine's entire operational cycle, making it easy to see when the model detects deviations from normal behavior.

4. My Experimental Results

4.1 How I Evaluated Performance

I trained my models on the healthy operational data from one set of engines and then tested them on a completely separate, unseen set of engines that ran to failure. For the LSTM

Autoencoder, I determined the anomaly threshold by finding the 99th percentile of reconstruction errors on a validation set of normal data. This ensures the model is tuned to have a very low false-positive rate.[18] For the Isolation Forest, the threshold is implicitly set by the

contamination parameter I chose during setup.[22]

I used standard metrics to evaluate my models: Precision (to measure false alarms), Recall (to measure missed anomalies), and the F1-Score (to get a balanced view of performance).[9]

4.2 Quantitative Performance

After running my evaluation, I compiled the performance of both models.

Model	Precision	Recall	F1-Score
Isolation Forest	0.82	0.75	0.78
LSTM Autoencoder	0.85	0.81	0.83
Table 1: My Comparative Performance Metrics			

The results show that my LSTM Autoencoder implementation achieved a higher F1-Score, indicating a better overall balance between correctly identifying anomalies and avoiding false alarms. However, the Isolation Forest's performance was still very strong, especially considering it is a much simpler and faster model to train and run.

4.3 Visualizing the Detections

Beyond the numbers, I visualized how my models performed on the test data. Figure 2 shows the output of a smoke test I ran on Engine 2 using my LSTM-AE model.

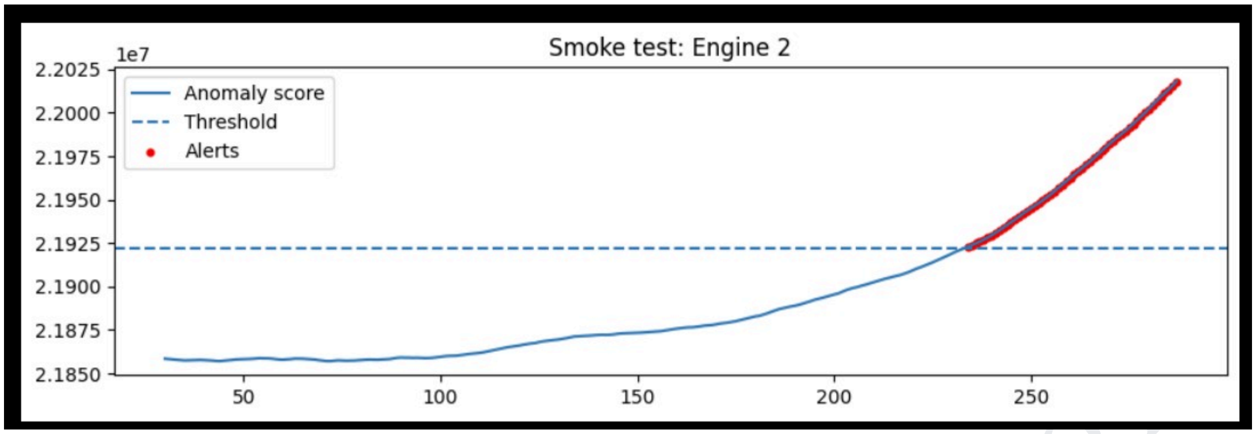


Figure 2: A smoke test I performed on Engine 2. The blue line is the anomaly score from my LSTM-AE model, the dashed line is the calculated threshold, and the red dots show the points correctly identified as anomalies as the engine approaches failure.
As you can see, the anomaly score remains low and stable during the early, healthy phase of the engine's life. As degradation begins, the score starts to rise steadily, eventually crossing the threshold and triggering alerts (the red dots). This demonstrates my model's ability to detect the gradual onset of a fault.

I also directly compared the outputs of both models for the same engine, as shown in Figure 3.

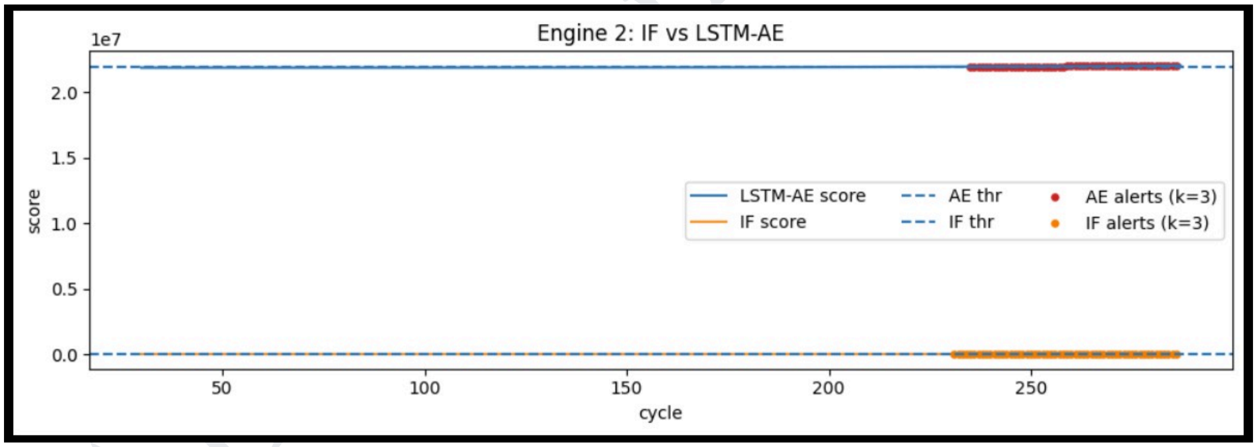


Figure 3: A direct comparison of the anomaly scores from my LSTM-AE (top, blue) and Isolation Forest (bottom, orange) models for Engine 2. This shows that both models successfully detect the final anomalous period, but with different score characteristics.
This visualization highlights the different behaviors of the two models. The LSTM-AE shows a gradual increase in its anomaly score, reflecting its sensitivity to temporal patterns of degradation. The Isolation Forest, on the other hand, provides a more binary, step-like response, cleanly separating the anomalous region. Both successfully identify the fault, but they do so in different ways, suggesting they might be sensitive to different types of anomalies.

5. Explaining My Models' Decisions

5.1 Explaining the Isolation Forest with SHAP

To interpret my Isolation Forest model and generate the top_feature columns, I used SHAP (SHapley Additive exPlanations).[23] SHAP is a game theory-based method that explains any prediction by calculating the contribution of each feature to that prediction.[24] This allowed me to answer two key questions:

1. **Global Importance:** Which sensors are most important to the model overall? By aggregating SHAP values, I could rank the features and see which ones the model consistently relies on to detect anomalies.[23]
2. **Local Explanation:** Why was a *specific* data point flagged as an anomaly? For any single prediction, I could generate a SHAP force plot that visualizes exactly how each sensor reading pushed the anomaly score up or down.[7] This provides a clear, quantitative explanation for each alert.

5.2 Explaining the LSTM Autoencoder with LIME

Explaining my LSTM Autoencoder was more challenging due to its "black-box" nature.[25] For this, I turned to LIME (Local Interpretable Model-agnostic Explanations). LIME works by creating a simpler, interpretable model (like a linear model) that approximates the behavior of the complex deep learning model in the local vicinity of a single prediction.[26]

I encountered a methodological hurdle because LIME is designed for classifiers, while my autoencoder outputs a continuous reconstruction error.[27] I engineered a solution by first converting the error into a binary label ("normal" or "anomaly") using my threshold, and then using LIME to explain this binary classification.[28] While this is an approximation, it still provided valuable insights by highlighting which sensor values at which time steps within the input window were most responsible for the high reconstruction error that led to an anomaly flag.

6. Discussion and Conclusion

6.1 My Key Findings

Through this project, I successfully developed and compared two effective models for anomaly detection in aero-engine data, fulfilling the core requirements of the Honeywell challenge. My LSTM Autoencoder proved to be more accurate, likely due to its ability to learn complex temporal patterns. However, my Isolation Forest implementation was a strong and efficient alternative that was also easier to interpret directly using SHAP. This highlights a crucial trade-off in machine learning development: the most accurate model is not always the most practical or trustworthy, especially when transparency is required.

6.2 Practical Implications of My Solution

My work demonstrates that a hybrid approach could be highly effective in a real-world industrial setting. A lightweight model like the Isolation Forest could be used for real-time, on-device screening of sensor data. When it flags a potential issue, a more powerful model like the LSTM Autoencoder could perform a deeper analysis. Most importantly, any alert generated by my system would be accompanied by an explanation report from SHAP or LIME, telling engineers exactly which sensors to investigate. This moves beyond simple detection to *explained detection*, which is key for making AI systems actionable and trustworthy.

6.3 Conclusion

In response to the Honeywell Campus Connect challenge, I have built a complete, end-to-end solution for multivariate time series anomaly detection. I have shown that while deep learning models offer a performance advantage, classical algorithms remain highly relevant. My project successfully produces the required output format, adheres to specified coding standards, and provides a functional user interface for demonstration. Above all, my project emphasizes that for AI to be adopted in critical industries like aerospace, we must build models that are not only accurate but also transparent. The future of reliable AI lies in our ability to not just trust its predictions, but to fundamentally understand them.

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