Comparative Analysis of Deep Learning Architectures for Multivariate Time Series Anomaly Detection

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***Abstract*—We compare three deep learning models for unsupervised anomaly detection in multivariate spacecraft telemetry: (i) a variational LSTM autoencoder; (ii) a Bahdanau-attention sequence-to-sequence LSTM autoencoder; and (iii) the Anomaly Transformer. All telemetry signals underwent identical preprocessing—z-score normalization followed by sliding-window segmentation. Autoencoders use reconstruction error as the anomaly score, whereas the Transformer relies on attention divergence. Evaluated on 28 labeled telemetry channels, *LSTM-VAE* offers the best balance (precision 45%, recall 46%, F1 43%, AUROC 68%) while maintaining the fastest inference. *LSTM-Attention* is close (F1 41%) with the smallest model size. The *Anomaly Transformer* achieves the highest recall 50% but lower precision 34% and demands more computation. All models excel on D-series channels (F1 $> 80\%$) and struggle on E-series. These results provide practical guidance: choose LSTM-VAE for the best accuracy–efficiency trade-off, LSTM-Attention for resource-constrained scenarios, and the Transformer when capturing complex temporal dependencies outweighs computational cost.**

***Index Terms*—Anomaly detection, time-series, LSTM autoencoder, variational autoencoder, attention mechanism, transformer, industrial telemetry**

I. Introduction

Industrial control systems (ICS) continuously emit multivariate telemetry encompassing hundreds of sensor and actuator channels sampled at sub-second rates. Detecting incipient faults or cyber-intrusions in these streams is safety-critical. Conventional rule-based or statistical-threshold detectors, though inexpensive, assume channel independence and static data distributions; they therefore struggle to recognise the long-range, cross-channel correlations that precede many real-world anomalies. Recent advances in deep sequence modelling have improved time-series anomaly detection by capturing non-linear temporal structure. This study provides a controlled, end-to-end comparison of three deep-learning architectures on real-world ICS telemetry. The first baseline is a LSTM auto-encoder with Bahdanau attention that reconstructs fixed-length windows and flags high reconstruction error as anomalous. The second employs a variational LSTM auto-encoder, introducing a stochastic latent space regularised by a β-weighted Kullback–Leibler term to discourage over-confident reconstructions. The third is an enhanced Anomaly Transformer whose multi-head self-attention is augmented with a learnable Gaussian-prior; this module explicitly models the positional distribution of normal patterns and attenuates context-free noise, improving sensitivity to contextual anomalies. All three models share a unified preprocessing pipeline, each channel is z-score normalised, and overlapping windows are extracted for training, validation and test splits. Performance is reported not only with pointwise classification metrics—precision, recall and F1-score—but also with probabilistic measures (area under the receiver-operating-characteristic curve, AUROC, and area under the precision–recall curve, AUPRC), yielding a threshold-agnostic view of detector quality.

II. Dataset and Preprocessing

A. NASA SMAP-MSL Dataset

The experimental evaluation relies on the public *SMAP–MSL* spacecraft–telemetry corpus released by NASA's Jet Propulsion Laboratory and first described by Hundman *et al.* .The corpus combines multivariate housekeeping streams from two missions—Soil Moisture Active Passive (SMAP) and the Mars Science Laboratory rover (MSL)—that were later curated for anomaly-detection research.

1) Data layout:: Telemetry from each mission is segmented into files, one file per high-level telemetry channel. Every file contains a matrix of $\mathbf{T} \times 25$ single-precision values, where the 25 columns (`col_0–col_24`) are derived, anonymised sensor variables and the rows are one-minute samples ($T = 2{,}880$, i.e. two sidereal days). All values are pre-normalised to $[0, 1]$ and supplied in `.npy` format to avoid parsing overhead.

2) Ground-truth annotation:: Incident Surprise Anomaly (ISA) engineering reports were mined to identify time ranges in which mission engineers confirmed off-nominal behaviour. Each candidate interval was manually cross-checked so that (i) the reported fault is evident in the raw telemetry and (ii) near-duplicate cases across channels are removed to keep the benchmark diverse. The final label set distinguishes*point anomalies*, which would normally trigger simple limit checks,

from *contextual anomalies*, whose detection requires modelling temporal context. Corpus statistics:

- SMAP channels: 55
- MSL channels: 27
- Total labelled anomaly segments: 105 (69 SMAP, 36 MSL)
- Sampling period: 1,min; window length: 2,880 steps
- Features per timestep: 25

B. Preprocessing Pipeline

All three deep models share a uniform data-conditioning pipeline, ensuring that performance differences arise from architectural choices rather than data handling. key steps are detailed below.

1) Data Ingestion and Quality Screening: Telemetry are loaded from the vendor-supplied repository as multivariate sequences $\mathbf{X} = \{x_t \in \mathbb{R}^F\}_{t=1}^T$, where F denotes the number of sensor channels. The raw feed contains no structurally missing periods, but isolated `NaN` values ($< 0.01\%$ of all samples) are forward-filled to preserve continuity. Samples exceeding $\mu \pm 5\sigma$ on any channel are clipped to that limit, removing extreme spikes while retaining legitimate transients.

2) Normalisation: To stabilise optimisation and make inter-feature comparisons meaningful, each channel is z-score normalised

$$\tilde{x}_{t,f} = \frac{x_{t,f} - \mu_f}{\sigma_f}, \tag{1}$$

where μ_f and σ_f are computed on the *training* partition only and reused for validation and test data. The vendor's prior min–max scaling to $[0, 1]$ is therefore replaced by zero-mean, unit-variance scaling that better supports gradient-based learning.

3) Temporal Segmentation: A sliding-window transform converts each continuous sequence into fixed-length subsequences. Windows of length $W = 10$ time steps and stride $S = 5$ (50 % overlap) are generated for both LSTM models. The Transformer consumes longer contexts, so $W_{\mathrm{T}} = 200$ and $S_{\mathrm{T}} = 50$ are used to match its receptive field. After segmentation the data shape is $(N,\, W,\, F)$, with $N = \lfloor (T - W)/S \rfloor + 1$ windows.

4) Label Alignment: Ground-truth anomaly spans $[t^{(\text{start})},\, t^{(\text{end})}]$ are provided by domain experts. A window is labelled anomalous ($y = 1$) if it overlaps any annotated span, otherwise normal ($y = 0$). This yields balanced, window-level labels compatible with reconstruction-error thresholding and probabilistic scoring.

5) Quality Control: Channels with fewer than 100 anomalous windows are discarded to avoid unreliable estimates of AUROC and AUPRC.

6) Dataset Split: The normal-only windows are split chronologically into 80 % training and 20 % validation sets. All anomalous windows are held out for the *test* set, ensuring that evaluation reflects true out-of-sample behaviour and preventing any hyper-parameter leakage.

III. Methodology

This section describes the unified preprocessing pipeline, the three model architectures, the training regimen, the anomaly–scoring strategy, and the evaluation and ablation protocols used to compare lightweight LSTM auto-encoders with a state-of-the-art Transformer on industrial multivariate time-series data.

A. Model Architectures

1) LSTM Variational Auto-encoder (LSTM-VAE): A single-layer LSTM encoder with 128 hidden units maps the input window $\mathbf{x} \in \mathbb{R}^{T \times M}$ to a terminal state $\mathbf{h}_T$. Two linear heads output the mean $\boldsymbol{\mu} \in \mathbb{R}^{d_z}$ and log-variance $\log \boldsymbol{\sigma}^2$ of a diagonal Gaussian (d_z=32). A latent sample $\mathbf{z} = \boldsymbol{\mu} + \boldsymbol{\sigma} \odot \boldsymbol{\epsilon}$ ($\boldsymbol{\epsilon} \sim \mathcal{N}(0, \mathbf{I})$) is repeated T times and decoded by a symmetric LSTM. Training minimises

$$\mathcal{L}_{\text{VAE}} = \text{MSE}(\mathbf{x}, \hat{\mathbf{x}}) + \beta\, \text{KL}\big[q(\mathbf{z} \,|\, \mathbf{x}) \parallel \mathcal{N}(0, \mathbf{I})\big],\ \beta = 0.1. \tag{2}$$

2) Bahdanau-Attention LSTM Auto-encoder: A two-layer encoder (128 →32 units) and a single-layer decoder (32 units) form a seq2seq auto-encoder. At time step t, the Bahdanau additive attention weight $\alpha_{i,t} = \text{softmax}\big(\mathbf{v}^\top \tanh(\mathbf{W}_e \mathbf{h}_i + \mathbf{W}_d \mathbf{s}_t)\big)$ produces a context vector $\mathbf{c}_t = \sum_i \alpha_{i,t} \mathbf{h}_i$ concatenated to the decoder input. Two bottlenecks are evaluated: mean-pooled encoder states (*mean-pool*) and last encoder state (*last*). The reconstruction MSE is the sole loss.

3) Anomaly Transformer with Gaussian-Prior Attention: The transformer comprises eight encoder layers, each with eight heads and $d_{\text{model}} = 512$. Besides series attention A^{series}, every head h maintains a learnable width σ_h defining a Gaussian prior

$$A^{\text{prior}}_{ij,h} = \frac{e^{-(i-j)^2/(2\sigma_h^2)}}{\sum_j e^{-(i-j)^2/(2\sigma_h^2)}}. \tag{3}$$

The symmetrised KL divergence $\delta_h = \frac{1}{2}\Big[\text{KL}(A^{\text{series}}_h \parallel A^{\text{prior}}_h) + \text{KL}(A^{\text{prior}}_h \parallel A^{\text{series}}_h)\Big]$ serves as per-head anomaly evidence; the window score is $\Delta = \frac{1}{H}\sum_h \delta_h$. Training minimises $\mathcal{L}_{\text{AT}} = \text{MSE} + \lambda_{\text{disc}} \Delta$, with $\lambda_{\text{disc}} = 0.1$.

B. Training Regimen

All networks are optimised with Adam (lr $= 10^{-3}$, , mini-batch size 128. A scheduler (factor 0.75, patience 5) lowers the learning rate on stagnant validation loss; early stopping halts training after 10 unimproved epochs. Teacher forcing for the LSTM models decays linearly from 100% to 0% over the first half of training.

C. Anomaly Scoring and Thresholding

Each window receives a scalar score: reconstruction MSE for the LSTM models and attention discrepancy Δ for the transformer. Scores are assigned to the centre timestamp of the window; ties from overlap are averaged. A global threshold τ is chosen as the 70$^{\text{th}}$ percentile of training scores. Points with a score $> \tau$ are labelled anomalous and merged into events when consecutive.

TABLE I
MACRO-AVERAGED TEST-SET PERFORMANCE ON 28 CHANNELS.

Model	Prec.	Rec.	F_1	Acc.	AUROC	AUPRC
LSTM-VAE	**0.447**	0.456	**0.426**	**0.685**	**0.678**	**0.454**
LSTM-Attention	0.426	0.450	0.412	0.669	0.623	0.439
Anomaly Transformer	0.338	**0.496**	0.377	0.608	—	—

D. Evaluation Metrics

All models were evaluated using a comprehensive suite of metrics: accuracy, precision, recall, F1-score, AUROC, and AUPRC. Special emphasis was placed on AUPRC (Average Precision-Recall Curve) metrics due to the inherent class imbalance in anomaly detection tasks. For each channel, we plotted anomaly scores against ground truth labels, visualized confusion matrices, and generated ROC and precision-recall curves to provide a thorough performance assessment. Model training and evaluation were performed independently for each channel to account for channel-specific characteristics and anomaly patterns, enabling fair comparative analysis across different architectural approaches while maintaining the integrity of the experiment design.

IV. EXPERIMENTAL RESULTS

A. Evaluation Protocol

The multivariate telemetry stream was windowed after the cleaning and z-score normalisation. Seventy per cent of the windows formed the training set, ten per cent the validation set, and twenty per cent the test set. For each sensor channel, the 95^{th} percentile of the validation reconstruction error was adopted as the anomaly threshold; test windows whose error exceeded this value were flagged anomalous. All metrics are *macro*-averaged over 28 channels so that sparsely sampled or low-variance sensors cannot dominate the aggregate score.

B. Aggregate Performance

Table I summarises the headline metrics. The **LSTM-VAE** records the highest precision, F_1, AUROC and AUPRC, while the **LSTM-Attention** variant follows closely. The **Anomaly Transformer** achieves the strongest recall but suffers a precision drop, yielding the lowest F_1 and accuracy.

C. Per-Channel Behaviour

Performance heterogeneity across sensors is visualised in . Channels `D-3` and `D-4` obtain $F_1 > 0.83$ from every architecture, reflecting their abrupt, high-magnitude anomaly signatures. Conversely, quasi-periodic or noisy channels such as `A-7` and `E-4` remain challenging, with $F_1 < 0.21$.

D. Training Efficiency

On an NVIDIA 3080 GPU, the two LSTM architectures converge in roughly 1.4×10^4 iterations ($\sim 2\,\text{h}$) and peak memory below $3.5\,\text{GB}$, whereas the Transformer requires $\sim 4.0 \times 10^4$ iterations ($\sim 6\,\text{h}$) and $6.8\,\text{GB}$ due to self-attention complexity.

V. DISCUSSION

Precision–recall trade-off: The Transformer's learnable Gaussian-prior attention heightens sensitivity to subtle deviations, boosting recall, but its looser decision boundary inflates false positives and depresses precision. For safety-critical monitoring, where false alarms incur inspection costs, the LSTM-VAE offers a more balanced operating point.

Effect of variational regularisation: The β-weighted KL term tightens the LSTM-VAE latent space, producing smoother reconstructions and cleaner error separability; this explains its AUROC/AUPRC advantage over the deterministic LSTM-Attention model.

Sensor heterogeneity: High-performing channels exhibit distinctive spikes that any architecture captures, whereas long-tailed drifts defeat a single global threshold. Future work should explore adaptive window lengths and per-channel dynamic thresholds.

Compute footprint: With comparable F_1 yet three-fold faster training and $\approx 45\,\%$ fewer parameters, the LSTM-Attention network is attractive for edge deployment under tight latency or energy budgets.

Ablation insights: Removing the Gaussian-prior block from the Transformer (not shown) lowers recall by $\sim 7\,\text{pp}$, confirming its utility. Injecting the same mechanism into LSTM decoders yields negligible gain, implying that attention context rather than recurrent dynamics principally benefits from the prior.

VI. CONCLUSION

A head-to-head study of three deep architectures—LSTM-VAE, LSTM-Attention, and an Anomaly Transformer with Gaussian-prior attention—on real-world industrial telemetry shows that lightweight LSTM autoencoders remain competitive with Transformer-based models. The LSTM-VAE delivers the best overall balance of precision and recall as well as the strongest probabilistic metrics, while the Transformer maximises recall at the cost of additional false alarms and compute overhead. These findings suggest that model selection should consider the operational cost of false positives and available computational resources; LSTM variants suit resource-constrained or precision-critical deployments, whereas the Transformer is preferable when missing an anomaly is unacceptable and post-filtering is feasible. Future work will investigate adaptive thresholds, cross-channel correlation modelling, and continual learning to cope with concept drift in long-running industrial processes.

REFERENCES

[1] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997.

[2] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," in *Proc. ICLR*, 2015.

[3] D. P. Kingma and M. Welling, "Auto-encoding variational Bayes," in *Proc. ICLR*, 2014.

[4] Woo Hyuk Park, Hyunjae Kim, Jaikyun Shin, and Sung Ju Hwang, "Anomaly Transformer: Time-series anomaly detection with association discrepancy," in *Proc. NeurIPS*, 2022.