

Physics-Guided Two-Stage Anomaly Detection Framework for Industrial Connector Fitting Verification

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In industrial connector fitting inspection, false negatives (FNs)—defective parts passed as normal—can trigger market recalls and even fatal accidents in safety-critical automotive systems. The ultimate goal is therefore not F1-score maximization but a guaranteed 100% recall, i.e., zero-defect outflow. Conventional rule-based methods using statistical features such as intersection magnitude (IM) cannot fully capture waveform variability arising from operator-force variation and connector-shape diversity. Supervised CNNs, although powerful, are inherently closed-set systems that misclassify unknown anomalies into known classes with high confidence—the open-set recognition (OSR) problem. Unsupervised autoencoders avoid OSR but tend to over-generalize, faithfully reconstructing even subtle unknown anomalies as “normal.”

We propose a physics-guided two-stage anomaly detection framework that integrates data-driven inference with deterministic physical evaluation:

Stage 1 (CWT-CAE detection): The fitting vibration signal is converted to a log-scale continuous-wavelet-transform (CWT) scalogram, which allocates greater pixel resolution to the low-frequency structural modes critical for defect discrimination. The scalogram is fed into a linear bottleneck convolutional autoencoder (CAE) whose fully connected layer ($d = 16$) intentionally destroys all spatial information, structurally suppressing over-generalization. Anomalies are scored via a hybrid metric combining MSE (intensity error) and SSIM (structural distortion).

Stage 2 (Physics-based fail-safe): For samples that pass Stage 1, the IM feature is evaluated using a modified z-score thresholding. Since IM is grounded in physical contact intensity, this layer deterministically blocks any FN that the AI model in Stage 1 may have missed, providing a hard guarantee that false negatives cannot leak through.

Five automotive wire-harness connectors (D2–D6) were evaluated using waveforms acquired by a fingertip-worn piezoelectric vibration sensor (Robosensor SHG350, 44.1 kHz). Only normal samples were used for CAE training; anomaly samples were reserved exclusively for testing. As shown in Table 1, the proposed method achieved $F1 = 99.36\%$ on the most challenging connector (D6) and $F1 = 100\%$ on all others at Stage 1; Stage 2 completely eliminated FNs and reduced FN count to zero across all five connector types.

Under open-set recognition conditions, where collision anomalies were withheld from CNN training and introduced only at test time, the supervised CNN baseline’s average recall collapsed from 99.64% to 83.32% (–16.3 pt). In contrast, the proposed method maintained an average recall of 99.97% without ever observing any anomaly data, confirming robustness to unknown anomalies. UMAP visualization of the latent space further provides physical interpretability for the model’s anomaly decisions.

We proposed a physics-guided two-stage framework that combines a CWT-CAE anomaly detector with a deterministic IM-based fail-safe layer to strictly guarantee zero-defect outflow in industrial connector fitting inspection. The framework demonstrated zero FNs across five connector types and maintained robust detection performance under open-set conditions where supervised CNNs catastrophically degraded. The design philosophy of complementing probabilistic deep learning with deterministic physical constraints offers a practical reference model for safety-critical industrial AI systems.

Table 1. Recall (%) / F1-score (%) by connector and average F1 across all connectors.

Method	Recall (%) / F1 (%) by Connector					Avg. F1
	D2	D3	D4	D5	D6	
Supervised: SVM	99.68 / 99.76	100.0 / 100.0	100.0 / 100.0	99.51 / 99.51	97.58 / 98.05	99.46
Supervised: XGBoost	99.52 / 99.60	99.86 / 99.93	99.31 / 99.42	99.18 / 99.26	91.13 / 94.75	98.59
Supervised: 1D-CNN	100.0 / 100.0	100.0 / 100.0	99.77 / 99.88	100.0 / 99.92	99.68 / 70.31	94.02
Supervised: 2D-CNN	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	99.84 / 99.92	100.0 / 99.68	99.92
Conventional: IM-only	98.38 / 99.10	100.0 / 100.0	94.00 / 96.33	99.01 / 99.42	96.94 / 95.93	98.16
Conventional: 1D-AE + IM	99.84 / 99.76	100.0 / 100.0	100.0 / 99.43	99.34 / 99.34	98.23 / 97.36	99.18
Proposed: Stage 1	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	99.84 / 99.36	99.87
Proposed: Stage 2	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	100.0 / 99.59	100.0 / 96.50	99.22