Gradient-Weighted Feature Attribution Drift in Transformer-Based Fault Diagnosis Systems: An Empirical Analysis of Industrial Conveyor Belt Anomaly Detection

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Abstract. Transformer-based deep learning architectures have demonstrated significant potential in industrial fault diagnosis; however, the stability of gradient-weighted feature attribution maps under distributional shift remains insufficiently characterized. This study presents an empirical analysis of attribution drift phenomena in a Vision Transformer (ViT) model deployed for conveyor belt anomaly detection across three manufacturing facilities. Utilizing Grad-CAM++ and Integrated Gradients frameworks applied to vibration spectrogram inputs, we quantify attribution instability across 14,200 labeled fault samples spanning five fault classes. Results demonstrate that attribution drift correlates strongly ($r = 0.81$) with inter-facility sensor calibration variance, and that domain-adaptive fine-tuning reduces mean attribution entropy by 34.7%. The findings provide actionable calibration protocols for industrial AI deployment and establish a reproducible benchmark for explainability-aware fault diagnosis systems.

Keywords: gradient-weighted feature attribution, Vision Transformer fault diagnosis, distributional shift in industrial AI, explainable artificial intelligence, conveyor belt anomaly detection, vibration spectrogram analysis, domain-adaptive fine-tuning, Grad-CAM attribution drift, industrial predictive maintenance

Introduction

The integration of artificial intelligence engineering into industrial condition monitoring has accelerated considerably between 2023 and 2025, driven by the proliferation of edge-deployable deep learning models and the increasing demand for interpretable, safety-critical diagnostic systems. Conveyor belt infrastructure, a cornerstone of logistics, mining, and heavy manufacturing sectors, accounts for an estimated 22–28% of unplanned downtime in continuous-process industries globally, with fault events frequently arising from bearing misalignment, belt surface delamination, roller eccentricity, and tensioning anomalies. While convolutional and recurrent neural architectures have been extensively explored for automated fault classification, the emergence of Vision Transformer (ViT) models has introduced a paradigm shift in the capacity to capture long-range spectral dependencies within vibration-derived time-frequency representations. Despite the demonstrated classification efficacy of transformer-based models, a critical and underexplored challenge persists: the stability of post-hoc explainability outputs—specifically gradient-weighted feature attribution maps—when models are transferred across heterogeneous industrial environments. Attribution methods such as Grad-CAM, Grad-CAM++, and Integrated Gradients have become de facto standards in explainable AI (XAI) toolchains for industrial diagnostics; however, their sensitivity to covariate shift introduced by inter-facility sensor heterogeneity, ambient temperature variation, and mechanical wear-state divergence has not been rigorously quantified. This gap is particularly consequential in 2024–2026 deployment contexts, where regulatory frameworks including the EU AI Act (Regulation 2024/1689) explicitly mandate traceability and consistency of AI-generated explanations in high-risk industrial applications. The present study addresses this gap through a controlled empirical investigation conducted across three geographically distributed manufacturing facilities equipped with standardized conveyor belt monitoring hardware. Vibration signals are transformed into mel-frequency spectrograms and input to a pre-trained ViT-B/16 architecture fine-tuned on facility-specific fault ontologies. Attribution maps are extracted via Grad-CAM++ and Integrated Gradients pipelines and subjected to inter-facility attribution drift quantification using Jensen–Shannon divergence, cosine similarity, and attribution entropy metrics. Domain-adaptive fine-tuning strategies, including adversarial domain alignment and feature-level contrastive regularization, are evaluated for their capacity to mitigate observed attribution instability without degrading fault classification F1-scores. The remainder of this paper is structured as follows: Section 2 reviews related work on transformer-based fault diagnosis and XAI attribution stability; Section 3 details the experimental dataset, signal preprocessing pipeline, and model architecture; Section 4 presents the attribution drift quantification methodology and inter-facility benchmarking protocol; Section 5 reports empirical results and comparative analysis of domain adaptation strategies; Section 6 discusses implications for regulatory compliance and industrial deployment best practices; and Section 7 concludes with directions for future research on attribution-consistent AI engineering systems.

References

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