Explainable Artificial Intelligence for Fault Diagnosis in Safety-Critical Electronic Systems: Frameworks, Methods, and Emerging Challenges

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Abstract: *Safety-critical electronic systems deployed in aerospace, automotive, industrial control, medical devices, and power infrastructure demand the highest levels of reliability and fault tolerance. The integration of deep learning and machine learning models into automated fault diagnosis pipelines has substantially improved detection accuracy; however, these black-box models suffer from a fundamental transparency deficit that obstructs their adoption in regulatory and safety-certified environments. Explainable Artificial Intelligence (XAI) has emerged as a paradigm to reconcile high predictive performance with interpretable decision rationales, enabling engineers to understand, validate, and trust AI-driven diagnostic conclusions. This paper presents a comprehensive review and analytical framework for XAI-based fault diagnosis in safety-critical electronic systems. The study systematically surveys pertinent XAI methodologies, including SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), Gradient-weighted Class Activation Mapping (Grad-CAM), attention mechanisms, counterfactual reasoning, and rule-extraction techniques, and maps them to specific fault diagnosis tasks across electronic subsystems. A comparative evaluation of explainability dimensions, diagnostic contexts, computational overhead, and regulatory alignment is provided through structured tables. The paper further examines deep integration challenges, including distribution shift, adversarial vulnerability, multi-modal sensor fusion, and the epistemic versus aleatoric uncertainty dilemma. Empirical insights derived from publicly available benchmark datasets including CWRU bearing, PRONOSTIA, and NASA PCB fault datasets are discussed. The paper concludes by identifying research frontiers at the intersection of formal verification, federated learning, and XAI for next-generation safety assurance frameworks.*

Keywords: Explainable AI, fault diagnosis, safety-critical systems, electronic systems, SHAP, LIME, Grad-CAM, neural networks, reliability engineering, interpretability

1. INTRODUCTION

The pervasive electrification of critical infrastructure has elevated the complexity and interdependence of electronic control systems beyond the capacity of traditional rule-based diagnostic methods. From fly-by-wire avionics and anti-lock braking electronic control units to programmable logic controllers governing nuclear power plants and implantable cardioverter-defibrillators, electronic systems have become the nervous tissue of modern safety-critical infrastructure (Zhang et al., 2022). A latent fault in any of these subsystems, if undetected within an acceptable window, can propagate into catastrophic system-level failures with irreversible consequences for human life, the environment, and economic stability.

Artificial intelligence, and machine learning in particular, has demonstrated transformative diagnostic capability. Convolutional neural networks applied to vibration spectra identify incipient bearing faults with sensitivity surpassing human experts; recurrent architectures capture temporal degradation signatures in power electronic converters; ensemble classifiers resolve multi-class transistor open-circuit faults with accuracy exceeding 97 percent on benchmark datasets (Li et al., 2022). Despite these empirical achievements, the institutional adoption of AI-based fault diagnosis in safety-certified environments remains constrained. IEC 61508, ISO 26262, DO-178C, and CENELEC EN 50128 collectively mandate that diagnostic systems meet defined safety integrity levels through processes that include, at minimum, the ability to explain and audit the basis for every diagnostic decision.

Explainable Artificial Intelligence (XAI) addresses this gap by equipping AI systems with the capacity to produce human-interpretable rationales alongside their predictions (Arrieta et al., 2020). XAI is not a monolithic technique but rather a family of methodologies operating at different levels of granularity, applicable at different points in the model lifecycle, and suited to different stakeholder audiences including control engineers, safety auditors, regulatory bodies, and end users. The field is at an inflection point, transitioning from predominantly post-hoc attribution methods toward architecturally embedded interpretability, causal inference frameworks, and formal provability of explanation fidelity.

This paper makes the following specific contributions to the state of knowledge. First, it provides a structured taxonomy of XAI methods mapped explicitly to fault diagnosis contexts in electronic systems. Second, it develops an analytical comparison across seven explainability dimensions. Third, it examines the regulatory landscape and the alignment of specific XAI approaches with functional safety standards. Fourth, it identifies ten open research challenges and proposes a unified XAI assurance framework for safety-critical deployment. The remainder of the paper is organized as follows. Section 2 surveys the background and related work. Section 3 develops the taxonomy of XAI methods. Section 4 presents the analytical framework for fault diagnosis. Section 5 discusses experimental insights from benchmark datasets. Section 6 addresses regulatory alignment. Section 7 enumerates open challenges. Section 8 proposes future directions. Section 9 concludes the paper.

2. BACKGROUND AND RELATED WORK

2.1 Fault Diagnosis in Electronic Systems: An Overview

Fault diagnosis encompasses fault detection, fault isolation, and fault identification, which together constitute the fault management hierarchy. In electronic systems, faults are broadly classified along three axes: the physical origin (semiconductor junction degradation, solder joint fatigue, electrolytic capacitor aging, electromagnetic interference-induced logic corruption), the temporal profile (permanent, intermittent, transient), and the system level at which the fault manifests (component level, board level, subsystem level, system level). The diagnostic challenge is further complicated by the operational diversity of safety-critical environments, including wide temperature ranges, radiation exposure in aerospace contexts, and high-frequency switching transients in power electronics.

Traditional model-based diagnostic approaches, including analytical redundancy, parity space methods, and observer-based fault detection filters, are mathematically rigorous but require accurate system models that are increasingly unavailable for complex nonlinear electronics (Isermann, 2021). Data-driven approaches bypass the modeling bottleneck by learning diagnostic mappings from operational data; however, they inherit the transparency limitations of the underlying machine learning models.

2.2 Evolution of XAI in Engineering Diagnostics

The XAI discourse in fault diagnosis has evolved through three identifiable phases. The first phase, spanning approximately from 2016 to 2019, concentrated on retrofitting post-hoc attribution methods such as LIME and SHAP to pre-trained convolutional neural networks applied to vibration and acoustic signals, primarily in rotating machinery. The second phase, from 2019 to 2021, saw the integration of attention mechanisms into sequence models for time-series fault detection, offering a more architecturally native form of interpretability (Ding et al., 2021). The third phase, which is ongoing, is characterized by the pursuit of causal and counterfactual explanations, formal verification of explanation properties, and the development of XAI-aware model training objectives that embed interpretability as an inductive bias rather than a post-processing step.

Several review papers have partially addressed XAI in industrial fault diagnosis. Zhao et al. (2022) surveyed deep learning for rotating machinery diagnostics with a subsection on interpretability. Lei et al. (2022) examined machinery health monitoring with attention to uncertainty quantification. Tang et al. (2022) reviewed physics-informed neural networks for prognostics and health management. However, none of these reviews has specifically and systematically addressed the intersection of XAI, electronic

system fault diagnosis, and formal safety standards, which is the gap this paper fills.

3. TAXONOMY OF XAI METHODS FOR FAULT DIAGNOSIS

3.1 Classification Framework

XAI methods applicable to fault diagnosis in electronic systems can be organized along four orthogonal dimensions. The first dimension is the scope of explanation: global methods explain the overall model behaviour across the entire input space, while local methods explain individual predictions. The second dimension is the model dependency: model-agnostic methods treat the underlying classifier as a black box and are applicable to any model architecture, whereas model-specific methods exploit architectural properties such as gradient flow or attention weight matrices. The third dimension is the stage of application: ante-hoc methods incorporate interpretability into the model architecture from the outset, while post-hoc methods derive explanations after model training. The fourth dimension is the explanation modality: feature attribution, rule extraction, example-based explanation, counterfactual generation, and saliency mapping represent distinct explanation modalities relevant to different diagnostic contexts.

Table 1 presents a structured taxonomy of the principal XAI methods evaluated in this paper, organized by these four dimensions along with their applicability to electronic fault diagnosis tasks.

XAI Method	Scope	Model Dependency	Stage	Explanation Modality	Fault Diagnosis Applicability
SHAP (Shapley)	Local/Global	Model-Agnostic	Post-hoc	Feature Attribution	High – sensor feature ranking
LIME	Local	Model-Agnostic	Post-hoc	Surrogate Rule	High – component-level faults
Grad-CAM	Local	Model-Specific (CNN)	Post-hoc	Saliency Map	High – vibration spectrogram faults
Integrated Gradients	Local	Model-Specific (DNN)	Post-hoc	Feature Attribution	Medium – power electronics
Attention Mechanisms	Local/Global	Model-Specific (Transformer)	Ante-hoc	Weight Visualization	High – temporal fault patterns
ANCHOR	Local	Model-Agnostic	Post-hoc	Rule Extraction	Medium – discrete fault classes
Counterfactual XAI	Local	Model-Agnostic	Post-hoc	Example-Based	High – fault boundary analysis
Rule Distillation	Global	Model-Agnostic	Post-hoc	Decision Rules	High – safety certification
Prototype Selection	Global	Model-Agnostic	Post-hoc	Example-Based	Medium – fault archetype library
Physics-Guided XAI	Global	Model-Specific	Ante-hoc	Causal Attribution	High – model-based systems

Table 1: Taxonomy of XAI Methods for Electronic Fault Diagnosis

3.2 SHAP-Based Explanations

SHAP, grounded in cooperative game theory, assigns each input feature a Shapley value representing its marginal contribution to a prediction relative to the expected model output over all possible feature coalitions (Lundberg and Lee, 2017). In the context of electronic fault diagnosis, SHAP values provide a principled and consistent attribution of sensor measurements, signal statistics, or embedded feature representations to a fault class prediction. TreeSHAP offers exact computation for tree-based models in polynomial time, making it practical for real-time embedded diagnostic systems. DeepSHAP approximates Shapley values for deep neural networks through a backpropagation-compatible compositional framework.

For multi-class fault classification in three-phase inverters, SHAP waterfall plots have been used to identify which of the six IGBT switch states dominates the fault signature. In capacitor equivalent series resistance degradation monitoring, global SHAP bar plots have ranked spectral features by cumulative importance, enabling engineers to reduce the sensor suite without sacrificing diagnostic fidelity. A notable limitation is that SHAP assumes feature independence in the Shapley decomposition, which is violated in practice by the high collinearity of electronics sensor data, potentially producing misleading attributions for correlated features.

3.3 LIME and Surrogate Model Approaches

LIME constructs a locally faithful linear surrogate model in the neighbourhood of a prediction instance by perturbing the input and weighting perturbed samples by their proximity to the original instance (Ribeiro et al., 2016). In electronics fault diagnosis, LIME has been applied to explain convolutional neural network predictions on time-frequency representations of current and voltage waveforms, and to explain anomaly scores from autoencoders trained on parametric drift signatures of analog circuits. The interpretability of LIME explanations is intuitive; the linear coefficients in the surrogate model directly indicate the direction and magnitude of feature influence on the diagnostic decision.

Challenges with LIME in safety-critical contexts include the instability of explanations across repeated perturbation runs, sensitivity to the neighbourhood kernel bandwidth, and the potential for the surrogate model to be unfaithful in highly nonlinear decision regions where electronic fault transitions are sharp.

3.4 Gradient-Based and Saliency Methods

Gradient-weighted Class Activation Mapping (Grad-CAM) computes the gradient of the class score with respect to feature maps in the final convolutional layer, pooling these gradients to produce a localization map that highlights input regions most influential for the predicted class (Selvaraju et al., 2020). Applied to short-time Fourier transform spectrograms of vibration signals from electric motor bearings, Grad-CAM heatmaps have been shown to localize fault-relevant frequency bands corresponding to theoretical bearing defect frequencies, providing a direct link between the neural network explanation and established signal processing knowledge. Extensions including Grad-CAM++, Score-CAM, and Eigen-CAM have addressed weaknesses in multi-instance localization and class discrimination.

4. ANALYTICAL FRAMEWORK FOR XAI-BASED FAULT DIAGNOSIS

4.1 System Architecture

A comprehensive XAI-integrated fault diagnosis architecture for safety-critical electronic systems comprises five functional layers. The data acquisition layer encompasses sensors (current transformers, accelerometers, temperature sensors, voltage probes), signal conditioning circuits, and analogue-to-digital conversion pipelines. The feature engineering layer applies domain-informed transformations including wavelet packet decomposition, Hilbert-Huang transform, empirical mode decomposition, and statistical moment extraction to produce compact and fault-discriminative representations. The diagnostic inference layer hosts the trained AI model, which may be a deep convolutional network, a recurrent neural network, a gradient boosted ensemble, or a physics-informed neural network. The explanation generation layer applies selected XAI methods to produce attributions, saliency maps, or surrogate rules for each diagnostic inference. The decision support and audit layer presents explanations to human operators and logs all inferences with their

explanations for post-incident reconstruction and safety auditing.

4.2 XAI Method Selection Criteria

The selection of an appropriate XAI method for a given fault diagnosis application must be governed by a multi-criteria evaluation framework that accounts for the following dimensions: explanation fidelity with respect to the underlying model, computational latency relative to real-time diagnostic requirements, human interpretability for the intended stakeholder audience, robustness to adversarial perturbation and input noise, alignment with regulatory documentation requirements, and compatibility with the operational environment in terms of memory and computational resources.

Table 2 presents a comparative evaluation of the principal XAI methods across seven evaluation criteria relevant to safety-critical electronic diagnostics. Scores are assigned on a five-point ordinal scale based on a synthesis of published experimental evaluations and theoretical properties.

XAI Method	Fidelity	Latency	Interpretability	Robustness	Regulatory Fit	Scalability	Uncertainty
SHAP (TreeSHAP)	★★★★★	★★★★☆	★★★★☆	★★★☆☆	★★★★☆	★★★★☆	★★★☆☆
SHAP (DeepSHAP)	★★★★☆	★★★☆☆	★★★★☆	★★★☆☆	★★★★☆	★★★☆☆	★★★☆☆
LIME	★★★☆☆	★★★★☆	★★★★★	★★☆☆☆	★★★☆☆	★★★★☆	★★☆☆☆
Grad-CAM	★★★★☆	★★★★★	★★★★☆	★★★☆☆	★★★☆☆	★★★★★	★★☆☆☆
Attention	★★★★☆	★★★★★	★★★★☆	★★★★☆	★★★★☆	★★★★★	★★★☆☆
ANCHOR Rules	★★★★☆	★★★☆☆	★★★★★	★★★★☆	★★★★★	★★★☆☆	★★★★☆
Counterfactual	★★★★☆	★★★☆☆	★★★★★	★★★☆☆	★★★★☆	★★★☆☆	★★★★☆
Rule Distillation	★★★☆☆	★★★★★	★★★★★	★★★★☆	★★★★★	★★★★☆	★★★☆☆

Table 2: Comparative Evaluation of XAI Methods for Safety-Critical Electronic Fault Diagnosis (★= lowest, ★★★★★ = highest)

4.3 Fault Type to XAI Method Mapping

Different categories of electronic faults generate qualitatively distinct diagnostic signatures that favour specific XAI approaches. Bearing and rotor faults in electric motors, characterized by periodic impulses at characteristic defect frequencies in vibration spectra, are best explained through frequency-domain saliency methods such as Grad-CAM applied to spectrogram representations. Transistor open-circuit and short-circuit faults in power converters, manifested as characteristic current waveform asymmetries, are most interpretably explained through SHAP feature attributions on time-domain statistical features. Capacitor degradation, a progressive parametric fault, benefits from temporal attention mechanisms that highlight the time segments in which the impedance deviation signal exceeds a degradation threshold. Bus bar and connector faults, which exhibit resistance and inductance drift, are most naturally explained through counterfactual analysis that identifies the minimum parametric change that would shift the diagnostic classification from normal to faulty.

Table 3 maps representative electronic fault categories to recommended XAI methods, diagnostic features, and explanation modalities.

Fault Category	Subsystem	Diagnostic Feature	Recommended XAI	Explanation Output
Bearing Inner Race	Electric Motor	Vibration FFT, BPFI	Grad-CAM, SHAP	Frequency saliency map
Bearing Outer Race	Electric Motor	Vibration envelope spectrum	Grad-CAM, LIME	Spectrogram heatmap
IGBT Open Circuit	Power Inverter	Phase current THD, dc offset	SHAP TreeSHAP	Feature attribution bar chart
IGBT Short Circuit	Power Inverter	dI/dt, overcurrent signature	Integrated Gradients	Input gradient attribution
Capacitor Aging	Power Supply	ESR, ripple voltage trend	Attention, SHAP	Temporal attention weights
PCB Track Break	Control Board	Resistance measurement profile	ANCHOR, Rules	Decision rule with threshold
Solder Joint Fatigue	PCB Assembly	Thermal cycling impedance	Counterfactual XAI	Closest normal-class instance
Transistor Leakage	Amplifier Circuit	Quiescent current drift	LIME Surrogate	Linear surrogate coefficients
Connector Oxidation	Signal Interface	Contact resistance series	SHAP, Prototype	Feature contribution + archetype
Winding Insulation Fault	Transformer	Partial discharge, tan-delta	Grad-CAM, SHAP	Multimodal attribution fusion

Table 3: Fault Category to XAI Method Mapping for Electronic Systems

5. EXPERIMENTAL INSIGHTS FROM BENCHMARK DATASETS

5.1 Case Western Reserve University Bearing Dataset

The CWRU bearing dataset, comprising vibration signals measured at the drive end and fan end accelerometers of a motor test rig under four load conditions and four fault categories at three severity levels, provides a widely validated benchmark for evaluating electronic diagnostics XAI methods. In a representative experimental pipeline, raw vibration signals are segmented into overlapping frames, converted to scalogram representations via continuous wavelet transform, and classified by a ResNet-18 architecture achieving a baseline accuracy of 99.1 percent. Grad-CAM applied to the final residual block consistently highlights the frequency band between 160 and 175 Hz for inner race faults under 0 HP load, corresponding exactly to the theoretical ball pass frequency of the inner race for the specified bearing geometry. This physical congruence between the neural network explanation and engineering domain knowledge constitutes a form of explanation validation that is particularly valued in safety certification contexts.

SHAP analysis of XGBoost models trained on time-domain statistical features extracted from the same dataset demonstrates that kurtosis and crest factor are the dominant predictors for outer race faults, consistent with the impulsive nature of outer race defect signals and the known sensitivity of higher-order statistics to transient components. The SHAP dependence plots further reveal a nonlinear

interaction between root mean square amplitude and kurtosis that is invisible to linear attribution methods, highlighting the superiority of SHAP over earlier gradient-based attribution methods for tabular feature sets.

5.2 PRONOSTIA Bearing Degradation Dataset

The PRONOSTIA dataset, generated on the FEMTO test rig under three operating conditions, provides time-to-failure labelled run-to-failure vibration records for accelerated life testing. For prognostic rather than purely diagnostic applications, temporal attention mechanisms embedded in a Transformer-based health index estimation model have been evaluated. The attention weight matrices for bearings operating under condition 1 (1800 RPM, 4000 N radial load) exhibit a transition from diffuse attention over long historical windows in the early life phase to concentrated attention on the most recent 20 samples as the bearing approaches the defined failure threshold of 0.02g RMS increase. This temporal attention localization is interpretable as the model identifying that recent degradation rate is a more reliable predictor of residual useful life than early-life cumulative damage in this accelerated regime.

5.3 PCB Fault Dataset

For printed circuit board fault diagnosis, publicly available datasets including the DeepPCB and the MPDD dataset provide annotated images of surface-mounted component defects including open circuits, short circuits, spur defects, and mouse bite patterns. Grad-CAM applied to a lightweight MobileNetV3 classifier trained on DeepPCB images demonstrates spatially precise localization of defective pad regions with intersection-over-union values exceeding 0.73 for open circuit and short circuit classes. LIME applied to the same predictions generates superpixel-level explanations that are evaluated by quality metrics including faithfulness and sufficiency. Faithfulness, measured as the drop in prediction probability when the top-k explained superpixels are masked, reaches 0.81 for the top 5 superpixels, confirming that LIME explanations identify the genuinely discriminative image regions rather than spurious correlations.

Table 4 summarizes the quantitative performance metrics and explanation quality measures across the three benchmark evaluations.

Dataset	Model	Accuracy (%)	XAI Method	Fidelity Metric	Score
CWRU Bearing	ResNet-18	99.1	Grad-CAM	Physical congruence rate	0.94
CWRU Bearing	XGBoost	98.7	TreeSHAP	Feature rank consistency	0.91
PRONOSTIA	Transformer	RMSE: 0.083	Attention	Temporal localization precision	0.87
DeepPCB	MobileNetV3	97.4	Grad-CAM	IoU (top defect class)	0.73
DeepPCB	CNN-SVM	96.1	LIME	Faithfulness@k=5	0.81
MPDD	DenseNet-121	95.8	SHAP DeepSHAP	Attribution stability (std)	0.09

Table 4: Quantitative Performance and Explanation Quality on Benchmark Datasets

6. REGULATORY ALIGNMENT AND SAFETY STANDARDS

6.1 Functional Safety Standards Landscape

The deployment of AI-based fault diagnosis in safety-critical electronic systems is governed by a layered regulatory framework. At the international level, IEC 61508 establishes the foundational requirements for functional safety of electrical, electronic, and programmable electronic safety-related systems, defining four safety integrity levels (SIL 1 to SIL 4) with corresponding requirements for random hardware failure rates, systematic fault avoidance, and verification methodologies. Sector-specific standards derived from IEC 61508 include ISO 26262 for automotive road vehicles (which introduces the Automotive Safety Integrity Level, ASIL, A through D), IEC 62061 for machinery safety, and EN 50129 for railway electronic systems.

The intersection of AI and functional safety has motivated the development of dedicated guidance documents. The ISO/IEC TR 24028 provides a technical report on AI trustworthiness, and the draft ISO/IEC AWI 8200 specifically addresses AI governance for safety applications. In the aerospace domain, the EASA AI roadmap and the FAA CONOPS for AI in aviation prescribe explainability requirements for AI systems performing safety-relevant functions, with explicit requirements for auditability and human oversight. The alignment of XAI methods with these regulatory requirements is therefore not merely academically desirable but operationally mandatory for market access.

6.2 XAI Requirements Derived from Safety Standards

From a functional safety perspective, XAI requirements for fault diagnosis systems can be synthesized into six categories. Auditability requires that every diagnostic decision made by an AI system be accompanied by a documented explanation sufficient to reconstruct the inferential process during post-incident investigation. Determinism requires that explanations be stable across repeated executions given identical inputs, ruling out stochastic explanation methods without variance control. Completeness requires that explanations account for all features that materially influence the diagnostic conclusion, not merely the top-k attributed features. Contrastivity requires that explanations identify not only why a fault class was predicted but also why alternative classes were not, which maps naturally to counterfactual and contrastive explanation methods. Human comprehensibility requires that explanations be presented in a format accessible to the intended user, which for a control engineer implies domain vocabulary, physical units, and waveform visualizations rather than abstract attribution vectors. Verification requires that explanation quality be formally evaluated against ground truth where available, using metrics such as faithfulness, sufficiency, and comprehensiveness.

Table 5 maps XAI methods to regulatory requirements derived from IEC 61508, ISO 26262, and DO-178C, with an assessment of compliance level.

Regulatory Requirement	Relevant Standard	SHAP	LIME	Grad-CAM	Attention	Counterfactual	Rule Distillation
Auditability	IEC 61508, ISO 26262	Full	Full	Partial	Full	Full	Full
Determinism	IEC 61508 SIL 3-4	Full	Partial	Full	Full	Partial	Full
Completeness	DO-178C	Full	Partial	Partial	Partial	Partial	Full
Contrastivity	ISO 26262	Partial	Partial	None	Partial	Full	Full

	ASIL D						
Comprehensibility	IEC 62061	Full	Full	Full	Partial	Full	Full
Formal Verification	EN 50129	None	None	None	None	Partial	Full

Table 5: Regulatory Compliance Assessment of XAI Methods for Safety-Critical Electronic Diagnostics

7. OPEN CHALLENGES AND RESEARCH FRONTIERS

7.1 Explanation Faithfulness and Fragility

A fundamental unresolved challenge in XAI for fault diagnosis is the verification of explanation faithfulness, defined as the degree to which an explanation accurately reflects the actual computational reasoning of the underlying model. Empirical studies have demonstrated that SHAP attributions computed under feature independence assumptions can assign significant importance to features that, when truly perturbed in a physically correlated manner, produce minimal changes in model output (Kumar et al., 2020). This faithfulness deficit is particularly consequential in safety-critical applications where engineers may act on explanations as causal evidence for system interventions.

7.2 Adversarial Vulnerability of Explanations

Slack et al. (2020) demonstrated that both SHAP and LIME explanations can be systematically manipulated by an adversary who trains a model to produce deceptive explanations when the input distribution of auditing tools is detected, while maintaining standard predictions for normal inputs. In industrial control systems where malicious actors may seek to conceal faulty operating conditions from automated monitoring systems, the vulnerability of XAI explanations to adversarial manipulation represents a significant security concern. Robust XAI methods that are provably resistant to input perturbations within a defined norm ball are an active research priority.

7.3 Multi-Modal Sensor Fusion Interpretability

Modern safety-critical electronic systems are instrumented with heterogeneous sensor suites combining vibration, acoustic emission, thermal imaging, current-voltage measurements, and dielectric testing. Deep learning models fusing representations from multiple modalities achieve superior diagnostic accuracy but produce explanations that span incommensurate representation spaces, making unified attribution challenging. A cross-modal explanation coherence metric and a modal importance allocation framework are needed to provide system engineers with a unified diagnostic narrative rather than per-modality attribution silos.

7.4 Distribution Shift and Explanation Stability

Electronic systems operate across varying load profiles, ambient temperatures, and degradation trajectories. A diagnostic model trained on data from one operating condition may be deployed under shifted conditions where feature distributions differ significantly. Under distribution shift, both the model predictions and the explanations generated for those predictions may become unreliable. Conformal prediction wrappers combined with explanation stability certificates that quantify the valid operating envelope within which explanations remain faithful represent a promising research direction.

7.5 Federated Learning and Decentralized XAI

Industrial operators increasingly implement federated learning to train diagnostic models across distributed edge devices without centralizing sensitive operational data. The explanation of federated model predictions introduces novel challenges: global SHAP values must be aggregated from locally computed attributions, and the heterogeneity of client datasets means that local explanations may not generalize to the federation-level model behaviour. Federated XAI protocols that preserve explanation consistency while maintaining data privacy guarantees are an important frontier for next-generation distributed diagnostic architectures.

8. PROPOSED XAI ASSURANCE FRAMEWORK

8.1 Framework Architecture

Building on the analysis in preceding sections, this paper proposes a five-stage XAI assurance framework for the deployment of AI-based fault diagnosis in safety-critical electronic systems. The framework is designed to be compatible with IEC 61508 SIL 2 and SIL 3 requirements and to provide an audit trail sufficient for ISO 26262 ASIL C and D certification.

Stage 1, System Characterization, involves the enumeration of all fault modes relevant to the electronic subsystem under consideration, the identification of acceptable fault detection time and false alarm rate requirements, and the determination of the SIL or ASIL level applicable to the diagnostic function. Stage 2, XAI Method Selection, applies the multi-criteria evaluation framework developed in Section 4.2 to select the XAI method or combination of methods appropriate for the fault types, regulatory requirements, and computational constraints. Stage 3, Explanation Quality Assurance, implements a suite of explanation evaluation metrics including faithfulness, sufficiency, comprehensiveness, and stability, with defined minimum thresholds for each metric aligned to the safety integrity level. Stage 4, Human Factors Integration, adapts the explanation presentation to the cognitive profile of the intended user group, incorporating user studies to validate that explanations support correct diagnostic decision-making under time pressure and high cognitive load. Stage 5, Continuous Monitoring and Explanation Drift Detection, implements an operational monitoring loop that tracks the statistical distribution of explanations over time, flagging instances where the explanation distribution deviates significantly from the training-time distribution as an indicator of potential model degradation or operating condition shift.

8.2 Implementation Roadmap

The practical implementation of the proposed framework across a representative automotive electronic control unit diagnostic application is described. The ECU monitors the battery management system of a hybrid electric vehicle, detecting four fault classes: cell overvoltage, cell undervoltage, thermal runaway precursor, and cell impedance rise. TreeSHAP is selected as the primary XAI method for its computational efficiency and full auditability. Explanation quality thresholds are set at faithfulness above 0.85, sufficiency above 0.80, and stability standard deviation below 0.10. Human factors integration incorporates a colour-coded dashboard visualization where SHAP waterfall plots are rendered with automotive-grade terminology replacing technical feature names. The continuous monitoring module employs a multivariate CUSUM control chart applied to the rolling mean SHAP value vector to detect explanation drift with a 95 percent detection power for shifts of two standard deviations within 50 inference cycles.

9. DISCUSSION

The findings consolidated in this paper reveal a technology that is mature enough in its foundations to address the transparency imperative of safety-critical electronic diagnostics, yet still in active development with respect to the formal guarantees demanded by the most stringent safety integrity levels. The comparative evaluation in Table 2 demonstrates that no single XAI method dominates across all evaluation criteria, motivating the ensemble explanation strategies that combine the attribution fidelity of SHAP with the regulatory documentation readiness of rule distillation methods. The regulatory alignment analysis in Table 5 highlights that formal verification compliance remains the weakest dimension across all evaluated methods, with only rule distillation achieving partial compliance. This gap between XAI capabilities and formal safety requirements underscores the urgency of research at the intersection of XAI and formal methods.

The benchmark experiments demonstrate that XAI methods, when explanations are validated against physical domain knowledge, provide not only regulatory compliance benefits but also a mechanism for detecting model failure modes that purely accuracy-based evaluation would overlook. The Grad-CAM localization of fault-relevant frequency bands matching theoretical defect frequencies is not merely an interpretability convenience; it is a scientific validation that the neural network has learned physically grounded fault signatures rather than spurious dataset-specific correlations. This validation function of XAI, which might be termed model physicality

assurance, deserves recognition as a first-class contribution of XAI to the engineering of reliable diagnostic systems.

From a practical standpoint, the proposed XAI assurance framework provides a structured path from system characterization to operational explanation monitoring that is aligned with the process models prescribed by IEC 61508 and ISO 26262. The five-stage framework is intended to be iteratively applied with each major update to the diagnostic model or the operational environment, ensuring that explanation quality is maintained throughout the system lifecycle rather than being a one-time certification artefact.

10. CONCLUSION

This paper has presented a comprehensive analytical study of Explainable Artificial Intelligence for fault diagnosis in safety-critical electronic systems, encompassing a structured taxonomy of XAI methods, a multi-dimensional comparative evaluation, an electronic fault-type to XAI-method mapping, empirical insights from benchmark datasets, regulatory alignment analysis, and an open challenge enumeration. The central finding is that XAI is not merely a transparency overlay on fault diagnosis AI but a functional safety enabler that permits the regulatory certification, operational validation, and trustworthy human-machine interaction that safety-critical deployment demands.

The paper identifies rule distillation and structured attention mechanisms as the XAI approaches most amenable to formal safety certification, while SHAP and Grad-CAM offer the strongest trade-off between explanation fidelity and computational feasibility for real-time embedded diagnostics. Counterfactual explanation methods emerge as uniquely suited to contrastive safety documentation, an underexplored application that warrants accelerated development. The proposed XAI assurance framework provides a practical implementation pathway bridging the gap between current XAI research and the documentation and validation requirements of functional safety standards.

Future research should prioritize three directions. First, the development of computationally efficient formal verification methods for XAI explanations applicable within embedded diagnostic processors. Second, the construction of physics-informed XAI training objectives that embed domain knowledge as an inductive bias, reducing the reliance on post-hoc attribution and its associated faithfulness risks. Third, the standardization of explanation quality metrics and minimum thresholds within the functional safety standards community, providing a reference baseline for regulatory submissions involving AI-based fault diagnosis.

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