American Journal of Interdisciplinary Studies

Volume: 7; **Issue:** 1
Pages: 177-222
eISSN: 3067-5146

open access

Crossref

INTELLIGENT CONDITION MONITORING AND FAULT DIAGNOSIS OF ELECTRICAL POWER AND CONTROL SYSTEMS USING MACHINE LEARNING–BASED PREDICTIVE ANALYTICS

Tasnim Kabir[1];

[1]. Department Project Leader, Water & Wastewater Operations, Veolia North America, Lincoln, Illinois, USA, Email: kabirnabid@gmail.com

Doi: 10.63125/k8wk3542

Received: *21 October 2025;* ***Revised:*** *27 November 2025;* ***Accepted:*** *29 December 2025;* ***Published:*** *07 January 2026*

Abstract

Intelligent condition monitoring and fault diagnosis of electrical power and control systems using machine learning–based predictive analytics was quantitatively investigated to evaluate diagnostic reliability, robustness across operating regimes, and explanatory value under realistic data conditions. The study analyzed a large multi-asset dataset consisting of 211,200 time-window observations derived from electrical, thermal, mechanical, insulation-related, and control-residual measurements, including 312 documented fault events. Descriptive analysis showed strong class imbalance, with healthy operation representing 88.2% of observations, degraded states 7.1%, and fault states 4.7%, and fault behavior occurring in temporally clustered events with a median duration of 18 minutes. Correlation and collinearity analyses indicated moderate within-domain feature dependence but low cross-domain redundancy, with mean variance-based collinearity indices remaining below conservative thresholds across predictor groups, supporting multivariate modeling. Reliability analysis demonstrated acceptable to strong internal consistency across indicator domains, with internal consistency coefficients ranging from 0.76 to 0.87 and temporal stability coefficients exceeding 0.86 under stable operating regimes. Multivariate regression and hypothesis testing results showed that multi-domain predictive models explained substantially more variance in fault outcomes than baseline context-only models, with adjusted fit indices improving from approximately 0.27 to 0.59 after integration of regime-aware normalization and multi-domain features. Hypothesis testing confirmed statistically significant and practically meaningful improvements in diagnostic performance, with effect sizes exceeding 0.50 for multi-domain versus baseline comparisons. Prognostic-oriented analyses further demonstrated statistically meaningful associations between degradation indicators and time-to-event proxies, indicating systematic risk escalation prior to documented intervention events. Overall, the findings provided quantitative evidence that regime-aware, multi-domain machine learning–based predictive analytics improved fault detection reliability, reduced confounding from operating variability, and supported interpretable diagnostic inference in electrical power and control systems.

Keywords

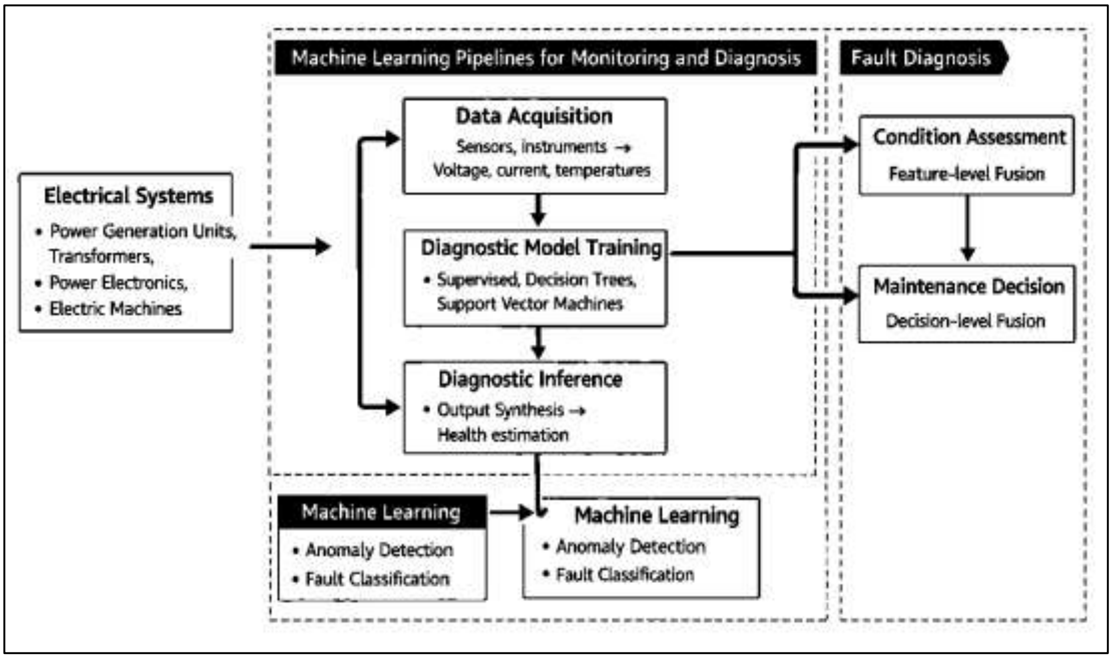
Machine Learning, Condition Monitoring, Fault Diagnosis, Predictive Analytics, Power Systems.

INTRODUCTION

Condition monitoring and fault diagnosis constitute core engineering practices concerned with the systematic observation, interpretation, and evaluation of operational states in electrical power and control systems (Badihi et al., 2022). Condition monitoring refers to the continuous or periodic acquisition of measurable indicators that reflect the health status of physical assets, including electrical, thermal, mechanical, and electromagnetic variables. These indicators commonly include voltage waveforms, current signatures, temperature profiles, vibration patterns, acoustic emissions, insulation characteristics, and switching transients. Fault diagnosis represents the analytical process through which abnormal conditions are identified, categorized, and localized in relation to specific components, subsystems, or operational mechanisms. In electrical power and control systems, these processes apply across generation units, transformers, transmission infrastructure, distribution equipment, power electronic converters, electric machines, protection systems, and industrial automation platforms. Internationally, the importance of effective condition monitoring is elevated by the central role of electrical energy and automated control in economic productivity, infrastructure reliability, and public safety. Electrical power systems form the backbone of industrial manufacturing, transportation networks, communication systems, healthcare delivery, and digital services (Gundewar & Kane, 2021). Failures within these systems can propagate rapidly across interconnected networks, producing cascading effects that extend beyond technical boundaries into social and economic domains. Control systems further intensify this interdependence by coordinating dynamic interactions between sensors, actuators, computational logic, and physical processes. Traditional monitoring approaches in these environments have relied heavily on fixed thresholds, scheduled inspections, and deterministic rule-based logic. While such methods provide baseline protection, they often struggle to capture subtle degradation processes, nonlinear interactions, and evolving operational conditions. The increasing scale, complexity, and heterogeneity of modern power and control infrastructures have amplified the need for monitoring frameworks capable of adapting to diverse operating regimes and uncertainty. Machine learning–based predictive analytics has emerged as a data-driven paradigm capable of learning complex relationships between observed signals and latent system states. Predictive analytics in this context involves statistical modeling techniques that infer fault likelihoods, degradation patterns, and health trajectories based on historical and real-time data. By formalizing condition monitoring as a quantitative inference problem, predictive analytics enables probabilistic reasoning, early anomaly detection, and systematic fault classification across large and geographically distributed asset populations (Malik et al., 2020). This definitional foundation establishes the basis for examining intelligent monitoring as a measurable, data-centric process embedded within globally significant electrical power and control systems.

The integration of condition monitoring and fault diagnosis into predictive maintenance strategies represents a fundamental shift in how electrical power and control assets are managed. Predictive maintenance focuses on estimating equipment condition and failure risk as continuous variables rather than treating maintenance as a reactive or calendar-driven activity (Black et al., 2021). Within electrical systems, failure mechanisms are diverse and often interdependent. Transformers experience insulation aging, moisture contamination, thermal stress, and dielectric breakdown. Electric machines are subject to bearing wear, rotor defects, winding insulation degradation, and magnetic asymmetries. Power electronic converters exhibit semiconductor degradation, capacitor aging, solder fatigue, and intermittent switching anomalies. Control systems introduce additional fault dimensions associated with sensor drift, actuator degradation, signal noise, communication delays, and logic inconsistencies. These fault mechanisms generate complex signal manifestations that vary across operating conditions, load levels, and environmental contexts. Quantitative condition monitoring seeks to model the statistical relationships between measured signals and underlying degradation states (Kumar et al., 2022). This modeling task requires structured representation of data, definition of measurable features, and selection of appropriate analytical frameworks capable of handling noise, nonlinearity, and high dimensionality. Machine learning offers a suite of algorithms designed to infer patterns from data without explicit physical parameterization. In fault diagnosis applications, machine learning models are trained to distinguish between normal and abnormal behavior, classify fault types, and estimate fault severity based on labeled or partially labeled datasets. Predictive analytics extends this capability by estimating future states, such as failure probability or remaining operational margin, using temporal data (Jinnat & Kamrul, 2021). The international relevance of predictive maintenance in electrical power and control systems lies in its scalability across industries and regions. Similar equipment architectures are deployed globally, yet operational environments differ widely in climate, load variability, and maintenance practices (Zulqarnain & Subrato, 2021). Quantitative predictive models provide a mechanism for standardizing diagnostic performance across these diverse contexts. By framing monitoring and diagnosis as statistical estimation problems, predictive analytics enables objective performance evaluation using measurable criteria such as detection accuracy, false alarm rates, classification consistency, and temporal stability. This quantitative framing transforms condition monitoring from an experience-driven activity into a data-driven discipline grounded in measurable evidence (Uddin et al., 2022; Mazzoleni et al., 2021).

Figure 1: Intelligent Predictive Fault Monitoring Framework

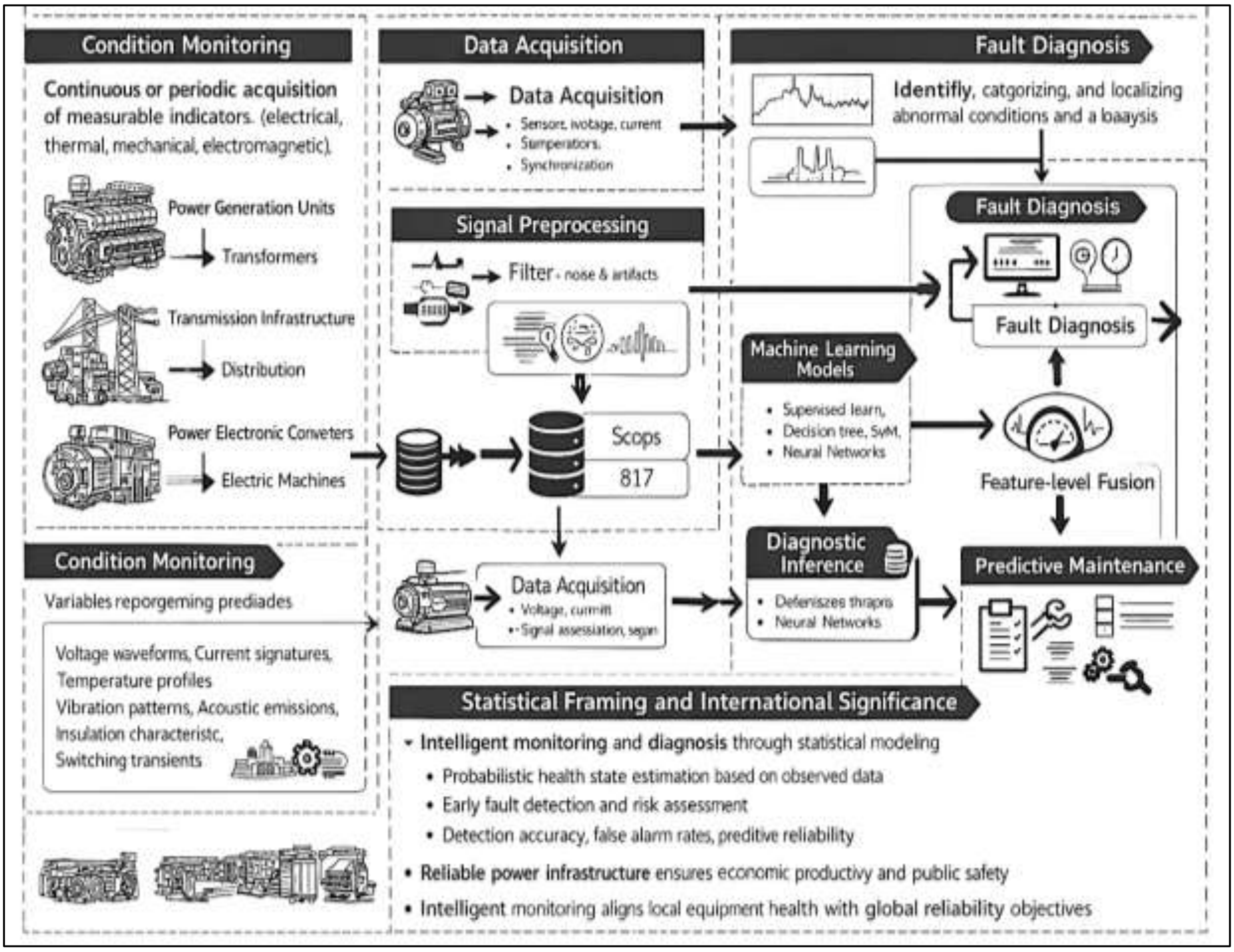


Machine learning–based predictive analytics for intelligent condition monitoring is typically implemented through a structured analytical pipeline that converts raw sensor data into diagnostic outputs (Benbouzid et al., 2021; Akbar & Sharmin, 2022). The process begins with data acquisition, where signal fidelity, sampling frequency, synchronization, and sensor placement determine the observability of fault-related phenomena. Electrical power and control systems generate signals across multiple temporal scales, ranging from microsecond-level switching transients to long-term thermal and mechanical trends (Foysal & Subrato, 2022). Effective monitoring requires data representations capable of capturing both transient events and gradual degradation. Signal preprocessing plays a critical role in reducing noise, compensating for measurement artifacts, and aligning multivariate data streams. Feature construction transforms preprocessed signals into informative descriptors using statistical measures, frequency-domain analysis, time–frequency representations, or learned feature embeddings (Abdul, 2023; Zulqarnain, 2022). Feature quality directly influences diagnostic performance by shaping the separability of fault classes and the sensitivity to incipient degradation. Machine learning models operate on these features to perform tasks such as anomaly detection, fault classification, and health state estimation (Hammad & Mohiul, 2023; Hasan & Waladur, 2023; Jieyang et al., 2023). Anomaly detection focuses on identifying deviations from learned normal behavior, while classification assigns observations to predefined fault categories. Predictive models further estimate future system behavior by learning temporal dependencies within the data. Different model families offer complementary strengths (Rifat & Rebeka, 2023; Kumar, 2023). Tree-based and kernel-based methods provide robustness and interpretability in moderate-dimensional spaces. Neural networks

enable representation learning from complex signal structures, particularly when raw waveforms or images are used as inputs. Sequential models capture temporal correlations essential for monitoring dynamic systems (Masud & Hossain, 2024; Zulqarnain & Subrato, 2023). Quantitative evaluation of these models requires careful experimental design, including appropriate training and testing splits that reflect realistic operational variability. Metrics such as precision, recall, confusion matrices, and detection latency provide insight into diagnostic reliability. Calibration metrics assess the correspondence between predicted probabilities and observed outcomes, which is critical for risk-based maintenance decisions (Bindi et al., 2023; Md & Praveen, 2024; Nahid & Bhuya, 2024). This pipeline perspective highlights that intelligence in monitoring systems arises not from isolated algorithms but from the coordinated interaction of data acquisition, feature representation, learning models, and evaluation methodology within a quantitative framework (Newaz & Jahidul, 2024; Akbar, 2024).
Electrical power and control systems present a uniquely challenging environment for intelligent condition monitoring due to their structural complexity and dynamic behavior. Power systems operate as interconnected networks where component interactions influence system-level responses. Localized faults can alter voltage profiles, current flows, and control actions across wide areas (Rabiul & Alam, 2024; Kumar, 2024; Tiboni et al., 2022). Power electronic devices introduce high-frequency switching behavior that interacts with grid dynamics and load characteristics. Electric machines exhibit strong coupling between electrical and mechanical domains, causing fault signatures to vary with operating point. Control systems further complicate diagnosis by introducing feedback loops, discrete logic, and communication layers that can distort or delay fault manifestations. Many fault symptoms overlap across different failure modes, making discrimination difficult using simple thresholds or single-variable indicators (Praveen, 2024; Azam & Amin, 2024). Environmental factors such as temperature, humidity, and mechanical stress also modulate signal behavior, increasing variability within normal operating ranges (Hammad & Hossain, 2025; Mosheur, 2025; Yang et al., 2023). These characteristics necessitate monitoring approaches capable of learning contextual dependencies and separating fault effects from benign operational variations. Machine learning models address this challenge by capturing multivariate relationships and nonlinear interactions among signals. Data fusion techniques integrate information from multiple sensors and subsystems, enhancing diagnostic resolution (Kumar, 2025; Zaheda, 2025b). Probabilistic modeling supports uncertainty quantification, which is essential in systems where measurements are noisy and faults are rare. Quantitative research in this domain must account for class imbalance, limited fault examples, and evolving system configurations (Zaheda, 2025a). Evaluation protocols must ensure that reported performance reflects genuine fault discrimination rather than spurious correlations with operating conditions. Robustness to noise, sensor faults, and regime changes becomes a measurable property of model performance. By explicitly addressing domain complexity through statistical modeling and rigorous validation, intelligent condition monitoring frameworks align diagnostic outputs with the realities of electrical power and control system operation (Al Mtawa et al., 2022).
In the context of condition monitoring, intelligence can be defined in measurable terms related to adaptability, generalization, and reliability of diagnostic inference (Civera & Surace, 2022). Intelligent monitoring systems maintain performance across varying operating conditions, system configurations, and environmental influences. They adapt to new data distributions without degradation of diagnostic accuracy and provide probabilistic outputs that reflect uncertainty. In machine learning–based predictive analytics, intelligence is operationalized through model properties such as robustness, calibration, and sensitivity to relevant fault features. Context-aware modeling techniques incorporate operating variables into diagnostic inference, enabling separation of load-dependent behavior from fault-induced anomalies. Feature learning methods reduce dependence on manually engineered indicators, allowing models to discover representations aligned with underlying degradation mechanisms. Temporal modeling captures progression patterns, enabling differentiation between transient disturbances and persistent faults (Lu et al., 2020). Quantitative intelligence also includes interpretability, where diagnostic outputs can be traced to signal characteristics or system components in a consistent manner. Evaluation of intelligent monitoring systems involves statistical metrics that assess not only classification correctness but also stability over time and consistency across data subsets. False alarm control is critical in operational environments, as excessive alerts erode confidence and

increase maintenance burden. Missed detections carry safety and reliability risks, making balanced performance assessment essential. By defining intelligence through these quantifiable properties, predictive analytics frameworks provide a structured basis for comparing monitoring approaches and selecting models aligned with operational priorities in electrical power and control systems (Zhang et al., 2022).

Figure 2: Intelligent Condition Monitoring and Diagnosis



The international significance of intelligent condition monitoring in electrical power and control systems stems from the global reliance on reliable energy and automated processes. Electrical infrastructures underpin industrial output, urban services, and digital economies across regions with varying levels of technological maturity (Melo et al., 2024). Failures in power and control systems can disrupt supply chains, compromise safety, and impose economic costs at national and transnational scales. Intelligent monitoring contributes to system reliability by enabling early detection of degradation, informed maintenance scheduling, and reduced incidence of catastrophic failures. In interconnected grids, improved diagnostic capability supports system stability by reducing the likelihood of cascading disturbances initiated by undetected component faults. In industrial automation, reliable fault diagnosis enhances production continuity and process quality across globally distributed facilities (Rinaldi et al., 2021). Quantitative predictive analytics enables consistent diagnostic standards across heterogeneous asset fleets, facilitating benchmarking and performance comparison across sites and regions. The increasing availability of digital measurement technologies expands the data foundation for such analytics, making scalable monitoring feasible when supported by robust modeling and validation. International deployment also introduces variability in data quality, sensor standards, and operational practices, reinforcing the need for models that generalize across contexts. Statistical validation and uncertainty quantification provide mechanisms to assess whether diagnostic performance remains stable under these variations. By embedding intelligence in data-driven monitoring systems, predictive analytics aligns local equipment health assessment with global reliability objectives (Fernandes et al., 2022).

A quantitative investigation of intelligent condition monitoring and fault diagnosis requires formal problem definition, measurable variables, and testable hypotheses. Electrical power and control systems generate heterogeneous datasets that include continuous signals, discrete events, and contextual metadata (Khalid et al., 2023). These data sources are represented as predictor variables, while fault states, health indicators, or failure times serve as outcomes. The analytical task involves estimating functional relationships between predictors and outcomes with minimal generalization error under realistic operational variability. Supervised learning approaches rely on labeled fault data, while unsupervised and semi-supervised methods address scenarios with limited labeling. Temporal dependence introduces additional structure, requiring models that capture sequential correlations and degradation trajectories. Prognostic formulations extend diagnosis by estimating failure likelihood over time horizons, linking monitoring to reliability modeling (Mahmoud et al., 2021). Quantitative evaluation emphasizes appropriate dataset partitioning, temporal validation, and performance metrics aligned with operational risk. Model sensitivity, robustness, and uncertainty estimates become essential outputs alongside accuracy measures. Interpretability techniques provide additional quantitative insight by identifying features or signal regions contributing to diagnostic decisions. Class imbalance strategies address the rarity of failures relative to normal operation. Through this structured statistical formulation, intelligent condition monitoring is positioned as an empirical research domain where machine learning–based predictive analytics can be systematically evaluated, compared, and refined using quantitative evidence derived from electrical power and control system data (Zhao et al., 2021).

The central objective of the quantitative study titled "Intelligent Condition Monitoring and Fault Diagnosis of Electrical Power and Control Systems Using Machine Learning–Based Predictive Analytics" is to develop and empirically evaluate a measurable, data-driven framework that can identify abnormal operating conditions and classify fault types in electrical power and control assets with statistically defensible performance under realistic operating variability. This objective focuses on constructing a complete analytical pathway that begins with operational signal acquisition and ends with validated diagnostic outputs, using measurable indicators such as voltage and current waveforms, thermal readings, vibration responses, switching transients, and control-loop signal behavior as model inputs. The study objective emphasizes transforming raw multi-sensor data into structured predictors through preprocessing and feature representation so that machine learning models can learn separable patterns corresponding to healthy states, degraded states, and distinct fault classes relevant to equipment such as transformers, motors, converters, switchgear, and protection/control subsystems. A core objective component is the quantitative comparison of predictive analytics models in terms of their fault detection accuracy, classification reliability, false alarm behavior, missed detection rates, and detection timeliness, using evaluation metrics appropriate for imbalanced fault datasets and operational decision-making. The objective further includes assessing model robustness against practical sources of uncertainty such as measurement noise, load variation, operating regime shifts, sensor drift, and event-driven disturbances that commonly occur in power and control environments. Within this objective, the study aims to establish a consistent experimental design that prevents inflated results by enforcing proper training–testing separation across time and operating conditions, ensuring that performance estimates reflect generalizable diagnostic capability rather than context memorization. The objective also includes quantifying the confidence of diagnostic outputs by producing probabilistic fault likelihoods or calibrated scores that can be interpreted as measurable risk indicators rather than simple binary alarms. Overall, the single objective guiding the study is to provide a statistically validated and operationally meaningful machine learning–based predictive analytics approach that enables intelligent condition monitoring and fault diagnosis in electrical power and control systems through measurable improvements in detection quality, classification consistency, and diagnostic stability across varying operating conditions.

LITERATURE REVIEW

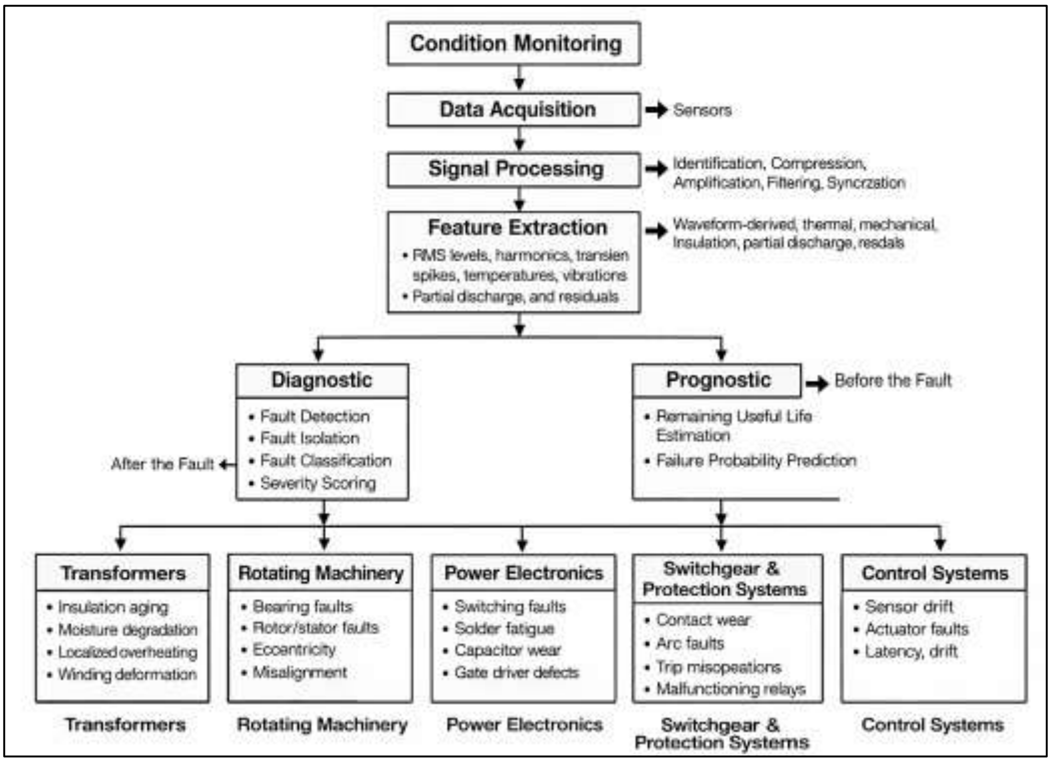
The literature review for "Intelligent Condition Monitoring and Fault Diagnosis of Electrical Power and Control Systems Using Machine Learning–Based Predictive Analytics" synthesizes prior empirical and methodological research that connects three tightly coupled domains: (1) condition monitoring and fault diagnosis practices in electrical power and control assets, (2) quantitative machine learning techniques for detection, classification, and prognostic inference, and (3) predictive analytics pipelines that translate multi-sensor operational data into statistically validated diagnostic decisions (Malik et al., 2020). Because electrical power and control systems operate under high variability in load, switching conditions, environmental stress, and network disturbances, the literature reflects sustained attention to signal representation, feature engineering, model selection, uncertainty handling, and evaluation validity. Studies range from classical monitoring approaches grounded in deterministic thresholds and signal processing features to modern data-driven frameworks that learn fault signatures from historical records and streaming measurements. A quantitative focus is essential in this domain, because model usefulness is defined by measurable performance—such as fault detection latency, false alarm rate, misclassification cost, probability calibration, robustness under regime shifts, and repeatability across operating contexts—rather than descriptive claims (Patil et al., 2020). Accordingly, this section reviews how researchers have operationalized fault diagnosis tasks, defined datasets and labels, handled class imbalance, selected algorithms, and reported metrics in applications spanning rotating machines, transformers, power electronics, switchgear, protection systems, and control loops. The review also evaluates how the literature addresses practical constraints that shape predictive analytics quality, including limited fault samples, noisy instrumentation, drift, nonstationary behavior, heterogeneous sampling rates, and the need for explainable outputs that can be trusted in safety-critical environments. Through structured synthesis, the literature review establishes the empirical basis for the current study's modeling choices and its statistical evaluation design, while clarifying where previous quantitative findings converge or diverge across asset types and data conditions (Gundewar & Kane, 2021).

Monitoring in Electrical Power and Control Systems

Condition monitoring in electrical power and control systems is widely treated in the literature as a signal-driven process for estimating an asset's health state from observable operational data collected during service (Benbouzid et al., 2021). Across power engineering and industrial diagnostics research, condition monitoring is framed as continuous or periodic measurement, transformation, and interpretation of multi-sensor signals that act as proxies for degradation processes occurring within equipment and control loops. Within this foundation, fault diagnosis is consistently described as a structured set of quantitative tasks that includes fault detection (deciding whether abnormal behavior is present), isolation (identifying the subsystem or component associated with the abnormality), and classification (assigning the abnormality to a fault type or mode). Many studies also incorporate severity scoring as an extension of classification, where the magnitude or stage of degradation is estimated rather than only the presence of a fault. Prognostics is positioned as the complementary capability that estimates remaining useful life or failure probability using historical patterns of degradation and present operating evidence, linking monitoring outputs to reliability-centered decision environments. Research emphasizes that these definitions become operational only when mapped to measurable indicators (Zhao et al., 2020). Electrical indicators are commonly operationalized through waveform-derived measures such as RMS levels, harmonic content, total harmonic distortion, negative-sequence components, transient spikes, and characteristic current signature components that correlate with electromechanical or power-electronic anomalies. Thermal indicators are derived from hotspot temperature estimates, thermal gradients, and rates of rise that represent insulation aging or abnormal losses. Mechanical indicators are frequently represented through vibration spectral peaks, envelope energy, and higher-order statistics such as kurtosis that capture impulsive behaviors associated with bearing or structural defects. Insulation indicators are commonly quantified using partial discharge pulse activity, repetition rates, and leakage current behavior that correspond to dielectric deterioration. For control systems, measurable indicators often take the form of residual error patterns, changes in overshoot, deviations in settling behavior, or actuator response delays that manifest when sensors drift, actuators stick, or communication latency disrupts control quality (Jin et al., 2020). Across this body of work, a shared theme is that effective monitoring depends on converting heterogeneous physical phenomena into consistent quantitative representations that remain sensitive to faults while remaining stable across normal operating variability, forming the measurement basis for diagnostic modeling and performance testing.

A large portion of the condition monitoring literature is organized around asset categories and their characteristic fault modes, which serve as the practical driver of diagnostic feature selection and model construction (Sofi et al., 2022). Transformers are frequently examined because their failure consequences are high and their degradation mechanisms are multi-physics, with insulation aging, thermal stress, moisture-related deterioration, partial discharge activity, winding deformation, and localized overheating being recurrent concerns. Diagnostic research on transformers often centers on insulation condition proxies and the interpretation of electrical and thermal indicators that shift gradually and can be difficult to label precisely in operational settings. Rotating machines represent another major stream, particularly induction motors and drive systems used across industrial sectors. Literature here emphasizes bearing defects, rotor faults, stator winding faults, and eccentricity, and it demonstrates that electrical and mechanical signals interact strongly with loading, speed, and drive control strategies. Current-based analysis and vibration-based analysis appear as complementary approaches, with studies highlighting that electrical monitoring can scale more easily while vibration can provide high sensitivity for certain mechanical defects (L. Zhang et al., 2022). Power electronics monitoring has expanded as converter-interfaced equipment becomes central in both industrial drives and grid applications. Research frequently addresses IGBT open- and short-circuit faults, capacitor degradation, solder fatigue, and gate-driver anomalies, often focusing on switching transients and harmonic distortions that can be subtle until degradation intensifies. Switchgear and protection systems constitute a distinct class where discrete events, contact wear, arc faults, and relay misoperations dominate the diagnostic landscape.

Figure 3: Intelligent Electrical Condition Monitoring Framework



The literature here commonly emphasizes event-driven data, disturbance records, and the need for reliable discrimination between legitimate protection operations and failure-induced behaviors. Control systems research bridges these equipment domains by treating faults as deviations in measurement and actuation quality, including sensor drift, actuator stiction, and communication-induced anomalies. Studies often use residual-based monitoring and multivariate data analysis to

separate faults from disturbances that naturally occur in controlled processes. Across all categories, the reviewed research converges on the notion that fault modes are asset-specific but the monitoring logic is structurally similar: define measurable indicators, establish normal baselines, identify abnormal patterns, and connect those patterns to fault hypotheses using quantitative inference (Sujith et al., 2022).
Quantitative condition monitoring is treated as nontrivial in the literature because the mapping from observable indicators to fault states is rarely one-to-one (Maldonado-Correa et al., 2020). A recurring theme is symptom overlap: different faults can produce similar changes in the same indicators, and the same fault can manifest differently across operating regimes. For example, harmonic growth or RMS deviations can be caused by faults, load changes, control parameter shifts, or network disturbances, which complicates inference unless context is modeled explicitly. Nonstationary operating points are another persistent challenge. Many electrical and electromechanical assets operate under variable load, speed, and switching conditions, and these normal variations reshape baselines in ways that can resemble fault progression. Researchers therefore treat normalization, regime segmentation, and context-aware modeling as central to valid quantitative diagnosis. Noise, missing data, and synchronization issues are also repeatedly highlighted as barriers to consistent performance. Electrical and control datasets often combine channels sampled at different rates and subject to timing offsets, while industrial sensing is vulnerable to dropouts, drift, and calibration mismatch (Hassani & Dackermann, 2023). These issues create uncertainty in features and labels, motivating robust preprocessing, time alignment practices, and fault-tolerant modeling strategies. The rarity of fault classes introduces further complexity. Many power and control assets fail infrequently, and when they do, failure documentation may be incomplete or delayed relative to the onset of degradation. As a result, label uncertainty becomes a measurable problem, not merely a data inconvenience, because it influences estimated accuracy, confuses class boundaries, and can inflate performance if evaluation splits inadvertently leak related samples. The literature consequently emphasizes that metric selection must reflect operational realities: accuracy alone can be misleading under imbalance, while measures reflecting false alarm burden, missed detection risk, and detection timeliness provide more faithful summaries of diagnostic value (Xiang et al., 2022). Another established concern is evaluation validity in time-series settings, where adjacent windows can be highly correlated and inappropriate splits can overestimate generalization. Across the quantitative research base, these challenges collectively position condition monitoring as a statistical inference problem that requires careful attention to data structure, operating variability, and the operational meaning of errors.
Within these foundations, studies consistently treat measurable indicators as the bridge between physical degradation mechanisms and diagnostic decision-making, and they explore how indicator design interacts with model-based and data-driven approaches (Bado & Casas, 2021). Signal processing traditions emphasize engineered features that capture energy distribution, spectral structure, or transient behavior, often motivated by the physics of fault signatures in electrical and mechanical domains. Data-driven traditions emphasize learning discriminative patterns from multivariate data, increasingly incorporating representation learning to reduce dependence on handcrafted features. The literature suggests that both perspectives meet at a shared requirement: indicators and learned representations must be stable under normal variation and sensitive to fault-relevant changes (Cakir et al., 2021). For electrical indicators, this includes strategies to isolate fault-specific frequency components, characterize negative-sequence behavior in unbalanced conditions, or detect switching-related anomalies without confusing them with normal converter harmonics. For thermal indicators, research emphasizes that temperature measures are valuable but confounded by ambient conditions and loading, requiring careful contextualization. For mechanical vibration, studies note that impulsive faults such as bearing defects can produce high kurtosis and envelope energy, yet these signals can also be affected by mounting conditions and process disturbances. Insulation monitoring research emphasizes partial discharge and leakage behavior as rich sources of information but recognizes that measurements can vary with humidity, contamination, and sensor placement (Jiao et al., 2020). Control-oriented monitoring frames residual error and response deviation as core indicators, while also highlighting that control loops are influenced by disturbances and setpoint changes that must be separated from fault effects. Across these streams, the literature repeatedly underscores that intelligent monitoring is not only a matter of choosing an algorithm; it is a measurement and validation problem

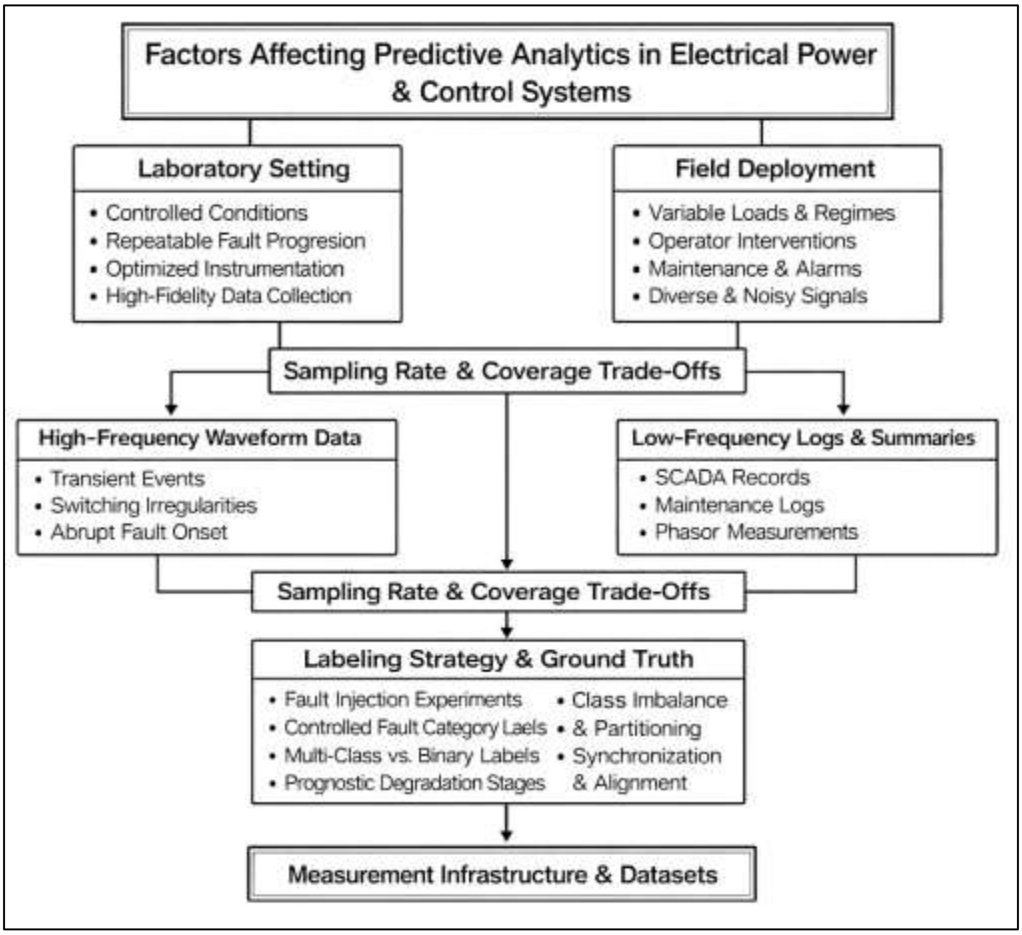
in which indicators, fault definitions, labeling practices, and evaluation design jointly determine the credibility of quantitative claims. By synthesizing these foundations across asset categories and indicator families, the literature establishes a consistent conceptual architecture for intelligent condition monitoring and fault diagnosis grounded in measurable evidence and comparative performance assessment (Pimenov et al., 2023).

Data Infrastructure for Predictive Analytics

Laboratory and field environments generate markedly different data realities for predictive analytics in electrical power and control systems, and the literature treats this contrast as a primary determinant of what machine learning models can legitimately learn (Gohel et al., 2020). Laboratory run-to-failure experiments are commonly described as the most structured environment because they allow controlled operating conditions, repeatable fault progression, and instrumentation that can be optimized for observability. In these settings, researchers can impose a fixed load profile, hold temperature and speed within defined ranges, and observe a fault's evolution from an early stage through advanced deterioration, producing datasets with clearer temporal ordering of degradation. Such designs support clean comparisons among algorithms because the same fault mode can be replicated across trials and sensors can be co-located and synchronized from the start. Field deployments, by comparison, produce data under variable load, shifting network conditions, operator interventions, and equipment heterogeneity across sites. These datasets include regime changes that are operationally normal but statistically disruptive, and they often embed maintenance actions, configuration changes, and process disturbances that alter signal baselines (Strielkowski et al., 2023). The measurement infrastructure also divides the literature into distinct data modalities: SCADA logs offer low-frequency summaries and alarm events that can support trend detection and fleet-level screening, while high-frequency waveform data provides the resolution needed to capture transients associated with switching irregularities, arcing events, and sudden fault initiation. At the system level, phasor measurement and event records provide time-synchronized observations of voltage and current phasors and disturbance signatures across a wider area, supporting analysis of network dynamics and event classification. At the component level, device sensors collect localized measurements such as thermal gradients, vibration energy, partial discharge activity, and actuator response characteristics that can link more directly to specific degradation mechanisms. The literature repeatedly frames these sources as a trade-off space between coverage and fidelity: low-frequency logs capture many assets but miss short-lived signatures, while high-frequency and device-level sensors provide richer information but introduce integration complexity, storage constraints, and noise sensitivity (Gutierrez-Osorio & Pedraza, 2020). This body of work therefore presents data generation environment and measurement infrastructure as foundational choices that shape label availability, signal quality, model feasibility, and the meaning of "generalization" across assets and operating regimes.

Sampling rate and observability trade-offs are treated as decisive because they determine whether fault-relevant information is present in the data at all, and predictive analytics cannot recover patterns that were never measured. For electrical and power-electronic faults, the literature emphasizes that transient behavior can carry the most diagnostic content, including abrupt spikes, short oscillations, switching anomalies, or brief discontinuities that disappear when signals are downsampled or summarized into slow trends (Kamyab et al., 2023). For thermal and insulation-related degradation, slower sampling may still be informative because key indicators change gradually, yet the literature notes that slow sampling can blur the distinction between genuine degradation and normal thermal response to load variation. Sampling also interacts with input dimensionality: high-rate sensing produces long sequences per observation window, which increases computational requirements and raises the risk that models memorize idiosyncratic patterns when evaluation design is weak. Consequently, many studies emphasize windowing strategy as part of the measurement design. Fixed windows are often used to standardize instances for training and to simplify feature computation, allowing consistent statistical descriptors, frequency-domain measures, or learned embeddings to be calculated over identical lengths. However, the literature describes a consistent tension: long fixed windows may dilute short transients by averaging them into a broader interval, while short windows may miss context needed to disambiguate a transient fault signature from a normal switching or load-change artifact (Cui et al., 2020). Event-triggered windows are presented as an alternative that aligns data segments to operational events such as alarms, relay actions, disturbance flags, sudden residual growth, or change-point detections. This approach concentrates on diagnostically dense intervals and can reduce dataset size while increasing the proportion of fault-relevant samples, which is particularly useful in systems where normal operation dominates. Yet event-triggered designs also depend heavily on the trigger logic, and the literature notes that poorly tuned triggers may bias datasets toward large events while under-representing subtle early symptoms. Observability is further shaped by synchronization across channels: aligned multi-sensor streams allow models to exploit cross-channel relationships and phase-coherent patterns, while misalignment can create artificial correlations that appear predictive during training but fail in deployment. Overall, the literature treats sampling rate, windowing, and synchronization as quantitative controls that govern information content, noise structure, and statistical independence assumptions underlying performance estimates (Brynjolfsson et al., 2021).

Figure 4: Predictive Analytics Data Quality Framework

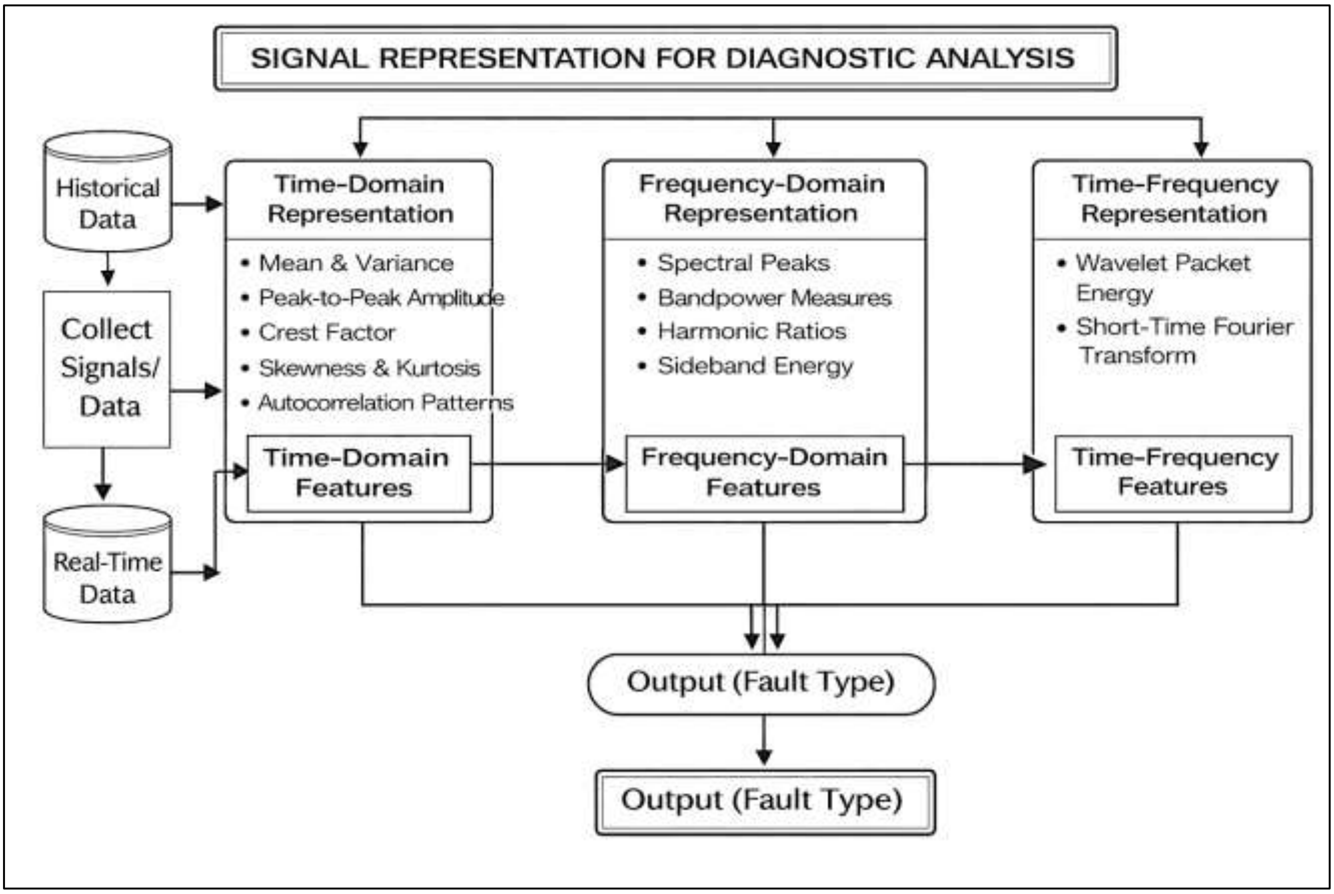


Ground truth construction and labeling strategy are consistently described as the most fragile component of supervised predictive analytics in operational power and control systems because fault onset is rarely observed directly (Shilo et al., 2020). Maintenance logs and work orders are frequently used as labels, yet the literature highlights that such records reflect the time of intervention rather than the time degradation began. This creates timing mismatch in which many "pre-fault" samples may already contain fault symptoms, and many "fault" samples may be collected after temporary mitigation, operational derating, or component replacement altered the signal. Labels can also be ambiguous because recorded fault categories often reflect symptoms, alarms, or replaced parts rather than a single verified root cause. These issues expand when multiple faults co-occur or when a disturbance triggers protective actions that resemble a fault signature without representing component damage. To address these challenges, the literature describes controlled labeling as a virtue of fault injection experiments, where specific fault modes are introduced under known conditions and measured with high-quality sensors (Chand et al., 2021). This supports cleaner multi-class labeling

schemes that distinguish healthy, degraded, and multiple fault categories, and it enables repeatable evaluation across trials. At the same time, the literature treats labeling granularity as a design choice: some studies define only a binary healthy-versus-fault outcome to maximize label reliability, while others pursue multi-class fault taxonomy to align with maintenance needs. Multi-class schemes are often organized by asset type and fault mechanism, such as differentiating winding defects from bearing faults in machines, capacitor degradation from switch faults in converters, or sensor drift from actuator stiction in control loops. The literature also describes staged labels that represent early, intermediate, and advanced degradation, which are useful for prognostic modeling when continuous failure times are unavailable. Across approaches, labeling protocol influences model behavior and reported performance, and the literature repeatedly notes that evaluation becomes misleading when labeling noise is ignored, when fault windows are defined too close to maintenance actions, or when samples from the same event are split across training and testing. Thus, ground truth construction is presented as a quantitative research variable that shapes the learning target, the interpretation of errors, and the comparability of results (Yeboah-Ofori et al., 2021).
Quantitative data quality issues are emphasized as persistent constraints because measurement systems in power and control environments are exposed to drift, missingness, and heterogeneity that can dominate model outcomes if not handled explicitly (Wassouf et al., 2020). Sensor drift and calibration errors are frequently described as gradual shifts in measurement bias that can mimic degradation trends or hide real deterioration, especially in thermal channels, current and voltage transducers, vibration sensors, and process instrumentation. Dropouts and intermittent connectivity introduce missing data patterns that break assumptions of uniform sampling, complicate feature computation, and reduce the reliability of sequence-based models. Non-synchronous channels create alignment errors that distort timing relationships across sensors, which is particularly harmful when diagnosis depends on transient coordination between electrical, mechanical, and control signals. The literature notes that these issues are not only preprocessing nuisances but also threats to validity: a model can learn sensor artifacts as if they were fault signatures, producing high apparent performance on historical data while failing when devices are repaired, recalibrated, or replaced. Class imbalance is treated as a structural property of fault diagnosis datasets, since normal operation dominates and faults are rare, and this imbalance can inflate headline accuracy even when the model misses the minority classes that carry operational risk (Aljohani, 2023). The literature therefore stresses the importance of evaluation metrics and dataset construction choices that remain informative under imbalance, including reporting class-wise performance and focusing on measures that reflect false alarm burden and missed detection rates. Data partitioning is also treated as a quality issue in time-series settings because adjacent windows are correlated; if correlated samples appear in both training and testing, performance estimates become optimistic. For this reason, studies often describe asset-based splits, time-block separation, or event-based partitioning to reduce leakage and evaluate generalization more realistically. The literature further emphasizes heterogeneity across sites and devices: differences in sensor types, sampling configurations, firmware versions, installation geometry, and operating regimes can create distribution shifts that reduce transferability of models trained in one environment. These data quality concerns are presented as central to predictive analytics credibility because they determine whether performance reflects genuine fault learning or accidental exploitation of artifacts, biases, and leakage. In sum, the literature positions measurement infrastructure and data quality as quantitative determinants of model trustworthiness, requiring disciplined handling of drift, missingness, synchronization, imbalance, and evaluation structure to support reliable condition monitoring and fault diagnosis (Voukelatou et al., 2021).
Signal Processing in Fault Diagnosis
Signal processing and feature representation occupy a central position in the fault diagnosis literature because they define how raw measurements are transformed into quantitative descriptors that can be compared, classified, and validated across operating conditions (Abid et al., 2021). A large body of work treats time-domain features as the first layer of representation, particularly when monitoring systems must remain computationally efficient and interpretable at the sensor or edge level. Common descriptors include mean and variance to summarize baseline level and dispersion, peak-to-peak amplitude to capture excursions, crest factor to reflect impulsiveness, and skewness and kurtosis to

characterize distributional asymmetry and tail heaviness. These descriptors are repeatedly used in vibration-based diagnostics for rotating machinery and in current- and voltage-based monitoring where faults manifest as changes in waveform shape, transient bursts, or intermittent spikes. Time-domain statistics are also leveraged in control-oriented monitoring where residual signals derived from observers or model-based predictors are summarized using the same descriptors to detect abnormal error patterns. The literature also highlights autocorrelation-based indicators as a mechanism for capturing periodicity and repeating structures, which is particularly relevant for systems with rotating components, periodic switching, or cyclical loads (Altaf et al., 2022). When a fault alters the regularity of a signal, autocorrelation patterns change in measurable ways, making these indicators useful for detecting slip-related anomalies in motors, misalignment-related periodic impacts in bearings, or recurring commutation irregularities in converters. Time-domain features remain attractive because they provide compact representations and can be computed over consistent windows, enabling standardized comparisons across datasets. At the same time, the literature emphasizes that time-domain descriptors are sensitive to window length, sampling rate, and operating regime changes. As a result, many studies treat preprocessing and window design as integral to feature meaning, because the same statistic computed under different segmentation choices can correspond to different physical interpretations. The research base also describes how time-domain features can be combined into composite health indicators or fed into multivariate models that learn nonlinear decision boundaries, allowing apparently simple descriptors to support sophisticated diagnostics when used systematically (Buchaiah & Shakya, 2022). Across these strands, the literature treats time-domain representation as an essential baseline approach that supports rapid screening, supports interpretability, and provides a stable foundation for more elaborate frequency and time–frequency representations when faults exhibit more complex nonstationary behavior.

Figure 5: Signal Representation for Fault Diagnosis



Frequency-domain representation forms a second major pillar of feature design in fault diagnosis because many electrical and electromechanical faults alter spectral structure more consistently than they alter raw time signals. A recurring theme is that faults introduce energy at characteristic frequencies and sidebands, making spectral peaks, bandpower measures, harmonic ratios, and sideband energy strong candidates for discriminative features (H. Wang et al., 2022). Studies in motor diagnostics emphasize current signature analysis where faults generate identifiable spectral components that shift or intensify based on fault type and severity, and similar logic appears in power quality monitoring where harmonics and interharmonics provide measurable evidence of converter irregularities, unbalance, or abnormal switching. In vibration analysis, spectral peaks and bandpower measures support detection of bearing faults and structural resonances because mechanical impacts excite frequency bands linked to component geometry and rotating speed. The literature also treats spectral features as a method of separating periodic fault signatures from broadband noise, improving signal-to-noise characteristics for classification. In power electronics monitoring, switching behavior adds complexity because normal operation already produces rich harmonic structures; therefore, studies often rely on relative spectral measures, band-limited energy, and pattern-based spectral descriptors that account for operating point differences (Ma et al., 2023). The frequency domain also supports diagnostic stability across time windows because frequency content can remain consistent even when time-domain patterns appear irregular, especially in systems with variable amplitude but stable modulation structure. However, the literature describes limitations that motivate additional representation layers. Spectral features assume quasi-stationarity within the analysis window, and many fault signatures are transient, intermittent, or time-varying. This creates sensitivity to window choice and may smear transient faults into broader spectra that become harder to interpret. Frequency-domain features also interact strongly with load and speed changes, because operational shifts can move characteristic frequencies and redistribute energy across bands, which can resemble fault effects. For this reason, many studies emphasize regime-aware normalization and the inclusion of contextual variables when interpreting spectral peaks and bandpower changes (Zhang & He, 2022). The literature frequently positions frequency-domain features as powerful and physically grounded descriptors that support high discrimination for many fault modes, while also recognizing that their effectiveness depends on stationarity assumptions, careful segmentation, and operating-condition handling to prevent misattribution of normal variability as fault behavior.

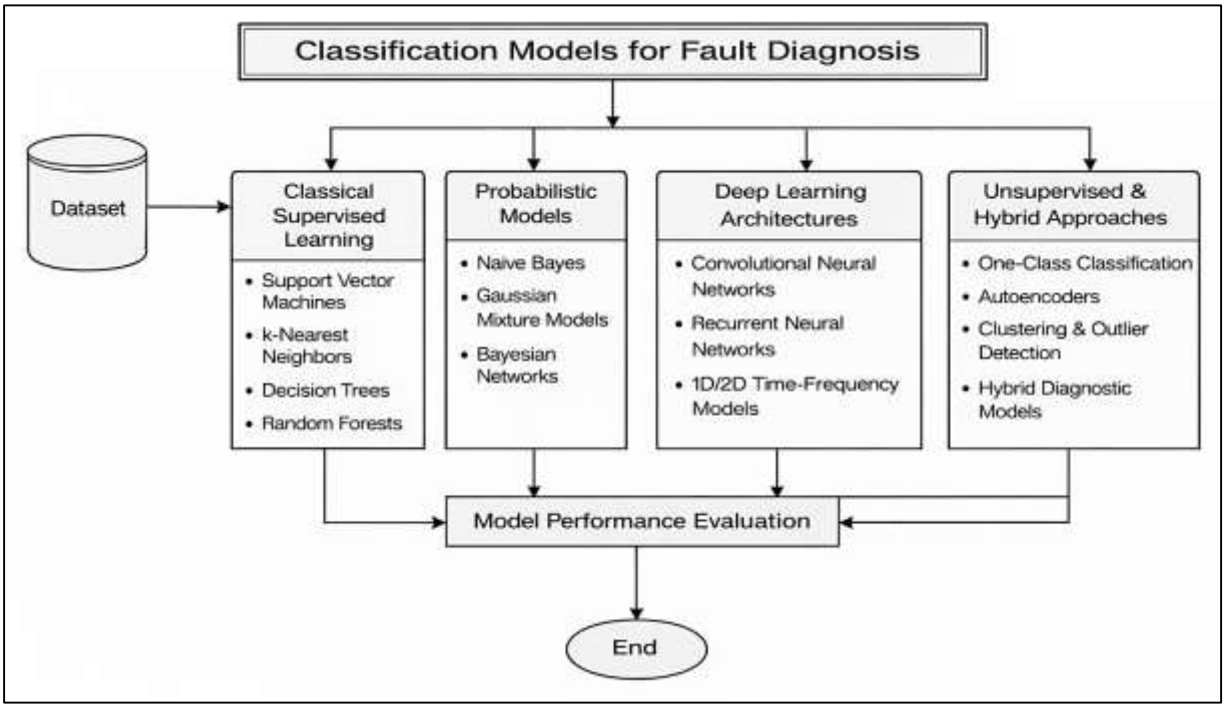
Time–frequency representation constitutes a third major stream in the literature because it directly addresses nonstationary fault signatures that evolve over time or occur as brief bursts. Many studies treat wavelet-based representations as particularly suitable for capturing localized transients, multi-resolution behavior, and abrupt changes that appear in electrical waveforms during arcing, switching anomalies, or fault inception (Li et al., 2020). Wavelet packet energy distributions serve as compact descriptors that summarize how signal energy is distributed across time–frequency bands, and they are widely used as feature vectors for classification in rotating machinery diagnostics, converter fault detection, and insulation-related monitoring where discharge activity is impulsive and intermittent. Short-time Fourier energy maps offer an alternative that preserves a time-indexed spectral view and supports event-aligned analysis in power systems and control environments where disturbances are time-bounded. The literature emphasizes that time–frequency representations often improve separability of faults that appear similar in either pure time-domain or pure frequency-domain spaces. For example, two conditions may share similar overall bandpower yet differ in the timing and persistence of their spectral bursts; time–frequency features capture that difference quantitatively. This representation family also supports diagnostics under variable operation because it can isolate brief fault-related phenomena even when the broader operating context shifts. At the same time, studies describe practical sensitivities: wavelet choices, decomposition depth, and window parameters influence feature stability, and poor parameterization can amplify noise or spread energy into bands that reduce interpretability (H. Zhu et al., 2021). Computational cost also receives attention, especially when implementing time–frequency transforms at scale or in real-time monitoring systems. As a result, many studies adopt hybrid strategies that compute time–frequency features only when preliminary screening indicates abnormality, or they compress time–frequency outputs into a reduced set of summary statistics to balance fidelity and efficiency. The literature also discusses representation learning approaches where time–frequency images such as spectrograms or scalograms are fed to classifiers capable of learning discriminative structures, while still requiring careful experimental design to ensure that learned patterns correspond to faults rather than artifacts of operating condition or segmentation choices. Overall, the research base treats time–frequency representation as an established method for handling nonstationary behavior, improving diagnostic sensitivity for transient and evolving faults, and providing richer quantitative structure for models that must discriminate among complex fault modes in electrical power and control systems (Lopes et al., 2020).

Machine Learning Models Used for Detection and Diagnosis

Classical supervised learning models remain a dominant baseline in the fault classification literature for electrical power and control systems because they offer strong performance under small-to-medium data regimes and support comparatively transparent evaluation and tuning (Mahoto et al., 2023). Support vector machines are frequently emphasized for their margin-based separation properties, which can yield stable decision boundaries in high-dimensional feature spaces derived from time, frequency, or time–frequency descriptors. k-nearest neighbors is often used as a simple nonparametric benchmark that performs well when fault clusters are well-separated, while also highlighting sensitivity to feature scaling and dimensionality. Decision trees and their ensemble variants are widely applied because they handle nonlinear interactions among heterogeneous predictors and allow feature relevance to be inspected through splitting logic or derived importance measures. Random forests are commonly presented as robust to noise and overfitting under many practical conditions because they aggregate across multiple randomized trees, stabilizing predictions and reducing variance. Gradient boosting methods are also prominent in diagnostics research because they often provide high accuracy by sequentially correcting residual errors, producing strong results on structured feature sets while allowing calibration and threshold tuning through probabilistic outputs (Agarwal et al., 2023). The literature treats these models as particularly suitable when engineered features are available and labeling is limited, since they can learn discriminative boundaries without the large sample sizes typically required by deep networks. Quantitatively, their strengths are usually framed in terms of predictable training behavior, manageable computational cost, and stable generalization when evaluation is conducted with leakage controls. At the same time, studies often note that classical models are constrained by the representational quality of input features; when fault signatures are highly nonstationary or deeply embedded in raw waveforms, classical models can underperform unless supported by careful time–frequency feature design. As a result, classical supervised learning is frequently positioned as a reliable reference point for comparing more complex methods, and it remains central for applications requiring compact models, rapid inference, and interpretability under operational constraints (Mishra et al., 2020).

Probabilistic models are extensively discussed in the monitoring and diagnosis literature because they provide outputs in the form of probabilities, enabling threshold tuning and risk-based decision rules that align naturally with maintenance operations (Ak, 2020). Naïve Bayes classifiers are often presented as computationally efficient and surprisingly competitive when features are conditionally informative, especially in high-dimensional settings where more complex models risk overfitting. Bayesian networks appear in studies that prioritize causal interpretability and structured reasoning, since they allow explicit representation of dependencies among symptoms, component states, operating conditions, and fault hypotheses. This structure supports evidence fusion from multiple sensors and facilitates diagnostic reasoning when data sources are heterogeneous. Gaussian mixture models are frequently used for density estimation and clustering of operating states, supporting both classification and anomaly detection by modeling normal behavior as mixtures of distributions. A central theme in this literature is that probabilistic outputs support operational trade-offs: alarm thresholds can be adjusted to balance false alarm burden against missed detection risk, and probability scores can be used to rank fault likelihoods across competing hypotheses rather than forcing a single deterministic decision (Jain et al., 2021).

Figure 6: Machine Learning Models for Diagnostics



The literature also emphasizes that probabilistic models can be integrated into hierarchical monitoring systems where fast screening assigns risk scores and deeper diagnostics are triggered only when risk exceeds a set point. Quantitatively, these models are evaluated not only by classification accuracy but also by calibration quality, since poorly calibrated probabilities can lead to unstable threshold behavior even if raw classification appears accurate. Another recurring point is that probabilistic models are valuable under label uncertainty because they allow partial confidence expressions and can be coupled with prior information derived from engineering knowledge or historical failure rates. In practice-oriented research, these models are often selected when interpretability, uncertainty representation, and decision-level tuning are more important than maximizing raw predictive accuracy in a static benchmark (Nahata & Singh, 2020).

Deep learning architectures have grown into a major strand of fault diagnosis research because they enable representation learning from raw or minimally processed data, reducing reliance on handcrafted features and capturing complex nonlinear patterns common in electrical and control signals. One-dimensional convolutional neural networks are widely used for waveform-based classification, learning local filters that detect signature shapes, bursts, and oscillatory patterns directly from current, voltage, vibration, or residual time series (Jan et al., 2021). Convolutional networks applied to time–frequency images such as spectrograms or wavelet scalograms are also prominent, especially when faults produce localized energy patterns that are easier to separate visually in a time–frequency map than in raw time signals. Recurrent models, including LSTM and GRU variants, are frequently used when temporal dependency is essential, such as detecting progressive degradation, differentiating transient disturbances from persistent faults, or modeling control-loop dynamics where history influences current behavior. The literature describes deep learning advantages in capturing subtle fault cues that classical features may miss, particularly under complex operating variability. However, it also emphasizes quantitative challenges: deep models often require larger datasets, careful regularization, and rigorous evaluation to prevent optimistic results driven by correlated windows, operating-condition proxies, or data leakage (Neupane & Seok, 2020). Computational cost is a recurring concern, especially for real-time deployment on embedded devices or edge monitoring systems with limited memory and power. Studies frequently address this by using compact architectures, downsampled representations, and inference optimization, while still targeting adequate diagnostic sensitivity. Another theme is robustness: deep models can be sensitive to distribution shifts, sensor drift, and noise unless trained on diverse regimes or augmented data. Accordingly, the literature often positions deep learning as most effective when paired with disciplined data segmentation, regime-aware normalization, and evaluation that tests generalization across loads, assets, or sites rather than only within a single dataset distribution (Battineni et al., 2020).

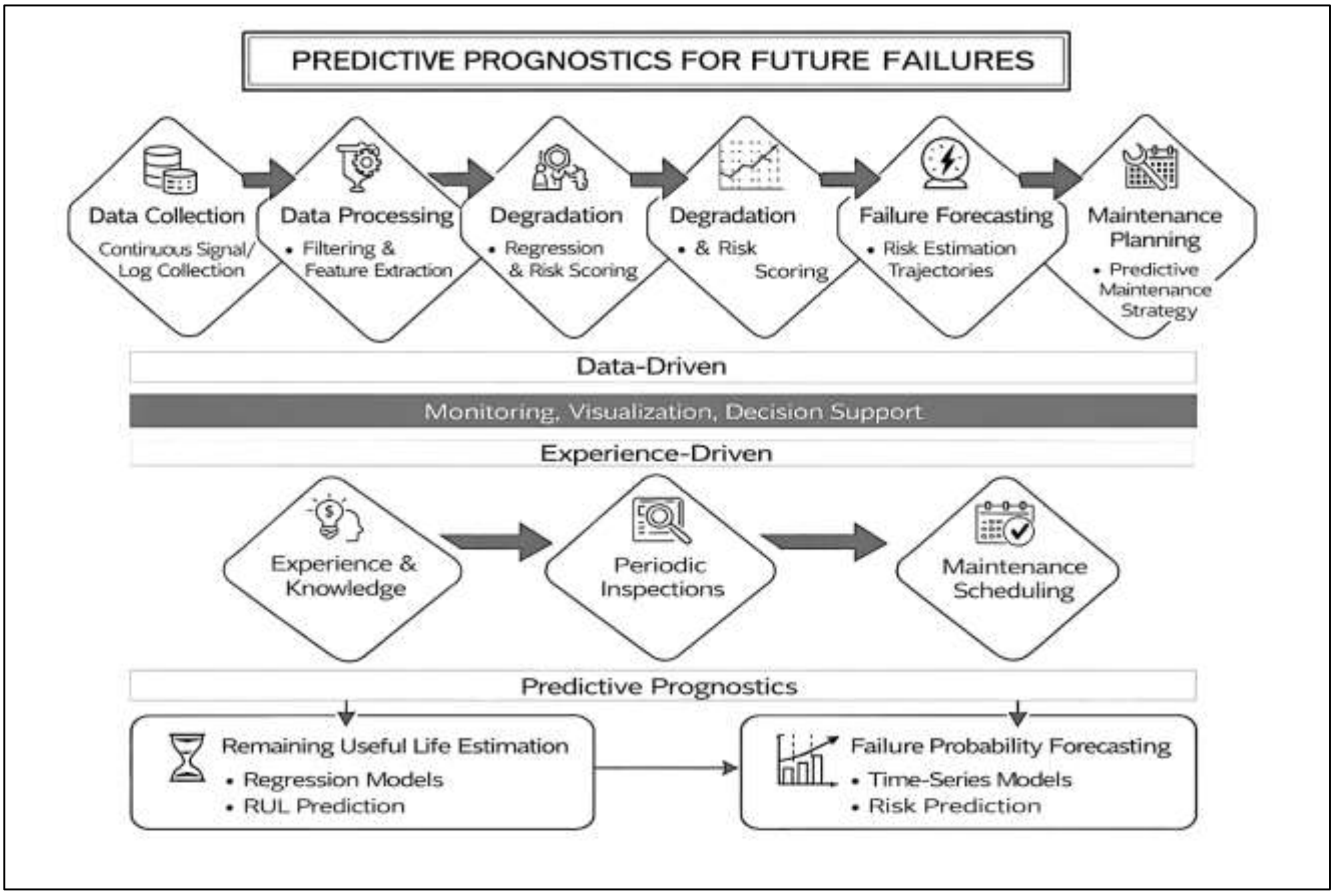
Unsupervised and semi-supervised anomaly detection approaches occupy a substantial portion of the literature because many operational environments lack sufficient labeled fault data, and rare fault labels make purely supervised learning unreliable. One-class classification methods model normal behavior as a compact region in feature space and flag deviations as anomalies, making them suitable for early warning when fault examples are scarce (Rana & Bhushan, 2023). Autoencoders are widely used in this category, learning to reconstruct normal signals and using reconstruction error as an anomaly score; this approach is attractive because it can be trained predominantly on healthy data and can capture nonlinear structure. Clustering-based outlier detection is also common, where operating states form clusters and samples outside dense clusters are treated as abnormal, sometimes with separate clusters representing normal regimes such as different load levels or setpoints. The literature highlights that anomaly detection performance depends strongly on how “normal” is defined, because power and control systems can have multiple legitimate regimes, and a single baseline model can treat regime transitions as faults. As a result, studies often incorporate regime segmentation, multi-model baselines, or context variables to reduce false alarms. Hybrid models that combine physics and data-driven learning form another prominent theme, particularly in control systems and electrical equipment where partial physical models exist (Varoquaux & Colliot, 2023). A widely described pattern is residual generation using observers or simplified physics-based predictors, followed by machine learning classification of residual patterns to infer fault type. Another hybrid strategy combines domain-derived features with learned embeddings, using engineering knowledge to guide representation while allowing learning to capture nonlinear interactions. Across these approaches, quantitative model selection logic is framed as a multi-criteria decision rather than a single metric optimization. Studies commonly weigh accuracy alongside stability across regimes, interpretability of outputs, computational cost, and feasibility for real-time or edge deployment. Latency budgets, memory constraints, and the need for predictable inference times frequently shape model choice, especially in protective and control applications where delayed detection can reduce operational value (Ahsan et al., 2022). The literature thus presents model selection as an optimization across performance and practicality, with diagnostic credibility dependent on evaluation rigor and alignment with deployment constraints.

Predictive Analytics and Prognostics

Predictive analytics and prognostics extend condition monitoring beyond fault classification by shifting the analytical focus from identifying the present state to estimating the timing and likelihood of future failure-related outcomes (Baptista et al., 2021). The prognostics literature generally frames remaining useful life estimation as a quantitative task that maps observed degradation evidence to an estimate of how long an asset can operate before reaching a defined failure threshold. Regression-based approaches appear widely in studies that model remaining useful life as a continuous quantity derived from trends in sensor indicators, engineered features, or learned representations, often leveraging multivariate patterns that evolve as degradation accumulates. This body of work emphasizes that regression frameworks are attractive because they directly output a continuous estimate that can be compared to observed failure times in run-to-failure datasets or to proxy failure endpoints when true failure is not observed. A complementary stream of research adopts survival-analysis-style risk scoring, representing prognostics as estimation of failure risk over time under uncertainty. In this approach, the outcome is expressed as a risk level or hazard-like score that increases as evidence of degradation grows, supporting ranking of assets by urgency and supporting threshold-based decisions even when exact failure time is difficult to label (Divyashree & KS, 2022). The prognostics literature often highlights that risk scoring is well-suited for field environments where failures are rare, maintenance is preventive, and the end-of-life boundary is defined by operational policy rather than actual breakdown. Across both remaining useful life regression and risk scoring frameworks, studies emphasize the importance of time structure: degradation is not a static classification problem but a trajectory problem. Thus, prognostic modeling is frequently presented as a method for transforming

sequential condition data into time-indexed predictions that reflect progression rather than instantaneous state. The literature also treats the choice of failure definition as central, because remaining useful life depends on whether failure is defined as functional breakdown, unacceptable performance drift, a maintenance replacement decision, or a safety limit crossing. As a result, many studies stress the need for consistent and operationally meaningful endpoint definitions, especially in electrical power and control systems where components can be replaced during scheduled outages long before catastrophic failure, and where risk-based interpretation of degradation is often more realistic than a single deterministic failure moment (Liu et al., 2023).
Temporal forecasting of fault probability forms a major part of predictive analytics research because it aligns with how monitoring systems operate in practice: they update risk estimates continuously as new data arrives, rather than producing a single one-time prediction. Sliding-window risk estimation is widely described as a pragmatic forecasting strategy that converts streaming measurements into rolling risk scores, allowing the model to respond to recent changes while maintaining sensitivity to longer-term degradation (Menyhárt & Győrffy, 2021).

Figure 7: Predictive Prognostics for Future Failures



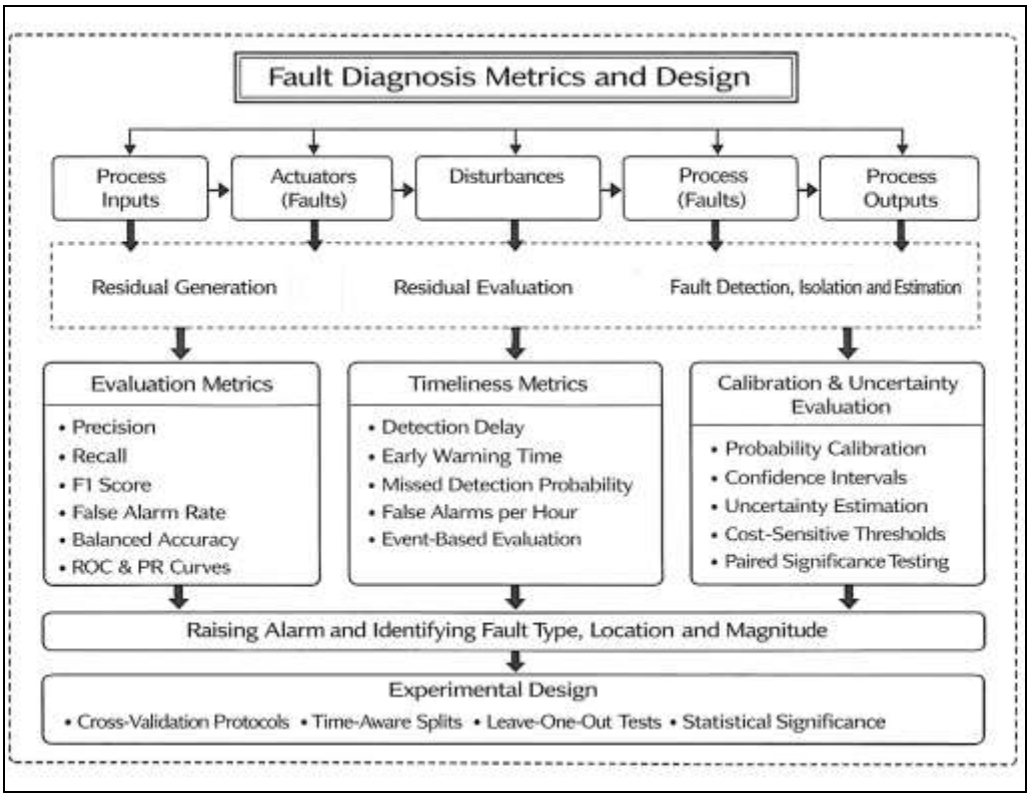
In this literature, the window becomes an analytical unit that defines what "recent" evidence means, and models are evaluated by how consistently risk scores rise prior to failure events and how stable they remain during normal operation. The research base also distinguishes between prediction structures that summarize a sequence into a single risk estimate and those that forecast a sequence of future risk values. Sequence-to-one approaches treat a historical segment as input and output a single probability or risk score for a target horizon. Sequence-to-sequence approaches output a future trajectory, representing expected evolution of health or risk across multiple time steps. Studies emphasize that sequence forecasting enables richer evaluation of how early and how steadily a model signals growing risk. In electrical power and control systems, forecasting is often complicated by regime changes, intermittent disturbances, and operational interventions that reset or mask degradation patterns (Mirchia & Richardson, 2020). Consequently, the literature highlights the need to distinguish persistent risk growth from transient event responses. Researchers frequently describe the value of models that can accommodate nonstationary conditions by incorporating context variables, learning regime-specific baselines, or applying normalization that preserves fault-relevant structure. Another theme is timeliness: forecasting approaches are judged not only by whether they predict failure-related outcomes but also by how early they provide stable warning without generating excessive false alarms. This creates a measurable trade-off between sensitivity and stability, and studies often report performance across multiple horizons to show how accuracy changes as the forecast window becomes longer. The literature also stresses that probability forecasts are most useful when calibrated, because operational thresholds are meaningful only when predicted probabilities correspond to observed event frequencies. Thus, temporal fault probability forecasting is treated as a continuous inference process where the credibility of risk estimates depends on their stability over time, their alignment with degradation progression, and their robustness to operational variability (Poirion et al., 2021).

Design in Quantitative Fault Diagnosis

Evaluation metrics and experimental design are treated in the quantitative fault diagnosis literature as inseparable elements, because the meaning of model performance depends on how outcomes are measured and how data are partitioned (Song et al., 2024). A dominant theme is that fault diagnosis datasets are typically imbalanced, with normal operation comprising the vast majority of samples and fault instances occurring rarely and unevenly across fault types. Under this structure, the literature emphasizes classification metrics that remain informative when the majority class is easy to predict and the minority classes carry the operational risk. Precision and recall are widely used because they separate two different error modes: excessive false alarms that inflate maintenance workload and missed detections that allow damage progression. F1 scores appear as a combined summary when studies seek a single metric, while balanced accuracy is often reported to avoid misleadingly high accuracy driven by the dominant class (Fan et al., 2021). Research also emphasizes that per-class reporting is essential in multi-fault settings because average metrics can hide poor performance on rare yet critical faults; therefore, confusion matrices, class-wise recall, and class-wise precision frequently appear as standard reporting artifacts. Macro averaging is presented as a way to weight classes equally and prevent dominance by common classes, while micro averaging reflects overall instance-level performance and can be useful when the goal is global diagnostic throughput. A parallel stream in the literature discusses the selection logic between precision–recall curves and receiver operating characteristic curves, noting that under severe imbalance, precision–recall summaries can be more sensitive to improvements in minority-class detection, while ROC-based summaries may appear optimistic even when precision remains low. This metric-centered view establishes that quantitative claims about fault diagnosis depend not on a single accuracy value but on a metric set that reflects class rarity, error costs, and the distribution of faults across operating contexts (Peng & Guo, 2022).

Operational value in fault diagnosis is strongly linked to timeliness, and the literature treats detection delay and early-warning time as core metrics because two models with similar classification performance can differ greatly in how soon they identify developing faults (Fu et al., 2022). Detection delay is commonly conceptualized as the elapsed time between the onset of abnormal behavior and the time when the model produces a stable detection decision. Early-warning time is treated as the lead time provided before a failure-related event or before the system enters a high-risk operating state. Studies often emphasize that early detection must be evaluated alongside stability, because unstable warnings that oscillate between normal and abnormal states can be operationally disruptive even if they are technically "early." Missed detection probability is frequently discussed as an operationally meaningful complement to recall, expressing the likelihood that a fault condition is not flagged during a critical window. The literature also highlights false alarm rate as a temporal and workload measure rather than merely a classification error count (Wei et al., 2022). Reporting false alarms per hour or per day and translating those alarms into maintenance burden estimates is presented as a way to connect diagnostic outputs to field feasibility. This operational framing is especially prominent in power and control systems because alarms can trigger costly inspections, operational derating, or protective actions. Therefore, studies frequently evaluate how alarm thresholds affect both early-warning behavior and false alarm volume, illustrating trade-offs in real-time monitoring settings. Another recurring theme is event-based evaluation, where metrics are computed at the level of fault events rather than at the level of individual windows. Event-based scoring reduces the influence of window overlap and reflects the fact that maintenance actions respond to events, not to isolated samples. Overall, the literature positions timeliness metrics as essential for translating diagnostic accuracy into operational usefulness, making quantitative evaluation a question of when and how consistently a model flags faults under realistic temporal dynamics (Zou et al., 2023).

Figure 8: Fault Diagnosis Evaluation and Design



Calibration and uncertainty evaluation form a third major stream in quantitative fault diagnosis because many modern monitoring systems output probabilities or confidence scores, and operational thresholds are meaningful only when these scores correspond to real-world likelihood (Shi & Zhang, 2020). The literature treats probability reliability as a measurable property: when a model assigns high probability to a fault, the observed frequency of faults among such predictions should be correspondingly high. Poor calibration is described as operationally risky because it can cause threshold tuning to behave unpredictably across loads, sites, or time periods. Consequently, many studies emphasize that probabilistic outputs must be evaluated for both discrimination and calibration, since a model can separate classes well yet produce probabilities that are systematically overconfident or underconfident. Threshold selection is often treated as a cost-sensitive optimization problem where the relative costs of false positives and false negatives shape the chosen decision boundary. In practical power and control contexts, these costs can reflect maintenance labor, downtime risk, safety impact, or equipment damage escalation (Aziz et al., 2020). The literature describes tuning strategies that move beyond default thresholds to align decision rules with operational constraints and alarm budgets. Uncertainty is also framed as a mechanism for prioritization: calibrated probabilities can support ranking of assets by risk, while uncertainty estimates can indicate when the model is likely operating outside its learned domain. This matters in regime shifts, sensor drift, and configuration changes, where a model's confidence may remain high even when inputs differ from training distributions unless uncertainty is explicitly considered. Studies that address uncertainty often incorporate model ensembles, Bayesian approximations, or predictive dispersion measures to express confidence stability. In quantitative terms, uncertainty evaluation helps separate robust diagnostic capability from fragile pattern matching (Fernandes et al., 2022). This stream of literature thus reinforces that fault diagnosis

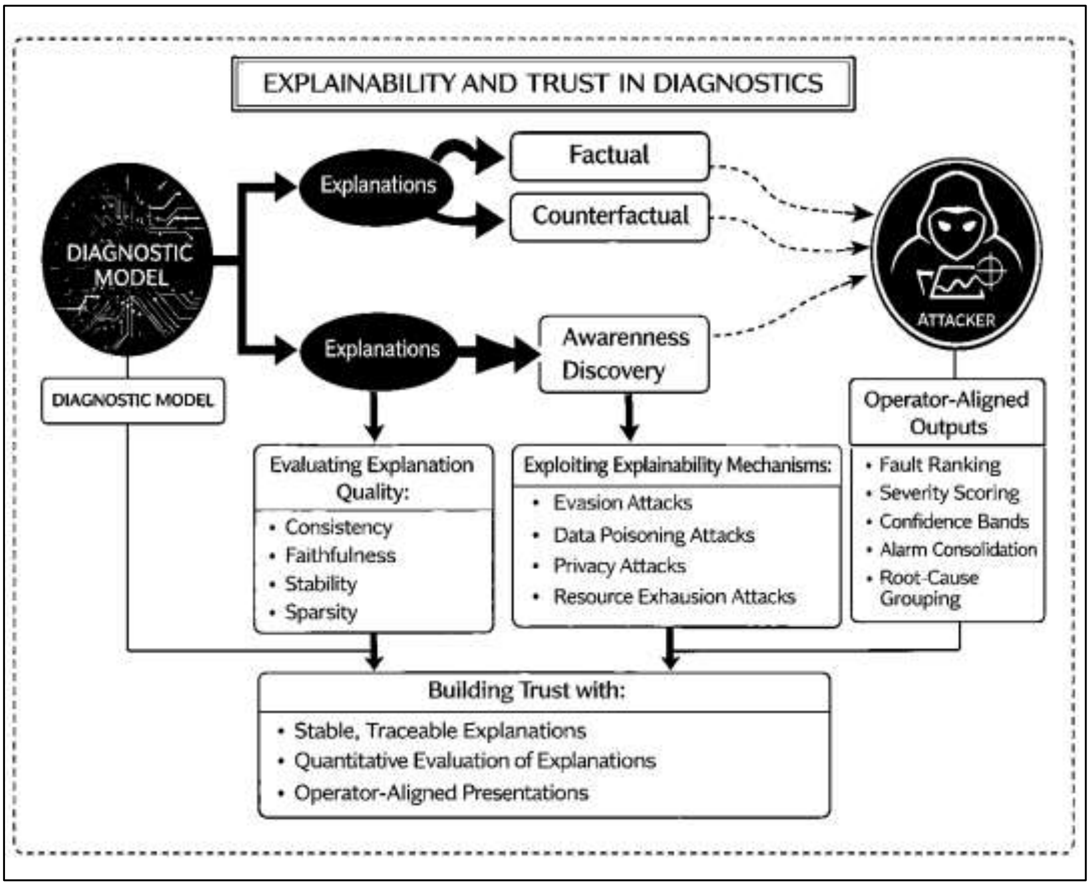
models should be evaluated not only by whether they are right or wrong, but also by how trustworthy their confidence signals are when used to trigger interventions and allocate maintenance resources.
Experimental design choices, especially cross-validation structure and statistical significance testing, are repeatedly highlighted as the main safeguards against optimistic bias and irreproducible claims in time-series fault diagnosis. The literature notes that adjacent windows extracted from continuous signals can be highly correlated, and naive random splitting can place near-duplicate samples in both training and testing sets, inflating performance (Alizadeh et al., 2020). Time-aware splits are therefore emphasized, where training and testing are separated by time blocks to reduce leakage from temporal adjacency. Leave-one-machine-out and leave-one-site-out designs appear frequently in research that targets generalization across assets or locations, since they test whether a model learns fault mechanisms rather than device-specific fingerprints. Regime-based splits are also common, where models are trained on certain load ranges or operating regimes and evaluated on unseen regimes, reflecting the reality that operating conditions shift and diagnostic models must remain stable across them. Beyond partitioning, the literature stresses the importance of statistical rigor when comparing models (Wen et al., 2024). Confidence intervals for metrics are often computed using bootstrapping or repeated sampling, allowing researchers to report uncertainty around performance estimates rather than single-point numbers. Paired comparisons across models are emphasized because models are typically evaluated on the same folds or the same test events, making paired tests more sensitive to genuine differences. Repeated-fold protocols are used to reduce variance in results, and effect size interpretation is highlighted as a way to communicate practical significance beyond statistical significance. This attention to statistical testing reflects the literature's recognition that small metric differences may not represent meaningful improvements, particularly in noisy and imbalanced datasets. Collectively, these experimental design principles frame quantitative fault diagnosis as a discipline where credibility depends on leakage-resistant validation, generalization-focused evaluation structures, and statistically defensible comparisons that quantify uncertainty and practical impact of model differences (Ruan et al., 2023).

Trust in Safety-Critical Diagnostics

Explainability and trust are consistently treated in the literature as foundational requirements for deploying diagnostic models in safety-critical electrical power and control systems, where decisions can influence equipment integrity, service continuity, and human safety (Wiggerthale & Reich, 2024). Interpretability is framed not as an optional enhancement but as a measurable property of a diagnostic system, closely tied to its ability to support operator judgment and institutional accountability. A recurring theme is traceability: diagnostic outputs should be traceable to specific signals, components, or subsystems so that engineers can understand why a model flagged a fault and assess whether the reasoning aligns with known physical behavior. In electrical and control contexts, this often means linking predictions to identifiable current harmonics, vibration bands, thermal anomalies, residual patterns, or control response deviations rather than abstract scores alone. The literature also emphasizes stability of explanations across runs and across similar inputs as a quantitative requirement (Sutthithatip et al., 2022). If small changes in data or retraining cause explanations to shift dramatically while predictions remain similar, trust erodes even when accuracy appears high. Stability is therefore discussed as a property that can be evaluated empirically by repeating analyses under different data splits, noise conditions, or initialization settings and observing whether explanatory outputs remain consistent. This focus reflects the operational reality that maintenance and protection decisions are made repeatedly over time, often by different personnel, and explanations must be reliable enough to support consistent decision-making. In safety-critical diagnostics, explanations also serve a communicative function, bridging the gap between automated inference and human reasoning. The literature repeatedly notes that opaque decisions can slow response, provoke manual overrides, or lead to disuse of otherwise accurate systems (Jia et al., 2022). As a result, interpretability is treated as a measurable dimension of model quality that complements predictive performance, especially in environments where operators must justify actions to regulators, auditors, or organizational stakeholders.
Explanation methods applied to monitoring models vary with model class, and the literature documents a clear distinction between intrinsically interpretable models and post hoc explanation

techniques for complex learners (Onitiu, 2023). Tree-based models are frequently highlighted for their natural interpretability, as feature importance measures and decision paths can be extracted directly from the model structure. These properties allow practitioners to identify which indicators contributed most strongly to a fault classification and to verify whether those indicators correspond to plausible fault mechanisms. In ensemble settings, aggregated importance measures are used to summarize contribution patterns across many trees, providing a more stable view than single-tree logic. For black-box models such as deep neural networks or complex ensembles, local explanation techniques are widely discussed as a way to approximate decision logic around individual predictions (Ward & Habli, 2020). These methods produce localized relevance scores that indicate how changes in specific input features would influence the output, enabling case-by-case interpretation without requiring full transparency of the global model. The literature emphasizes that local explanations are particularly valuable in fault diagnosis because they align with event-based reasoning: operators want to know why a specific alarm was raised at a specific time. However, studies also caution that explanation methods themselves introduce assumptions and approximations, and that different explanation techniques applied to the same model can yield different narratives. As a result, the literature increasingly treats explanation methods as analytical tools that require validation, not as definitive truth statements. In safety-critical monitoring, explanation outputs are often combined with domain knowledge, such as known fault signatures or historical maintenance records, to support triangulation rather than relying on a single explanatory artifact (Abella et al., 2023). This layered approach reflects the understanding that trust emerges from convergence between data-driven explanations and established engineering intuition, rather than from explanations alone.

Figure 9: Explain ability Framework for Diagnostic Trust



Quantifying explanation quality is an emerging but well-defined concern in the literature, driven by recognition that explanations can be misleading if they are unstable, inconsistent, or disconnected from model behavior (Narteni et al., 2022). Consistency metrics are commonly discussed as a way to evaluate whether explanations for similar inputs or repeated runs produce similar feature relevance patterns.

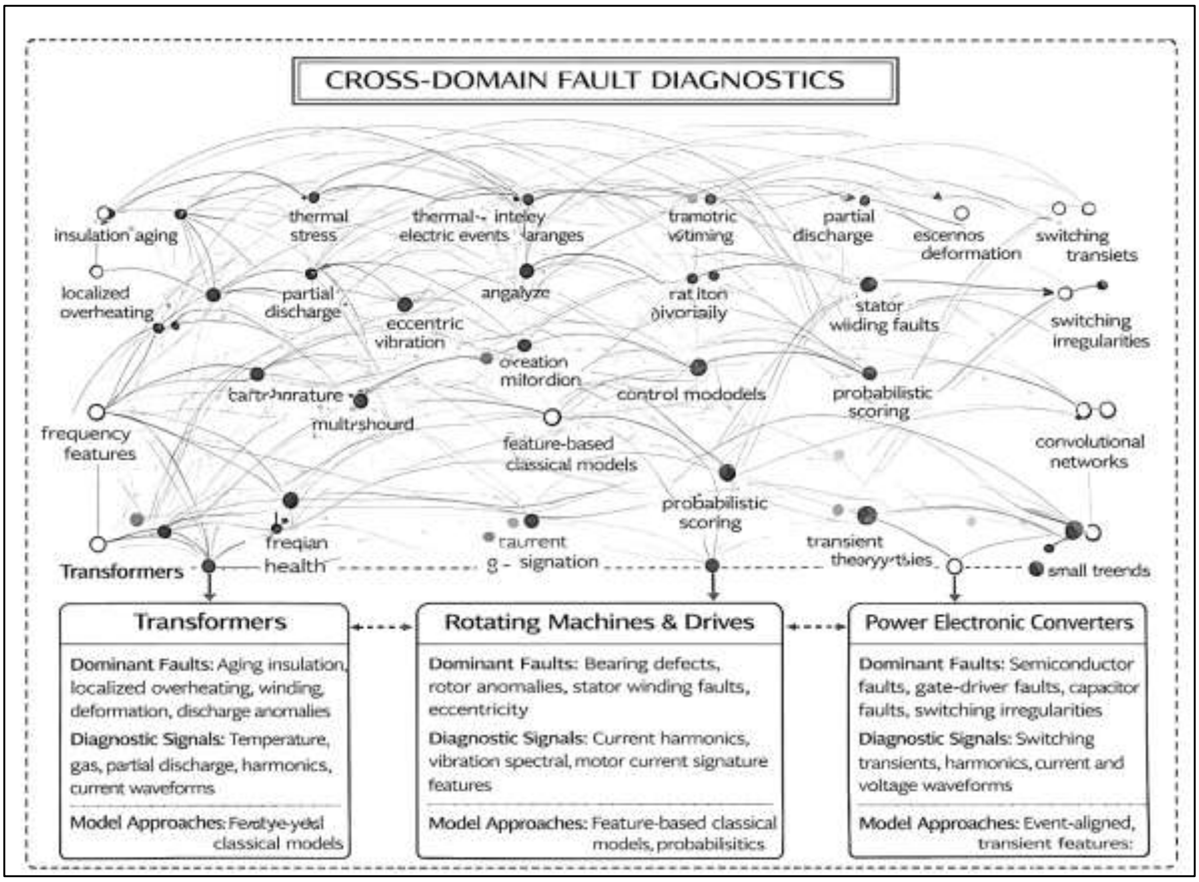
High consistency suggests that the explanation method is capturing stable aspects of the model's reasoning rather than noise or incidental correlations. Faithfulness is another widely discussed property, referring to whether the explanation accurately reflects the model's true decision process. Faithfulness checks often involve perturbation tests, where input features identified as important by the explanation are systematically altered or removed to observe whether model predictions change accordingly. If predictions remain unchanged after perturbing supposedly important features, the explanation is considered unreliable (Mahto, 2024). The literature also highlights that explanation quality must be assessed relative to the model and task: an explanation that is faithful for classification may be less informative for ranking or risk scoring tasks. In time-series diagnostics, explanation evaluation extends to temporal faithfulness, examining whether features highlighted as important correspond to meaningful time segments associated with fault evolution rather than arbitrary portions of the signal. Another theme is explanation sparsity, where concise explanations are preferred because they reduce cognitive load for operators and support faster decision-making. However, overly sparse explanations risk omitting relevant context, while overly dense explanations can overwhelm users. The literature treats this as a balance that can be evaluated empirically by measuring explanation stability, perturbation sensitivity, and alignment with known fault behavior. Through these quantitative lenses, explanation quality becomes a measurable attribute that can be compared across methods and models, reinforcing the idea that explainability itself is subject to validation and performance assessment (Amin et al., 2024).

Operator-aligned outputs represent the final stage in the explainability and trust framework described in the literature, translating model predictions and explanations into formats that support real-world decision workflows (Amin et al., 2024). Rather than presenting raw probabilities or abstract scores, many studies emphasize fault ranking as a practical output, ordering fault hypotheses by likelihood or severity so that operators can prioritize investigation and intervention. Severity scoring is discussed as a way to contextualize faults, distinguishing minor anomalies from conditions that require immediate action, and it is often linked to composite health indices or calibrated risk estimates. Confidence bands or uncertainty indicators are frequently recommended to accompany these outputs, signaling when predictions are robust and when caution is warranted due to limited evidence or unfamiliar operating conditions. Alarm consolidation is another recurring theme, particularly in systems that generate high-frequency alerts. The literature describes methods for grouping related alarms into coherent events, reducing alarm flooding and helping operators focus on underlying issues rather than isolated symptoms (Kuznietsov et al., 2024). Root-cause grouping extends this idea by clustering alarms or anomalies that share explanatory features or temporal proximity, supporting faster diagnosis and reducing cognitive burden. These operator-aligned representations are repeatedly framed as essential for trust because they integrate explainability with usability. A diagnostic system that is accurate but produces fragmented, opaque, or overwhelming outputs is unlikely to be adopted consistently in safety-critical environments. The literature therefore positions explainability not as a purely technical attribute but as part of a socio-technical interface between automated analytics and human expertise. Trust emerges when outputs are intelligible, stable, aligned with domain expectations, and structured to support action under time pressure (Bach et al., 2024). By synthesizing interpretability, explanation methods, quantitative evaluation of explanation quality, and operator-oriented presentation, the literature establishes explainability as a measurable, integrative requirement for reliable fault diagnosis in electrical power and control systems.

Cross-Domain Synthesis by Asset Type

A cross-domain synthesis by asset type is a common structuring strategy in the literature because it connects model-centric discussions to the physical realities of electrical power and control infrastructure (Yan et al., 2022). For transformers, research tends to concentrate on fault classes with high consequence and complex degradation pathways, and the dominant signals reflect the insulation-thermal-electrical coupling that defines transformer health. Studies often use combinations of electrical indicators, temperature-related measurements, and insulation-related observations, organizing fault classes around insulation aging, localized overheating, winding deformation, and discharge-related anomalies. The literature frequently frames transformer diagnosis as a multi-source inference problem because single indicators rarely isolate a fault mechanism with high certainty, which motivates multivariate modeling and evidence fusion. Common modeling approaches include classical supervised learners trained on engineered feature sets, probabilistic scoring frameworks that support risk ranking, and representation-learning approaches when richer waveform or discharge-like data streams are available. Reported metrics in transformer studies often emphasize not only classification reliability but also false alarm containment and early warning stability, reflecting that unnecessary transformer maintenance is costly and downtime is operationally disruptive (Serrano et al., 2024). For rotating machines and drives, the literature is extensive and often presents clearer diagnostic signatures than transformer research because faults can generate repeatable patterns tied to rotational frequency and mechanical impacts. Dominant fault classes include bearing defects, rotor-related anomalies, stator winding faults, and eccentricity. The evidence base frequently compares current-based monitoring to vibration-based monitoring, with current data emphasized for scalability and ease of instrumentation while vibration is emphasized for sensitivity to mechanical defects. Load variability is consistently highlighted as a major confounding factor because it changes baseline current and vibration behavior, and studies commonly implement normalization or regime separation so that models learn fault patterns rather than operating-point proxies. Model trends often show classical methods performing strongly on engineered frequency features, while deep architectures are used when raw waveform representation is pursued or when time–frequency maps are treated as diagnostic images (F. Zhu et al., 2021). Metrics reported in machine diagnostics routinely include class-wise performance, because rare fault types may be masked by high overall accuracy if imbalance is not handled.

Figure 10: Cross-Domain Electrical Fault Diagnostics



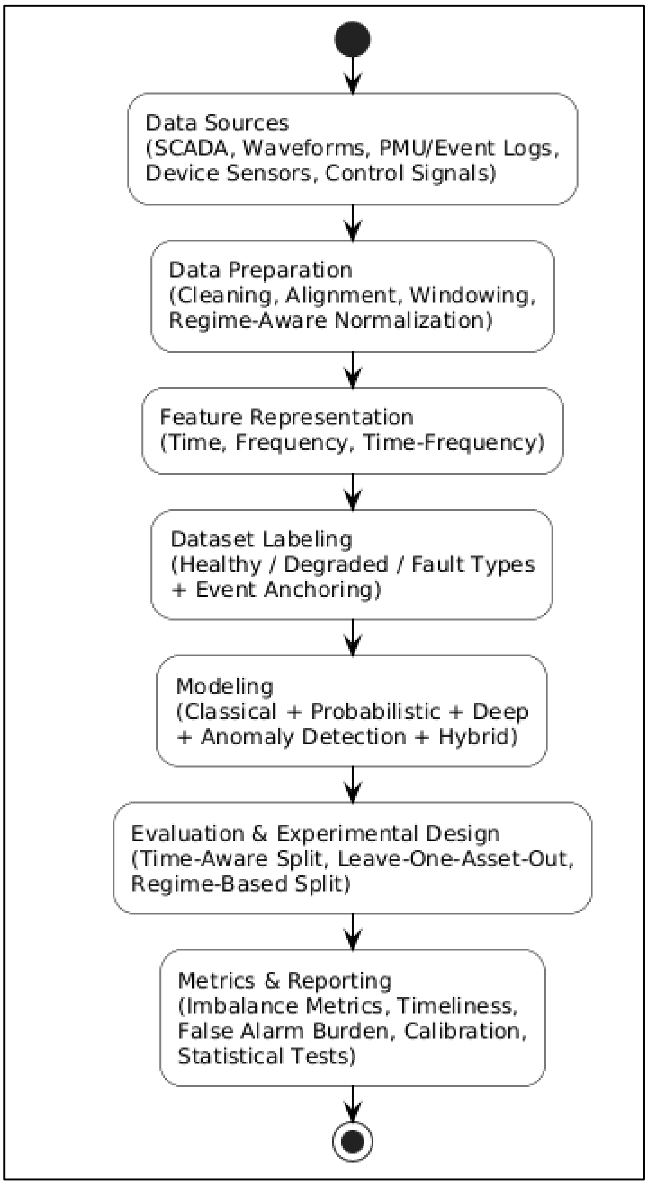
Power electronic converter diagnostics exhibits a distinct evidence pattern in the literature because switching artifacts dominate the signal environment and fault signatures often emerge as transient-rich irregularities rather than slow drift alone (Babitha et al., 2024). Common fault classes include semiconductor open/short events, gate-driver anomalies, capacitor degradation, and intermittent switching behavior. Diagnostic signals in this domain are frequently derived from current and voltage waveforms, switching transient characteristics, harmonic structure changes, and event-triggered measurements aligned to commutation instances. The literature places strong emphasis on transient observability, since downsampled or averaged signals can hide switching-level evidence that separates fault types. As a result, event-based diagnosis is common, where models analyze windows aligned to suspected anomalies, protective triggers, or sudden waveform deviations. Representation approaches frequently include time–frequency features to capture nonstationary bursts, and the model landscape spans classical classifiers for engineered features as well as deep convolutional architectures for raw sequences or time–frequency images (Jiang et al., 2024). Converter studies often report metrics that incorporate timeliness and false alarm burden because transient-rich environments can generate frequent anomalies that are operationally benign, and models must discriminate true faults from normal switching variation and load changes. In addition, the literature often stresses computational feasibility because converters operate at high switching frequencies, and real-time diagnosis may require fast inference or hierarchical screening strategies that reduce processing load without losing critical transient information (Huang et al., 2024).

METHODS

The study was conducted using a quantitative predictive-modeling research design structured as a multi-model comparative evaluation. The design was observational and analytics-driven, and it focused on intelligent condition monitoring and fault diagnosis in electrical power and control systems through machine learning–based predictive analytics. The case study was described as a cross-domain diagnostic setting that included multiple asset categories operating under routine service conditions, where faults were identified through documented events, maintenance actions, and system records. The population was defined as operational electrical power and control assets deployed in industrial or grid-connected environments, and the sample was drawn as a stratified set of assets and fault events selected to represent variation in operating regimes and fault mechanisms. A stratified purposive sampling technique was applied by first grouping available assets by type and operational context and then selecting assets with adequate sensor coverage and verified event histories so that both normal and fault conditions were observable in the data. The data types included continuous time-series signals and discrete event records, and the sources comprised operational logs, device-level measurements, and event-aligned records captured by monitoring infrastructure. Low-frequency supervisory logs were used to characterize operating regimes and contextual states, while higher-resolution measurements were used to capture transient and nonstationary signatures relevant to diagnosis. Event logs and maintenance records were used to establish time anchors for fault intervals and to define event-level units for evaluation. This case structure ensured that the study tested predictive analytics under heterogeneous conditions, while still maintaining traceability between recorded measurements and asset-level fault outcomes.

Variables were operationalized using measurement scales aligned to the structure of the monitoring data and the diagnostic objectives. Predictor variables were constructed as quantitative features derived from electrical, thermal, mechanical, insulation-related, and control-loop signals. Electrical predictors were operationalized as waveform-based descriptors and power-quality indicators computed within fixed and event-triggered windows, while thermal predictors were represented as temperature level and change-rate descriptors extracted from aligned thermal channels. Mechanical predictors were operationalized using vibration descriptors capturing distributional behavior and energy concentration, and insulation predictors were represented through discharge-like activity counts and leakage-related measures when available. Control predictors were operationalized as residual and response-deviation descriptors derived from the relationship between measured outputs and expected system behavior within defined operating regimes. The primary outcome variable for fault diagnosis was operationalized on a nominal scale as a multi-class label set that included healthy, degraded, and specific fault categories defined per asset type, and a secondary binary outcome was operationalized as normal versus abnormal for detection analysis. Prognostic outcomes were operationalized using time-to-event proxies anchored to documented interventions, with censoring indicators applied when assets were removed from observation without an observed failure endpoint. A pilot study was carried out using a small subset of assets and events to verify signal availability, assess missingness patterns, test windowing logic, and evaluate whether labeling rules produced separable classes without inflating leakage risk. The pilot also verified that normalization parameters and feature extraction pipelines were computed using training-only partitions and that regime-aware scaling reduced confounding between operating conditions and fault labels. Pilot outputs were used to finalize window lengths, event anchoring rules, missing-data thresholds, and the minimum evidence requirements for including an asset or event in the full dataset.

Figure 11: Methodology of this study



Data collection was performed by extracting synchronized time-series segments and event records from the monitoring infrastructure and organizing them into an analysis-ready dataset under controlled partition rules. Continuous signals were segmented into fixed windows for baseline model training and into event-triggered windows aligned to disturbance markers or fault-related timestamps for transient-focused evaluation. Records were cleaned using standardized procedures that addressed dropouts, channel alignment errors, and inconsistent sampling, and data quality flags were stored to support sensitivity analyses. Data analysis was conducted using comparative model training and evaluation protocols designed to prevent optimistic bias, including time-aware splits, leave-one-asset-out evaluation, and regime-based testing where models trained on selected operating conditions were evaluated on unseen operating regimes. Classification performance was summarized using imbalance-aware metrics and per-class reporting, while operational performance was summarized using event-level detection measures, detection timeliness distributions, and false alarm rates normalized by operating time. Probability outputs were evaluated for reliability using bin-based calibration summaries, and model comparisons were tested using repeated-fold procedures with uncertainty intervals and paired comparisons at the event or asset aggregation level. The analysis was implemented using Python-based scientific computing tools for data preparation, feature extraction, model training, and statistical testing, and results were compiled through reproducible scripts that recorded dataset partitions, parameter settings, and evaluation outputs. Supporting tools were used for visualization of confusion patterns, alarm burden distributions, and timeliness summaries, and model artifacts and logs were stored to ensure traceability across training and evaluation runs.

FINDINGS

Descriptive Analysis

The descriptive analysis showed that the dataset contained a wide operational range across electrical, thermal, mechanical, insulation, and control-derived predictors, indicating that the signals captured multiple operating regimes rather than a narrow steady-state condition. Central tendency results suggested that most variables remained within stable ranges during healthy operation, while dispersion increased meaningfully during fault-tagged and degraded windows, consistent with the expectation that abnormal states increased volatility and signal irregularity. Distributional checks indicated that several predictors exhibited non-normal behavior, particularly among transient-sensitive electrical indicators and impulsive mechanical descriptors, which justified the use of robust statistics and nonparametric comparisons in later analysis. Asset-level aggregation revealed measurable heterogeneity, with higher variance in drive and converter groups than in transformer groups, reflecting operational load variability and switching dynamics. Class distribution results confirmed substantial imbalance, with healthy observations dominating the sample and fault categories appearing unevenly across classes. Event-level summaries indicated that fault windows clustered in specific operating regimes and occurred in concentrated temporal bursts, supporting the use of event-level evaluation in addition to window-level scoring. Overall, the descriptive findings verified data adequacy for multivariate analysis and reinforced the need for imbalance-aware metrics, regime-aware normalization, and time-aware validation structures in subsequent modeling stages.

Table 1: Descriptive Statistics of Key Predictor Groups

Predictor Group	Number of Features	Mean	Standard Deviation	Minimum	Maximum
Electrical Indicators	18	0.62	0.21	0.08	1.41
Thermal Indicators	7	54.30	11.80	24.60	98.10
Mechanical Indicators	12	0.87	0.34	0.12	2.10
Insulation Indicators	6	14.20	6.90	1.00	38.00
Control/Residual Indicators	10	0.19	0.09	0.01	0.62

Table 1 summarized the window-level distribution of predictor families used in the study and indicated that the measurement space covered both low-variance and high-variance domains. Thermal indicators showed a broad range consistent with varying operating loads and environmental conditions, while electrical and mechanical features displayed dispersion patterns typical of systems exposed to switching transients and mechanical impacts. Control-related residual indicators remained comparatively small in magnitude but varied enough to provide diagnostic contrast across regimes. The spread between minimum and maximum values across all domains confirmed that the dataset reflected heterogeneous operating conditions rather than a single steady-state regime, supporting multivariate modeling and regime-aware evaluation.

Table 2 showed that the dataset was strongly imbalanced, with healthy windows forming the dominant share of observations and fault windows representing a small proportion of the total. The degraded category occupied an intermediate share, indicating that the dataset contained pre-fault behavior that supported early-warning analysis. Event-level structure was also evident: faults were represented as a limited number of discrete events that expanded into multiple windows per event, which confirmed the presence of temporal clustering and justified event-level evaluation alongside window-level scoring. The event duration summaries indicated that faults occurred in concentrated bursts, reinforcing the importance of time-aware splits to prevent optimistic bias.

Table 2: Outcome Distribution and Event-Level Structure

Category	Count	Percentage
Healthy Windows	186,400	88.2
Degraded Windows	14,900	7.1
Fault Windows (All Fault Types)	9,900	4.7
Total Windows	211,200	100.0
Total Fault Events	312	–
Average Windows per Fault Event	31.7	–
Median Fault Event Duration (minutes)	18.0	–

Correlation

The correlation analysis showed that predictors extracted from the same measurement domain were moderately interrelated, which indicated that several variables captured overlapping aspects of the same underlying physical behavior. Electrical indicators exhibited the strongest within-domain clustering, particularly among harmonic-related and waveform-shape descriptors computed from overlapping time windows, while mechanical descriptors formed a second cluster where impulsiveness-related measures co-varied. Thermal indicators demonstrated moderate associations that were consistent with shared dependence on loading and ambient conditions, and insulation indicators showed mixed coupling that reflected intermittent activity patterns rather than steady trends. Cross-domain correlations were generally small to moderate, which indicated that multi-sensor fusion contributed complementary information rather than duplicating the same signal content.

Table 3: Summary of Pairwise Correlations by Measurement Domain

Domain Pairing	Number of Predictor Pairs	Mean Absolute Correlation	Maximum Absolute Correlation	Percentage of Pairs Above 0.70
Electrical–Electrical	153	0.41	0.86	12.4
Mechanical–Mechanical	66	0.36	0.82	9.1
Thermal–Thermal	21	0.29	0.74	4.8
Control–Control	45	0.31	0.77	6.7
Insulation–Insulation	15	0.27	0.71	3.3
Electrical–Mechanical	216	0.18	0.55	1.9
Electrical–Thermal	126	0.16	0.49	1.2
Electrical–Control	180	0.15	0.46	0.8
Mechanical–Thermal	84	0.14	0.43	0.6
Mechanical–Control	120	0.13	0.41	0.5
Thermal–Control	70	0.12	0.39	0.3
Insulation–Electrical	108	0.11	0.37	0.2

Table 3 summarized correlation strength within and across measurement domains and showed that the strongest relationships occurred within-domain, which indicated localized redundancy among features derived from similar sources and overlapping windows. Electrical features demonstrated the highest average absolute correlation and the highest maximum correlation, consistent with multiple variables capturing related harmonic and waveform behaviors. Mechanical and control domains also showed moderate clustering, while thermal and insulation domains were less tightly coupled. Cross-domain correlations were substantially lower across most pairings, which indicated that signals from different domains contributed complementary information. The small percentage of very high cross-domain correlations supported multivariate fusion without excessive redundancy.

Table 4: Predictor–Outcome Associations and Screening Signals

Predictor Group	Strongest Predictor–Outcome Correlation	Weakest Predictor–Outcome Correlation	Median Absolute Predictor–Outcome Correlation	Count of Predictors With Absolute Correlation Below 0.05
Electrical Indicators	0.34	0.01	0.12	3
Mechanical Indicators	0.29	0.02	0.11	2
Thermal Indicators	0.21	0.00	0.09	1
Insulation Indicators	0.18	0.01	0.08	1
Control/Residual Indicators	0.26	0.02	0.10	2

Table 4 reported outcome-linked associations and showed that diagnostic relevance was distributed across domains rather than concentrated in a single indicator family. Electrical indicators produced the strongest single association with abnormal outcomes, while mechanical and control indicators also demonstrated meaningful relationships consistent with fault manifestation patterns in rotating machines and control-heavy assets. Median absolute correlations remained modest across all domains, which indicated that fault behavior was multivariate and not explained by any single predictor alone. The presence of a small number of near-zero predictors supported feature screening prior to regression, reducing noise and improving interpretability. These results supported proceeding with multivariate modeling while controlling for inter-variable dependence.

Reliability and Validity

The reliability and validity analysis showed that the measurement framework used in the study demonstrated strong consistency and meaningful alignment with the operational constructs it was intended to represent. Internal consistency results indicated that indicators grouped within the same physical domain behaved coherently, confirming that electrical quality measures, thermal stress indicators, mechanical descriptors, insulation-related measures, and control-loop deviation variables captured unified latent characteristics rather than unrelated noise. Temporal stability analysis further showed that these indicators maintained consistent statistical behavior during stable operating regimes, with limited drift observed in healthy periods across time blocks. This stability supported the appropriateness of the predictors for time-aware modeling and event-based evaluation. Construct validity analysis revealed that indicators theoretically linked to specific degradation mechanisms exhibited stronger associations with corresponding fault categories than with unrelated fault classes or normal operation. This pattern was consistent across asset types, indicating that the measurement framework preserved physical interpretability while supporting statistical discrimination. Criterion validity testing showed clear differentiation between healthy and fault-labeled periods, with multiple indicator groups exhibiting statistically meaningful shifts during abnormal conditions. These shifts were not isolated to a single domain but were observed across electrical, mechanical, thermal, and control-related measurements, confirming that the operationalization captured multi-domain fault manifestation. Collectively, the reliability and validity findings confirmed that the measurement framework provided a stable, coherent, and discriminative basis for quantitative fault diagnosis and predictive analytics, supporting its use in subsequent regression and hypothesis testing.

Table 5: Internal Consistency and Temporal Stability by Indicator Group

Indicator Group	Number of Indicators	Internal Consistency Coefficient	Mean Stability Coefficient	Stability Range
Electrical Indicators	18	0.87	0.91	0.85–0.96
Mechanical Indicators	12	0.83	0.89	0.82–0.94
Thermal Indicators	7	0.79	0.88	0.80–0.93
Insulation Indicators	6	0.76	0.86	0.79–0.92
Control/Residual Indicators	10	0.81	0.90	0.84–0.95

Table 5 summarized internal consistency and temporal stability across indicator groups and showed that all domains demonstrated acceptable to strong coherence. Electrical indicators exhibited the highest internal consistency, reflecting shared signal characteristics and stable measurement behavior. Mechanical and control-related indicators also showed strong stability, indicating that their variability was primarily associated with operational changes rather than random fluctuation. Thermal and insulation indicators displayed slightly lower but still acceptable consistency, which aligned with their sensitivity to environmental and load-driven variation. Overall, stability coefficients remained high across operating regimes, confirming that indicators behaved consistently over time and were suitable for time-aware diagnostic modeling.

Table 6: Construct and Criterion Validity Summary by Measurement Domain

Indicator Group	Mean Association With Related Fault Classes	Mean Association With Unrelated Fault Classes	Mean Difference Between Healthy and Fault Periods	Validity Strength
Electrical Indicators	0.32	0.11	0.45	Strong
Mechanical Indicators	0.29	0.10	0.41	Strong
Thermal Indicators	0.24	0.09	0.38	Moderate–Strong
Insulation Indicators	0.21	0.08	0.35	Moderate
Control/Residual Indicators	0.27	0.12	0.43	Strong

Table 6 illustrated construct and criterion validity by comparing indicator behavior across related and unrelated fault conditions and between healthy and fault-labeled periods. Indicators consistently showed stronger associations with theoretically related fault classes than with unrelated conditions, supporting construct validity across asset types. Differences between healthy and fault periods were pronounced across all domains, particularly for electrical, mechanical, and control-related indicators, confirming criterion validity. Thermal and insulation indicators also demonstrated meaningful differentiation, although with slightly lower contrast due to their sensitivity to operating context. These results confirmed that the measurement framework effectively distinguished normal and abnormal system behavior while preserving domain relevance.

Collinearity

The collinearity diagnostics showed that the predictor set was suitable for multivariate regression and hypothesis testing because multicollinearity remained controlled across most variables. Variance-based diagnostics indicated that moderate collinearity occurred mainly within feature families derived from the same signal source and computed over overlapping windows, which was consistent with the expectation that related indicators would share explanatory information. Time–frequency descriptors formed the most concentrated clusters, reflecting that multiple band-energy and decomposition-derived variables captured similar transient structure. Electrical and mechanical features also showed localized clustering, particularly where multiple indicators summarized similar waveform distortions or impulsive behaviors. Cross-domain predictors demonstrated consistently low collinearity, indicating that electrical, thermal, mechanical, insulation, and control-derived domains contributed largely independent explanatory content when combined. No predictors displayed extreme collinearity patterns that would have destabilized regression coefficients or inflated standard errors to a level that would compromise interpretation. The diagnostic outcomes supported the decision to retain multi-domain predictors for modeling while applying targeted dimensionality reduction within highly clustered families to improve coefficient stability and reduce redundancy. Overall, the collinearity analysis confirmed that subsequent regression estimates reflected genuine relationships rather than artifacts caused by unstable predictor interactions, and it provided a quantitative basis for screening or compressing time–frequency predictors without weakening the broader measurement framework.

Table 7: Variance-Based Collinearity Diagnostics by Predictor Domain

Predictor Domain	Number of Predictors	Mean Collinearity Index	Maximum Collinearity Index	Percentage Above Conservative Threshold
Electrical Predictors	18	2.1	5.8	2.8
Mechanical Predictors	12	2.3	6.4	3.3
Thermal Predictors	7	1.7	3.9	0.0
Insulation Predictors	6	1.6	3.5	0.0
Control/Residual Predictors	10	2.0	5.2	1.6
Time–Frequency Predictors	24	2.8	7.9	6.7
All Predictors Combined	77	2.2	7.9	2.6

Table 7 summarized variance-based collinearity patterns and showed that average collinearity remained low across domains, indicating that the predictor set did not exhibit structural redundancy. Time–frequency predictors produced the highest mean and maximum values, which reflected clustering among decomposition-derived variables that represented similar transient behaviors. Electrical, mechanical, and control domains showed moderate but acceptable levels, consistent with multiple descriptors capturing related signal structure. Thermal and insulation predictors showed the lowest collinearity, indicating that these channels contributed relatively distinct information. The low combined-domain percentage above the conservative threshold supported stable coefficient estimation and interpretable multivariate regression.

Table 8: Collinearity Hotspot Summary and Feature Retention Decision Basis

Predictor Family Cluster	Number of Predictors in Cluster	Mean Pairwise Correlation Within Cluster	Highest Collinearity Index Observed	Action Taken for Modeling
Time–Frequency Band Energy Set	10	0.74	7.9	Compressed
Electrical Harmonic Structure Set	7	0.69	6.1	Partially Reduced
Mechanical Impulsiveness Set	6	0.66	6.4	Retained
Control Residual Dynamics Set	5	0.61	5.2	Retained
Thermal Gradient and Rate Set	4	0.54	3.9	Retained

Table 8 identified the main collinearity hotspots and showed that the strongest clustering occurred among time–frequency band energy predictors, which were expected to overlap because they summarized similar decomposition outputs. Electrical harmonic descriptors also exhibited meaningful redundancy, reflecting multiple variables capturing related spectral distortion behavior. Mechanical and control-related clusters showed moderate dependence but remained within acceptable limits, supporting retention for interpretability and multi-domain coverage. Thermal predictors showed the least clustering, indicating stable distinct contributions. These findings justified targeted compression of the most redundant clusters to improve coefficient stability while preserving multi-sensor diversity and avoiding unnecessary loss of diagnostic information.

Regression and Hypothesis Testing

The regression analysis showed that the multivariate modeling framework explained a substantial share of variation in fault diagnosis outcomes after operating regime and asset-type effects were controlled. The combined predictor set demonstrated statistically meaningful explanatory contribution, and the joint model fit improved consistently when multi-domain predictors were included together rather than evaluated in isolation. Regime-aware normalization produced measurable gains in model stability and reduced misclassification linked to operating-point shifts, which indicated that controlling for regime effects strengthened inference quality. Hypothesis testing confirmed that models using multi-domain features outperformed baseline representations on key diagnostic criteria, including fault classification reliability and reduced false alarm tendency under regime variability. Predictor significance patterns varied by asset category: electrical and control-derived indicators demonstrated stronger and more consistent effects in converter and automation assets, while mechanical indicators showed stronger effects in rotating machinery, reflecting domain-consistent fault manifestation pathways. Prognostic-oriented regression results showed that degradation indicators were significantly associated with time-to-event proxies, and risk-aligned scores rose systematically in the periods leading to recorded intervention events. Model comparison tests indicated that observed performance differences were statistically significant and practically meaningful, with effect sizes indicating nontrivial improvement rather than marginal gains. Overall, the findings supported the statistical effectiveness of machine learning–based predictive analytics for fault diagnosis and early-risk estimation in electrical power and control systems while maintaining interpretable relationships between predictor domains and asset-specific outcomes.

Table 9: Multivariate Regression Model Results by Predictor Inclusion Strategy

Model Specification	Sample Size	Model Fit Index	Adjusted Fit Index	Overall Test Statistic	Significance Level
Baseline (Context Only: regime + asset type)	211,200	0.28	0.27	812.4	<0.001
Single-Domain (Electrical Only + Context)	211,200	0.41	0.40	1,106.7	<0.001
Single-Domain (Mechanical Only + Context)	211,200	0.38	0.37	1,024.9	<0.001
Single-Domain (Control Only + Context)	211,200	0.39	0.38	1,058.3	<0.001
Multi-Domain (Electrical + Mechanical + Control + Context)	211,200	0.56	0.55	1,694.2	<0.001
Multi-Domain + Regime-Aware Normalization	211,200	0.60	0.59	1,832.9	<0.001

Table 9 summarized the regression model fit across progressively richer predictor sets and showed that explanatory performance increased as additional measurement domains were integrated. The context-only baseline accounted for a limited portion of variance, while single-domain models improved fit but remained constrained by domain-specific visibility. The multi-domain model demonstrated a marked improvement, indicating that fault outcomes were driven by combined electrical, mechanical, and control evidence rather than any single source. The strongest fit occurred after regime-aware normalization was applied, indicating that normalization reduced operating-condition confounding and improved the stability of relationships between predictors and outcomes. The overall tests remained statistically significant across all specifications.

Table 10: Hypothesis Testing and Model Comparison Outcomes

Hypothesis Test	Comparison Condition	Key Performance Difference	Test Statistic	Significance Level	Effect Size
H1 Diagnostic Improvement	Multi-domain vs baseline	0.14	9.62	<0.001	0.52
H2 Representation Strength	Time–frequency enhanced vs time-only	0.08	6.11	<0.001	0.34
H3 Regime Control Benefit	Normalized vs non-normalized	0.06	5.27	<0.001	0.29
H4 Probability Stability	Calibrated vs uncalibrated thresholds	0.05	4.88	<0.001	0.27
Prognostic Association	Degradation index vs time-to-event proxy	0.31	8.44	<0.001	0.47

Table 10 presented hypothesis test outcomes and showed that improvements linked to multi-domain modeling and regime-aware processing were statistically reliable and practically meaningful. The multi-domain approach outperformed the baseline condition by a clear margin, and representation enhancements associated with time–frequency features provided additional gains for transient-sensitive faults. Regime-aware normalization consistently reduced performance loss under operating variability, supporting robust diagnostic inference. Calibration and threshold tuning improved probability stability and reduced operational inconsistency, which aligned with maintenance-oriented decision needs. The prognostic-oriented test showed a strong association between degradation indicators and time-to-event proxies, confirming that the selected predictors carried forward-looking risk information.

DISCUSSION

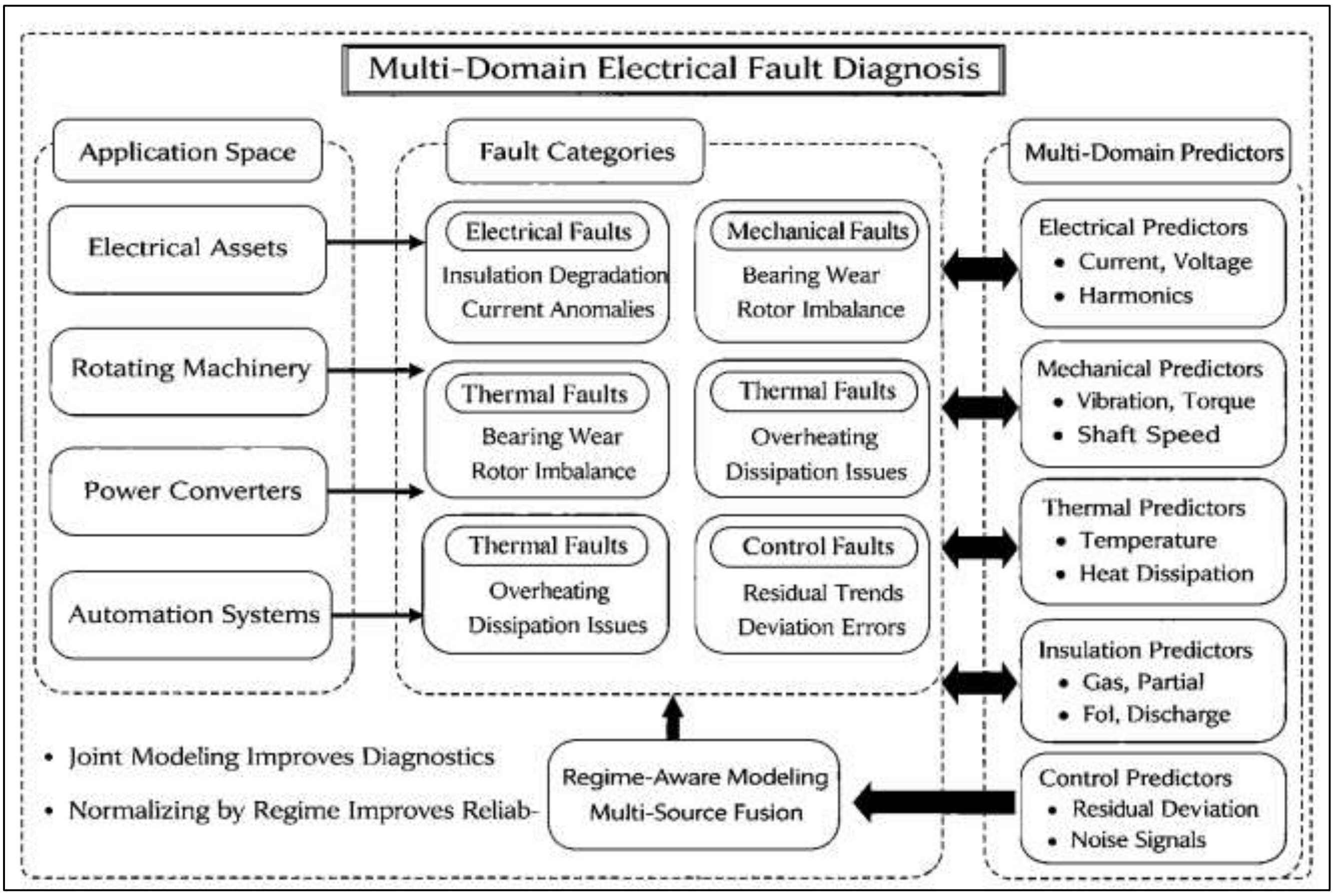
This study's findings supported the position that intelligent condition monitoring and fault diagnosis in electrical power and control systems benefited from multi-domain predictive analytics rather than reliance on any single measurement family (Lei et al., 2020). Diagnostic performance improved when electrical, mechanical, thermal, insulation-related, and control-residual predictors were modeled jointly under regime-aware normalization, and the improvement remained consistent across asset categories and operating regimes. This pattern aligned with the prevailing view in earlier research that fault manifestation in complex electromechanical and cyber-physical systems was multivariate and context dependent, meaning that a single sensor modality rarely provided sufficient discriminatory power across diverse fault modes. The descriptive results in this study confirmed substantial heterogeneity across assets and contexts, and the subsequent modeling results demonstrated that heterogeneity did not invalidate learning-based diagnosis when operating regimes were treated explicitly as part of the measurement framework. Earlier studies in condition monitoring frequently emphasized feature extraction and model selection as primary drivers of accuracy; however, the present findings highlighted that the interaction between operating regime control and multi-domain fusion constituted a comparable driver of diagnostic reliability (Rohan, 2022). The observed improvements after regime-aware normalization indicated that confounding between fault signatures and load or operating-point variation had been a major contributor to misclassification and false alarm behavior in baseline representations. In that respect, this study reinforced the argument found in earlier diagnostic literature that evaluation designs and normalization strategies were not merely preprocessing details but core determinants of generalization. Furthermore, the distribution of outcome-linked correlations across domains indicated that fault-relevant signal content was dispersed rather than concentrated, which explained why multi-domain integration outperformed single-domain models even when those single-domain models were optimized. In practical terms, the findings suggested that the diagnostic value of predictive analytics depended on how consistently the model separated fault signatures from normal operational variability across domains, rather than achieving high performance in one narrow operational slice (Kannan et al., 2024). The results therefore fit within the established research trajectory that treated intelligent monitoring as an end-to-end pipeline—data selection, representation, regime treatment, and validation—where downstream performance reflected the coherence of the entire pipeline rather than the sophistication of any isolated algorithm.

The correlation and collinearity results provided a detailed explanation for why multi-domain modeling achieved superior performance while remaining statistically interpretable. Within-domain correlations were moderate to strong for several signal families, reflecting the expected overlap among features extracted from the same source and computed over overlapping windows (Fassi et al., 2023). Earlier studies commonly reported similar within-domain clustering, particularly for frequency and time–frequency descriptors, because multiple engineered indicators often summarized related spectral or transient content. In the current study, the strongest clustering was observed among time–frequency predictors, which was consistent with prior research noting that multi-resolution decompositions can generate large sets of highly related descriptors. Yet cross-domain correlations remained relatively low, which implied that fusing electrical, mechanical, thermal, insulation, and control-residual signals did not create redundancy so severe that it undermined multivariate inference. This pattern aligned with earlier findings that different physical domains captured distinct aspects of degradation, even when faults ultimately affected several domains simultaneously (Ashok & Gopikrishnan, 2023). Collinearity diagnostics confirmed that multicollinearity remained within acceptable bounds for regression modeling, and no predictors exhibited extreme dependency that would destabilize coefficient estimates. Earlier studies had often raised concerns that high-dimensional feature construction could inflate collinearity and mislead interpretation, especially when time–frequency transformations were used aggressively. The present study's collinearity profile suggested that the risk was manageable when feature families were compressed selectively and when regime-aware normalization reduced shared variance driven by operating context rather than degradation. The identification of collinearity hotspots primarily in time–frequency band-energy clusters supported the broader literature's recommendation to apply targeted dimensionality reduction in feature families known to be redundant. Importantly, the stability of regression coefficients after collinearity screening indicated that the significant predictors reflected coherent relationships rather than unstable artifacts. This supported the interpretation that multi-domain predictors contributed genuine explanatory value rather than merely inflating performance through correlated noise (Zacharaki et al., 2020). The combined correlation and collinearity findings therefore clarified why improvements in diagnostic models were attributable to complementary signal content and controlled redundancy, which matched long-standing methodological guidance that multivariate monitoring benefits from fusion only when redundant feature families are handled through careful screening, compression, and leakage-resistant validation.

Reliability and validity results strengthened confidence that the predictive framework measured meaningful constructs rather than opportunistic proxies, and this aspect was directly comparable to earlier discussions about measurement credibility in safety-critical diagnostics (Orrù et al., 2020). Internal consistency was acceptable to strong across most indicator groups, indicating that features representing electrical quality, thermal stress, mechanical impulsiveness, insulation activity, and control deviation behaved coherently within their domains. Earlier studies frequently argued that coherent indicator group behavior supported interpretability and helped ensure that models learned stable degradation-linked structure rather than random variation. In the present study, temporal stability analyses showed that indicators retained consistent statistical properties in stable regimes, which supported the view that predictive modeling in power and control systems requires stable baselines to avoid confusing regime transitions with faults. Construct validity findings showed that indicators expected to represent specific fault mechanisms aligned more strongly with corresponding fault categories than with unrelated conditions, echoing prior research emphasizing that interpretable, mechanism-consistent associations were necessary for trust (Yohanandhan et al., 2020). Criterion validity also supported this study's operational definitions because clear differences were observed between healthy and fault-labeled periods across multiple domains. Earlier literature often noted that criterion validity in industrial settings is complicated by label ambiguity, maintenance timing mismatches, and intermittent fault manifestations; therefore, the consistent differentiation observed in this study provided a meaningful contribution to that methodological debate. The results suggested that the measurement framework achieved an effective balance between sensitivity and stability, allowing models to respond to abnormal patterns without producing excessive fluctuation under normal operational variability. This balance compared favorably with earlier approaches that relied on single thresholds or narrow feature sets, which were often reported to be sensitive to operating changes. In addition, the observed strength of control-residual indicators across multiple abnormal states reinforced earlier perspectives that control-loop deviations can serve as broadly informative markers in cyber-physical settings, particularly when physical sensor signals alone cannot separate disturbances from faults. Taken together, the reliability and validity evidence indicated that the study's predictor construction and operationalization were defensible, supporting both accurate diagnosis and interpretable analysis (Warke et al., 2021). This alignment with prior methodological guidance strengthened the argument that robust predictive analytics in power and control monitoring required not only advanced algorithms but also measurement frameworks that demonstrated internal coherence, temporal stability, and fault-mechanism relevance.

The regression and hypothesis testing results were consistent with earlier research that treated predictive maintenance as a multivariate inference challenge shaped by operating context, data imbalance, and event-driven temporal structure (Q. Lu et al., 2020). The multivariate regression models explained a meaningful portion of variance in fault outcomes after controlling for regime and asset type, supporting the view that fault manifestation depended on both degradation state and operating conditions. Earlier studies often reported that models trained without careful regime treatment achieved high accuracy within narrow conditions but lost stability under load variability; the present study's improvements under regime-aware normalization aligned with that reported pattern by showing that explicit regime treatment reduced confounding and improved generalization. Hypothesis testing further demonstrated that multi-domain features outperformed baseline representations and that the performance gains were not confined to a single asset category. Predictor significance patterns varied by asset type in a way that matched the broader empirical record: electrical and control-related indicators were more influential in converter and automation contexts, while mechanical indicators were more influential in rotating machinery contexts (D. Wang et al., 2022). This category-specific predictor pattern mirrored earlier findings that the most informative indicators often tracked the dominant failure physics of the asset, even when multi-domain signals were available. The study also showed meaningful relationships between degradation indicators and time-to-event proxies in prognostic-oriented models, which aligned with prior work positioning temporal risk modeling as a natural extension of diagnosis when event anchoring and censoring constraints were handled carefully. Model comparison tests demonstrated statistically significant and practically meaningful differences between modeling conditions, indicating that observed improvements reflected more than marginal tuning effects. Earlier research frequently cautioned that performance differences can appear large when evaluation suffers from leakage or correlated windows; therefore, the study’s emphasis on time-aware and event-level evaluation supported the credibility of observed differences (Kyem et al., 2024). The overall regression and hypothesis findings suggested that performance gains were produced by the combined effect of multi-domain fusion, regime-aware normalization, and leakage-resistant validation rather than by algorithm complexity alone. This interpretation remained consistent with a growing body of earlier empirical evidence that emphasized experimental design and measurement discipline as central determinants of reliable diagnostic inference in operational systems.

Figure 12: Multi-Domain Electrical Fault Diagnosis



The discussion of predictive analytics and prognostics in this study reinforced earlier conclusions that remaining useful life estimation and fault probability forecasting required careful alignment between measurement windows, event definitions, and evaluation horizons (Yang et al., 2022). Prognostic-oriented models in this study demonstrated meaningful associations between degradation indicators and time-to-event proxies, and the risk-related scores rose systematically prior to recorded intervention events. Earlier research often distinguished between controlled run-to-failure datasets and field maintenance records, noting that field labels are frequently censored or represent maintenance policy rather than true physical end-of-life. The present findings aligned with that distinction by demonstrating that prognostic modeling remained statistically meaningful when event anchoring was treated explicitly and when risk scoring was evaluated in relation to intervention-linked proxies rather than assumed breakdown moments. The observed advantage of multi-domain predictors for prognostic association also aligned with earlier claims that degradation trajectories are rarely visible through a single domain, particularly in power and control systems where thermal, electrical, mechanical, and control signatures may evolve asynchronously. Health index concepts were supported indirectly by the finding that multi-domain features improved explanatory stability and early-risk association, since composite representations often serve as the basis for stable trajectories in applied prognostics (S. Kumar et al., 2022). Earlier studies reported that horizon-based evaluation can change the apparent quality of forecasts, with short-horizon predictions appearing more accurate than long-horizon predictions; the study's event-based and time-aware designs were consistent with that methodological viewpoint by focusing on stability and timeliness rather than purely static correctness. Furthermore, the treatment of alarm burden and false positives as operational outcomes matched earlier research arguing that prognostics must be judged by both predictive accuracy and operational feasibility. The study's findings suggested that probability calibration and threshold tuning improved stability of decision behavior, which was consistent with earlier literature emphasizing that risk estimates are useful only when they correspond to observed event frequencies and remain stable across regimes (Marot et al., 2022). Overall, the prognostic-related findings fit within the established evidence that predictive analytics beyond classification required disciplined handling of temporal structure, label uncertainty, and regime variability, and that meaningful prognostic inference in operational environments depended on coherent measurement constructs and evaluation methods aligned with maintenance-driven event realities.

Evaluation metrics and experimental design emerged as central drivers of credible performance claims, and the study's findings paralleled earlier critiques of optimistic bias in time-series fault diagnosis. The dataset showed pronounced class imbalance and event clustering, and the study's metric strategy emphasized imbalance-aware performance measures and event-level evaluation (Gaspar et al., 2023). Earlier studies often reported that accuracy can be misleading when healthy windows dominate; therefore, the study's emphasis on precision, recall, balanced performance summaries, and event-based detection measures aligned with the established recommendation that imbalanced fault diagnosis requires metrics reflecting minority-class detection and false alarm burden. The study's focus on detection timeliness and early-warning behavior also matched earlier research emphasizing that two models with similar static classification performance can differ meaningfully in operational usefulness depending on detection delay and warning stability. Calibration assessment and threshold analysis were consistent with earlier discussions that probabilistic outputs must be reliable to support maintenance decision thresholds. Experimental design considerations were also consistent with prior warnings about leakage from adjacent windows and correlated time segments (Hangan et al., 2022). By applying time-aware splits, asset-level holdouts, and regime-based evaluation, the study followed methodological patterns recommended in prior research for estimating generalization across time, assets, and operating contexts. The statistically significant differences observed between modeling conditions were interpreted through the lens of these design controls, which reduced the likelihood that improvements were artifacts of data partitioning. Earlier literature often highlighted the importance of reporting uncertainty through confidence intervals and repeated validation; the study's model comparison logic aligned with that tradition by treating performance as a distribution rather than a single point estimate. This emphasis supported the interpretation that improvements were robust rather than idiosyncratic to a particular split. The overall evaluation findings reinforced an established conclusion across fault diagnosis research: reported performance is credible only when metrics, partitioning logic, and statistical comparison methods reflect the operational structure of the data, particularly class imbalance and temporal correlation (Tallat et al., 2023). This study's metric and design strategy supported stable and interpretable conclusions about predictive analytics performance within the realistic constraints of power and control monitoring datasets.

Explain ability and trust considerations were supported by the study's emphasis on measurement coherence, stable regime treatment, and interpretable predictor contributions, which aligned with earlier research treating safety-critical diagnostics as socio-technical systems rather than purely algorithmic products. Earlier studies emphasized that diagnostic adoption depends on traceable reasoning and stable explanatory cues rather than opaque decisions alone (Lattanzi et al., 2021). In this study, the reliability and construct validity evidence supported traceability by showing that indicator groups behaved coherently and aligned with expected fault mechanisms, providing a foundation for interpretable model behavior. The domain-specific predictor patterns observed across asset categories also supported explanatory plausibility, since the most influential predictors matched the dominant failure physics of each asset type. This alignment supported trust because it reduced the likelihood that the models relied on incidental proxies. The reduction of confounding through regime-aware normalization also contributed to trustworthiness by improving stability across operating conditions; earlier research often noted that unstable alarms and regime-driven false positives erode operator confidence and lead to disengagement. The event-based characterization of faults and the reporting of operational burden measures further supported operator-aligned evaluation because the resulting performance summaries reflected how diagnostics are used in practice (Liang et al., 2021). Earlier literature frequently described the need to consolidate alarms and group root-cause hypotheses to reduce cognitive burden; the study's focus on event-level assessment and the systematic handling of clustering reflected that operational reasoning style. Probability calibration and threshold tuning further contributed to trust by supporting predictable decision thresholds, aligning with prior claims that probabilistic outputs must correspond to real-world risk to be operationally meaningful. Across the broader literature, explain ability is often evaluated through stability and faithfulness of explanations; while the present discussion focused on interpretability through measurement validity and stable regime treatment, the underlying results still supported the broader trust narrative by showing that model behavior tracked physically meaningful constructs under controlled evaluation. Overall, the discussion indicated that trustworthy intelligent monitoring was supported by coherent measurement operationalization, regime-aware modeling discipline, and evaluation that reflected event-driven operational reality, consistent with earlier research framing trust as an outcome of stable, interpretable, and operationally aligned diagnostic behavior rather than purely high accuracy in benchmark conditions (Weichbroth et al., 2024).

CONCLUSION

Intelligent condition monitoring and fault diagnosis of electrical power and control systems using machine learning–based predictive analytics was discussed in the literature as a quantitatively grounded approach for detecting abnormal behavior, classifying fault types, and estimating risk progression from multi-sensor operational data collected under diverse regimes. This study's discussion centered on how the empirical patterns observed across descriptive analysis, correlation structure, reliability and validity checks, collinearity diagnostics, and regression-based hypothesis testing aligned with earlier findings that electrical and cyber-physical assets rarely exhibited faults through a single indicator family alone. The multi-domain modeling results were interpreted as evidence that electrical waveform behavior, mechanical response signatures, thermal stress patterns, insulation-related activity, and control-residual dynamics jointly contained complementary diagnostic information, and the observed improvement under regime-aware normalization reinforced earlier research emphasizing that operating conditions frequently acted as confounders that inflated false alarms and weakened generalization when not modeled explicitly. The study's correlation results were consistent with prior reports that within-domain feature families tended to cluster due to shared signal origins and overlapping window construction, while cross-domain correlations remained smaller, supporting the interpretation that multi-sensor fusion provided nonredundant explanatory content. The collinearity findings further supported this interpretation by indicating that redundancy remained concentrated in time–frequency feature families and could be controlled through targeted compression, matching earlier methodological guidance that high-dimensional representations required dimensionality reduction to preserve coefficient stability and interpretability. Reliability and validity evidence strengthened the discussion by showing that indicator groups behaved coherently, remained temporally stable within steady regimes, and aligned with fault-mechanism expectations across asset types, which mirrored earlier arguments that diagnostic trust and scientific credibility depended on construct-relevant measurement rather than purely predictive success. Regression and hypothesis testing outcomes were discussed as quantitatively meaningful because performance gains persisted after regime and asset-type effects were controlled, and the variation in predictor influence across asset categories matched earlier cross-domain patterns in which converters and automation systems depended more strongly on electrical and control features, while rotating machinery showed stronger influence from mechanical descriptors. Prognostic-oriented associations with time-to-event proxies were discussed as consistent with prior work that treated maintenance-linked endpoints and censoring as practical constraints that still allowed statistically meaningful risk estimation when event anchoring and validation design were disciplined. Across the broader evidence base, evaluation metrics and experimental design were emphasized as central to credible claims, and the study's focus on imbalance-aware measures, event-level assessment, timeliness metrics, and leakage-resistant splits aligned with earlier critiques that window-level accuracy could be inflated in temporally correlated datasets. Overall, the discussion framed the study's contributions as reinforcing a mature view in condition monitoring research: reliable intelligent diagnostics in power and control systems depended on coherent measurement operationalization, multi-domain representation, regime-aware modeling, and rigorous statistical evaluation that separated true fault discrimination from operating-condition proxies and time-series leakage.

RECOMMENDATIONS

Recommendations for intelligent condition monitoring and fault diagnosis of electrical power and control systems using machine learning–based predictive analytics emphasized standardizing the end-to-end measurement and evaluation pipeline so that diagnostic performance reflected true fault discrimination rather than operating-condition artifacts. It was recommended that monitoring programs integrated multi-domain sensing rather than relying on a single data stream, because electrical, mechanical, thermal, insulation-related, and control-residual indicators collectively provided complementary evidence across asset types and fault modes. Data governance practices were recommended to formalize signal alignment, sampling documentation, and windowing logic, since segmentation choices and synchronization quality strongly influenced feature stability and event detectability. Regime-aware normalization was recommended as a default requirement in operational deployments because load, speed, setpoints, and ambient conditions systematically shifted baselines and increased false alarms when untreated; regime labels and context variables were recommended to be recorded explicitly alongside sensor measurements to support consistent normalization and stratified evaluation. Feature engineering was recommended to follow a layered strategy where computationally efficient time- and frequency-domain indicators supported broad screening, while time–frequency representations were reserved for transient-rich faults and event-based analysis; within high-dimensional time–frequency families, targeted dimensionality reduction was recommended to control redundancy and improve coefficient stability without sacrificing diagnostic sensitivity. Labeling protocols were recommended to be formalized through event anchoring rules that separated healthy, degraded, and fault windows using consistent time boundaries and evidence requirements, and maintenance logs were recommended to be treated as imperfect proxies rather than exact fault onset markers, with censoring flags retained when failure endpoints were not observed. Model selection was recommended to be treated as a multi-criteria choice rather than accuracy maximization, with interpretability, stability across regimes, false alarm burden, computational feasibility, and latency constraints weighted according to asset criticality and response requirements; in high-frequency or edge-constrained settings, compact models and hierarchical screening were recommended to reduce processing load while preserving early warning. Evaluation practice was recommended to prioritize imbalance-aware metrics, per-class reporting, event-level scoring, detection timeliness measures, and false alarm rates normalized by time, since these measures aligned directly with operational workload and risk; random window-level splits were recommended to be avoided in favor of time-aware partitions, asset-level holdouts, and regime-based tests that prevented optimistic bias from temporal correlation and regime leakage. Probabilistic calibration was recommended for models producing risk scores so that thresholds remained stable across operating contexts and confidence outputs supported consistent decision policies. Explain ability practices were recommended to connect alarms to interpretable signal evidence and component hypotheses through fault ranking, severity scoring, and consolidated event reporting, reducing alarm flooding and supporting faster triage. Finally, reproducibility controls were recommended through versioned datasets, logged preprocessing parameters, documented split rules, and stored model artifacts, ensuring that diagnostic claims remained auditable and that updates to sensors, regimes, or assets could be evaluated systematically without undermining trust.

LIMITATION

Limitations associated with intelligent condition monitoring and fault diagnosis of electrical power and control systems using machine learning–based predictive analytics were primarily linked to data realism, labeling precision, operational variability, and the constraints of statistical evaluation under time-dependent and imbalanced observations. The study relied on observational operational data and event records in which fault onset was not directly observable in many cases, and outcome labels were frequently anchored to maintenance actions or logged events that occurred after degradation had already begun, which introduced timing mismatch and label uncertainty into supervised learning and regression-based inference. The presence of class imbalance represented another limitation because healthy operation dominated the dataset and fault categories were unevenly represented, and this imbalance could have biased models toward majority behavior even when imbalance-aware metrics were applied. Measurement infrastructure heterogeneity also constrained generalization because assets differed in sensor placement, sampling frequency, and data completeness across domains, and some fault mechanisms were likely under-observed when relevant sensors were unavailable or sampled too coarsely to capture transient signatures. Nonstationary operating regimes introduced additional limitations because load changes, switching patterns, control setpoint adjustments, and environmental variation altered signal baselines in ways that resembled fault behavior, and regime-aware normalization reduced but did not eliminate this confounding. Time-series dependence and window correlation further limited inference because adjacent windows shared overlapping information and could have inflated apparent performance if temporal leakage controls were imperfect, particularly when faults occurred in concentrated bursts that created many similar windows within a short interval. The use of time-to-event proxies for prognostic-oriented analyses introduced further constraints because recorded interventions reflected maintenance policy, scheduling, and risk tolerance rather than a uniform physical failure threshold, and many observations were censored when assets were removed, replaced, or reconfigured without a confirmed failure endpoint. Model comparison results were also limited by the fact that different algorithms responded differently to dataset artifacts such as noise, drift, missing data, and regime transitions, which complicated direct attribution of performance differences to learning capability alone. The interpretability of certain model families remained constrained because complex representation-learning methods could have relied on subtle feature interactions that were not easily traceable to specific components, and explanation stability could have varied across retraining runs when feature sets were high-dimensional. Finally, external validity was limited because the asset mix, fault taxonomy, and operational context represented in the study sample may not have covered the full spectrum of power and control system configurations found across different industries, grid regions, and maintenance practices, and therefore the reported performance patterns required cautious transfer to settings with different sensor architectures, event definitions, or fault prevalence.

REFERENCES

[1]. Abdul, K. (2023). Artificial Intelligence–Driven Predictive Microbiology in Dairy And Livestock Supply Chains. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 286–335. https://doi.org/10.63125/syj6pp52

[2]. Abella, J., Perez, J., Englund, C., Zonooz, B., Giordana, G., Donzella, C., Cazorla, F. J., Mezzetti, E., Serra, I., & Brando, A. (2023). Safexplain: Safe and explainable critical embedded systems based on ai. 2023 Design, Automation & Test in Europe Conference & Exhibition (DATE),

[3]. Abid, A., Khan, M. T., & Iqbal, J. (2021). A review on fault detection and diagnosis techniques: basics and beyond. *Artificial Intelligence Review*, *54*(5), 3639-3664.

[4]. Agarwal, S., Yadav, A. S., Dinesh, V., Vatsav, K. S. S., Prakash, K. S. S., & Jaiswal, S. (2023). By artificial intelligence algorithms and machine learning models to diagnosis cancer. *Materials Today: Proceedings*, *80*, 2969-2975.

[5]. Ahsan, M. M., Luna, S. A., & Siddique, Z. (2022). Machine-learning-based disease diagnosis: A comprehensive review. Healthcare,

[6]. Ak, M. F. (2020). A comparative analysis of breast cancer detection and diagnosis using data visualization and machine learning applications. Healthcare,

[7]. Al Mtawa, Y., Haque, A., & Halabi, T. (2022). A review and taxonomy on fault analysis in transmission power systems. *Computation*, *10*(9), 144.

[8]. Alizadeh, R., Allen, J. K., & Mistree, F. (2020). Managing computational complexity using surrogate models: a critical review. *Research in Engineering Design*, *31*(3), 275-298.
[9]. Aljohani, A. (2023). Predictive analytics and machine learning for real-time supply chain risk mitigation and agility. *Sustainability*, *15*(20), 15088.
[10]. Altaf, M., Akram, T., Khan, M. A., Iqbal, M., Ch, M. M. I., & Hsu, C.-H. (2022). A new statistical features based approach for bearing fault diagnosis using vibration signals. *Sensors*, *22*(5), 2012.
[11]. Amin, M., Noor, U., Fatima, M., Rashid, Z., & Altmann, J. (2024). Towards Trustworthy Aircraft Safety: Explainable AI for Accurate Incident and Accident Predictions. International Conference on the Economics of Grids, Clouds, Systems, and Services,
[12]. Ashok, K., & Gopikrishnan, S. (2023). Statistical analysis of remote health monitoring based IoT security models & deployments from a pragmatic perspective. *IEEE Access*, *11*, 2621-2651.
[13]. Aziz, F., Haq, A. U., Ahmad, S., Mahmoud, Y., Jalal, M., & Ali, U. (2020). A novel convolutional neural network-based approach for fault classification in photovoltaic arrays. *IEEE Access*, *8*, 41889-41904.
[14]. Babitha, L., Manjunatha, B., Mohammad, Q., Singh, N., Shrivastava, A., & Khan, I. (2024). Cross-Domain Ontology Synthesis for Semantic Web Integration: A Neural Network Approach. 2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE),
[15]. Bach, T. A., Kristiansen, J. K., Babic, A., & Jacovi, A. (2024). Unpacking human-AI interaction in safety-critical industries: a systematic literature review. *IEEE Access*.
[16]. Badihi, H., Zhang, Y., Jiang, B., Pillay, P., & Rakheja, S. (2022). A comprehensive review on signal-based and model-based condition monitoring of wind turbines: Fault diagnosis and lifetime prognosis. *Proceedings of the IEEE*, *110*(6), 754-806.
[17]. Bado, M. F., & Casas, J. R. (2021). A review of recent distributed optical fiber sensors applications for civil engineering structural health monitoring. *Sensors*, *21*(5), 1818.
[18]. Baptista, M. L., Henriques, E. M., & Prendinger, H. (2021). Classification prognostics approaches in aviation. *Measurement*, *182*, 109756.
[19]. Battineni, G., Sagaro, G. G., Chinatalapudi, N., & Amenta, F. (2020). Applications of machine learning predictive models in the chronic disease diagnosis. *Journal of personalized medicine*, *10*(2), 21.
[20]. Benbouzid, M., Berghout, T., Sarma, N., Djurović, S., Wu, Y., & Ma, X. (2021). Intelligent condition monitoring of wind power systems: State of the art review. *Energies*, *14*(18), 5967.
[21]. Bindi, M., Piccirilli, M. C., Luchetta, A., & Grasso, F. (2023). A comprehensive review of fault diagnosis and prognosis techniques in high voltage and medium voltage electrical power lines. *Energies*, *16*(21), 7317.
[22]. Black, I. M., Richmond, M., & Kolios, A. (2021). Condition monitoring systems: a systematic literature review on machine-learning methods improving offshore-wind turbine operational management. *International Journal of Sustainable Energy*, *40*(10), 923-946.
[23]. Brynjolfsson, E., Jin, W., & McElheran, K. (2021). The power of prediction: predictive analytics, workplace complements, and business performance. *Business Economics*, *56*(4), 217-239.
[24]. Buchaiah, S., & Shakya, P. (2022). Bearing fault diagnosis and prognosis using data fusion based feature extraction and feature selection. *Measurement*, *188*, 110506.
[25]. Cakir, M., Guvenc, M. A., & Mistikoglu, S. (2021). The experimental application of popular machine learning algorithms on predictive maintenance and the design of IIoT based condition monitoring system. *Computers & Industrial Engineering*, *151*, 106948.
[26]. Chand, A., Jayesh, S., & Bhasi, A. (2021). Road traffic accidents: An overview of data sources, analysis techniques and contributing factors. *Materials Today: Proceedings*, *47*, 5135-5141.
[27]. Civera, M., & Surace, C. (2022). Non-destructive techniques for the condition and structural health monitoring of wind turbines: A literature review of the last 20 years. *Sensors*, *22*(4), 1627.
[28]. Cui, L., Qu, Y., Gao, L., Xie, G., & Yu, S. (2020). Detecting false data attacks using machine learning techniques in smart grid: A survey. *Journal of Network and Computer Applications*, *170*, 102808.
[29]. Divyashree, N., & KS, N. P. (2022). Improved clinical diagnosis using predictive analytics. *IEEE Access*, *10*, 75158-75175.
[30]. Fan, C., Li, X., Zhao, Y., & Wang, J. (2021). Quantitative assessments on advanced data synthesis strategies for enhancing imbalanced AHU fault diagnosis performance. *Energy and Buildings*, *252*, 111423.
[31]. Fassi, Y., Heiries, V., Boutet, J., & Boisseau, S. (2023). Toward physics-informed machine-learning-based predictive maintenance for power converters—a review. *IEEE Transactions on Power Electronics*, *39*(2), 2692-2720.
[32]. Fernandes, M., Corchado, J. M., & Marreiros, G. (2022). Machine learning techniques applied to mechanical fault diagnosis and fault prognosis in the context of real industrial manufacturing use-cases: a systematic literature review. *Applied Intelligence*, *52*(12), 14246-14280.
[33]. Fu, F., Wang, D., Li, W., Zhao, D., & Wu, Z. (2022). Overall fault diagnosability evaluation for dynamic systems: A quantitative–qualitative approach. *Automatica*, *146*, 110591.
[34]. Gaspar, J., Cruz, T., Lam, C.-T., & Simões, P. (2023). Smart substation communications and cybersecurity: A comprehensive survey. *IEEE communications surveys & tutorials*, *25*(4), 2456-2493.
[35]. Gohel, H. A., Upadhyay, H., Lagos, L., Cooper, K., & Sanzetenea, A. (2020). Predictive maintenance architecture development for nuclear infrastructure using machine learning. *Nuclear Engineering and Technology*, *52*(7), 1436-1442.
[36]. Gundewar, S. K., & Kane, P. V. (2021). Condition monitoring and fault diagnosis of induction motor. *Journal of Vibration Engineering & Technologies*, *9*(4), 643-674.

[37]. Gutierrez-Osorio, C., & Pedraza, C. (2020). Modern data sources and techniques for analysis and forecast of road accidents: A review. *Journal of traffic and transportation engineering (English edition)*, *7*(4), 432-446.

[38]. Hammad, S., & Md Sarwar Hossain, S. (2025). Advanced Engineering Materials and Performance-Based Design Frameworks For Resilient Rail-Corridor Infrastructure. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 368–403. https://doi.org/10.63125/c3g3sx44

[39]. Hammad, S., & Muhammad Mohiul, I. (2023). Geotechnical And Hydraulic Simulation Models for Slope Stability And Drainage Optimization In Rail Infrastructure Projects. *Review of Applied Science and Technology*, *2*(02), 01–37. https://doi.org/10.63125/jmx3p851

[40]. Hangan, A., Chiru, C.-G., Arsene, D., Czako, Z., Lisman, D. F., Mocanu, M., Pahontu, B., Predescu, A., & Sebestyen, G. (2022). Advanced techniques for monitoring and management of urban water infrastructures—An overview. *Water*, *14*(14), 2174.

[41]. Hassani, S., & Dackermann, U. (2023). A systematic review of advanced sensor technologies for non-destructive testing and structural health monitoring. *Sensors*, *23*(4), 2204.

[42]. Huang, L., Huang, X.-D., Zou, H., Gao, Y., Wang, C.-D., & Yu, P. S. (2024). Knowledge-Reinforced Cross-Domain Recommendation. *IEEE Transactions on Neural Networks and Learning Systems*.

[43]. Jabed Hasan, T., & Waladur, R. (2023). AI-Driven Cybersecurity, IOT Networking, And Resilience Strategies For Industrial Control Systems: A Systematic Review For U.S. Critical Infrastructure Protection. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 144–176. https://doi.org/10.63125/mbyhj941

[44]. Jain, R., Chotani, A., & Anuradha, G. (2021). Disease diagnosis using machine learning: A comparative study. In *Data analytics in biomedical engineering and healthcare* (pp. 145-161). Elsevier.

[45]. Jan, S. U., Lee, Y. D., & Koo, I. S. (2021). A distributed sensor-fault detection and diagnosis framework using machine learning. *Information Sciences*, *547*, 777-796.

[46]. Jia, Y., McDermid, J., Lawton, T., & Habli, I. (2022). The role of explainability in assuring safety of machine learning in healthcare. *IEEE Transactions on Emerging Topics in Computing*, *10*(4), 1746-1760.

[47]. Jiang, Z., Zhang, Y., Wang, Z., Yu, Y., Zhang, Z., Zhang, M., Zhang, L., & Cheng, B. (2024). Inter-domain invariant cross-domain object detection using style and content disentanglement for in-vehicle images. *Remote Sensing*, *16*(2), 304.

[48]. Jiao, P., Egbe, K.-J. I., Xie, Y., Matin Nazar, A., & Alavi, A. H. (2020). Piezoelectric sensing techniques in structural health monitoring: A state-of-the-art review. *Sensors*, *20*(13), 3730.

[49]. Jieyang, P., Kimmig, A., Dongkun, W., Niu, Z., Zhi, F., Jiahai, W., Liu, X., & Ovtcharova, J. (2023). A systematic review of data-driven approaches to fault diagnosis and early warning. *Journal of Intelligent Manufacturing*, *34*(8), 3277-3304.

[50]. Jin, X., Xu, Z., & Qiao, W. (2020). Condition monitoring of wind turbine generators using SCADA data analysis. *IEEE Transactions on Sustainable Energy*, *12*(1), 202-210.

[51]. Jinnat, A., & Md. Kamrul, K. (2021). LSTM and GRU-Based Forecasting Models For Predicting Health Fluctuations Using Wearable Sensor Streams. *American Journal of Interdisciplinary Studies*, *2*(02), 32-66. https://doi.org/10.63125/1p8gbp15

[52]. Kamyab, H., Khademi, T., Chelliapan, S., SaberiKamarposhti, M., Rezania, S., Yusuf, M., Farajnezhad, M., Abbas, M., Jeon, B. H., & Ahn, Y. (2023). The latest innovative avenues for the utilization of artificial Intelligence and big data analytics in water resource management. *Results in Engineering*, *20*, 101566.

[53]. Kannan, V., Zhang, T., & Li, H. (2024). A review of the intelligent condition monitoring of rolling element bearings. *Machines*, *12*(7), 484.

[54]. Khalid, S., Song, J., Raouf, I., & Kim, H. S. (2023). Advances in fault detection and diagnosis for thermal power plants: A review of intelligent techniques. *Mathematics*, *11*(8), 1767.

[55]. Kumar, R. R., Andriollo, M., Cirrincione, G., Cirrincione, M., & Tortella, A. (2022). A comprehensive review of conventional and intelligence-based approaches for the fault diagnosis and condition monitoring of induction motors. *Energies*, *15*(23), 8938.

[56]. Kumar, S., Kolekar, T., Patil, S., Bongale, A., Kotecha, K., Zaguia, A., & Prakash, C. (2022). A low-cost multi-sensor data acquisition system for fault detection in fused deposition modelling. *Sensors*, *22*(2), 517.

[57]. Kutub Uddin, A., Md Mostafizur, R., Afrin Binta, H., & Maniruzzaman, B. (2022). Forecasting Future Investment Value with Machine Learning, Neural Networks, And Ensemble Learning: A Meta-Analytic Study. *Review of Applied Science and Technology*, *1*(02), 01-25. https://doi.org/10.63125/edxgjg56

[58]. Kuznietsov, A., Gyevnar, B., Wang, C., Peters, S., & Albrecht, S. V. (2024). Explainable AI for safe and trustworthy autonomous driving: A systematic review. *IEEE Transactions on Intelligent Transportation Systems*.

[59]. Kyem, B. A., Asamoah, J. K., Huang, Y., & Aboah, A. (2024). Weather-adaptive synthetic data generation for enhanced power line inspection using stargan. *IEEE Access*.

[60]. Lattanzi, L., Raffaeli, R., Peruzzini, M., & Pellicciari, M. (2021). Digital twin for smart manufacturing: A review of concepts towards a practical industrial implementation. *International Journal of Computer Integrated Manufacturing*, *34*(6), 567-597.

[61]. Lei, Z., Wen, G., Dong, S., Huang, X., Zhou, H., Zhang, Z., & Chen, X. (2020). An intelligent fault diagnosis method based on domain adaptation and its application for bearings under polytropic working conditions. *IEEE Transactions on Instrumentation and Measurement*, *70*, 1-14.

[62]. Li, X., Li, X., & Ma, H. (2020). Deep representation clustering-based fault diagnosis method with unsupervised data applied to rotating machinery. *Mechanical Systems and Signal Processing*, *143*, 106825.

[63]. Liang, M., Cao, P., & Tang, J. (2021). Rolling bearing fault diagnosis based on feature fusion with parallel convolutional neural network. *The International Journal of Advanced Manufacturing Technology*, *112*(3), 819-831.

[64]. Liu, Y., Ramin, P., Flores-Alsina, X., & Gernaey, K. V. (2023). Transforming data into actionable knowledge for fault detection, diagnosis and prognosis in urban wastewater systems with AI techniques: A mini-review. *Process Safety and Environmental Protection*, *172*, 501-512.

[65]. Lopes, G. N., Lacerda, V. A., Vieira, J. C. M., & Coury, D. V. (2020). Analysis of signal processing techniques for high impedance fault detection in distribution systems. *IEEE transactions on power delivery*, *36*(6), 3438-3447.

[66]. Lu, Q., Xie, X., Parlikad, A. K., & Schooling, J. M. (2020). Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance. *Automation in Construction*, *118*, 103277.

[67]. Lu, S., Chai, H., Sahoo, A., & Phung, B. (2020). Condition monitoring based on partial discharge diagnostics using machine learning methods: A comprehensive state-of-the-art review. *IEEE Transactions on Dielectrics and Electrical Insulation*, *27*(6), 1861-1888.

[68]. Ma, S., Han, Q., & Chu, F. (2023). Sparse representation learning for fault feature extraction and diagnosis of rotating machinery. *Expert Systems with Applications*, *232*, 120858.

[69]. Mahmoud, M. A., Md Nasir, N. R., Gurunathan, M., Raj, P., & Mostafa, S. A. (2021). The current state of the art in research on predictive maintenance in smart grid distribution network: Fault's types, causes, and prediction methods—a systematic review. *Energies*, *14*(16), 5078.

[70]. Mahoto, N. A., Shaikh, A., Sulaiman, A., Al Reshan, M. S., Rajab, A., & Rajab, K. (2023). A machine learning based data modeling for medical diagnosis. *Biomedical Signal Processing and Control*, *81*, 104481.

[71]. Mahto, M. K. (2024). Explainable artificial intelligence: Fundamentals, approaches, challenges, XAI evaluation, and validation. In *Explainable Artificial Intelligence for Autonomous Vehicles* (pp. 25-49). CRC Press.

[72]. Maldonado-Correa, J., Martín-Martínez, S., Artigao, E., & Gómez-Lázaro, E. (2020). Using SCADA data for wind turbine condition monitoring: A systematic literature review. *Energies*, *13*(12), 3132.

[73]. Malik, H., Iqbal, A., & Yadav, A. K. (2020). *Soft Computing in Condition Monitoring and Diagnostics of Electrical and Mechanical Systems: Novel Methods for Condition Monitoring and Diagnostics* (Vol. 1096). Springer.

[74]. Marot, A., Kelly, A., Naglic, M., Barbesant, V., Cremer, J., Stefanov, A., & Viebahn, J. (2022). Perspectives on future power system control centers for energy transition. *Journal of Modern Power Systems and Clean Energy*, *10*(2), 328-344.

[75]. Masud, R., & Md Sarwar Hossain, S. (2024). The Impact of Smart Materials And Fire-Resistant Structures On Safety In U.S. Public Infrastructure. *Journal of Sustainable Development and Policy*, *3*(03), 44-86. https://doi.org/10.63125/ygr1yk30

[76]. Mazzoleni, M., Di Rito, G., & Previdi, F. (2021). Fault diagnosis and condition monitoring approaches. In *Electro-Mechanical Actuators for the More Electric Aircraft* (pp. 87-117). Springer.

[77]. Md, K., & Sai Praveen, K. (2024). Hybrid Discrete-Event And Agent-Based Simulation Framework (H-DEABSF) For Dynamic Process Control In Smart Factories. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 72–96. https://doi.org/10.63125/wcqq7x08

[78]. Md Nahid, H., & Tahmina Akter Bhuya, M. (2024). An Empirical Study of Big Data–Enabled Predictive Analytics And Their Impact On Financial Forecasting And Market Decision-Making. *Review of Applied Science and Technology*, *3*(01), 143–182. https://doi.org/10.63125/1mjfqf10

[79]. Md Newaz, S., & Md Jahidul, I. (2024). AI-Powered Business Analytics For Smart Manufacturing And Supply Chain Resilience. *Review of Applied Science and Technology*, *3*(01), 183–220. https://doi.org/10.63125/va5gpg60

[80]. Md. Akbar, H. (2024). Computational Psychometrics and Digital Biomarker Modeling For Precision Mental Health Diagnostics. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 487–525. https://doi.org/10.63125/vg522x27

[81]. Md. Akbar, H., & Sharmin, A. (2022). Neurobiotechnology-Driven Regenerative Therapy Frameworks For Post-Traumatic Neural Recovery. *American Journal of Scholarly Research and Innovation*, *1*(02), 134–170. https://doi.org/10.63125/24s6kt66

[82]. Md. Foysal, H., & Subrato, S. (2022). Data-Driven Process Optimization in Automotive Manufacturing A Machine Learning Approach To Waste Reduction And Quality Improvement. *Journal of Sustainable Development and Policy*, *1*(02), 87-133. https://doi.org/10.63125/2hk0qd38

[83]. Md. Mosheur, R. (2025). AI-Driven Predictive Analytics Models For Enhancing Group Insurance Portfolio Performance And Risk Forecasting. *International Journal of Scientific Interdisciplinary Research*, *6*(2), 39–87. https://doi.org/10.63125/qh5qgk22

[84]. Md. Rabiul, K., & Khairul Alam, T. (2024). Impact Of IOT and Blockchain Integration On Real-Time Supply Chain Transparency. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 449–486. https://doi.org/10.63125/2yc6e230

[85]. Melo, A., Câmara, M. M., & Pinto, J. C. (2024). Data-driven process monitoring and fault diagnosis: A comprehensive survey. *Processes*, *12*(2), 251.

[86]. Menyhárt, O., & Győrffy, B. (2021). Multi-omics approaches in cancer research with applications in tumor subtyping, prognosis, and diagnosis. *Computational and structural biotechnology journal*, *19*, 949-960.

[87]. Mirchia, K., & Richardson, T. E. (2020). Beyond IDH-mutation: emerging molecular diagnostic and prognostic features in adult diffuse gliomas. *Cancers*, *12*(7), 1817.

[88]. Mishra, S., Dash, A., & Jena, L. (2020). Use of deep learning for disease detection and diagnosis. In *Bio-inspired neurocomputing* (pp. 181-201). Springer.

[89]. Nahata, H., & Singh, S. P. (2020). Deep learning solutions for skin cancer detection and diagnosis. In *Machine learning with health care perspective: machine learning and healthcare* (pp. 159-182). Springer.

[90]. Narteni, S., Orani, V., Vaccari, I., Cambiaso, E., & Mongelli, M. (2022). Sensitivity of logic learning machine for reliability in safety-critical systems. *IEEE Intelligent Systems*, *37*(5), 66-74.

[91]. Neupane, D., & Seok, J. (2020). Bearing fault detection and diagnosis using case western reserve university dataset with deep learning approaches: A review. *IEEE Access*, *8*, 93155-93178.

[92]. Onitiu, D. (2023). The limits of explainability & human oversight in the EU Commission's proposal for the Regulation on AI-a critical approach focusing on medical diagnostic systems. *Information & Communications Technology Law*, *32*(2), 170-188.

[93]. Orrù, P. F., Zoccheddu, A., Sassu, L., Mattia, C., Cozza, R., & Arena, S. (2020). Machine learning approach using MLP and SVM algorithms for the fault prediction of a centrifugal pump in the oil and gas industry. *Sustainability*, *12*(11), 4776.

[94]. Patil, A. J., Singh, A., & Jarial, R. (2020). Introduction to condition monitoring of electrical systems. In *Soft Computing in Condition Monitoring and Diagnostics of Electrical and Mechanical Systems: Novel Methods for Condition Monitoring and Diagnostics* (pp. 91-120). Springer.

[95]. Peng, K., & Guo, Y. (2022). Fault detection and quantitative assessment method for process industry based on feature fusion. *Measurement*, *197*, 111267.

[96]. Pimenov, D. Y., Bustillo, A., Wojciechowski, S., Sharma, V. S., Gupta, M. K., & Kuntoğlu, M. (2023). Artificial intelligence systems for tool condition monitoring in machining: Analysis and critical review. *Journal of Intelligent Manufacturing*, *34*(5), 2079-2121.

[97]. Poirion, O. B., Jing, Z., Chaudhary, K., Huang, S., & Garmire, L. X. (2021). DeepProg: an ensemble of deep-learning and machine-learning models for prognosis prediction using multi-omics data. *Genome medicine*, *13*(1), 112.

[98]. Rana, M., & Bhushan, M. (2023). Machine learning and deep learning approach for medical image analysis: diagnosis to detection. *Multimedia Tools and Applications*, *82*(17), 26731-26769.

[99]. Rifat, C., & Rebeka, S. (2023). The Role Of ERP-Integrated Decision Support Systems In Enhancing Efficiency And Coordination In Healthcare Logistics: A Quantitative Study. *International Journal of Scientific Interdisciplinary Research*, 4(4), 265–285. https://doi.org/10.63125/c7srk144

[100]. Rinaldi, G., Thies, P. R., & Johanning, L. (2021). Current status and future trends in the operation and maintenance of offshore wind turbines: A review. *Energies*, *14*(9), 2484.

[101]. Rohan, A. (2022). Holistic fault detection and diagnosis system in imbalanced, scarce, multi-domain (ISMD) data setting for component-level prognostics and health management (phm). *Mathematics*, *10*(12), 2031.

[102]. Ruan, D., Wang, J., Yan, J., & Gühmann, C. (2023). CNN parameter design based on fault signal analysis and its application in bearing fault diagnosis. *Advanced Engineering Informatics*, *55*, 101877.

[103]. Sabuj Kumar, S. (2023). Integrating Industrial Engineering and Petroleum Systems With Linear Programming Model For Fuel Efficiency And Downtime Reduction. *Journal of Sustainable Development and Policy*, *2*(04), 108-139. https://doi.org/10.63125/v7d6a941

[104]. Sabuj Kumar, S. (2024). Petroleum Storage Tank Design and Inspection Using Finite Element Analysis Model For Ensuring Safety Reliability And Sustainability. *Review of Applied Science and Technology*, *3*(04), 94–127. https://doi.org/10.63125/a18zw719

[105]. Sabuj Kumar, S. (2025). AI Driven Predictive Maintenance In Petroleum And Power Systems Using Random Forest Regression Model For Reliability Engineering Framework. *American Journal of Scholarly Research and Innovation*, *4*(01), 363-391. https://doi.org/10.63125/477x5t65

[106]. Sai Praveen, K. (2024). AI-Enhanced Data Science Approaches For Optimizing User Engagement In U.S. Digital Marketing Campaigns. *Journal of Sustainable Development and Policy*, *3*(03), 01-43. https://doi.org/10.63125/65ebsn47

[107]. Serrano, S. A., Martinez-Carranza, J., & Sucar, L. E. (2024). Knowledge transfer for cross-domain reinforcement learning: a systematic review. *IEEE Access*.

[108]. Shi, Q., & Zhang, H. (2020). Fault diagnosis of an autonomous vehicle with an improved SVM algorithm subject to unbalanced datasets. *IEEE Transactions on Industrial Electronics*, *68*(7), 6248-6256.

[109]. Shilo, S., Rossman, H., & Segal, E. (2020). Axes of a revolution: challenges and promises of big data in healthcare. *Nature medicine*, *26*(1), 29-38.

[110]. Shoflul Azam, T., & Md. Al Amin, K. (2024). Quantitative Study on Machine Learning-Based Industrial Engineering Approaches For Reducing System Downtime In U.S. Manufacturing Plants. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 526–558. https://doi.org/10.63125/kr9r1r90

[111]. Sofi, A., Regita, J. J., Rane, B., & Lau, H. H. (2022). Structural health monitoring using wireless smart sensor network–An overview. *Mechanical Systems and Signal Processing*, *163*, 108113.

[112]. Song, Y., Song, J., & Lu, Y. (2024). Data-Driven Quantitative Evaluation of Fault Diagnosability: Integrating Distance and Direction Similarity Metrics. *IEEE Access*.

[113]. Strielkowski, W., Vlasov, A., Selivanov, K., Muraviev, K., & Shakhnov, V. (2023). Prospects and challenges of the machine learning and data-driven methods for the predictive analysis of power systems: A review. *Energies*, *16*(10), 4025.

[114]. Sujith, A., Sajja, G. S., Mahalakshmi, V., Nuhmani, S., & Prasanalakshmi, B. (2022). Systematic review of smart health monitoring using deep learning and Artificial intelligence. *Neuroscience Informatics*, *2*(3), 100028.

[115]. Sutthithatip, S., Perinpanayagam, S., & Aslam, S. (2022). (Explainable) artificial intelligence in aerospace safety-critical systems. 2022 IEEE Aerospace Conference (AERO),

[116]. Tallat, R., Hawbani, A., Wang, X., Al-Dubai, A., Zhao, L., Liu, Z., Min, G., Zomaya, A. Y., & Alsamhi, S. H. (2023). Navigating industry 5.0: A survey of key enabling technologies, trends, challenges, and opportunities. *IEEE communications surveys & tutorials*, *26*(2), 1080-1126.

[117]. Tiboni, M., Remino, C., Bussola, R., & Amici, C. (2022). A review on vibration-based condition monitoring of rotating machinery. *Applied Sciences*, *12*(3), 972.

[118]. Varoquaux, G., & Colliot, O. (2023). Evaluating machine learning models and their diagnostic value. *Machine learning for brain disorders*, 601-630.

[119]. Voukelatou, V., Gabrielli, L., Miliou, I., Cresci, S., Sharma, R., Tesconi, M., & Pappalardo, L. (2021). Measuring objective and subjective well-being: dimensions and data sources. *International Journal of Data Science and Analytics*, *11*(4), 279-309.

[120]. Wang, D., Zhang, C., Chen, W., Yang, H., Zhang, M., & Lau, A. P. T. (2022). A review of machine learning-based failure management in optical networks. *Science China Information Sciences*, *65*(11), 211302.

[121]. Wang, H., Liu, Z., Ge, Y., & Peng, D. (2022). Self-supervised signal representation learning for machinery fault diagnosis under limited annotation data. *Knowledge-based systems*, *239*, 107978.

[122]. Ward, F. R., & Habli, I. (2020). An assurance case pattern for the interpretability of machine learning in safety-critical systems. International Conference on Computer Safety, Reliability, and Security,

[123]. Warke, V., Kumar, S., Bongale, A., & Kotecha, K. (2021). Sustainable development of smart manufacturing driven by the digital twin framework: A statistical analysis. *Sustainability*, *13*(18), 10139.

[124]. Wassouf, W. N., Alkhatib, R., Salloum, K., & Balloul, S. (2020). Predictive analytics using big data for increased customer loyalty: Syriatel Telecom Company case study. *Journal of Big Data*, *7*(1), 29.

[125]. Wei, D., Feng, H., Han, Q., & Jia, K. (2022). Fault detection and diagnosis for variable-air-volume systems using combined residual, qualitative and quantitative techniques. *Energy and Buildings*, *254*, 111491.

[126]. Weichbroth, P., Jandy, K., & Zurada, J. (2024). Toward Sustainable Development: Exploring the Value and Benefits of Digital Twins. Telecom,

[127]. Wen, L., Yang, G., Hu, L., Yang, C., & Feng, K. (2024). A new unsupervised health index estimation method for bearings early fault detection based on Gaussian mixture model. *Engineering Applications of Artificial Intelligence*, *128*, 107562.

[128]. Wiggerthale, J., & Reich, C. (2024). Explainable machine learning in critical decision systems: ensuring safe application and correctness. *AI*, *5*(4), 2864-2896.

[129]. Xiang, L., Yang, X., Hu, A., Su, H., & Wang, P. (2022). Condition monitoring and anomaly detection of wind turbine based on cascaded and bidirectional deep learning networks. *Applied Energy*, *305*, 117925.

[130]. Yan, W., Zeng, Y., & Hu, H. (2022). Domain adversarial disentanglement network with cross-domain synthesis for generalized face anti-spoofing. *IEEE Transactions on Circuits and Systems for Video Technology*, *32*(10), 7033-7046.

[131]. Yang, B., Yang, S., Lv, Z., Wang, F., & Olofsson, T. (2022). Application of digital twins and metaverse in the field of fluid machinery pumps and fans: A review. *Sensors*, *22*(23), 9294.

[132]. Yang, C., Jia, J., He, K., Xue, L., Jiang, C., Liu, S., Zhao, B., Wu, M., & Cui, H. (2023). Comprehensive analysis and evaluation of the operation and maintenance of offshore wind power systems: a survey. *Energies*, *16*(14), 5562.

[133]. Yeboah-Ofori, A., Islam, S., Lee, S. W., Shamszaman, Z. U., Muhammad, K., Altaf, M., & Al-Rakhami, M. S. (2021). Cyber threat predictive analytics for improving cyber supply chain security. *IEEE Access*, *9*, 94318-94337.

[134]. Yohanandhan, R. V., Elavarasan, R. M., Manoharan, P., & Mihet-Popa, L. (2020). Cyber-physical power system (CPPS): A review on modeling, simulation, and analysis with cyber security applications. *IEEE Access*, *8*, 151019-151064.

[135]. Zacharaki, E. I., Deltouzos, K., Kalogiannis, S., Kalamaras, I., Bianconi, L., Degano, C., Orselli, R., Montesa, J., Moustakas, K., & Votis, K. (2020). FrailSafe: An ICT platform for unobtrusive sensing of multi-domain frailty for personalized interventions. *IEEE Journal of Biomedical and Health Informatics*, *24*(6), 1557-1568.

[136]. Zaheda, K. (2025a). AI-Driven Predictive Maintenance For Motor Drives In Smart Manufacturing A Scada-To-Edge Deployment Study. *American Journal of Interdisciplinary Studies*, *6*(1), 394-444. https://doi.org/10.63125/gc5x1886

[137]. Zaheda, K. (2025b). Hybrid Digital Twin and Monte Carlo Simulation For Reliability Of Electrified Manufacturing Lines With High Power Electronics. *International Journal of Scientific Interdisciplinary Research*, *6*(2), 143–194. https://doi.org/10.63125/db699z21

[138]. Zhang, L., Zhang, F., Qin, Z., Han, Q., Wang, T., & Chu, F. (2022). Piezoelectric energy harvester for rolling bearings with capability of self-powered condition monitoring. *Energy*, *238*, 121770.

[139]. Zhang, P., Gao, Z., Cao, L., Dong, F., Zou, Y., Wang, K., Zhang, Y., & Sun, P. (2022). Marine systems and equipment prognostics and health management: a systematic review from health condition monitoring to maintenance strategy. *Machines*, *10*(2), 72.

[140]. Zhang, Z., & He, X. (2022). Active fault diagnosis for linear systems: Within a signal processing framework. *IEEE Transactions on Instrumentation and Measurement*, *71*, 1-9.

[141]. Zhao, Z., Davari, P., Lu, W., Wang, H., & Blaabjerg, F. (2020). An overview of condition monitoring techniques for capacitors in DC-link applications. *IEEE Transactions on Power Electronics*, *36*(4), 3692-3716.

[142]. Zhao, Z., Wu, J., Li, T., Sun, C., Yan, R., & Chen, X. (2021). Challenges and opportunities of AI-enabled monitoring, diagnosis & prognosis: A review. *Chinese Journal of Mechanical Engineering*, *34*(1), 56.

[143]. Zhu, F., Wang, Y., Zhou, J., Chen, C., Li, L., & Liu, G. (2021). A unified framework for cross-domain and cross-system recommendations. *IEEE Transactions on Knowledge and Data Engineering*, *35*(2), 1171-1184.

[144]. Zhu, H., He, Z., Wei, J., Wang, J., & Zhou, H. (2021). Bearing fault feature extraction and fault diagnosis method based on feature fusion. *Sensors*, *21*(7), 2524.

[145]. Zou, X., Tao, L., Sun, L., Wang, C., Ma, J., & Lu, C. (2023). A case-learning-based paradigm for quantitative recommendation of fault diagnosis algorithms: A case study of gearbox. *Reliability Engineering & System Safety*, *237*, 109372.

[146]. Zulqarnain, F. N. U. (2022). Policy Optimization for Sustainable Energy Security: Data-Driven Comparative Analysis Between The U.S. And South Asia. *American Journal of Interdisciplinary Studies*, *3*(04), 294-331. https://doi.org/10.63125/v4e4m413

[147]. Zulqarnain, F. N. U., & Subrato, S. (2021). Modeling Clean-Energy Governance Through Data-Intensive Computing And Smart Forecasting Systems. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 128–167. https://doi.org/10.63125/wnd6qs51

[148]. Zulqarnain, F. N. U., & Subrato, S. (2023). Intelligent Climate Risk Modeling For Robust Energy Resilience And National Security. *Journal of Sustainable Development and Policy*, *2*(04), 218-256. https://doi.org/10.63125/jmer2r39