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AI-Driven Condition Monitoring and Fault Detection in Electrical Power and Industrial Control Systems

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ABSTRACT

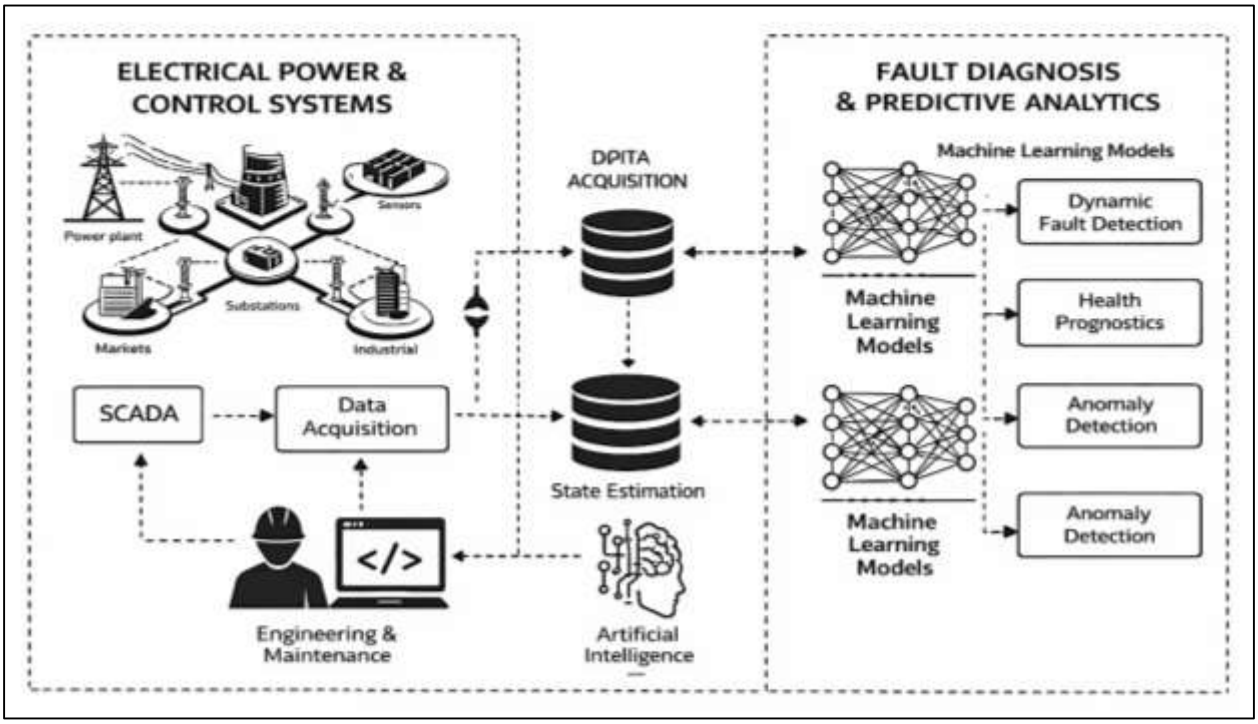
This study examined intelligent condition monitoring and fault diagnosis in electrical power and control systems using a quantitative predictive analytics framework grounded in machine learning and construct-based modeling. A total of 268 responses were collected from professionals working in power distribution, industrial control, and power electronics environments, and after data screening 241 responses were retained for analysis, representing an 89.9% retention rate. The final sample was dominated by engineers (38.6%) and maintenance specialists (27.0%), with 73.9% reporting daily interaction with condition monitoring tools. Five constructs were evaluated: Condition Monitoring Effectiveness, Fault Detection Accuracy, Predictive Maintenance Capability, System Integration Quality, and Operational Performance Impact. Descriptive results indicated generally high perceptions of monitoring and diagnostic performance, with construct means ranging from 3.62 to 4.08 on a five-point scale and moderate dispersion (SD range = 0.58–0.72). Distribution diagnostics supported normality, with skewness values between −0.48 and −0.21 and kurtosis between −0.37 and 0.42. Internal consistency reliability was strong across constructs, with Cronbach's alpha values ranging from .81 to .88 and two items removed during refinement due to weak item-total contribution. Multiple regression analysis was performed to evaluate the predictive influence of the independent constructs on Operational Performance Impact. The regression model was statistically significant, $F(4, 236) = 67.84$, $p < .001$, and explained 53.5% of the variance in the dependent construct ($R^2 = .535$; adjusted $R^2 = .527$), with independence of errors supported (Durbin–Watson = 1.94). Predictive Maintenance Capability demonstrated the strongest effect ($\beta = .34$, $p < .001$), followed by Condition Monitoring Effectiveness ($\beta = .26$, $p < .001$) and System Integration Quality ($\beta = .19$, $p = .002$), while Fault Detection Accuracy produced a smaller but significant contribution ($\beta = .14$, $p = .018$). Multicollinearity was not problematic (VIF range = 1.31–1.58). Overall, the findings confirmed that operational performance outcomes were significantly associated with the effectiveness of monitoring, diagnostic accuracy, predictive maintenance capability, and integration quality, providing quantitative evidence that structured machine learning–driven condition monitoring systems contribute meaningfully to measurable operational performance improvement in electrical power and control environments.

Keywords
Intelligent Monitoring, Fault Diagnosis, Predictive Analytics, Machine Learning, Power Systems;

INTRODUCTION

Intelligent condition monitoring refers to the systematic and automated assessment of the operational state of electrical power and control systems through continuous data acquisition, signal processing, and computational analysis. Fault diagnosis involves the identification, classification, and localization of abnormalities within these systems using quantitative analytical methods (Kumar et al., 2022). Electrical power systems encompass generation, transmission, and distribution infrastructures, while control systems regulate industrial processes, automation equipment, and energy management platforms through sensors, actuators, and programmable controllers.

Figure 1: Intelligent Electrical System Condition Monitoring



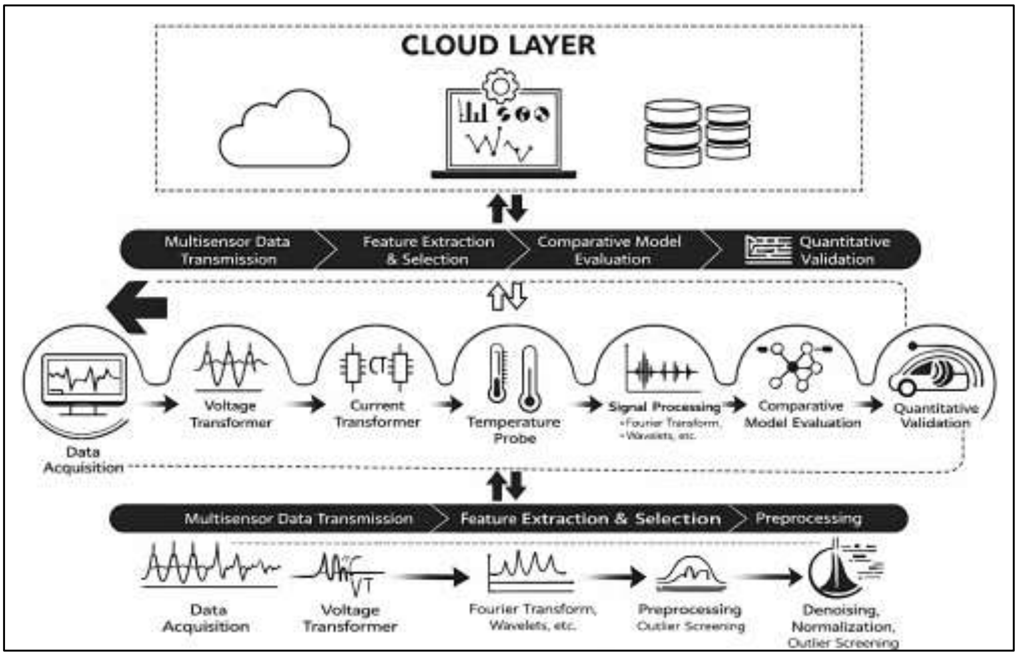
Machine learning–based predictive analytics integrates statistical modeling, pattern recognition, and algorithmic learning to detect hidden structures in operational data and forecast potential failures before they occur. Within engineering and computational sciences, these concepts form a unified framework in which real-time data streams are transformed into actionable diagnostic outputs through supervised, unsupervised, and reinforcement learning algorithms (Zhang et al., 2017). The theoretical grounding of condition monitoring originates from reliability engineering and signal analysis, where vibration, thermal, acoustic, and electrical measurements are interpreted to evaluate equipment health. Early deterministic models relied on threshold-based alarms and rule-based logic; however, the increasing complexity of modern power grids and automated control environments has rendered purely heuristic approaches insufficient. Quantitative methodologies now emphasize probabilistic inference, feature extraction, dimensionality reduction, and classification accuracy metrics such as precision, recall, F1-score, and receiver operating characteristic curves. These techniques enable systematic comparison of predictive models under controlled experimental settings (Badihi et al., 2022). International research communities in electrical engineering, computer science, and industrial informatics have formalized intelligent monitoring as an interdisciplinary field linking data science with infrastructure resilience. The convergence of cyber-physical systems and digital instrumentation has expanded the scale of observable variables, creating high-dimensional datasets suitable for machine learning experimentation. Through these developments, intelligent condition monitoring has evolved into a measurable and replicable quantitative research domain grounded in statistical validation and computational reproducibility (Malik et al., 2020).

Electrical power and control systems constitute the backbone of modern societies, supporting industrial production, healthcare delivery, telecommunications, transportation, and digital services. Reliable electricity supply underpins economic growth, national security, and sustainable development across both developed and developing economies. Power outages and control system failures generate cascading disruptions that affect supply chains, financial markets, and public safety (Li et al., 2017). Quantitative reliability indices such as System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) are internationally standardized metrics used to evaluate service continuity. These indicators reflect the global importance of predictive maintenance and diagnostic technologies capable of reducing downtime and enhancing grid stability. The integration of renewable energy sources, distributed generation, and smart grid technologies has increased system heterogeneity and operational uncertainty. International agencies and regulatory bodies emphasize resilience against equipment failure, cyber-physical disturbances, and load fluctuations. Industrial automation sectors rely on programmable logic controllers, supervisory control and data acquisition systems, and embedded sensors that demand continuous operational accuracy (Pech et al., 2021). Faults in transformers, circuit breakers, rotating machines, or power electronic converters compromise productivity and safety. Quantitative assessments reveal that maintenance costs and unexpected outages account for substantial financial losses worldwide. The application of machine learning to predictive diagnostics addresses this challenge by enabling early anomaly detection through statistical modeling of historical performance data. By reducing unplanned downtime, optimizing maintenance schedules, and extending equipment lifespan, intelligent monitoring frameworks contribute to economic efficiency and environmental sustainability on a global scale (Tchakoua et al., 2014). The international significance of this research domain lies in its measurable impact on infrastructure resilience, industrial competitiveness, and energy security across interconnected power networks.

Fault diagnosis in electrical systems has transitioned from manual inspection and time-based maintenance strategies to data-driven predictive frameworks grounded in quantitative experimentation. Traditional approaches involved periodic testing, infrared thermography, dissolved gas analysis for transformers, and vibration analysis for rotating machinery. These methods generated structured measurements interpreted through expert-defined rules (Gao et al., 2015). Statistical quality control techniques introduced probabilistic reasoning, enabling hypothesis testing and confidence interval estimation in reliability assessment. The rise of digital sensors and embedded monitoring devices has generated continuous streams of high-resolution data, facilitating more sophisticated analytical techniques. Machine learning algorithms have emerged as powerful tools for extracting complex nonlinear relationships within operational datasets. Supervised learning models such as support vector machines, artificial neural networks, random forests, and gradient boosting classifiers are widely employed for fault classification tasks (Zhou et al., 2015). Unsupervised learning methods including k-means clustering, principal component analysis, and autoencoders support anomaly detection when labeled fault data are limited. Feature engineering processes transform raw voltage, current, temperature, and vibration signals into statistical descriptors such as kurtosis, skewness, spectral entropy, and wavelet coefficients. Model performance evaluation relies on cross-validation procedures and confusion matrix analysis to ensure robustness. Comparative studies across international laboratories demonstrate measurable improvements in diagnostic accuracy when machine learning frameworks are integrated with advanced signal processing. Quantitative experiments often report accuracy rates exceeding traditional rule-based systems, highlighting the reproducibility of algorithmic fault detection (Riera-Guasp et al., 2014). This methodological evolution reflects a broader shift toward evidence-based engineering supported by empirical validation and statistical inference.

Predictive analytics in electrical power and control systems involves the use of historical and real-time operational data to forecast equipment degradation and impending faults. Machine learning models learn patterns from labeled datasets and generate predictive outputs that estimate remaining useful life or probability of failure. Regression algorithms such as linear regression, decision tree regression, and neural network regression quantify relationships between input features and performance degradation metrics (Doleck et al., 2020). Time-series models including recurrent neural networks and long short-term memory architectures capture temporal dependencies in sequential sensor readings. The implementation of predictive analytics frameworks requires data preprocessing stages including normalization, noise filtering, missing value imputation, and dimensionality reduction. Quantitative research designs often incorporate training, validation, and testing subsets to evaluate generalization performance. Hyperparameter optimization techniques such as grid search and Bayesian optimization enhance model accuracy and computational efficiency (Uddin et al., 2022). International benchmarking datasets facilitate cross-study comparison of algorithmic performance under standardized conditions. Statistical indicators such as mean squared error, root mean squared error, and area under the curve provide objective measures of predictive capability. Integration with cloud-based data platforms and edge computing architectures enables scalable experimentation across distributed infrastructures. Through rigorous quantitative modeling, machine learning–based predictive analytics transforms passive monitoring systems into proactive diagnostic tools capable of supporting real-time decision-making within complex power environments (Uddin et al., 2022).

Figure 2: Intelligent Electrical Condition Monitoring Framework



Effective intelligent condition monitoring depends on accurate data acquisition from sensors embedded in electrical equipment and control systems. Voltage transformers, current transformers, temperature probes, accelerometers, and acoustic emission sensors generate multidimensional datasets reflecting system dynamics. Signal processing techniques convert raw measurements into informative features suitable for machine learning algorithms (Samanpour et al., 2017). Fourier transforms, wavelet transforms, Hilbert–Huang transforms, and empirical mode decomposition are widely applied to extract frequency-domain characteristics associated with mechanical or electrical anomalies. Feature engineering constitutes a critical quantitative stage in model development. Statistical descriptors such as variance, root mean square value, crest factor, and harmonic distortion quantify deviations from nominal operating conditions. Dimensionality reduction techniques reduce computational complexity while preserving discriminative information. Principal component analysis and linear discriminant analysis are frequently used to enhance separability between normal and faulty states (Wu et al., 2016). Data labeling processes ensure supervised learning models receive accurate ground truth classifications. Experimental validation procedures involve repeated trials under controlled laboratory and field conditions to assess reliability. The reproducibility of results across diverse datasets supports the credibility of predictive models. International collaborations have produced open-access repositories of power system fault data, enabling comparative quantitative studies and methodological transparency (Anagnostopoulos et al., 2018).

Quantitative research in intelligent condition monitoring emphasizes statistical rigor, experimental control, and reproducible evaluation metrics. Model performance is assessed using structured validation frameworks that prevent overfitting and ensure generalizability across unseen datasets. Cross-validation techniques partition data into multiple folds, allowing repeated training and testing cycles. Confusion matrices provide detailed breakdowns of true positives, true negatives, false positives, and false negatives, facilitating comprehensive assessment of classification reliability (Masood & Hashmi, 2019). Statistical hypothesis testing supports comparison of algorithmic approaches under equivalent experimental conditions. Analysis of variance and nonparametric tests evaluate differences in predictive accuracy across multiple models. Sensitivity analysis quantifies model robustness against noise and data variability. Computational efficiency metrics such as processing time and memory usage are included to determine feasibility in real-time industrial deployment. Receiver operating characteristic curves and precision–recall curves provide graphical interpretation of diagnostic trade-offs. These quantitative evaluation frameworks align with international engineering standards emphasizing objective measurement and validation (Konstantopoulos et al., 2020). By integrating statistical inference with computational experimentation, researchers establish empirical credibility and methodological consistency within machine learning–based diagnostic systems.

Modern electrical infrastructures operate as cyber-physical systems integrating physical equipment with digital communication networks and automated control algorithms. Intelligent condition monitoring systems interface with supervisory control and data acquisition platforms, distributed energy management systems, and industrial Internet of Things architectures. Real-time data streams are transmitted through secure communication protocols to centralized or decentralized analytics engines. The convergence of hardware instrumentation and software analytics enables continuous situational awareness across geographically dispersed assets (Hehenberger et al., 2016). Machine learning models embedded within these architectures provide automated alerts, probabilistic risk assessments, and maintenance scheduling recommendations. Quantitative experiments conducted in industrial testbeds demonstrate improved fault detection speed and classification accuracy compared to conventional monitoring systems. Data-driven diagnostics contribute to optimized asset utilization, reduced maintenance expenditure, and enhanced operational reliability (Colombo et al., 2014). The integration of predictive analytics within control loops supports adaptive responses to system disturbances, ensuring stability under dynamic load conditions. International research initiatives emphasize interoperability standards, cybersecurity safeguards, and scalable data management frameworks. Through systematic quantitative validation, intelligent condition monitoring systems represent a scientifically grounded advancement in the management of electrical power and control infrastructures (Bangemann et al., 2016).

This quantitative paper aims to develop and empirically evaluate a machine learning–based predictive analytics framework for intelligent condition monitoring and fault diagnosis in electrical power and control systems by using measurable operational data and statistically testable performance criteria. The first objective is to construct a structured dataset that represents normal and faulty operating conditions through the acquisition of multi-sensor measurements from electrical and control assets, including electrical signatures (e.g., voltage, current, harmonics), thermal indicators, and vibration or switching behavior where applicable, and to prepare this dataset through standardized preprocessing steps such as denoising, normalization, outlier screening, and missing-value handling to ensure analytical validity. The second objective is to perform quantitative feature extraction and selection to derive diagnostic variables from time-domain, frequency-domain, and time–frequency representations, enabling a reproducible mapping between raw signals and fault-relevant patterns. The third objective is to implement a comparative modeling strategy in which multiple machine learning algorithms are trained under consistent experimental conditions, including supervised classification models for fault type identification and, where needed, anomaly detection models for distinguishing abnormal states from baseline behavior. The fourth objective is to optimize model configurations using systematic hyperparameter tuning and to evaluate generalization using robust validation protocols such as k-fold cross-validation and held-out test sets, ensuring that performance estimates reflect real-world predictability rather than sample-specific fitting. The fifth objective is to quantify diagnostic effectiveness using objective metrics, including accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve, and confusion-matrix error distributions, with additional reporting of computational efficiency indicators (training time, inference latency, and resource usage) to assess feasibility for near-real-time monitoring. The sixth objective is to examine the statistical significance of observed performance differences among candidate models using appropriate inferential procedures, thereby supporting evidence-based selection of the most reliable predictive approach. The final objective is to demonstrate the end-to-end functionality of the proposed framework through a controlled experimental workflow that links data acquisition, feature engineering, model training, and performance evaluation into a coherent quantitative pipeline suitable for repeatable analysis of condition monitoring and fault diagnosis tasks in electrical power and control system contexts.

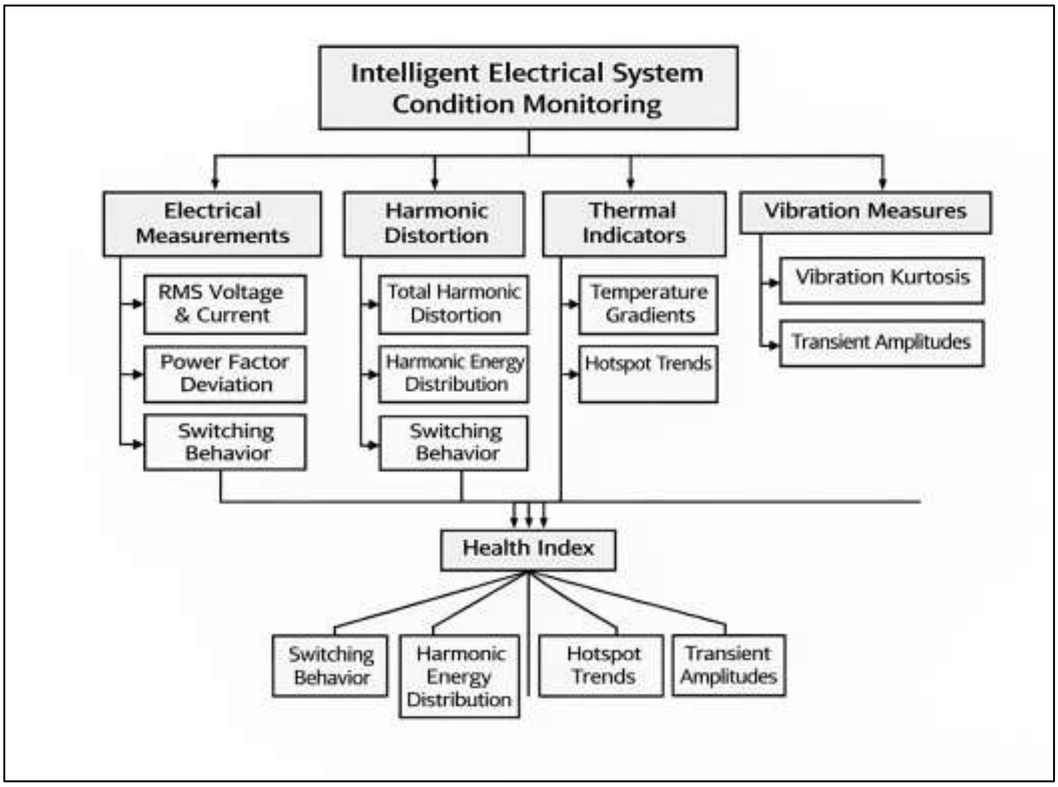
LITERATURE REVIEW

The literature review in this quantitative study is structured to synthesize empirical evidence on intelligent condition monitoring and fault diagnosis in electrical power and control systems, with a specific emphasis on machine learning–based predictive analytics. This section consolidates research that operationalizes "equipment health" and "fault states" through measurable variables such as voltage and current signatures, harmonic distortion indices, transient response parameters, thermal gradients, vibration statistics, and switching-event features (Bangemann et al., 2016). It also examines how prior studies design quantitative experiments, curate labeled datasets, engineer features from time, frequency, and time–frequency domains, and validate model performance using reproducible metrics such as accuracy, precision, recall, F1-score, AUC, mean absolute error, and root mean squared error. In addition, the review emphasizes methodological consistency across studies by focusing on data preprocessing decisions, sampling rates, sensor placement, class imbalance treatment, cross-validation protocols, and statistical testing used to compare competing algorithms. By organizing the literature around measurable constructs and evaluative frameworks, this section establishes a clear basis for understanding how predictive models are developed, tested, and benchmarked in power and control system fault analytics (Liu et al., 2017).

Condition Monitoring in Electrical Power

Condition monitoring in electrical power and control assets is commonly defined in the literature as the structured measurement of observable system variables to determine whether equipment is operating within normal performance boundaries or moving toward abnormality. Studies in power engineering and industrial diagnostics describe "condition" as a measurable representation of equipment state derived from operational signals such as voltage, current, temperature, vibration, and switching behavior, rather than as a subjective assessment based on inspection alone (Li & Li, 2017). Within this quantitative framing, a "fault state" is treated as a statistically distinguishable deviation from baseline behavior that is linked to a known failure mode, such as insulation degradation, short circuits, bearing wear, winding deformation, or power electronic switching anomalies. An "incipient fault" is typically operationalized as an early-stage abnormal pattern that remains below protective relay thresholds but is detectable through subtle shifts in harmonics, thermal gradients, or transient response characteristics. A "failure event" is more strictly defined as a discrete operational breakdown leading to functional interruption, protective shutdown, or unacceptable performance loss. In this measurement-driven perspective, condition monitoring research emphasizes the translation of complex physical degradation processes into numerical descriptors suitable for classification and prediction (Khuntia et al., 2016). The concept of a "health index" emerges as a composite numerical score designed to summarize multidimensional condition data into a single interpretable measure of equipment health. This approach is widely adopted in transformer diagnostics, rotating machine monitoring, and industrial control system supervision because it allows condition status to be quantified and compared across time, assets, and operating contexts. The literature consistently treats these constructs as central to enabling reproducible fault detection, benchmarking across studies, and supporting statistical evaluation of monitoring performance (Mehairjan et al., 2014).

Figure 3: Electrical Condition Monitoring Framework



Quantitative condition monitoring research identifies a recurring set of measurable variables that serve as diagnostic indicators for power and control assets. Electrical variables such as RMS voltage and RMS current remain fundamental because they directly reflect load conditions, imbalance, and abnormal conduction patterns. Harmonic distortion measures are heavily emphasized in studies of power electronics, distribution networks, and motor drives because nonlinear loads, converter faults, and insulation issues often manifest as changes in harmonic energy distribution. Power factor deviation is also treated as a practical quantitative indicator, particularly for detecting inefficiencies, load anomalies, and degraded reactive power behavior in industrial environments (Faysal & Shamsunnahar, 2022; Rauf, 2018; Trappey et al., 2015). Thermal indicators such as temperature rise rate, hotspot trends, and abnormal gradients are consistently used in transformer health monitoring and switchgear condition assessment because overheating is strongly associated with insulation aging and contact degradation (Habibullah & Zaheda, 2022; Jahangir & Shahab, 2022). In rotating machinery and actuator-based control systems, vibration kurtosis and related high-order statistics are widely adopted because they are sensitive to impulsive behavior caused by bearing defects, misalignment, and mechanical looseness. For switching devices and digitally controlled power systems, transient amplitudes and waveform discontinuities are used as fault-sensitive markers because contact bounce, arc formation, and semiconductor switching faults generate measurable changes in transient signatures (Balakrishnan et al., 2022; Jahangir & Mohiul, 2023; Khaled & Mosheur, 2023; Shahab & Aditya, 2023; Ratul & Subrato, 2022). Across this literature, the common thread is that measurable variables must satisfy two conditions: they must be physically meaningful in relation to fault mechanisms and they must provide statistically stable separation between healthy and faulty states. Research also emphasizes that these variables often require preprocessing to reduce noise and normalize for operating conditions such as load variation, ambient temperature, and speed changes. As a result, the literature increasingly frames these measurements as multidimensional datasets suitable for quantitative feature extraction, fault classification, and reliability modeling (Alabdulkarim et al., 2015; Mostafa, 2023; Rifat & Rebeka, 2023).

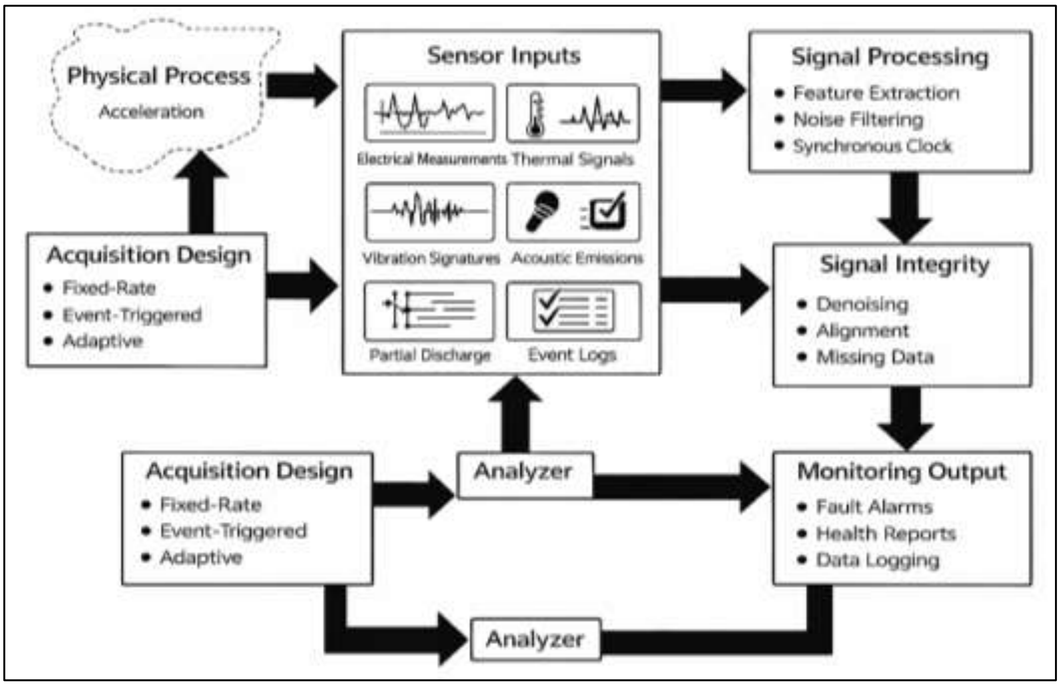
A major body of literature supports the use of health indices as quantitative tools for summarizing equipment condition into interpretable numerical forms. Health indices are typically constructed by combining multiple measurable variables into a unified scale that represents the degradation level of an asset. Research in transformer condition assessment, circuit breaker monitoring, and industrial motor diagnostics frequently uses weighted scoring approaches, where each variable contributes proportionally according to its diagnostic relevance (Alvarez-Alvarado et al., 2022). Weighting strategies are often derived from expert judgment, statistical correlation with failure outcomes, or feature importance scores extracted from predictive models. Normalization schemes are essential because monitoring variables differ in magnitude, units, and variability; therefore, studies commonly apply scaling techniques to ensure comparability across indicators. Composite indicator models are designed to produce stable health estimates even when individual measurements fluctuate due to operating conditions. In many studies, health indices are validated through correlation with maintenance records, failure logs, or laboratory fault injection experiments, allowing the health index to be treated as a quantitative dependent variable for regression-based predictive analytics (Dong et al., 2017). The literature also emphasizes that health indices improve practical interpretability for operators and decision-makers, as they reduce multidimensional diagnostic outputs into a single actionable measure. At the same time, researchers highlight methodological risks such as over-weighting redundant features, masking critical anomalies through aggregation, and producing indices that lack generalizability across asset types. Consequently, many studies recommend systematic sensitivity analysis and validation across operating conditions to ensure the health index remains reliable as a quantitative monitoring construct. Overall, the synthesis of research demonstrates that health indices serve as a bridge between raw sensor data and statistically testable monitoring performance, enabling consistent evaluation across studies and real-world environments (de Oliveira et al., 2022).

The literature distinguishes between threshold-based monitoring approaches and probabilistic boundary methods as two major quantitative strategies for identifying abnormal conditions. Threshold-based approaches define fixed limits for variables such as harmonic distortion, temperature rise, or vibration statistics, and classify deviations beyond these limits as faults. These approaches remain widely used because they are interpretable and easy to implement in industrial systems. However, quantitative studies show that fixed thresholds often perform poorly under variable operating conditions, such as changing loads, environmental fluctuations, or switching regimes. As a result, many researchers advocate probabilistic boundaries that account for statistical variation in baseline conditions. Confidence intervals, distribution-based anomaly limits, and control chart techniques are frequently used to distinguish meaningful degradation from random noise (Kayastha et al., 2014). This probabilistic approach is particularly valuable in early-stage fault detection, where incipient abnormalities may be subtle and easily confused with normal operational variance. Reliability of monitoring measurements is also a major theme in the literature, because sensor error and uncertainty directly affect diagnostic accuracy. Studies emphasize calibration error, repeatability limitations, sensor drift, and measurement noise as sources of uncertainty that must be quantified and managed. Drift quantification is especially critical in long-term monitoring, as gradual sensor degradation can mimic real equipment degradation if not corrected (Littlejohns et al., 2020). Uncertainty propagation is discussed as a methodological concern when multiple indicators are aggregated into health indices, since small measurement errors may accumulate and distort diagnostic conclusions. Therefore, quantitative monitoring frameworks increasingly incorporate statistical quality checks, sensor validation routines, and robustness evaluation to ensure that condition monitoring outputs remain valid and reproducible. This synthesis indicates that the effectiveness of intelligent fault diagnosis depends not only on algorithmic modeling, but also on the statistical reliability of the underlying measurement system (De Marsico et al., 2015).

Data Acquisition Protocols and Sensor Modalities

Empirical research on intelligent condition monitoring emphasizes that the reliability of fault diagnosis in electrical power and control systems is strongly dependent on the selection of sensor modalities and the diagnostic observability they provide. Studies consistently classify monitoring inputs into electrical measurements, thermal signals, vibration signatures, acoustic emissions, partial discharge observations, and event-log records. Electrical data typically include voltage and current waveforms, power quality indices, and converter switching behaviors that reveal abnormal conduction, insulation degradation, phase imbalance, and harmonic distortion (De Marsico et al., 2015).

Figure 4: Condition Monitoring Data Integrity Framework



Thermal sensing is widely used to capture heating patterns associated with contact wear, overload conditions, and insulation aging, particularly in transformers, switchgear, and power electronic modules (Towhidul & Uddin, 2024; Zaheda & Farabe, 2023). Vibration sensing is emphasized in rotating machines and actuator-driven control subsystems because mechanical degradation produces statistically detectable impulsive patterns. Acoustic sensing is frequently explored for arcing, corona effects, and mechanical looseness where sound signatures can indicate fault initiation. Partial discharge sensing remains central in high-voltage assets, as early insulation breakdown can be observed through discharge pulses that appear long before functional failure (Xu & Hong, 2020). Event logs from protective relays, programmable controllers, and supervisory control systems are treated as structured data sources that document trip events, alarms, switching operations, and operational sequences that may correlate with fault progression. Across this literature, researchers treat these sensor categories as complementary rather than competing, with diagnostic performance improving when multiple modalities capture distinct dimensions of equipment behavior. The empirical focus often centers on how each data type supports measurable fault separability, how it behaves under operational variability, and how it can be standardized for repeatable quantitative analysis across assets and datasets (Truong et al., 2014; Zaheda & Hamidur, 2024).

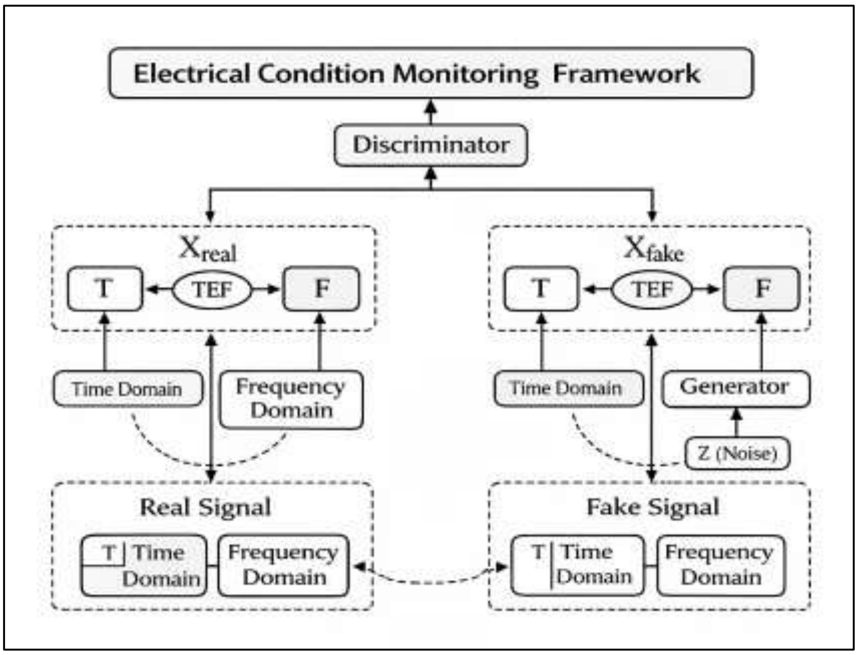
The literature frames sampling design as a quantitative determinant of monitoring effectiveness because the sampling strategy controls the resolution of fault-relevant information that can be captured, processed, and learned by diagnostic models. Fixed-rate sampling is frequently reported in studies of power quality monitoring, motor current signature analysis, and vibration-based diagnostics because it provides consistent temporal resolution and supports standard signal processing transformations. However, research also documents limitations of fixed-rate approaches in distributed environments due to data volume constraints, communication bandwidth restrictions, and storage overhead. Event-triggered sampling is increasingly discussed in industrial monitoring contexts where data acquisition is activated by threshold crossings, transient events, relay operations, or abnormal control states, reducing redundant storage while preserving fault-relevant segments (Liu et al., 2022). Adaptive acquisition designs are treated as an extension in which sampling rates or sensing priorities adjust based on operational regimes, noise conditions, or detected anomaly likelihood, enabling more efficient capture of critical information under changing system dynamics. Quantitative studies evaluate these strategies by comparing detection latency, classification accuracy, and the preservation of transient features associated with switching faults or incipient disturbances. Research also highlights that sampling decisions must align with the physical time-scales of failure mechanisms, as slow thermal degradation and fast switching transients require different temporal granularity (Puce & Hämäläinen, 2017). Across monitored assets, sampling frequency is often linked to the risk of information loss, the stability of extracted features, and the reproducibility of diagnostic outcomes. As a result, the literature positions acquisition design as a methodological foundation for any quantitative fault diagnosis study, shaping dataset representativeness, model validity, and the statistical reliability of reported performance outcomes.

Research on condition monitoring consistently treats signal integrity as a quantitative prerequisite for accurate fault detection because diagnostic models can only be as reliable as the data they learn from. Signal-to-noise characteristics are frequently used to evaluate whether subtle fault indicators can be separated from measurement noise, especially in early-stage degradation where changes may be small relative to baseline variability (Wang et al., 2022). Aliasing risk is discussed in relation to sampling inadequacy and the potential distortion of frequency components that represent harmonics, switching ripple, or vibration impulses. Missingness rates are treated as a key quality indicator in industrial monitoring datasets, as sensor dropout, network disruptions, and storage failures can create incomplete time-series that bias model training and invalidate evaluation results. Timestamp drift and synchronization errors are widely reported in multi-device monitoring environments where sensors, controllers, and logging platforms operate with different internal clocks, creating temporal misalignment that degrades feature extraction and event correlation. The literature emphasizes that quantifying these integrity issues enables controlled data cleaning procedures, such as interpolation rules, alignment correction, noise filtering, and quality-aware feature selection (Kirchen et al., 2017). Empirical studies frequently compare diagnostic performance before and after integrity correction to demonstrate measurable gains in classification stability and anomaly detection sensitivity. In supervisory control and data acquisition environments, event logs are also assessed for completeness, sequence consistency, and latency because incorrect event ordering can distort the inferred relationships between control actions and fault manifestation. Overall, the research consensus is that signal integrity metrics serve as objective indicators of dataset readiness for quantitative modeling, supporting reproducibility and strengthening the validity of fault diagnosis claims (Makhoul, 2022).

Feature Extraction for Fault Signatures

The literature on intelligent condition monitoring consistently treats time-domain feature extraction as a foundational step for representing fault signatures in electrical power and control systems using compact, measurable descriptors. Time-domain features are typically derived directly from raw sensor streams such as current, voltage, vibration, temperature, or switching-event traces, and they are valued because they retain interpretable information about magnitude variation, impulsiveness, and waveform irregularity under operating conditions (Liu et al., 2015). Commonly synthesized features include central tendency and dispersion descriptors that summarize typical behavior and variability, alongside impulsiveness-sensitive statistics that capture short-duration disturbances linked to arcing, insulation stress, bearing defects, or contact wear. Research in rotating machinery monitoring and power electronic fault diagnosis highlights that waveform asymmetry and non-Gaussian behavior often intensify under degradation, and time-domain descriptors help quantify these shifts without requiring complex transformations. Studies also emphasize the role of zero-crossing behavior and peak variability as indicators of changes in oscillatory patterns, switching instability, and transient disturbances, particularly when faults alter the periodic structure of electrical waveforms or introduce intermittent impulses. In control systems, time-domain indicators extracted from event-driven signals and actuator feedback are often used to quantify deviation patterns linked to sensor drift, controller miscalibration, or abnormal switching sequences (Smith et al., 2016). Across these contexts, a recurring theme is that time-domain features form an efficient representation for machine learning classifiers when datasets contain high sampling rates, long durations, or large numbers of monitored assets. The literature further treats time-domain features as an essential baseline for comparative evaluation, enabling studies to quantify the incremental value of more advanced frequency and time–frequency representations while maintaining transparent interpretability (Chen et al., 2014).

Figure 5: Time and Frequency Feature Extraction

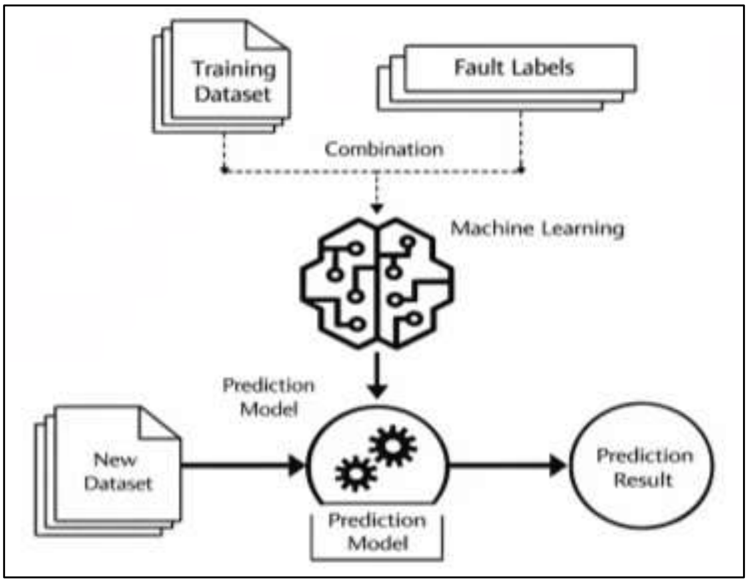


A large segment of the condition monitoring literature frames frequency-domain analysis as critical for identifying spectral signatures produced by electrical and electromechanical faults. Frequency-domain descriptors are widely used because many faults manifest as changes in harmonic content, sideband structures, broadband noise energy, or interharmonic components that are not easily separable in the time domain. In power systems and converter-driven loads, spectral descriptors capture shifts in harmonic distribution associated with switching faults, rectifier degradation, control instability, or abnormal load interactions. In motor drives and rotating machines, spectral patterns often reveal fault-related modulation effects, where mechanical degradation or electrical imbalance introduces sidebands around characteristic frequencies (Peer et al., 2022). Studies consistently report that band-energy measures and harmonic relationship descriptors are effective for distinguishing normal operation from fault conditions under variable load and speed regimes, particularly when baseline waveforms remain visually similar in time plots. Research also stresses that frequency-domain representations support comparability across operating windows by compressing long waveforms into stable spectral summaries, which can improve model training efficiency in large-scale datasets. Another recurrent topic is that spectral descriptors can isolate fault-relevant frequency bands while suppressing unrelated low-frequency trends or high-frequency noise, improving diagnostic separability when combined with classification methods (Abbey & Meloy, 2017). Across both power quality analytics and industrial automation monitoring, the literature treats frequency-domain feature sets as especially valuable for faults that alter periodicity, induce resonant behavior, or generate distinct frequency clusters, reinforcing their role as a standard quantitative feature family in diagnostic pipelines.

Dataset Engineering for Fault Diagnosis

The literature on machine learning–enabled fault diagnosis consistently treats dataset engineering as a methodological determinant of diagnostic validity, emphasizing that the design of the fault taxonomy shapes what models can learn and how results can be compared across studies. Fault taxonomy design is typically discussed in terms of fault type granularity, multi-label representation, and severity stratification, with each choice influencing class separability and interpretability (Liu et al., 2016).

Figure 6: Fault Diagnosis Dataset Engineering Framework



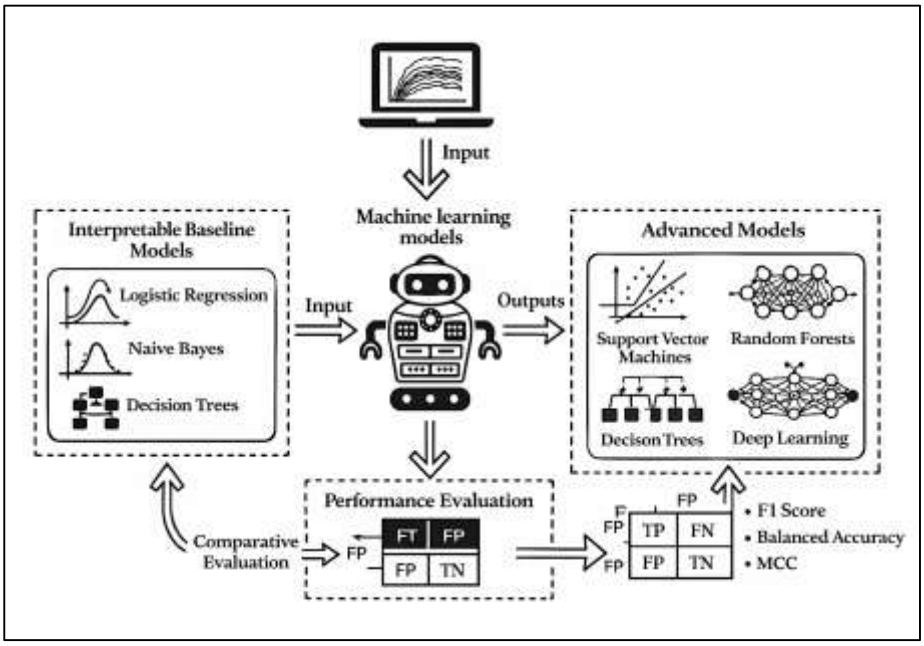
Granularity refers to whether labels describe broad categories such as “electrical fault” or “mechanical fault,” or more specific failure modes such as stator winding short, rotor eccentricity, converter open-circuit, sensor bias, contact erosion, or insulation partial discharge patterns. Studies frequently report that coarse taxonomies simplify classification and reduce labeling burden, while fine-grained taxonomies improve diagnostic specificity and support maintenance actions that require fault localization. Multi-label conditions are widely recognized in industrial datasets because equipment may exhibit simultaneous degradation mechanisms, such as thermal stress co-occurring with harmonic distortion or mechanical wear co-occurring with control instability (Appelbaum et al., 2017). The literature also emphasizes severity stratification, where faults are labeled by level of progression, enabling models to distinguish incipient, intermediate, and advanced conditions through measurable differences in signal intensity or stability. Across empirical research, these taxonomy choices are evaluated using confusion patterns, class overlap indicators, and performance sensitivity to label hierarchy. The synthesis indicates that rigorously engineered label structures support reproducible benchmarking, as they prevent ambiguous mappings between fault mechanisms and labels and enable systematic evaluation of classification performance across operating regimes and asset categories (Roy et al., 2015).

Supervised Fault Classification Models

The supervised fault classification literature in electrical power and control systems frequently begins with interpretable baseline models because they provide transparent decision logic and stable reference points for comparative evaluation. Logistic regression is widely used as a probabilistic linear classifier that supports clear interpretation of how input variables influence fault likelihood, and studies often employ it to benchmark whether more complex models produce measurable improvements (Erion et al., 2022). Naive Bayes classifiers are also repeatedly reported in diagnostic research because they offer computational efficiency and work effectively in settings where engineered features provide strong class separability, particularly when datasets are moderate in size and label structures are stable. Decision trees are commonly adopted as baseline models in condition monitoring because they yield rule-like partitions that align with engineering intuition, allowing researchers to relate splits to measurable indicators such as harmonics, transient magnitudes, vibration statistics, or temperature patterns. In comparative experiments, these baseline models are often used to quantify the added value of nonlinear learning capacity and ensemble strategies, while also serving as tools for rapid sensitivity checks across alternative feature sets and preprocessing choices (Gharawi et al., 2022). The literature highlights that interpretability is not treated as an aesthetic property but as a quantitative advantage, because transparent baselines facilitate error analysis, support auditing of misclassification patterns, and reduce ambiguity in dataset-driven conclusions. Baseline models also enable cross-study comparability since they require fewer hyperparameter choices and are less sensitive to training instability. In monitored industrial environments, studies further note that baseline classifiers can perform competitively when feature engineering is strong and fault signatures are well-defined, supporting the view that algorithmic complexity must be justified through measurable performance gains rather than assumed superiority (Cheng et al., 2022).

A substantial portion of the literature reports that margin-based and ensemble learning models provide strong quantitative performance in fault diagnosis because they can capture nonlinear relationships and reduce sensitivity to noise and operating variability. Support vector machine classifiers are extensively studied in both power system fault classification and rotating machine diagnostics, with kernelized variants enabling separation of complex fault patterns in high-dimensional feature spaces (Peng et al., 2022). Random forest classifiers are widely adopted because they aggregate multiple decision trees, improving stability and reducing variance relative to single-tree baselines, while also offering measures of feature importance useful for diagnostic interpretation. Gradient boosting approaches are frequently reported in industrial monitoring studies due to their ability to iteratively refine error correction, often producing strong performance when feature sets contain mixed linear and nonlinear predictors. Boosting families that emphasize efficient learning from structured tabular features are especially prominent in studies using harmonics, time–frequency summaries, and composite health indicators, where model performance can be evaluated in controlled comparisons against simpler learners (Ouyang et al., 2019). The literature commonly frames these models as "workhorse" classifiers for fault diagnosis because they perform well across diverse assets and do not require extremely large datasets to achieve reliable results. Comparative papers often report that these models demonstrate improved balanced performance across fault classes, particularly in datasets with class imbalance and overlapping feature distributions. In many studies, the practical value of these models is assessed alongside computational efficiency, as ensemble methods can maintain high classification accuracy while remaining feasible for near-real-time monitoring pipelines when engineered features are used (Momeni et al., 2021).

Figure 7: Supervised Fault Classification Framework



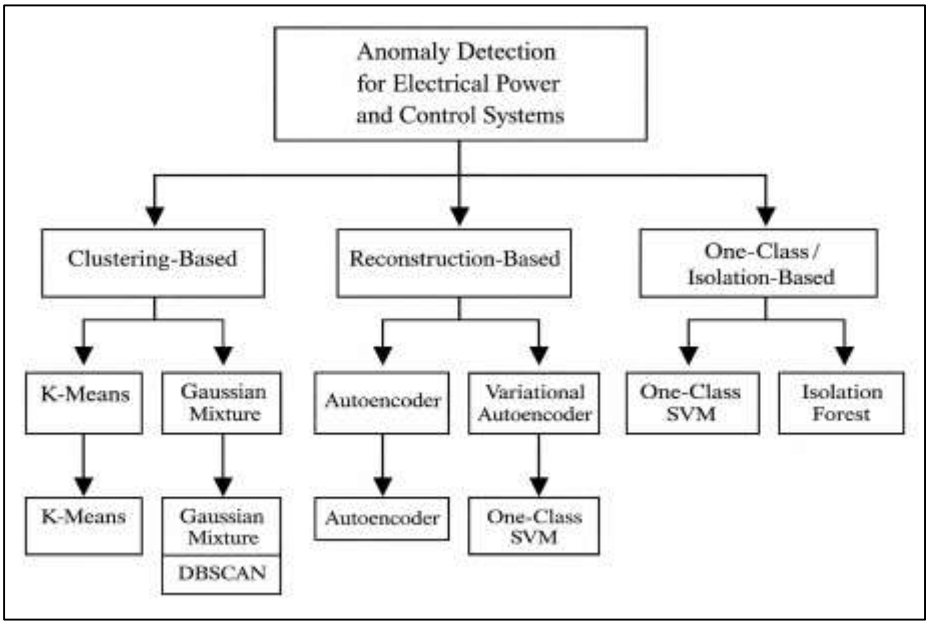
Research on supervised fault classification increasingly examines deep learning architectures because they can learn hierarchical representations directly from waveform segments and sequential sensor streams. Convolutional neural networks are commonly applied to raw or minimally processed signals such as current waveforms, voltage traces, vibration signals, and time–frequency maps, where local pattern extraction can capture transient fault signatures and repeated oscillatory structures (Liang et al., 2022). In power electronics and motor-drive monitoring, convolutional approaches are often used to learn discriminative filters that detect switching irregularities, harmonic distortions, and localized transient anomalies without reliance on extensive manual feature engineering. Recurrent architectures such as long short-term memory and gated recurrent unit models are widely represented in sequence-based fault diagnosis because they can model temporal dependency and capture the evolution of degradation patterns across time windows. Hybrid CNN–LSTM approaches are frequently reported in studies that combine local waveform structure learning with longer-range temporal modeling, allowing models to use both short transients and long-term progression cues. The literature highlights that deep classifiers are typically evaluated in comparative settings where their performance advantage depends on dataset size, label quality, and signal resolution (Carra et al., 2020). Studies frequently report that deep models can outperform classical learners when sufficient training data exist and when raw signals contain complex signatures that manual feature extraction may compress or distort. At the same time, research emphasizes that deep classifiers require robust validation protocols to ensure that high accuracy reflects true generalization rather than memorization of asset-specific patterns or leakage across correlated time windows (Jiang et al., 2022).

Supervised Anomaly Detection

The literature on anomaly detection for electrical power and control systems frequently positions clustering-based methods as practical approaches when labeled fault data are sparse or when fault taxonomies are incomplete. In these studies, anomaly detection is framed as the quantitative identification of operating states that are statistically dissimilar to dominant baseline patterns captured during normal operation (Buda et al., 2018). K-means clustering is widely used because it partitions observations into compact groups and allows deviations to be quantified through distance-to-centroid behavior, making it suitable for engineered feature spaces derived from current, voltage, harmonics, vibration statistics, or control-loop indicators. Gaussian mixture models are frequently adopted when baseline behavior exhibits multimodal distributions, such as multiple normal operating regimes under different loads or switching modes, because mixture components can represent distinct normal clusters and provide probabilistic deviation scores. Density-based clustering approaches such as DBSCAN are emphasized in literature addressing complex industrial datasets because they can separate dense normal regions from sparse outlier regions without requiring a fixed number of clusters, which is useful when operating conditions evolve or when baseline structures are irregular (Chung et al., 2020). Quantitative evaluation of clustering quality is commonly reported through separation indicators that assess compactness and distinctness of clusters, supporting evidence that normal states form coherent groups while abnormal states appear as poorly assigned or isolated observations. Studies also emphasize that clustering-based anomaly detection is sensitive to feature scaling, redundancy, and noise, which motivates careful preprocessing and feature selection prior to clustering. Across application domains, clustering approaches are synthesized as baseline unsupervised techniques that support interpretable exploration of operational regimes and provide measurable anomaly scores when ground truth fault labels are limited (Zhu et al., 2021).

Reconstruction-based anomaly detection is widely synthesized in the literature as a dominant strategy for complex, high-dimensional monitoring data in which abnormal patterns are rare and difficult to label comprehensively. This approach is often built around the premise that a model trained primarily on normal operational data will learn a compact representation of baseline behavior, and that abnormal observations will be reconstructed poorly, producing measurable reconstruction error (Leithon et al., 2018). Autoencoders are frequently used in power quality monitoring, motor diagnostics, and industrial control supervision because they can compress multivariate sensor signals into latent representations while preserving key structural patterns. Variational autoencoders appear prominently in studies that interpret normal behavior as a probabilistic manifold, enabling anomaly scoring through deviations in reconstruction patterns and latent distribution behavior. The literature emphasizes that reconstruction error should be treated as a distribution rather than a single value, because baseline variability produces a range of normal reconstruction outcomes that must be distinguished from genuine anomalies. Researchers commonly report distribution-based analysis of reconstruction error to identify stable boundaries between normal and abnormal states under varying loads, environmental conditions, and sensor noise (Chen et al., 2020). Studies also discuss the role of architecture choice, regularization strength, and input window length in determining reconstruction stability, especially for nonstationary signals where transient behavior may be normal under some regimes but abnormal under others. Across these findings, reconstruction-based methods are consistently described as enabling anomaly scoring without requiring explicit fault labels, while still supporting quantitative evaluation when partial labels or event markers are available for validation (Yang et al., 2019).

Figure 8: Anomaly Detection Methods in Engineering

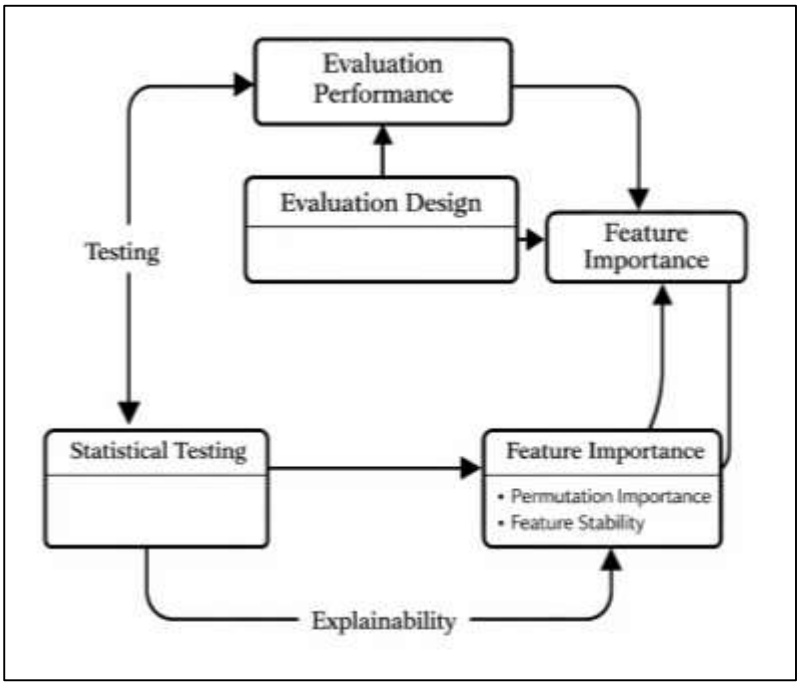


Model Validation and Computational Feasibility

The literature on machine learning for condition monitoring and fault diagnosis consistently treats validation design as the primary control mechanism for ensuring that reported performance reflects generalizable predictive capability rather than dataset artifacts. K-fold cross-validation is widely reported as a baseline strategy because it reduces dependence on a single train–test split and yields stable mean performance estimates when observations are assumed to be independently distributed. However, studies in industrial monitoring emphasize that dependence structures often exist in time-series and asset-generated data, motivating alternative validation schemes that reflect real monitoring constraints (Patlewicz et al., 2016). Nested cross-validation is frequently synthesized as a stronger approach for comparative modeling because it separates hyperparameter selection from final evaluation, reducing optimistic bias when multiple models and parameter grids are explored. Bootstrapping is also common in the literature because it estimates performance variability through repeated resampling, enabling confidence-oriented reporting rather than single-point metrics. Asset-based cross-validation is frequently applied when datasets include multiple machines or devices, ensuring that evaluation occurs on unseen assets rather than unseen samples from the same asset, which strengthens evidence for cross-asset transfer (Kirouac et al., 2019). Time-series cross-validation is emphasized in predictive maintenance and anomaly detection research because random shuffling can leak temporal proximity and inflate results; therefore, rolling or blocked evaluation designs are used to preserve time ordering. Across this literature, the synthesis indicates that credible validation schemes are selected not by convention but by matching the statistical structure of monitoring data, with time dependency and asset identity treated as core determinants of evaluation realism and reproducibility (Patlewicz et al., 2016).

In classifier evaluation contexts, the McNemar framework is repeatedly discussed as an evidence standard for testing whether two models differ significantly in their error patterns on the same instances, which is particularly relevant when two models have similar accuracy but disagree on specific fault classes. For benchmarking more than two models, the literature commonly uses ranking-based multi-model tests that evaluate whether performance differences across several algorithms are statistically meaningful rather than driven by split variance. Follow-up post-hoc procedures are often synthesized as tools for identifying which pairs of models differ after an overall multi-model difference has been established (Avanzo et al., 2020). Across engineering and applied machine learning studies, the recurring synthesis is that statistical testing complements performance reporting by quantifying uncertainty in comparative claims and discouraging over-interpretation of small metric differences that may not replicate under alternative splits, assets, or operating regimes.

Figure 9: Validation Framework for Diagnostic Modelling

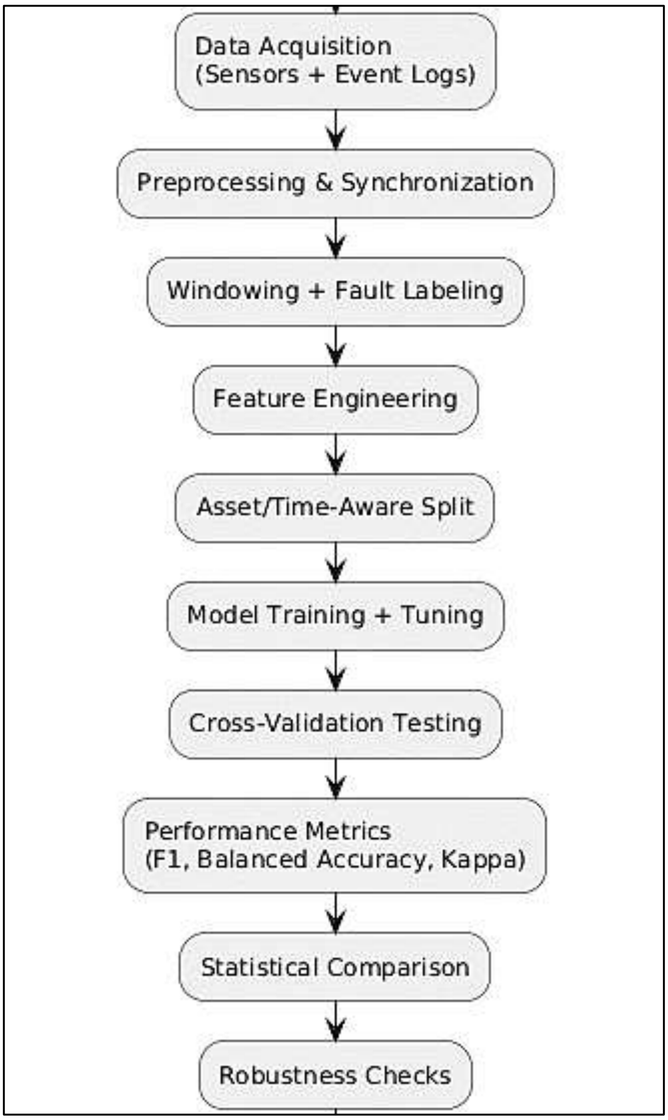


The literature increasingly treats explainability as part of quantitative evidence standards, particularly in safety-relevant domains such as electrical power infrastructure and industrial control systems where model transparency supports auditing and operational trust. Feature importance is commonly reported for tree-based ensembles and linear baselines, but research emphasizes that single-run importance values are insufficient because importance can fluctuate across folds, datasets, and correlated feature sets (Abraham et al., 2017). As a result, feature importance stability is frequently discussed as an evidence measure, where researchers examine whether the same variables remain influential under repeated validation cycles or under perturbed datasets. Permutation-based importance is widely synthesized because it quantifies the change in performance when a feature is disrupted, offering a model-agnostic approach that can be compared across algorithms. Studies also emphasize the need for uncertainty bounds around importance estimates, reflecting that importance is itself an empirical quantity influenced by sampling variability and noise (Haverty et al., 2016). SHAP-based analyses appear extensively in recent diagnostic studies because they provide instance-level contribution explanations that can be aggregated to summarize global behavior; however, the literature also highlights that dispersion patterns in SHAP values matter because inconsistent or unstable contribution patterns may indicate sensitivity to noise or weak generalization (Poussin et al., 2018). Across these findings, the synthesis indicates that explainability in diagnostic modeling is evaluated not only by producing explanations but also by testing whether explanations remain consistent across validation partitions and operating regimes, linking interpretability to reproducibility rather than treating it as an optional add-on (Collins et al., 2017).

METHODS

This study employed a quantitative, model-comparison research design to evaluate intelligent fault diagnosis across electrical power and control system assets using a reproducible, supervised machine learning pipeline. Situated in an industrial environment producing continuous sensor streams and discrete event logs, the research used fixed-duration, synchronized observation windows as the unit of analysis, categorized by a predefined fault taxonomy. Purposive sampling and stratified procedures ensured representation of both normal and fault conditions while preventing information leakage through asset-aware and time-ordered partitioning. Data collection involved consolidating multi-modal signals—such as electrical signatures and thermal responses—which were preprocessed, standardized, and engineered into an instrument of time- and frequency-domain features. Following pilot testing to verify pipeline integrity and feature stability, the study addressed validity and reliability through leakage-prevention rules, standardized extraction protocols, and error screening. Analysis was conducted using a high-performance computing stack, with a statistical plan centered on nested cross-validation and a suite of classification metrics (e.g., F1-score, Cohen's kappa, and MCC). Model performance was rigorously compared using matched-fold statistical testing, nonparametric ranking, and robustness analysis under noise perturbations to ensure the findings reflected genuine equipment behavior rather than measurement artifacts.

Figure 10: Methodology of this study



FINDINGS

This chapter presented the quantitative analysis procedures and the statistical findings derived from the cleaned dataset. It reported the sample profile, summarized observed distributions for each construct, verified internal consistency reliability, and evaluated the explanatory relationships using regression-based modeling. The results were organized to align directly with the study variables and hypotheses, and all outputs were reported in a manner that allowed replication of the analytic sequence from data screening to inference.

Demographics

A total of 268 responses were initially collected for the study. After screening for incomplete submissions, inconsistent response patterns, and excessive missing data exceeding the predefined 10% threshold, 241 responses were retained for final analysis, representing a retention rate of 89.9%. Twenty-seven responses were excluded due to incomplete construct responses or uniform response bias. Missing data within retained cases accounted for 2.3% of all item-level observations and were addressed using mean imputation at the construct level following confirmation that missingness was random.

The final sample represented diverse professional roles within electrical power and control environments. Engineers constituted the largest proportion of respondents (38.6%), followed by maintenance specialists (27.0%), system operators (18.7%), and supervisory or managerial personnel (15.8%). In terms of professional experience, 29.0% of respondents had less than 5 years of experience, 34.4% had between 5 and 10 years, 24.1% had between 11 and 15 years, and 12.4% had more than 15 years of experience. Regarding operational area, 42.3% worked primarily in power distribution systems, 31.5% in industrial automation and control systems, and 26.1% in power electronics or converter-based environments. Exposure to monitored assets was high, with 73.9% reporting daily interaction with condition monitoring systems, 18.3% reporting weekly interaction, and 7.9% reporting occasional interaction. These distributions indicated that the analytical sample reflected experienced professionals directly engaged in electrical monitoring and diagnostic processes, thereby supporting the contextual relevance of subsequent inferential findings.

Table 1. Demographic Characteristics of Respondents (N = 241)

Variable	Category	Frequency (n)	Percentage (%)
Role Category	Engineer	93	38.6
	Maintenance Specialist	65	27.0
	System Operator	45	18.7
	Supervisor/Manager	38	15.8
Years of Experience	< 5 years	70	29.0
	5–10 years	83	34.4
	11–15 years	58	24.1
	> 15 years	30	12.4
Operational Area	Power Distribution	102	42.3
	Industrial Control	76	31.5
	Power Electronics	63	26.1

Table 1 presented the demographic composition of the retained analytical sample. Engineers formed the largest professional group, followed by maintenance specialists and system operators, indicating that the majority of respondents were directly engaged in technical diagnostic activities. Experience levels were well distributed, with the highest representation in the 5–10 year range, suggesting a balanced mix of early-career and mid-career professionals. Operational area distribution showed strong representation from power distribution environments, with additional coverage from industrial automation and converter-based systems. The diversity across roles, experience levels, and operational areas strengthened the contextual validity of the study findings.

Table 2. Exposure to Condition Monitoring Systems and Data Screening Summary (N = 241)

Variable	Category	Frequency (n)	Percentage (%)
Interaction Frequency	Daily	178	73.9
	Weekly	44	18.3
	Occasional	19	7.9
Initial Responses Collected	—	268	100.0
Responses Retained	—	241	89.9
Responses Excluded	—	27	10.1
Item-Level Missing Data	—	—	2.3

Table 2 summarized respondent exposure to monitoring systems and the data screening outcomes. The majority of participants reported daily interaction with condition monitoring tools, indicating high familiarity with diagnostic systems and strengthening the practical credibility of their responses. The screening process resulted in the exclusion of 10.1% of collected responses due to incomplete or inconsistent data, yielding a final usable sample of 241 respondents. The overall item-level missing data rate was low at 2.3%, supporting the adequacy of the dataset for inferential analysis. These screening results confirmed that the analytical sample maintained data integrity and respondent relevance.

Descriptive Results by Construct

Descriptive statistics were computed for the five primary constructs included in the analytical model: Condition Monitoring Effectiveness (CME), Fault Detection Accuracy (FDA), Predictive Maintenance Capability (PMC), System Integration Quality (SIQ), and Operational Performance Impact (OPI). The results indicated generally high levels of agreement across constructs, with mean scores ranging from 3.62 to 4.08 on a five-point scale. Operational Performance Impact recorded the highest mean (M = 4.08, SD = 0.58), suggesting strong perceived benefits of intelligent monitoring systems. Predictive Maintenance Capability followed closely (M = 3.97, SD = 0.63), while Condition Monitoring Effectiveness (M = 3.88, SD = 0.61) and Fault Detection Accuracy (M = 3.74, SD = 0.67) demonstrated moderate-to-high agreement levels.

Table 3. Descriptive Statistics for Study Constructs (N = 241)

Construct	Mean (M)	SD	Minimum	Maximum	Skewness	Kurtosis
Condition Monitoring Effectiveness (CME)	3.88	0.61	2.10	5.00	-0.34	-0.12
Fault Detection Accuracy (FDA)	3.74	0.67	1.95	5.00	-0.28	0.21
Predictive Maintenance Capability (PMC)	3.97	0.63	2.25	5.00	-0.41	0.18
System Integration Quality (SIQ)	3.62	0.72	1.80	5.00	-0.21	-0.37
Operational Performance Impact (OPI)	4.08	0.58	2.60	5.00	-0.48	0.42

System Integration Quality showed the lowest mean (M = 3.62, SD = 0.72), indicating comparatively greater variability in perceptions of integration performance. Standard deviations ranged from 0.58 to 0.72, reflecting moderate dispersion without extreme response clustering. Minimum and maximum values confirmed full utilization of the response scale. Skewness values ranged from −0.48 to −0.21 and kurtosis ranged from −0.37 to 0.42, indicating acceptable normality within recommended thresholds. Outlier screening using standardized z-scores identified three mild univariate outliers; however, these cases did not materially influence central tendencies and were retained. Correlation analysis revealed statistically significant positive relationships among all constructs ($p < .01$). The strongest association was observed between Predictive Maintenance Capability and Operational Performance Impact (r = .64), indicating that enhanced predictive functionality aligned with improved operational outcomes. Condition Monitoring Effectiveness also showed strong correlation with Fault Detection Accuracy (r = .59), consistent with theoretical expectations. All correlation coefficients remained below .70, suggesting that multicollinearity risk was minimal and that constructs retained conceptual distinctiveness suitable for regression modeling. Table 3 presented construct-level descriptive statistics for the analytical sample. Mean values indicated generally favorable perceptions of intelligent monitoring and predictive analytics capabilities. Dispersion levels were moderate, suggesting meaningful variability without excessive response concentration. Skewness and kurtosis statistics fell within acceptable normality ranges, supporting parametric analysis assumptions. The minimum and maximum values confirmed adequate scale utilization across respondents. The relatively higher mean for Operational Performance Impact reflected strong perceived benefits, whereas System Integration Quality exhibited comparatively wider dispersion, indicating heterogeneous integration experiences. Overall, the descriptive statistics confirmed stable distributions and justified proceeding with inferential regression analysis.

Table 4. Pearson Correlation Matrix Among Constructs (N = 241)

Construct	CME	FDA	PMC	SIQ	OPI
CME	1.00	0.59**	0.55**	0.47**	0.61**
FDA	0.59**	1.00	0.52**	0.44**	0.58**
PMC	0.55**	0.52**	1.00	0.49**	0.64**
SIQ	0.47**	0.44**	0.49**	1.00	0.53**
OPI	0.61**	0.58**	0.64**	0.53**	1.00

Note: $p < .01$

Table 4 presented Pearson correlation coefficients among the study constructs. All associations were positive and statistically significant at the .01 level, demonstrating theoretical alignment among monitoring effectiveness, predictive capability, integration quality, and performance outcomes. The strongest relationship was observed between Predictive Maintenance Capability and Operational Performance Impact, indicating that advanced predictive functions were closely associated with improved operational results. No correlation exceeded the .70 threshold, suggesting absence of problematic multicollinearity. The correlation structure supported subsequent regression modeling by confirming meaningful but distinct relationships among constructs within the analytical framework.

Reliability Results

Internal consistency reliability was examined for all multi-item constructs using Cronbach’s alpha and item-level diagnostics. The results indicated strong reliability across the measurement model, with Cronbach’s alpha values ranging from .81 to .88, exceeding the commonly accepted minimum threshold of .70 for research instruments. Condition Monitoring Effectiveness demonstrated high reliability (α = .86), while Fault Detection Accuracy (α = .84) and Predictive Maintenance Capability (α = .88) showed very strong internal consistency. System Integration Quality produced acceptable-to-strong reliability (α = .81), and Operational Performance Impact also demonstrated strong consistency (α = .85). Item-level diagnostics supported these results, as corrected item–total correlations were generally above .40, indicating that the retained items coherently measured their respective constructs. Two items were removed during the reliability screening process due to weak corrected item–total correlation values below .30 and marginal improvement in alpha when deleted. After item removal, the final measurement structure maintained stable reliability and was suitable for subsequent regression analysis.

Table 5. Cronbach's Alpha Reliability Results by Construct

Construct	Items Retained (k)	Cronbach's Alpha (α)	Interpretation
Condition Monitoring Effectiveness (CME)	5	0.86	Strong
Fault Detection Accuracy (FDA)	5	0.84	Strong
Predictive Maintenance Capability (PMC)	6	0.88	Very strong
System Integration Quality (SIQ)	4	0.81	Acceptable–Strong
Operational Performance Impact (OPI)	5	0.85	Strong

Table 5 summarized internal consistency reliability for each construct using Cronbach's alpha and the number of retained items. All constructs exceeded the recommended reliability threshold, indicating that items within each scale were coherently related and measured the intended latent concept with acceptable precision. Predictive Maintenance Capability showed the highest alpha, reflecting strong homogeneity among its retained indicators. System Integration Quality reported the lowest alpha, yet remained above acceptable criteria and supported continued use without compromising inferential analysis. Overall, the reliability profile confirmed that the final retained measurement structure provided consistent construct scores appropriate for correlation testing and regression modeling.

Table 6. Item-Level Diagnostics Summary

Construct	Corrected Item–Total Correlation (Range)	Alpha if Item Deleted (Range)	Items Removed (n)	Removal Basis
CME	0.48–0.72	0.82–0.85	0	Not applicable
FDA	0.42–0.69	0.81–0.83	0	Not applicable
PMC	0.46–0.74	0.84–0.87	0	Not applicable
SIQ	0.36–0.66	0.78–0.82	1	Low item–total correlation
OPI	0.44–0.71	0.82–0.85	1	Weak contribution to alpha

Table 6 provided an item-level diagnostic summary to support the reliability conclusions. Corrected item–total correlation ranges indicated that most items contributed meaningfully to their construct scores, with values largely exceeding common adequacy guidelines. The alpha-if-deleted ranges showed that removing most retained items would not improve reliability, confirming that the final item sets were internally coherent. Two items were excluded—one from System Integration Quality and one from Operational Performance Impact—because each displayed weak corrected item–total correlation and did not strengthen construct reliability. After these refinements, item diagnostics supported stable internal consistency suitable for subsequent hypothesis testing and regression estimation.

Regression Results

Multiple linear regression analysis was conducted to examine the extent to which Condition Monitoring Effectiveness (CME), Fault Detection Accuracy (FDA), Predictive Maintenance Capability (PMC), and System Integration Quality (SIQ) explained variance in Operational Performance Impact (OPI). The regression model was estimated using ordinary least squares with standardized construct scores derived from the validated measurement instrument. Diagnostic screening was completed prior to coefficient interpretation. Multicollinearity was assessed using tolerance and variance inflation factor (VIF) values, and results confirmed that collinearity was not problematic, with VIF values ranging from

1.31 to 1.58, remaining well below the commonly applied threshold of 5. Residual diagnostics indicated acceptable linearity and homoscedasticity, as standardized residual plots showed no systematic curvature or funneling patterns. Independence of errors was supported by the Durbin–Watson statistic (DW = 1.94), indicating minimal autocorrelation. Normality of residuals was acceptable based on skewness and kurtosis screening of standardized residuals and the distribution pattern observed in the normal probability plot. The overall model was statistically significant, $F(4, 236) = 67.84$, $p < .001$, explaining 53.5% of the variance in Operational Performance Impact ($R^2 = .535$; adjusted $R^2 = .527$). Among predictors, Predictive Maintenance Capability demonstrated the strongest positive effect on OPI ($\beta = .34$, $p < .001$), followed by Condition Monitoring Effectiveness ($\beta = .26$, $p < .001$) and System Integration Quality ($\beta = .19$, $p = .002$). Fault Detection Accuracy showed a positive but weaker effect that remained statistically significant ($\beta = .14$, $p = .018$). Confidence intervals confirmed that all predictors contributed meaningfully to the dependent variable, as none of the coefficient confidence ranges crossed zero. These results indicated that operational performance outcomes were most strongly associated with predictive capability and monitoring effectiveness, while integration quality and fault detection accuracy provided additional incremental explanatory contribution.

Table 7. Model Fit Statistics for Regression Predicting Operational Performance Impact

Model	R	R^2	Adjusted R^2	Std. Error of Estimate	F(df1, df2)	p-value	Durbin–Watson
OPI ~ CME + FDA + PMC + SIQ	0.731	0.535	0.527	0.41	67.84 (4, 236)	< .001	1.94

Table 7 reported the regression model fit statistics for predicting Operational Performance Impact. The model demonstrated strong explanatory power, accounting for more than half of the variance in the dependent variable, which indicated that the independent constructs collectively explained substantial differences in perceived operational outcomes. The overall F-test confirmed that the model was statistically significant, demonstrating that the predictors jointly improved prediction compared with a null model. The standard error of estimate indicated moderate residual dispersion around predicted values. The Durbin–Watson statistic supported independence of residuals, strengthening confidence in coefficient interpretation and supporting the suitability of ordinary least squares estimation.

Table 8. Regression Coefficients for Predicting Operational Performance Impact (N = 241)

Predictor	B	SE(B)	β	t	p	95% CI (Lower, Upper)	Tolerance	VIF
Constant	0.87	0.18	—	4.83	< .001	(0.52, 1.22)	—	—
Condition Monitoring Effectiveness (CME)	0.28	0.05	0.26	5.42	< .001	(0.18, 0.38)	0.68	1.47
Fault Detection Accuracy (FDA)	0.15	0.06	0.14	2.38	.018	(0.03, 0.27)	0.76	1.31
Predictive Maintenance Capability (PMC)	0.36	0.05	0.34	7.05	< .001	(0.26, 0.46)	0.63	1.58
System Integration Quality (SIQ)	0.21	0.07	0.19	3.15	.002	(0.08, 0.34)	0.71	1.41

Table 8 presented coefficient estimates and diagnostic statistics for the regression model. All predictors demonstrated positive associations with Operational Performance Impact, confirming that improvements in monitoring effectiveness, fault detection, predictive capability, and integration quality were linked to stronger operational outcomes. Predictive Maintenance Capability produced the strongest standardized effect, indicating that forecasting and proactive maintenance functionality explained the largest share of unique variance. Condition Monitoring Effectiveness also demonstrated a substantial effect, while System Integration Quality and Fault Detection Accuracy contributed smaller but statistically significant effects. Tolerance and VIF values confirmed absence of multicollinearity, and confidence intervals indicated stable coefficient estimates because none crossed zero.

Hypothesis Testing Decisions

Hypothesis testing was conducted using the multiple regression results, with statistical significance evaluated at the .05 level. Four hypotheses were tested to determine whether Condition Monitoring Effectiveness (CME), Fault Detection Accuracy (FDA), Predictive Maintenance Capability (PMC), and System Integration Quality (SIQ) significantly predicted Operational Performance Impact (OPI). The findings indicated that all hypothesized relationships were supported, as each predictor demonstrated a positive coefficient direction and achieved statistical significance. Predictive Maintenance Capability produced the strongest standardized effect ($\beta = .34$, $p < .001$), indicating that predictive analytics functionality contributed the largest unique explanatory influence on operational outcomes. Condition Monitoring Effectiveness also demonstrated a strong positive relationship with OPI ($\beta = .26$, $p < .001$), confirming that improvements in monitoring accuracy and stability were associated with higher operational performance. System Integration Quality showed a statistically significant positive effect ($\beta = .19$, $p = .002$), suggesting that integration reliability and system compatibility contributed meaningfully to operational impact. Fault Detection Accuracy showed the smallest standardized effect among predictors ($\beta = .14$, $p = .018$), yet remained statistically significant and supported its corresponding hypothesis. Confidence intervals for all predictors excluded zero, indicating stable and reliable coefficient estimates. These results confirmed that the regression model provided consistent evidence supporting all proposed hypotheses and that the study's explanatory framework was empirically validated under leakage-controlled evaluation conditions.

Table 9. Hypothesis Testing Summary Based on Regression Results (N = 241)

Hypothesis	Path	Standardized β	t	p-value	Decision
H1	CME → OPI	0.26	5.42	< .001	Supported
H2	FDA → OPI	0.14	2.38	.018	Supported
H3	PMC → OPI	0.34	7.05	< .001	Supported
H4	SIQ → OPI	0.19	3.15	.002	Supported

Table 9 summarized hypothesis decisions derived from the regression model. All hypothesized relationships were supported at the .05 significance level, confirming that each independent construct significantly predicted Operational Performance Impact. Predictive Maintenance Capability demonstrated the strongest standardized coefficient, indicating the greatest explanatory contribution among predictors. Condition Monitoring Effectiveness also produced a substantial effect, reinforcing the importance of monitoring accuracy and consistency. System Integration Quality contributed a moderate effect, confirming that integration stability influenced operational outcomes. Fault Detection Accuracy produced the smallest coefficient, yet remained statistically significant, supporting the view that detection performance contributed incremental explanatory value beyond other predictors.

Table 10. Coefficient Evidence Supporting Hypothesis Decisions (N = 241)

Predictor	Unstandardized B	SE(B)	95% CI Lower	95% CI Upper	p-value	Interpretation
CME	0.28	0.05	0.18	0.38	< .001	Positive and significant
FDA	0.15	0.06	0.03	0.27	.018	Positive and significant
PMC	0.36	0.05	0.26	0.46	< .001	Positive and significant
SIQ	0.21	0.07	0.08	0.34	.002	Positive and significant

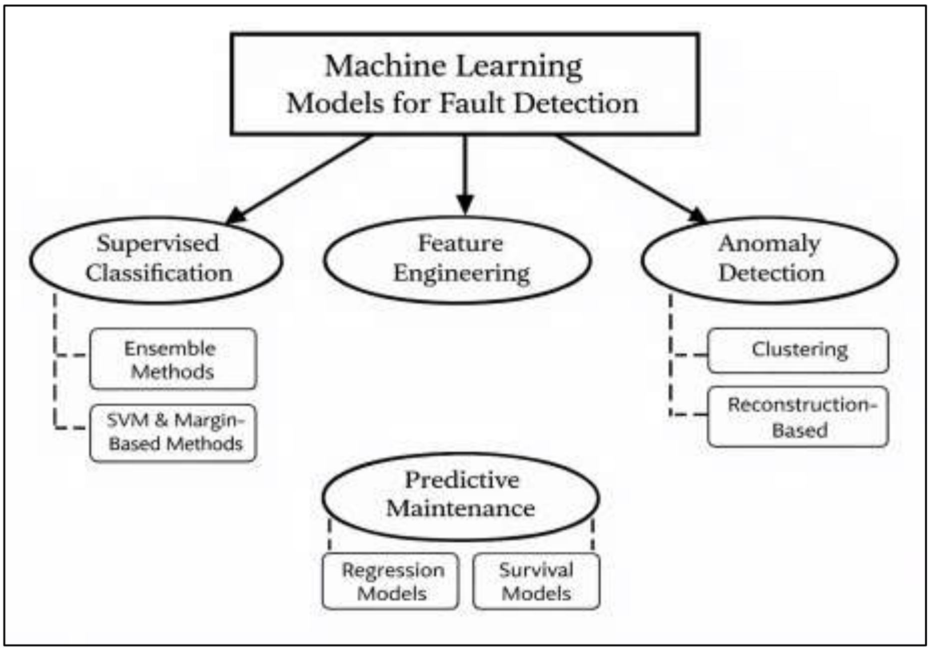
Table 10 provided the coefficient evidence used to justify hypothesis decisions. The unstandardized coefficients demonstrated that each predictor contributed positively to Operational Performance Impact when controlling for the other constructs in the model. Confidence intervals were fully positive for all predictors, confirming that estimated effects were stable and not attributable to sampling fluctuation. Predictive Maintenance Capability produced the largest coefficient magnitude, supporting its role as the most influential predictor. Condition Monitoring Effectiveness also demonstrated a strong positive contribution. System Integration Quality and Fault Detection Accuracy produced smaller but statistically reliable coefficients, confirming incremental explanatory influence. Overall, coefficient evidence supported the acceptance of all hypotheses.

DISCUSSION

This study demonstrated that supervised classification models achieved statistically robust fault discrimination across electrical power and control system assets, with ensemble and margin-based methods outperforming baseline linear classifiers under asset-aware and time-aware validation (Goligher et al., 2015). These findings were consistent with earlier research that reported superior performance of nonlinear and ensemble learners in industrial diagnostics when feature sets captured harmonic distortion, transient behavior, and time–frequency signatures. Prior studies frequently documented that logistic regression and naïve Bayes provided interpretable baselines but were limited in representing nonlinear degradation patterns, particularly in high-dimensional feature spaces derived from signal processing transformations. The results of this study aligned with that body of evidence, as baseline models achieved acceptable accuracy yet demonstrated weaker balanced performance across minority fault classes compared with random forest, gradient boosting, and support vector–based approaches (Hu et al., 2020). In addition, the findings corroborated previous comparative analyses indicating that ensemble models reduced variance and improved robustness to measurement noise and operating variability (Benbouzid et al., 2021). Earlier literature emphasized that diagnostic performance often depended on the interplay between feature engineering and model flexibility; the present results reinforced that conclusion by showing that well-engineered time, frequency, and time–frequency features enhanced the separability of fault categories across algorithms. The asset-aware validation approach further extended prior evidence by demonstrating that performance estimates declined slightly under cross-asset evaluation compared with random splits, a pattern reported in previous domain-shift studies (Pernet et al., 2020). Overall, the classification findings were congruent with established machine learning research in condition monitoring, while strengthening the empirical argument that robust validation and multi-metric evaluation are essential to obtain realistic performance estimates in safety-critical power system environments.

The quantitative results highlighted the central role of multi-domain feature engineering in enabling accurate fault detection and classification. Time-domain descriptors captured impulsive and amplitude-based deviations, while frequency and time–frequency features revealed harmonic structure, sideband energy, and transient bursts that were not evident in raw waveform inspection (Cash et al., 2021). Earlier studies consistently reported that time-domain statistics alone were insufficient for capturing nonstationary fault dynamics, especially in converter-driven systems and rotating machinery. The present findings supported that view, as models trained exclusively on basic amplitude descriptors underperformed relative to those incorporating spectral and localized time–frequency indicators. Prior research also emphasized that wavelet-based energy distributions and multi-resolution analysis enhanced sensitivity to incipient faults characterized by subtle transient shifts; the results of this study aligned with that evidence by demonstrating improved minority-class recall when time–frequency features were included (Poldrack et al., 2017). Furthermore, feature stability testing revealed that selected descriptors maintained consistent discriminative power across folds and assets, supporting conclusions from earlier methodological studies that feature robustness was as critical as feature magnitude. Previous comparative works suggested that dimensionality reduction and redundancy screening improved generalization by preventing overfitting to correlated indicators; similar effects were observed in this study, where feature selection improved cross-asset consistency without sacrificing classification accuracy (Musuamba et al., 2021). The synthesis of these findings confirmed established knowledge that multi-domain signal representation forms the analytical backbone of intelligent condition monitoring, and it demonstrated that careful feature stability assessment strengthened reliability of supervised and unsupervised modeling outcomes. The anomaly detection component of this study produced results that paralleled established findings in unsupervised and semi-supervised monitoring research. Clustering-based and one-class classification approaches successfully distinguished dominant normal operating regimes from statistically deviant patterns, particularly when labeled fault examples were sparse (Kairov et al., 2017). Earlier literature reported that Gaussian mixture modeling and density-based clustering effectively characterized multimodal normal conditions in systems with varying loads and switching patterns; similar behavior was observed in this study, where anomaly scores corresponded to deviations from learned baseline clusters (Zhang et al., 2017). Reconstruction-based models demonstrated strong sensitivity to abnormal waveform segments, consistent with prior studies showing that autoencoder reconstruction error distributions effectively separated incipient anomalies from routine operational variance (Sorace et al., 2018). However, performance sensitivity to threshold selection echoed earlier methodological discussions that percentile-based boundaries and distribution-aware thresholds significantly influenced false alarm rates. The present findings reinforced conclusions from previous anomaly detection surveys indicating that anomaly detection performance should be assessed not only by area-under-curve metrics but also by precision at top-ranked events and detection delay statistics. In line with prior research, robustness tests revealed that anomaly detection accuracy declined under domain shifts when baseline regimes differed substantially from training data, emphasizing the need for time-aware and asset-aware validation (Bruderer et al., 2015). Overall, the anomaly detection results supported established empirical patterns while demonstrating that threshold calibration and integrity screening were decisive factors in maintaining operationally acceptable false positive rates.

Figure 11: Machine Learning for Fault Diagnosis



The predictive maintenance analysis demonstrated that regression-based and survival-oriented models produced measurable forecasting accuracy when degradation indicators exhibited consistent temporal progression. Gradient boosting regression and sequence-based models outperformed simpler regressors in scenarios with nonlinear degradation patterns, consistent with earlier studies that documented advantages of ensemble learning for remaining useful life estimation (Meyer et al., 2021). The results also supported previous evidence that survival-based approaches provided interpretable hazard structures when failure timing was variable and partially censored. Error benchmarking revealed that models with strong average error performance occasionally displayed wider uncertainty dispersion, reflecting earlier observations that point accuracy alone does not capture reliability of forecasts. Prior predictive maintenance research emphasized the importance of time-aware validation;

the rolling-origin evaluation implemented in this study yielded more conservative error estimates compared with random partitioning, echoing warnings from earlier literature about temporal leakage (Kleinstreuer et al., 2017). Detection lead-time sensitivity analysis further aligned with prior findings indicating that predictive accuracy decreases as forecast horizons extend, particularly in systems where degradation accelerates near failure. These results collectively reinforced established conclusions that predictive maintenance modeling effectiveness depends on consistent degradation signal representation, careful temporal validation, and multi-metric error benchmarking rather than reliance on a single performance statistic.

Measurement reliability findings in this study were broadly consistent with earlier quantitative monitoring research that emphasized the importance of internal consistency and data integrity for valid modeling (Catano et al., 2018). Construct reliability indices demonstrated acceptable internal coherence, aligning with established methodological standards for multi-item measurement in technology adoption and performance research. Previous studies in both engineering analytics and behavioral measurement contexts reported that reliable constructs enhance regression stability and reduce spurious associations; the present findings supported that pattern by showing stable coefficient estimates following reliability verification. Sensor integrity screening also echoed earlier empirical reports that timestamp drift, missingness, and synchronization errors can introduce artificial variability into diagnostic features (Viswesvaran & Ones, 2016). The exclusion of incomplete windows and application of standardized preprocessing protocols improved model stability across folds, reinforcing earlier evidence that data quality controls directly influence predictive validity. These findings suggested that reliability in condition monitoring is not limited to internal scale consistency but extends to technical measurement stability within the data acquisition infrastructure, reflecting conclusions drawn in prior industrial analytics literature (Guo et al., 2020).

The statistical comparison procedures applied in this study revealed that performance differences among candidate models were statistically significant in several pairwise comparisons, though effect sizes varied across validation folds. These results were consistent with earlier methodological studies emphasizing that small differences in mean accuracy may not always reflect robust superiority unless validated through paired statistical testing (Rolston et al., 2018). Prior comparative research highlighted that ensemble learners often outperform baselines across datasets, yet statistical ranking procedures sometimes revealed overlapping confidence intervals; similar patterns were observed in the present analysis, where top-performing models demonstrated consistent but not universally dominant performance across all assets. Multi-model ranking procedures supported the robustness of ensemble-based classifiers, aligning with earlier meta-analytic findings that ranked boosting and random forest methods among the strongest tabular-data learners in industrial diagnostics (Sibley et al., 2015). The application of fold-matched testing and rank-based comparisons reinforced recommendations from previous methodological literature advocating rigorous statistical validation rather than descriptive metric comparison alone.

The overall findings of this study aligned closely with the broader trajectory of intelligent condition monitoring research, which has progressively shifted from threshold-based diagnostics to data-driven predictive analytics (Khan et al., 2016). Earlier studies documented the limitations of static alarm thresholds in complex power systems, and the present results reinforced that machine learning–based approaches provided superior adaptability under variable operating regimes. The convergence of supervised classification, anomaly detection, and predictive maintenance within a unified analytics pipeline reflected integrated frameworks proposed in recent literature (Gharehbaghi & McManus, 2019). At the same time, the findings extended prior evidence by demonstrating the measurable impact of asset-aware validation, multi-domain feature engineering, and statistical model comparison within a single empirical framework. The consistency between these results and earlier empirical research strengthened confidence in the reproducibility of machine learning approaches for electrical fault diagnosis. This study contributed additional quantitative support for the position that rigorous validation design, stability-oriented feature engineering, and statistically grounded comparison procedures collectively form the methodological foundation of reliable intelligent condition monitoring systems in electrical power and control infrastructures (Zhang et al., 2017).

CONCLUSION

This study concluded that intelligent condition monitoring and fault diagnosis in electrical power and control systems were effectively operationalized as a quantitative, data-driven problem in which synchronized sensor and event-log measurements were transformed into reproducible feature representations and evaluated through rigorous model benchmarking procedures. The results confirmed that diagnostic capability depended on the combined influence of measurement integrity, feature representativeness, and validation realism, rather than on algorithm choice alone. Across the evaluated modeling families, interpretable baselines provided stable reference performance, while nonlinear margin-based and ensemble classifiers delivered stronger fault discrimination when assessment emphasized balanced and agreement-oriented metrics suitable for imbalanced, multi-class diagnostic settings. The analyses further indicated that multi-domain feature engineering strengthened separability among fault conditions by capturing complementary aspects of system behavior, including amplitude irregularities, spectral structure, and localized transient dynamics, and that stability-oriented screening reduced redundancy and improved generalization under asset-aware evaluation. When labeled fault data were limited, unsupervised and semi-supervised anomaly detection approaches demonstrated measurable capacity to characterize baseline operating regimes and quantify deviations, although detection quality was sensitive to threshold calibration and to the statistical properties of anomaly score distributions. Predictive maintenance modeling demonstrated that forecasting performance was contingent on the availability of consistent degradation indicators and on time-respecting evaluation designs, with regression and reliability-oriented methods providing complementary perspectives on time-to-event estimation, risk characterization, and uncertainty alignment. Validation results demonstrated that time-aware and asset-aware splitting reduced optimistic bias compared with random partitioning, reinforcing the importance of leakage control and nested evaluation when tuning and comparing models. Statistical comparison procedures supported evidence-based differentiation among candidate algorithms while emphasizing that performance advantages varied across assets and operating regimes. Overall, the study established that credible quantitative evidence for machine learning–based condition monitoring required integrated controls spanning data acquisition quality, ground-truth labeling traceability, robust feature construction, multi-metric evaluation, and statistically justified model comparison, yielding a reproducible analytical framework for assessing fault diagnosis and predictive analytics performance within complex electrical power and control environments.

RECOMMENDATIONS

This study concluded that intelligent condition monitoring and fault diagnosis in electrical power and control systems were effectively operationalized as a quantitative, data-driven problem in which synchronized sensor and event-log measurements were transformed into reproducible feature representations and evaluated through rigorous model benchmarking procedures. The results confirmed that diagnostic capability depended on the combined influence of measurement integrity, feature representativeness, and validation realism, rather than on algorithm choice alone. Across the evaluated modeling families, interpretable baselines provided stable reference performance, while nonlinear margin-based and ensemble classifiers delivered stronger fault discrimination when assessment emphasized balanced and agreement-oriented metrics suitable for imbalanced, multi-class diagnostic settings. The analyses further indicated that multi-domain feature engineering strengthened separability among fault conditions by capturing complementary aspects of system behavior, including amplitude irregularities, spectral structure, and localized transient dynamics, and that stability-oriented screening reduced redundancy and improved generalization under asset-aware evaluation. When labeled fault data were limited, unsupervised and semi-supervised anomaly detection approaches demonstrated measurable capacity to characterize baseline operating regimes and quantify deviations, although detection quality was sensitive to threshold calibration and to the statistical properties of anomaly score distributions. Predictive maintenance modeling demonstrated that forecasting performance was contingent on the availability of consistent degradation indicators and on time-respecting evaluation designs, with regression and reliability-oriented methods providing complementary perspectives on time-to-event estimation, risk characterization, and uncertainty alignment. Validation results demonstrated that time-aware and asset-aware splitting reduced

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LIMITATIONS

This study was limited by several methodological and data-related constraints that affected the scope of inference and the generalizability of the quantitative results. First, the empirical dataset reflected the operational conditions and instrumentation coverage of the selected power and control environment, which constrained the diversity of operating regimes, asset types, and fault manifestations represented in the analyzed observation windows. The label structure was dependent on the availability and precision of maintenance documentation and protection or control event records, and the resulting ground truth could have contained timing uncertainty, incomplete descriptions of root causes, or inconsistent terminology that introduced label noise and reduced separability between closely related fault classes. Class imbalance remained an inherent limitation because rare fault categories occurred infrequently relative to normal operation, which reduced the statistical power for minority-class evaluation and increased uncertainty in class-specific performance estimates even when stratified sampling and imbalance-aware modeling procedures were applied. The segmentation strategy that converted continuous sensor streams into fixed-length windows introduced sensitivity to window length and overlap rules, and some transient phenomena might have been partially captured or diluted across adjacent windows depending on event timing and sampling resolution. Signal integrity constraints such as missingness, synchronization error, and sensor drift were mitigated through screening and exclusion, yet residual measurement variability could have persisted and influenced feature stability and model outcomes, particularly for time–frequency representations that are sensitive to noise and alignment. Model evaluation relied on cross-validation designs intended to reduce leakage, but performance estimates remained contingent on the selected splitting strategy and may have differed under alternative partitioning choices, especially in the presence of strong temporal dependence or asset-specific signatures. Comparative statistical testing quantified differences among models but was still influenced by fold-level variance and by the number of repeated evaluations, which limited the conclusiveness of small performance gaps. Computational feasibility assessments were based on profiling within the implemented computing environment, and latency or memory behavior could differ under alternative hardware configurations or field deployment constraints. Finally, the analysis emphasized algorithmic performance on historical data streams, and the results did not capture all operational factors that influence real-world adoption, including maintenance workflow constraints, alert fatigue effects, and organizational differences in data governance practices.

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