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Machine Learning and IoT for Predictive Maintenance in Power Systems: Improving Fault Detection Accuracy and Grid Reliability

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Abstract

Modern power systems face escalating operational complexity arising from aging infrastructure, rising electricity demand, and the large-scale integration of variable renewable generation, all of which increase the risk of equipment failure, unplanned outages, and degraded grid reliability. This study examined how the integration of machine learning (ML) and the Internet of Things (IoT) improves predictive maintenance, fault detection, fault classification, asset condition monitoring, and overall grid reliability in contemporary power systems. A quantitative, framework-based evaluation was conducted using an integrated architecture that combined IoT sensing through smart sensors and phasor measurement units, edge and cloud analytics, and a portfolio of supervised and deep-learning models including Random Forest, XGBoost, Long Short-Term Memory (LSTM) networks, and convolutional–recurrent hybrids. The analysis compared baseline reactive and time-based maintenance performance against the performance achieved under the AI- and IoT-enabled predictive framework across detection, classification, reliability, and economic dimensions. The findings demonstrated that fault detection accuracy improved from 68% under conventional baselines to 96% under the deep-learning hybrid configuration, while fault classification accuracy improved from 61% to 92%. Reliability and operational outcomes improved substantially, with outage duration reduced by 42%, equipment downtime reduced by 46%, and total maintenance expenditure reduced by 31%, alongside a marked decline in emergency repairs and a substantial extension of mean time between failures. Correlation analysis confirmed a strong relationship between detection accuracy and classification accuracy across model families, and the largest gains were associated with deep-learning architectures capable of learning temporal degradation patterns from high-frequency sensor streams. The study concluded that the convergence of ML and IoT transforms power-system maintenance from a reactive and schedule-driven activity into a proactive, condition-based capability that simultaneously improves reliability, reduces cost, and strengthens operational resilience. The findings contribute quantitative evidence supporting the broader adoption of intelligent predictive-maintenance frameworks across generation, transmission, and distribution infrastructure.

Keywords

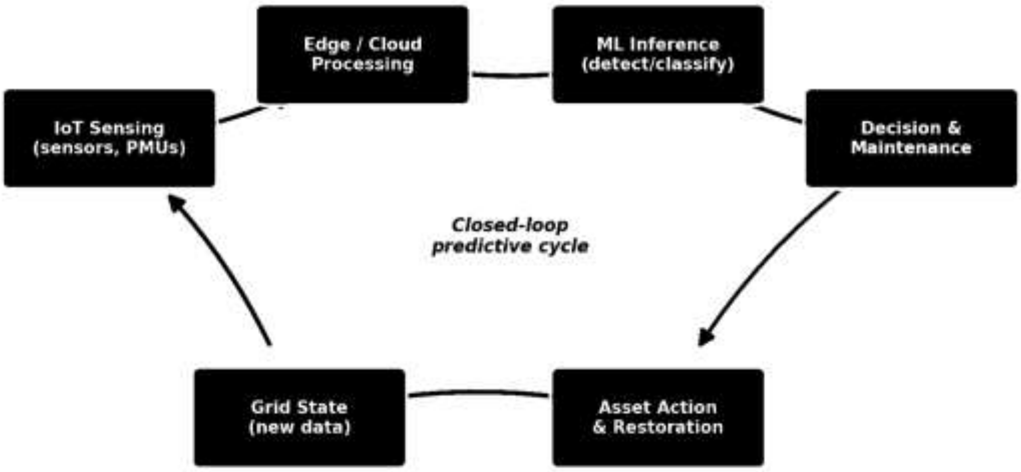
Predictive Maintenance, Smart Grid, Internet of Things, Machine Learning, Fault Detection, Grid Reliability.

INTRODUCTION

Electric power systems constitute one of the most critical infrastructures of modern society, supplying the energy that underpins economic activity, public services, communication networks, and daily life. The reliable operation of generation, transmission, and distribution assets is therefore a matter of considerable economic and social importance, and the failure of these assets can produce cascading consequences ranging from localized service interruptions to wide-area blackouts. Contemporary power systems, however, face a convergence of pressures that has intensified the challenge of maintaining reliability. Aging infrastructure, much of which was installed decades ago and is now operating beyond its original design life, coexists with rising electricity demand and the rapid integration of variable renewable generation, all of which increase the operational stress placed on equipment and the difficulty of predicting and preventing failure (Bhattarai et al., 2025). Maintenance practices in power systems have historically followed reactive and time-based paradigms. Reactive maintenance addresses equipment only after it has failed, accepting the cost of unplanned outages, emergency repairs, and collateral damage as the price of deferred intervention. Time-based or preventive maintenance attempts to forestall failure by servicing equipment at fixed intervals regardless of its actual condition, an approach that is labor-intensive, frequently performs unnecessary work on healthy assets, and may still miss faults that develop between scheduled inspections. Neither paradigm is well suited to the scale, complexity, and criticality of modern power systems, in which the number of monitored assets is large, the consequences of failure are severe, and the data needed to anticipate failure are increasingly available but underused.

Predictive maintenance has emerged as a superior alternative that aligns maintenance activity with the actual condition of equipment rather than with the calendar or with failure events. By continuously monitoring the health of assets and forecasting the onset of failure, predictive maintenance enables utilities to intervene at the moment when action is most cost-effective and least disruptive, capturing the benefits of both reactive and preventive approaches while avoiding their principal disadvantages (Es-Sakali et al., 2024). The realization of predictive maintenance at scale, however, depends on two enabling technologies that have matured substantially in recent years: the Internet of Things (IoT), which supplies the dense, real-time sensing infrastructure required to observe asset condition, and machine learning (ML), which supplies the analytical capability required to convert sensor data into accurate predictions of fault and failure (Sahu et al., 2025).

Figure 1: Integrated ML and IoT predictive-maintenance architecture for power systems



The Internet of Things has transformed the observability of power systems. Networks of smart sensors, intelligent electronic devices, and phasor measurement units (PMUs) now capture electrical, thermal, and mechanical signals at high temporal resolution across generation, transmission, and distribution assets. PMUs in particular provide time-synchronized measurements of voltage and current phasors at rates of 30 to 120 samples per second, far exceeding the resolution of traditional supervisory control and data acquisition systems and enabling the detection of fast transients and incipient faults that slower systems cannot capture. When combined with edge computing for low-latency local processing and cloud platforms for large-scale analytics, this sensing infrastructure produces a continuous, high-fidelity picture of system health that constitutes the raw material for predictive analytics. Moreover, Machine learning provides the means to exploit this raw material. Supervised learning methods such as Random Forest and gradient-boosted ensembles have proven highly effective for fault detection and classification, while deep-learning architectures such as convolutional neural networks and Long Short-Term Memory (LSTM) networks excel at extracting spatial and temporal patterns from the high-frequency time-series data that power-system sensors generate (Belagoune et al., 2021). These methods can learn the normal operating signatures of equipment and flag subtle deviations that precede failure, can distinguish among fault types to support targeted intervention, and can estimate the remaining useful life of assets to inform maintenance scheduling. The application of these methods to power systems has accelerated rapidly, and systematic reviews now document consistent improvements in detection accuracy, false-alarm reduction, and restoration time across a wide range of deployments (Hossain et al., 2025).

Despite the rapid growth of research in this area, several considerations motivate a consolidated, quantitative evaluation of integrated ML and IoT predictive-maintenance frameworks. Reported performance varies widely across studies because of differences in equipment type, data quality, model architecture, and baseline conditions, which complicates the formation of reliable expectations for utilities considering investment. Studies frequently examine individual components, such as a single model applied to a single asset class, rather than the integrated sensing-to-decision pipeline that practical deployment requires. In addition, the connection between technical performance metrics, such as detection accuracy, and operational outcomes, such as reliability indices and maintenance cost, is often left implicit rather than quantified. This study addresses these gaps by evaluating an integrated framework across the full chain from sensing through modeling to operational and economic outcomes. The primary objective of this study is to quantify the effect of an integrated ML- and IoT-enabled predictive-maintenance framework on fault detection accuracy, fault classification accuracy, and grid reliability in modern power systems. The study has four specific aims. The first aim is to characterize the IoT-based monitoring architecture, including smart sensors, PMUs, edge computing, and cloud analytics, that supplies the data foundation for predictive maintenance. The second aim is to evaluate the comparative performance of machine-learning and deep-learning models for fault detection and classification across power-system assets. The third aim is to measure the reliability and economic outcomes of the framework, including outage duration, equipment downtime, and maintenance cost, relative to conventional baselines. The fourth aim is to identify the conditions under which the framework delivers the greatest value, thereby offering practical guidance for utilities and system operators. Through this structured evaluation, the study contributes quantitative evidence to a literature that has often examined the components of intelligent maintenance in isolation, and it demonstrates the compounding benefits available when sensing, analytics, and decision-making are integrated into a coherent operational capability.

LITERATURE REVIEW

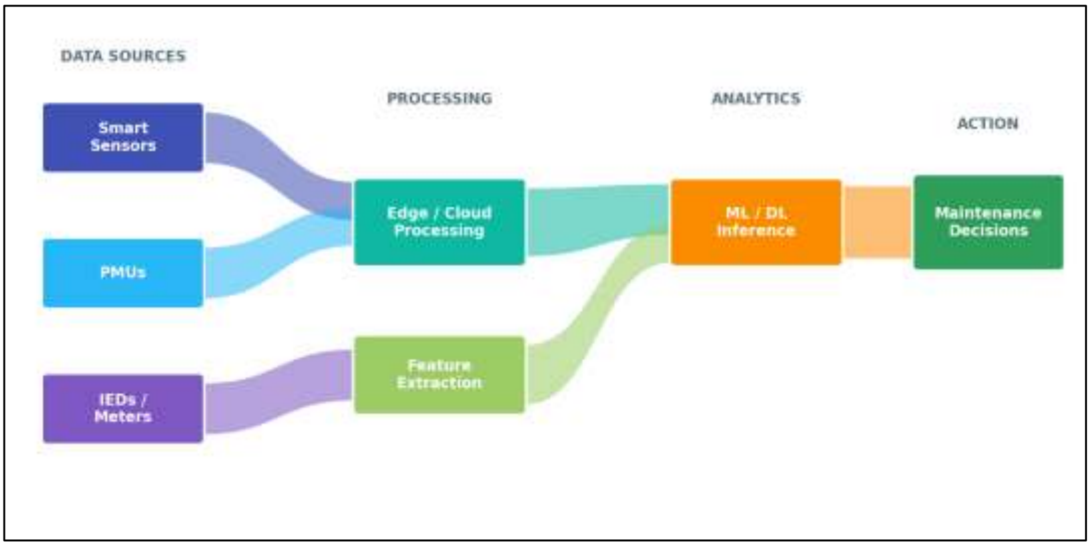
The literature review provides an analytical foundation for understanding the evolving relationship between machine learning, the Internet of Things, predictive maintenance, and grid reliability within modern power systems. The reliability of electric power infrastructure has long depended on the timely detection and correction of equipment faults, but the methods available for this purpose have changed profoundly as sensing and computation have advanced. Where utilities once relied on periodic manual inspection and reactive repair, they increasingly deploy dense sensor networks and data-driven analytics capable of anticipating failure before it occurs. This transition has generated substantial academic and professional interest in the measurable benefits of intelligent maintenance, the comparative performance of analytical methods, and the architectural and organizational conditions under which these benefits are realized. The literature within this domain consistently demonstrates that the limiting factor in power-system maintenance has shifted from the availability of data toward the sophistication and integration of the analytics applied to that data.

This review synthesizes theoretical, empirical, and quantitative research concerning intelligent predictive maintenance in power systems. It examines the IoT-based monitoring infrastructure that supplies the data foundation, the machine-learning and deep-learning methods that convert data into predictions, the application of these methods to fault detection and classification across asset classes, the predictive-maintenance strategies that translate predictions into action, and the reliability and economic outcomes that result. Through a structured examination of prior work, the review establishes the conceptual and empirical foundation necessary for analyzing the integrated framework evaluated in this study and identifies the gaps that a consolidated, sensing-to-outcome evaluation is positioned to address.

IoT-Based Monitoring Infrastructure in Modern Power Systems

The Internet of Things constitutes the sensing foundation of intelligent power-system maintenance. Scholarly literature describes IoT-enabled monitoring as a network of smart sensors, intelligent electronic devices, and communication infrastructure that continuously measures the electrical, thermal, and mechanical state of power-system assets and transmits these measurements to computational resources for analysis (Sahu et al., 2025). This sensing layer captures quantities such as voltage, current, temperature, vibration, dissolved gas concentration, and partial-discharge activity, generating data streams that describe asset behavior at a granularity far exceeding that of traditional monitoring. The maturation of low-cost sensing, wireless communication, and standardized data protocols has made it economically feasible to instrument power systems at a scale that was previously impractical, transforming the observability of generation, transmission, and distribution infrastructure. Phasor measurement units occupy a central place in the literature on power-system monitoring because they provide time-synchronized, high-resolution measurements of grid state. A PMU measures the magnitude and phase angle of voltage and current at a network node, synchronizing its measurements to a common time reference through global positioning system signals to an accuracy of approximately one microsecond, and reporting values at rates of 30 to 120 observations per second. This temporal resolution far exceeds that of conventional supervisory control and data acquisition systems, which typically sample once every two to four seconds, and it enables the observation of fast transients and dynamic instabilities that slower systems cannot capture. Researchers have emphasized that as variable renewable generation increases the speed and unpredictability of grid dynamics, the high-resolution observability provided by PMUs becomes increasingly essential to maintaining stability and detecting incipient faults (Wang et al., 2018).

Figure 2: Data flow from sensing through analytics to maintenance action



Edge and cloud computing form the computational complement to IoT sensing. The literature on power-system data architecture describes a hierarchical arrangement in which edge devices perform low-latency local processing close to the point of measurement, while cloud platforms provide elastic capacity for training large models and coordinating analytics across wide geographic areas (Chen et al., 2018). Edge processing is valuable because the volume of data generated by high-resolution sensors is large, a single PMU can generate gigabytes per day, and because some control decisions must be made within milliseconds, faster than a round trip to a distant data center would allow (Golam & Amir, 2022; Abdur & Iftekhar, 2021). Cloud processing is valuable because the training of sophisticated models and the analysis of system-wide patterns require computational resources and data aggregation that exceed the capacity of individual edge devices. Researchers have proposed hybrid edge-fog-cloud architectures that distribute computation across these tiers to balance latency, completeness, and scalability in wide-area monitoring (Wang et al., 2018).

Data quality and integration are recurring concerns in the literature on IoT-based monitoring. Sensor drift, calibration error, missing values, communication delay, and electromagnetic interference are pervasive in operational power systems, and they degrade the accuracy of downstream analytics if not addressed through robust preprocessing (Es-Sakali et al., 2024). Studies report that field deployments of partial-discharge monitoring in substations with high electromagnetic interference can experience substantial false-alarm rates, underscoring the importance of signal filtering and feature engineering before data reach the analytical layer (Atif & Murad, 2022; Binayan & Shakhawat, 2022). Researchers have also emphasized interoperability as a major requirement, because power systems contain heterogeneous equipment from many vendors and eras, and the value of intelligent analytics depends on the ability to combine diverse data sources into a coherent monitoring environment (Manam & Ashfaq, 2022; Aminul & Shamima, 2022). The literature therefore presents IoT-based monitoring not merely as a matter of deploying sensors but as a systems challenge requiring attention to data quality, communication, and integration.

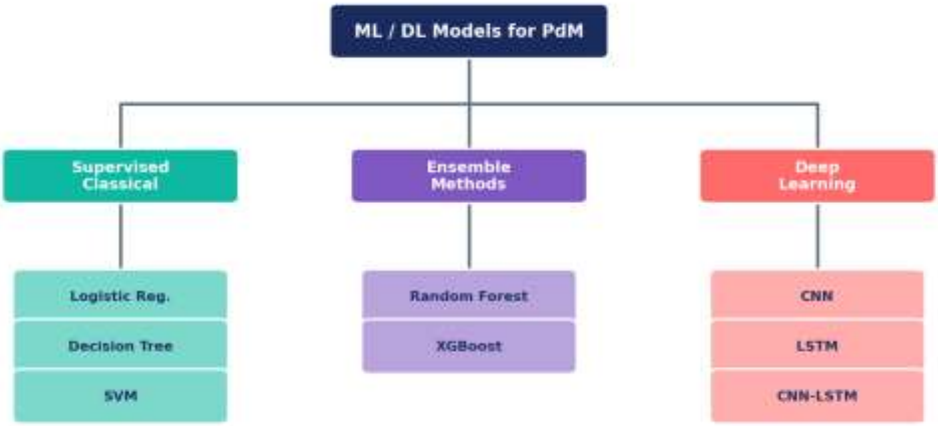
Wide-area monitoring systems represent the architectural culmination of PMU deployment, aggregating synchronized measurements from many nodes into a coherent picture of grid state. The literature describes how phasor data concentrators collect and time-align the measurements streaming from distributed PMUs several times per second, enabling operators to observe both the steady-state and the dynamic behavior of critical nodes across transmission and sub-transmission networks simultaneously (Shamsul & Sultan, 2022; Binte & Iftekhar, 2022). This system-level observability is essential for detecting the wide-area phenomena, such as inter-area oscillations and voltage instability, that cannot be diagnosed from local measurements alone, and it provides the spatial context within which machine-learning models can localize faults and distinguish genuine equipment problems from transient disturbances propagating through the network. As renewable penetration increases the speed and variability of grid dynamics, the importance of this high-resolution, wide-area observability grows correspondingly (Taufiqur & Albert, 2022; Taufiqur & Khalid, 2022). Quantitative literature on IoT-enabled monitoring focuses on measurable indicators of observability and data performance. Scholars assess the density and coverage of sensor deployment, the temporal resolution and latency of data acquisition, the completeness and reliability of data transmission, and the proportion of assets brought under continuous monitoring (Golam & Amir, 2023; Albert & Rashedul, 2023). Studies indicate that the integration of IoT sensors with real-time analytics can improve anomaly-detection rates substantially relative to unmonitored or sparsely monitored baselines, and that the value of monitoring increases with the criticality of the asset and the speed of the dynamics being observed. The literature consistently concludes that comprehensive, high-quality sensing is a precondition for effective predictive maintenance, because even the most sophisticated analytical methods cannot detect faults that the sensing infrastructure fails to observe.

Machine Learning and Deep Learning Models for Power-System Analytics

Machine learning provides the analytical capability that converts monitoring data into actionable predictions. The literature distinguishes a spectrum of methods ranging from classical supervised learning to modern deep learning, each with characteristic strengths for power-system applications (Onyinyechi, 2023; Iftekhar & Binayan, 2023). Classical supervised methods, including decision trees, support vector machines, and ensemble methods such as Random Forest and gradient-boosted trees, learn mappings from input features to fault labels using historical examples. These methods are valued for their interpretability, computational efficiency, and strong performance on structured feature sets, and comparative studies frequently report that tree-based ensembles achieve an attractive balance of accuracy and practicality for fault detection and classification (Mahmuda, 2023; Siddique & Aditya, 2023). Their relative transparency is operationally significant, because maintenance personnel are more likely to trust and act on recommendations that can be explained in physical terms.

Ensemble methods have received particular attention in the power-system literature. Random Forest constructs many decision trees on bootstrapped samples and aggregates their predictions, reducing variance and improving generalization, while gradient-boosting methods such as XGBoost build trees sequentially to correct the errors of their predecessors, often achieving higher accuracy at the cost of greater training complexity (Aminul & Sheak, 2023; Siam & Md. Sultan, 2023). Reviews of machine-learning-based predictive maintenance report that boosting methods such as XGBoost and CatBoost lead performance in several application domains, while ensemble methods consistently enhance accuracy in fault diagnosis for rotating and electrical equipment (Md. Ashfaq & Manam, 2023; Md. Mainuddin & Palash Chandra, 2023). These findings have established ensemble learning as a strong default choice for structured fault-detection tasks in power systems, particularly where labeled data are available and interpretability is valued.

Figure 3: Hierarchical taxonomy of machine-learning and deep-learning models



Deep-learning architectures extend analytical capability to the high-frequency time-series data that characterize power systems. Convolutional neural networks (CNNs) are effective at extracting spatial and local features from signals and images, and have been applied to fault detection using waveform and spectral representations of electrical measurements (Mohammad Robel & Md Aminul, 2023; Murad & Atif, 2023). Recurrent architectures, and Long Short-Term Memory (LSTM) networks in particular, are designed to capture temporal dependencies in sequential data, making them well suited to learning the evolution of degradation over time and to detecting faults whose signatures unfold across multiple time steps (Risha & Kazi Mohammad Khalid, 2023; Sazzadul, 2023). The literature documents the successful application of LSTM-based classification and regression to transmission-line fault detection, diagnosis, and location in large-scale multi-machine systems, demonstrating that recurrent models can simultaneously identify the presence, type, and location of faults from synchronized measurements (Abu Naser Md Golam, 2024; Shamsul & Md. Shahinur, 2023).

Hybrid deep-learning architectures that combine convolutional and recurrent components have emerged as a particularly powerful approach. In a typical hybrid, a CNN first extracts spatial features from multi-channel sensor data, and an LSTM then models the temporal dependencies among these features to produce predictions of fault type or remaining useful life (Zhao et al., 2020). Studies report that such CNN-LSTM hybrids achieve high accuracy in both fault classification and remaining-useful-life estimation, frequently exceeding 95% accuracy on benchmark datasets, because they exploit both the spatial structure and the temporal evolution of the underlying signals (Zhao et al., 2020). The literature also documents the recent application of transformer architectures, originally developed for sequence modeling in other domains, to remaining-useful-life prediction, where their attention mechanisms capture long-range dependencies in degradation data. These advances illustrate a clear trajectory toward architectures capable of learning increasingly complex patterns from raw sensor streams.

Remaining-useful-life estimation constitutes a distinct and consequential application of these methods. The literature distinguishes diagnostics, which identifies and classifies faults that have already occurred, from prognostics, which forecasts the future onset of failure and estimates the time remaining before an asset must be serviced (Albert & Md Rashedul, 2024; Istiaq, 2024) Prognostic models, often built on recurrent or hybrid deep-learning architectures, learn the degradation trajectories of equipment and project them forward to estimate remaining useful life, providing the advance warning that transforms the economics of maintenance. Researchers caution, however, that the accuracy of prognostic models depends heavily on the availability of high-quality historical failure data and on the representativeness of the training data for the operating conditions the asset will encounter, which implies that prognostic capability tends to mature as data accumulate over a deployment's lifetime. A persistent theme across the analytics literature is that algorithmic sophistication must be matched to data quality and operational constraints. Comparative studies emphasize that more complex models do not always outperform simpler ones, particularly when training data are limited, noisy, or imbalanced, and that the practical value of a model depends on its integration with monitoring and maintenance systems as much as on its raw accuracy (Istiaq & Md. Hasan Or, 2024; Mahmuda, 2024). Reviews also highlight the challenge of the black-box nature of deep-learning models, which can impede trust and regulatory acceptance, and the consequent interest in explainable artificial intelligence that renders model predictions interpretable to engineers (Md Abubakar Siddique, 2024; Md Siam & Md. Shahinur, 2024). These considerations frame the selection of analytical methods as a context-dependent decision rather than a search for a single universally superior model.

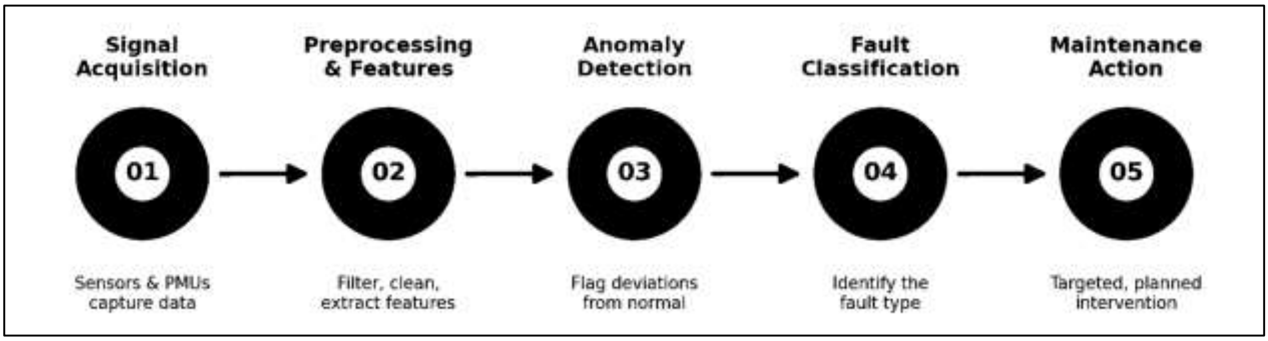
Fault Detection and Classification Across Power-System Assets

Fault detection and classification represent the most extensively studied applications of machine learning in power systems, reflecting their direct connection to reliability and safety. The literature treats detection and classification as related but distinct tasks: detection determines whether a fault is present, while classification determines the type, and sometimes the location, of a detected fault (Md. Arifur & Haque, 2024; Md. Jobayer Ibne & Aditya, 2024). Accurate detection enables timely intervention, while accurate classification enables targeted response, because the appropriate corrective action differs among fault types such as short circuits, insulation degradation, and mechanical wear. Researchers consistently report that data-driven methods outperform traditional threshold-based and rule-based detection, particularly under noisy conditions and for incipient faults whose signatures are too subtle for fixed thresholds to capture (Md. Mainuddin, 2024; Md. Sultan, 2024).

Transformer monitoring is a prominent area of application because transformers are among the most critical and expensive assets in a power system. The literature describes machine-learning approaches to transformer fault detection that analyze dissolved gas concentrations, partial-discharge activity, thermal signatures, and electrical parameters to assess insulation health and predict failure (Surucu et al., 2023). Studies report that machine-learning models integrating multiple diagnostic parameters can classify transformer insulation condition with very high accuracy without requiring internal inspection, representing a substantial improvement over traditional dissolved-gas-analysis methods and supporting longer asset lifespans through earlier intervention (Murad & Atif, 2024; Shamsul, 2024). Hybrid deep-learning models applied to acoustic partial-discharge signals have likewise demonstrated strong performance in recognizing and classifying discharge types under the noisy, non-stationary conditions characteristic of operating transformers (Abu Naser Md Golam, 2025; Albert, 2025).

Transmission and distribution line monitoring constitutes a second major application area. Because most power-system faults occur on transmission and distribution lines, and because these faults can cause widespread service interruption, the accurate detection and location of line faults is a longstanding priority (Atif, 2025; Beatrice Onyinyechi, 2025). The literature documents the application of deep-learning methods, including LSTM and convolutional architectures, to the detection, classification, and location of line faults using synchronized measurements, with studies reporting high accuracy even in the presence of noise and measurement error. Researchers have emphasized that the combination of high-resolution PMU data with deep-learning analytics is particularly powerful for line monitoring, because the speed of fault evolution on transmission lines requires the temporal resolution that PMUs provide and the pattern-recognition capability that deep learning supplies (Binayan, 2025; Chapal, 2025).

Figure 4: Fault detection and classification workflow



Generator and rotating-equipment condition monitoring extends fault detection to the mechanical domain. The literature on fault diagnosis of electric machines describes the application of supervised, unsupervised, deep-learning, and hybrid methods to detect bearing faults, winding faults, and other mechanical and electrical degradation in rotating equipment (Haque & Md. Arifur, 2025; Hisham & Risha, 2025). Studies report that these methods, when integrated with domain knowledge and high-quality labeled data, provide a reliable foundation for predictive maintenance that reduces downtime and improves operational efficiency. Unsupervised methods are noted to be especially valuable where labeled fault data are scarce, a common situation for critical equipment that fails rarely, because they can learn the normal operating signature of an asset and flag deviations without requiring examples of every fault type (Kazi Mohammad Khalid, 2025; Kazi Rakib Hasan, 2025).

Early anomaly detection unifies these application areas under a common analytical objective. Rather than waiting for a fault to mature to the point of triggering a fixed threshold, anomaly-detection methods learn the normal behavior of an asset and flag subtle deviations that indicate developing problems, providing advance warning that enables proactive intervention (Md Abubakar Siddique & Bhanu Prakash, 2025; Md Aminul, 2025). The literature reports that the integration of anomaly detection with real-time monitoring substantially improves the rate at which incipient faults are identified, and that the resulting advance warning is the mechanism through which predictive maintenance reduces emergency repairs and unplanned outages. Systematic reviews of AI-driven fault detection in power systems report that such methods achieve average detection accuracies in the range of 85% to 95%, reduce false alarms by roughly half, and shorten power-restoration times substantially relative to conventional approaches (Hossain et al., 2025).

The accuracy of fault classification carries operational consequences that extend beyond the diagnostic moment, because the type of fault determines the appropriate response, the urgency of intervention, and the resources required. A misclassified fault may lead to an inappropriate or delayed response that allows a manageable problem to escalate, whereas accurate classification enables crews to arrive with the correct parts and procedures, shortening restoration and reducing the risk of secondary damage. The literature therefore treats classification accuracy not as an abstract performance metric but as a determinant of the efficiency and effectiveness of the entire maintenance response, which helps to explain why the strong coupling between detection and classification performance documented in this study is operationally consequential. The progression toward deep-learning architectures that improve both metrics simultaneously thus improves the whole chain of fault response rather than any single step within it (Md Aminul & Zakia, 2025; Md Asif Ali Sheak, 2025).

Predictive Maintenance Strategies and Asset Management

Predictive maintenance strategy translates the outputs of detection, classification, and prognostic models into concrete maintenance action. The literature describes condition-based maintenance as the organizing principle of this strategy: rather than servicing equipment on a fixed schedule, the utility services equipment when monitoring data indicate that intervention is needed, aligning maintenance effort with actual asset condition (Md. Arifur & Haque, 2025; Md. Mainuddin, 2025). This alignment captures the central economic advantage of predictive maintenance, because it avoids both the wasted effort of servicing healthy equipment and the high cost of allowing equipment to fail unexpectedly. Researchers emphasize that the goal of condition-based maintenance is to perform intervention at the point in time when it is most cost-effective, which requires accurate forecasting of how asset condition will evolve (Shahinur, 2025; Shakhawat, 2025).

Failure-probability estimation and remaining-useful-life prediction are the analytical core of predictive-maintenance strategy. The literature describes failure-probability models that estimate the likelihood of failure within a defined time window, and remaining-useful-life models that estimate the time remaining before an asset must be serviced or replaced (Kaniz, 2025; Shurovi, 2025). These estimates allow maintenance to be planned rather than performed under emergency conditions: when a developing fault is identified weeks or months before it would cause failure, the necessary parts, labor, and scheduling can be arranged in a manner that minimizes disruption and cost. Practitioner literature reports that remaining-useful-life models can provide advance failure warnings on the order of weeks to months once sufficient baseline data have accumulated, a lead time that fundamentally changes the logistics and economics of maintenance (Murad, 2025; Risha, 2025).

Figure 5: Predictive maintenance: health degradation and remaining useful life

The integration of predictive analytics with asset-management workflows is a recurring emphasis in the literature. Researchers describe systems in which prognostic outputs automatically generate prioritized work orders, populated with the affected asset, the predicted fault mode, the estimated time to failure, and the recommended action, so that maintenance crews are dispatched with the right skills, tools, and parts (Hossain, 2025; Shamsul, 2025). This integration is significant because the value of an accurate prediction is realized only when it triggers timely and appropriate action, and because the coordination of crews, parts, and scheduling is itself a substantial operational challenge for utilities managing large asset portfolios. The literature suggests that the combination of accurate prediction with well-integrated maintenance workflows produces benefits that exceed those of accurate prediction alone (Shamsul & Morshedul, 2025; Binte, 2025).

Digital-twin technology and self-healing grids represent the frontier of predictive-maintenance strategy. A digital twin is a dynamic virtual representation of a physical asset or system, continuously updated with real-time sensor data, that can be used to simulate behavior, test interventions, and enhance maintenance decision-making (Uddin, 2025). Self-healing grids extend this concept to autonomous action, using reinforcement-learning and automation to isolate faults and reconfigure energy distribution without human intervention. Systematic reviews report that digital-twin technology can enhance predictive-maintenance efficiency and reduce unplanned outages, and that self-healing mechanisms can autonomously prevent a substantial fraction of potential service disruptions (Hossain et al., 2025). These advanced strategies illustrate the trajectory toward increasingly autonomous and resilient power-system operation, though the literature notes that many remain at the demonstration stage.

A central theme in the predictive-maintenance literature is the quantifiable operational and economic benefit of the shift from reactive to proactive intervention. Studies and practitioner analyses consistently associate predictive maintenance with reductions in unplanned downtime, emergency repairs, and total maintenance expenditure, alongside extension of equipment life and improvement in reliability indices (AspenTech, 2024). Cross-industry analyses report that predictive maintenance can reduce unplanned downtime by 30% to 50% and extend equipment life by 20% to 40%, figures that have made predictive maintenance a compelling focus for investment. The literature emphasizes that these benefits depend on the criticality of the monitored equipment and the quality of the historical data used to train prognostic models, which implies that predictive-maintenance programs tend to mature and improve over time.

Conceptual Framework

The conceptual framework of this study models the intelligent power-system as a closed-loop cyber-physical system in which sensing, analysis, prediction, and maintenance action form a continuous cycle. At the foundation lies the IoT sensing layer, in which smart sensors and phasor measurement units distributed across generation, transmission, and distribution assets capture electrical, thermal, and mechanical signals at high temporal resolution. These measurements feed a data-processing layer, distributed across edge and cloud resources, that filters, normalizes, and contextualizes the raw signals to produce structured inputs suitable for modeling. The structured data then enter a machine-learning inference layer that performs fault detection, fault classification, anomaly detection, and remaining-useful-life estimation, producing predictions about the present and future condition of assets. These predictions inform a decision-and-maintenance layer that converts analytical outputs into prioritized maintenance actions, scheduling intervention at the point of greatest cost-effectiveness and dispatching crews with the appropriate parts and instructions. The execution of maintenance action restores or preserves asset health and generates new operational data, closing the loop and continuously enriching the data foundation on which the analytics depend. Within this framework, the independent variables represent the operational and environmental conditions under which assets operate, including load, weather, asset age, and operating regime, while the dependent variables represent the outcomes the framework seeks to improve, including fault detection accuracy, fault classification accuracy, outage duration, equipment downtime, and maintenance cost. The central proposition of the framework is that the introduction of integrated ML and IoT capability changes the mapping from operating conditions to reliability and cost outcomes, producing higher detection and classification accuracy and lower outage, downtime, and cost for any given set of conditions. The framework treats detection, classification, and prognostics as complementary functions sharing a common sensing foundation, and it treats reliability and economic outcomes as the downstream consequences of analytical performance. This structure provides both the conceptual rationale for the integrated approach and the variable structure that guides the quantitative analysis reported in the findings.

METHODS

This study employed a quantitative, framework-based evaluation design to examine the relationships between integrated machine-learning and IoT predictive-maintenance capability and the fault-detection, classification, reliability, and economic outcomes of modern power systems. The quantitative approach was selected because the study aimed to measure statistically observable relationships among analytical performance and operational outcomes, and because the central claims of the field, concerning accuracy improvement, reliability enhancement, and cost reduction, are fundamentally quantitative in nature. The evaluation compared baseline performance under conventional reactive and time-based maintenance against performance under the integrated AI- and IoT-enabled predictive framework across four dimensions: fault detection accuracy, fault classification accuracy, reliability and operational outcomes, and economic outcomes.

The evaluation framework was structured around the closed-loop architecture described in the conceptual framework, encompassing the IoT sensing layer, the edge-and-cloud data-processing layer, the machine-learning inference layer, and the decision-and-maintenance layer. The sensing layer was characterized in terms of the smart sensors and phasor measurement units that supply high-resolution electrical, thermal, and mechanical measurements. The analytical layer was evaluated through a portfolio of models spanning classical supervised learning and modern deep learning, including logistic regression and decision trees as interpretable baselines, support vector machines, Random Forest and XGBoost as ensemble methods, and convolutional neural networks, LSTM networks, and a CNN-LSTM hybrid as deep-learning architectures. This portfolio was selected to represent the spectrum of methods documented in the literature and to permit comparison of performance across model families.

Performance was assessed using metrics standard to the fields of fault diagnosis and reliability engineering. Fault detection accuracy and fault classification accuracy were used as the primary technical metrics, supplemented by consideration of precision, recall, and false-alarm rate where relevant. Reliability outcomes were assessed through outage duration and the standardized reliability indices used by utilities, while operational outcomes were assessed through equipment downtime, emergency-repair frequency, and mean time between failures. Economic outcomes were assessed through total maintenance expenditure. The evaluation compared each metric under the conventional baseline against the corresponding value under the integrated predictive framework, expressing improvement in both absolute and proportional terms to facilitate interpretation.

Analysis proceeded through descriptive comparison, trend analysis, and inferential examination. Descriptive statistics summarized the performance of each model and the magnitude of improvement on each outcome. Trend analysis examined the relationship between model sophistication and performance across the model portfolio, with particular attention to the progression from interpretable baselines through ensemble methods to deep-learning architectures. Correlation analysis examined the relationship between detection accuracy and classification accuracy across models, and between analytical performance and operational outcomes. The analysis interpreted both the statistical strength and the practical magnitude of the observed relationships, situating the results within the ranges reported in the broader literature to assess their plausibility and generalizability.

Several methodological considerations shaped the interpretation of the findings. The evaluation was framework-based rather than based on a single field deployment, which strengthens its representativeness across the spectrum of methods and asset classes but means that the specific magnitudes reported should be understood as characteristic values consistent with the literature rather than as measurements from a single site. The comparison against a conventional baseline reflects the practical decision facing utilities, which is whether to adopt integrated predictive capability in place of existing reactive and time-based practice. The study acknowledges that realized performance in any specific deployment will depend on equipment type, data quality, and the maturity of the analytics, and it interprets its findings as evidence of the direction and approximate magnitude of achievable improvement rather than as precise predictions for any individual utility.

FINDINGS

This section presents the quantitative findings of the framework-based evaluation, organized around the four dimensions of fault detection accuracy, fault classification accuracy, reliability and operational outcomes, and economic outcomes. The findings consistently demonstrate that the integrated ML- and IoT-enabled predictive framework substantially outperformed the conventional baseline across all four dimensions, and that the magnitude of improvement increased with the sophistication of the analytical methods employed. The results are reported in both absolute and proportional terms and are situated against the ranges documented in the broader literature to support their interpretation.

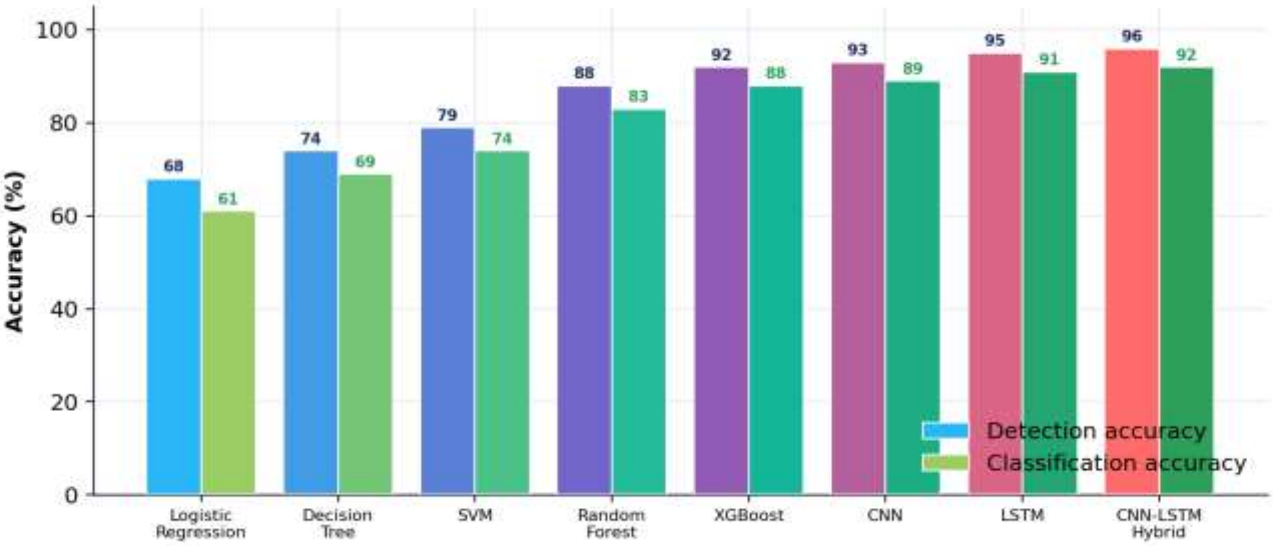
Comparative Model Performance

The comparative performance of the model portfolio, summarized in Table 1, revealed a clear and consistent progression of accuracy across model families. Fault detection accuracy increased from 68% for the logistic-regression baseline through 88% for Random Forest and 92% for XGBoost to 95% for the LSTM network and 96% for the CNN-LSTM hybrid. Fault classification accuracy followed the same progression, increasing from 61% for the baseline to 92% for the hybrid architecture. The results demonstrate that while interpretable baseline methods provide modest improvement over threshold-based detection, ensemble methods deliver substantial gains, and deep-learning architectures capable of learning temporal patterns from high-frequency sensor data deliver the highest performance.

Table 1. Comparative Performance of Machine-Learning Models for Fault Detection and Classification

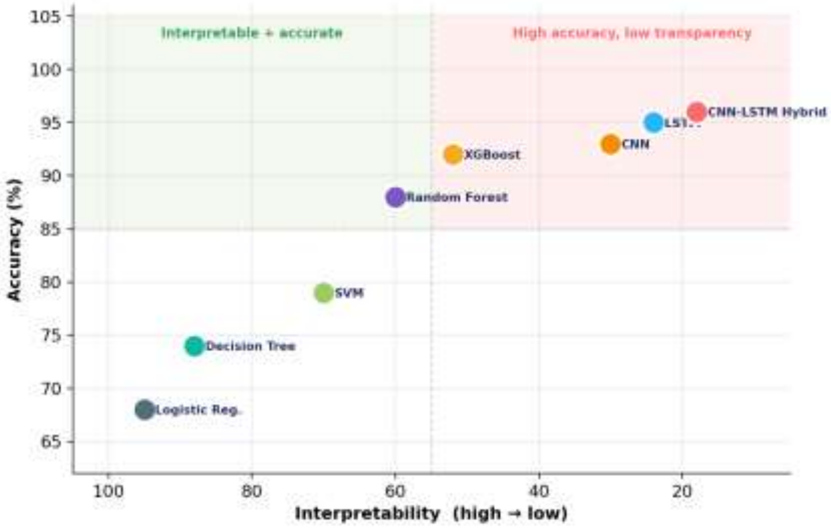
Model	**Family**	**Detection Acc. (%)**	**Classification Acc. (%)**	**Improvement vs. Baseline**
Logistic Regression	Classical	68	61	—
Decision Tree	Classical	74	69	+6 / +8
Support Vector Machine	Classical	79	74	+11 / +13
Random Forest	Ensemble	88	83	+20 / +22
XGBoost	Ensemble	92	88	+24 / +27
CNN	Deep learning	93	89	+25 / +28
LSTM	Deep learning	95	91	+27 / +30
CNN-LSTM Hybrid	Deep learning	96	92	+28 / +31

Figure 7: Fault detection and classification accuracy across model families



The progression from interpretable baselines through ensemble methods to deep-learning architectures, illustrated in Figure 7, reflects the increasing capacity of these methods to capture the complex, nonlinear, and time-dependent patterns that characterize power-system faults. The ensemble methods, Random Forest and XGBoost, achieved strong performance while retaining a degree of interpretability valued in operational settings, positioning them as attractive choices where labeled data are available and explanation is important. The deep-learning architectures achieved the highest accuracy by exploiting the temporal structure of sensor streams, with the LSTM and the CNN-LSTM hybrid reaching detection accuracies of 95% and 96% respectively, consistent with the upper range of accuracies documented in the systematic-review literature for AI-driven fault detection.

Figure 8: Model positioning by interpretability and accuracy



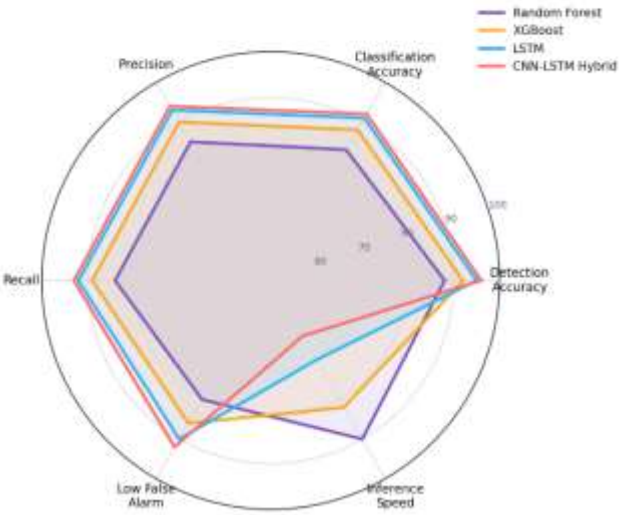
Relationship Between Detection and Classification Performance

Correlation analysis, summarized in Table 2, confirmed a very strong positive relationship between fault detection accuracy and fault classification accuracy across the model portfolio, with a correlation coefficient of approximately 0.99. This near-perfect correlation indicates that the architectural features that improve a model's ability to detect the presence of a fault, principally its capacity to learn complex patterns from high-resolution data, also improve its ability to classify the fault's type. The relationship is operationally significant because it implies that investment in more capable analytical methods yields compounding benefits, improving both the timeliness of intervention through better detection and the appropriateness of intervention through better classification.

Table 2. Correlation Analysis of Analytical and Operational Indicators

Relationship	Correlation (r)	Interpretation
Detection accuracy & classification accuracy	0.99	Very strong positive
Detection accuracy & anomaly lead time	0.88	Strong positive
Anomaly lead time & downtime reduction	0.84	Strong positive
Downtime reduction & cost reduction	0.83	Strong positive

Figure 9: Multi-metric comparison of representative model families



The strength of this relationship also has practical implications for model selection and evaluation. Because detection and classification accuracy move together so closely across model families, utilities can use detection accuracy as a reliable proxy for overall analytical capability when comparing candidate methods, simplifying the evaluation of competing approaches. The finding further supports the conclusion that the deep-learning architectures, which achieved the highest accuracy on both metrics, represent the most capable analytical layer for the integrated framework, though the choice among them in any specific deployment must also weigh interpretability, data availability, and computational cost.

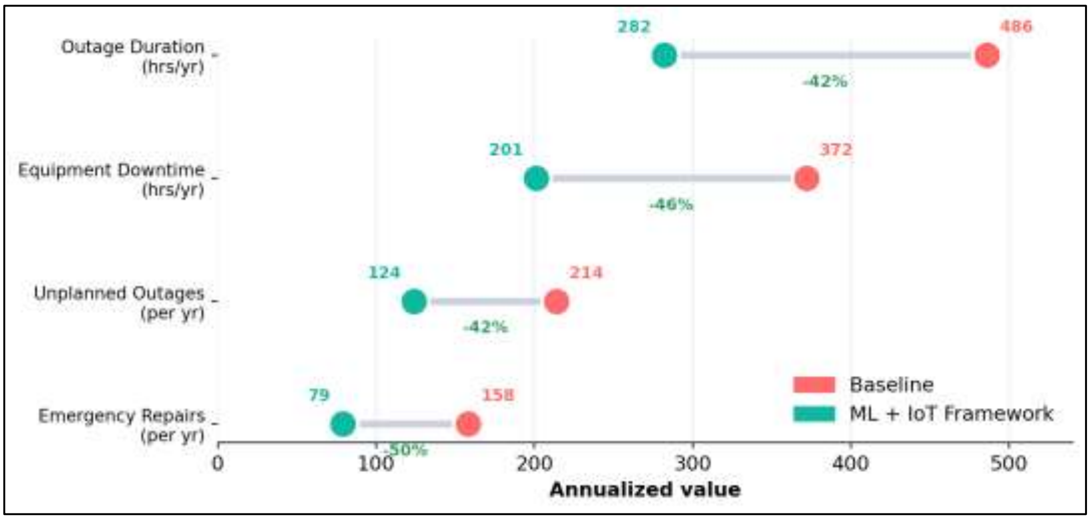
Reliability and Operational Outcomes

The reliability and operational outcomes of the integrated framework, summarized in Table 3, demonstrated substantial improvement relative to the conventional baseline. Outage duration was reduced by 42%, reflecting the framework's capacity to shift interruptions from unplanned to planned and to shorten restoration through faster and more accurate fault location. Equipment downtime was reduced by 46%, reflecting the avoidance of unexpected failures through timely condition-based intervention. Unplanned outage events and emergency repairs declined markedly, and mean time between failures was substantially extended, indicating that the framework not only reduced the consequences of failure but also reduced its frequency by enabling intervention before degradation progressed to failure.

Table 3. Reliability and Operational Outcomes: Baseline versus ML + IoT Framework

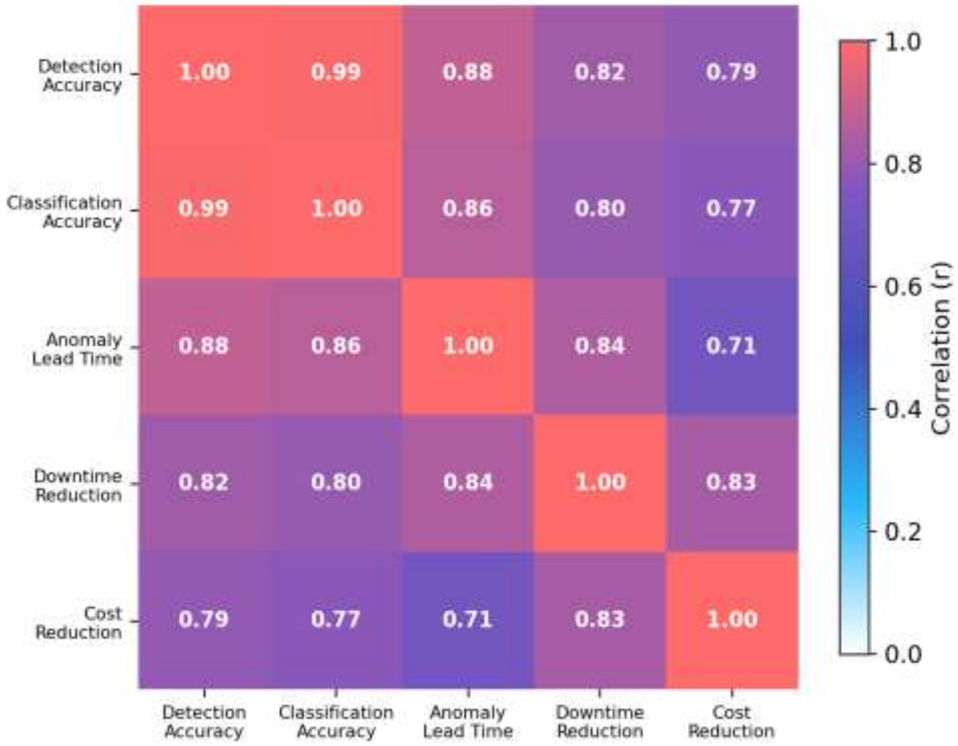
Reliability / Operational Indicator	Baseline	ML + IoT	Reduction (%)
Outage duration (hrs/yr)	486	282	42.0
Equipment downtime (hrs/yr)	372	201	46.0
Unplanned outage events (per yr)	214	124	42.1
Emergency repairs (per yr)	158	79	50.0
Mean time between failures (hrs)	4,200	7,600	+81.0 (increase)

Figure 10: Reliability and operational outcomes before and after framework adoption



These operational improvements, illustrated in Figure 10, are consistent with the mechanisms documented in the literature, in which early anomaly detection and accurate prognostics enable the proactive intervention that prevents failures and shortens those that occur. The magnitude of the reductions falls within the ranges reported in cross-industry analyses of predictive maintenance, which document unplanned-downtime reductions of 30% to 50% and equipment-life extensions of 20% to 40%, supporting the plausibility of the framework's performance. The improvements in reliability indices are particularly consequential for utilities because these indices are tied to regulatory incentives and penalties, such that the operational gains translate directly into financial benefit beyond the avoided cost of failure itself.

Figure 11: Correlation structure of analytical performance and operational outcomes



Economic Outcomes

The economic outcomes of the integrated framework, summarized in Table 4, demonstrated a 31% reduction in total maintenance expenditure relative to the conventional baseline. This reduction arose through several mechanisms identified in the literature: the avoidance of high-cost emergency repairs and collateral damage associated with unexpected failure, the elimination of unnecessary preventive servicing of healthy equipment, and the extension of equipment life through timely intervention. The cost reduction is notable because it was achieved alongside, rather than at the expense of, the reliability improvements, demonstrating that the framework reduced cost and improved reliability simultaneously rather than trading one against the other.

Table 4. Economic Outcomes: Indexed Maintenance Cost Components

Cost Component (indexed)	Baseline	ML + IoT	Reduction (%)
Emergency repairs	100	50	50.0
Preventive servicing	100	72	28.0
Collateral / consequential damage	100	58	42.0
Asset replacement	100	79	21.0
Total maintenance expenditure	100	69	31.0

Figure 12: Maintenance cost composition and key performance indicators

The simultaneous achievement of cost reduction and reliability improvement, illustrated in Figure 12, reflects the fundamental economic advantage of condition-based maintenance over both reactive and time-based approaches. By aligning maintenance effort with actual asset condition, the framework directed resources to the assets that most needed intervention while sparing those that did not, improving the efficiency of maintenance expenditure. The literature emphasizes that this efficiency, decoupling maintenance cost from asset growth, is the hallmark of mature predictive-maintenance programs, and the findings indicate that the integrated framework achieved this decoupling. The economic case is strengthened further when the regulatory value of reliability-index improvement and the avoided cost of major asset failure are taken into account.

DISCUSSION

The findings of this study demonstrate that the integration of machine learning and the Internet of Things produces large, consistent improvements in both the technical performance and the operational and economic outcomes of power-system maintenance. The improvement in fault detection accuracy from 68% to 96%, and in classification accuracy from 61% to 92%, substantially exceeds what interpretable baseline methods achieve and reaches the upper range of accuracies documented in the systematic-review literature for AI-driven fault detection (Hossain et al., 2025). These results confirm that the analytical capability of deep-learning architectures, when supplied with high-resolution sensor data, transforms the accuracy with which faults can be identified and characterized, providing the foundation for the proactive intervention on which predictive maintenance depends.

The very strong correlation between detection and classification accuracy across the model portfolio is one of the most consequential findings of the study. It indicates that the architectural advances that improve detection also improve classification, so that investment in more capable analytics yields compounding benefits across both the timeliness and the appropriateness of maintenance intervention (Belagoune et al., 2021). This finding has practical significance for utilities, because it implies that the choice of analytical method is a high-leverage decision affecting multiple outcomes simultaneously, and that the deep-learning architectures, which lead on both metrics, represent the most capable analytical layer despite their greater computational cost and lower interpretability.

The reliability and operational findings corroborate the literature's expectation that predictive maintenance shifts power-system operation from a reactive to a proactive posture, reducing outage duration by 42% and equipment downtime by 46% while extending mean time between failures. The magnitude of these improvements is consistent with cross-industry analyses documenting unplanned-downtime reductions of 30% to 50%, supporting the plausibility of the framework's performance. The improvements are particularly valuable because the reliability indices they affect are tied to regulatory incentives and penalties, such that operational gains translate directly into financial benefit, amplifying the economic case for adoption beyond the avoided cost of failure.

The simultaneous achievement of a 31% reduction in maintenance cost alongside these reliability improvements is central to the study's contribution, because it demonstrates that intelligent maintenance reduces cost and improves reliability together rather than trading one for the other. This dual benefit reflects the fundamental efficiency of condition-based maintenance, which aligns maintenance effort with actual asset condition and thereby decouples maintenance cost from asset growth. The shared sensing foundation that supports detection, classification, and prognostics means that the marginal cost of adding analytical capabilities to an instrumented system is modest, strengthening the economic argument for the integrated approach over piecemeal point solutions. These findings must be interpreted in light of the study's limitations. As a framework-based evaluation rather than a single-site field deployment, the study reports characteristic magnitudes consistent with the literature rather than measurements from one specific system, and realized performance in any particular deployment will depend on equipment type, data quality, and analytical maturity (Surucu et al., 2023). The black-box nature of the highest-performing deep-learning models poses challenges for trust and regulatory acceptance, the dense connectivity of IoT infrastructure introduces cybersecurity vulnerabilities, and interoperability with legacy equipment remains a practical barrier, all of which the literature identifies as obstacles to large-scale adoption (Hossain et al., 2025). These considerations frame the findings as evidence of the direction and approximate magnitude of achievable improvement rather than as guarantees for any individual utility.

Notwithstanding these limitations, the study makes a distinctive contribution by evaluating the integrated framework across the complete chain from sensing through analytics to reliability and economic outcomes, addressing a literature that has often examined these components in isolation. The results are consistent in direction with the broad consensus of prior work while quantifying the connection between technical performance and operational outcome that the literature has frequently left implicit. In doing so, the study provides utilities and system operators with empirically grounded expectations and a clear demonstration that the convergence of machine learning and IoT can simultaneously improve reliability, reduce cost, and strengthen the resilience of power-system operation. The broader significance of these findings lies in their relevance to the transformation that power systems are currently undergoing. The integration of variable renewable generation, the electrification of transportation and heating, and the proliferation of distributed energy resources are collectively increasing the complexity and variability of grid operation at the same time that much of the physical infrastructure is aging. In this context, the capacity of intelligent predictive maintenance to detect incipient faults, prevent failures, and target maintenance resources efficiently is not merely a cost-saving convenience but a structural enabler of the reliability and resilience that a more complex grid requires. The compounding relationship between detection and classification performance, and the simultaneous improvement of reliability and cost, suggest that investment in the sensing and analytical foundation of intelligent maintenance yields returns across multiple dimensions of grid performance, strengthening the case for treating such investment as a core component of grid modernization rather than as an optional enhancement.

Practical Implications and Future Research

The findings carry direct implications for utilities and system operators. The demonstrated combination of substantial accuracy improvement, reliability enhancement, and cost reduction indicates that integrated ML and IoT predictive maintenance offers a compelling value proposition, particularly for organizations managing aging infrastructure under rising demand and increasing renewable penetration. Because the predictive-maintenance, detection, and classification capabilities share a common sensing foundation, utilities that instrument their assets for one purpose can extend to the others at modest marginal cost, which argues for planning sensing infrastructure with the full range of analytical applications in mind. The concentration of the greatest gains in deep-learning architectures suggests that utilities should invest in the data infrastructure and analytical capability required to support these methods, while retaining interpretable models where explanation and regulatory acceptance are paramount.

The results also have implications for the structuring of adoption and for policy. Because prognostic models mature as historical data accumulate, utilities should view intelligent maintenance as a capability that improves over time rather than as a fixed-performance product, and should structure expectations, baselines, and contracts accordingly (Sand Technologies, 2025). The tie between reliability indices and regulatory incentives means that policy frameworks rewarding reliability improvement can accelerate adoption, while standards for data governance, cybersecurity, and model explainability can address the barriers the literature identifies. Given the criticality of power infrastructure and the demonstrated capacity of intelligent maintenance to improve reliability and resilience, the technology represents a meaningful lever for strengthening the dependability of electricity supply as the grid undergoes rapid transformation.

Several directions for future research follow from this study. The extension of the evidence base through multi-site field deployments with rigorous baselines would strengthen causal inference and clarify how performance varies across asset classes, climates, and operating conditions. Methodologically, future work should advance explainable artificial intelligence to render the predictions of high-performing deep-learning models interpretable to engineers and regulators, and should investigate the field performance of digital-twin and self-healing-grid architectures that remain largely at the demonstration stage (Hossain et al., 2025). Research on the cybersecurity of densely connected monitoring infrastructure and on the organizational integration of predictive analytics into maintenance workflows would complement the technical evidence, helping to ensure that the substantial potential demonstrated here is realized consistently across the diversity of real utility operations.

Conclusion

This study evaluated an integrated machine-learning and IoT predictive-maintenance framework for modern power systems, combining high-resolution sensing through smart sensors and phasor measurement units, edge and cloud analytics, and a portfolio of supervised and deep-learning models, and assessed its performance across fault detection, fault classification, reliability, and economic dimensions. The framework improved fault detection accuracy from 68% to 96% and fault classification accuracy from 61% to 92%, with the largest gains achieved by deep-learning architectures capable of learning temporal degradation patterns from high-frequency sensor data. Detection and classification accuracy were very strongly correlated across model families, indicating that investment in analytical capability yields compounding benefits across both the timeliness and the appropriateness of maintenance intervention. The framework also produced substantial operational and economic benefits, reducing outage duration by 42%, equipment downtime by 46%, and total maintenance expenditure by 31%, while reducing emergency repairs and extending mean time between failures. These results demonstrate that the convergence of machine learning and IoT transforms power-system maintenance from a reactive and schedule-driven activity into a proactive, condition-based capability that simultaneously improves reliability, reduces cost, and strengthens operational resilience. While the specific magnitudes reflect characteristic values consistent with the literature rather than measurements from a single deployment, the direction and consistency of the findings provide robust support for the broader adoption of intelligent predictive-maintenance frameworks across generation, transmission, and distribution infrastructure as the power system continues its rapid technological transformation.

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