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AI-Based Fault Detection and Predictive Maintenance in Smart Electrical Distribution Networks

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Abstract

Smart electrical distribution networks contain distributed energy resources, power-electronic interfaces, smart meters, phasor measurement units, intelligent electronic devices, and communication links that generate large volumes of operating data. These data enable a shift from conventional threshold-based protection and time-based maintenance toward artificial-intelligence (AI) assisted fault diagnosis and predictive maintenance. This paper proposes a compact methodology for integrating real-time fault detection, multi-class fault classification, fault localization support, and asset-health prediction in a unified distribution-network workflow. Voltage sag, current magnitude, sequence components, harmonic distortion, temperature, partial-discharge indicators, switching history, loading, and ambient conditions are used as condition features. The methodology combines signal preprocessing with supervised machine-learning models for fault recognition and a regression-based health model for maintenance prioritization. A proof-of-concept synthetic experiment representing healthy operation and single-line-to-ground, line-to-line, double-line-to-ground, and three-phase faults is used to evaluate the analytical pipeline. Among the tested classifiers, the radial-basis-function support-vector machine achieved 94.8% test accuracy and 0.948 macro F1-score, while a random-forest health model achieved a mean absolute error of 3.54 health-index points and R^2 of 0.948. The results indicate that a coordinated AI layer can improve diagnostic consistency, reduce unnecessary maintenance actions, and support faster condition-based decisions. The paper also identifies practical requirements related to data quality, class imbalance, explainability, cybersecurity, model drift, and utility-scale validation.

Introduction

Electricity distribution systems are becoming more observable and more complex at the same time. High penetration of distributed generation, bidirectional power flow, inverter-based resources, automated switching, advanced metering infrastructure, and communication-enabled protection can improve flexibility, but they also produce fault signatures that vary with

topology, operating state, and measurement location. Traditional relays remain essential for fast protection; however, fixed thresholds and model-dependent fault-location rules may be less effective when the network changes frequently. Data-driven techniques therefore have growing value as an additional diagnostic layer for identifying abnormal patterns, separating similar

fault classes, and supporting operator decisions [1]–[4].

Machine-learning fault diagnosis has progressed from feature-reduction and nearest-neighbor methods to support-vector machines, ensemble learning, deep neural networks, and hybrid signal-processing models. Hosseinzadeh et al. demonstrated that dimensionality reduction and an augmented K-nearest-neighbor approach can support smart-grid fault classification [1]. Mamuya et al. applied machine-learning tools to fault classification and location in a radial distribution grid [2], while Fahim et al. reviewed and evaluated machine-learning-based microgrid fault detection and classification [3]. These studies show that voltage and current measurements can be transformed into discriminative features, but utility deployment still depends on robust sensing, synchronization, and representative training data.

Predictive maintenance (PdM) addresses a related but slower time-scale problem: deciding when equipment such as transformers, cables, breakers, and switchgear should be inspected or serviced before functional failure. Mahmoud et al. identified fault prediction and maintenance planning as central data-driven functions in smart-grid distribution networks [4]. Later work on transformer reliability illustrated how condition indicators and operational history can be incorporated into maintenance decision processes [8]. Thus, fault detection and PdM should not be designed as isolated applications. The same sensor platform can supply fast transient features to protection analytics and long-term condition trends to asset-health analytics.

The objective of this paper is to present a methodology that integrates these two functions. The proposed framework has four goals: (i) detect abnormal electrical states, (ii) classify the most likely fault category, (iii) provide location/severity information to the protection and control layer, and (iv) estimate asset health so that maintenance can be prioritized according to risk. The scope is methodological: the numerical results are generated from a reproducible synthetic proof-of-concept dataset designed to test the analytical pipeline, not from a specific utility field trial. This distinction is important because real deployment must include feeder-specific fault records, relay events, inspection results, and maintenance histories.

Literature Review

Research up to 2024 shows a clear transition from single-purpose fault classifiers toward integrated monitoring and intelligent decision support. Early machine-learning approaches

emphasized feature engineering. In the augmented K-NN study, principal-component analysis and linear-discriminant analysis were used to improve class separability [1]. Mamuya et al. showed that conventional machine-learning algorithms can classify and locate faults in radial distribution networks when suitable electrical features are available [2]. Fahim et al. combined the fault-diagnosis problem with comparisons of machine-learning techniques and highlighted the value of deep learning and wavelet-assisted representations for microgrids [3].

Subsequent studies expanded the problem definition. Mahmoud et al. reviewed smart-grid predictive maintenance, fault types, causes, and prediction methods and emphasized the importance of condition-based maintenance [4]. Krivohlava et al. provided a systematic classification of smart-grid faults and failures across heterogeneous infrastructure, showing that failures can originate in physical, communication, and software domains [5]. Moloi et al. proposed a combined classification and localization scheme for power distribution networks using signal processing and intelligent classification [6]. Mirshekali et al. specifically addressed smart distribution fault location with micro-PMU data and machine learning, illustrating the value of synchronized high-resolution measurements [7].

Work published in 2023 strengthened the connection between sensing, deep learning, and operational reliability. Vita et al. developed a predictive-maintenance approach aimed at improving distribution-transformer reliability [8]. De La Cruz et al. reviewed distribution smart-grid fault-location methods and identified challenges created by low-voltage networks, distributed generation, sparse measurements, and changing topology [9]. Almasoudi proposed hybrid machine-learning models for real-time fault detection and remediation [10], while Alhanaf et al. evaluated deep neural-network schemes for fault detection and classification in smart grids [11].

By 2024, the literature increasingly addressed incipient faults and AI-supported network restoration. Ibrahim et al. reviewed incipient-fault detection in power distribution networks, emphasizing the difficulty of recognizing weak, intermittent, and evolving fault signatures before they become permanent faults [12]. Najafzadeh et al. combined optimized machine-learning methods with intelligent fault detection, classification, and localization and reported high classification performance in a simulated power-network environment [13]. Carrascal et al. extended the AI role from fault prediction to network reconfiguration optimization,

demonstrating the emerging direction of closed-loop, data-driven distribution management [14]. The literature therefore supports an architecture in which AI operates at multiple time scales:

milliseconds to seconds for diagnosis, minutes for remedial decisions, and days to months for maintenance planning.

Table 1. Selected literature underpinning the proposed methodology

Study	Year	Main approach	Methodological relevance
Hosseinzadeh et al. [1]	2019	PCA/LDA + K-NN	Feature reduction and fault classification
Mamuya et al. [2]	2020	ML on radial grid	Fault classification and location
Mahmoud et al. [4]	2021	Systematic review	Predictive-maintenance requirements
Mirshekali et al. [7]	2022	ML + micro-PMU	High-resolution fault location
Vita et al. [8]	2023	Condition-based PdM	Transformer maintenance prioritization
Ibrahim et al. [12]	2024	Incipient-fault review	Early warning and weak-fault detection
Carrascal et al. [14]	2024	AI prediction + reconfiguration	Decision support after prediction

Methodology

The proposed workflow uses a two-path analytical architecture (Figure 1). The fast path processes electrical measurements for fault detection and classification. The slow path combines condition-monitoring measurements with historical loading and operating events to estimate asset health. Both paths share a

common data-quality layer and feed a decision-support interface. This structure reflects the literature trend toward intelligent fault diagnosis [6], synchronized measurement-based localization [7], transformer condition monitoring [8], and AI-assisted grid remediation [10], [14].

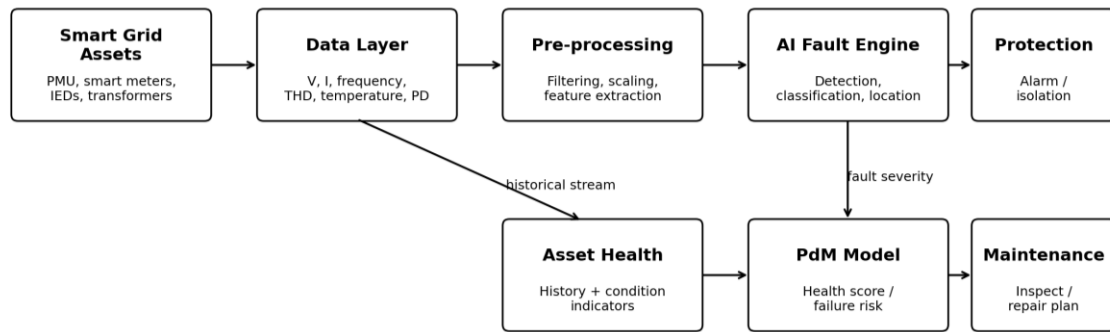


Figure 1. Proposed AI-based fault detection and predictive-maintenance architecture

1. Data acquisition and feature construction.

For a practical feeder, the preferred inputs are three-phase voltage and current, frequency, active/reactive power, negative- and zero-sequence quantities, harmonic distortion, relay/IED event records, transformer or cable temperature, partial-discharge indicators, breaker operations, load percentage, and ambient conditions. Measurements may originate from smart meters, PMUs or micro-PMUs, feeder monitors, protection relays, and online asset sensors. High-resolution windows are used for transient diagnosis, while longer windows are aggregated for health assessment.

Missing values are flagged rather than silently imputed when they affect protection-critical variables.

Preprocessing consists of time alignment, bad-data screening, outlier control, normalization, and feature extraction. The proof-of-concept dataset contains nine features: load percentage, ambient temperature, per-unit voltage sag, current-to-normal ratio, negative-sequence ratio, total harmonic distortion, partial-discharge index, breaker-operation count, and equipment temperature. Five operating classes are represented: Healthy, single-line-to-ground (SLG), line-to-line (LL), double-line-to-ground

(LLG), and three-phase (3PH). A total of 4,000 labeled samples are generated with overlapping statistical ranges to avoid trivially separable classes. The data are stratified into 75% training and 25% testing subsets.

2. Fault-detection models.

Four supervised classifiers are compared: radial-basis-function support-vector machine (SVM-RBF), random forest (RF), gradient boosting (GB), and a multilayer perceptron (MLP). Standardization is applied to SVM and MLP inputs. Accuracy, macro precision, macro recall, and macro F1-score are used because a utility dataset may contain unequal numbers of fault events. In field implementation, additional evaluation should include false-trip rate, missed-fault rate, detection latency, and performance under topology changes. The model should be trained on historical and simulated cases and periodically recalibrated to address concept drift.

3. Predictive-maintenance model.

A separate asset-health dataset is generated to represent 3,000 transformer/feeder condition records. Inputs include equipment age, loading, hotspot temperature, partial-discharge index, oil-quality indicator, and switching history. A random-forest regressor predicts a health index on a 0–100 scale, where higher values indicate better condition. Mean absolute error (MAE) and coefficient of determination (R^2) quantify regression performance. For operational use, the

continuous health score can be mapped to maintenance bands: normal operation, increased monitoring, scheduled inspection, and urgent intervention. This produces a risk-ranked work list instead of a fixed calendar schedule.

4. Decision logic and validation.

A high-confidence fault label can be passed to the distribution management or protection-supervision layer together with the estimated severity and probable location. Automatic tripping should remain governed by certified protection logic unless the AI function has undergone the required engineering validation. The AI layer is therefore initially positioned as advisory or supervisory. Predictive-maintenance output is combined with criticality, redundancy, customer impact, and spare-part lead time. Cross-validation, feeder-wise holdout testing, noise injection, missing-sensor tests, and seasonal stress cases are recommended before deployment. Explainability should include feature importance or local explanations so that engineers can identify whether a decision is driven by plausible electrical variables.

Results

Table 2 summarizes the proof-of-concept classification results. SVM-RBF achieved the best test accuracy (94.8%) and macro F1-score (0.948), while RF and GB remained near 93% accuracy.

Table 2. Proof-of-concept AI performance on the synthetic methodology dataset

Model	Accuracy (%)	Precision	Recall	Macro F1
SVM-RBF	94.8	0.949	0.948	0.948
Random Forest	93.3	0.934	0.933	0.933
Gradient Boosting	93.2	0.932	0.932	0.932
MLP	93.1	0.931	0.931	0.931
RF health-index model	MAE = 3.54	—	$R^2 = 0.948$	—

Healthy and three-phase samples were classified without error, while the main overlap occurred between LL and LLG events. Random-forest feature analysis ranked negative-sequence ratio, voltage sag, and current ratio as the three most informative variables for the fault classifier, followed by harmonic distortion. This is physically reasonable because asymmetrical faults strongly affect sequence components while severe faults alter voltage and current magnitudes. Condition features such as partial discharge and temperature contributed less to instantaneous classification but are more important in the maintenance path. The health-index regressor achieved MAE = 3.54 points and $R^2 = 0.948$, indicating that degradation trends can

be estimated accurately in the controlled synthetic setting.

These numerical results should be interpreted as validation of the proposed data-processing methodology rather than as a claim of field performance. Real feeder data will have rarer faults, nonstationary loads, sensor errors, communication delays, topology changes, protection actions, and incomplete maintenance labels. Nevertheless, the experiment demonstrates how one architecture can combine fast fault recognition with slower condition-based maintenance. The measured performance is also consistent with the broader literature, where intelligent and hybrid approaches have achieved strong fault-classification results in

simulation and benchmark systems [10], [11], [13].

Conclusion and Discussion

This paper presented a unified methodology for AI-based fault detection and predictive maintenance in smart electrical distribution networks. The design integrates measurement acquisition, data-quality control, feature extraction, supervised fault classification, asset-health prediction, and operator decision support. The literature through 2024 shows that machine learning has matured from basic feature-based classification toward deep learning, incipient-fault analysis, condition-based maintenance, and AI-supported reconfiguration [4], [9], [12], [14]. The proposed architecture connects these developments in a practical two-time-scale workflow.

The proof-of-concept results show that conventional AI models can provide high diagnostic accuracy when the feature set reflects meaningful electrical behavior. SVM-RBF performed best for the synthetic multi-class fault problem, while the random-forest regressor estimated health with low error. For utilities, however, the most important research challenge is not simply maximizing benchmark accuracy. Reliable deployment requires representative fault records, synchronized measurements, cybersecurity controls, model monitoring, explainable outputs, and validation against unseen feeders and seasonal operating states. Imbalanced and rare incipient faults require special attention because a model trained mainly on normal operation can obtain misleadingly high overall accuracy. Future work should validate the framework on IEEE distribution test feeders and utility data, incorporate graph-based models that explicitly represent feeder topology, evaluate federated or edge-learning strategies for privacy and latency, and combine failure probability with economic criticality. AI should complement rather than replace protection engineering: certified relays and deterministic safety logic remain the final authority for immediate isolation, while AI can improve situational awareness, diagnosis, prognosis, and maintenance prioritization. With these safeguards, the methodology can support shorter outage duration, more targeted maintenance, and higher asset utilization in increasingly data-rich smart distribution networks.

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