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Machine Learning Models for Predicting Microgrid Faults in Critical Healthcare Infrastructure

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ABSTRACT

Background: Hospital and healthcare-facility microgrids increasingly combine distributed generation, battery storage, and multiple simultaneously active sources to sustain life-critical electrical loads during utility outages, but this added architectural complexity makes fault behavior difficult to detect and clear using conventional overcurrent-based protection. Machine learning (ML) has become the leading approach to microgrid fault detection, classification, and prediction, yet much of the literature and prior reviews emphasize artificial neural network and deep learning methods, leaving the broader landscape of classical and ensemble ML models comparatively underexamined for critical-healthcare relevance. Objective: This narrative review synthesizes published literature on classical machine learning models-including support vector machines, decision trees, random forests, k-nearest neighbours, naive Bayes classifiers, and gradient-boosted ensembles such as XGBoost and LightGBM-alongside neural network and deep learning approaches for microgrid fault detection, classification, and prediction, with particular attention to the reliability and interpretability requirements of hospital and critical-healthcare infrastructure. Methods: A narrative synthesis approach was used, drawing on peer-reviewed engineering studies of machine learning-based microgrid and power-system fault diagnosis and on the separate literature addressing hospital microgrid design, resilience quantification, and healthcare-facility infrastructural resilience, without a systematic meta-analytic pooling of effect sizes. Findings: Across the studies reviewed, classical and ensemble ML models frequently matched or exceeded neural network and deep learning baselines on the same or comparable microgrid and power-system fault-diagnosis tasks, with optimized random forest and heterogeneous stacked ensembles reaching test accuracies above 99% for fault detection and classification while degrading only marginally under injected measurement noise, and doing so with lower computational and training-data requirements and more auditable decision logic than many deep architectures. Separately, the hospital microgrid resilience literature has developed detailed optimization and resilience-quantification frameworks for sizing storage and generation against outage risk, but these frameworks generally treat fault detection and clearing as an idealized, instantaneous background process rather than incorporating the finite detection latency and residual misclassification risk that empirical ML models, classical or deep, actually exhibit. Conclusions: Classical and ensemble machine learning models represent an underexploited but well-evidenced foundation for hospital-relevant microgrid fault prediction, and integrating their documented accuracy, robustness, and interpretability characteristics into hospital-representative resilience models is a necessary next step for translating laboratory-validated fault diagnosis into dependable protection for critical healthcare infrastructure.

Keywords: *microgrid fault detection; machine learning fault classification; random forest and ensemble learning; hospital backup power reliability; critical healthcare infrastructure resilience*

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Introduction

Hospitals and other critical healthcare facilities depend on an uninterrupted supply of electrical power to operating theatres, intensive care units, imaging suites, and life-support equipment, a dependency that has driven many health systems toward on-site microgrids combining photovoltaic generation, battery energy storage, and dispatchable backup generation as a more flexible complement to conventional utility-and-generator backup architectures [1,2]. A hospital microgrid can island itself from the utility grid during an outage and continue serving prioritized critical loads, but the same multi-source, bidirectionally fed

topology that gives it this flexibility also makes fault behavior far more complex than in a conventional radial feeder: fault current contributions vary with inverter control mode and state of charge, and conventional overcurrent-based protection schemes are prone to both nuisance tripping and failure to trip [3]. Because a hospital cannot tolerate the multi-second to multi-minute detection and reconfiguration delays acceptable in many industrial or residential microgrids, the machine learning (ML) models used to detect, classify, and increasingly predict incipient faults in these systems have become a subject of direct clinical relevance rather than a purely electrical engineering concern.

A large and methodologically diverse literature has applied ML to microgrid fault diagnosis over the past decade, and it is broader than deep learning alone. Classical supervised learners-support vector machines (SVM), decision trees, random forests, k-nearest neighbours (KNN), naive Bayes classifiers, and gradient-boosted ensembles such as XGBoost and LightGBM-have repeatedly demonstrated fault detection and classification accuracies at or above 99% on simulated and hardware-in-the-loop microgrid test systems, often matching or exceeding artificial neural network (ANN) and deep learning baselines while requiring substantially less training data and offering more interpretable decision logic [4,5,6,7]. This narrative review synthesizes that broader classical-and-ensemble ML literature alongside the neural network and deep learning work with which it is often compared, first examining individual classical model families and their reported performance, then turning to ensemble and gradient-boosting approaches that combine multiple learners, then situating neural and deep learning methods within this comparative landscape, and finally considering what the hospital backup-power reliability literature requires of any ML-based protection scheme before it can be trusted with life-critical loads. The aim is not to declare a single best algorithm but to characterize the actual performance, robustness, and interpretability trade-offs documented across model families, since it is this trade-off space-rather than headline accuracy figures alone-that will determine which ML approaches are suitable for hospital microgrid deployment [8].

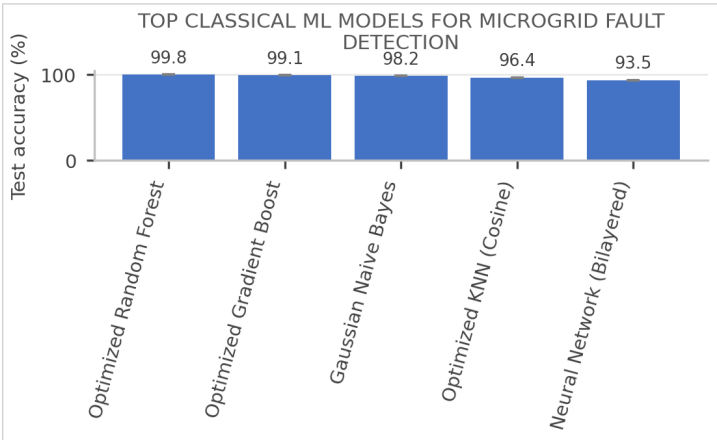
Classical Machine Learning Models for Microgrid Fault Detection

Among individual classical learners, tree-based and margin-based classifiers have received the most sustained attention in the microgrid fault-diagnosis literature, generally using time- or frequency-domain features extracted from measured bus voltages and branch currents as inputs. Fahim and colleagues conducted a comparative study evaluating support vector machines, kernel extreme learning machines (KELM), and a multi-KELM configuration against a proposed deep belief network for fault detection and classification across four operating configurations of a test microgrid-grid-tied radial, grid-tied loop, islanded radial, and islanded loop-explicitly designed to probe how well each classifier generalized across the operating-mode changes that are characteristic of, and especially consequential for, a microgrid that must switch between grid-connected and islanded operation during a utility outage [4]. Uzair and colleagues took a particularly systematic approach to model comparison, training thirty-five distinct classification learners spanning support vector machines, decision trees, k-nearest neighbours, naive Bayes classifiers, ensemble methods, and neural networks on eighteen extracted electrical features for both fault detection and combined fault-type-and-faulted-phase classification in a low-voltage AC microgrid, finding that an optimized random forest classifier outperformed every other model family tested, reaching 99.8% test accuracy for fault detection and 99.4% test accuracy for fault type classification with phase identification, ahead of optimized gradient boosting, Gaussian naive Bayes, cosine-distance KNN, and both wide and bilayered neural network configurations [5].

Principal classical and ensemble machine learning model families applied to microgrid and power-system fault detection, classification, and localization in the studies reviewed.

Model family	Representative input features	Reported diagnostic role	Key reference
Support vector machine / kernel extreme learning machine	Time- or wavelet-domain current/voltage features	Fault detection and classification across grid-tied/islanded operating modes	Fahim et al. 2020
Random forest	Sequence-current, harmonic, and phase features	Fault detection, fault-type/phase classification, line-to-ground vs line-to-line-to-ground discrimination	Uzair et al. 2022; Taheri et al. 2026
Gradient boosting / XGBoost / LightGBM	MODWT wavelet coefficients; voltage harmonics and phase differences	Real-time fault detection and classification; interpretable feature attribution	Patnaik et al. 2021; Lu et al. 2024
Decision tree ensembles	Pre-/post-fault voltage and current magnitudes	Fault zone identification and faulted-phase selection	Saleh & Ayad 2021
Optimized/hybrid tree ensembles	Fuzzy pre-detection features with metaheuristic-tuned inputs	Noise-robust fault classification and localization on extended feeder lines	Najafzadeh et al. 2024
Heterogeneous stacked ensembles	Combined tree-model and recurrent sequence-model outputs	Binary and multi-label fault classification via meta-learner stacking	Anwar et al. 2025

Test-set accuracy of the top-performing classical machine learning models for fault detection in a low-voltage AC microgrid, among thirty-five classifiers trained on eighteen extracted electrical features (Uzair et al., 2022).



Random forest classifiers specifically have also been developed for more electrically demanding fault categories. Taheri and colleagues proposed a random forest-based diagnostic scheme targeting line-to-ground and line-to-line-to-ground faults in an AC microgrid populated with inverter-based distributed

generators, a fault category historically difficult to distinguish reliably because inverter current-limiting control masks some of the fault-current asymmetries that conventional relays rely upon, and reported that the random forest approach achieved accurate discrimination between these closely related fault types across the distributed-generation penetration levels tested [6]. Complementing this work at the level of protection zones rather than fault types, Saleh and Ayad developed a decision-tree-ensemble approach for fault zone identification and faulted-phase selection in microgrids, framing the problem less as waveform classification and more as a structured decision problem over pre-fault and post-fault electrical quantities, and demonstrating that an ensemble of decision trees could reliably localize a fault to the correct protection zone as a computationally lightweight complement to phase-selection logic [9].

These classical-model results carry two implications for hospital-relevant fault identification. First, the consistent finding that random forest and related tree-ensemble methods match or exceed neural network baselines on the same datasets [5,4] indicates that the choice of learning algorithm is not simply a trade-off between "old" and "new" methods but a genuine multi-way comparison in which ensemble tree methods currently hold an empirical edge for several fault-diagnosis subtasks. Second, tree-based classifiers offer a degree of decision transparency-explicit split thresholds on physically meaningful features such as sequence-current magnitudes-that is valuable in a hospital setting where facilities engineers and biomedical equipment staff must be able to audit why a protective action was triggered, a property that purely black-box neural architectures do not straightforwardly provide [8].

Ensemble Learning and Gradient Boosting Approaches

A second major thread in this literature moves beyond single classifiers to explicitly combine multiple learners, motivated by the observation that different model families tend to make partially uncorrelated errors on the same fault-classification task. Gradient-boosted decision tree ensembles have been a particularly productive direction. Patnaik and colleagues proposed a fault detection and classification scheme for smart microgrids combining maximal overlap discrete wavelet transform (MODWT) feature extraction with an XGBoost classifier, using the wavelet decomposition to generate multi-resolution features from raw current and voltage signals before boosting; the resulting MODWT-XGBoost pipeline was validated across multiple fault types and operating conditions and was proposed explicitly as a computationally efficient alternative to deep neural network pipelines for real-time smart-microgrid protection [7]. Lu and colleagues extended the gradient-boosting approach further by combining a lightweight gradient boosting classifier, enhanced with bootstrap aggregating to reduce variance, with a downstream neural network stage for fault identification from voltage harmonic and phase-difference features, and used Shapley-value feature-attribution analysis to make the resulting hybrid model's predictions more interpretable while reducing the volume of measurement data the scheme required, explicitly targeting the overfitting risk that arises when training data are limited-a realistic constraint for any single hospital microgrid installation, which cannot ethically generate an extensive real-fault dataset from its own live system [10].

Beyond boosting, explicit ensemble-of-classifiers architectures that stack heterogeneous model types have shown some of the strongest reported performance gains over any single constituent model. Anwar and colleagues proposed a stacked ensemble combining a random forest classifier with a long short-term memory (LSTM) recurrent network, further refined by a tuned KNN meta-learner, for fault detection and classification in power transmission systems; considered individually, their random forest attained 99.72% binary-fault-detection accuracy and 97.50% multi-label classification accuracy, while their LSTM network reached 98.70% and 96.62% respectively on the same tasks, but the stacked RF-LSTM-KNN ensemble exceeded both individual models, reaching 99.96% multi-label classification accuracy and 99.97% accuracy with 99.96% cross-validation agreement on an independent real-time-simulation dataset [11]. Although developed for transmission-level protection rather than a microgrid specifically, this result is instructive for microgrid and hospital-relevant fault diagnosis because it demonstrates a broader empirical pattern also visible in the microgrid-specific literature: heterogeneous ensembles that combine a tree-based model's discrete decision boundaries with a sequence model's temporal sensitivity tend to outperform either model family alone, and the resulting gains are largest precisely on the harder multi-label and out-of-sample generalization tasks that matter most for real-world deployment rather than on the easiest binary detection task where most single models already exceed 99% accuracy [5,11].

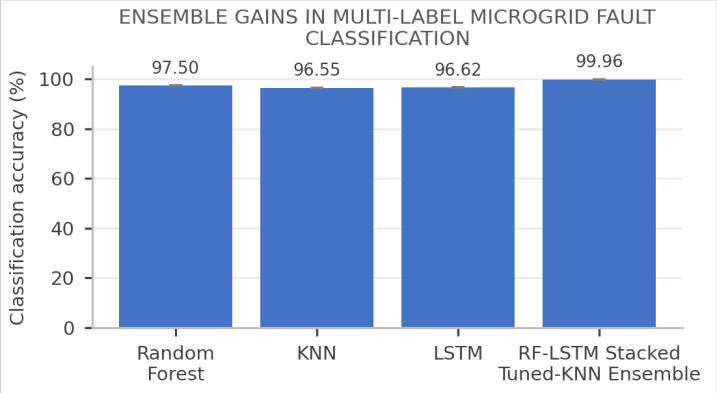
Hybrid metaheuristic-optimized tree ensembles constitute a related but distinct approach, in which a bio-inspired or evolutionary optimization algorithm is used to tune ensemble hyperparameters or feature weights rather than combining multiple model types directly. Najafzadeh and colleagues combined a Wild Horse Optimizer-tuned random forest with a fuzzy-logic pre-detection stage and an adaptive neuro-fuzzy inference system for downstream fault localization along an extended power line, reporting that the optimized random forest reached essentially perfect classification accuracy under nominal conditions and 99.93% accuracy when ten-decibel mixed measurement noise was deliberately injected, a noise-robustness result directly relevant to any hospital microgrid application where nearby variable-frequency drives, imaging equipment, and switched-mode power supplies constitute a comparatively noisy electromagnetic environment [12].

Neural Network and Deep Learning Approaches in Comparative Perspective

Neural network and deep learning methods remain heavily represented in the microgrid fault-diagnosis literature and are frequently used as the comparison baseline against which classical and ensemble ML methods are benchmarked, making them an unavoidable part of any comparative synthesis even though this review's primary focus is the broader classical ML landscape. Zaben and colleagues conducted a systematic review synthesizing more than one hundred studies on machine learning methods for fault diagnosis in AC microgrids, characterizing the field's progression from classical feedforward and shallow ANNs toward convolutional, recurrent, and hybrid deep architectures, while cataloguing recurring challenges including limited or imbalanced fault datasets, sensitivity to changes in microgrid topology and operating mode, and a persistent gap between accuracies reported on simulated data and the requirements of real-time hardware implementation-challenges that, as the classical-ML literature above shows, are not unique to deep architectures [3]. Within this landscape, wavelet-domain feature extraction paired with artificial neural networks remains a widely used approach: Jayasinghe and colleagues combined

discrete wavelet transform features with an ANN for both fault classification and localization in an AC microgrid, reporting training and validation classification accuracies of 99.83% and 99.39%, respectively, but finding that independent validation in PSCAD simulation dropped to 95.9% correct classification (511 of 533 simulated faults), a result that underscores how peak accuracy on a training or validation split can substantially overstate performance under more diverse independent test conditions-a caution that applies to classical ML pipelines exactly as it does to deep networks [13].

Multi-label fault classification accuracy of individual random forest and LSTM models versus their stacked RF-LSTM-tuned-KNN ensemble, illustrating the accuracy gain from heterogeneous ensembling on the harder multi-label task (Anwar et al., 2025).



More recent deep sequence-model work has begun to explicitly probe robustness under the noisy, variable-impedance conditions realistic for field deployment, a design objective that mirrors the noise-robustness testing seen in the classical-ML ensemble literature discussed above. Esmaeilbeigi and colleagues proposed a fault classification scheme built around protective agents using deep neural networks combining dense and gated recurrent unit layers, reporting fault detection accuracy as high as 99.895% and fault type-and-phase identification accuracy of 99.79% under favorable parameter combinations, but with accuracy falling to roughly 95.5-96% under the most adverse parameter combinations tested and fault-location error rising to as much as 6.51% of feeder length [14]. Read alongside the classical-ML results, this pattern suggests two mutually reinforcing conclusions: first, that no single model family-classical, ensemble, or deep-has yet demonstrated qualitatively superior robustness to fault-resistance variation, sensor noise, and out-of-distribution operating conditions, and second, that reported comparisons between deep and classical methods on the same or similar test systems tend to show classical ensemble methods (random forest, gradient boosting, stacked heterogeneous ensembles) matching or exceeding deep architectures at substantially lower computational and data cost [5,11,7]. This has direct implications for hospital microgrid deployment, where computational resources at protection relays are constrained, retraining data are scarce, and interpretability requirements favor simpler models wherever performance parity holds [8].

Hospital Microgrids and Reliability Requirements for Critical Healthcare Infrastructure

A separate body of work has examined hospital and healthcare-facility backup power from the standpoint of system design, resilience quantification, and outage-scenario planning, generally treating the protection and fault-identification layer as an idealized, near-instantaneous background function rather than as the object of study. Hervás-Zaragoza and colleagues presented a post-COVID-19 case study examining how a hospital microgrid combining distributed generation and storage could improve energy resilience during grid outages, framing the pandemic period as having sharpened attention to the clinical consequences of any interruption to hospital power given the surge in critical-care and ventilated-patient loads observed during that period [1]. Eissa and colleagues used the U.S. National Renewable Energy Laboratory's REopt platform to optimize the sizing of a hybrid photovoltaic, battery storage, and diesel generator hospital microgrid across outage scenarios of varying duration and seasonal timing, finding that a resilience-constrained design achieved a system resilience index of 1.0 (complete critical-load service) while adding only a small increment to net present cost relative to an economically optimized baseline [15]. Nazartalab and Alavi-Rad extended this optimization approach to explicitly prioritize loads by medical criticality-differentiating, for example, intensive care, operating room, imaging, and pharmacy loads-through a mixed-integer linear programming framework evaluated across Monte Carlo-simulated outage scenarios, reporting that multi-node battery storage placement reduced energy not supplied by 55-63% relative to baseline configurations while maintaining at least 95% service to life-critical loads across most stochastic scenarios [16].

Representative hospital and healthcare-facility microgrid resilience studies cited in this review, illustrating that fault clearing is generally modeled as instantaneous rather than incorporating ML-based detection latency or misclassification risk.

Study	System modeled	Key resilience finding	Treatment of fault protection layer
Hervas-Zaragoza et al. 2022	Hospital PV + storage microgrid, post-COVID-19 case study	Microgrid adoption framed as improving energy resilience during grid outages	Not modeled explicitly
Eissa et al. 2026	REopt-optimized PV/battery/diesel hospital microgrid	Resilience-constrained design achieved system resilience index of 1.0 with small cost increment	Assumed instantaneous, idealized
Nazartalab & Alavi-Rad 2026	MILP-scheduled multi-node storage with criticality-ranked loads	Multi-node storage reduced energy not supplied by 55-63% versus baseline	Assumed instantaneous, idealized
Hubner et al. 2023	Hospital critical-infrastructure categorization framework	Electrical backup treated as one interdependent element among several infrastructure systems	Not modeled as a discrete technical system

Complementing these engineering optimization studies, a health-services literature has approached backup power reliability as one component of a broader concept of hospital infrastructural resilience rather than as a discrete technical system. Hübner, Küsel, and Oestmann proposed a categorization and quantification framework for critical infrastructure resilience in hospitals, situating electrical power supply and its

backup arrangements alongside water, medical gas, and information technology as elements requiring systematic risk categorization and explicit modeling of interdependencies rather than isolated engineering treatment [17]. Khalil and colleagues conducted a scoping review of how "hospital resilience" has been conceptualized and measured across the health-services literature, finding substantial heterogeneity in definitions and noting that infrastructural resilience, including power continuity, is frequently treated as one dimension within multidimensional frameworks that also encompass workforce, supply chain, and organizational dimensions [18]. At a broader systems level, Zidane and colleagues reviewed power system and microgrid resilience enhancement strategies spanning network reconfiguration, distributed energy resource deployment, and control strategies for maintaining service to critical loads such as hospitals during extreme events, providing wider technical context for hospital-specific resilience work [2]. None of these hospital-focused studies model the finite detection latency or residual misclassification risk of the ML-based fault identification schemes reviewed in the preceding sections; their resilience metrics implicitly assume that a fault, once it occurs, is instantaneously and correctly identified and cleared.

Toward Deployable ML-Based Fault Prediction for Hospital Microgrids

Reading the classical-ML fault-diagnosis and hospital-resilience literatures side by side reveals a clear and addressable gap. Essentially all of the classical, ensemble, and neural ML models reviewed above are developed and validated on generic microgrid or transmission test systems-IEEE bus configurations, laboratory feeders, or simulated distribution networks-rather than on models explicitly representing a hospital's layered normal-emergency-critical branch architecture, its automatic transfer switches, or its typically high degree of load and source redundancy [5,11,3]. Conversely, the hospital microgrid resilience and optimization literature, including the mixed-integer linear programming frameworks of Eissa and colleagues and of Nazartalab and Alavi-Rad, generally treats fault clearing as instantaneous, omitting the finite detection and classification latency and the residual misclassification risk that every empirical ML-based scheme, classical or deep, actually exhibits [15,16]. Bridging this gap would mean evaluating the strongest-performing classical and ensemble ML fault-diagnosis pipelines-such as the optimized random forest and stacked heterogeneous ensembles that have repeatedly matched or exceeded deep learning baselines at lower computational cost [5,11]-on hospital-representative feeder topologies, and explicitly incorporating the resulting detection latency and residual misclassification probability into the energy-not-supplied and resilience-index calculations that the hospital microgrid design literature already computes for storage and generation sizing [16].

The noise- and impedance-robustness findings emerging from the classical-ML literature are directly relevant to this integration task. The demonstration by Najafzadeh and colleagues that an optimized random forest degrades only marginally, from essentially perfect to 99.93% accuracy, under substantial injected measurement noise is an encouraging signal for hospital deployment, where electrically noisy diagnostic and life-support equipment constitutes a realistic operating environment [12]. Similarly, the interpretability advantage of tree-based and gradient-boosted models-explicit, auditable decision paths over physically meaningful features, reinforced in some implementations by explicit feature-attribution analysis [10]-addresses a governance requirement that is largely absent from the deep-learning fault-diagnosis literature but is likely to matter for clinical engineering staff and accreditation bodies who must be able to explain why a hospital microgrid's protection system took a given action. Given that classical and ensemble ML methods already match or exceed deep learning accuracy on the fault-diagnosis subtasks studied to date while requiring less training data, less computation, and offering more auditable decisions, they represent a currently underexploited starting point for hospital-specific fault prediction research, rather than a legacy approach to be superseded by deep learning as the field matures [4,8].

Conclusion

The machine learning literature on microgrid fault detection, classification, and prediction is substantially broader than its deep-learning subset, encompassing support vector machines, decision trees, random forests, k-nearest neighbours, naive Bayes classifiers, gradient-boosted ensembles, and heterogeneous stacked ensembles that have repeatedly matched or exceeded neural network and deep learning baselines on the same simulated microgrid and power-system test cases, often exceeding 99% classification accuracy while demonstrating better documented robustness to noise and lower computational and data requirements [5,11,7,12,4]. A separate literature, situated at the intersection of energy systems engineering and hospital administration, has developed optimization frameworks and resilience-categorization schemes for sizing and operating hospital microgrids against outage risk, generally without close attention to the specific ML-based protection and fault-identification layer that would have to operate correctly, quickly, and interpretably for these designs to deliver their promised reliability in practice [15,16,17,18,1,2]. The central opportunity identified by reading these literatures together is not a further increase in reported classification accuracy on generic test systems, where performance in the high-90s percentage range is already common across model families, but the deliberate evaluation, robustness testing, and interpretability characterization of the strongest-performing classical and ensemble ML fault-prediction pipelines on hospital-representative electrical topologies, with resilience metrics that explicitly account for detection latency and residual misclassification risk. Achieving this integration would allow the demonstrated diagnostic capability of modern machine learning-classical and deep alike-to translate more directly into the dependable, continuous power supply on which hospital critical care depends.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Bruun I conceived the review, conducted the literature search and synthesis across the classical and ensemble machine learning fault-diagnosis literature, and drafted the manuscript. Lepik K contributed the electrical engineering framing of microgrid protection and fault-identification methods and critically revised the manuscript for important technical content. Johansson S contributed the hospital administration and healthcare-facility resilience perspective, reviewed the clinical relevance of the synthesized findings, and approved the final version for submission.

Ethics Statement

Not applicable. This is a narrative review of previously published literature and did not involve new experimental data, human participants, or animal subjects.

Data Availability

No new data were generated or analyzed for this review. All sources synthesized are cited in the reference list and are available through their original publishers.

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