



Machine Learning-Based Fault Detection and Classification in Smart Electrical Power Systems

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Abstract

Reliable protection of smart electrical power systems requires rapid discrimination between normal operating conditions and short-circuit faults despite changing loads, distributed generation, measurement noise, and network reconfiguration. This methodology paper develops a machine-learning framework for fault detection and classification using three-phase voltage and current measurements. A reproducible synthetic benchmark was generated to represent normal operation and ten common fault classes: single-line-to-ground, line-to-line, double-line-to-ground, and three-phase faults. The pipeline applies normalization and physically meaningful features based on phase RMS values, symmetrical-component proxies, unbalance indices, residual current, and voltage-current ratios. Five supervised classifiers—k-nearest neighbours (KNN), support vector machine (SVM), random forest (RF), gradient boosting, and multilayer perceptron (MLP)—were trained on an 80% stratified training set and evaluated on a held-out 20% test set. The best models achieved 99.80% test accuracy and macro F1-score of approximately 0.998, while KNN achieved 98.18%. The results show that compact engineered features can support accurate and computationally efficient fault classification, while also highlighting the need for validation on field measurements and inverter-dominated networks before deployment.

Introduction

Smart electrical power systems increasingly combine conventional generation with distributed renewable energy, inverter-based resources, advanced metering infrastructure, intelligent electronic devices, and bidirectional communication. These capabilities improve observability and control, but they also change fault-current signatures and complicate the operating environment faced by traditional protection schemes. Machine learning (ML) is therefore being investigated as a data-driven complement to impedance, travelling-wave, and rule-based protection because it can learn nonlinear relationships between measured signals and fault states (Vaish et al., 2021). The

goal is not to replace protection fundamentals, but to support faster and more adaptive event recognition under conditions where fixed thresholds may become less reliable.

Transmission and distribution faults can be grouped into single-line-to-ground (AG, BG, CG), line-to-line (AB, BC, CA), double-line-to-ground (ABG, BCG, CAG), and balanced three-phase (ABC) events. Accurate classification is important because it determines which phases are involved, supports selective isolation, and can reduce restoration time. Earlier SVM-based studies demonstrated that wavelet-derived or current-based features can classify transmission-line faults with high accuracy (Parikh et al., 2010; Ekici, 2012; Ray & Mishra, 2016). Later work

extended intelligent classification toward smart distribution networks with real-time metering and distributed generation (Usman et al., 2020). Recent studies up to 2022 show a shift from hand-crafted classifiers toward optimized ML and deep-learning models. Al Kharusi et al. (2022) proposed a two-layer ML approach for transmission lines connected to inverter-based generators; Elmasry and Wadi (2022) used an ensemble of deep models; Bhuiyan et al. (2022) investigated deep-belief-network-based transient classification in multimachine microgrids; and Uddin et al. (2022) reported an optimized supervised-learning framework designed to remain effective under source noise and parameter variations. CNN-based work has also shown that automatically learned features can provide highly accurate short-circuit classification (Guo et al., 2022). These studies motivate a compact, reproducible comparison of conventional supervised ML models using features that can be calculated directly from measured voltage and current quantities.

Accordingly, this paper proposes a simulation-oriented methodology with three objectives: (i) construct a balanced multi-class dataset representing realistic variation in loading, fault severity, phase involvement, and measurement noise; (ii) compare several supervised ML classifiers using the same feature set and data split; and (iii) evaluate classification performance using accuracy, macro precision, macro recall, F1-score, and a confusion matrix. The study is intentionally methodological: the results demonstrate the reproducibility and comparative behaviour of the pipeline rather than claiming field deployment performance.

Literature Review

The evolution of ML-based power-system fault diagnosis can be viewed in three stages. First, conventional intelligent protection relied mainly on engineered signal features combined with classifiers such as SVMs. Parikh et al. (2010) used current samples to classify faults on series-compensated lines, while Ekici (2012) combined wavelet analysis with SVMs for fault classification

and location. Ray and Mishra (2016) further coupled wavelet-packet features with an optimized SVM and reported high classification accuracy across fault conditions. These works established the usefulness of supervised learning but also depended strongly on feature engineering and simulation assumptions.

Second, smart-grid sensing expanded the available data. Usman et al. (2020) demonstrated ANN-based fault classification and location using event-driven measurements from advanced metering infrastructure and a digital real-time simulator. This is important because modern protection analytics increasingly depend on synchronized or event-driven measurements rather than only local relay quantities. Vaish et al. (2021), in a broad review, concluded that supervised, unsupervised, reinforcement, and transfer-learning methods are increasingly relevant as distributed generation and power-electronic interfaces challenge conventional protection.

Third, 2022 research emphasized robustness, deep feature learning, and inverter-dominated systems. Al Kharusi et al. (2022) explicitly considered inverter-based generators and separated detection from fault-type classification. Elmasry and Wadi (2022) combined data preprocessing, feature/hyperparameter optimization, and ensemble deep learning. Bhuiyan et al. (2022) applied a deep belief network to transient features in a multimachine microgrid, while Uddin et al. (2022) used optimized supervised learning for transmission-line fault analysis under variations in noise and system parameters. Guo et al. (2022) showed that CNNs can learn fault representations from fixed data windows, and Krivohlava et al. (2022) emphasized that smart-grid dependability must consider diverse failure modes across physical, communication, software, and business layers. Together, these studies indicate that high accuracy alone is insufficient; generalization, interpretability, sensing requirements, computation, and deployment context must also be evaluated.

Table 1. Selected literature used to define the methodology

Study	System / data	Method	Main relevance
Ray & Mishra (2016)	Long transmission line	Wavelet + SVM	Feature-based fault classification
Usman et al. (2020)	Smart DN + AMI	ANN	Real-time smart-meter measurements
Al Kharusi et al. (2022)	Inverter-based line	Two-layer ML	Detection followed by classification
Uddin et al. (2022)	IEC microgrid model	Optimized ML	Noise and parameter robustness
Elmasry & Wadi (2022)	Power-line dataset	Deep ensemble	Preprocessing and ensemble design

Methodology

The proposed methodology follows a conventional supervised-learning workflow but constrains every stage to quantities that are plausible for digital relays, PMUs, smart meters, or simulation records. Figure 1 summarizes the process. The benchmark is synthetic and reproducible: it is intended to evaluate the classification methodology under controlled variations rather than to substitute for field fault records.

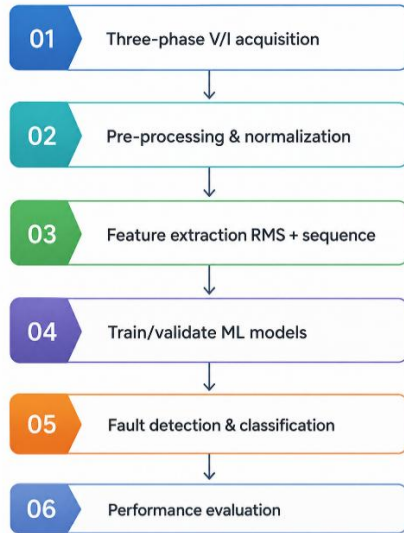


Figure 1. Proposed machine-learning workflow for fault detection and classification.

1. Data generation and fault classes.

The dataset contains 4,950 labeled observations: 450 samples for each of 11 classes (normal, AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, and ABC). For each observation, the pre-fault load multiplier is randomly varied between 0.75 and 1.25 p.u. Fault severity is randomized to represent changes in fault impedance and inception conditions. Affected phases experience voltage depression and fault-current increase, healthy phases retain smaller coupled changes, and ground faults

include a residual-current component. Gaussian measurement noise is added to both voltage and current magnitudes. This design follows the literature practice of testing classifiers across fault type, location/strength, loading, and measurement uncertainty rather than at a single operating point (Ray & Mishra, 2016; Uddin et al., 2022).

2. Feature extraction.

Each sample is converted into a compact feature vector containing phase RMS voltages (V_a , V_b , V_c), phase RMS currents (I_a , I_b , I_c), positive-, negative-, and zero-sequence magnitude proxies for voltage and current, voltage and current unbalance indices, minimum-to-maximum voltage ratio, maximum-to-mean current ratio, mean voltage-to-current ratio, residual current, and a residual-current ratio. These features combine phase-specific fault information with sequence and unbalance information commonly used in protective analysis. Using engineered quantities also keeps the feature dimension low and reduces the computational burden compared with large raw-waveform deep-learning inputs.

3. Data preparation and learning algorithms.

The complete dataset is divided using an 80/20 stratified split, yielding 3,960 training and 990 testing samples with identical class proportions. Standardization is applied inside the pipeline for KNN, SVM, and MLP to prevent information leakage. Five models are compared: KNN with distance weighting, RBF-kernel SVM, random forest, gradient boosting, and a two-hidden-layer MLP. The random forest uses 250 trees with depth and leaf-size constraints; the SVM uses a moderate penalty parameter; and the MLP uses 48 and 24 hidden units. This multi-model comparison reflects the literature trend of evaluating both classical and neural methods rather than assuming one algorithm is universally superior (Vaish et al., 2021).

Table 2. Experimental design and evaluation settings

Parameter	Setting
Classes	11: Normal + 10 short-circuit fault types
Samples	4,950 total (450 per class)
Train / test split	80% / 20%, stratified
Measurements	Three-phase voltage and current in p.u.
Feature family	RMS, sequence proxies, unbalance, ratios, residual current
Models	KNN, SVM-RBF, Random Forest, Gradient Boosting, MLP
Metrics	Accuracy, macro precision, macro recall, macro F1, confusion matrix

4. Evaluation metrics.

For a test set of N observations, accuracy is the proportion of correct predictions. Because the

dataset is balanced and multi-class, macro precision, macro recall, and macro F1-score are also reported by first calculating the

corresponding metric for each class and then averaging across all 11 classes. A confusion matrix is used to identify class-specific errors. Model selection is based primarily on held-out performance, while model complexity and suitability for protection applications are discussed qualitatively.

Results

All five classifiers achieved strong held-out performance, indicating that the selected

electrical features contain discriminative information for fault type. Table 3 shows that SVM-RBF, random forest, and MLP each achieved 99.80% accuracy with macro F1 of about 0.998. Gradient boosting achieved 99.49%, while KNN achieved 98.18%. The small gap between models suggests that feature quality is a major contributor to performance in this controlled benchmark; however, the result should not be interpreted as evidence that the same accuracy will be obtained on field data.

Table 3. Test-set performance of the evaluated classifiers

Model	Accuracy (%)	Precision	Recall	F1-score
SVM-RBF	99.80	0.9980	0.9980	0.9980
Random Forest	99.80	0.9980	0.9980	0.9980
MLP	99.80	0.9980	0.9980	0.9980
Gradient Boosting	99.49	0.9950	0.9949	0.9950
KNN	98.18	0.9827	0.9818	0.9817

Random forest was selected for detailed class-level inspection because it combines high accuracy with straightforward feature-importance analysis and does not require standardized inputs. The confusion matrix in Figure 2 contains only two errors among 990 test samples: one CG observation was classified as normal and one ABG observation as AB. This pattern is physically plausible because high-resistance or weak ground faults can move toward the boundary between faulted and normal/non-ground signatures. The remaining classes were correctly identified in the held-out set.

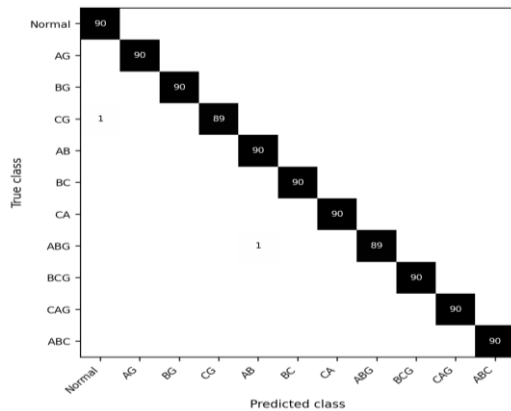


Figure 2. Random Forest confusion matrix for the 990-sample held-out test set.

The performance is consistent with the direction of prior literature, where carefully engineered or learned features have produced very high simulated classification accuracies. For example, Guo et al. (2022) reported 99.95% for a CNN-based short-circuit classifier, and Uddin et al. (2022) reported overall accuracy above 99% for an optimized ML framework. The present study

differs in that it deliberately uses low-dimensional features and a common benchmark across five algorithms. This improves interpretability and reduces training cost, although it may sacrifice some robustness when raw waveform morphology contains information not captured by RMS and sequence features.

Conclusion and Discussion

This paper presented a concise methodology for ML-based fault detection and classification in smart electrical power systems using three-phase voltage and current measurements. A reproducible 11-class synthetic benchmark was created, physically motivated features were extracted, and five supervised classifiers were evaluated under one stratified train/test protocol. SVM-RBF, random forest, and MLP achieved 99.80% test accuracy, while gradient boosting and KNN achieved 99.49% and 98.18%, respectively. The confusion matrix showed that errors occurred mainly near boundaries involving weak ground-fault signatures. These results support the core methodological proposition that compact combinations of RMS, sequence, unbalance, and residual-current features can provide strong discrimination among common fault types. The results should be interpreted with appropriate limits. First, the dataset is simulation-oriented and synthetic; it does not reproduce every electromagnetic transient, instrument-transformer error, switching event, harmonic disturbance, topology change, or communication impairment present in an operational smart grid. Second, balanced class counts simplify metric interpretation but do not reflect the natural rarity of severe faults. Third, high test accuracy on data generated from a common stochastic process can overestimate

deployment performance if the field distribution differs from the training distribution. These limitations are consistent with broader concerns in ML-based power-system diagnosis regarding dataset realism, generalization, and changing network conditions (Vaish et al., 2021; Elmasry & Wadi, 2022). Future validation should therefore use electromagnetic-transient simulation and, where available, relay/PMU/AMI records from real systems; include inverter-control diversity, distributed-generation penetration, topology reconfiguration, high-impedance faults, power swings, switching transients, and class imbalance; and evaluate detection latency in addition to classification accuracy. The two-layer structure used by Al Kharusi et al. (2022) is particularly suitable for future extensions because binary event detection can be separated from fault-type classification. For deployable protection support, model confidence, explainable features, drift monitoring, and fallback to deterministic relay logic should also be considered. Thus, ML is best treated as an adaptive analytical layer integrated with established protection principles rather than as an isolated replacement for them.

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