



Archives available at journals.mriindia.com

**International Journal of Electrical, Electronics and
Computer Systems**

ISSN: 2347-2820

Volume 10 Issue 01, 2021

Machine Learning Techniques for Fault Detection in Electrical Power Networks

Myeong Ghaznavi

Department of Electrical and Computer Engineering, Aurora Metropolitan Institute of Technology, Philippines
myeong.ghaznavi@amit-ph.edu

Peer Review Information

Submission: 08 Jan 2021

Revision: 03 Feb 2021

Acceptance: 10 March 2021

Keywords

Fault Detection, Machine Learning, Power System Protection, Support Vector Machine, Random Forest.

Abstract

Reliable fault detection is fundamental to the security and continuity of electrical power networks. Conventional protection schemes are fast and interpretable but may lose sensitivity when operating conditions change because of distributed generation, topology variation, high fault resistance, measurement noise, and non-stationary transients. This methodology paper develops a structured machine-learning framework for detecting and classifying power-network faults from three-phase voltage and current measurements. The framework combines signal segmentation, normalization, physically meaningful features, supervised classifiers, stratified validation, and protection-oriented performance metrics. Support vector machine (SVM), random forest (RF), and multilayer perceptron (MLP) models are compared because they represent margin-based, ensemble, and neural-learning paradigms that can be implemented with modest computational resources. A reproducible physics-informed synthetic benchmark of 5,400 operating cases is used only to demonstrate the evaluation procedure; it contains normal operation and five aggregated fault categories under variable loading, severity, and measurement perturbations. The illustrative test results show classification accuracies of 97.56% for SVM, 98.15% for RF, and 97.56% for MLP, with RF providing the strongest macro F1-score. The methodology emphasizes that accuracy alone is insufficient: relay-oriented deployment must also consider class recall, noise robustness, detection latency, data leakage, and validation on electromagnetic-transient or field measurements. The resulting workflow provides a concise, reproducible basis for future experimental work on intelligent protection of transmission and distribution networks.

Introduction

Electrical power networks are exposed to short-circuit faults, insulation failures, equipment deterioration, lightning, switching disturbances, and external contact events. Because a fault can produce large currents, voltage depression, thermal stress, instability, and interruption of supply, protection systems must identify abnormal conditions and isolate the affected section quickly. Traditional overcurrent,

differential, and distance protection remain essential, but fixed settings may be challenged by changing generation patterns, network reconfiguration, converter-interfaced resources, and uncertain fault resistance. These conditions motivate data-driven protection methods that can learn discriminative patterns from measured waveforms rather than relying exclusively on predetermined thresholds.

Artificial neural networks were investigated early for transmission-line protection because nonlinear decision boundaries can be learned from offline fault simulations; Yadav and Dash (2014) summarized ANN applications for detection, classification, location, and directional discrimination. SVM-based approaches later demonstrated that current or wavelet-derived features could support accurate classification on compensated lines (Parikh et al., 2010), while wavelet-SVM and extreme-learning-machine schemes showed the value of transient features for protection decisions (Veluchamy et al., 2010). These studies established a core pattern that remains relevant: collect representative fault signals, extract robust information, train a classifier, and evaluate it under operating variations.

More recent work has moved from engineered features toward deep and end-to-end representations. CNN-based models can learn directly from sampled three-phase measurements and have been evaluated in distribution systems with distributed generation (Rai et al., 2021). A 2021 review by Vaish et al. concluded that machine learning is increasingly important for adaptive fault diagnosis but emphasized the need for systematic data preparation, model selection, and validation. The purpose of the present paper is therefore not to propose a single opaque classifier, but to specify a transparent methodology that can be reproduced and extended in a laboratory or utility setting.

Literature Review

Fault diagnosis in power networks is usually separated into detection, classification, and location, although the three tasks are interdependent. Chen et al. (2016) reviewed these stages and stressed that feature extraction strongly influences the success of downstream decision methods. For example, Koley et al. (2015) combined wavelet transform and ANN for detection, classification, and location using single-ended measurements, illustrating how transient information can be converted into inputs suitable for supervised learning. Ray and Mishra (2016) used wavelet packet energy and entropy together with SVM and parameter optimization, showing that statistical

representations of post-fault current can support both classification and distance estimation.

Deep-learning research extended these ideas by learning features from raw or transformed sequences. Fan et al. (2019) combined convolutional and LSTM components for single-ended fault-location learning, explicitly exploiting both local signal structure and temporal correlation. Fahim et al. (2020) proposed a self-attention CNN with time-series imaging and wavelet denoising to improve transmission-line fault detection and classification under sampling and noise variations. Rai et al. (2021) demonstrated a CNN that operates directly on sampled voltage and current signals in distribution networks containing distributed generators, reducing the dependence on manual feature engineering.

The literature therefore indicates three design choices. First, engineered features with SVM or tree ensembles remain attractive when datasets are moderate and interpretability is desirable. Second, neural models are useful when abundant sequential data are available and temporal signatures are important. Third, validation must include operating diversity and noise rather than a single nominal case. The present methodology adopts these principles and compares three conventional-to-neural classifiers on a common feature set so that performance differences can be attributed to learning behavior rather than inconsistent preprocessing.

A remaining research gap is the gap between classifier accuracy reported on simulated datasets and dependable operation of a protective relay. Random train-test splits can overestimate generalization when waveforms generated from the same operating point appear in both subsets. In addition, class balance in research datasets is often unlike the highly imbalanced stream encountered by a relay, where normal operation dominates and faults are rare. A stronger methodology should therefore separate scenarios by operating condition, retain a final unseen test set, and document false-positive as well as false-negative behavior. The same data pipeline should be used for all candidate classifiers so that improvements are attributable to the learning algorithm rather than to unequal preprocessing. These considerations motivate the controlled comparison adopted here.

Table 1. Representative fault-diagnosis studies used to motivate the methodology

Study	Method	Application	Methodological relevance
Parikh et al. (2010)	SVM	Series-compensated transmission line	Margin-based supervised classification from current samples.

Koley et al. (2015)	Wavelet + ANN	Transmission-line protection	Combines transient features with nonlinear learning.
Ray & Mishra (2016)	WPT + SVM	Long transmission line	Feature selection and model-parameter optimization.
Fan et al. (2019)	CNN + LSTM	Fault location	Learns spatial and temporal structure from sequences.
Fahim et al. (2020)	DWT + attention CNN	Transmission-line FDC	Addresses denoising, sampling rate, and robust classification.
Rai et al. (2021)	CNN	DG-integrated distribution network	Uses raw sampled voltage/current without manual feature engineering.
Belagoune et al. (2021)	LSTM/DRNN	Multi-machine system	Uses PMU sequences for region, class, and location.
Rafique et al. (2021)	End-to-end LSTM	Power transmission lines	Direct sequence learning under varied operating conditions.

Methodology

The study follows a supervised-learning workflow in which synchronized three-phase voltage and current signals are converted into labeled examples of healthy and faulty operation. The framework can be implemented using MATLAB/Simulink, PSCAD, an electromagnetic-transient simulator, or synchronized field measurements. For this paper, a compact physics-informed synthetic benchmark is used to demonstrate the analysis sequence without claiming utility-field validation.

The experimental design treats each fault case as one observation produced from a defined combination of network state and disturbance parameters. To improve repeatability, all random seeds, parameter ranges, sampling frequencies, window lengths, and feature formulas should be stored with the dataset. When a detailed simulator is used, training and test cases should be generated in separate batches so that identical time-series realizations cannot leak across subsets. Where field data are available, simulator-trained models should be evaluated without retraining first, followed by controlled fine-tuning. This sequence reveals the domain gap between synthetic and real measurements and provides a more realistic estimate of deployment risk.

Step 1 - Define the protection classes. Use six output classes: Normal, line-to-ground (LG), line-to-line (LL), double-line-to-ground (LLG), three-line (LLL), and three-line-to-ground (LLLG). In a full relay implementation these aggregated labels may be expanded into phase-specific classes such as A-G, B-G, A-B, and A-B-G. Aggregation is useful in the methodology stage because it tests

whether the model first learns the physical fault family before phase selection is added.

Step 2 - Generate or collect representative operating cases. Create fault cases across loading level, fault severity/resistance, inception angle, location, and measurement perturbation. The illustrative benchmark contains 5,400 balanced cases (900 per class). For every case, three-phase voltage and current quantities are varied around nominal values; faulted phases experience voltage depression and current rise, while zero- and negative-sequence quantities are increased according to whether ground and/or phase unbalance is present. Random operating drift is added so that the learning problem is not a set of fixed templates.

Step 3 - Segment and preprocess measurements. Extract a short window immediately after fault inception, preferably from one-quarter to one power-frequency cycle depending on the intended relay speed. Remove missing samples, apply anti-aliasing or denoising where required, and normalize features using parameters estimated from the training set only. This avoids data leakage. In field studies, CT saturation, PMU synchronization error, and communication dropouts should be separately tagged because they can imitate fault signatures.

Step 4 - Extract physically meaningful features. For each window compute the RMS values of V_a , V_b , V_c , I_a , I_b , and I_c ; normalized zero- and negative-sequence voltage and current magnitudes; transient-energy index; and total-harmonic-distortion proxy. These 12 features summarize voltage depression, current escalation, phase unbalance, ground involvement, and high-frequency disturbance

content. Feature-based inputs make SVM, RF, and MLP directly comparable and reduce the computational load compared with high-dimensional waveform learning.

Step 5 - Split data and train classifiers. Perform a stratified 75/25 train-test split, preserving the proportion of every fault class. Within the training portion, use cross-validation for hyperparameter selection. The SVM uses a radial-basis-function kernel; RF uses multiple bootstrapped decision trees with random feature selection; the MLP uses two hidden layers with nonlinear activation and regularization. Hyperparameters should be finalized without inspecting the held-out test labels.

Step 6 - Evaluate protection-oriented metrics. Report overall accuracy together with macro precision, macro recall, and macro F1-score. Macro averages weight all fault categories equally and therefore reveal poor performance

on a less frequent or difficult fault family. A confusion matrix should be inspected to identify systematic misclassification between related categories such as LL and LLG. For deployment, add detection time, inference latency, false-trip rate, missed-trip rate, and robustness at multiple signal-to-noise ratios.

Step 7 - Validate under unseen operating conditions. A model should not be considered relay-ready simply because random-split accuracy is high. The final validation set should include operating points, fault resistances, topology states, and distributed-generation levels not used during training. This requirement follows the broader concerns in ML-based fault diagnosis summarized by Vaish et al. (2021), and it is consistent with robustness testing reported in recent CNN and LSTM studies (Fahim et al., 2020; Rafique et al., 2021).

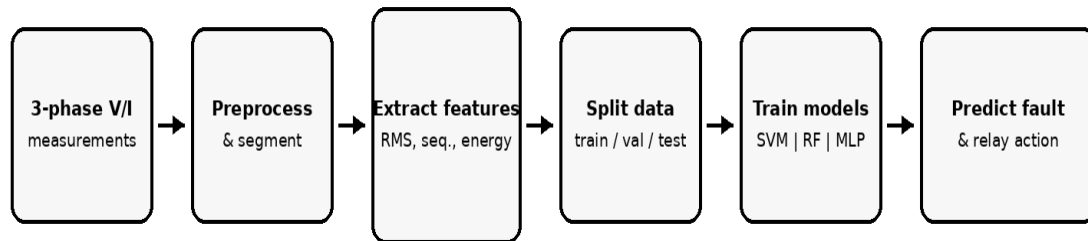


Figure 1. Step-by-step workflow for machine-learning-based fault detection and classification.

Results

To demonstrate how the proposed evaluation should be reported, the three classifiers were trained on 4,050 cases and tested on an independent set of 1,350 cases. These cases are generated from the simplified physics-informed benchmark described above; therefore, the

numbers below are illustrative methodological results rather than measurements from a specific utility network. The purpose is to show a reproducible reporting structure and to identify which learning paradigm merits more detailed electromagnetic-transient testing.

Table 2. Illustrative classification performance on the held-out synthetic benchmark

Classifier	Accuracy (%)	Macro Precision	Macro Recall	Macro F1
SVM (RBF)	97.56	0.976	0.976	0.976
Random Forest	98.15	0.982	0.981	0.981
MLP	97.56	0.976	0.976	0.976

RF produced the best illustrative accuracy (98.15%) and macro F1-score (0.981). Its advantage is plausible for this feature set because tree ensembles can capture nonlinear threshold interactions such as simultaneous voltage depression, current rise, and sequence-component changes without requiring feature scaling. The SVM and MLP both achieved 97.56% accuracy, indicating that the same physically meaningful features are sufficiently discriminative across different classifier families. The small gap among models also shows why a

final selection should not be made from nominal accuracy alone.

The outcome is consistent with the historical development of intelligent protection. SVM methods have repeatedly demonstrated strong fault separation when paired with transient or wavelet features (Parikh et al., 2010; Ray & Mishra, 2016). Deep architectures may exceed feature-based models when large waveform datasets are available, as shown by CNN and LSTM studies on distribution and transmission systems (Rai et al., 2021; Belagoune et al., 2021). However, end-to-end models normally demand

more data, computational capacity, and careful robustness testing. For a practical research project, RF or SVM can therefore serve as transparent baselines before CNN/LSTM models are introduced.

A deployable experiment should repeat the analysis at multiple noise levels and on unseen fault resistances, inception angles, and network topologies. It should also separate binary detection from multiclass classification: the detection stage must minimize missed faults and false trips, whereas the classifier may tolerate a slightly longer inference window. The results should finally be verified in a detailed power-system simulator or hardware-in-the-loop platform. This staged validation prevents optimistic performance caused by overly similar training and test simulations.

For protection engineering, an error analysis should accompany the aggregate scores. False classification among fault families may be recoverable if the binary detector has already issued a secure trip, whereas a false normal decision during a true fault is much more serious. Conversely, a normal operating transient classified as a fault can cause an unnecessary outage. Threshold selection should therefore be based on asymmetric costs, not only on maximum accuracy. Calibration curves or class probabilities can also be used to define a low-confidence region in which the intelligent classifier defers to conventional relay logic. Such hybrid decision making is particularly appropriate during early deployment because it retains established protection principles while allowing the ML model to contribute additional discrimination.

Conclusion and Discussion

This paper presents a step-by-step methodology for applying machine learning to fault detection and classification in electrical power networks. The framework begins with representative fault and normal cases, continues through signal preprocessing and physically grounded feature extraction, and compares SVM, RF, and MLP classifiers using a leakage-free train/test protocol. A small synthetic benchmark was used to demonstrate the reporting process, where RF obtained the highest illustrative accuracy and macro F1-score. These values should be interpreted as a proof of methodological execution, not as a claim of field performance. The literature up to 2021 shows a clear transition from ANN and SVM models using engineered transient features toward CNN and LSTM models that learn from raw or sequential measurements. Early SVM and ANN research established the feasibility of data-driven protection (Veluchamy et al., 2010; Yadav & Dash, 2014), while later

reviews clarified the importance of feature extraction and coordinated detection-classification-location design (Chen et al., 2016). Deep-learning studies then demonstrated the potential of temporal and spatial representation learning in increasingly complex networks (Fan et al., 2019; Fahim et al., 2020; Rai et al., 2021; Belagoune et al., 2021; Rafique et al., 2021). The broad review by Vaish et al. (2021) further supports the need for structured ML workflows and robust evaluation. For future work, the proposed benchmark should be replaced with a detailed IEEE test network or utility dataset. Fault cases should include high fault resistance, renewable-generation variability, CT/CVT nonidealities, topology changes, load switching, power swings, and communication noise. Cross-system validation and hardware-in-the-loop testing are particularly important because protection decisions are safety-critical and time constrained. Under these conditions, the preferred model will be the one that balances sensitivity, selectivity, speed, robustness, interpretability, and computational cost rather than the one with the highest nominal accuracy. From an implementation perspective, the intelligent classifier should be positioned as one layer in a coordinated protection architecture rather than as an isolated replacement for established relays. The data-acquisition stage must provide deterministic sampling and time alignment, the inference engine must meet a documented worst-case latency, and a confidence or validity check should reject inputs outside the training domain. Model explanations can be supported through feature importance for RF, sensitivity analysis for SVM, or post-hoc attribution for neural networks. These diagnostics are valuable during commissioning because engineers can verify whether the model is responding to physically sensible quantities such as phase-current increase, voltage depression, and sequence imbalance instead of to spurious correlations. Operational maintenance is equally important. A deployed model should be version controlled together with its training dataset, feature definitions, thresholds, and validation report. Periodic performance audits can identify distribution shift caused by new generation, network reinforcement, sensor replacement, or seasonal loading. Retraining should be performed offline and the updated model should pass the same unseen-scenario and hardware-in-the-loop tests before release. This governance approach preserves reproducibility and reduces the risk that an automatically updated model changes protection behavior without engineering review. In this way, machine learning becomes a controlled enhancement to

power-system protection rather than an unverified black-box decision mechanism.

References

Belagoune, S., Bali, N., Bakdi, A., Baadji, B., & Atif, K. (2021). Deep learning through LSTM classification and regression for transmission line fault detection, diagnosis and location in large-scale multi-machine power systems. *Measurement*, 177, 109330. <https://doi.org/10.1016/j.measurement.2021.109330>

Chen, K., Huang, C., & He, J. (2016). Fault detection, classification and location for transmission lines and distribution systems: A review on the methods. *High Voltage*, 1(1), 25-33. <https://doi.org/10.1049/hve.2016.0005>

Fahim, S. R., Sarker, Y., Sarker, S. K., Sheikh, M. R. I., & Das, S. K. (2020). Self attention convolutional neural network with time series imaging-based feature extraction for transmission line fault detection and classification. *Electric Power Systems Research*, 187, 106437. <https://doi.org/10.1016/j.epsr.2020.106437>

Fan, R., Yin, T., Huang, R., Lian, J., & Wang, S. (2019). Transmission line fault location using deep learning techniques. In 2019 North American Power Symposium (NAPS). IEEE. <https://doi.org/10.1109/NAPS46351.2019.9000224>

Koley, E., Verma, K., & Ghosh, S. (2015). An improved fault detection classification and location scheme based on wavelet transform and artificial neural network for six phase transmission line using single end data only. *SpringerPlus*, 4, 551. <https://doi.org/10.1186/s40064-015-1342-7>

Parikh, U. B., Das, B., & Maheshwari, R. (2010). Fault classification technique for series compensated transmission line using support vector machine. *International Journal of Electrical Power & Energy Systems*, 32(6), 629-636. <https://doi.org/10.1016/j.ijepes.2009.11.020>

Rafique, F., Fu, L., & Mai, R. (2021). End to end machine learning for fault detection and classification in power transmission lines. *Electric Power Systems Research*, 199, 107430. <https://doi.org/10.1016/j.epsr.2021.107430>

Rai, P., Londhe, N. D., & Raj, R. (2021). Fault classification in power system distribution network integrated with distributed generators

using CNN. *Electric Power Systems Research*, 192, 106914. <https://doi.org/10.1016/j.epsr.2020.106914>

Ray, P., & Mishra, D. P. (2016). Support vector machine-based fault classification and location of a long transmission line. *Engineering Science and Technology, an International Journal*, 19(3), 1368-1380. <https://doi.org/10.1016/j.jestch.2016.04.001>

Vaish, R., Tewari, S., Tripathi, S. M., & Dwivedi, U. D. (2021). Machine learning applications in power system fault diagnosis: Research advancements and perspectives. *Engineering Applications of Artificial Intelligence*, 106, 104504. <https://doi.org/10.1016/j.engappai.2021.104504>

Veluchamy, M., Marimuthu, N. S., & Baskar, S. (2010). Intelligent approaches using support vector machine and extreme learning machine for transmission line protection. *Neurocomputing*, 73(10-12), 2160-2167. <https://doi.org/10.1016/j.neucom.2010.02.001>

Yadav, A., & Dash, Y. (2014). An overview of transmission line protection by artificial neural network: Fault detection, fault classification, fault location, and fault direction discrimination. *Advances in Artificial Neural Systems*, 2014, 230382. <https://doi.org/10.1155/2014/230382>