

Intelligent Artificial Neural Networks for Low-Latency Fault Detection and Precise Localization in Electrical Transmission Lines: A Critical Review

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Abstract - Fast transmission-line protection requires fault detection, type classification, faulty-line identification, and distance estimation to be completed within a defensible end-to-end time budget. This review critically synthesizes 45 studies published mainly during 2021–2026 and organizes them by signal representation, learning architecture, diagnostic output, validation maturity, and deployment readiness. Classical artificial neural networks, neuro-fuzzy systems, extreme learning machines, and ensemble trees remain competitive when measurement boundaries are stable and engineered features are physically meaningful. Convolutional, recurrent, temporal-convolution, attention, transformer, graph, transfer-learning, and physics-informed models improve representation learning, multi-task integration, or cross-domain adaptability. Nevertheless, simulated accuracies above 99% frequently overstate field readiness. A Conformer model achieved 100% simulation validation but 88.88% accuracy on 108 historical utility events, while a sequence-model study reported real-data accuracies ranging from 62.05% to 100%, depending on architecture. Stronger localization evidence was obtained from PMU and OPAL-RT testing, where an attention-BiLSTM framework reported a mean absolute error of 0.0228 km and an R^2 of 0.9894. The review shows that the principal gap is not another isolated high-accuracy classifier, but a compact, uncertainty-aware, physics-consistent, topology-adaptive framework validated with event-wise data separation, unseen utility events, high-resistance faults, measurement errors, communication impairment, and complete acquisition-to-trip timing. A deployment-oriented research agenda is proposed for trustworthy intelligent protection.

Key Words: artificial neural network; transmission-line protection; fault detection; fault classification; fault location; low latency; PMU; transformer; physics-informed learning; domain shift.

1. INTRODUCTION

Electrical transmission lines are geographically extensive assets exposed to lightning, insulation failure, vegetation contact, conductor clashing, equipment malfunction, and operating-point changes. An ANN-based framework has demonstrated the feasibility of integrating low-latency fault detection and location from three-phase measurements [1]. Topology-dependent ensemble learning has further shown that inverter-based generation status must be recognized before selecting a protection model [2]. A hybrid PCA, Fourier, and Hilbert-transform architecture has linked detection, diagnosis, breaker operation, and recovery timing within a single analytical chain [3]. Neural-network comparisons for post-fault localization also show that architecture selection and measurement placement can be as important as depth alone [4]. Recent studies increasingly combine several protection outputs. ANN and 1D-CNN models on an IEEE 6-bus system achieved high faulty-line, fault-type, and location performance within a coordinated design [5]. A 400 kV study extended this direction

by treating classification and distance estimation as distinct but connected tasks [6]. Attention-guided multi-task learning reduces duplicated feature extraction by sharing representations across detection, classification, and localization [7]. Physics-informed neural networks add Kirchhoff-based constraints to discourage physically inconsistent decisions when training data are sparse or noisy [8].

However, practical evidence remains uneven. An ANN location method evaluated with series-compensated field records provides stronger external validity than simulation-only studies [9]. A Conformer trained on simulation reached 100% validation accuracy but fell to 88.88% on 108 historical events, directly exposing simulation-to-field domain shift [10]. A 1D-CNN study using real, synthetic, and public datasets likewise demonstrates the need for cross-dataset testing [11]. Inverter-connected-line studies further show that fault-current signatures depend on converter controls, penetration level, class imbalance, and topology [12]. Therefore, the present review evaluates not only headline accuracy but also measurement origin, event separation, localization error, end-to-end latency, uncertainty, and hardware or field validation. The paper makes three contributions. First, it provides a concise thematic synthesis of 45 studies rather than a paper-by-paper catalogue. Second, it compares classical ANN and feature-engineered methods with CNN, LSTM, TCN, transformer, GNN, transfer-learning, federated, explainable, and physics-informed approaches. Third, it derives a technically bounded research gap for a protection-grade framework that jointly optimizes detection confidence, fault class, line identity, distance, inference time, and safe fallback behavior under unseen operating conditions.

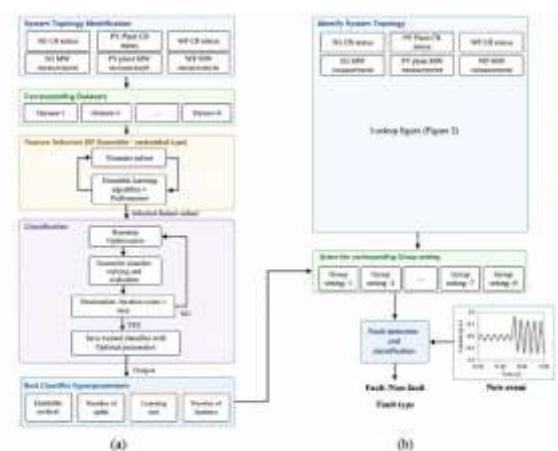


Figure 1. Adaptive offline-online transmission-line fault-detection workflow

Figure 1 separates offline topology-specific feature selection and classifier optimization from online topology recognition and model selection. This distinction is important for renewable-rich systems because a single static classifier may experience changing fault-current distributions as synchronous

generation, photovoltaic plants, and wind farms enter or leave service. The workflow also reveals that reported inference time is only one component of operational latency: topology identification, lookup, feature calculation, and group-setting selection precede the final fault decision. A stronger future architecture should preserve this adaptation while reducing the maintenance burden associated with multiple separately trained classifiers.

2. REVIEW DESIGN AND CONCEPTUAL BACKGROUND

2.1 Evidence Scope and Appraisal

The review retained the 30 screened open-access records supplied with the project and added 15 complementary peer-reviewed studies to strengthen evidence on field oscillography, real-time simulation, low-latency computation, explain ability, and physics-informed learning. Multiple-classifier systems have been used to improve robustness under noisy and imbalanced data [13]. Bayesian optimization combined with LSTM and attention has been applied to tune sequential fault classifiers [14]. An RF-LSTM-KNN ensemble reported 99.96% multi-label accuracy, illustrating the continuing strength of heterogeneous models [15]. Relay-assisted LSTM prediction has also been investigated for faults occurring at multiple points on a line [16]. Broader optimized ML pipelines have reported sub-cycle detection and low distance errors, but their multi-stage structure can increase tuning and maintenance complexity [17]. Topology-aware GNN methods are emerging for inspection and spatial fault reasoning [18]. UAV-oriented CNN systems address visible component defects rather than instantaneous electrical protection [19]. Edge/cloud grid analytics combine spatial and temporal learning while explicitly reporting response time [20]. These complementary domains were included to identify transferable concepts, but electrical waveform protection remained the primary evidence base. Each paper was appraised using six criteria: data origin, measurement representation, protection task, train/test separation, quantitative metric, and deployment evidence. Simulation-only random splits were assigned lower evidential weight than topology-wise testing, independent datasets, historical events, field oscillography, or hardware-in-the-loop validation. Classification accuracy was not treated as interchangeable with localization MAE, line-identification F1 score, or total protection latency. This prevents misleading comparisons between binary detectors, multi-class classifiers, and continuous distance repressors.

2.2 Fault-Diagnosis Chain and Performance Measures

A complete intelligent protection chain contains acquisition, synchronization, windowing, preprocessing, inference, communication, and trip logic. Consequently, total decision time should be reported as $T_{total} = T_{acq} + T_{sync} + T_{window} + T_{pre} + T_{inf} + T_{comm} + T_{logic}$. Many papers report only T_{inf} , even though window accumulation and signal transformation can dominate the budget. Classification should be evaluated using class-wise precision, recall, F1 score, confusion matrices, and calibration. Localization should report MAE or RMSE in kilometers and percentage line-length error, preferably across resistance, inception angle, topology, source impedance, loading, synchronization error, and noise.

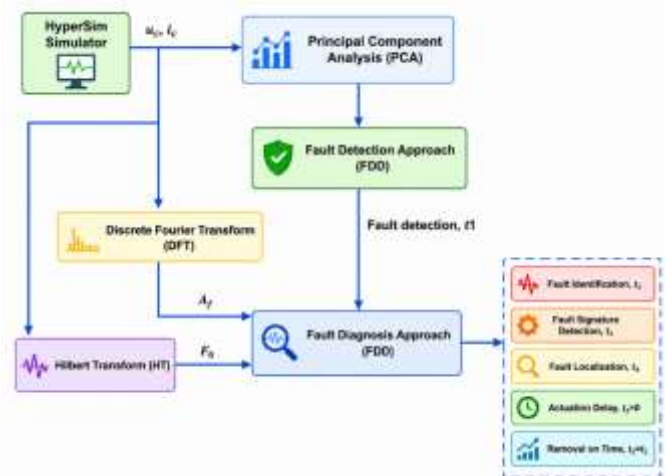


Figure 2. High-level hybrid fault detection and diagnosis architecture

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The architecture in Figure 2 illustrates why fault protection is better treated as a coordinated diagnostic process than as an isolated classifier. PCA identifies departures from the healthy voltage subspace, while Fourier- and Hilbert-domain features support fault diagnosis and timing estimates. The output includes detection time, fault identification, circuit-breaker opening and closing, recovery, actuation delay, and reconnection time. Its principal advantage is functional completeness; its limitation is the accumulated computational and calibration burden of several transforms and decision stages. ANN frameworks can learn some of these mappings directly, but should preserve the architecture's explicit timing and event-state outputs.

3. THEMATIC LITERATURE REVIEW

3.1 Transfer, Wavelet, and Compact Learning Approaches

Transfer learning has been proposed to reuse a pertained LeNet-5 model across lines with different lengths and impedances, addressing limited labels in newly monitored corridors [21]. Image processing of relay R-X trajectories followed by ANN regression offers an alternative representation for location estimation [22]. Scaled continuous-wavelet scalograms combined with pertained CNNs reported 100% classification from one-end measurements, indicating that transient time frequency structure can be highly discriminative [23]. Attention temporal-convolution networks preserve local and global structure while avoiding recurrent inference [24]. Cat Boost trained on 93,340 simulated records achieved 99.54% accuracy with 0.46% error, demonstrating that compact boosted trees remain competitive with deeper architectures [25]. Recent taxonomies organize fault analysis by detection, classification, and localization tasks and emphasize the heterogeneity of inputs and validation protocols [26]. A broader survey of ML-based transmission protection similarly identifies data quality, generalization, and practical integration as persistent challenges [27]. These reviews support a central methodological conclusion: architectural novelty is meaningful only when comparisons use event-independent splits, identical fault taxonomies, and common latency and location-error definitions.

3.2 Deep Spatial, Temporal, and Hybrid Models

Visual edge deployment has motivated a Leaner YOLOv7-Tiny model with a 20% reduction in model size [28]. Federated insulator diagnosis keeps images local while exchanging model parameters, thereby addressing cross-utility privacy [29]. Few-shot meta-attention and feature reconstruction target rare transmission-line defects with limited labels [30]. In the electrical-signal domain, a deep intelligent approach based on learned representations improved fault detection and classification under noisy and small-sample conditions [31]. A comprehensive diagnosis study using 24,000 RTDS faults and 46 real utility faults achieved near-perfect phase and electrical-nature recognition, but only about 80% root-cause accuracy, showing that causal diagnosis is harder than fault-type classification [32].

Extreme learning machines reported detection accuracies of 99.53% and 99.60% and classification accuracies of 99.18% and 99.09% on two simulated line models [33]. A comparative deep-learning study reported 42.98% for a baseline ANN, 99.98% for LSTM, and 99.99% for LSTM with window regression [34]. ANFIS outperformed BPNN, self-organizing maps, and a DWT-ANFIS hybrid in an IEEE 9-bus comparison, although field latency was not demonstrated [35]. These results indicate that temporal memory and fuzzy rule structures can be valuable, but unusually large performance gaps should be audited for equal preprocessing, class balance, parameter count, and split strategy.

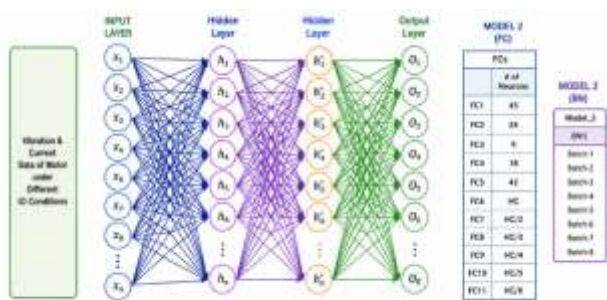


Figure 3. ANN architecture for fault type, distance band, and faulty-line identification [5].

Figure 3 maps voltage and current features to fault type, distance band, and faulty-line outputs. Its modularity simplifies task-specific training, but independent models can duplicate computation and produce inconsistent decisions, such as estimating distance on the wrong line. A stronger multi-task design would share the encoder, condition distance regression on line identity and detection confidence, and replace coarse 10% bands with calibrated continuous estimates and uncertainty intervals.

3.3 Transformer, Multi-Terminal, and Deployment-Oriented Evidence

A hierarchical transformer architecture performs detection, classification, and location directly from synchronized raw three-phase samples, reducing manual feature engineering [36]. PMU-based bidirectional gradient-boost random forest localization has achieved up to 97% accuracy on multi-terminal lines under different tapping configurations [37]. A DNN trained on a four-bus system reached 98.775% overall classification accuracy and localized more than 80% of cases within 2% of line length [38]. Direct comparisons between a ten-layer DNN and SVM-PCA found that the simpler SVM

offered an advantageous accuracy-computation balance [39]. The strongest deployment evidence in the reviewed set comes from an FDIL framework using optimally placed PMUs and OPAL-RT validation; its attention-BiLSTM locator reported MAE = 0.0228 km, MSE = 0.001, $R^2 = 0.9894$, and an 89.2% MAE reduction relative to CNN-LSTM [40]. A common 10 ms evaluation window produced $F1 = 0.991 \pm 0.018$ and processing time of 0.342 ± 0.509 ms for the best model, offering a more protection-relevant benchmark than accuracy alone [41]. A CNN framework reported 98% classification accuracy, 0.05 s detection latency, and localization $R > 0.997$, but 50 ms remains above a single 50 or 60 Hz cycle and was simulation-based [42].

A 500 kV comparison of BiLSTM, GRU, and TCN is especially informative because it reports both simulated and real-time sequential data: simulation accuracies were 98.31%, 94.27%, and 99.8%, while real-data accuracies were 62.05%, 96.43%, and 100%, respectively [43]. An explainable CNN-transformer achieved 97% accuracy and outperformed XGBoost, LSTM-GRU, LSTM, ViT, and ELM while using SHAP for interpretation [44]. A high-voltage study comparing atom-search optimization with cubic-spline ML suggests that hybrid optimization can improve localization accuracy while lowering the computational burden of pure met heuristics [45]. Together, these studies shift the research target from simulation accuracy toward domain transfer, calibrated uncertainty, physical plausibility, and measured end-to-end latency.

4. COMPARATIVE ANALYSIS OF REPRESENTATIVE ELECTRICAL-SIGNAL STUDIES

This section compares representative electrical-signal studies developed for rapid fault detection, classification, and precise localization in transmission networks. The reviewed methods include artificial neural networks, ensemble learning, convolutional and recurrent architectures, transformers, physics-informed models, ANFIS, Cat Boost, and PMU-based frameworks. Their performance is evaluated using classification accuracy, localization error, detection time, robustness, and validation maturity. Particular attention is given to differences between simulation-only testing, historical utility events, field disturbance records, and real-time hardware platforms. The comparison highlights that high numerical accuracy alone is insufficient unless supported by practical latency measurements, topology adaptability, noise tolerance, and physically interpretable localization performance under uncertainty.

The table 1. Shows that numerical superiority depends strongly on validation maturity. Simulation-only ANN, boosted-tree, and deep sequence models frequently report 99–100% classification, but the historical-event Conformer result [10] and the simulated-versus-real sequence comparison [43] reveal substantial domain shift. The most decision-useful localization result is the 0.0228 km MAE obtained with PMU and OPAL-RT evidence [40], because the metric is physically interpretable and the platform approximates real-time operation. Latency evidence is less mature: the 0.342 ms processing result [41] is promising, whereas the 50 ms CNN value [42] illustrates why window and preprocessing time must be reported separately. Across the matrix, no single study simultaneously covers field events, topology transfer, high-resistance faults, uncertainty calibration, cyber/communication impairment, and a complete trip-time budget.

Table 1. Compact comparative matrix of representative fault-detection and localization studies.

Ref.	Research objective	System / dataset	Methodology	Key quantitative outcome
[1]	Low-latency ANN detection and localization on a 330 kV, 500 km line	MATLAB/Simulink three-phase voltage and current; 330 kV, 500 km	Feed-forward ANN for detection and distance estimation	Reported 100% detection, about 99.5% localization, 0–0.5% average distance error and 0.0017 μ s detection time
[2]	Adaptive fault detection/classification with inverter-based generation	39-bus New England system; synchronous, PV and type-3 wind scenarios	Topology-dependent optimized ensemble-tree setting groups	Average accuracy 99.4%, precision 99.5%, specificity 99.9%, sensitivity 99.4%
[3]	Hybrid short-circuit detection and diagnosis	HyperSim/Portuguese transmission-line signals; noisy current and voltage	PCA detection plus sliding-window DFT/DHT and probabilistic rules	Robust detection across signal-to-noise cases; 50 μ s simulation step and two-cycle analysis window reported
[5]	ANN and 1D-CNN unified smart-grid diagnosis	IEEE 6-bus; raw three-phase voltage/current	ANN and one-dimensional CNN for faulty-line identification, class and location	ANN/1D-CNN: faulty line 99.99/99.98%; class 99.75/99.99%; location 98.25/96.85%
[6]	Fault class and location on a mixed-conductor 400 kV line	400 kV high-voltage line parameters and simulated fault scenarios	Multiple machine-learning classifiers and regression models	Reports high classification and precise distance prediction across fault cases
[7]	Attention-guided multi-task diagnosis	IEEE 39-bus; varied loads, fault types, resistances and locations	Shared representation with attention and task-specific heads; Optuna tuning	Unified detection, classification and localization outperformed separate SVM/MLP baselines
[8]	Physics-informed detection and classification on a 380 kV HVAC line	MATLAB/Simulink model of Marjan–Safaniyah 380 kV line	Deep learning constrained by Kirchhoff-current residuals	Lower false negatives and stronger physical consistency than unconstrained DL; exact headline metric not stated in abstract
[9]	ANN fault location for series-compensated lines with field data	Simulated cases plus substation disturbance records	ANN distance estimator tailored to series compensation	Low errors reported for simulation and field cases
[10]	Conformer transformer classification with historical utility events	Two-terminal simulation for training; 108 Taiwan power-system events for testing	Conformer convolution-augmented transformer on time-series samples	100% validation accuracy but 88.88% historical-event accuracy; four samples/cycle adequate
[11]	1D-CNN classification across real, synthetic and public data	Three datasets: real, generated and public transmission-line records	One-dimensional CNN	High accuracy across all three domains; complete per-dataset values must be read from the full article
[12]	ML protection for lines connected to inverter-based generators	PV and DFIG scenarios; time, frequency and time-frequency features	DT, SVM, k-NN and ensembles with SMOTE and Bayesian optimization	Bag ensemble with forward selection achieved 100% binary metrics; AdaBoost 99.4% class accuracy
[15]	Ensemble multi-label transmission-line diagnosis	Voltage/current patterns in binary and multi-label datasets	RF, KNN, LSTM and RF–LSTM tuned-KNN ensemble	99.96% multi-label accuracy; RF 97.50%, KNN 96.55%; binary KNN 99.85%
[17]	Optimized detection, class and location with fuzzy/ML/ANFIS	735 kV, 600 km simulated line; voltage and frequency features	Fuzzy threshold, WHO-optimized DT/RF and ANFIS localization	Detection under 1.2 cycles; DT 98.1%, RF 100%; location error <153.6 m
[23]	One-sided wavelet-scalogram fault classification	One-end voltage/current records under varied resistance, angle and location	Scaled CWT scalograms with pretrained CNNs	Reported 100% classification accuracy

Ref.	Research objective	System / dataset	Methodology	Key quantitative outcome
[25]	CatBoost multi-dataset classification	93,340 samples from a 330 kV, 500 km MATLAB/Simulink line	CatBoost compared with SVM, ANN and boosting alternatives	99.54% accuracy, 0.46% error; 58.5 s training; selected fault classes reached 100%
[32]	Comprehensive diagnosis from relay oscillography	24,000 RTDS faults and 46 real utility faults	Optimized engineered features and decision-tree classifiers	Near 100% phase/nature accuracy, 90% impedance class, 80% root cause
[34]	LSTM versus ANN for fault classification	Transmission-line simulations with five short-circuit categories	ANN, LSTM and LSTM with window regression	42.98% ANN, 99.98% LSTM and 99.99% LSTM-WR accuracy
[35]	ANFIS, neural and wavelet-hybrid comparison	IEEE 9-bus one-end three-phase V/I in MATLAB/Simulink	ANFIS versus BPNN, SOM and DWT–ANFIS	ANFIS gave the lowest reported percentage error across detection, class and location
[40]	PMU-based FDIL with attention BiLSTM	IEEE 9-bus and OPAL-RT testbed; optimally placed PMUs	Fault detection/isolation plus BiLSTM-attention localization	MAE 0.0228 km, MSE 0.001, R^2 0.9894; 89.2% MAE reduction over CNN-LSTM
[41]	Systematic real-time ML comparison for line identification	Grid measurements in a 10 ms operational window	Multiple ML classifiers evaluated under a common protocol	$F1 = 0.991 \pm 0.018$; processing 0.342 ± 0.509 ms
[42]	CNN low-latency detection, class and location	Three-bus MATLAB/Simulink R2024b dataset	CNN on spatial-temporal representations	98% class accuracy, 0.05 s latency and localization $R > 0.997$
[43]	Sequence-model comparison on 500 kV simulated and real data	500 kV Jamshoro–Karachi line; simulated and real-time sequential records	BiLSTM, GRU and TCN	Simulation: 98.31/94.27/99.8%; real: 62.05/96.43/100% for BiLSTM/GRU/TCN
[44]	Explainable CNN–transformer diagnosis	MATLAB/Simulink fault data across resistance values	CNN–transformer with SHAP; comparison to XGBoost, ELM, LSTM, LSTM-GRU and ViT	97% versus 93%, 87%, 88%, 92% and 93%, respectively
[45]	Metaheuristic and ML high-voltage location	High-voltage faults with varied type, resistance and distance	Atom-search optimization and cubic-spline ML hybrid	Hybrid reported improved real-time localization with lower computational burden than pure metaheuristic

Table 2. Method-family comparison for a protection-grade intelligent framework.

Method family	Representative refs.	Primary strength	Main weakness	Recommended role
ANN / MLP	[1], [5], [6], [38]	Simple nonlinear mapping; compact inference	Sensitive to scaling, topology, and data split	Baseline multi-output detector and regressor
ANFIS / ELM	[33], [35]	Fast learning or interpretable fuzzy rules	Rule growth or random-feature sensitivity	Compact edge model and interpretable benchmark
Tree ensembles / CatBoost	[2], [12], [13], [15], [25]	Strong tabular performance; limited preprocessing	Can memorize simulator-specific amplitudes	Fast detector, line selector, and fallback model
CNN / wavelet CNN	[23], [31], [42]	Automatic local transient-feature extraction	Window/scalogram cost and domain shift	Raw-waveform or time–frequency encoder

Method family	Representative refs.	Primary strength	Main weakness	Recommended role
LSTM / GRU / TCN	[14], [34], [43]	Temporal context and sequence discrimination	Model-dependent transfer; recurrent cost	Short-window temporal encoder; TCN preferred for parallelism
Transformer / attention MTL	[7], [10], [36], [44]	Shared multi-task features and long-range context	Data hungry; calibration and compression needed	Unified detector–classifier–locator with uncertainty
GNN / PMU topology models	[18], [20], [37], [40]	Uses grid connectivity and distributed measurements	Communication, synchronization, PMU placement	Wide-area line isolation and topology-conditioned location
Transfer / federated / PINN	[8], [21], [29]	Addresses label scarcity, privacy, and physical consistency	Training complexity and incomplete real-time evidence	Domain adaptation, continual learning, and physics regularization

The strongest design is likely hybrid rather than monolithic. Tree ensembles or compact ANN models are suitable for high-speed screening and fail-safe fallback, while TCN or transformer encoders can learn temporal representations for multi-task diagnosis. PMU/GNN layers add topology context where communication is dependable, and PINN regularization can reject physically inconsistent predictions. Transfer learning and federated training are needed to adapt across line corridors without centralizing proprietary event records. Architecture comparison should therefore use a common event-wise benchmark and report accuracy, calibration, MAE, memory, operations per inference, and complete end-to-end latency.

5. RESEARCH METHODOLOGIES, PARAMETERS, AND TECHNOLOGIES

Previous studies generate data using MATLAB/Simulink, PSCAD/EMTDC, DIgSILENT PowerFactory, HyperSim, standard IEEE bus systems, RTDS, OPAL-RT, relay oscillography, PMUs, and historical utility event records. Common inputs are instantaneous or RMS three-phase voltage and current, symmetrical components, frequency, impedance trajectories, swing-center voltage, and wavelet coefficients. Important test variables include fault type, distance, resistance, inception angle, line length, source impedance, loading, renewable penetration, topology, sampling rate, sensor location, noise, synchronization error, and class imbalance. The literature can be divided into feature-engineered ML, end-to-end representation learning, sequence learning, topology-aware models, and physics-constrained learning. SVM, decision trees, ensembles, Cat Boost, ELM, and ANFIS are computationally attractive but may depend on system-specific features. CNN and wavelet-CNN models learn local transients; LSTM, GRU, and TCN exploit time dependence; transformers capture long-range relations; GNNs model connectivity; transfer and federated learning address domain and data-sharing constraints; PINNs embed circuit laws; and XAI exposes feature influence. No architecture is universally superior because dataset design often dominates model capacity.

6. MAJOR FINDINGS AND DISCUSSION

The first major finding is that model accuracy has saturated on many synthetic benchmarks. ANN, CNN, LSTM, Cat Boost, and ensemble models can all exceed 99% when the simulator, topology, preprocessing, and random split are favorable. Such results demonstrate learnability but do not establish relay

dependability. The operationally important question is whether errors remain bounded for unseen events generated by a different topology, source impedance, instrument transformer, relay recorder, noise distribution, or utility practice. The second finding is that temporal and topology context matter, but their benefits are architecture dependent. LSTM and TCN models can exploit pre-fault and post-fault evolution, transformers can coordinate long-range samples and multiple tasks, and GNN/PMU methods can distinguish which line is faulty before distance estimation. Yet the real-data comparison in [43] shows that recurrent and convolutional sequence models do not transfer equally. This makes domain-wise validation more informative than small differences in random-split accuracy.

Third, localization requires a different evidence standard from classification. A percentage accuracy for distance bands can obscure kilometer-scale error, particularly on long EHV lines. Continuous MAE, RMSE, maximum error, percentile error, and calibrated intervals should be reported. The OPAL-RT PMU framework [40] provides a useful benchmark because 0.0228 km MAE is interpretable and linked to a real-time platform. Similar evidence is needed for single-ended, series-compensated, multi-terminal, and inverter-dominated lines. Fourth, low latency is frequently claimed but incompletely measured. A neural network can infer in microseconds while still requiring one or more cycles for windowing, synchronization, filtering, scalogram generation, or communication. Consequently, studies should publish acquisition rate, window duration, preprocessing time, inference time, hardware, communication assumptions, and decision-logic time. Protection should also include abstention or fallback to conventional relaying when confidence, data quality, or physical residuals exceed limits.

7. LIMITATIONS OF EXISTING STUDIES AND CRITICAL RESEARCH GAP

The reviewed literature is limited by simulator dependence, overlapping event windows across train and test sets, small or undisclosed field datasets, incomplete high-resistance and evolving-fault coverage, inconsistent definitions of localization accuracy, and limited hardware timing. Many studies optimize one model for one line and do not test topology changes, series compensation, renewable controls, CT/PT saturation, synchronization loss, missing phases, packet delay, adversarial

Inputs, or class-prior drift. Accuracy is commonly reported without calibration, uncertainty, false-trip cost, or comparison with a conventional protection baseline under the same conditions. The critical research gap is therefore a compact, unified ANN framework that performs four linked tasks—fault/no-fault detection, faulty-line identification, fault-type classification, and continuous distance localization—while satisfying protection-grade constraints. The framework should combine a short raw-waveform encoder, topology-aware context, multi-task heads, physics-residual regularization, uncertainty calibration, and a deterministic fallback path. It should be trained with event-wise and topology-wise separation and validated sequentially using simulation, cross-simulator transfer, RTDS/OPAL-RT, historical relay oscillography, and prospective utility events. The test matrix must include variable resistance, inception angle, loading, renewable penetration, line parameters, compensation, noise, CT/PT errors, PMU loss, communication delay, and cyber perturbations. Success should be defined jointly by sensitivity, security, class-wise F1, kilometer MAE, maximum error, calibration, memory, computation, and total acquisition-to-trip time.

8. FUTURE RESEARCH DIRECTIONS

Future work should establish open, event-separated benchmarks that combine synthetic waveforms with anonymized utility oscillography and record complete metadata. Self-supervised pertaining can exploit abundant unlabeled waveform streams, while transfer and federated learning can adapt models across utilities without exchanging raw records. Physics-informed losses should include sequence-network constraints and line-parameter uncertainty rather than only static residuals. Multi-task models should condition location on line identity and expose confidence intervals. Continual-learning mechanisms must detect distribution drift without catastrophic forgetting, and explain ability should be evaluated for relay engineering usefulness rather than visual appeal alone. Finally, deployment studies should implement quantized models on relay-class CPUs, FPGAs, or edge accelerators and measure worst-case—not average—latency, memory, energy, communication failure, and safe fallback operation.

9. CONCLUSION

Artificial intelligence has substantially improved the ability to detect, classify, and locate transmission-line faults from voltage, current, PMU, relay, and inspection data. The literature demonstrates that classical ANN, ANFIS, ELM, boosted trees, CNN, LSTM, TCN, transformer, GNN, transfer-learning, federated, explainable, and physics-informed approaches each address different parts of the problem. Reported simulation accuracy is often excellent, but field and hardware evidence shows that domain shift, topology, data quality, and complete latency remain decisive. The most credible future contribution is not a marginally higher random-split score. It is a unified, calibrated, physically constrained, topology-adaptive, low-computation framework validated on unseen events and measured from acquisition to trip decision. Such a framework can convert promising data-driven diagnosis into dependable protection support while retaining deterministic fallback and operator trust.

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