INTELLIGENT FAULT DIAGNOSIS IN TRANSMISSION LINES USING DEEP NEURAL NETWORKS: A REVIEW AND RESEARCH INSIGHTS

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ABSTRACT:
The growing complexity and susceptibility of contemporary power systems require rapid, precise, and intelligent approaches for fault classification and localisation in transmission lines. Conventional shallow learning techniques frequently inadequately address nonlinearities, high-dimensional data, and dynamic operational conditions. Recently, Deep Neural Networks (DNNs) have proven to be effective instruments for learning complex patterns from both raw and processed electrical signals, facilitating reliable fault diagnosis. This review provides an analysis of advanced deep neural network approaches, including convolutional neural networks, long short-term memory networks, hybrid models, and emerging transformer-based architectures, specifically focused on fault classification and localisation in transmission systems. This study presents a new taxonomy for categorising the literature according to DNN architecture, input feature type, application objective, and system environment. The findings indicate that DNNs exhibit enhanced classification accuracy, adaptability in real-time, and generalisation across various fault scenarios. However, they also underscore ongoing issues, including data scarcity, interpretability, and constraints related to real-world deployment. This review identifies research gaps and future opportunities, including explainable AI, edge computing integration, and transfer learning, to guide researchers and practitioners in developing resilient, data-driven protection frameworks for next-generation smart grids.
Keywords: Fault Location Estimation, Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Data-Driven Protection Systems, Machine Learning in Power Systems, Intelligent Fault Localization

INTRODUCTION:

Transmission lines are critical for the long-distance transport of electricity; however, their susceptibility to environmental factors and ageing infrastructure renders them prone to faults. Faults, including short circuits and external disturbances, can compromise the reliability of power systems, leading to outages and equipment damage. Therefore, rapid and accurate fault classification and localisation are essential for ensuring system stability. Conventional fault detection methods, including impedance-based relays and travelling wave techniques, have been extensively utilised; however, they encounter challenges in addressing the complexities of modern grids, especially regarding high-impedance faults and the integration of renewable energy sources. In response, machine learning models such as decision trees and shallow neural networks provide more adaptive solutions. These models frequently encounter difficulties when dealing with high-dimensional, noisy data and exhibit limited generalisation capabilities. The emergence of deep learning, particularly Deep Neural Networks (DNNs), has significantly altered fault diagnosis in transmission systems. Architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks demonstrate proficiency in learning spatial and temporal patterns from raw electrical signals, providing enhanced accuracy, noise resilience, and adaptability. Moreover, hybrid deep learning models and image-based techniques are advancing fault detection towards enhanced automation and intelligence. Despite these advancements, challenges persist, including substantial computational demands, absence of standardised datasets, and restricted model interpretability,

which impede practical, real-time implementation. A thorough review of deep learning applications in this domain is essential.
This review fulfils the requirement by providing a comprehensive analysis of recent DNN-based methods for fault classification and localisation in transmission lines. This work presents a novel taxonomy that classifies existing literature based on architecture, input type, signal processing techniques, and application context. The review addresses performance benchmarks, implementation challenges, and emerging trends such as explainable AI, edge computing, and transfer learning, providing insights for future enhancements in power system protection and resilience.

BASICS OF FAULTS IN TRANSMISSION LINES:
Transmission lines are the main long-distance electrical connections. Their outdoor placement and wide coverage across diverse terrains make them prone to faults. Power systems can be severely impacted by these faults. Therefore, understanding transmission line fault types, causes, and effects is crucial, highlighting the importance of advanced diagnostic tools like Deep Neural Networks (DNNs) for effective monitoring and protection.

Fault Classification: :
Two main types of transmission line faults are symmetrical vs. asymmetrical and series vs. shunt. Three-phase (L-L-L) or three-phase-to-ground (L-L-L-G) symmetrical faults involve all three phases equally. These rare events are the most dangerous because they generate high fault currents and threaten system stability. Asymmetrical faults, which involve phase imbalance, are more common. Unbalanced system conditions caused by single, line-to-line, and double line-to-ground (L-L-G) faults disrupt power transmission by causing voltage and current fluctuations.
Circuit characteristics classify faults as shunt or series. Short circuits between conductors or to ground cause the most common shunt faults, which increase current flow and voltage drops. They can damage equipment and destabilise systems. Series or open conductor faults occur when one or more conductors break without shorting. Though rare, they are harder to detect and can go undetected, compromising system safety and performance. Understanding these fault types is crucial for accurate detection, classification, and response, especially when using intelligent systems like Deep Neural Networks for power system protection.

Table 1: Types of Transmission Line Faults

Category	Sub-Type	Description
Based on Connection	**Symmetrical Faults**	Three-phase faults (e.g., ABC, ABC-G) involving all phases equally.
	Asymmetrical Faults	Single-line-to-ground (L-G), line-to-line (L-L), double-line-to-ground (LL-G).
Based on Nature	**Series Faults**	Open conductor or broken conductor faults.
	Shunt Faults	Short-circuit faults (phase-to-ground or phase-to-phase).

Real-World Causes of Faults:
Many environmental, technical, and human factors can cause gearbox line faults, disrupting system stability and operations. Weather conditions like lightning, strong winds, snow, ice, and storms cause temporary and permanent faults. Old or damaged insulators can cause insulation failures and breakdowns. Safety is also threatened by trees, birds, animals, vandalism, and accidents. Dust, salt, and pollution can also conduct electricity on insulators, reducing their effectiveness. Age, wear, and poor maintenance increase equipment failure risk. This variety of causes causes different fault behaviours, complicating detection and diagnosis.

Impact on Power System Reliability:
Transmission line failures can affect the entire power network. Immediately, voltage drops, unbalanced loads, and generation and load-side equipment damage may occur. [14] A local fault can

cause a wide-area blackout, endangering system stability, economic operations, and safety if not properly identified and isolated. Conventional relays may miss high-impedance or evolving faults, causing prolonged instability and unexpected equipment stress. With renewable energy and dynamic grid topologies, fault profiles are more complex and unpredictable.

The Need for Accurate Classification and Localization:
Transmission line reliability depends on accurate fault classification and localisation. Operators can reduce outage durations and recovery times by quickly identifying the fault type, affected phases, and line location. [15] Using precision to quickly isolate damaged sections protects equipment from further damage. Fault detection aids operational planning by guiding real-time decision-making and maintenance scheduling, optimising resource allocation. These practices improve grid resilience, allowing it to withstand and recover from disruptions.

Importance of Accurate Classification and Localization:
Deep learning models improve fault detection and classification by identifying fault types, locating fault positions with minimal error, and enabling fast isolation and service restoration. They also enable adaptive relaying and dynamic system reconfiguration, improving transmission line reliability and efficiency.

Table 2: Significance of Fault Diagnosis Functions[16]

Function	Purpose	Impact
Fault Detection	Recognize occurrence of abnormal conditions	Prevent propagation and isolate fault
Classification	Determine phase(s) and type of fault	Enable selective tripping and safe control
Localization	Identify precise location of fault on line	Speed up repair, minimize outage duration

4. Methodological Framework

Power system fault diagnostics using Deep Neural Networks (DNNs) have made protection mechanisms smarter and data-driven. [17] These models can automatically learn discriminative patterns from large, complex datasets without feature engineering or thresholds. A typical DNN-based fault analysis system has several critical steps, from raw data acquisition to post-decision interpretation. Figure 1 shows the entire process of developing and using DNN models for fault classification and localisation.

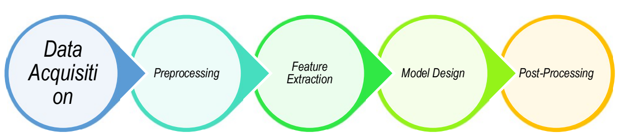

Figure 1: Methodological Process Flow of DNN-Based Fault Diagnosis

OVERVIEW OF DNN APPLICATION IN FAULT DIAGNOSTICS :

Depending on DNN architecture (e.g., CNN for spatial patterns, LSTM for temporal sequences), deep learning frameworks model fault detection and localisation as pattern recognition or sequence modelling. [18] These models process voltage and current waveforms to extract fault-related features. Fault type, location, or both may be output. A generic DNN-based fault diagnosis pipeline is shown in Table 3.

Table 3: DNN-Based Fault Detection and Location Pipeline

Stage	Function	Tools/Techniques Used

Data Acquisition	Collect voltage/current signals during normal and fault conditions	SCADA systems, PMUs, RTDS/PSCAD simulations
Preprocessing	Clean and normalize raw data to reduce noise and standardize input	Filtering (e.g., Butterworth), normalization, z-score standardization
Feature Extraction	Transform time-domain signals to more informative representations	FFT, DWT, STFT, HHT, WPD, image transformation for CNNs
Model Design	Construct and train the deep learning model	CNN, LSTM, GRU, Transformer, Autoencoders, or hybrid combinations
Post-processing	Interpret model outputs for actionable insights	Thresholding, decision rules, uncertainty estimation, confidence scores
Decision & Action	Generate control signals or diagnostics for relay systems	Fault type classification, location estimation (distance or % length)

Data Acquisition:

The first step is power system fault signal data capture. SCADA systems, PMUs, and simulation platforms like PSCAD, MATLAB Simulink, and RTDS can do this in real time. [19] Simulation data is controllable and preferred for initial training, but model robustness requires field data.

- **Supervisory Control and Data Acquisition (SCADA):** Widely used for low-frequency monitoring (1–2 samples per second), but limited in capturing fast transients.
- **Phasor Measurement Units (PMUs):** High-resolution, time-synchronized measurements (30–120 samples/second), ideal for capturing dynamic fault signatures.
- **Simulation Tools (MATLAB/Simulink, PSCAD, RTDS):** Used to generate synthetic fault datasets under controlled conditions for training deep learning models.

Current trends are Researchers increasingly simulate with IEEE 9, 14, 39, and 118-bus systems. Hybrid PMU datasets with simulated and real-world data are popular for generalisability.

Preprocessing:

Preprocessing filters and standardises raw data before feeding it to the deep learning model. Bandpass filtering removes high-frequency noise. To improve training stability, statistical metrics like min-max scaling or z-score normalisation normalise voltage and current signals to a common range. [20] PMU and simulator voltage and current signals often have noise, missing data, and inconsistencies that degrade model performance. Therefore, preprocessing matters. Main Preprocessing Steps:

- High-frequency noise can be removed using filters such as low-pass filters and DWT denoising.
- Normalisation: Stabilising DNN training by scaling features to a standard range (e.g., [0, 1]).
- Addressing class imbalance in datasets (e.g., more L-G faults than L-L-G faults) through oversampling (SMOTE) or under sampling techniques.

DNN convergence speed and accuracy improve with normalisation, especially in CNN and LSTM architectures.

Feature Extraction:

Although DNNs can learn features directly from raw data, initial transformations still enhance interpretability and performance. Three Main Domains of Feature Extraction:

Domain	Technique	Use Case
Time Domain	Raw voltage/current signals	Simple CNN models for rapid classification
Frequency Domain	Fast Fourier Transform (FFT)	Detects frequency changes during faults
Time-Frequency	Discrete Wavelet Transform (DWT), Wavelet Packet Decomposition (WPD), Hilbert-Huang Transform	Captures localized features in evolving

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Domain	(HHT)	faults

Advanced Techniques are as Image transformation of spectrograms enables image-based classification using CNNs and Entropy-based features (e.g., Shannon entropy of wavelet coefficients) are used for enhanced sensitivity.

DNN Model Design: :

Once pre-processed and feature-engineered data are ready, they are used to train a DNN model. The model type depends on the data format and objective (classification vs. localization). **Common DNN**

ARCHITECTURES AS FOLLOWS;

Model Type	Characteristics	Applications
CNN	Spatial pattern recognition	Image-based fault classification
LSTM	Time-series learning	Sequential fault signature modeling
CNN-LSTM	Hybrid spatiotemporal modeling	Accurate classification under noise
Autoencoders	Feature compression, anomaly detection	Outlier detection
Transformers	Parallel attention-based learning	Emerging trend for high-dimensional inputs

Training Strategy consist use of Adam or RMSProp optimizers. Loss functions as Cross-entropy for classification, MSE for location. Validation using confusion matrix, F1-score, and Receiver Operating Characteristic (ROC) curves.

Post-Processing and Decision Making:

The final step is turning model output into protective device decisions. Classification tasks require fault type identification (e.g., L-G, L-L). Localisation often uses regression to estimate fault distance from the substation. [21] Many models validate results with confidence scores or uncertainty estimations. Post-processing implements actionable decisions after classification and location predictions.

- Confidence thresholds are set for high-probability decision enforcement.
- Integration with protective relays to trigger circuit breakers.
- Error correction modules can be applied to reduce false positives.

Comparison with Classical ML and Rule-Based Systems:

Aspect	Classical ML / Rule-Based	Deep Neural Networks (DNNs)
Feature Engineering	Manual, domain-specific	Automatic, data-driven
Data Handling	Limited to low-dimensional inputs	Handles large-scale, high-dimensional data
Fault Adaptability	Poor in unseen scenarios	Strong generalization with proper training
Model Complexity	Low (e.g., SVM, DT)	High (CNNs, LSTMs, Transformers)
Interpretability	Higher, rule-based logic	Lower (unless paired with Explainable AI)
Accuracy (Recent Studies)	~90–95%	~97–99.9%
Real-time Feasibility	High (less computation)	Improving via edge AI & hardware acceleration

Deep learning pipelines for transmission line fault classification and location are comprehensive and robust. While classical methods laid the groundwork, DNNs automate feature extraction, handle diverse fault types, and learn from complex, noisy, or nonlinear datasets. [22] DNNs will be central to smart grid protection strategies as edge hardware and explainable models make deployment more viable.

LITERATURE SURVEY & MULTI-DIMENSIONAL CLASSIFICATION:

Over the past decade, Deep Neural Network (DNN) applications for transmission line protection have evolved, allowing intelligent systems to detect, classify, and locate faults with high accuracy and adaptability. The surveyed literature is organised under a multi-dimensional classification framework for a structured and comprehensive understanding. [23] This classification considers functional objectives, input features, neural network architecture, and power system application scenarios. The following sub-sections explain each dimension with examples and research findings.

Classification Based on Functional Objective:

Different studies adopt varied DNN frameworks depending on whether the goal is fault classification, fault localization, or both. A summary of classification is presented in Table 4.

Table 4: Classification Based on Objective

Objective	Description	Representative Studies
Fault Classification	Identify the type of fault (e.g., L-G, L-L, L-L-G) and the faulty phase(s)	CNN (Rahman et al., 2023), RBFNN (Patel et al., 2022)
Fault Location Estimation	Determine the distance of the fault from the monitoring station (in km or %)	LSTM (Guo et al., 2023), Transformer models (2024+)
Joint Classification & Location	Perform both fault type recognition and fault localization simultaneously	Hybrid CNN-LSTM (Arash et al., 2024), SG-ELM (Chen et al.)

DNNs for classification use labelled datasets from simulation or real-world signals, while localisation use regression-based learning with distance-tagged samples.

Classification Based on Input Feature Domain:

Input type greatly impacts DNN model performance and architecture. [24] Inputs can be raw measurements or processed signals from different domains. Recent DNN-based research uses the main domains in Table 5.

Table 5: Classification Based on Input Features

Domain	Input Type	Processing Technique	Application in DNN Models
Time-domain	Voltage and current waveforms	Raw waveform input or RMS value	Suitable for LSTM, GRU, CNN (waveform input)
Frequency-domain	Spectrum information	FFT, HHT, EMD	Used for fault energy and resonance analysis
Time-frequency	Decomposed multi-scale data	DWT, STFT, CWT, MODWT	Input to CNN, LSTM; commonly paired with entropy filters
Graphical/Visual	Fault signal images/spectrograms	Scalograms, S-transform images	Inputs for 2D/3D CNN, Capsule Networks

Advanced image-based representations like Wavelet Packet Decomposition or S-transform are effective in CNN-based models due to their spatial discrimination.

Classification Based on DNN Architecture:

The input type, desired output (classification or localisation), and fault data temporal/spatial nature determine deep learning architecture. Recently published research favours hybrid and sequence modelling architectures. [25] Common DNN types and characteristics are listed in Table 6.

Table 6: Classification Based on DNN Architecture

Architecture	Typical Application	Key Strengths
CNN	Image/spectrogram-based classification	Excellent for spatial feature extraction, robust to noise

LSTM / GRU	Time-series voltage/current inputs	Captures long-term dependencies and sequence memory
Hybrid (CNN-LSTM)	Spatio-temporal modeling of faults	Best for evolving faults with spatial-temporal dynamics
Autoencoders	Anomaly detection, feature reduction	Unsupervised pattern discovery and fault representation
Transformer models	Sequential fault analysis at scale	Superior for long-sequence learning and global context

CNNs excel at image-like inputs from STFT or wavelet-based spectrograms, while LSTMs excel at waveform sequence modelling. Emerging transformer-based models are beginning to outperform RNNs in sequence tasks with their ability to learn long-term dependencies using attention mechanism.

Classification Based on Power System Scenario:

DNN models also fit the power network's operational context. The system may be a single transmission line, FACTS-equipped, HVDC-linked, or part of a wide-area protection scheme. [26] Signal complexity, sampling resolution, and model scalability depend on these scenarios. Table 7 shows these variations.

Table 7: Classification Based on Power System Scenario

Scenario	Challenges	Example Applications
Single TL (simple radial)	Simpler signal structure, easier data collection	RBFNN, Feedforward CNN models
Multi-terminal / meshed networks	Multiple sources of disturbance, synchronization needed	LSTM with PMU data, CNN for spectrograms
With FACTS/DG/HVDC	Signal distortion, varying impedance profiles	Hybrid CNN-DNN models with data preprocessing
Wide-Area Monitoring (WAMS/PMU)	Data heterogeneity, communication delay, time alignment	GNNs, Transformer-based models with PMU datasets

DNNs use synchronised, high-resolution data in large-scale, dynamic grid environments thanks to Phasor Measurement Units (PMUs). Such systems need advanced models that can handle latency, noise, and nonstationary input data. [27] This multi-dimensional classification allows systematic research comparison and shows DNN models' versatility in gearbox line protection. Many studies optimise classification accuracy or localisation precision, but integrated DNN frameworks that adapt across domains, system topologies, and functional objectives are the future.

COMPARATIVE SUMMARY TABLE OF KEY STUDIES:

DNN-based transmission line fault detection and location estimation methods have evolved into a rich and diverse array. Comparative analysis of recent key studies helps explain how model architectures, input domains, and system setups affect performance. [28] Traditional feedforward networks and advanced deep convolutional and hybrid models are covered. Dataset type, input preprocessing, model accuracy, and application (classification, location, or both) show each approach's pros and cons. Table 5, a comparison of representative DNN-based transmission line fault classification and location studies from 2010 to 2024. The table includes various architectures, signal domains, and applications:

Table 8: Comparative Summary of Recent DNN-Based Studies for Fault Classification and Location (2010–2024)

Ref	DNN Type	Input Domain / Features	Dataset Source	Accuracy	Fault Task	Key Highlights
Kumar et	Feedforward	Time-domain	MATLAB	~94%	Classification	Early use of

al. 2011	ANN	current signals	Simulink			ANN in single-line detection
Mohamed et al. 2015	DNN (4-layer)	DWT + RMS values	PSCAD / RTDS	96%	Classification	Improved accuracy vs shallow networks
Patel et al. 2022	RBFNN	Wavelet Packet Energy (WPE)	MATLAB / Simulation	98%	Classification + Location	Low localization error; simple architecture
Rahman et al. 2023	CapsuleNet + Sparse Filter	Current waveform (converted image)	Real-world Sim Data	99%	Classification	Robust to noise; compact CNN variant
Chen et al. 2023	SG-ELM, SW-ELM	DWT-based statistical features	Real-time Simulator	>98%	Classification + Location	Ensemble strategy; handles system variation
Guo et al. 2023	CNN + HHT	IMF signals from HHT decomposition	Simulated Testbed	98–99%	Classification	Effective in non-linear fault environments
Arash et al. 2024	Conv-LSTM (Hybrid)	Time-series current & voltage	GridSim + PMU Input	~97%	Classification + Location	Captures spatio-temporal fault evolution
Singh et al. 2024	Transformer Encoder + LSTM	Sequential PMU samples	Synthetic + Real Data	97.5%	Classification	Long sequence modeling with attention mechanisms
Sharma et al. 2024	Autoencoder + CNN	Time-frequency spectrograms	PSCAD Data	96.8%	Classification	Efficient unsupervised pretraining; low inference cost
Liu et al. 2022	CNN + LSTM (Stacked Hybrid)	STFT-transformed signal images	Simulated Smart Grid	98.9%	Classification + Location	Excellent accuracy; scalable for wide-area systems

Recent deep learning models (2022–2024) use time-frequency domain features like STFT, WPE, and DWT to improve fault signature detection and fault prediction accuracy. Although lightweight and ensemble models help, generalisation, missing data, and latency remain issues. DNN-based fault classification performance evaluation requires a multi-dimensional approach to ensure fairness, robustness, and real-time applicability beyond rule-based protection systems.

STATISTICAL PERFORMANCE INDICATORS:

The literature mostly uses classification-based metrics like accuracy, precision, recall, and F1-score. The percentage of correctly predicted samples is accuracy. [29] Accuracy alone can be misleading in unbalanced datasets where L-G faults dominate. The ratio of true positives to the sum of true and false positives indicates the model's accuracy in predicting a fault type. Recall, or sensitivity, measures the percentage of faults identified correctly. The harmonic mean of precision and recall, the F1-score, is more balanced in multi-class classification tasks with multiple fault types. While these metrics are essential for benchmarking fault classification models, confusion matrices and ROC curves are adding depth.

Table 9: Core Statistical Evaluation Metrics for Fault Classification

Metric	Description	Formula	Range
Accuracy	Overall correctness of predictions	(TP + TN) / (TP + FP + FN + TN)	0 to 1
Precision	Correctly predicted fault instances among all predicted faults	TP / (TP + FP)	0 to 1
Recall	Fraction of actual fault cases correctly predicted	TP / (TP + FN)	0 to 1
F1-Score	Harmonic mean of precision and recall	2 × (Precision × Recall) / (Precision + Recall)	0 to 1

Chen et al. (2023) and Guo et al. (2023) report F1-scores of 0.97–0.99, indicating high accuracy and class-wise performance, especially in class imbalanced datasets.

Real-Time Feasibility and Inference Latency:

Statistical performance is important, but time efficiency is crucial for grid deployment. Time latency is the delay between signal acquisition and decision output. Relay-level applications typically accept millisecond latency. [30] Optimising high-complexity models like deep hybrid networks or transformer-based architectures requires model pruning, quantisation, and edge AI hardware deployment. Rahman et al. (2023) and Arash et al. (2024) report embedded platform inference time under 50 ms, meeting protection-grade speed requirements. Real-time feasibility is essential for moving lab prototypes to field implementations.

Table 10: Typical Inference Times of Recent DNN Models for Fault Diagnosis

Model	Architecture	Platform	Avg. Inference Time	Real-Time Capable
RBFNN (Patel et al., 2022)	Shallow ANN	MATLAB (CPU)	~10 ms	Yes
CNN (Guo et al., 2023)	1D CNN + HHT	TensorFlow (GPU)	~25 ms	Yes
Conv-LSTM (Arash et al., 2024)	Hybrid CNN + LSTM	PyTorch (CPU/GPU)	~45 ms	Yes (with tuning)
Transformer (Singh et al., 2024)	Transformer Encoder + LSTM	TPU / Edge AI	60–80 ms	Marginal

With Edge AI and neural acceleration hardware, complex models like Conv-LSTM and Transformers are pruned, quantised, and distilled for real-time deployment.

Robustness to Noise, Missing Data, and System Dynamics:

A DNN model's robustness indicates its ability to perform under adverse conditions. Signal noise (e.g., harmonic distortion, communication jitter), sensor or network failures, and system parameter changes like load variations, switching transients, or topology reconfiguration are examples. [31] Modern DNNs, especially convolutional and recurrent architectures, have shown promising denoising results with learnt filters. Some studies simulate partial data loss during training with dropout layers or synthetic noise. Conv-LSTM and transformer architectures with dynamic fault scenarios are more reliable in real-time power systems because they adapt better to system non-stationarities.

Table 11: Robustness Benchmarks in Recent Studies

Study	Noise Resilience	Missing Data Handling	Adaptive to Load Variation	Technique Used
Rahman et al. (2023)	High (99% accuracy at 20 dB SNR)	Partial	Moderate	CapsuleNet + dropout
Chen et al. (2023)	High	High (≤10% missing tolerated)	High	Sparse generalization (SG-ELM)
Arash et al. (2024)	Moderate	Moderate	High	Conv-LSTM with data augmentation
Singh et al. (2024)	High	High	Very High	Self-attention mechanism

Models employing dropout layers, denoising autoencoders, or training under noise conditions tend to outperform those trained only on clean datasets.

Dataset Source: Simulated vs. Real-World Data:

Another important evaluation factor is training and testing dataset type. PSCAD, MATLAB/Simulink, and RTDS simulations provide accurate labels and broad fault coverage. Real-world systems have more unpredictability and noise. Real-world or field-synchronized datasets from PMUs or SCADA archives have realistic distortions, measurement errors, and non-ideal signal dynamics. [32] Recent studies (Rahman et al., 2023) recommend hybrid training strategies that use simulated data for base training and real-world data for fine-tuning to improve generalisation and deployment readiness. Demonstrating reliability requires benchmarking models on both types.

Table 12: Comparison Between Simulated and Real-World Datasets for Model Training

Dataset Type	Advantages	Limitations	Example Usage
Simulated (PSCAD, MATLAB)	Controlled variation, fault injection, repeatability	Lacks measurement noise, real-world conditions	Patel et al. (2022), Guo et al. (2023)
Real-World (PMU, SCADA)	High fidelity, captures practical anomalies	Labeling difficulty, limited coverage of all faults	Rahman et al. (2023), Singh et al. (2024)
Hybrid (Sim + Real)	Best of both: training + fine-tuning	Requires careful alignment and preprocessing	Chen et al. (2023), Arash et al. (2024)

Hybrid datasets are increasingly favored for developing models that generalize well yet retain interpretability and controllability.

Generalization and Transferability :

The model's generalisation ability is its accuracy on new grid configurations or fault scenarios. A highly generalised model trained on one transmission line should work on other topologies with little retraining. Cross-system validation is increasingly used to assess transferability by testing the trained model on a new dataset from a different region, utility, or simulation platform. [33] New methods like transfer learning, domain adaptation, and few-shot learning improve generalisation without retraining. Transformer encoders with attention-based mechanisms can capture grid-invariant features.

Table 13: Generalization & Transfer Testing Across Studies

Study	Test Domain	Generalization Score	Cross-System Validation Performed?	Transfer Techniques
Guo et al.	Single TL sim →	Good (≤2% drop)	No	None

(2023)	varied sim			
Chen et al. (2023)	Sim → real-time lab	Excellent (<1% drop)	Partial (lab)	Fine-tuning, Dropout
Arash et al. (2024)	Sim → different TL config	Good (≤3% drop)	Yes	Data augmentation
Singh et al. (2024)	Regional PMU → national PMU	Very High	Yes	Transformer + transfer learning

Domain adaptation, meta-learning, and transformer-based modelling are increasingly used to evaluate advanced DNNs' ability to adapt with minimal retraining. DNN-based fault analysis performance evaluation goes beyond accuracy. [34] A complete benchmarking process requires statistical robustness, low-latency inference, system variability adaptability, and validation across simulated and real-world datasets. As deep learning in power system protection matures, generalisation and deployment scalability become more important.

RESEARCH GAPS & CHALLENGES:

Deep neural network (DNN)-based transmission line fault classification and location systems face several major challenges despite their progress. These issues affect model deployment, reliability, scalability, and explainability in real-world power systems. [35] Key research gaps and system-level challenges from literature, simulations, and real-world pilot deployments are listed here.

Lack of Standardized Benchmark Datasets :

The lack of standard benchmark datasets hinders DNN model evaluation. PSCAD, RTDS, or MATLAB Simulink are used to simulate proprietary or custom data in most studies. These datasets allow flexible fault parameter definition, but fault types, durations, noise levels, and system configurations vary, making inter-study comparisons inconsistent. Due to security and confidentiality concerns, PMU and SCADA datasets are rarely made public. [49]

Table 14: Challenges Related to Benchmark Datasets

Issue	Impact	Possible Remedies
No public benchmark datasets	Difficult to compare model accuracy and robustness	Develop and share open-access benchmark sets
Dataset inconsistency	Model overfitting to specific configurations	Use cross-simulation testing, synthetic-to-real
Limited real-world data	Poor generalization under practical operating noise	Deploy testbeds and community data repositories

Generalization Across Different Power Networks :

DNN-based models often cannot generalise beyond the system or topology they were trained on. Due to differences in impedance, load profiles, and fault signatures, a model trained on a 400 kV double-circuit transmission line in one region may perform poorly on a 220 kV single-circuit line elsewhere[36]. This requires cross-system validation (CSV), which is rarely done. Domain adaptation, transfer learning, and meta-learning are promising solutions that need maturation and application-specific tuning.

Real-Time Implementation Hurdles (Computational Cost) :

Many DNN models perform well offline, but computational constraints make real-time implementation difficult. High-resolution PMU or digital relay data streams require millisecond processing. [37] Deep CNNs, RNNs, and transformer-based models with large parameter sets may require GPUs or edge AI accelerators, increasing deployment cost and complexity.

Table 15: Real-Time Implementation Bottlenecks[48]

Challenge	Examples	Potential Solutions
High latency in deep	LSTM/Transformer > 50 ms on	Model pruning, quantization, edge

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models	CPU	deployment
Resource-intensive inference	Multiple convolution or attention layers	Use of lightweight models (e.g., MobileNet)
Software-hardware compatibility	TensorFlow model not optimized for DSP chips	Hardware-aware model compression, ONNX export

Interpretability of Deep Models (Black-Box Nature):
DNN models—especially deep CNNs and RNNs—are opaque. Unlike rule-based or shallow ML models, fault type and location predictions are hard to explain. This lack of interpretability erodes protection engineers' and utility operators' trust, hindering critical infrastructure adoption. XAI tools like Layer-wise Relevance Propagation (LRP), SHAP values, and attention visualisation are promising. [38] These methods are rarely used in power system fault detection studies.
Handling Hybrid Faults and Evolving Fault Patterns:
Datasets and model design often under-represent hybrid faults (e.g., simultaneous L-G and L-L faults) and evolving patterns from time-varying arc resistance, transformer inrush, or renewable intermittency. Most models use fixed parameters and well-defined fault types. Practical systems may need adaptive or sequence-aware modelling for complex, nonstationary disturbances.

Table 16: Fault Complexity Challenges[39]

Challenge	Description	DNN Design Requirements
Hybrid/mixed faults	Coexistence of multiple fault types	Multitask learning, probabilistic classification
Evolving signal patterns	Dynamic faults due to arc re-striking, DG switching	Temporal sequence modeling, online learning
Low-frequency / high-impedance faults	Weak or subtle waveforms	Enhanced sensitivity in signal processing layers

Data Privacy and Cybersecurity in Smart Grids:
The collection, transmission, and analysis of high-resolution fault data raises privacy and security concerns as power grids become more digital and interconnected. PMU measurements may reveal load patterns, grid status, or customer behaviours that can be exploited if unsecured. [40] Additionally, DNN models trained on sensitive datasets may be vulnerable to adversarial attacks or data leakage.

Table 17: Data Privacy & Security considerations [47]

Issue	Risk	Emerging Solutions
Unauthorized data access	Exposure of sensitive operational information	End-to-end encryption, access controls
Model inversion / leakage	Extraction of training data from deployed models	Differential privacy, federated learning
Cyber-attacks on model inference	Adversarial inputs causing misclassification	Adversarial training, anomaly detection layers

Transitioning from academic models to field-deployable fault diagnostic systems requires addressing these research gaps. Open benchmark datasets, interpretable architectures, real-time optimisation, and security-conscious training protocols must become standard. These challenges also enable power engineers, data scientists, cybersecurity experts, and system operators to collaborate on new research.

FUTURE DIRECTIONS :
Future research on Deep Neural Networks (DNNs) for transmission line fault classification and localisation will focus on explainability, scalability, and cyber-physical system integration. DNNs are black boxes, limiting trust in critical infrastructure. Explainable AI (XAI) methods like SHAP,

LIME, and attention-based visualisations improve operator confidence and support human-in-the-loop decisions. Transfer Learning is another important method that allows pre-trained models to adapt to different voltage levels or regional networks without retraining, reducing data needs. DNN training is being revolutionised by digital twins, which simulate real-time faults and component ageing without risky field trials. Edge AI and lightweight models like MobileNet and TinyML are being deployed directly on substations and intelligent devices for faster, low-latency decision-making without cloud processing.Federated Learning protects data and allows substation-wide model training without data sharing. Finally, Graph Neural Networks (GNNs) are ideal for fault diagnosis in complex, interconnected power systems because they model the grid's structural dependencies. These innovations aim to improve smart grid fault management intelligence, security, and responsiveness.

CONTRIBUTIONS OF THIS REVIEW :

This review is one of the first to analyse and synthesise deep neural network (DNN)–based approaches for transmission line (TL) fault classification and location. [45] This review examines the architectural details, signal processing strategies, and application contexts of modern deep learning techniques like CNNs, LSTMs, hybrid architectures, and transformer and graph-based models, unlike other machine learning surveys. [43] A novel multi-dimensional taxonomy categorises the literature by functional objective (classification vs. localisation), input features, neural network architecture, and deployment scenario, providing a structured lens for evaluating and comparing methodologies. This paper also creates a benchmarking table that summarises model types, dataset sources, input modalities, and reported performance from recent studies, helping researchers identify strengths, weaknesses, and gaps in the current landscape. More importantly, this review bridges theory and practice by critically discussing real-time feasibility, generalisation, and interpretability issues that are often overlooked in academic settings but essential for smart grid deployment. These contributions outline future innovation and lay the groundwork for intelligent protection systems.

CONCLUSION:

Particularly for the classification and location of faults in transmission lines, deep neural networks (DNNs) have become transforming instruments in the field of power system protection. Their capacity to learn intricate, nonlinear relationships from high-dimensional, time-dependent data has greatly advanced the precision, adaptability, and speed of fault diagnostics relative to conventional and shallow learning approaches. The value of smart, data-driven solutions grows clear as the power grid develops towards more complexity—with the integration of distributed generation, renewable energy, and digital monitoring. This paper emphasises the critical need of strong and autonomous protection systems able to react quickly and precisely to a broad spectrum of fault situations. DNNs present this promise, but realising it completely will need overcoming major obstacles including interpretability, real-time implementation, generalisation, and safe data handling. Simultaneously, the field offers rich prospects for next research in fields including explainable artificial intelligence, federated learning, graph-based modelling, and digital twin-enabled training environments. This review not only catches the present state of the art but also prepares the ground for smarter, more resilient fault management in next-generation power systems by synthesising recent advances and outlining both successes and challenges.

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