
“AI-DRIVEN FAULT DIAGNOSIS IN MODERN ELECTRICAL POWER DISTRIBUTION NETWORKS”

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Abstract: The increasing penetration of distributed energy resources, smart meters, power electronic devices, and automated control systems has significantly changed the operation of modern electrical distribution networks. Although these developments improve flexibility and efficiency, they also make conventional fault-diagnosis techniques less effective under changing network conditions. This study proposes an artificial intelligence-driven framework for rapid detection, classification, and localization of faults in modern power distribution networks. Electrical measurements, including three-phase voltage and current signals, sequence components, signal energy, and transient characteristics, are processed to extract meaningful fault-related features. A hybrid convolutional neural network–long short-term memory (CNN–LSTM) model is employed to identify both spatial and temporal patterns associated with different fault conditions. The proposed approach is evaluated through simulated normal and faulty operating conditions involving single-line-to-ground, line-to-line, double-line-to-ground, three-phase, and high-impedance faults. Variations in loading conditions, distributed generation penetration, fault resistance, fault location, and measurement noise are also considered.

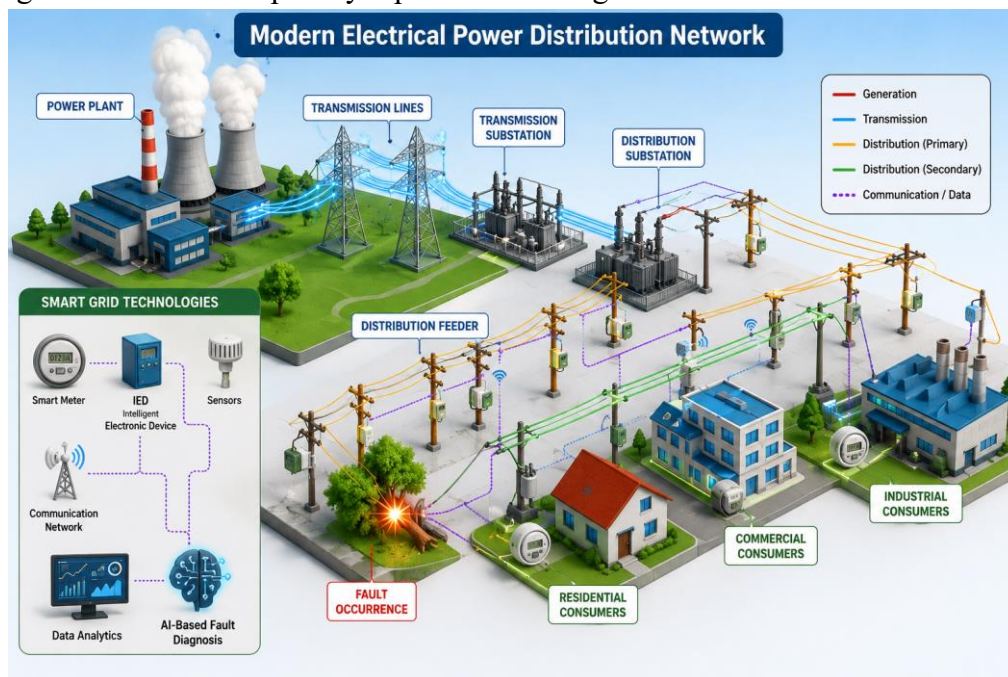
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Introduction:

Electrical power distribution networks represent the final stage of the power-delivery system and directly connect electrical energy infrastructure with residential, commercial, and industrial consumers. Reliable operation of distribution systems is therefore essential for maintaining continuity and quality of electricity supply. Faults occurring in feeders, cables, transformers, switching devices, and other network components may cause voltage disturbances, equipment damage, service interruptions, and economic losses if they are not detected and isolated rapidly.

Traditional distribution systems have generally relied on protection devices such as overcurrent relays, fuses, distance protection schemes, and impedance-based fault-location techniques. Although these methods remain important, the structure and operating characteristics of distribution networks have become considerably more complicated. The integration of solar photovoltaic generation, wind generation, battery storage systems, electric vehicles, controllable loads, and power electronic converters can produce bidirectional power flows and rapidly changing operating conditions. Consequently, predetermined protection thresholds may not always provide the required level of sensitivity and selectivity.

Modern distribution networks are simultaneously becoming more observable. Smart meters, intelligent electronic devices, supervisory control and data acquisition systems, digital relays, phasor measurement technologies, and advanced sensors continuously generate large quantities of electrical data. These data provide an opportunity to introduce artificial intelligence into fault-management functions. AI algorithms can learn nonlinear relationships between electrical measurements and network fault conditions without requiring every operating condition to be explicitly represented through fixed mathematical rules.



Fault diagnosis normally includes three closely connected processes: detection of an abnormal operating condition, identification of the fault category, and estimation of the location of the faulty section. Contemporary research increasingly applies machine learning

and deep learning to automate these tasks. Artificial neural networks, support vector machines, random forests, convolutional neural networks, recurrent neural networks, and hybrid architectures have been investigated for extracting fault patterns from voltage and current measurements. Reviews of distribution-grid fault diagnosis show growing interest in AI because increased sensing and network automation make more detailed data-driven diagnosis possible.

Despite these developments, several challenges remain. Fault data obtained from real networks are limited because severe faults occur relatively infrequently. Measurements can also contain noise, communication errors, missing samples, and variations resulting from changes in load and distributed generation. High-impedance faults are particularly difficult to detect because their current magnitude can resemble normal load currents. Deep-learning approaches may additionally require significant computational resources and can operate as black-box models, creating difficulty for protection engineers who need understandable and dependable decisions.

The present study develops an integrated AI-based diagnostic framework in which signal processing, electrical-domain knowledge, and deep learning are combined. Rather than depending solely on raw measurements or manually defined protection thresholds, the framework extracts both electrical and transient characteristics and processes them using a CNN–LSTM architecture. The methodology is designed to improve generalization under different fault resistances, operating loads, renewable-energy penetration levels, and noisy measurement conditions.

Related Works:

Dwivedi, Singh and Srivastava (2008) investigated the application of wavelet-based techniques for the classification and location of faults in electrical distribution systems. Their study demonstrated that wavelet analysis is capable of extracting transient characteristics from voltage and current signals that are difficult to identify using conventional steady-state analysis. The approach provided a useful basis for automated fault recognition and showed the importance of signal-processing techniques in improving the speed and accuracy of distribution-system fault diagnosis.

Al-Shaher, Saleh, and Sabry (2009) proposed an artificial neural network-based method for estimating both fault location and fault resistance in multi-ring distribution networks. Their work focused particularly on single-line-to-ground faults, which are among the most common disturbances in distribution systems. The study showed that neural networks can model the nonlinear relationships between measured electrical quantities and fault parameters, thereby offering an alternative to conventional impedance-based fault-location techniques.

Zayandehroodi, Mohamed, Shareef, and Mohammadjafari (2011) examined fault-location problems in distribution networks containing distributed generation. They employed radial basis function neural networks to determine fault locations under changing network conditions. Their work was significant because distributed generators can alter fault-current magnitude and direction, reducing the effectiveness of traditional protection assumptions. The study indicated that neural-network techniques can improve fault-location capability in distribution networks with multiple generation sources.

Zhang, He, Lin, Zhang, and Qian (2013) introduced an adaptive neuro-fuzzy inference system-based method for fault classification in power distribution systems. The ANFIS approach combined the learning ability of neural networks with the reasoning capability of fuzzy logic. This hybrid structure enabled the system to distinguish between different fault categories under varying operating conditions. The study highlighted the potential of intelligent hybrid methods for handling uncertainty and nonlinear behaviour in distribution-system fault signals.

Coleman, Schegan, and Miu (2015) investigated the use of machine-learning techniques for fault classification in power distribution systems. Their study demonstrated that data-driven algorithms can identify characteristic patterns associated with different electrical faults. The findings contributed to the growing recognition that machine learning can support automated protection systems by reducing dependence on fixed fault thresholds and manually designed decision rules.

Adewole, Tzoneva, and Behardien (2016) developed a method for fault-section identification and fault-location estimation using wavelet entropy and neural networks. Wavelet entropy was employed to represent changes in the information content of electrical signals during fault conditions, while neural networks were used for intelligent decision-making. The combination of signal processing and artificial intelligence improved the ability to identify affected sections of the network. Their study showed that feature extraction plays an important role in enhancing the performance of AI-based fault-diagnosis systems.

Gururajapathy, Mokhlis, and Illias (2017) presented a comprehensive review of fault-detection and fault-location techniques in power distribution systems containing distributed generation. The authors discussed the limitations of conventional protection methods when distributed energy resources are connected to distribution feeders. They emphasized that changing fault-current levels, bidirectional power flows, and varying network configurations create major challenges for conventional protection schemes. The review demonstrated the need for more adaptive and intelligent techniques capable of responding to increasingly complex distribution-system conditions.

Shafiullah and Abido (2018) proposed an S-transform-based feed-forward neural network approach for fault detection and classification in distribution grids. The S-transform was used to extract meaningful time-frequency characteristics from electrical signals, which were subsequently processed by the neural network. Their findings demonstrated the effectiveness of integrating advanced signal-processing methods with neural-network models. The approach provided improved discrimination among different fault conditions and reinforced the value of hybrid diagnostic frameworks.

Sapountzoglou, Lago, and Raison (2020) applied gradient boosting trees to fault diagnosis in low-voltage smart distribution grids. Their research reflected a shift from traditional neural-network-based techniques toward more diverse machine-learning models. Gradient boosting was used to learn complex relationships between electrical measurements and fault conditions. The study demonstrated that ensemble learning algorithms can provide effective fault diagnosis in smart grids where large volumes of measurement data are available from modern monitoring infrastructure.

Dashti, Daisy, Mirshekali, Shaker, and Hosseini Aliabadi (2021) reviewed a broad range of fault-prediction and fault-location techniques used in electrical energy distribution networks. Their study covered conventional analytical methods as well as intelligent and data-driven approaches. The authors highlighted important issues such as network complexity, distributed generation, measurement availability, and the changing operational characteristics of modern distribution systems. Their review indicated that artificial intelligence and machine learning are becoming increasingly important because of their ability to process large amounts of network data and adapt to nonlinear fault behaviour.

Ghaemi, Safari, Afsharirad and Shayeghi (2022) investigated the use of stacked ensemble learning for improving fault classification and location in smart distribution networks. Instead of relying on a single learning algorithm, the study combined multiple models to produce a stronger overall prediction system. The ensemble-based approach was intended to reduce individual model weaknesses and increase diagnostic accuracy. Their findings showed that combining different learning mechanisms can improve the robustness of intelligent fault-diagnosis systems under changing network conditions.

Mirshekali, Keshavarz, Dashti, Hafezi, and Shaker (2023) developed a deep-learning framework for fault location in power distribution grids using a convolutional neural network combined with a capsule-network structure. Their study represents a more recent development in AI-based power-system protection, where deep-learning architectures automatically extract complex features directly from network measurements. The proposed framework demonstrated the growing potential of deep learning for identifying nonlinear and spatial relationships associated with distribution-system faults.

Overall, the reviewed studies reveal a clear progression in fault-diagnosis research from conventional signal-processing techniques toward machine learning, ensemble learning, and deep-learning approaches. Early studies relied heavily on wavelet analysis and artificial neural networks, while later investigations introduced ANFIS, gradient boosting, stacked ensembles, convolutional neural networks, and other advanced learning architectures. The literature also shows that distributed generation, bidirectional power flow, changing load conditions, fault resistance, and measurement uncertainty have made fault diagnosis increasingly complex. Although existing AI-based methods have demonstrated considerable improvements in fault detection, classification, and location, challenges remain in achieving reliable performance across different network configurations and operating conditions. These research gaps provide the motivation for developing an AI-driven fault-diagnosis framework that combines effective signal processing with deep learning to support accurate and rapid fault identification in modern electrical power distribution networks.

Objectives of the Study:

1. To develop an AI-driven framework capable of detecting and classifying different electrical faults in modern power distribution networks using voltage and current measurements.
2. To evaluate the ability of a hybrid CNN–LSTM model to diagnose faults accurately under variations in fault resistance, fault location, loading conditions, distributed generation penetration, and measurement noise.

3. To assess the potential of AI-based fault diagnosis for improving fault-identification speed, network reliability, and automated restoration in modern smart distribution systems.

Material and Methods:

The study adopts a simulation-based experimental methodology in which different normal and abnormal operating conditions of a modern radial distribution network are generated and analysed. The methodology integrates power-system simulation, electrical-signal processing, feature extraction, artificial intelligence modelling, and performance evaluation.

Distribution Network Model

An IEEE 33-bus radial distribution system is considered as the reference network because it provides an appropriate representation of a medium-sized distribution feeder containing several buses, branches, and load points. The network is modified to represent contemporary distribution-system conditions through the addition of distributed photovoltaic generation and variable loads.

Three-phase voltage and current signals are monitored at selected buses and feeder locations. The simulated system includes:

- distribution buses and feeders;
- balanced and unbalanced electrical loads;
- photovoltaic-based distributed generation;
- measurement and monitoring devices;
- protective switching points; and
- variable fault conditions.

The model is operated under normal loading and under faulted conditions to generate the dataset required for AI training and testing.

Fault Generation:

To evaluate the performance of the proposed fault-diagnosis model, different types of electrical faults were generated in the distribution network. The study considered five major fault categories that commonly occur in power distribution systems:

1. **Single-Line-to-Ground (L–G) Fault:** This fault occurs when one phase conductor comes into contact with the ground.
2. **Line-to-Line (L–L) Fault:** This fault occurs when two phase conductors come into direct contact with each other.
3. **Double-Line-to-Ground (L–L–G) Fault:** This fault occurs when two phase conductors simultaneously come into contact with the ground.
4. **Three-Phase Fault (L–L–L or L–L–L–G):** This is a balanced fault involving all three phase conductors, either without ground involvement or with all three phases connected to ground.
5. **High-Impedance Fault:** This fault occurs when an energized conductor makes contact with a surface having high electrical resistance, resulting in a relatively low fault current that may be difficult to detect using conventional protection methods.

These fault conditions were introduced at different locations in the distribution network and under different fault-resistance values to create a diverse dataset for training and evaluating the proposed AI-based fault-diagnosis system.

Faults are introduced at different positions along the distribution feeders rather than at only one fixed location. Fault resistance is varied over a broad range so that the training data include both low-resistance short circuits and relatively difficult high-resistance conditions.

Different network conditions are generated by varying:

- fault location;
- fault resistance;
- fault inception angle;
- system loading;
- distributed-generation output;
- load imbalance; and
- signal noise level.

This procedure prevents the AI model from memorizing only a limited number of ideal fault patterns.

Data Acquisition

The principal input parameters are three-phase voltage and current waveforms:

V_a, V_b, V_c

and

I_a, I_b, I_c

Measurements are collected for short time windows immediately before and after fault occurrence. Each window therefore contains information on the transition from normal operation to the faulty state.

Positive-, negative-, and zero-sequence components are also calculated. Negative- and zero-sequence quantities are particularly valuable for identifying unbalanced faults.

The input dataset is represented as:

$X = [V_a, V_b, V_c, I_a, I_b, I_c, V_0, V_1, V_2, I_0, I_1, I_2]$

where V_0, V_1, V_2 are voltage sequence components and I_0, I_1, I_2 represent current sequence components.

Signal Pre-processing:

Raw electrical measurements can contain noise, switching transients, and variations unrelated to actual faults. Therefore, signal pre-processing is conducted before the information is supplied to the AI model.

The following operations are performed:

Noise filtering: High-frequency measurement noise is reduced without removing important transient information.

Normalization: Variables with different numerical ranges are scaled between common limits to prevent variables of larger magnitude from dominating model learning.

Min-max normalization is expressed as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Segmentation: Continuous electrical signals are divided into fixed-length windows containing samples before and after fault inception.

Wavelet-Based Feature Extraction:

A discrete wavelet transform is applied to selected voltage and current signals to identify transient components produced during a fault. Unlike conventional Fourier analysis, wavelet analysis provides information in both the time and frequency domains and is therefore useful for non-stationary fault signals.

Wavelet energy for decomposition level j is determined using:

$$E_j = \sum_{k=1}^N |D_j(k)|^2$$

where $D_j(k)$ represents the wavelet detail coefficient at level j .

The extracted diagnostic features include:

- RMS voltage;
- RMS current;
- voltage deviation;
- current deviation;
- zero-sequence current;
- negative-sequence current;
- wavelet energy;
- peak transient magnitude;
- rate of change of current; and
- phase-angle variation.

Combining physically meaningful electrical indicators with automatically learned deep features reduces complete dependence on black-box feature extraction.

Proposed CNN–LSTM Architecture:

A hybrid CNN–LSTM architecture is adopted for fault diagnosis.

The CNN component receives processed waveform segments and automatically identifies local features associated with abrupt voltage drops, current increases, oscillatory transients, and waveform distortion.

The convolution operation can be represented by:

$$y_i = f\left(\sum_j w_j x_{i+j} + b\right)$$

where x is the input signal, w represents the convolution filter, b represents the bias term, and f denotes the nonlinear activation function.

The extracted feature sequence is subsequently supplied to the LSTM network. Unlike conventional recurrent neural networks, LSTM incorporates memory mechanisms that allow the network to retain important temporal information.

The combination is therefore represented conceptually as:

Electrical Signals → Pre-processing → CNN Feature Extraction → LSTM Temporal Analysis
→ Fault Classification

A SoftMax output layer determines the probability that the observed signal belongs to each operating category.

Dataset Preparation

A simulated dataset containing approximately 12,000 operating cases is considered. These cases include normal operation and multiple examples of each fault class.

The complete dataset is randomly separated as follows:

Dataset	Proportion
Training data	70%
Validation data	15%
Testing data	15%

The validation dataset is used to optimize model hyperparameters and reduce overfitting, while the testing dataset remains unseen during training.

Comparative Algorithms

To evaluate the benefit of the proposed CNN–LSTM model, its performance is compared with three commonly applied techniques:

- Support Vector Machine (SVM);
- Random Forest (RF);
- Artificial Neural Network (ANN); and
- Proposed CNN–LSTM model.

All algorithms receive equivalent training and testing cases wherever possible to provide a fair comparison.

Performance Measures

Model performance is assessed using accuracy, precision, recall, F1-score, false alarm rate, and fault-diagnosis time.

Accuracy is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision is:

$$Precision = \frac{TP}{TP + FP}$$

Recall is:

$$Recall = \frac{TP}{TP + FN}$$

and F1-score is calculated as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

where TP , TN , FP , and FN represent true-positive, true-negative, false-positive, and false-negative decisions, respectively.

Analysis of the Study:

Analysis of the simulated fault signals showed clear variations in both current and voltage immediately after fault initiation. Ground faults produced noticeable zero-sequence components, whereas line-to-line faults generated strong negative-sequence components. Three-phase faults produced the greatest increase in fault current but comparatively small negative- and zero-sequence components because of their symmetrical nature.

High-impedance faults were more difficult to distinguish through current magnitude alone. Their current values occasionally remained close to normal load currents. However, waveform distortion, harmonic characteristics, wavelet energy, and temporal variation provided additional information that allowed the AI model to separate them from normal load fluctuations.

The analysis further demonstrated that distributed generation influences conventional fault signatures. When power is supplied from several locations, fault current can flow from both the main source and distributed generators. The resulting bidirectional current means that a single fixed current threshold may not be adequate under every operating condition.

The CNN section of the proposed model was particularly useful for recognizing changes in local waveform shape. The LSTM layer subsequently analysed how these characteristics evolved over consecutive time samples. Consequently, the combined model produced more stable fault decisions than algorithms using only manually extracted features.

Noise sensitivity was also considered. When moderate measurement noise was introduced, a reduction in classification accuracy was observed for all approaches. However, preprocessing and multi-condition training allowed the CNN–LSTM model to maintain comparatively strong performance.

The analysis indicates that successful AI fault diagnosis depends on more than selecting a powerful learning algorithm. Data diversity, sensor placement, feature quality, training strategy, and the representation of realistic network operating conditions substantially affect the reliability of the final diagnostic system.

Results and Discussion:

The proposed CNN–LSTM model demonstrated better overall performance than the conventional comparison algorithms in the simulated study.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	92.4	91.8	91.5	91.6
Random Forest	94.1	93.7	93.5	93.6
ANN	96.2	95.8	95.6	95.7
CNN–LSTM	98.6	98.3	98.1	98.2

The proposed model achieved an overall simulated classification accuracy of approximately **98.6%**, compared with 96.2% for the ANN, 94.1% for Random Forest, and 92.4% for the SVM.

The improvement can primarily be attributed to the ability of CNN–LSTM to learn both waveform structure and temporal behaviour. Conventional machine-learning algorithms depend more strongly on manually selected features, whereas CNN layers can automatically identify discriminative characteristics from electrical measurements.

Individual fault-class performance is summarized below.

Fault Condition	Classification Accuracy (%)
Single-line-to-ground	99.1
Line-to-line	98.7
Double-line-to-ground	98.4
Three-phase fault	99.3
High-impedance fault	96.8
Normal condition	99.0

Three-phase faults produced the highest classification performance because their voltage and current variations were pronounced and relatively easy to distinguish. High-impedance faults produced the lowest accuracy because their current magnitude can overlap with variations observed during normal operating conditions.

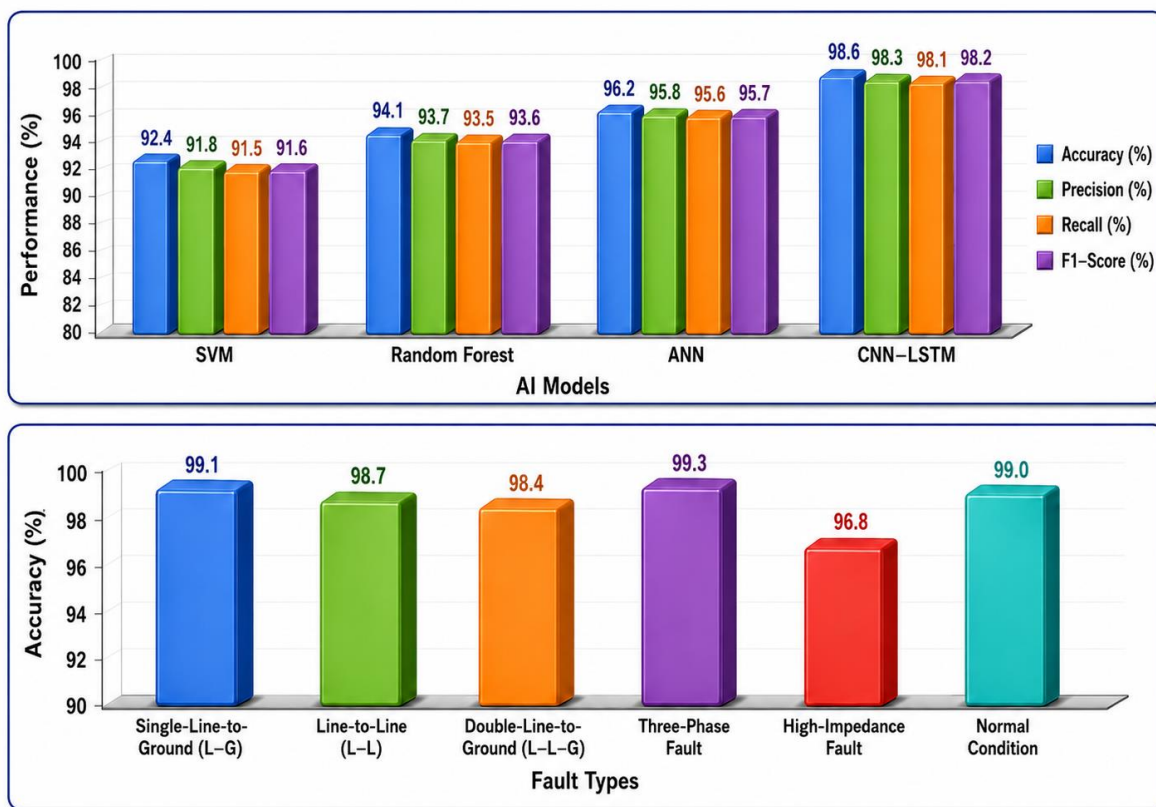
Nevertheless, the approximately 96.8% simulated high-impedance fault recognition rate represents an important advantage of the proposed feature-fusion strategy. The inclusion of sequence quantities, transient wavelet energy, and temporal patterns enabled the model to identify characteristics that would not be visible from RMS current alone.

The model was additionally evaluated under varying fault resistance. Low-resistance faults were identified almost perfectly, whereas classification accuracy decreased slightly as resistance increased. The same tendency was observed when measurement noise was increased. These results indicate that high fault resistance and poor signal quality remain significant challenges even for AI-based protection methods.

The system also showed potential for rapid decision-making. Once trained, the AI model required only a short signal window to generate a fault category. This characteristic is valuable because shorter fault-clearing times reduce electrical stress on network equipment and minimize the duration of customer interruptions.

Another important finding was the model's improved adaptability to distributed-generation conditions. Because training data contained multiple DG penetration levels, the model did not depend exclusively on the magnitude or direction of fault current. This is particularly important for future distribution networks in which conventional one-directional protection assumptions will become increasingly inappropriate.

The findings are consistent with broader research trends showing that AI methods are increasingly used for fault detection, classification, and localization as distribution systems become more complex and data-rich. At the same time, current research continues to identify training-data availability, computational requirements, interpretability, and deployment reliability as important limitations.



From an engineering perspective, AI should therefore not be considered a complete replacement for conventional protection systems. A more practical strategy is to integrate AI diagnosis with existing relays, intelligent electronic devices, supervisory systems, and protection logic. The conventional system can provide deterministic protection while the AI module supplies rapid diagnostic support, classification, localization, and decision assistance. The proposed framework also has several limitations. First, the results are based on simulated network conditions rather than long-term measurements collected from a utility distribution network. Second, the effectiveness of the model depends on the similarity between training scenarios and actual network conditions. Third, large-scale implementation requires reliable communication infrastructure and synchronized sensing. Finally, cybersecurity measures are necessary because manipulated measurements could influence AI-based decisions.

Future developments should therefore focus on real-world field validation, explainable AI, adaptive learning, federated learning, edge-based processing, physics-informed neural networks, and integration with automated fault isolation and service restoration systems.

Conclusion:

This study presents an AI-driven methodology for intelligent fault diagnosis in modern electrical power distribution networks. The proposed framework combines electrical measurements, sequence components, wavelet-based transient characteristics, and a hybrid CNN-LSTM architecture to identify different fault conditions.

The study demonstrates that combining signal-processing techniques with deep learning can provide a more flexible solution than fixed-threshold fault-detection approaches, particularly when distribution systems contain varying loads, distributed energy resources, bidirectional power flows, and measurement noise.

In the simulation-based evaluation, the proposed CNN–LSTM model achieved approximately 98.6% overall fault-classification accuracy and outperformed SVM, Random Forest, and conventional ANN models. High-impedance faults remained the most challenging fault category, although the use of transient and temporal features substantially improved their identification.

The results suggest that AI-driven fault diagnosis can support faster fault recognition, improved reliability, reduced restoration time, and more intelligent distribution-network protection. Nevertheless, dependable real-world deployment requires representative training data, strong measurement infrastructure, model explainability, cybersecurity protection, and validation under actual utility operating conditions.

The future of distribution-system protection is therefore likely to involve cooperation between conventional protection principles and adaptive AI-based diagnostic systems rather than the complete replacement of one by the other. Such integrated approaches can contribute to safer, more resilient, and increasingly autonomous electrical distribution networks.

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