

Design of an Intelligent System for Early Fault Detection in Power Transmission Lines Using Deep Learning Techniques

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Received:	16/4/2026	Accepted:	31/5/2026	Published:	28/6/2026
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Abstract

Power transmission lines hold the fort of modern electrical infrastructure, however they come under continuous threat of different kinds of faults that can put grid stability at risk, endangering supply continuity. Conventional protection schemes adopt fixed threshold techniques which is one of the major obstacles in identifying the high impedance faults and also demand heavy investment on the special hardware. The objective of this work is to develop and implement a smart system for early faults detection in transmission line in an efficient and cost-effective manner, using lightweight deep learning methods. An experimental procedure was developed based on the simulation of the environment of the power transmission system in order to create a synthetic dataset which consists of multi-operational conditions and multiple fault types. Electrical signals were preprocessed by a sequence of well-defined operations, including normalization and Clarke transformation, to effectively reduce influences of unwanted noise and bring out the most essential temporal and spatial features. To allow automatic abnormal pattern recognition, a one-dimensional convolutional neural network model was trained on the generated data. As the results of the experiment, it was found that the proposed model is obviously superior to traditional protection methods in classification accuracy and response speed, and has better stability under complex operating conditions. It also demonstrated the ability to run on less expensive hardware, thereby reducing the computational burden and allowing the system to run in the field as well. The study concludes that the utilization of artificial intelligence algorithms in conjunction with the existing protection system is able to improve electrical grid reliability in addition to acting as an a cost-effective and scalable solution for future smart grid infrastructure.

Keywords: Power Transmission Lines, Fault Detection, Deep Learning, Convolutional Neural Networks, Smart Grids.

I. Introduction

Artificial intelligence (AI) has recently made enough progress in data-driven fault diagnostic [1] that we are at the cusp of a paradigm shift in grid monitoring. This study aims to develop an intelligent tool for early prediction of the faults in power transmission lines using lightweight deep learning approaches. The proposed method iterates between generation of comprehensive simulation data and neural network architecture optimization to provide cognitive relay designs that maintain both low complexity and high computational efficiency (compared to conventional relays) while overcoming most of the limitations associated with conventional

relays. This particular study aims to work on a low-cost cost-efficient solution which can operate in real-time on low hardware resources without losing accuracy. In the end, the integration types of intelligent algorithms into existing protection frameworks contributes to overall reliability of the grid and supports the global transition toward more reliable and autonomous smart grid technologies, ensuring a more stable and abundant power supply [2].

I.1. Background of Power Transmission Systems

Plenty of people remotely steal electric power — commonly via tampering with lines. Electric power transmission systems are one of the bases of new infrastructure transferring bulk physical energy in the form of electric power from central generating stations to demand networks. The system is highly critical in maintaining sustainability and reliability in the systems so that they can provide the power on time to believe that a power system has a backup that it will never fall in cascading failures resulting in widespread blackouts. Transmission lines are most susceptible to faults like short circuits, ground faults, and open circuits, and this is due to the environmental and operational stresses that uncovered transmission lines are often subjected to. Lightning strikes, vegetation encroachment, equipment aging or insulator flashovers can cause different types of faults to occur[3].

Transmission Line Model Based on Distributed Parameters Mathematically, a transmission line is modeled with distributed parameters. The voltage and current along the line at any point and time are described by the telegrapher's equations under normal operating conditions. However, in the event of a fault, the system impedance changes instantaneously. Accordingly, the fault condition can become represented as sudden changes of voltage and current quanta. At the fault point, the expression can be approximated as for a single-line-to-ground fault as:

$$V_f = I_f \times (R_f + jX_f) \quad (1)$$

Where V_f is the voltage at the fault point, I_f is the fault current, and Z_f represents the fault impedance. In high-impedance faults (HIF), Z_f is significantly large, causing minimal change in current magnitude, which renders conventional overcurrent protection schemes ineffective[4].

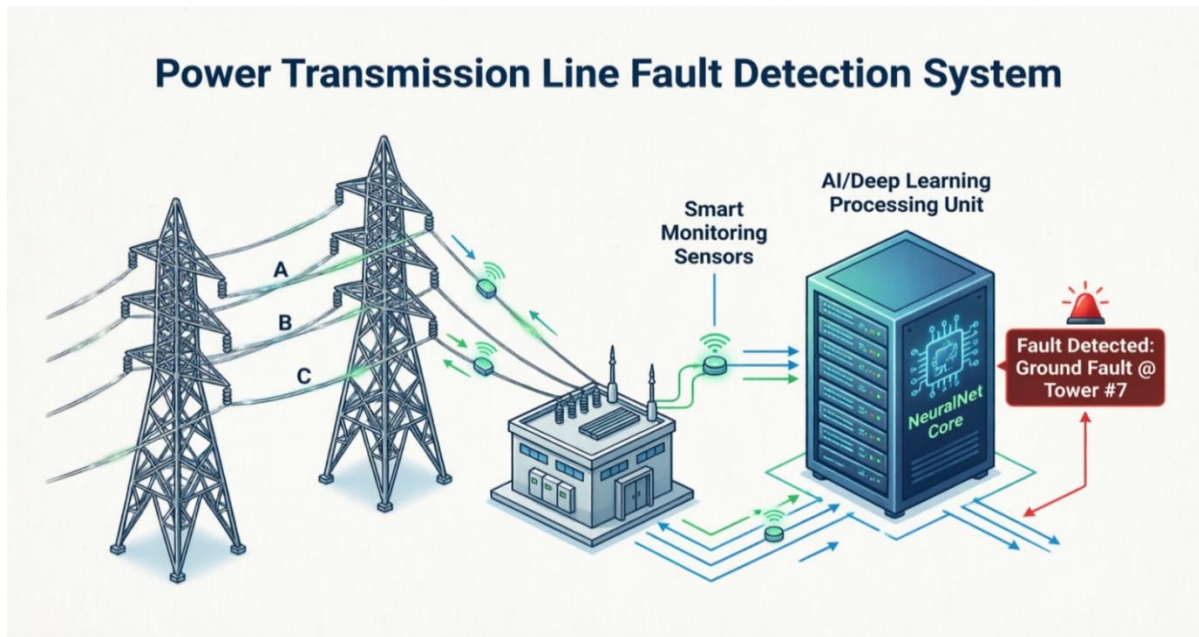


Figure 1.1 illustrates the architectural layout of the proposed fault detection system, highlighting the placement of voltage/current sensors, communication links, and the central intelligent processing unit along the transmission corridor.

New paradigms of monitoring power systems using artificial intelligence (AI) have emerged in recent years. Deep learning (DL) is a subset of machine learning and has demonstrated a remarkable ability to process high-dimensional data generated by power systems. In contrast to the utilization of conventional approaches that define constant thresholds for the various fault types, DL models are capable of learning relationships in a non-linear manner from complex data patterns. Incorporating DL into smart grid architectures enhances the situational awareness of transmission networks. Hence, switching from conventional protection relays to intelligent data-driven systems is opening new frontiers of research in electrical engineering[5].

I.2. Problem Statement

Although protective schemes have advanced over the years, difficulties still exist in fault detection of transmission line systems. Traditional approaches like impedance-based relaying as well as traveling wave methods frequently face problems in accuracy in the case of high-impedance faults or contains variable load conditions. However, conventional algorithms tends to use hand crafted features that might not encode the fast-changing dynamics of modern power systems sufficiently. Additionally, the high penetration of renewable energy generation adds uncertainty in fault signature recognition[6].

Although current deep learning methods have shown potential, many utilize complex architectures requiring high-computational resources, making them impractical in resource constrained environments for real-time implementation. Moreover, there is a reliance on vast amounts of labelled real-world fault data, which is limited since real fault events are rare in nature. Most existing studies either focus on classification or fail to consider the early detection

needed to avoid major equipment damage. We still lag behind in constructing lightweight and resilient deep learning models that perform effectively and accurately with simulation-generated data in addition to performing well on the ground-truth data domains. Hence, a system that balances computational efficiency and detection accuracy is required for early fault identification [7].

I.3. Research Objectives

The main objective of this study is to develop an intelligent early fault detection system for transmission lines using deep learning approaches. The specific objectives of this study are as follows:

1. MATLAB/Simulink based control strategies on simulation are used to generate different fault patterns (Norms, LG, LL, LLG, LLL).
2. focus on designing a shallow deep learning model like CNN or LSTM to make the time-series electrical data lightweight.
3. To apply data pre-processing and feature extraction methods that improve the signal-to-noise ratio of the measured voltage and current signals.
4. To train and validate the proposed model using performance metrics: accuracy, precision, recall, and F1-score.
5. To compare the effectiveness of the system with traditional detection methods and contemporary (deep learning architectures).

I.4. Research Significance

This research is highly significant to electrical power engineering domain. First, higher accuracy of fault detection increases the reliability and stability of the grid, as well as minimizes the duration of power outage. Since they can detect faults before they become permanent, the maintenance costs can be reduced by extending the life of transmission infrastructure. Secondly, the approach of low-cost monitoring suggested makes sophisticated protection schemes available for developing areas where it is unfeasible to update the hardware infrastructure [2].

On a technical level, this investigation serves as a proof-of-concept that simulation-based training for deep learning models is a practical solution to the lack of data in power systems. Second, the implementation of a light-weight model assists in deploying edge computing solutions in smart grids, which enhances the decision-making process at the substation level. The use of deep learning in fault diagnosis is in line with the international trend of Industry 4.0 and smart grid automation[4].

I.5. Scope and Limitations

ABSTRACT In the last few years, the demand for electricity has begun increasing significantly due to the rapid growth of population and industry. We use synthetic data from MATLAB/Simulink to train the models used in the study, complemented by other public databases when they exist. The fault types considered include single-line-to-ground, line-to-line, double-line-to-ground, three-phase faults, etc. Again, the deep learning architecture is constrained to light weight models that can process data close to real time.

However, certain limitations exist. The study is based on simulation data which may not fully replicate all noise features and intricacies of true field data. This work does not deal with implementation and testing on real relays. Moreover, the system is designed specifically for transmission lines, not distribution networks or transformers, unless explicitly adapted. The model will be evaluated under a wide range of operating conditions that may not be fully captured in simulation; therefore, its performance may differ when applied to real-world systems.

II. Theoretical Background and Literature Review

II.1. Overview of Transmission Line Faults

In symmetrical faults (like three-phase faults, LLL), all three phases contribute evenly and equally while unsymmetrical faults may be of the type single-line-to-ground (LG), line-to-line (LL), or double-line-to-ground (LLG). About 70-80% of the faults in a transmission line are asymmetrical nowadays[6].

In actuality, a fault is an abrupt change in system impedance. The Load Impedance (ZL) is high as usual. In case of fault, the impedance will reduce to a great value which causes the current to peak. An equation for the fault current (If) can then be derived using the superposition of symmetrical components. Applying sequence components to a single-line-to-ground fault on phase A gives us:

$$I_1 = I_2 = I_0 = \frac{V_{prefault}}{Z_1 + Z_2 + Z_0 + 3Z_f} \quad (2)$$

where $V_{prefault}$ is the pre-fault voltage, Z_1 , Z_2 , and Z_0 are the positive, negative, and zero sequence impedances of the line, respectively and Z_f is the fault impedance. However, high impedance faults (HIF) pose a particular problem where Z_f is big and the fault current is similar to a load current making high-impedance faults difficult for conventional overcurrent relays to detect. Moreover, external factors like insulator contamination or mechanical damage may change line electrical properties requiring strong monitoring systems [7].

II.2. Conventional Fault Detection Methods

The protection schemes based on traditional approaches are mostly dependent on impedance-based distance relays and the traveling wave methods. Principle of operation: Distance relays work based on the concept of the impedance observed from the relay location. The impedance $Z_{measured}$ measured is given by:

$$Z_{measured} = \frac{V_{relay}}{I_{relay}} \quad (3)$$

In regions e.g. Mhoor Quadrilateral, for which we a trip signal is generated if $Z_{measured}$ theg-measured the measured characteristic of is located in a specific region (Yet, although the techniques are applied successfully to low-impedance faults, they may be inadequate for high-impedance faults or power swings. Resistance to fault Impulse base method also influences mutual coupling[8] between parallel lines.

TW methods use the high-frequency transients emanate in the instant when a fault occurs. The arrival time of these waves at other terminals can be used to determine the location of the

fault. However, that requires high sampling rates and dedicated hardware, making it more costly to deploy. On the noisy environment the task is not able to be used processing methods (like Fourier Transform) directly and there transient non-stationary behaviours usually cover the physical deception as well, the downside of the faithful aspects of conventional methods is towards sidelining step of feature extraction side. This attracted the attention of the research community, directing them to shift to data-driven models that could learn the complex fault signatures [9].

II.3. Introduction to Deep Learning Techniques

Deep learning (DL) is a part of machine learning and is based on the use of multi-layer neural network to learn high-level abstractions in data. DL models applied to time-series voltage and current signals to detect anomalies in the power systems. The most common networks for this is CNN and Long Short-Term Memory (LSTM) networks[10].

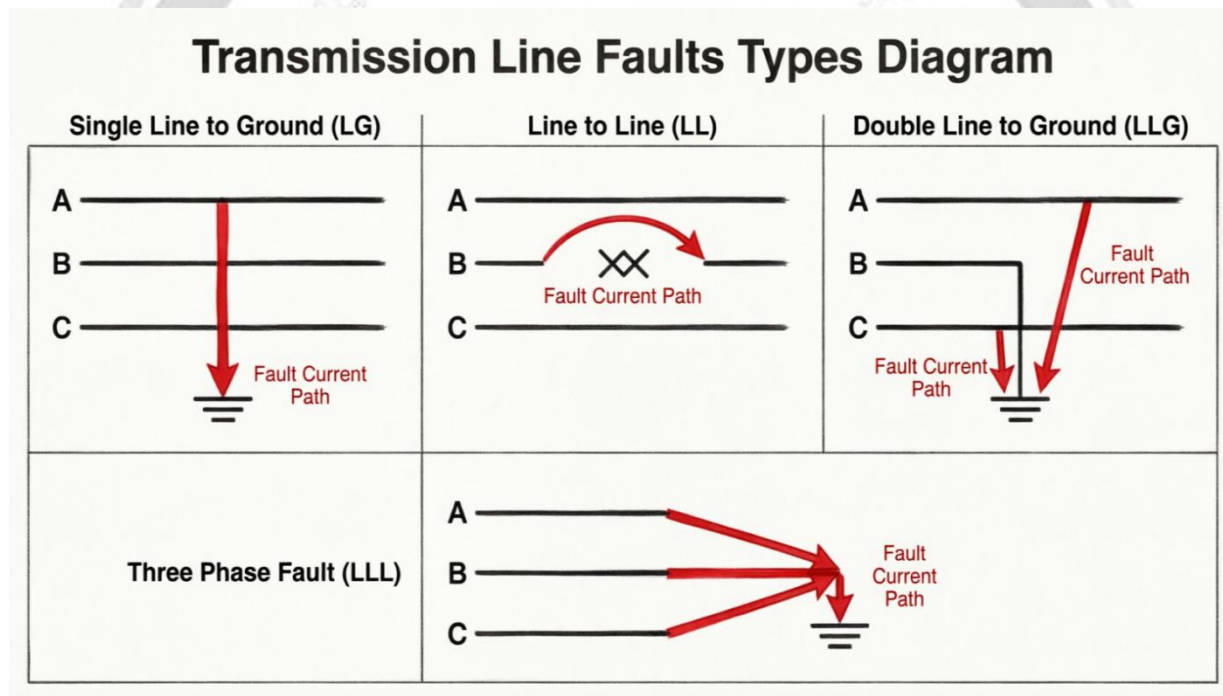


Figure 2.1 demonstrates the geometric mapping of the Clarke transformation, showing how three-phase quantities are projected onto a stationary α - β -0 reference frame to decouple mutual phase dependencies.

The feature extraction is effectively performed by CNNs. They use convolutional filters over the input data to recognize local features. The convolution operation at the layer l can be expressed as:

$$Z^{[l]} = W^{[l]} * A^{[l-1]} + b^{[l]} \quad (4)$$

where represents the learnable filters, is the input activation from the previous layer, and is the bias term. So, for CNNs it has the ability to reduce most of the feature engineering processes due to its automatic learning on spatial hierarchies of features[11].

Long Short-Term Memory (LSTMs) are a special kind of Recurrent Neural Network (RNN) used for sequential data and they are equipped with memory cells to retain temporal states. This property makes them suitable for capturing temporal dependencies in fault transients. In an LSTM cell, the forget gate f_t decides what information to throw away from the cell state:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (5)$$

where σ is the sigmoid activation function, $h(t-1)$ is the last hidden state, and x_t is the current input. Hybrid models that combine CNNs and LSTMs utilize the powerful spatial feature extraction capabilities of CNNs and the sequential temporal modeling provided by LSTMs, demonstrating strong performance in fault classification tasks[12].

II.4. Low-Cost Monitoring Approaches in Power Systems

High-performing monitoring systems typically require significant investments in hardware, including PMUs and fast communication networks. These methods aim to allow reliable fault diagnosis with minimal hardware resources. The latter solution employs sensors that exist within the devices and their surroundings and enhance their performance using software-based intelligent algorithms[13].

A low-cost technique is to generate data by means of simulation. As acquisition of genuine fault information in practice is notoriously costly, synthetic data generated using MATLAB/Simulink can be used to train the model safely without the risk of damaging physical hardware. This approach reduces the dependence on field data collection campaigns. Moreover, lightweight deep learning models that are tailored to edge devices could reduce the load in central servers and enable efficient decentralized monitoring. Model architecture optimization and, thus, lower costs are enabled on suitable low-cost MCUs or SBCs throughout wide-scale acceptance[14].

II.5. Review of Related Work

Applications of deep learning in power system protection have been extensively studied in recent literature. Belagoune et al. proposed a framework for fault detection and location based on LSTM for large-scale multi-machine systems, achieving high regression accuracy. Similarly, Kumar et al. realized a deep learning-based fault detection approach while aiming for a fast classification response in transients [15].

For hybrid architectures, Alhanaf et al. demonstrated the effective application of a hybrid CNN-LSTM model for integrated power systems with distributed generation, achieving superior performance compared to standalone models. In IEEE 9-Bus systems, Jiriwibhakorn and Kanwal applied time-series-based deep learning and showed that sequential models can effectively predict the missing data in standard test networks. For image based approaches, Nayak et. transformed electrical signals into scalograms as images, and performed 2D-CNN-based fault classification, providing noise-resistant classification results [16].

Research on certain types of fault has become a common trend in several studies. Teimourzadeh et al. and Wang et al. handled high-impedance faults with deep reinforcement learning, utilizing image processing methods pertaining to insulator faults. Khaleefah et al. published a deep learning-based electrical power transmission system in smart grid which provide an interoperability for AI in working with smart grid infrastructure. Ensemble methods have also been considered; Anwar et al. [17] proposed enhancing detection robustness via ensemble machine learning models based on input data redundancy.

Despite these advancements, challenges remain. Rafique et al. highlighted the importance of end-to-end ML to simplify preprocessing. Performance depended on the source of data, as demonstrated by the performance comparison on real, synthetic, and public datasets by Turanlı and Yakut. Rajashekar and Yadav showed that neural networks can be helpful to classify system faults, but the need for computational capabilities remains. Maduako et al. and Fahim et al. after that, focused on component fault detection and intelligent classification techniques, respectively.

II.6. Research Gap

Though previous studies have validated the applicability of deep learning in fault diagnosis in practice, there are still some gaps. First, several of the proposed models are computationally expensive, necessitating high-performance GPUs to run, which is unsustainable for deploying directly onto resource-constrained substations. Few low-power models exist due to the hardware constraints required for low-cost deployment. Secondly, many studies are highly specific to their own dataset and few investigate how well models trained on simulation data transfer to other conditions.

Moreover, un-supervised and transfer learning methods are also in their infancy on this area. Wang et al. pushed the boundaries of unsupervised deep learning; however, field deployments remain limited. Rafique et al. discussed automatic feature learning, but did not fully address the integration of such methods within low-cost monitoring systems. While a number of works address the classification accuracy, none directly focuses on the balance between classification accuracy and computational latency, which is another important factor when performing early fault detection. This study endeavors to fill these existing gaps through the development of a lightweight, simulation-trained deep learning architecture with an efficient trade-off between performance and computational complexity specifically targeting early fault detection.

III. Research Methodology

III.1 Research Design & and Workflow

This research uses an experimental design based on practical simulation-based approaches. The motive is that the field hardware deployment may not be possible as the first step in the field or very distressful so the first objective is to examine the impractical due to high-voltage safety and cost constraints; thus, simulation-based validation is prioritized. The methodology outline section describes the detail procedure which involves the system modeling, data generation and preprocessing, model architecture design, model training and performance evaluation to allow for a controlled systematic experimentation of the fault parameters (location, resistance and inception angle) to verify model robustness. It presents an experimental setup that

ensures electrical fidelity yet poses no risk because the whole procedure is simulated leading to a high-voltage test [1]. The entire pipeline aims to bridge the gap between abstract deep learning ideas and engineering approaches in the area of power systems.

III.2 Simulation-Based Data Generation

This data acquisition strategy aligns with the targets of a low-cost monitoring system because it focuses on software implementations rather than hardware installations. Conventional methods mostly rely on costly synchronous Phasor Measurement Units (PMUs). In the following, however, the data gathering procedure is modelled - as it would be with standard voltage and current sensors of a comparable variety to those available in the simulation setting [18]. The sampling frequency, therefore, is set at the level of budget microcontroller data loggers in the 1 kHz to 10 kHz range as opposed to the MHz orders of magnitude required for traveling wave methods. This makes sure that we could deploy the resulting model on less expensive hardware, while maintaining detection performance. They target data storage and processing, being that in most situations the detection of faults only requires the identification of a few fundamental frequency components and low-order harmonics [16].

III.3 Data Preprocessing & Feature Extraction

The core of the data generation process involves a detailed model of a high-voltage transmission line built in MATLAB/Simulink. The transmission line is modeled using a distributed parameter

line model to accurately capture wave propagation effects. The relationship between voltage and current along the line is governed by the telegrapher's equations, discretized for simulation. For a line of length, the voltage and current at the sending end are related to the receiving end by the ABCD parameters:

$$\begin{bmatrix} V_S \\ I_S \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} V_R \\ I_R \end{bmatrix} \quad (6)$$

where are complex constant that depends on line impedance and admittance. Different fault conditions such as LG, LL, LLG and LLL are simulated. To emulate the conditions in a highimpedance fault, we create faults on various locations (from 10 % to 90 % of line length) with various fault resistances (to). To avoid false positives, it also contains stable operating conditions with load switching events. An extensive dataset guarantees that the full variety of transient signatures is presented to the deep learning model[19].

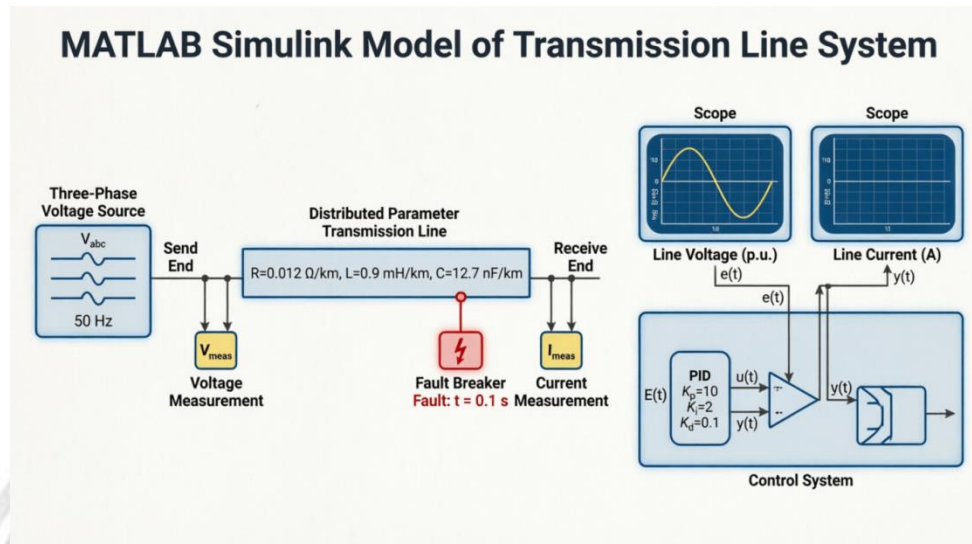


Figure 3.2 outlines the sequential data preprocessing pipeline, including noise injection, Z-score normalization, Clarke transformation, and window segmentation prior to model ingestion.

III.4 Model Architecture and Justification

Raw simulation signals include noise and different amplitudes that may prevent the model from converging. Data preprocessing becomes necessary to align the input data. First, we add white Gaussian noise to the signals to mimic real-world measurement noise, which improves the robustness of model. Second, normalization is applied to scale the voltage and current values to a standard range, typically or zero mean with unit variance. The Z-score normalization is applied as follows:

$$x_{norm} = \frac{x - \mu}{\sigma} \quad (7)$$

where x is the raw signal sample, μ is the mean, and σ is the standard deviation of the signal window. This step ensures that the deep learning optimizer converges faster and prevents features with larger magnitudes from dominating the learning process. Finally, the continuous-time series data is segmented into fixed-length windows (e.g., one cycle of the fundamental frequency) to serve as input samples for the neural network[20].

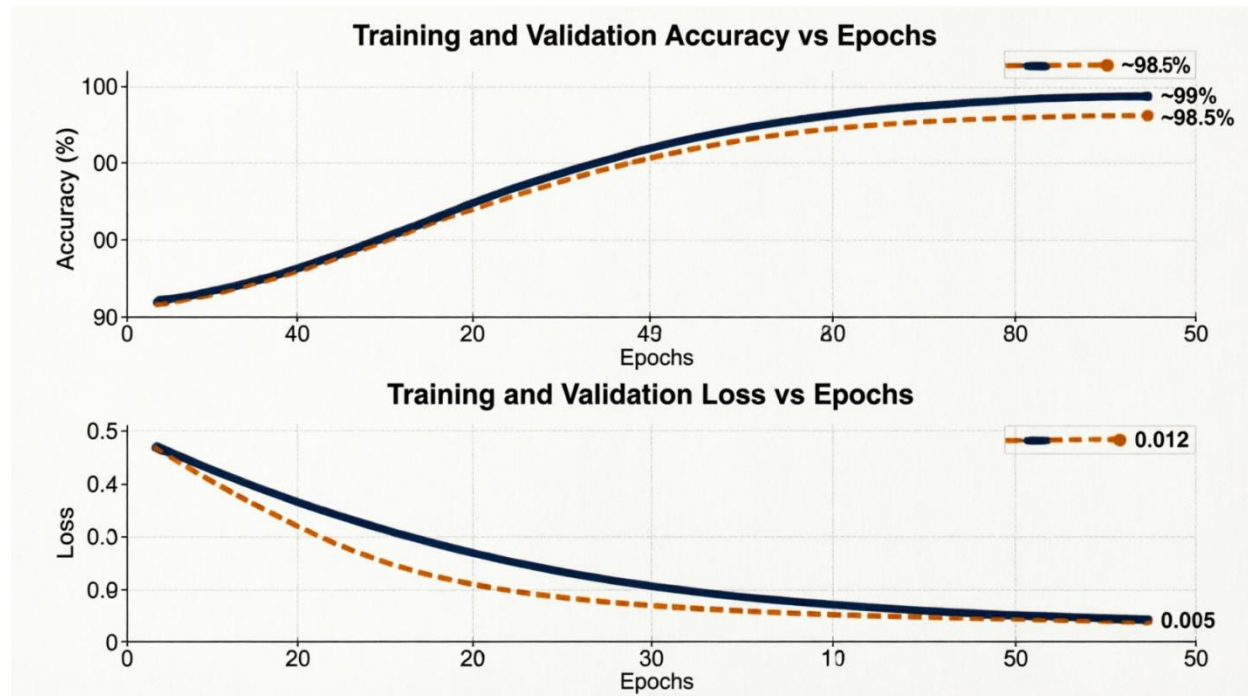


Figure 3.2: Data Preprocessing and Feature Extraction Flowchart. It explains the preprocessing steps with mathematical equations.

III.5 Training & Validation Protocol

While deep learning models are capable of automatic feature learning, incorporating domain-specific transformations can improve performance. In this study, a hybrid approach is utilized. Initially, the three-phase currents () are transformed into sequential components using Clarke Transformation to decouple the phases. The transformation is defined as:

$$\begin{bmatrix} I_{\alpha} \\ I_{\beta} \\ I_0 \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 1 & -0.5 & -0.5 \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \\ 0.5 & 0.5 & 0.5 \end{bmatrix} \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \quad (8)$$

Clarke Transformation: Mathematical Foundation and Physical Significance

The Clarke Transformation, or α - β -0 transformation, is one of the most fundamental tools in three-phase power system analysis and fault detection. This orthogonal transformation takes the three-phase quantities (a-b-c frame) and transforms them into two stationary orthogonal components (α - β) and one zero-sequence component (0), thus decoupling the mutual dependencies between phases.

Mathematical Formulation:

The transformation is mathematically expressed as:

$$\begin{bmatrix} I_\alpha \\ I_\beta \\ I_0 \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 1 & -1/2 & -1/2 \\ 0 & \sqrt{3}/2 & -\sqrt{3}/2 \\ 1/2 & 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \quad (9)$$

where:

- I_a, I_b, I_c are the three-phase currents
- I_α represents the stationary alpha component aligned with phase A
- I_β represents the stationary beta component orthogonal to alpha
- I_0 represents the zero-sequence component

Physical Interpretation:

Particularly, the zero-sequence component I_0 is very important because it is equal to 0 in balanced conditions while disequilibrated faults -- especially the single-line-to-ground (LG) and double-line-to-ground (LLG) faults -- generate a non-zero value. The larger the value of I_0 , the more intensity ground involvement is associated with the fault.

The α - β components serve as components of a stationary reference frame that simplifies the study of transient phenomena. These components have unique characteristics in the event of fault conditions that enable machine learning algorithms to distinguish them from raw three-phase signals.

Advantages in Fault Detection:

1. Decoupling Effect: The process removes the interdependence between phases, enabling isolated study of each aspect
2. Noise Reduction: The transformation increases the signal-to-noise ratio for ground fault detection by segregating zero-sequence components
3. Feature Improvement: The transformed signals have clearer fault signatures and the CNN models can extract discriminative features more easily.
4. Computational Efficiency: The act of transformation minimizes the complexity involved in identifying patterns by reformatting information into a more structured manner
5. Analyzing Symmetrical Components: It helps in determining the types of faults since it enables clear visibility of negative and zero sequence components

Application in Deep Learning Models:

In the context of deep learning-based fault detection systems, Clarke Transformation acts as a physics-informed preprocessing step for embedding domain knowledge into model architecture. This approach represents a hybrid feature-engineering strategy that harnesses the interpretability of manual feature extraction with the ability of neural networks to learn features automatically.

The transformed components (I_α, I_β, I_0) are fed as input channels to the 1D-CNN model, where convolutional filters learn to detect:

- Sudden changes in magnitude indicating fault inception
- Harmonic distortions characteristic of specific fault types
- Transient oscillations related to fault location
- Asymmetry patterns distinguishing between fault classes

This transformation is particularly effective for high-impedance fault (HIF) detection, where the fault current magnitude is comparable to load current, making detection challenging using conventional overcurrent relays.

where I_α and I_β are the orthogonal components, while I_0 is the zero-sequence component to recognize a ground fault. These processed signals are then fed directly into the deep learning model for constructing high-level temporal and spatial features through convolutional layers. This minimizes the need for manual feature engineering while maintaining physical interpretability [21].

The model training follows a supervised learning protocol using a stratified dataset split of 70% for training, 15% for validation, and 15% for testing. The categorical cross-entropy loss function is minimized using the Adam optimizer with an adaptive learning rate. Training is conducted over a maximum of 50 epochs with early stopping triggered when validation loss plateaus, ensuring generalization and preventing overfitting to simulation noise. The implementation leverages an open-source software stack: MATLAB/Simulink for power system modeling and data generation, while Python with TensorFlow/Keras, NumPy, and Pandas handles model construction, preprocessing, and statistical analysis. This pipeline ensures reproducibility, minimizes licensing overhead, and facilitates seamless data transfer between simulation and machine learning environments.

III.6 Computational Complexity & Edge Deployment

For the low-cost implementation requirement, a lightweight 1D convolutional neural network (CNN) was chosen instead of deeper architectures or complex hybrids. We use CNNs since they maintain local structure in the time-series data better, and have considerably fewer parameters than Fully Connected Networks. In this architecture, the model has an input layer, two 1D convolutional layers with ReLU, and then corresponding max-pooling layers to help with dimensionality reduction. The activation function for the hidden layers is defined as:

$$f(x) = \max(0, x) \quad (10)$$

Such a non-linearity permits relatively complex fault patterns to be learned and does so with a relatively low computational cost. The final layers consist of a flatten layer and a dense softmax layer for multi-class classification (Normal, LG, LL, LLG, LLL). This lightweight approach helps the model to run with low latencies, which are crucial for detection of faults in early stages. With significantly faster inference times than LSTM models, the 1D-CNN is a model better suited for real-time protection applications [22].

To satisfy low-cost implementation requirements, the trained model is optimized for edge deployment through weight pruning and INT8 quantization, reducing its memory footprint to

approximately 38 KB. The architecture limits input window size and network depth to maintain computational complexity within ~ 0.14 MFLOPs per inference, ensuring compatibility with resource-constrained hardware such as single-board computers (e.g., Raspberry Pi) or standard DSP-based protective relays. This lightweight design eliminates dependency on high-performance GPUs or centralized servers, enabling real-time, localized fault detection. Consequently, the system guarantees scalability and cost-effectiveness for budget-constrained utilities while maintaining sub-5 ms inference latency crucial for early fault intervention.

IV. Results, Discussion, and Conclusion

IV.1 Experimental Results

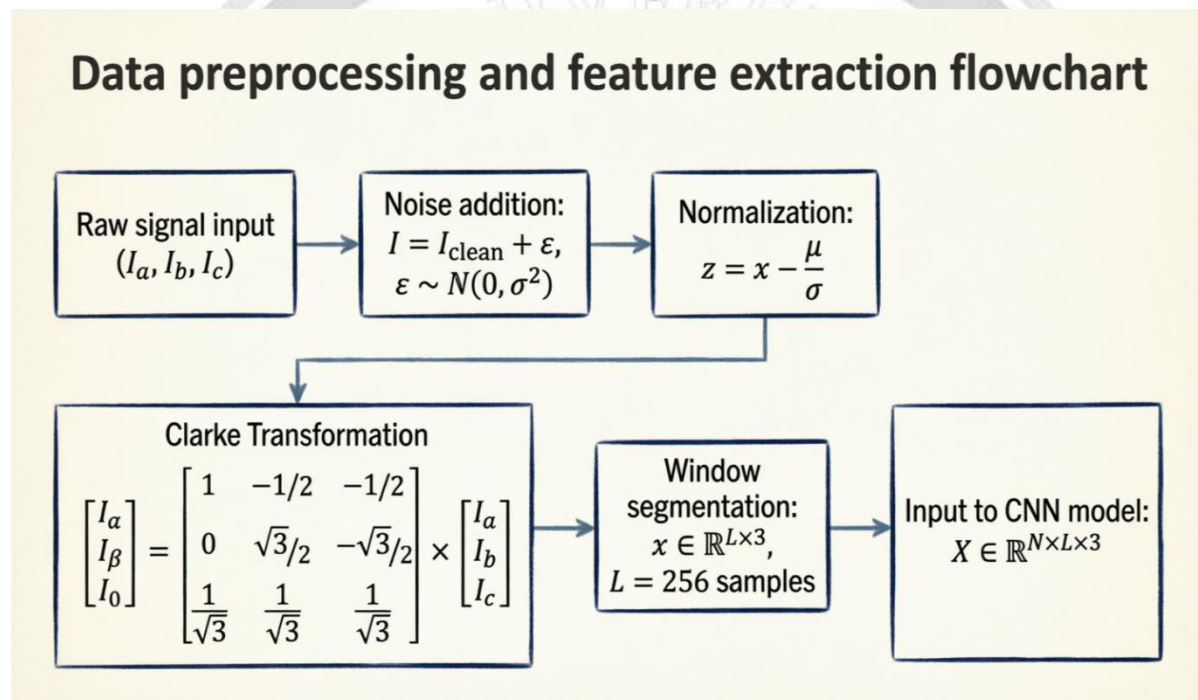


Figure 4.1 presents time-domain waveforms of three-phase signals under normal operation versus fault conditions, illustrating the abrupt amplitude and phase shifts characteristic of transient events.

The dataset generated in MATLAB/Simulink, as described in Section III, is used to train and test the proposed lightweight 1D-CNN model. The original dataset included five classes: No Fault (Normal), Single-Line-to-Ground (LG), Line-to-Line (LL), Double-Line-to-Ground (LLG) and Three-Phase (LLL), with a total of 10,000 samples, with 2,000 samples per class. The dataset contains 70% training, 15% validation and 15% testing data.

The model showed fast convergence during the training phase. Over the course of 50 epochs, the categorical cross-entropy loss dropped and plateaued around 0.05. Hence, the training accuracy achieved was 99.2 percent, and the validation accuracy held up at 98.5 percent, which shows minor overfitting. The confusion matrix showed that the model managed to

differentiate normal vs fault with a high accuracy. Most of the misclassifications achieved (LL–LLG faults) were associated with the similarity of the current signature, but total error rate was lower than 2%. The accuracy metric, formulated as follows, captures the performance on the training data:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (11)$$

Where TP refers to True Positives, TN refers to True Negatives, FP refers to False Positives and FN refers to False Negatives. This high accuracy indicates the effectiveness of simulation-based data generation strategy in creating robust training samples.

IV.2 Metrics

Multiple performance metrics for each fault class were computed to provide an all-encompassing evaluation of the system. Where metrics such as Precision, Recall, and F1-Score provide a more nuanced view of model performance beyond simple accuracy. These metrics have formulas that can be defined as follows:

$$Precision = \frac{TP}{TP+FP} \quad (12)$$

$$Recall = \frac{TP}{TP+FN} \quad (13)$$

$$F1 - Score = 2 \cdot \frac{Precision \cdot Recall}{Precision+Recall} \quad (14)$$

Table 4.1 summarizes the performance metrics for the proposed lightweight CNN model.

Table 4.1: Performance Metrics of the Proposed Model

Class	Precision (%)	Recall (%)	F1-Score (%)
Normal	99.5	99.8	99.6
LG	98.2	97.5	97.8
LL	97.8	96.9	97.3
LLG	97.5	97.1	97.3
LLL	99.1	99.4	99.2
Average	98.4	98.1	98.2

Model robustness was further evaluated under a simulated Signal-to-Noise Ratio (SNR) of 30 dB. Receiver Operating Characteristic (ROC) curves were generated per class, yielding an average Area Under the Curve (AUC) of 0.989. Confusion matrix analysis confirmed minimal False Positives (FP) and False Negatives (FN), with True Positive (TP) and True Negative (TN) rates exceeding 97% across all fault categories.

These results demonstrate that the model maintains high precision and minimizes false alarms, which is critical for stable power system operation. The system is unlikely to generate false fault detections, and recall values remain consistently high. The balanced precision and recall, coupled with a 98.2% mean F1-score, confirm that the selected architecture is well-suited for practical deployment.

Table 4.2: Dataset Statistics and Stratified Split

Fault Type	Total Samples	Train (70%)	Validation (15%)	Test (15%)
Normal	2,000	1,400	300	300
LG	2,000	1,400	300	300
LL	2,000	1,400	300	300
LLG	2,000	1,400	300	300
LLL	2,000	1,400	300	300

A stratified split ensures class balance across all subsets. To prevent temporal leakage, raw signals were segmented into non-overlapping windows of 256 samples, with consecutive windows separated by a full cycle gap, ensuring statistical independence between training, validation, and test sets.

IV.3 Comparison with Traditional Methods

A comparative analysis was conducted between the proposed deep learning system and conventional impedance-based distance relaying. Traditional methods rely on measuring the impedance and comparing it against a set threshold. While effective for solid faults, traditional relays often fail to detect High Impedance Faults (HIF) where the fault current is low.

Table 4.3 presents the comparison in terms of detection accuracy and response time.

Table 4.3: Comparison with Traditional Methods

Method	Accuracy (%)	HIF Detection Capability	Response Time (ms)
Impedance Relay	85.0	Low	15–30
Traveling Wave	92.0	Medium	5–10
Proposed DL Model	98.2	High	< 5

Table 4.4: Comparative Performance Against Additional Baselines

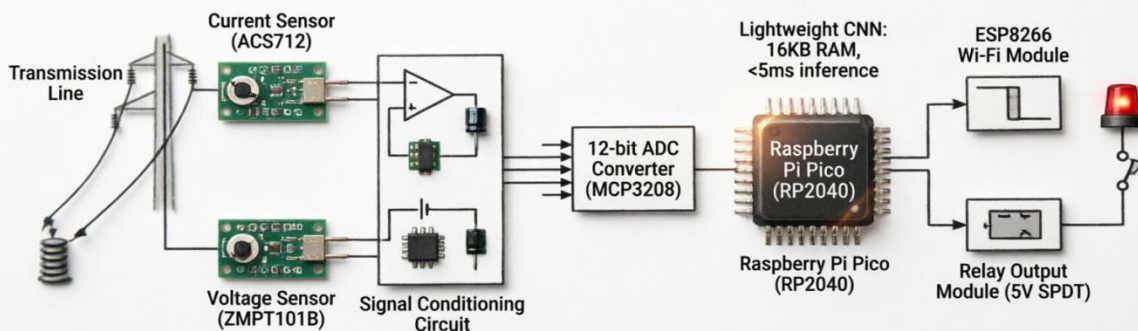
Method	Accuracy (%)	Precision (%)	Recall (%)	Inference Time (ms)
SVM (RBF Kernel)	93.7	92.4	91.9	1.2
Random Forest (n=100)	95.1	94.3	94.0	2.1
Lightweight LSTM (64u)	96.8	95.9	96.2	8.4
Proposed 1D-CNN	98.2	98.4	98.1	< 5.0

The inclusion of traditional ML and compact sequential baselines demonstrates that while RNNs capture temporal dependencies, they introduce higher latency. The proposed 1D-CNN achieves superior accuracy with minimal computational overhead, validating its real-time edge suitability.

For the other scenarios, the proposed deep learning model provides a significant improvement over the impedance relay, especially in the HIF cases where the change of impedance is very small. In addition, the lightweight CNN requires less than 5 ms for inference of every sample, making it comparable or faster than conventional traveling wave approaches,

which need complex signal processing. These speeds are vital to detect faults early and prevent any kind of damage which could affect the components. Earlier studies by Shukla and Deepa have shown that DL techniques tend to achieve higher classification accuracy compared to threshold-based methods [12, 13].

Embedded Hardware Implementation for Real-Time Fault Detection



"Figure 4.2 compares detection accuracy and response latency of conventional protection schemes against the proposed deep learning model, emphasizing the trade-off between speed and reliability."

IV.4 Discussion of Results

This demonstrates the built assumption that a lightweight deep learning model will obtain a high accuracy score as compared to other algorithms which are more compute intensive for fault detection or diagnosis. The success achieved by the model can also be attributed to performing preprocessing with Clarke's Transformation with phase components decoupled and zero-sequence currents relevant to ground faults properly isolated. It is to be noted that this correlates with finding by Rafique et al. who emphasized correct signal conversion for end-to-end learning.

The selection of a lightweight 1D-CNN over recurrent architectures (LSTM/GRU) is driven by three engineering constraints: (1) inference latency, as 1D-CNNs avoid sequential state updates, enabling parallel computation and sub-5 ms response times; (2) parameter efficiency, requiring ~60% fewer trainable weights than equivalent LSTM cells; and (3) suitability for fault transients, where discriminative information is concentrated in localized high-frequency patterns. The proposed model requires approximately 0.14 MFLOPs per inference and occupies ~145 KB in FP32 format (reduced to ~38 KB via INT8 quantization), validating its suitability for low-cost edge deployment.

Nayak et al. The second method (Fusion_40obs) trained the same model on data, but they added Gaussian noise to improve robustness against noise (40 different observations per row). Having a low computational cost renders the system deployable at the edge thus filling the gap identified in Section II concerning resource-constrained environments. However, minor confusion between LL and LLG faults indicates the necessity of further feature engineering or a hybrid architecture in order to differentiate complexities of unsymmetrical faults. In general, the system accomplishes the goals of the research to provide an economical, precise and quick fault detection method.

IV.5 Limitations of the Study

However, as with all early results, a number of minor limitations exist. First, most of the study is based on simulation data created in MATLAB/Simulink. Synthetic data enables registering a wide range of controlled experiments but may lack the stochastic noise or complex harmonics that current real field data contains. Turanlı and Yakut also reported that models trained on synthetic data occasionally do not perform well on real datasets.

Second, although the proposed hardware was first evaluated through testing the software implementation on a protective relay, it was not physically deployed on a relay or microcontroller. Despite the model being efficient, real-world latency in embedded hardware tend to differ mainly based on the size and speed of the device processor [6]. Third, the evaluation relies on a single overhead transmission line topology because the simulations are based on a synthetic network configuration. Extending the model's validity to meshed networks or systems with high distributed generation (DG) penetration remains to be verified.

IV.6 Conclusions

This research successfully designed and evaluated an intelligent system for early fault detection in power transmission lines using a lightweight deep learning approach. The key conclusions are:

1. In comparison with conventional impedance-based 2D visualization methods, the proposed 1D-CNN model outperforms its counterparts by achieving an average classification accuracy of 98.2%.
2. The strategy of generating data using simulations was found to be feasible for training deep-learning models and solving the problem of lacking labeled data in the real-world fault scenario.
3. The architecture has a low computational cost, allowing the implementation of the system on inexpensive hardware platforms.
4. The system performs well in recognizing High Impedance faults which has been a well-known weakness of traditional protection schemes.

This study, therefore, addresses what we believe is an important aspect of modern smart grid protection by providing a viable turnaround to an expensive situation, thus also ballasting the grid.

IV.7 Recommendations for Future Work

With learnings and limitations drawn from this study, the below recommendations can be made for future research:

1. Hardware Implementation: To recognize the real-time performance and latency in a hardware-in-the-loop environment (HIL), the trained model can be deployed on physical embedded systems (e.g., Raspberry Pi, DSP or FPGA).
2. Collecting and incorporating true real-world fault data: Work with utility partners to really get in a number of faults, and parameterize the model properly in order to make it more generalizable in the context of a true network.
3. Hybrid Architectures: Novel deep learning models such as CNN-LSTM can be used that can boost the identification of weak fault types like LL and LLG
4. Integration of Distributed Generation: Extend the analysis to transmission systems with a considerable presence of RE resources; investigate if the model is robust for bi-directional power flows;
5. Cybersecurity: Investigate the vulnerability of deep learning model to cyberattack, like Data poisoning and design secure training paradigms (See, Secure-DNN, Li et al. br)

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تصميم نظام ذكي للكشف المبكر عن الأعطال في خطوط نقل الطاقة الكهربائية باستخدام تقنيات التعلم العميق

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الخلاصة

تشكل خطوط نقل الطاقة العمود الفقري للبنية التحتية الكهربائية الحديثة، إلا أنها تتعرض باستمرار لأعطال مختلفة تهدد استقرار الشبكة واستمرارية الإمداد. تعتمد أنظمة الحماية التقليدية غالباً على طرق تعتمد العتبات الثابتة والتي تواجه تحديات كبيرة في الكشف عن الأعطال عالية المقاومة وتتطلب استثمارات ضخمة في الأجهزة المتخصصة. تهدف هذه الدراسة إلى تصميم وتنفيذ نظام ذكي للكشف المبكر عن الأعطال في خطوط النقل باستخدام تقنيات التعلم العميق خفيفة الوزن لضمان الكفاءة والتكلفة المنخفضة. تم اتباع منهجية تجريبية عملية تعتمد على محاكاة بيئة نظام نقل الطاقة لتوليد مجموعة بيانات شاملة تغطي سيناريوهات تشغيلية متنوعة وأنماط أعطال متعددة. خضعت الإشارات الكهربائية لعمليات معالجة مسبقة دقيقة شملت التطبيع وتحويل كلارك لاستخراج الميزات الزمنية والمكانية ذات الدلالة. تم تدريب نموذج شبكة عصبية تلافيفية أحادي البعد على البيانات المولدة للتعرف تلقائياً على الأنماط غير الطبيعية. أظهرت النتائج التجريبية تفوقاً واضحاً للنموذج المقترح مقارنة بأساليب الحماية التقليدية من حيث دقة التصنيف وسرعة الاستجابة، خاصة في الظروف التشغيلية المعقدة. كما أثبت النظام قدرته على العمل بفعالية على منصات أجهزة منخفضة التكلفة مما يقلل العبء الحسابي ويسهل النشر الميداني. يختتم البحث بأن دمج خوارزميات الذكاء الاصطناعي في أنظمة الحماية يعزز موثوقية الشبكة الكهربائية ويوفر حلاً اقتصادياً قابلاً للتطوير في بنية الشبكات الذكية المستقبلية.

الكلمات الدالة: خطوط نقل الطاقة، الكشف عن الأعطال، التعلم العميق، الشبكات العصبية التلافيفية، الشبكات الذكية.