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Robust Fault Detection and Classification in Power Systems via Physics-Informed and Data-Driven Learning

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Abstract

Electrical faults in power transmission systems can severely affect grid stability, equipment safety, and operational reliability. Traditional protection schemes, particularly distance relays, depend on apparent impedance computation that changes with error, creating a risk of misclassification. The results from relay overreach, underreach, or complete maloperation due to CT/PT saturation lead to developing problems in high impedance situations. These limitations highlight the need for adaptive, data-driven alternatives. This paper proposes an intelligent fault detection and classification model based on supervised machine learning techniques that overcome these challenges. The system's robustness was validated under different training sizes and Gaussian noise levels, demonstrating consistent accuracy and generalization across diverse learning conditions. The presented approaches learn the complex nonlinear mapping between three-phase voltage/current patterns and the associated fault type, without assuming fixed impedance paths like traditional protection schemes. This method extracts a high set of derived features to represent the distinguishing characteristics of six fault categories by utilizing line voltages and currents. Different models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, XGBoost, Long Short-Term Memory (LSTM), and Physics-Informed Neural Networks (PINN) are developed and processed on SMOTE-balanced datasets. These models classify the errors without fixed thresholds or fault loop assumptions, improving sensitivity and robustness. The supervised machine learning approaches bridge the gap between traditional impedance-

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based protection and smart, scalable data-driven grid analytics that are implemented into a wide area monitoring and control system. The PINN achieved the highest fault detection accuracy of 99.86% while sustaining 99.79% multiclass classification accuracy on the clean dataset. The PINN maintains high accuracy under 2–5% noise and 1–60% training data, providing millisecond-level inference by embedding power system equations, which enables accurate real-time protection by understanding the missing simple data-driven parameters.

Keywords: Fault Detection, Fault Classification, Supervised Learning, Transmission Line Protection, LSTM, Artificial Neural Networks (ANN), XGBoost.

1. Introduction

The effective operation of electrical power systems is essential for current infrastructure and productivity in industries. Line-to-ground (LG), line-to-line (LL), double-line-to-ground (LLG), three-phase (LLL), and three-phase-to-ground (LLLG) are all types of disturbances that have a significant impact on power transmission. These faults cause equipment damage and result in numerous blackouts. Early accurate detection and classification of these errors are important for maintaining grid stability, reducing outage duration, and avoiding catastrophic failures in electrical power systems. Traditional protection mechanisms such as impedance-based relays and overcurrent relays are normally unable to detect high-impedance faults, evolving grid topologies, and multiple simultaneous faults. As highlighted in [1], the apparent impedance measured by distance relays can change based on the fault type and location, making accurate classification essential for reliable protection. Recent advancements in artificial intelligence, particularly machine learning (ML) provide new possibilities in fault analysis. In this work, supervised machine learning-based approaches have been widely adopted for detecting and classifying faults. Anwar et al. [2] demonstrated the effectiveness of ensemble models for robust classification under noisy conditions. Porawagamage et al. [3] reviewed recent challenges in ML-based protection and proposed strategies for better data representation and real-time decision-making. The study by Chen et al. [4] emphasizes the significance of feature extraction for fault classification models using different methods. Moreover, advanced techniques combining ANNs with signal processing or optimization methods have shown high accuracy under various grid conditions [5], [6]. Data-driven methods for the detection and classification of faults have caused significant changes among research scholars who use leveraging algorithms such as Support Vector Machines (SVM), Random

Forests (RF), XGBoost, Long Short-Term Memory (LSTM), and optimized Artificial Neural Networks (ANN), which are widely accepted. Such methods have demonstrated improved performance when combined with engineered features along with data balancing methods such as SMOTE [7], [8]. Recent advances also highlight the importance of resilience-oriented intelligent frameworks for strengthening modern grid protection [9]. Most recently, Physics-Informed Neural Networks (PINNs) include physics loss in the learning process enhancing interpretability along with the robustness of power system fault analysis [10]. The above developments indicate the increasing possibilities of smart learning models for exact, reliable, and real-time protection in smart grid operations and the planning of future transmission systems [11]. However, existing techniques are frequently limited in scope, mostly concentrated on a small number of fault categories, requiring large clean data, and depending solely on data-driven learning without real-time integration. This limitation reduces robustness and real-time applicability, creating a need for models that include physics-based restrictions with supervised models.

This paper proposes a combined supervised learning model for fault detection and classification in power systems. The architecture utilizes voltage and current signals to train separate models for binary detection and multi-class classification. Six algorithms including ANN, LSTM, SVM, Random Forest, XGBoost, and PINN are evaluated consistently using engineered features and statistical measures. The dataset combines field-based reality with the variability of simulations to allow for generalization. This proposed system aids in maintaining modularity in real-time implementation. The aim is to provide scalable, automated, and accurate decision-making for wide-area monitoring, protection, and control (WAMPAC) for both traditional power systems and smart grid systems [12], [13].

2. Overview: Faults and Fault Types

2.1 Fault Types

Electrical power transmission systems are naturally dependable but vulnerable to a variety of disturbances, ranging from lightning strikes and insulation breakdowns to equipment aging and human error. These disturbances frequently cause incorrect electrical connections or faults. Fault areas represent harmful behavior that requires immediate attention for the system's stability, reliability, and safety. Traditional protection systems focus on detecting and isolating errors, while modern networks demand smarter systems that can detect, classify, and localize faults swiftly to support dynamic relay coordination, situational awareness, and self-healing grid operations [14]. The most common type is the single line-to-ground (LG) fault, which accounts for approximately 70–80% of all transmission line faults. LG faults result in high errors in the affected phase and a drop in its voltage, while the other phases may experience transient overvoltage, which affects insulation coordination and can lead to tripping if not accurately classified [15]. Line-to-line (LL) faults account for 10–15% of situations and are characterized by high current exchange between the two involved phases; abnormal voltage conditions can exacerbate high-risk error types, particularly when magnitude-based detection is utilized. Double line-to-ground (LLG) faults make up the remaining 10–15% and involve two phases shorted to the ground, producing large, unbalanced currents and the presence of zero-sequence components that significantly affect relay behavior. Although three-phase faults (LLL and LLLG) occur infrequently, they can cause the most serious system damage due to symmetrical high fault currents and continuous voltage decreases in all phases [16].

2.2 Importance of Fault Identification and Classification

The effects of faults on system functions are important to learn for developing effective protection schemes [1]. For example, LG implements a low-impedance path to ground causing a high fault current along with a continuous voltage decrease in the affected phase:

$$I_{fault} = \frac{V_{prefault}}{Z_{line}+Z_{ground}} \tag{1}$$

where Z_{ground} is very low resulting in a high fault current in the phase, while other phases remain relatively unaffected. In contrast, line-to-line (LL) faults create high current in the two involved phases, and are controlled by the inter-phase impedance:

$$I_{LL} = \frac{V_{ab}}{Z_{ab}} \tag{2}$$

Double line-to-ground (LLG) faults combine phase-to-phase and ground paths resulting in unbalanced currents and modified system stability. These variations demand accurate fault classification for appropriate relay response. Misclassification or failure to identify the fault type can lead to incorrect relay operation, miscoordination, delayed acceptance and an increased risk of prolonged outages or widespread blackouts [17]. The risk arises when relays detect the wrong fault impedance, tripping early (overreach) or failing to trip when required (underreach) from a protection standpoint.

This challenge becomes more important in distance relays, where the apparent impedance observed by the relay is used to estimate the distance to a fault. That impedance is calculated as:

$$Z_{app} = \frac{V}{I} \tag{3}$$

However, the value of Z_{app} changes the fault location and with the type of fault. For example, a relay calibrated for a three-phase fault may significantly miscalculate the impedance when it receives an LLG fault resulting in protection failure [1]. In pilot protection and differential protection schemes, accurate fault type learning enables better coordination between line terminals. This reduces unnecessary tripping and improves system dependability. Fault classification also plays a vital role in self-adaptive protection systems, where protection features are easily modified based on fault characteristics. For example, protection zones may be scaled using:

$$Z_{zone} = Z_{line}(1 + k_{fault}) \tag{4}$$

where k_{fault} is a small modification factor that depends on characteristics like ground current. Fault classification facilitates real-time control, predictive maintenance, and better planning in bidirectional DER-dense systems [2], [16]. In modern systems, classification provides that the appropriate action is taken when the detection activates the alarm. This smart classification is the key to future-oriented, fault-tolerant protection.

3. Problem Formulation

Fault detection is important to grid dependability, preventing outages and providing timely protective steps. While traditional systems focused only on detection, modern protection schemes require both detection and classification to support selective isolation and adaptive responses. The fault type, its transient behavior, and the need for preventive measures depend on the nature of the fault and the phases involved. This paper evaluates fault detection and classification as two related supervised learning tasks. The system study is a simulated three-phase transmission line, where line voltages and currents are captured under both normal and errored conditions. Each instance is transformed into a 13-dimensional feature vector using time-domain statistics such as average (Iavg, Vavg), range (Irange), standard deviation (Istd), magnitude (Imag), and zero-sequence components (I0, V0). All these features were selected with the aim of improving the discriminability of the model for complicated fault situations. Two data sets are used in the training and testing of the models. The first set is for the binary classification between fault and non-fault. The second is for the multi-class classification with a 4-bit ground and phase involvement representation (G, C, B, A). The realization is in line with practical requirements as the type of fault affects the impedance measurable to the relays and zone estimation. Misclassification results in overreach, underreach, or miscoordination in distance protection [1].

The proposed architecture focuses on real-time implementation at high-resolution inputs using either PMUs or IEDs. Relevant models such as XGBoost, SVM, ANN, and PINN provide the implementation of high-performance, interpretable, and scalable decision-making suitable for digital substation extended protection and control using engineered statistical features [18].

4. Methodology

This section describes the proposed model for smart fault detection and classification. It implements data generation through simulation, domain-specific feature engineering, class balancing, and supervised learning using six current models. Figure 1 presents an overview of the proposed methodology, feature extraction, SMOTE balancing, and model training using six machine learning algorithms. It will be followed by performance evaluation under clean, noisy, and low-data conditions.

4.1 Data Generation

The IEEE 13-node test feeder has been employed to simulate realistic unbalanced distribution network behavior. Fault situations were simulated including six conditions: no fault, LG, LL, LLG, LLL, and LLLG. Voltage and current signals (Va, Vb, Vc, Ia, Ib, Ic) were sampled at 10 kHz. Each instance was labeled using a 4-bit vector [G, C, B, A], where each bit represents the involvement of ground and phase conductors.

The datasets were modified by including Gaussian noise to simulate real-time measurement imperfections. Initially, the model tested up to 20%, with noise levels placed at 5% for model stability.

Each sample represents a 4–5 cycle interface at 50 Hz. Z-score normalization has been used and is defined by:

$$x' = \frac{x-\mu}{\sigma} \tag{5}$$

Stratified sampling was applied to develop training and testing sets with balanced class representation. The final dataset comprised approximately 10000 samples per class across the six fault categories with included variability. The proposed model evaluated on the IEEE 13-node feeder can be extended to larger highlighted systems (e.g., IEEE 33-, 118-node) and real PMU datasets as the feature extraction and learning modules expand according to the system size.

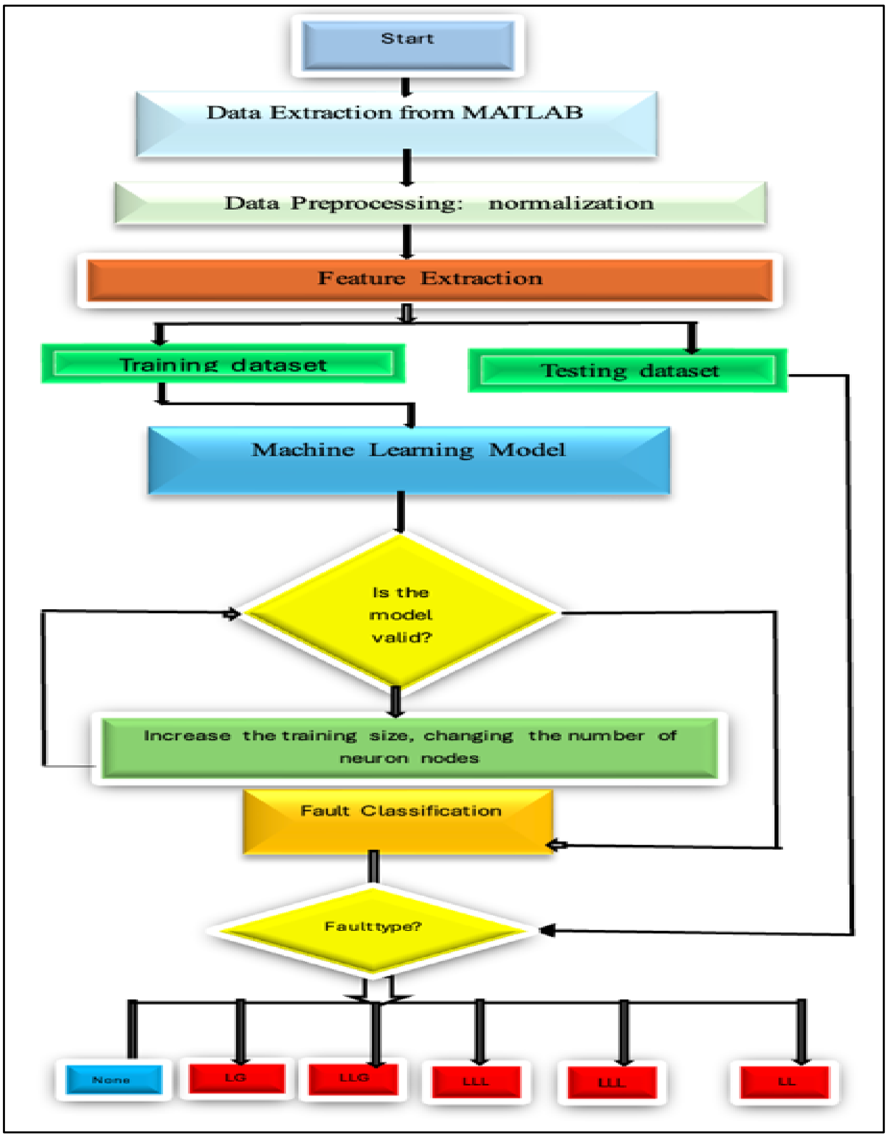

Figure 1. Flow Chart of Proposed Methodology

4.2 Feature Engineering and Balancing

A 13-dimensional feature vector was generated for each sample based on established practices in power system protection, considering accuracy. These include Iavg, Vavg, Irange, Vrange, Istd, Vstd, Imag (RMS magnitude of currents), and approximated zero-sequence components I_0 and V_0. These features characterize fault signatures including phase imbalance and asymmetrical behavior. For instance, high I_0 and V_0 values are associated with LG and LLG faults when LLL faults remain balanced [1].

The Synthetic Minority Oversampling Technique (SMOTE) has been applied to address class imbalance for rare cases like LLLG or LL faults. SMOTE generates synthetic samples for minority classes, improving model recall and sensitivity without overfitting, thus avoiding the unstable random oversampling and excessive noise of adaptive methods such as ADASYN.

4.3 Machine Learning Models

Six supervised machine learning models for fault classification and detection were developed from the same standardized feature set, undergoing SMOTE balancing. The Artificial Neural Network (ANN) was implemented with a three-layer Multi-layer Perceptron (MLP) network architecture. The binary detection network comprised two hidden layers with 256 and 128-neurons layers, while the classification network comprised three deeper layers with 256, 64, 32 neurons. Stable convergence for both networks was achieved with ReLU activation functions along with early stopping techniques and adaptive learning rates. The ANN performed effectively by establishing non-linear connections between the feature dimensions.

Support Vector Machines with a radial basis function (RBF) kernel were trained for these tasks. The hyperparameters including the regularization coefficient (C) and kernel width(γ) were optimized using grid search with three-fold cross-validation. The SVMs performed well in developing non-linear decision limits and consistently predicted fault types, with minor variation due to feature changes.

Random Forest classifiers with 200 trees and a maximum tree depth of 20 were applied for classification in most scenarios. Their interpretability and generalizability were enhanced by feature impact rankings associated with them. The Random Forest generalized effectively to balanced and imbalanced types of faults.

XGBoost classifiers were utilized for classification as well as for detection problems since they possessed the gradient boosting algorithm with regularization built into them. The model for detection had 100 estimators with a max depth of 5 and a 0.1 learning rate, the of classification possessed 250 estimators with a depth of 8 and a 0.05 learning rate. XGBoost was found to have steady resistance to noise as well as b multicollinearity, achieving high accuracy for all the fault classes.

Long Short-Term Memory (LSTM) networks were used to learn temporal relationships from the waveforms of voltage and current. The input data streams were reshaped three-dimensionally to match LSTM input formats. The models included two stacked LSTMs with 64 units and 32 units, respectively, along with a dense output layer with dropout regularization. LSTM models trained using the Adam optimizer and categorical cross-entropy error function were competitive in learning waveform dynamics and dependencies based on time.

Physics-Informed Neural Networks (PINNs) extended classical deep learning with the addition of physical constraints of Ohm's Law in the learning objective. Total loss is minimized in the learning process.

$$\text{Total Loss} = \text{Data Loss} + \lambda \times \text{Physics Loss}$$

Here, the Data Loss corresponds to binary or categorical cross-entropy, while the Physics Loss represents the residuals of the three-phase Ohm's law equations. The weighting factor λ is introduced to preserve the dominance of data-driven learning while enforcing physical consistency. In addition, dropout was applied from the outset to prevent overfitting, along with batch normalization to stabilize training. The block diagram for this is shown in Figure 2. The selected models reflect a balance between interpretability, computational feasibility, and prior adoption in fault analysis. SVM, RF, and XGBoost are established baselines in power system protection; ANN and LSTM capture nonlinear and temporal patterns; and PINN introduces physics-guided regularization to improve robustness. Other advanced architectures with very high parameter counts were not prioritized, as their training and deployment costs reduce suitability for real-time relays where fast and interpretable decisions are critical.

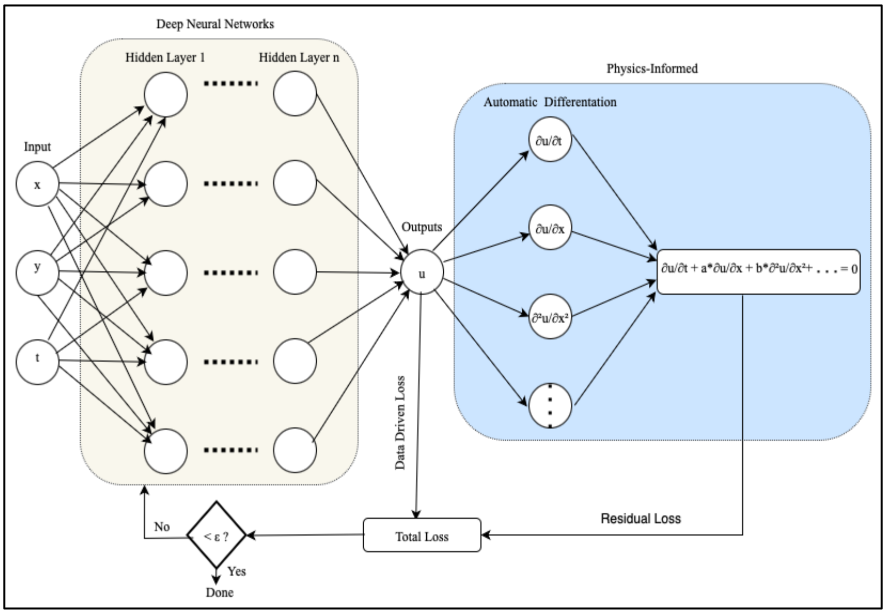

Figure 2. Physics-Informed Neural Network Block Diagram

4.4 Evaluation Metrics

Performance was assessed using accuracy, precision, recall, and F1-score, with macro-averaging to verify a balanced assessment across all fault types. Mean Squared Error (MSE) and Mean Absolute Error (MAE) were also evaluated to establish dependability in probability outputs and stability in regression. Confusion matrices were analyzed to provide a clear vision at the class level for model behavior. Models were tested on two challenging scenarios: variable train sizes (1-60%) and included Gaussian noise (2-5%) that simulate data constraints and confusion at the practical level. These metrics were selected as accuracy establishes overall correctness, precision/recall/F1 ensure reliability across minority fault types, and MSE/MAE quantify prediction stability under noisy or uncertain conditions is essential for protective relaying applications.

5. Results and Simulation

In this work, six machine learning models, ANN, LSTM, SVM, Random Forest (RF), XGBoost, and Physics-Informed Neural Network (PINN), are compared for fault detection and classification of transmission system faults. The performance of the models was compared based on three criteria: (i) accuracy on a clean dataset, (ii) generalizability with sparse data for training, and (iii) immunity to Gaussian noise (2-5%) during training. The performance measurement used for accuracy, precision, recall, F1-score, Mean Squared Error (MSE), and Mean Absolute Error (MAE) complies with the real-time protective relaying requirements of smart grids.

5.1 Models' Performance Under the Clean Dataset

All the models achieved higher-than 99% classification and detection accuracies with clean test data (Table 1). PINN achieved the highest detection accuracy of 99.86% while maintaining generalizability with the basic physics-based constraint. The optimal classification accuracy of 99.81% achieved in the case of SVM resulted from its ability to learn high-dimensional boundaries (Figure 3).

Table 1. Accuracy Comparison across Fault Detection and Classification Models

Model	Fault Detection Accuracy	Fault Classification Accuracy
ANN	99.34%	99.74%
LSTM	99.38%	99.75%
PINN	99.86%	99.79%
SVM	99.65%	99.81%
Random Forest	99.72%	99.74%
XGBoost	99.72%	99.80%

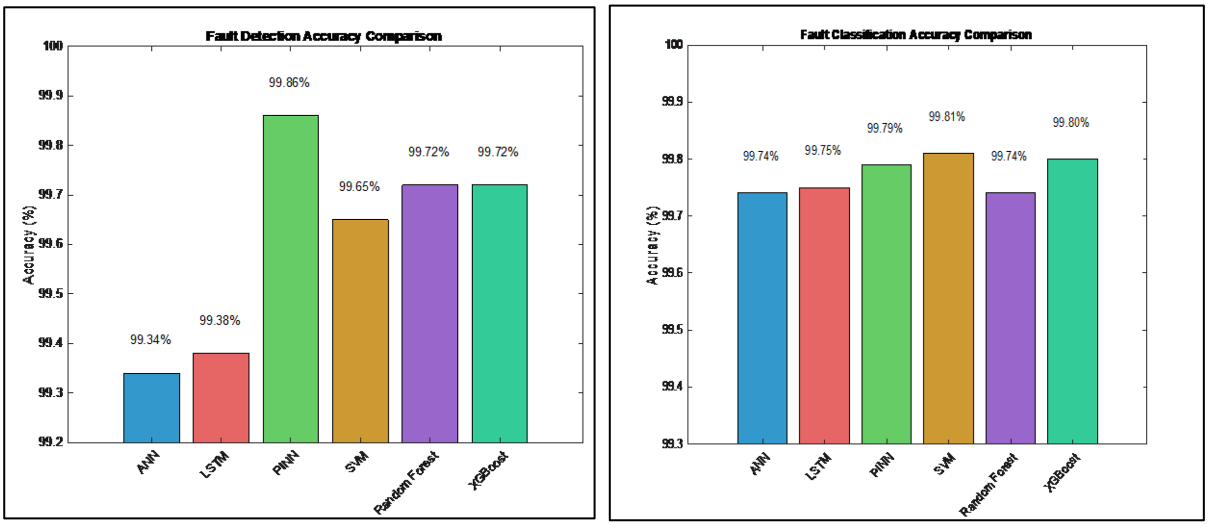

Figure 3. Bar Graphs of Accuracy Across Fault Detection and Classification Models

5.2 MSE and MAE Error Analysis

In addition to accuracy, prediction consistency has been assessed using MSE and MAE (Table 2.). PINN received the lowest error values in both tasks (detection MSE: 0.0014, classification MSE:0.0210), as expected in high-confidence PINN predictions in a suitable setting (Figure 4). Low error rates in each class were observed in SVM and XGBoost, while ANN and LSTM recorded relatively higher variability.

Table 2. MSE and MAE Across Fault Detection and Classification Models

Model	Fault Detection MSE	Fault Classification MSE	Fault Detection MAE	Fault Classification MAE
ANN	0.0066	0.0309	0.0066	0.0085
LSTM	0.0062	0.0293	0.0062	0.0081
PINN	0.0014	0.0210	0.0014	0.0061
SVM	0.0035	0.0197	0.0035	0.0057
RF	0.0028	0.0243	0.0028	0.0073
XGBoost	0.0028	0.0134	0.0028	0.0045

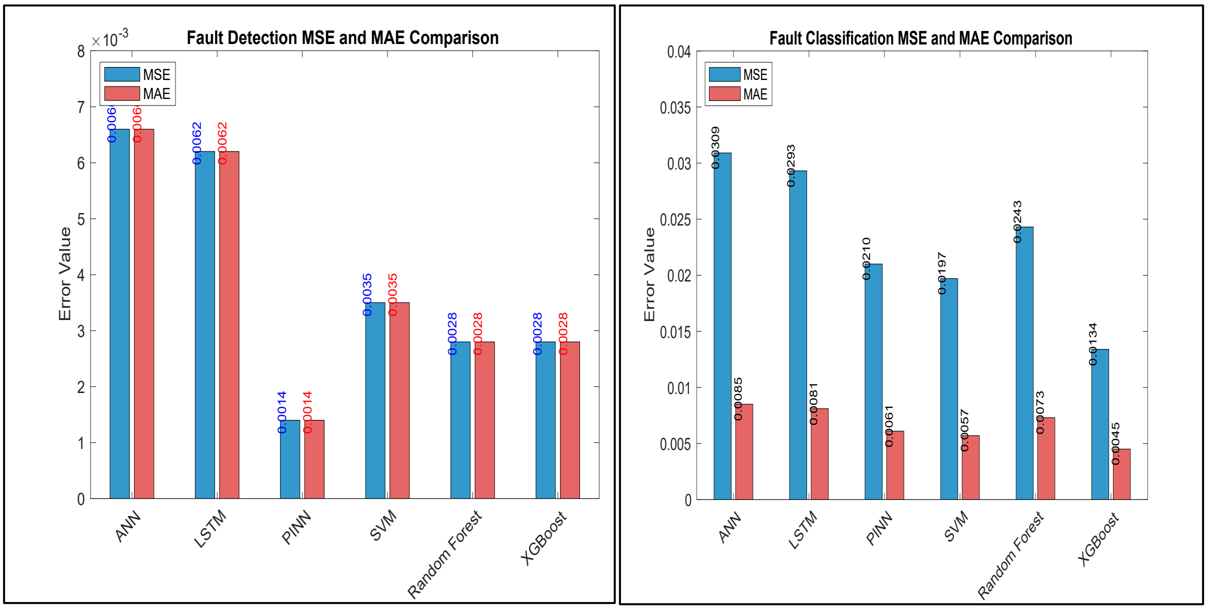

Figure 4. Bar Graph of MSE and MAE Across Fault Detection and Classification Models

5.3 Models' Precision, Recall, and F1-Score

Power grids of the 19th and 20th centuries were designed for the unidirectional flow of electrical energy from central stations to consumers. Communication in those systems based on low-speed digital and early analog technologies used only for basic monitoring and control functions [8], [9]. Macro-averaged F1-score, precision, and recall were evaluated class-wise reliability with particular interest in minority classes such as LLL and LLLG. All three metrics exceeded 0.99 for each model. PINN and SVM scored 1.00 regarding the three metrics that suggested highly balanced and consistent classification among fault types (Table 3).

Table 3. Precision, Recall, and F1-Score Comparison Across Models

Model	Precision	Recall	F1-Score
ANN	0.99	0.99	0.99
LSTM	0.99	0.99	0.99
SVM	1.00	1.00	1.00
Random Forest	1.00	0.99	1.00
XGBoost	1.00	0.99	1.00
PINN	1.00	1.00	1.00

5.4 Confusion Matrix Interpretation

The confusion matrices for the Physics-Informed Neural Network (PINN) implement complete generalization in both detection and classification tasks. The confusion matrices for PINN highlight that each matrix shows strong diagonal dominance with high off-diagonal entries, demonstrating minimal false positives and false negatives.

This level of accuracy reflects the model's ability to distinguish fault types reliably. The integration of physics-informed residual loss further reinforces this consistency by enforcing physical plausibility in predictions, thereby increasing confidence in the model's outputs for real-world protection applications. Compared to purely data-driven models, this physics-guided regularization reduces confusion between statistically similar fault signatures and improves generalization under noisy or limited training data, explaining PINN's consistent outperformance.

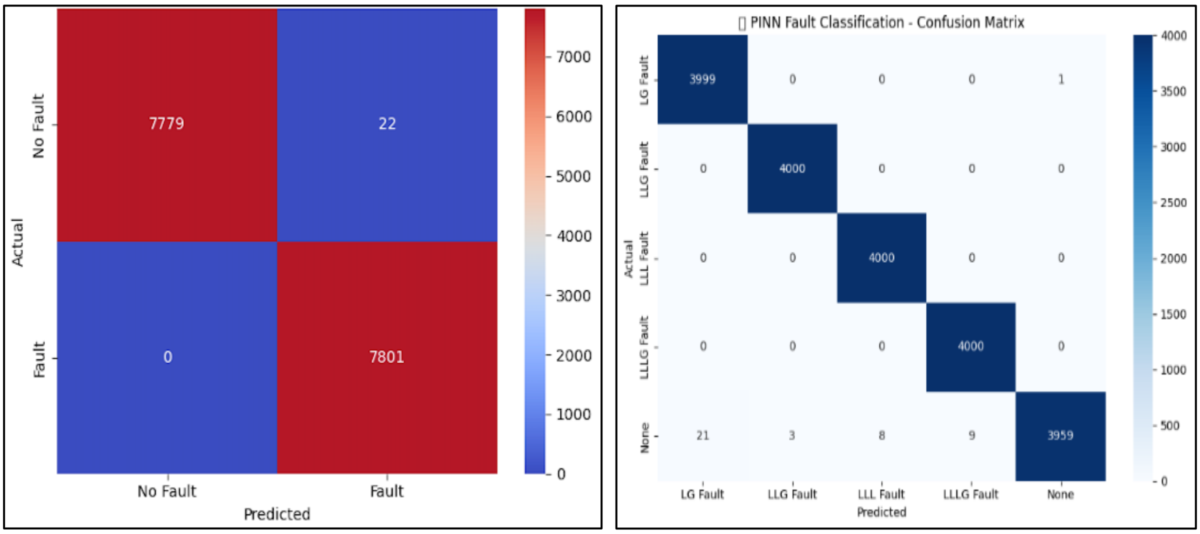

Figure 5. PINN Fault Detection and Classification Model Confusion Matrix

5.5 Models' Performance under Varying Training Size

Model performance across varying training sizes (1%—60%) revealed consistent trends. Detection and classification errors steadily decreased as training data increased, with most models reaching performance saturation around the 30% mark (Figure 6).

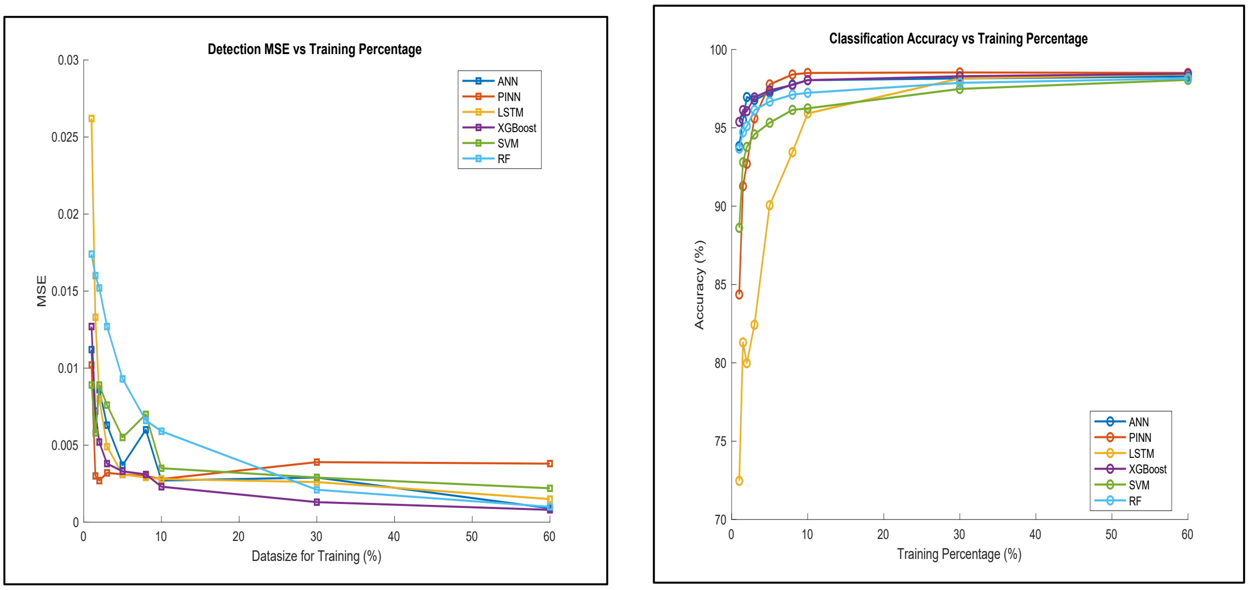

Figure 6. Fault Detection, Classification MSE vs Training Data Size (%)

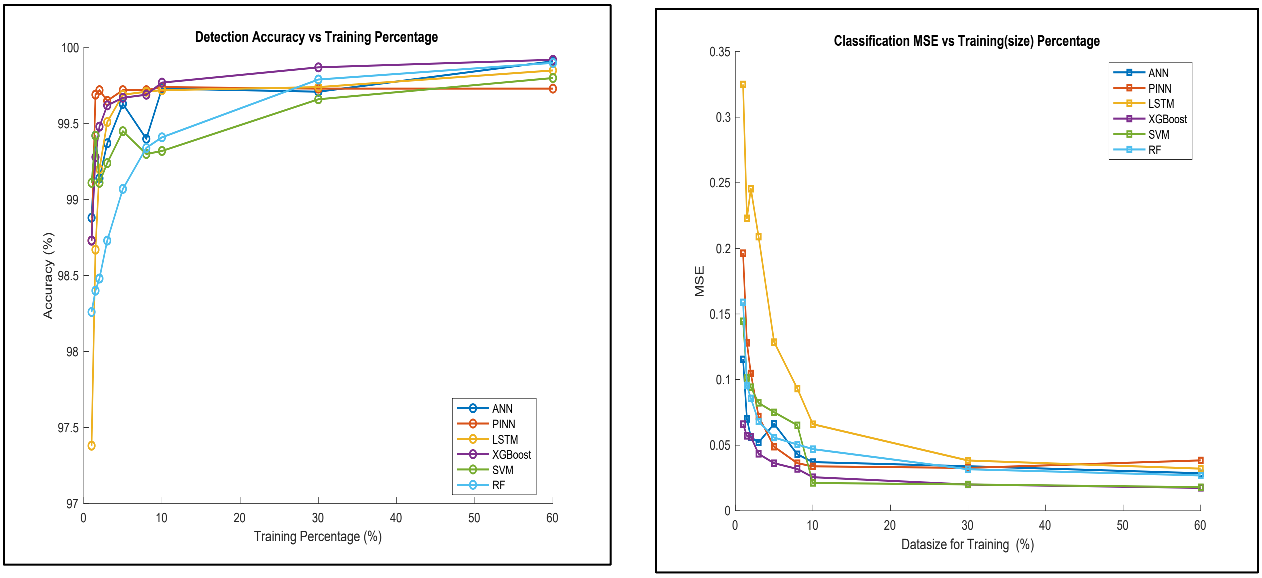

Figure 7. Fault Detection & Classification Accuracy vs Training Data size (%)

PINN and XGBoost demonstrated strong generalization even with less than 20% training data, while SVM and Random Forest required larger datasets to stabilize. The slower stabilization of SVM and RF arises from their reliance on dense data distributions to establish decision boundaries, whereas XGBoost exploits boosting regularization and PINN leverages physics-informed constraints to achieve robust generalization with smaller training sizes. Accuracy curves for classification also exhibited saturation beyond 20% training data in most cases (Figure 7), highlighting the effectiveness of engineered features and learning capacity under constrained data availability.

5.6 Model's Performance with Varying Noise Level

To assess robustness, all models were trained on data with 2-5% noisy data. Figures 8, 9, and 10 show accuracy comparisons across fault detection and classification tasks, highlighting each model's tolerance to noisy training conditions.

The Random Forest and SVM remained highly stable, showing minimal accuracy decay with increasing noise. The ANN and PINN exhibited minor fluctuations but maintained overall reliable performance. Similarly, LSTM and XGBoost maintained stability in detection but experienced moderate fluctuations in classification accuracy.

In addition to accuracy under noise, computational feasibility was verified. ANN and LSTM incur higher training costs but yield millisecond-level inference. RF and XGBoost remain efficient with low memory overhead, while PINN adds physics-loss overhead during training, yet preserves inference latency comparable to ANN. These results confirm practicality for real-time PMU/IED-based deployment.

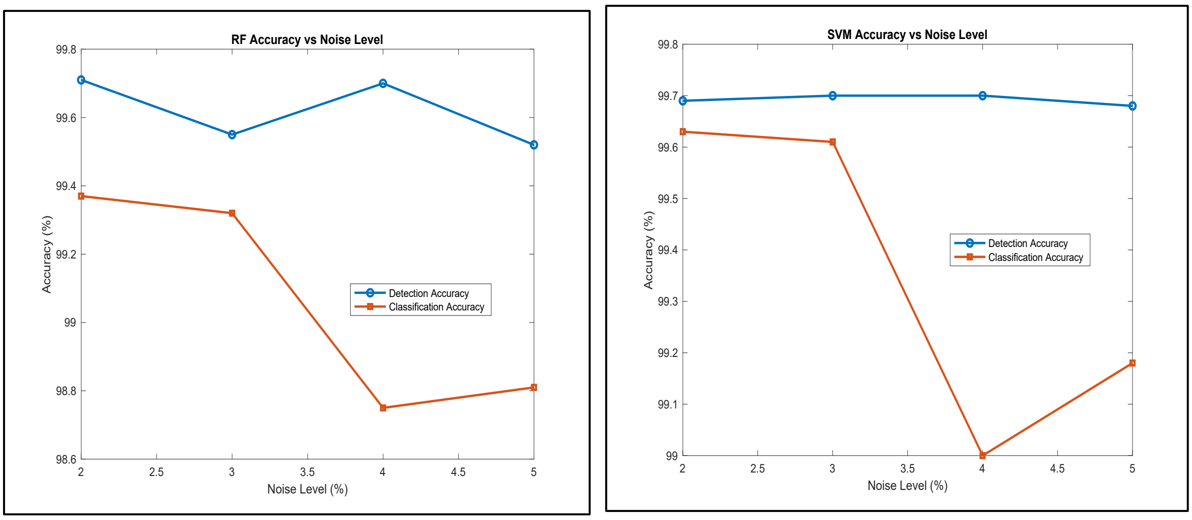

Figure 8. RF and SVM Accuracy Vs Noise Level

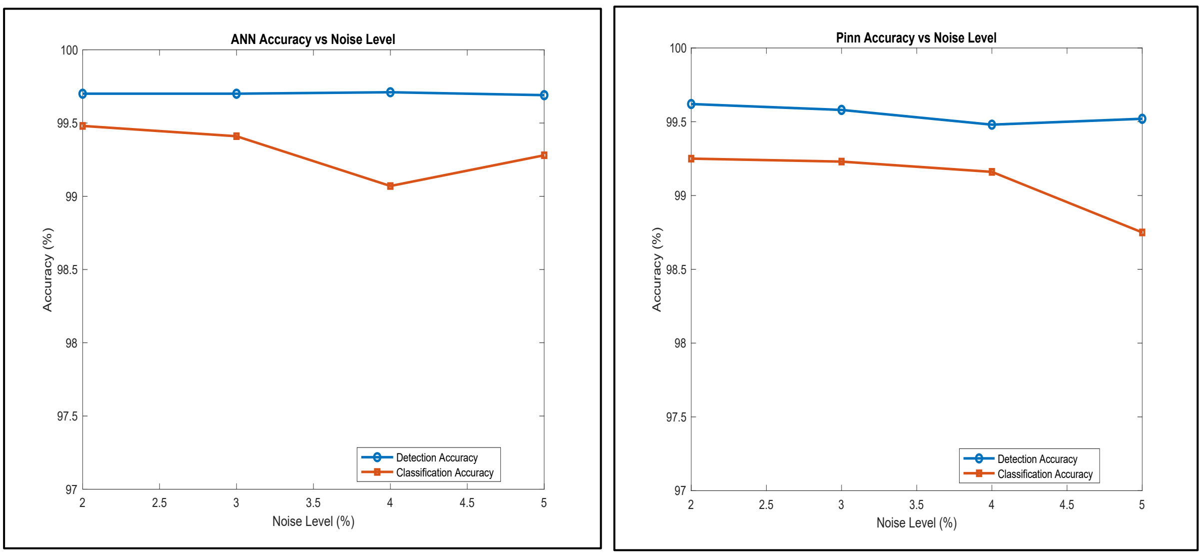

Figure 9. ANN and PINN Accuracy Vs Noise Level

The models consistently achieved high accuracy, with precision, recall, and F1 values exceeding 0.99, and error metrics limited to small ranges (Tables 1–3, Figs. 3–10) that cover clean, reduced-data conditions and various noise levels. All results under multiple metrics and situations provide a strong indication of statistical validation and reproducibility of the reported findings; precise ranges of confidence are not included.

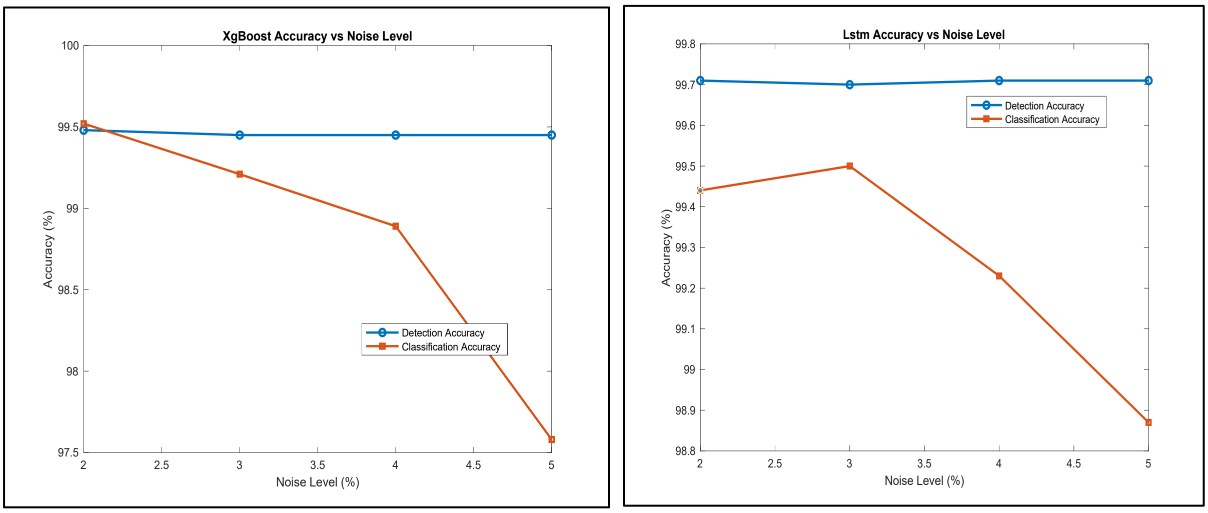

Figure 10. XGBoost and LSTM Accuracy Vs Noise Level

6. Conclusion and Future Scope

This proposed work introduces a supervised learning model for fault detection and classification in a power transmission system. This method is improved with engineered features to train six models: ANN, LSTM, SVM, Random Forest, XGBoost, and a Physics-Informed Neural Network (PINN) using time-domain voltage and current signals from IEEE 13-bus feeder simulations. All the models achieved above 99% accuracy with normal data, but the PINN demonstrated high accuracy in terms of performance with limited data and also with noisy data. The PINN reduces confusion between same types of faults and produces highly stable predictions implemented by Ohm's law combined with loss function. The comparison results also validate that ensemble methods, such as Random Forest, XGBoost, and LSTM, perform well; however, compared to the PINN, they require improved generalizability and interpretability for in-field use in protection relaying. The results show the advantage of embedding domain knowledge within learning models to enable the reliable analysis of faults. In the future, this system aims to extend the PINN architecture by including adaptive balancing of the losses, convolutional or recurrent models and dynamic real models that extend beyond Ohm's Law. This work will evaluate the scheme on a realistic PMU dataset, leveraging transfer learning to reduce latency and handle missing values. It will explore edge implementing techniques with compression and reduction. Explainable AI is used to allow rapid executable performance in real smart grid situations.

References

[1] “Distance Relaying Fundamentals | What Is Apparent Impedance? – PAC Basics.” n.d. Accessed April 7, 2025. https://pacbasics.org/distance-relaying-apparent-impedance/.

[2] Anwar, Tahir, Chaoxu Mu, Muhammad Zain Yousaf, Wajid Khan, Saqib Khalid, Ahmad O. Hourani, and Ievgen Zaitsev. "Robust fault detection and classification in power transmission lines via ensemble machine learning models." Scientific Reports 15, no. 1 (2025): 2549.

[3] Porawagamage, Gayashan, Kalana Dharmapala, J. Sebastian Chaves, Daniel Villegas, and Athula Rajapakse. "A review of machine learning applications in power system protection and emergency control: opportunities, challenges, and future directions." Frontiers in Smart Grids 3 (2024): 1371153.

[4] Chen, Kunjin, Caowei Huang, and Jinliang He. "Fault detection, classification and location for transmission lines and distribution systems: a review on the methods." High voltage 1, no. 1 (2016): 25-33.

[5] Ravesh, Narges Rezaee, Nabiollah Ramezani, Iraj Ahmadi, and Hassan Nouri. "A hybrid artificial neural network and wavelet packet transform approach for fault location in hybrid transmission lines." Electric Power Systems Research 204 (2022): 107721.

[6] Sen, Varsha, and Biswash Basnet. "Neural Network-Based Detection and Multi-Class Classification of FDI Attacks in Smart Grid Home Energy Systems." arXiv preprint arXiv:2508.10035 (2025).

[7] Mahanty, R. N., and P. B. Dutta Gupta. "Comparison of fault classification methods based on wavelet analysis and ANN." Electric Power Components and Systems 34, no. 1 (2006): 47-60.

[8] Bhattacharya, Debshree, and Manoj Kumar Nigam. "Energy efficient fault detection and classification using hyperparameter-tuned machine learning classifiers with sensors." Measurement: Sensors 30 (2023): 100908.

[9] Rafy, Md Fazley, Ellis Oti Boateng, Vignesh Venkata Gopala Krishnan, and Anurag K. Srivastava. "Cyber-Resilient IoT-Based Battery Energy Storage Systems in Power Distribution System." IEEE Transactions on Industry Applications (2025).

[10] Zideh, Mehdi Jabbari, and Sarika Khushalani Solanki. "Physics-informed convolutional autoencoder for cyber anomaly detection in power distribution grids." In 2024 IEEE Power & Energy Society General Meeting (PESGM), IEEE, 2024, 1-5.

[11] Dhamala, Bhuban, and Mona Ghassemi. "Unconventional high surge impedance loading (HSIL) lines and transmission expansion planning." In 2023 North American Power Symposium (NAPS), IEEE, 2023, 1-6.

[12] Torkaman, Hooman, Ehsan Zeraatkar, Nasim Deyhimi, Hassan Haes Alhelou, and Pierluigi Siano. "Rearrangement method of reducing fault location error in tied uncompleted parallel lines." IEEE Access 10 (2022): 51862-51872.

[13] Basnet, Biswash, and Varsha Sen. "Networking for Power Grid and Smart Grid Communications: Structures, Security Issues, and Features." rrrj 4, no. 1 (2025): 120-140.

[14] Ogar, V. N., D. N. Abara, and E. J. Akpama. "Symmetrical and unsymmetrical faults analysis: Using Nigeria 330-KV grid as case study." In 2017 IEEE 3rd International Conference on Electro-Technology for National Development (NIGERCON), IEEE, 2017, 1-7.

[15] Ray, Papia, Debani Prasad Mishra, Koushik Dey, and Pratikshya Mishra. "Fault detection and classification of a transmission line using discrete wavelet transform & artificial neural network." In 2017 International Conference on Information Technology (ICIT), IEEE, 2017, 178-183.

[16] Deepika, Dugganapalli, Maridinapalli Madhu Charan, Sri Chakradhar Nossam, and P. V. Manitha. "Advanced Machine Learning Models for Electrical Fault Detection and Classification in Transmission Lines." In 2025 3rd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), IEEE, 2025, 1338-1341.

[17] Alhanaf, Ahmed Sami, Murtaza Farsadi, and Hasan Hüseyin Balik. "Fault detection and classification in ring power system with DG penetration using hybrid CNN-LSTM." Ieee Access 12 (2024): 59953-59975.

[18] Martins, L. Sousa, J. F. Martins, V. Fernao Pires, and C. M. Alegria. "The application of neural networks and Clarke-Concordia transformation in fault location on distribution power systems." In IEEE/PES Transmission and Distribution Conference and Exhibition, vol. 3, IEEE, 2002,2091-2095.