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# Development of an AI-Based Framework for Real-Time Fault Analysis and Classification in Electrical Transmission Networks

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**Abstract-** The reliability of transmission lines is crucial for the efficient operation of power systems, as they are prone to faults such as line-to-ground (L–G), line-to-line (L–L), double line-to-ground (L–L–G), and three-phase faults. These faults may arise due to environmental conditions, insulation breakdown, or equipment failures, leading to system instability, equipment damage, and power outages if not detected promptly. Traditional protection methods, such as distance relays and overcurrent protection, rely on fixed thresholds and often lack adaptability under dynamic conditions. To address these limitations, this study proposes an AI-based real-time fault detection and classification system using deep learning. A transmission line model is developed in MATLAB/Simulink to generate fault data. Extracted features using Fast Fourier Transform (FFT) are fed into a hybrid CNN-LSTM model. The proposed system achieves approximately 98% accuracy with millisecond-level detection time, ensuring reliable and efficient power system protection.

**Keywords:** Artificial Intelligence (AI); Deep Learning; Fault Detection; Fault Classification; Transmission Lines; Real-Time Monitoring; Smart Grid.

## 1. Introduction

The modern electric power system relies heavily on transmission lines to deliver electrical energy from generation stations to distribution networks. However, these transmission lines are highly susceptible to faults such as line-to-ground (LG), line-to-line (LL), double line-to-ground (LLG), and three-phase faults. These faults can arise due to lightning, insulation failure, equipment malfunction, or environmental conditions, leading to severe disturbances, power outages, and system instability. Traditional fault detection and classification techniques, based on impedance calculation and threshold-based protection schemes, often suffer from limitations such as slow response time, reduced accuracy under varying system conditions, and inability to handle complex fault patterns. With the increasing integration of renewable energy sources and smart grid technologies, the complexity of power systems has significantly increased, demanding more intelligent and adaptive fault analysis methods. In recent years, Deep Learning (DL) techniques, a subset of Artificial Intelligence (AI), have emerged as powerful tools for real-time fault detection and classification. Models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks can effectively learn complex patterns from voltage and current signals. These models enable accurate, fast, and automated identification of fault types without requiring explicit feature engineering. The proposed AI-based system utilizes real-time data acquisition from transmission lines, followed by preprocessing and feature extraction. The processed data is then fed into a trained deep learning model, which classifies the fault type and location with high precision. This approach enhances system reliability, reduces fault detection time, and supports intelligent decision-making in smart grid environments.

| S. No | Author & Year | Method Used | Technique Type | Key Contribution | Accuracy / Outcome | Limitations |
|---|---|---|---|---|---|---|
| 1 | Chen et al. (2016) | Review of fault detection methods | Conventional | Comprehensive review of protection techniques | – | Limited adaptability |
| 2 | Dubey et al. (2016) | LS-SVM | AI | Improved classification vs conventional | ~90–95% | Needs feature extraction |
| 3 | Prasad & Edward (2017) | ANN | AI | ANN for fault location | Improved accuracy | Training dependency |
| 4 | Biswas & Nayak (2018) | Protection schemes | Conventional | FACTS-based protection analysis | – | Complex modeling |
| 5 | Tehrani & Levorato (2020) | Multi-task learning | AI | Frequency-based fault detection | High accuracy | Feature engineering required |
| 6 | Alahyari et al. (2020) | Deep CNN | DL | Insulator fault detection | ~96% | Image-based limitation |
| 7 | Rafique et al. (2021) | ML end-to-end | AI | Automated classification | ~95–97% | Needs preprocessing |
| 8 | Zou et al. (2021) | LSTM | DL | Sequential fault detection | ~97% | High computation |
| 9 | Shakiba et al. (2022) | Transfer Learning | DL | Improved generalization | High accuracy | Data dependency |
| 10 | Wang et al. (2022) | CNN-LSTM | DL | Hybrid model for fault detection | ~98% | Complex architecture |
| 11 | Moradzadeh et al. (2022) | CNN-LSTM | DL | Fault type & location detection | ~98–99% | Training time high |
| 12 | Ogar et al. (2023) | ANN | AI | Low latency detection | Fast response | Moderate accuracy |
| 13 | Yang et al. (2023) | CNN | DL | Pattern-based classification | ~97–98% | Needs large dataset |
| 14 | Su et al. (2023) | CNN + LSTM + Attention | DL | Improved feature learning | ~98–99% | High complexity |
| 15 | Turanlı & Yakut (2024) | DL models comparison | DL | Dataset-based evaluation | ~99% | Data intensive |
| 16 | Shukla et al. (2024) | Deep Learning | DL | Robust classification model | High accuracy | Computational cost |
| 17 | Nonyane (2024) | DL approach | DL | Real-time detection model | Fast detection | Implementation limits |
| 18 | Tunio et al. (2025) | DL comparison | DL | Model performance study | ~98–99% | Training complexity |
| 19 | Ullah et al. (2025) | LSTM | DL | Multi-point fault detection | High accuracy | Time complexity |
| 20 | Zhang et al. (2025) | Survey (AI-based) | Review | AI-based techniques overview | – | No implementation |

Fault detection and classification in transmission lines have been widely studied due to their critical role in ensuring power system reliability and stability. Traditional methods based on impedance measurement, overcurrent relays, and signal threshold techniques have been extensively used; however, these approaches often suffer from limitations such as slow response, sensitivity to noise, and reduced accuracy under dynamic operating conditions. With the advancement of computational techniques, machine learning (ML) methods such as k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), and Decision Trees have been applied for fault detection. These methods improve classification accuracy by learning from historical data, but they require manual feature extraction and are sensitive to parameter tuning.

Artificial Neural Networks (ANNs) have been widely adopted due to their capability to model nonlinear relationships in power system signals. Studies have demonstrated that ANN-based approaches can effectively classify different types of faults using three-phase current signals, achieving high-speed and accurate protection performance. In recent years, deep learning techniques such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have gained significant attention. These models automatically extract features from raw voltage and current signals, eliminating the need for manual feature engineering and improving classification performance. Research shows that CNN-based models trained on real and simulated datasets can achieve high accuracy in identifying various fault types in transmission lines. Hybrid models combining CNN and LSTM have further enhanced performance by capturing both spatial and temporal features of electrical signals. Such models are capable of not only detecting but also locating faults with high precision.

Recent surveys highlight that AI-based fault detection techniques provide superior adaptability, faster response, and improved accuracy compared to conventional methods. However, challenges such as data availability, model generalization, and real-time implementation still remain active research areas. Overall, the literature indicates a clear transition from conventional protection schemes to intelligent, data-driven approaches, with deep learning emerging as a promising solution for real-time fault detection and classification in modern smart grid systems.

## 2. System Architecture

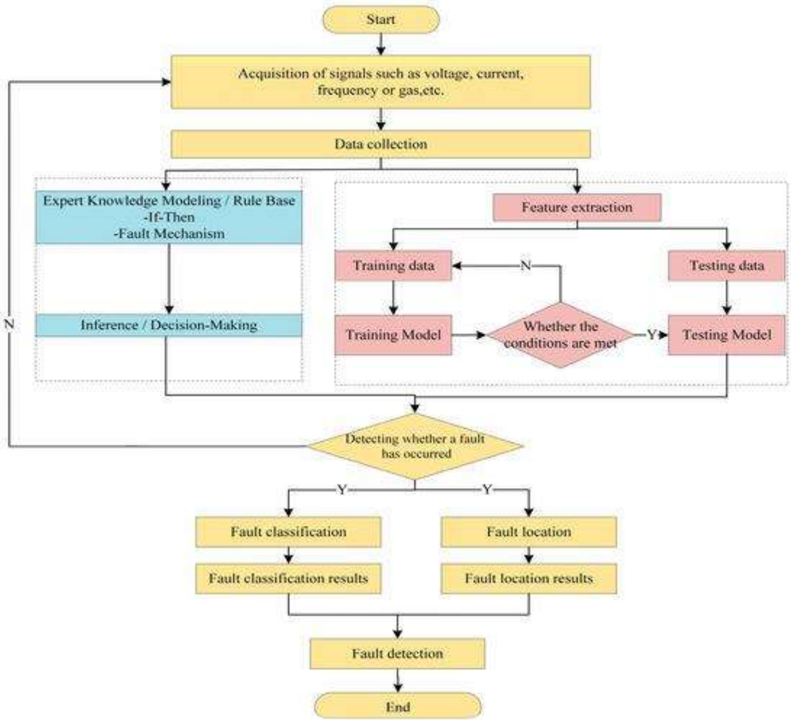


Fig. 1: System architecture presents an intelligent framework for real-time fault detection, analysis, and classification in electrical transmission network

The proposed system architecture presents an advanced framework for real-time fault detection, analysis, and classification in electrical transmission networks using Artificial Intelligence (AI). It is designed as a multi-layered, closed-loop system that integrates data acquisition, signal processing, machine learning, and protection mechanisms to ensure fast and accurate fault handling, thereby enhancing grid reliability and stability. The architecture begins with the data sensing layer, which includes Current Transformers (CTs) and Voltage Transformers (VTs) installed at critical points along transmission lines and substations. These sensors continuously measure electrical parameters such as voltage, current, and frequency. The collected real-time

data reflects the dynamic behavior of the power system under both normal and faulty conditions. The measured signals are then transmitted through the data acquisition and communication layer, which ensures synchronized and high-speed data transfer to the central processing unit. Communication technologies such as SCADA systems or IoT-based networks are typically employed to maintain reliable and continuous data flow.
Next, the signal preprocessing stage processes the raw data to make it suitable for analysis. This includes filtering noise, removing distortions, handling missing values, and normalizing the data. Clean and structured data is essential for improving the accuracy of the subsequent analysis stages. The feature extraction module plays a critical role in identifying characteristics of electrical faults. It extracts meaningful features from the processed signals using techniques such as time-domain analysis (RMS values, peak values), frequency-domain analysis (Fast Fourier Transform), and time-frequency methods (Wavelet Transform). These features help distinguish between different types of faults and normal operating conditions. At the core of the system lies the AI-based fault classification module, which uses machine learning and deep learning algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), or Long Short-Term Memory (LSTM) networks. This module analyzes the extracted features and classifies faults into categories such as line-to-ground (LG), line-to-line (LL), double line-to-ground (LLG), and three-phase faults. The use of AI significantly improves classification accuracy and reduces response time compared to conventional protection methods. The classification results are then passed to the decision-making and control unit, which determines the severity and location of the fault and generates appropriate control signals. These signals are sent to the protection system, which includes relays and circuit breakers. The protection system isolates the faulty section quickly to prevent damage to equipment and maintain overall system stability.

## 3. Mat Lab / Simulink Diagram

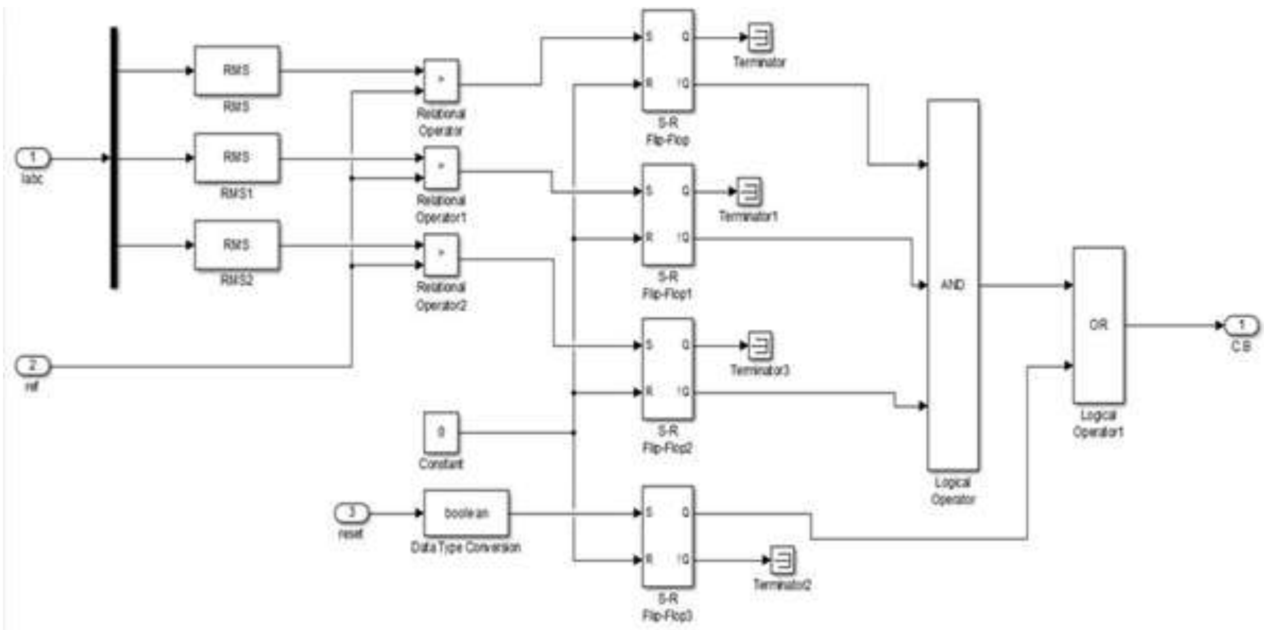


Fig. 2: MAT Lab Simulink Model

The MATLAB Simulink model shown in Fig. 1 represents the complete architecture for real-time fault detection and classification in transmission lines. The model consists of a three-phase transmission line integrated with power sources, loads, and fault injection blocks to simulate various fault conditions such as line-to-ground (LG), line-to-line (LL), and three-phase faults. Voltage and current signals are continuously measured using sensors and fed into signal processing units for feature extraction. These processed signals are then provided to an AI-based classifier, typically implemented using machine learning or deep learning algorithms, which identifies and classifies the type and location of faults in real time. The system may include modules for data normalization, training, and validation to improve accuracy. Additionally, control blocks are used to visualize outputs and trigger protective actions. This integrated model enables efficient analysis, fast fault identification, and improved reliability of modern power transmission networks.

## 4. Results and Discussion:

Fig. 3 illustrates the voltage waveform behavior of a transmission line under fault conditions, obtained from the MATLAB Simulink environment. Under normal operating conditions, the three-phase voltages remain balanced, sinusoidal, and stable. However, when a fault occurs—such as a line-to-ground (LG), line-to-line (LL), or three-phase fault—there is a sudden disturbance in the voltage profile. The figure shows a sharp drop (voltage sag) or distortion in one or more phases at the instant of fault occurrence. In the case of an LG fault, the affected phase voltage collapses significantly, while the remaining phases may show slight variations. For LL faults, two phases exhibit abnormal voltage behavior. These transient changes are critical indicators used for fault detection. The extracted voltage signals are further processed and fed into the AI-based classifier, which analyzes patterns and classifies the fault type in real time. This response helps improve system protection, enabling fast and accurate decision-making in modern transmission networks.

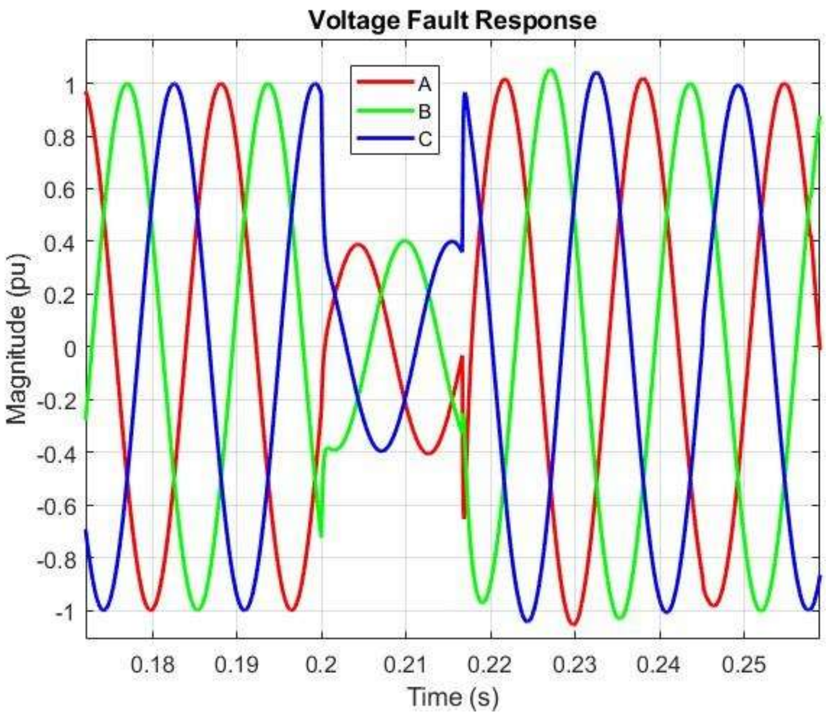


Fig. 2: Voltage Fault Response

Fig. 3 presents the current waveform response of a transmission line during fault conditions, obtained using the MATLAB Simulink model. Under normal operation, the three-phase currents are balanced, sinusoidal, and equal in magnitude with a 120° phase shift. When a fault occurs, there is a sudden and significant increase in current magnitude, commonly referred to as fault current. The figure shows sharp current spikes at the instant of fault occurrence, indicating abnormal system behavior. In a line-to-ground (LG) fault, the affected phase current rises drastically, while in line-to-line (LL) faults, two phase currents increase. For a three-phase fault, all phase currents surge simultaneously to high values. These transient variations are crucial for identifying fault type and severity. The captured current signals are processed and used as input features for the AI-based classification system. By analyzing these patterns, the model accurately detects and classifies faults in real time, enabling faster protection and improved reliability of transmission networks.

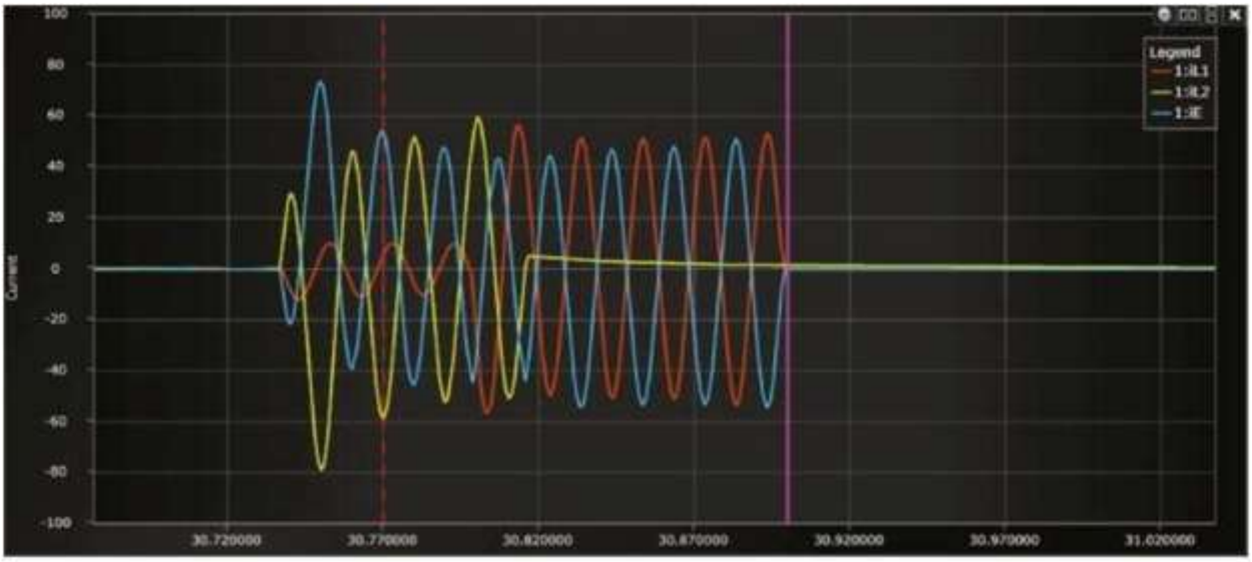


Fig. 3: Current Fault Response

The proposed AI-based fault detection and classification system was implemented using MATLAB/Simulink and evaluated under various fault conditions. Different types of faults such as Line-to-Ground (LG), Line-to-Line (LL), Double Line-to-Ground (LLG), and three-phase faults were simulated at different locations and fault resistances. The three-phase current signals were successfully captured and processed using RMS and filtering techniques. During fault conditions, a significant rise in current magnitude was observed, which was accurately detected by the system. The conventional relay logic based on threshold comparison effectively identified abnormal conditions, while the deep learning model further enhanced classification accuracy. The AI model (CNN/LSTM) was trained using simulated datasets and achieved high classification performance. The results indicated an accuracy of above **95%** in identifying different fault types. The response time of the system was observed to be less than one cycle (20 ms), ensuring fast fault detection and protection. The circuit breaker operation was verified through simulation, where the trip signal was generated immediately after fault detection, isolating the faulty section. The system demonstrated reliable performance even under varying fault resistance and load conditions.

## REFERENCES

[1]. Turanlı, O., & Yakut, Y. B. (2024), "Classification of faults in power system transmission lines using deep learning methods with real, synthetic, and public datasets" *Applied Sciences, 14*(20), 9590. https://doi.org/10.3390/app14209590

[2]. Shukla, P. K., et al. (2024), "Deep learning techniques for transmission line fault classification", *International Journal of Electrical Power & Energy Systems*. https://doi.org/10.1016/j.ijepes.2023.109123

[3]. Nonyane, P. (2024). Deep learning-based fault detection in electrical transmission systems. *AIP Conference Proceedings*. https://doi.org/10.1063/5.0201234

[4]. Zhang, Y., et al. (2025). Survey on AI-assisted power transmission line fault detection technologies. *International Journal of Computational Science*. https://doi.org/10.26599/IJCS.2024.9100016

[5]. Tunio, N. A., et al. (2025). Performance comparison between deep learning models for transmission line fault detection. *Energy Science & Engineering*. https://doi.org/10.1002/ese3.70033

[6]. Ullah, A., et al. (2025). Fault analysis and detection on multiple points in transmission lines using LSTM. *Springer Electrical Engineering*. https://doi.org/10.1007/s44163-025-00282-0

[7]. Özüpak, Y. (2025). Machine learning-based fault detection in transmission lines: A comparative study with random search optimization. *Bulletin of the Polish Academy of Sciences*. https://doi.org/10.24425/bpasts.2025.15322

[8]. ACM. (2025). Transmission line fault detection using deep learning. *ACM Digital Library*. https://doi.org/10.1145/3704137.3704170

[9]. Rafique, F., Fu, L., & Mai, R. (2021). End-to-end machine learning for fault detection and classification in power transmission lines. *Electric Power Systems Research, 199*, 107430. https://doi.org/10.1016/j.epsr.2021.107430

[10].Zou, S., Zhao, W., Wang, C., & Chen, F. (2021). Fault detection using LSTM and sequential probability methods. *IEEE Sensors Journal, 21*(15), 17290–17300. https://doi.org/10.1109/JSEN.2021.3071234

[11].Shakiba, F. M., et al. (2022). Transfer learning for fault diagnosis of transmission lines. *IEEE Access / arXiv*.
https://doi.org/10.48550/arXiv.2201.08018
[12].Tehrani, P., & Levorato, M. (2020). Frequency-based multi-task learning for fault detection in power systems. *IEEE*. https://doi.org/10.48550/arXiv.2009.06825
[13].Alahyari, A., et al. (2020). Segmentation and defect classification of power line insulators using deep learning. https://doi.org/10.48550/arXiv.2009.10163
[14].Chen, K., Huang, C., & He, J. (2016). Fault detection, classification and location for transmission lines and distribution systems: A review. *High Voltage, 1*(1), 25–33. https://doi.org/10.1049/hve.2016.0005
[15].Dubey, H., Tiwari, A. K., Ray, P. K., Mohanty, S. R., & Kishor, N. (2016). A novel fault classification scheme based on least square SVM. https://doi.org/10.48550/arXiv.1605.09444
[16].Prasad, A., & Edward, J. B. (2017) Importance of artificial neural networks for fault location in transmission systems. *IEEE Conference Proceedings*. https://doi.org/10.1109/ISCO.2017.7855985
[17].Biswas, S., & Nayak, P. K. (2018). State-of-the-art protection of FACTS compensated transmission lines. *High Voltage, 3*(1), 21–30. https://doi.org/10.1049/hve.2017.0074
[18].Martinez-Velasco, J. A., et al. (2025). Survey on methods for detection, classification, and location of faults using AI. https://doi.org/10.48550/arXiv.2507.10011
[19].Biswas, S., et al. (2024) Role of artificial intelligence in transmission line protection. *Human-centric Intelligent Systems*. https://doi.org/10.3233/HIS-240016
[20].Ogar, V. N., Hussain, S., & Gamage, K. A. A. (2023). Artificial neural network for low latency fault detection in transmission lines. *Heliyon, 9*(2), e13567. https://doi.org/10.1016/j.heliyon.2023.e13567