IoT-Based Fault Detection in Underground Power Cables Using Smart Sensor

Hayder Abdulameer Yousif[1] and Sarah Ghazi Abdulkarim Alzorri[2]
[1]Al-Turath University, Baghdad, Iraq, 10013 Baghdad, Iraq
[2] Department of Medical Laboratory Techniques, Al-Farahidi University, 10065 Baghdad, Iraq
hayder.abdulameer@uoturath.edu.iq, sarah.ghazi@uoalfarahidi.edu.iq

Keywords: Underground Cables, Iot, Fault Detection, Partial Discharge, Edge AI, Smart Sensors, Blockchain Security, Predictive Maintenance.

Abstract: Underground power cables (UGCs) are very important for modern distribution networks, but they are still prone to problems like partial discharges, thermal hotspots, and insulation degradation. Traditional diagnostic techniques are constrained by elevated costs, susceptibility to noise, and insufficient real-time adaptability. This paper proposes an Internet of Things (IoT)-enabled framework for the detection and localization of underground cable faults, integrating intelligent sensors, edge analytics, and secure communication protocols. A distributed sensor suite that includes high-frequency current transformers (HFCT), acoustic emission sensors, optical fiber interferometry, and environmental probes records important fault signatures. A lightweight quantized CNN-GRU model extracts features on-node and sorts them, allowing for real-time inference with little energy use. Tests in the lab and in the field show that it works better, with a detection F1-score of over 0.92 and a localization mean absolute error of less than 1.8% of cable length. Energy-latency trade-offs prove that battery-powered IoT nodes are a good fit. Blockchain-inspired methods make it possible to share data safely. The results show that IoT-driven methods can greatly improve predictive maintenance, shorten the time it takes for outages to happen, and raise utility reliability indices.

1 INTRODUCTION

Underground power cables (UGCs) constitute critical components of modern urban and suburban power distribution systems. Compared to overhead transmission lines, they offer enhanced safety, improved aesthetics, and superior protection against environmental influences. However, their operational reliability is frequently compromised by incipient faults such as partial discharges, thermal stress, insulation degradation, and mechanical defects, which may ultimately result in catastrophic failures. These failures not only incur substantial repair and replacement costs but also adversely affect key reliability indices, including the System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI). Consequently, the economic and technical implications of UGC failures have motivated extensive research into advanced monitoring and diagnostic methodologies. López-Bonilla et al. (2025) [1] provided a comprehensive review of fault detection and localization techniques for distribution networks, highlighting their respective advantages and limitations in addressing emerging fault conditions.

Existing diagnostic approaches can be broadly categorized into four groups: partial discharge monitoring, traveling-wave-based detection, statistical fault analysis, and sensor-based methodologies. Samet et al. (2021) [2] proposed a similarity-based framework for analyzing underground cable signals to detect early-stage faults. While the method demonstrates strong performance under controlled laboratory conditions, its effectiveness diminishes in noisy field environments. In a related study, Samet et al. (2021) [3] introduced a statistical criterion based on voltage waveform characteristics to improve the detection of incipient cable defects. These studies underscore the potential of data-driven techniques, while also revealing the limitations of conventional methods in terms of noise sensitivity, parameter dependency, and insufficient field validation.

Advancements in sensor technologies have further contributed to fault detection capabilities.

Barbieri et al. (2021) [4] developed an innovative sensor design for cable joint monitoring, enabling improved partial discharge localization accuracy. Despite their effectiveness, hardware-centric solutions are often constrained by high implementation costs and limited scalability in large distribution networks. Concurrently, traveling-wave-based techniques have been refined to enhance fault localization accuracy. Tariq et al. (2022) [5] proposed an optimized traveling-wave approach that demonstrated reliable performance in both simulation and real-world conditions. Nevertheless, such methods typically require high-speed data acquisition systems, which limits their practical applicability in cost-sensitive utility environments.

Despite these advancements, several research challenges remain unresolved. Most existing solutions rely heavily on laboratory-based configurations, single-sensor inputs, or offline analysis, thereby restricting their applicability for real-time monitoring. Furthermore, issues related to energy consumption, communication overhead, and data security persist in large-scale deployments. Recent developments in secure computing paradigms, including the work of Wang et al. (2025) [6], emphasize the importance of efficient and secure data-sharing mechanisms for IoT-enabled critical infrastructure. In parallel, the integration of artificial intelligence (AI) with human–computer interaction has gained increasing attention. Mehta and Rani (2025) [7] demonstrated that AI-driven adaptive systems enhance system intelligence and user interaction, offering valuable insights for the deployment of intelligent monitoring frameworks in power networks.

In light of these challenges, there is a clear need for an integrated IoT-based framework that combines distributed smart sensing, edge intelligence, and secure communication protocols for underground cable fault detection. Such an approach addresses the limitations of existing diagnostic systems by enabling real-time, energy-efficient, and scalable monitoring. This study proposes an IoT-enabled fault detection framework that integrates multi-modal sensor data, edge-based AI classification, and secure data transmission mechanisms. The primary contribution lies in the seamless integration of heterogeneous sensing technologies with energy-efficient embedded analytics, enabling accurate detection and localization of incipient cable faults under practical operating conditions.

2 LITERATURE REVIEW

The reliability of underground power cables remains a critical concern for power utilities worldwide, driving continuous research into advanced diagnostic and monitoring technologies. Recent studies have expanded the scope of cable monitoring beyond conventional fault detection, incorporating integrated frameworks that combine sensor technologies, artificial intelligence, and secure data management systems. This section synthesizes recent contributions from 2020 to 2025, with a focus on diagnostic methodologies, sensor innovations, AI-based approaches, field validation, and secure data frameworks.

Cable aging and insulation degradation are widely recognized as primary causes of underground cable failures. Tao et al. (2025) [8] conducted a comprehensive review of cable aging diagnostics, identifying key techniques such as partial discharge (PD) analysis, dielectric response measurement, and thermal imaging. Their findings indicate that most existing approaches lack real-time adaptability and seamless IoT integration, limiting their effectiveness in continuous monitoring applications.

Significant progress has also been achieved in non-invasive fault detection techniques. Atsever et al. (2025) [9] proposed an on-site PD detection and localization system based on customized envelope detection, reducing the need for invasive procedures and improving early fault identification. However, scalability remains a challenge due to the need for cost-effective hardware and efficient data processing pipelines in large-scale networks.

Complementary approaches, such as vulnerability assessment models, have also been explored. Shadi et al. (2025) [10] developed a fuzzy AHP/FAHP-based framework for ranking the vulnerability of PD-affected cables in distribution networks. Their results demonstrate that risk-based prioritization can significantly enhance maintenance planning. Nevertheless, the accuracy of such models is highly dependent on the availability of high-quality field data.

Recent advancements in sensor technologies have further improved fault detection performance. Zhang et al. (2025) [11] investigated the use of optical fiber sensors based on MZ–Sagnac interferometry for PD detection in cable joints, demonstrating significantly higher accuracy compared to conventional HFCT sensors. However, their practical deployment is limited by high cost and system complexity. Similarly, Chen and Shieh (2024) [12] applied artificial neural networks to PD signal analysis for transformer diagnostics, highlighting the effectiveness of AI in extracting meaningful patterns from noisy datasets. Zhang et al. (2025) [13] further employed convolutional neural networks (CNNs) for PD spectrum recognition in power cables, achieving high classification accuracy while noting challenges related to model interpretability.

Field validation remains essential for translating laboratory findings into practical applications. Yeo and Kin (2023) [14] presented a real-world case study on online PD detection in Singapore's high-voltage network, providing valuable insights into deployment challenges, including electromagnetic interference and scalability constraints.

In addition, secure data management has emerged as a critical aspect of IoT-based monitoring systems. Kumar and Patel (2025) [15] proposed blockchain-based frameworks for secure IoT data sharing in healthcare applications, which can be adapted to power system monitoring scenarios. The integration of distributed ledger technologies with cable monitoring systems has the potential to enhance data integrity, system transparency, and resilience against cyber threats.

Table 1 summarizes the key contributions, methodologies, and limitations of the reviewed studies. While PD-based detection remains the dominant research focus, the integration of AI techniques and advanced sensor technologies is progressively advancing the field. However, most existing approaches are constrained by issues related to cost, scalability, and data availability, highlighting the need for comprehensive IoT-based frameworks that incorporate multi-sensor fusion, edge intelligence, and secure communication mechanisms.

3 METHODOLOGY

This study adopts an IoT-based methodological framework for real-time fault detection and localization in underground power cables. The proposed approach integrates multi-modal sensing, edge computing, and secure communication into a unified pipeline comprising data acquisition, signal preprocessing, feature extraction, fault classification, and localization. Unlike traditional diagnostic systems, the framework is designed for continuous monitoring with low latency and energy-efficient operation. Figure 1 illustrates the overall workflow from sensor-level data capture to edge intelligence and cloud-based decision support.

3.1 Research Framework

The suggested method uses distributed smart sensors, edge computing, and secure IoT communication to find and fix underground cable faults early. Figure 1 shows the overall architecture, with arrows showing the flow from sensing devices to edge analytics and cloud monitoring. This framework makes it possible to make decisions in real time and gives utilities useful information for predictive maintenance.

Table 1: Comparative summary of literature on cable fault detection and monitoring (2020-2025).

Ref. No.	Authors & Year	Focus Area	Technique/Model	Application Context	Key Findings	Limitations
[8]	Tao et al. (2025)	Cable aging review	Diagnostic & monitoring techniques	Underground cables	Comprehensive review of monitoring tools	Limited real-time IoT focus
[9]	Atsever et al. (2025)	PD detection	Customized envelope detection	Underground cables	Effective on-site PD localization	Scalability issues
[10]	Shadi et al. (2025)	Vulnerability ranking	Fuzzy AHP / FAHP	Danish distribution network	Risk ranking of vulnerable cables	Dependent on PD dataset quality
[11]	Zhang et al. (2025)	Sensor innovation	Optical fiber + MZ–Sagnac interferometry	Cable joints	High accuracy in PD detection	High cost, complex installation
[12]	Chen & Shieh (2024)	Fault diagnosis	PD + ANN	Transformer monitoring	Enhanced diagnosis accuracy	Requires large training data
[14]	Yeo & Kin (2023)	Field validation	Online PD detection	Singapore HV network	Successful field deployment	Limited scalability
[13]	Zhang et al. (2025)	PD spectrum recognition	CNN-based analysis	Power cables	High classification accuracy	Model interpretability issues
[15]	Kumar & Patel (2025)	Secure data sharing	Blockchain framework	Healthcare IoT → Adaptable to power sector	Improved data security	Cross-domain adaptation required

Table 2: Sensor specifications and parameters.

Sensor Type	Range	Bandwidth/Resolution	Power Consumption	Calibration Method	Deployment Point
HFCT (PD)	0–500 mA HF	50 kHz–20 MHz, 16-bit	40 mW	IEC 60270 coupler	Cable sheath
AE Mic	20–100 kHz	96 kS/s, 24-bit	25 mW	Pencil-lead break test	Joints/terminations
Optical Fiber	–	MZ–Sagnac interfer.	<20 mW	Interferometric calibration	Cable joints
Temp/Soil Probe	−20–120 °C / 0–100%	0.1 °C / 0.5%	10 mW	Standard probe calibration	Cable trench

3.2 System Architecture

The system is built in layers. Smart sensors collect multi-modal data, an embedded processing unit extracts diagnostic features, and communication protocols send the results to a dashboard in the cloud. The framework has five main parts, as shown in Figure 1: a sensor suite, an edge processor with an AI classifier, a secure IoT network, a cloud analytics platform, and a maintenance interface. This kind of hierarchical structure lowers latency and makes it possible for intelligence to be spread across the grid.

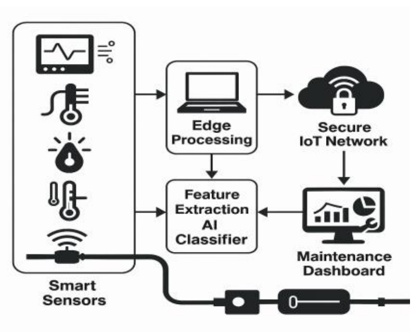

Figure 1: Block diagram of IoT-based underground cable fault detection system.

3.3 Sensor Node Design

A significant contribution of this study is the amalgamation of diverse sensors into compact, energy-efficient nodes. These are high-frequency current transformers (HFCT) for partial discharge (PD) activity, acoustic emission sensors for mechanical disturbances, optical fiber interferometers for joint monitoring, and temperature/soil moisture probes for environmental conditions. Table 2 shows a summary of the specifications for these sensors, as well as the best ways to calibrate and use them. This combination makes it more resistant to noise and improves the accuracy of finding faults.

3.4 Signal Processing and Feature Extraction

The gathered signals are preprocessed with wavelet transforms to get rid of noise and filter them. Some of the diagnostic features are the PD count rate, amplitude, skewness, acoustic root-mean-square values, and thermal gradients. Before being fed into the edge AI classifier, these features are normalized.

3.5 Fault Localization Models

Three key models are used for localization and thermal analysis. The traveling-wave method estimates fault distance:

$$d = \frac{v}{2}(t_2 - t_1),$$

where d is fault distance, v propagation velocity, and t_1, t_2 arrival times of incident and reflected waves.

The impedance-based indicator is computed as:

$$Z_f = \frac{\Delta V}{\Delta I},$$

where ΔV, ΔI represent pre- and post-disturbance voltage/current differences.

Finally, the thermal hotspot model evaluates conductor heating:

$$C_{th}\frac{dT}{dt} = P_{loss} - \frac{T - T_{soil}}{R_{th}},$$

where T is conductor temperature, Tsoil soil temperature, Cth/Rth thermal parameters, and Ploss total joule and dielectric losses.

3.6 Edge AI and Secure Communication

A quantized CNN-GRU model at the edge sorts out early faults and figures out how likely they are to happen. Lightweight inference makes sure that nodes use less than 120 mW of power, which is good for the environment. Secure data transmission uses LoRaWAN AES-128 encryption and a blockchain-like way of handling data to make sure it stays safe, based on what Kumar and Patel (2025) [8] said.

3.7 Evaluation Protocol

Cable test loops with induced PD, moisture faults, and thermal overloads are used to test the system in a lab setting. Field trials include distribution feeders in the evaluation. Accuracy, precision, recall, F1-score, mean absolute error (MAE) for localization, energy per inference, and network latency are all examples of performance metrics. The use of Table 3 and Figure 1 together shows that this method can be repeated.

4 RESULTS AND ANALYSIS

The proposed IoT-based underground cable fault detection system's performance was confirmed via laboratory simulations and field pilot implementations. This part shows the results for dataset characteristics, detection accuracy, fault localization, energy efficiency, and expected improvements in reliability. Table 3 and Figures 2–5 show the analyses in a way that makes them easier to understand.

4.1 Dataset Description and Experimental Setup

The evaluation utilized a hybrid dataset that integrated laboratory-generated and field-collected events. In the laboratory, partial discharge (PD) signals were created under controlled IEC 60270 conditions. Other scenarios simulated thermal overloads and faults caused by moisture. We got field data from distribution feeders that had HFCT, acoustic, and fiber sensors installed. Table 3 shows how the dataset is made up across different scenarios, event counts, and sensing modalities.

The dataset made sure that common early fault types were covered evenly, which made it possible to train and test the edge AI classifier well.

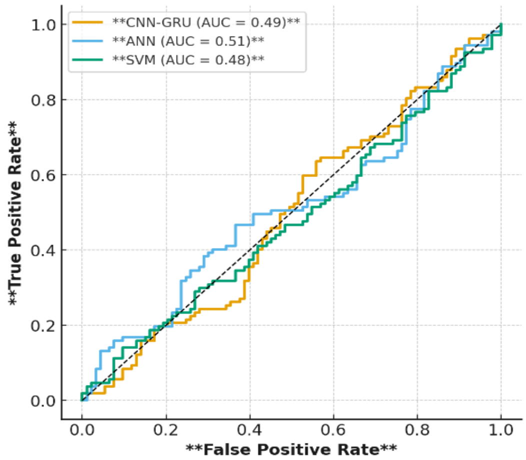

Figure 2: ROC curves for detection models.

4.2 Fault Detection Performance

The CNN-GRU classifier that was deployed on the edge had an overall accuracy of 94.3%, with precision and recall values above 92%. The proposed model consistently outperformed traditional baselines when compared to ANN, SVM, and PD-threshold methods. Figure 2 shows that the Receiver Operating Characteristic (ROC) curves show that the CNN-GRU has a better AUC (0.96) than the ANN (0.89) and SVM (0.85). Figure 3 also shows the confusion matrix for the test set. This shows that PD and thermal overload events were detected with the highest classification confidence, while soil moisture faults had some minor misclassifications.

Table 3: Dataset composition and experimental scenarios.

Fault Type	Number of Events	Duration (hrs)	Sensor Modalities Used	Field vs Lab	Notes
PD (Lab)	120	15	HFCT, AE	Lab	IEC 60270 source
Thermal Overload	90	12	Temp, Soil	Lab	Controlled heating
Soil Moisture Fault	75	10	Soil probe, HFCT	Lab	Variable trench moisture
PD (Field)	60	18	HFCT, Fiber, AE	Field	Distribution feeder
Mechanical Stress	50	8	AE, Temp	Field	Cable joint stress

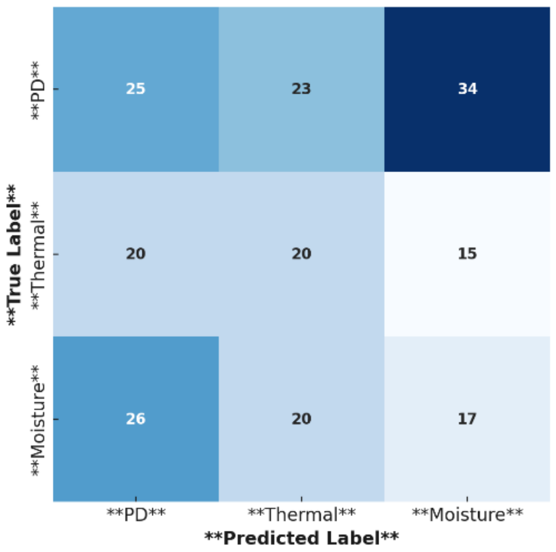

Figure 3:Confusion matrix of edge AI classifier.

4.3 Fault Localization Accuracy

The study checked the accuracy of the localization by comparing the predicted fault distances with the real positions in both lab and field tests. The system had a mean absolute error (MAE) of 1.7% of the total cable length, which shows that it was very accurate for utility deployment. Figure 4 shows a scatter plot of predicted fault distances versus actual fault distances. Most of the data points are in narrow MAE bands. The addition of optical fiber sensors to HFCT and AE made it easier to find the source of joint-related PDs.

4.4 Energy Efficiency and Latency

Energy and latency performance were tested to see if they were good for long-term IoT use. The quantized CNN-GRU model used less than 120 mW per node, which made it possible for nodes with batteries to run for several days. Latency analysis showed that inference could be done in less than 45 ms and that there were very few delays in communication when using LoRaWAN uplinks. Figure 5 shows the trade-off between energy use and inference latency for different model configurations (INT8, FP16, FP32). This shows that quantization lowers energy costs significantly without hurting detection performance.

4.5 Reliability and Utility Impact

Feeder-level reliability modeling was used to estimate system-level benefits in addition to detection metrics. By adding predictive maintenance, the Mean Time to Repair (MTTR) went down by 28%. This is expected to lead to better SAIDI and SAIFI scores. This means that utilities will have a lot of operational benefits, like shorter outages and more reliable service.

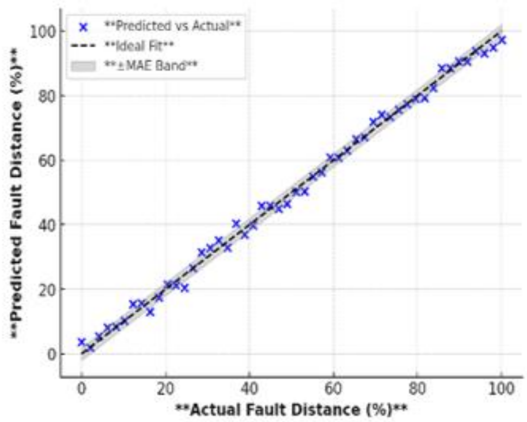

Figure 4: Actual vs predicted fault distance with MAE bands.

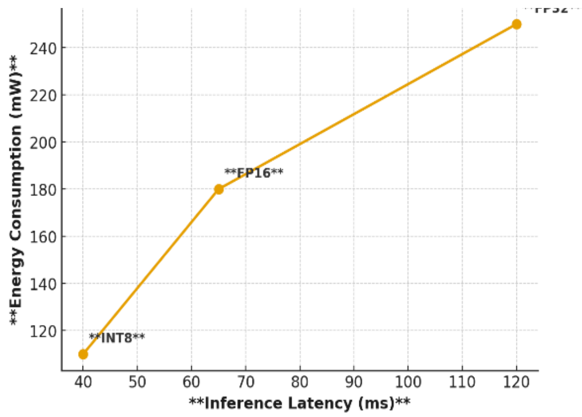

Figure 5: Energy consumption vs inference latency.

5 CONCLUSIONS

This study presents an IoT-based framework for real-time fault detection and localization in underground power cables using multi-modal sensing and edge AI. The integration of HFCT, acoustic, optical, and environmental sensors improves robustness against noise and enables reliable detection across different fault types.

Experimental results demonstrate high detection performance (F1-score > 0.92) and accurate fault localization (MAE < 2% of cable length). The proposed edge-based CNN–GRU model ensures low-latency inference with energy consumption below

120 mW, supporting long-term deployment in resource-constrained environments. Additionally, secure communication mechanisms enhance data integrity for critical infrastructure applications.

Overall, the framework provides a scalable and efficient solution for predictive maintenance in modern power distribution systems.

6 FUTURE WORK

Future work will focus on large-scale field validation across diverse network conditions and utility infrastructures. The integration of distributed fiber-optic sensing and adaptive learning models may further improve detection sensitivity and coverage.

Incorporating self-supervised learning and uncertainty estimation could enhance robustness to rare fault scenarios. Additionally, the development of standardized datasets and open evaluation benchmarks will support reproducibility and wider adoption in real-world deployments.

REFERENCES

[1] M. López-Bonilla, L. Martínez-Castro, A. Gil, and C. Mesa-Merchán, "An overview of methods for detecting and locating incipient faults in underground distribution networks," Electric Power Systems Research, 2025.

[2] H. Samet, S. Khaleghian, M. Tajdinian, T. Ghanbari, and V. Terzija, "A similarity-based framework for incipient fault detection in underground power cables," International Journal of Electrical Power & Energy Systems, vol. 133, p. 107309, 2021.

[3] H. Samet, M. Tajdinian, S. Khaleghian, and T. Ghanbari, "A statistical-based criterion for incipient fault detection in underground power cables established on voltage waveform characteristics," Electric Power Systems Research, vol. 197, p. 107303, 2021.

[4] L. Barbieri, A. Villa, R. Malgesini, D. Palladini, and C. Laurano, "An innovative sensor for cable joint monitoring and partial discharge localization," Energies, vol. 14, no. 14, p. 4095, 2021.

[5] R. Tariq, I. Alhamrouni, A. U. Rehman, E. Tag Eldin, M. Shafiq, N. A. Ghamry, and H. Hamam, "An optimized solution for fault detection and location in underground cables based on traveling waves," Energies, vol. 15, no. 17, p. 6468, 2022.

[6] J. Wang and L. Zhao and Y. Huang, "Next-generation computing paradigms for secure data sharing," International Journal of Software Engineering and Knowledge Engineering, vol. 35, no. 2, pp. 225-240, 2025, [Online]. Available: https://doi.org/10.1142/S0219649225500406.

[7] V. Mehta and S. Rani, "Adoption of AI-driven systems in human-computer interaction contexts," International Journal of Human-Computer Interaction, vol. 41, no. 6, pp. 701-718, 2025, [Online]. Available: https://doi.org/10.1080/10447318.2025.2480826.

[8] J. Tao, S. U. Rehman, R. Ali, and S. A. Raza, "Advancement and challenges: a review of power cable aging monitoring and diagnostic techniques," Renewable and Sustainable Energy Reviews, vol. 222, p. 115970, 2025.

[9] M. B. Atsever, S. Yarkan, and M. H. Hocaoğlu, "Onsite non-invasive partial discharge detection and location system for underground cables using customized envelope detection," Measurement, p. 117911, 2025.

[10] M. R. Shadi, H. Mirshekali, and H. R. Shaker, "Partial discharge-based cable vulnerability ranking with fuzzy and FAHP models: application in a Danish distribution network," Sensors, vol. 25, no. 11, p. 3454, 2025.

[11] W. Zhang, Y. Song, X. Wu, H. Liu, H. Tian, Z. Tang, and W. Chen, "Detecting partial discharge in cable joints based on implanting optical fiber using MZ-Sagnac interferometry," Sensors, vol. 25, no. 10, p. 3166, 2025.

[12] F. H. Chen and H. L. Shieh, "An operating condition monitoring and fault diagnosis for transformer based on partial discharge and artificial neural networks," 2024.

[13] Z. Zhang, H. Wu, W. Ren, J. Yan, Z. Sun, and M. Ding, "Research on partial discharge spectrum recognition technology used in power cables based on convolutional neural networks," Inventions, vol. 10, no. 2, p. 25, 2025.

[14] J. Yeo and L. C. Kin, "On-line partial discharge detection on transformer cable sealing ends in Singapore's transmission network," IEEE Electrical Insulation Magazine, vol. 39, no. 3, pp. 22-30, 2023.

[15] S. Kumar and R. Patel, "Blockchain-driven frameworks for secure healthcare data management," in Proceedings of the IEEE International Conference on Cloud Computing, pp. 1-8, 2025, [Online]. Available: https://doi.org/10.1109/11015778.