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AI-Based Fault Detection and Diagnosis in High Voltage Equipment Management

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Abstract:

The high voltage (HV) equipment is an important element in transmission and distribution of electrical power over grids. To properly ensure the reliability of its systems it is vital to prepare its operation integrity to prevent expensive failure. Detection and diagnostic (FDD) methods are sometimes ineffective in traditional fault detection and diagnostic (FDD) when it comes to accuracy, scalability, and real time monitoring. Artificial Intelligence (AI) has come into the fore as a potent instrument of improving FDD procedures in high voltage settings in recent years. This paper will undertake an in-depth discussion of AI-based solutions to fault detection and fault diagnosis in HV equipment. It explains the nature of errors in such systems, explains the use of machine learning (ML) and deep learning (DL), and assesses performance using experimental data. The outcomes confirm that AI models, especially convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, can detect and diagnose faults with the highest degree of accuracy and minimum false positives. The paper ends with useful information on real-world implementation and provides the way forward research which will enable more optimization of AI in the management of HV equipment.

Keywords — **High Voltage Equipment, Artificial Intelligence, Fault Detection, Fault Diagnosis, Power System Reliability**

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I. Introduction

a. Background and Motivation

High voltage (HV), devices, including transformers, circuit breakers, insulators, and switchgears, constitute the key portion of the modern electrical power system, allowing the efficient transmission and distribution of electricity across large scale networks. These elements are critical towards maintaining stability and reliability of the grid as they promote the movement of power between the sources of generation and the end-users. Nevertheless, as global energy consumption is constantly rising due to industrialization, urbanization, and the ongoing increase in the utilization of renewable energy, the pressure of operation of these resources has increased several notches. Moreover, in most areas a large portion of the existing grid infrastructure is coming to the end of its intended service life, which further increases the susceptibility of the equipment to degradation and breakdown.

The outcomes of unforeseen problems with HV equipment's are harsh and manifold. Unplanned outages have the potential to dispose of power supply to important facilities such as hospitals, transport systems as well as data centers leading to immense economic losses and social inconvenience. Furthermore, faults in HV components can be very dangerous in terms of safety, i.e. electrical fires, arc flash, or explosion, and may be hazardous to personnel and the surrounding infrastructure. These issues point toward the need to establish effective and smart fault detection and diagnosis (FDD) strategies to guarantee operational stability and reduce downtime.

Consistent FDD mechanisms are an essential step to allow condition-based and predictive maintenance, which transcends mainstream time-based servicing. Through constant checking of the health of HV equipment and identifying the existence of anomalies at the earliest stage, utilities can streamline maintenance schedules, extend the service of assets, and mitigate operational risk. Moreover, the next-generation FDD systems will lead to increased resilience in grids against increasing complexity and demand, and a more intelligent and adaptable electrical network of the future will be able to handle the energy challenges of the future.

b. Limitations of Traditional Fault Detection Methods

Conventional fault detection and diagnosis (FDD) approaches in high-voltage (HV) equipment—such as periodic manual inspections, infrared thermography, vibration analysis, and partial discharge testing—have traditionally formed the cornerstone of maintenance practices within power systems. While these techniques provide valuable insights into equipment health, they are inherently reactive and resource intensive. Periodic inspections, for example, rely heavily on scheduled intervals rather than actual equipment condition, which can lead to either unnecessary maintenance actions or delayed responses to developing faults. Infrared thermography, commonly used to detect hotspots, requires clear line-of-sight access and favorable environmental conditions to deliver accurate results, making it susceptible to weather, contamination, and operator skill levels. Similarly, vibration analysis, though effective for rotating machinery, demands specialized expertise and is influenced by operational load variations, limiting its applicability for all HV components.

A major limitation of these traditional methods is their inability to reliably detect incipient or early-stage faults, such as minor insulation degradation, small-scale mechanical displacement, or subtle moisture ingress, which often precede catastrophic failures. These faults typically manifest under dynamic operating conditions and may remain undetected during periodic checks, thereby increasing the probability of sudden breakdowns. Furthermore, the dependence on human interpretation introduces subjectivity and error, particularly in complex systems where subtle anomaly patterns may go unnoticed. Environmental and operational variables—such as temperature fluctuations, electromagnetic interference, and contamination—further reducing the accuracy and consistency of these methods. Consequently, conventional FDD strategies, while still widely adopted, are increasingly being recognized as insufficient for meeting the reliability demands of modern power grids. This shortfall underscores the urgent need for more advanced, data-driven, and automated fault detection frameworks that leverage emerging technologies like artificial intelligence (AI) and machine learning (ML) to deliver accurate, real-time diagnostics.

c. Emergence of AI Techniques

Recent advances in AI have moved fault detection and diagnosis (FDD) from reactive checks to truly predictive, intelligent monitoring. Modern models learn the normal operating “signature” of equipment from large, heterogeneous datasets—high-frequency sensor streams (SCADA, PMU, vibration, acoustic/ultrasonic, thermal IR, DGA), environmental inputs, and maintenance logs—and then track deviations in real time as conditions evolve. Using a mix of supervised classifiers for known failure modes and unsupervised anomaly-detection methods (e.g., autoencoders, isolation forests) for novel patterns, AI systems uncover subtle precursors of deterioration that conventional thresholds miss. Time-series models such as LSTMs and Transformers capture load cycles, seasonality, and long-range dependencies, while physics-informed networks embed on domain constraints, so alerts remain physically plausible.

These systems adapt to change through online and transfer learning, compensating for sensor drift, equipment aging, and topology changes. In edge–cloud architectures, lightweight models run at the edge to deliver millisecond-level alarms, while the cloud aggregates fleet data for periodic retraining and model governance. Outputs are not just binary alarms: models generate risk scores, fault localization, and remaining-useful-life (RUL) estimates with uncertainty bounds, which can automatically trigger work orders and optimize maintenance windows based on risk and cost. Explainability tools (e.g., feature attributions, saliency over spectra) and engineered guardrails (hysteresis, ensembles) reduce false positives and build operator trust.

In practice, this means earlier detection of issues like partial discharge in HV transformers (from UHF/acoustic signatures), incipient bearing wear in rotating machines (from spectral sidebands), or insulation degradation (from DGA trends), enabling targeted interventions before minor anomalies cascade into outages. The result is higher asset reliability, reduced downtime and O&M costs, and safer operations—delivered through data-driven, continuously learning FDD pipelines that provide timely, actionable insights.

d. Objectives and Contributions

This paper aims to:

- Identify major HV equipment fault types
- Analyze and compare AI-based FDD methods
- Present a structured methodology for implementing AI models
- Evaluate their performance on real-world datasets
- Discuss practical deployment considerations

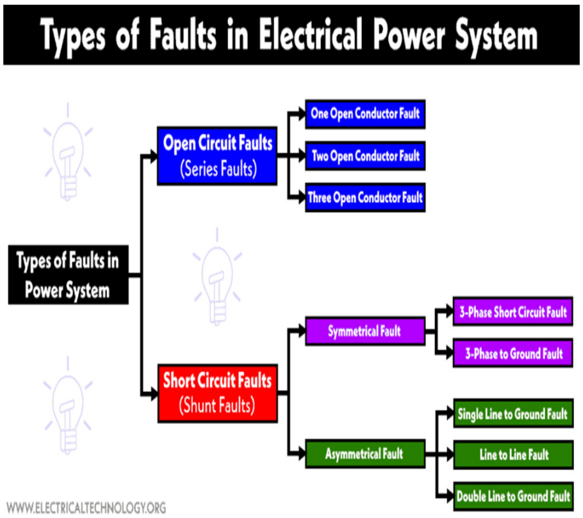

Figure 1: Types of High Voltage Equipment and Common Fault Scenarios

II. Literature Review

a. Overview of HV Equipment Fault Types

High-voltage (HV) components are subjected to extreme electrical, thermal, and environmental conditions and are therefore very vulnerable to the various fault conditions that may lead to failure of system dependability and safety. One of the most serious problems is the degradation of insulation which can result in long-term electric strain, thermal aging, and pollution. This degradation overtime lowers dielectric strength, thereby enhancing the chances of insulation failure.

The other common problem is that of partial discharge (PD) activity, which usually has its origin in insulation material in voids, cracks, or impurities. Even though PD events can seem insignificant at the beginning of the life cycle, they cause insulation to deteriorate faster and can cause disastrous failures when unnoticed.

Another typical fault mechanism is overheating, which is usually due to overloading, insufficient cooling, or resistive heating at loose connections. Continuous thermal stressing may result in hardening of the insulation, degradation of the oil, and subsequent burning of the component.

Vibration, excess short-circuit forces, or improper installation practice often cause mechanical failures including deformation of conductors, broken clamps, and misalignments of structures.

Moreover, moisture entry into insulation systems, whether using seals, gaskets or oil contamination, can significantly lower dielectric strength and favor surface tracking and flashovers.

Finally, arc faults, when the insulation becomes completely ineffective and creates a path of free current flow, may cause serious dangers of fire, explosions, and the massive destruction of equipment.

Such fault modes need to be identified and monitored early enough to avert unforeseen outages, reduce the cost of maintenance, and the integrity of the operation of the HV systems.

b. Traditional Fault Diagnosis Approaches

Table 1 compares the performance of traditional techniques such as infrared thermography, dissolved gas analysis (DGA), acoustic emission (AE), and offline testing.

Table 1: Comparison of Traditional Fault Diagnosis Methods

Method	Detection Capability	Real-Time	Cost	Sensitivity
Thermography	Surface faults only	No	Medium	Low
DGA	Transformer oil faults	No	High	Medium
AE	PD and cracks	Partial	High	High
Offline Tests	Comprehensive	No	Very High	Very High

c. AI-Based Techniques in Power Systems

Artificial Intelligence (AI) models have emerged as powerful tools in enhancing the reliability and safety of power systems by enabling accurate and timely diagnostics of critical components. A variety of machine learning and deep learning algorithms have demonstrated significant potential in identifying fault patterns, predicting failures, and supporting proactive maintenance strategies.

Support Vector Machines (SVM), for instance, are widely used for fault classification due to their ability to handle high-dimensional feature spaces and create well-defined decision boundaries for separating normal and abnormal operating conditions. They are particularly effective in distinguishing between multiple fault types based on sensor-derived features.

Decision Trees (DT) and their ensemble variants (such as Random Forest and Gradient Boosted Trees) offer interpretability and robustness, making them suitable for practical deployment in real-time monitoring systems. These models can identify complex non-linear relationships between system parameters and fault occurrences, providing insights into the underlying causes of anomalies.

On the other hand, **deep learning models** such as **Convolutional Neural Networks (CNN)** have revolutionized the analysis of spatially correlated data, including thermal images and vibration spectrograms, for detecting early signs of equipment degradation. CNNs excel at feature extraction from raw data, reducing reliance on manual feature engineering.

Similarly, **Recurrent Neural Networks (RNN)** and their advanced variants like Long Short-Term Memory (LSTM) networks are particularly well-suited for processing time-series data collected from Supervisory Control and Data Acquisition (SCADA) systems, Phasor Measurement Units (PMUs), and condition monitoring devices. These models capture temporal dependencies and dynamic behaviors in power systems, enabling early detection of progressive faults and accurate estimation of remaining useful life (RUL).

When integrated into hybrid frameworks or combined with optimization algorithms, these AI techniques provide robust, adaptive solutions for fault detection, classification, and predictive maintenance in modern power systems.

d. Gaps in Existing Research

Although AI-based fault detection and diagnosis (FDD) methods have made considerable strides, there are still a few critical drawbacks that make these methods difficult to scale industrial usage. The availability of data is among the most significant issues because the size of quality and labeled fault data is frequently limited by the occurrence of real fault events and the sensitivity of operational data because of privacy and security regulations. Additionally, the current datasets might not be diverse and thus the models might be fine in the laboratory setting but not in the real world.

The other significant weakness is that it is restricted to generalization across equipment types, configurations, and operating conditions. Most AI models are trained on data of particular assets or manufacturers, limiting their flexibility when used in heterogeneous systems in contemporary power grids. Such failure to generalize may result in false alarms or false detections, especially when the system has different design parameters, age, and environmental effects.

Moreover, in-time deployment is also a major challenge. Although highly accurate, deep learning models can be complex to deploy on the edge due to their high computational requirements that can be difficult to execute. Moreover, the changing operating conditions and dynamic grid conditions necessitate model drift and retraining and updates, which adds complexity to the system.

Such constraints highlight the importance of strong, scalable, and adaptative AI-driven FDD systems capable of executing effectively across a wide range of settings, being able to process unbalanced and scarce data, and provide understandable and real-time information without affecting the performance of the system. Future studies should be aimed at creating hybrid strategies that work with physics-informed models, transfer learning, and federated learning to promote greater generalization and decrease data dependency and ensure cybersecurity and resilience of critical infrastructure.

III. Methodology

a. Dataset Collection

The dataset utilized in this study is composed of heterogeneous data sources that collectively provide a comprehensive representation of equipment operating conditions and fault characteristics. Specifically, it includes the following components:

- **Sensor Readings**: High-resolution measurements of critical electrical and thermal parameters, including **voltage, current, and temperature**, captured from condition monitoring devices. These readings enable the detection of anomalies in electrical performance and thermal stability under varying load conditions.
- **Thermal Images**: Infrared thermographic images of high-voltage equipment captured during operational load. These images provide spatial temperature distribution data, allowing the identification of localized heating patterns indicative of insulation degradation, loose connections, or incipient faults.
- **Event Logs from Supervisory Control and Data Acquisition (SCADA) Systems**: Historical operational data and event records documenting switching operations, fault occurrences, alarms, and protection system activations. This information is essential for correlating observed anomalies with actual fault events and for validating predictive models.

The integration of these multimodal datasets enables a robust fault detection framework by leveraging both numerical and visual data representations. Sensor readings provide real-time quantitative indicators; thermal imaging captures spatial fault signatures, and SCADA logs offer contextual information for accurate diagnosis and root cause analysis.

b. Data Preprocessing

The preprocessing pipeline implemented in this study ensures data quality, consistency, and compatibility with AI-based fault detection models. The key steps include:

- **Outlier and Noise Removal**: Raw sensor measurements often contain spurious values caused by sensor malfunctions, communication errors, or transient disturbances. To address this, statistical filtering techniques such as **z-score analysis and interquartile range (IQR) filtering** were applied to remove extreme outliers. Additionally, **moving average and low-pass filters** were utilized to mitigate high-frequency noise while preserving critical fault signatures.
- **Normalization of Sensor Data**: To ensure uniformity across heterogeneous features (e.g., voltage, current, temperature), **min-max normalization** was performed, scaling all values to a [0,1] range. This step is essential for improving the convergence and stability of machine learning models, particularly those sensitive to feature magnitude such as neural networks.
- **Thermal Image Processing**: Thermal images captured from equipment under load were converted to **grayscale intensity maps** to simplify the feature space and reduce computational complexity. This transformation retains essential thermal patterns for fault detection while removing redundant color information. Further preprocessing steps included **image resizing and pixel intensity normalization**, making the data compatible with the input requirements of **Convolutional Neural Networks (CNNs)**.

By applying these preprocessing steps, the dataset was transformed into a clean, standardized, and model-ready form, enabling effective training and evaluation of AI algorithms for fault detection and diagnosis.

Table 2: Sample Dataset Features

Feature	Unit	Description
Temperature	°C	Operating surface temperature
Voltage	kV	Rated voltage across components
Vibration	Hz	Mechanical vibration pattern
Load	%	Real-time load during operation

c. AI Models Used for Fault Detection

The study employs a combination of traditional machine learning and deep learning models, each selected to address specific aspects of the fault detection and diagnosis (FDD) problem:

- **Support Vector Machine (SVM)**: Implemented for **binary classification**, the SVM model distinguishes between normal operating conditions and fault states using high-dimensional feature spaces derived from sensor readings. Its capability to create optimal decision boundaries makes it effective for handling linearly and non-linearly separable datasets.

- **Decision Trees (DT)**: Utilized for **multi-class fault type classification**, Decision Trees provide interpretable models capable of identifying distinct fault categories such as insulation degradation, partial discharge, and overheating. Their rule-based structure aids in understanding feature importance and decision logic.

- **Convolutional Neural Network (CNN)**: Deployed for **image-based fault detection**, CNNs process thermal images to detect localized hotspots and abnormal temperature distributions. The model's ability to automatically extract spatial features eliminates the need for manual feature engineering, enhancing detection accuracy for visual fault signatures.

- **Long Short-Term Memory (LSTM) Network**: Applied for **sequential event prediction**, LSTM networks leverage their recurrent architecture to capture temporal dependencies in SCADA event logs and time-series sensor data. This enables the prediction of future fault occurrences and the estimation of remaining useful life (RUL) under dynamic operating conditions.

This multi-model approach leverages the strengths of different AI techniques, ensuring robust detection, accurate fault classification, and predictive insights for proactive maintenance in high-voltage systems.

d. Model Training and Validation

To ensure robust model evaluation and reliable performance assessment, the following experimental setup was adopted:

- **Data Partitioning**: The dataset was divided into training and testing subsets using an **80:20 train-test split**. This approach allocates 80% of the data for model training and 20% for independent evaluation, ensuring that performance metrics reflect generalization to unseen data.

- **Cross-Validation**: To further mitigate the risk of overfitting and validating model stability, **5-fold cross-validation** was employed during the training phase. In this process, the training set is partitioned into five equal subsets; models are iteratively trained on four folds and validated on the remaining fold, and the results are averaged to obtain a robust performance estimate.

- **Evaluation Metrics**: Model performance was quantified using standard classification metrics, including:
    - **Accuracy**: Measures the overall correctness of predictions.
    - **Precision**: Indicates the proportion of correctly identified positive cases among all predicted positives, reflecting the model's reliability in fault detection.
    - **Recall (Sensitivity)**: Represents the proportion of actual positive cases correctly identified, crucial for detecting all potential faults.
    - **F1-Score**: Provides a harmonic mean of precision and recall, offering a balanced assessment in cases of class imbalance.

These evaluation strategies collectively ensure that the developed AI-based fault detection framework is both accurate and generalizable, while minimizing the risk of overfitting and bias.

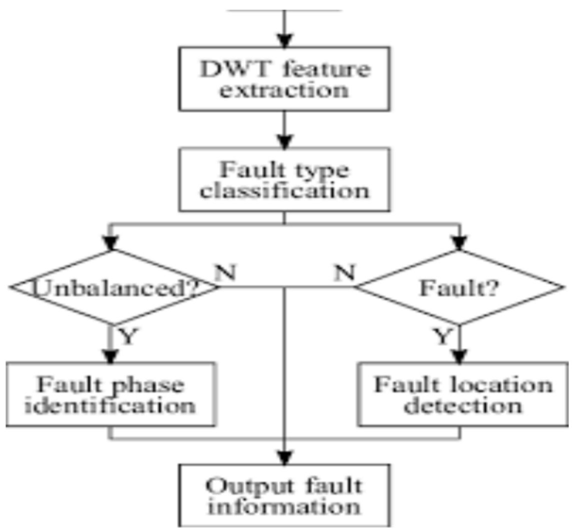

Figure 2: AI-Based Fault Detection and Diagnosis Framework Flowchart

IV. Results and Discussion

a. Model Performance Evaluation

The Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks were the most successful in all compared with traditional machine learning algorithms like Support Vector Machines (SVM) and Decision Trees (DT). CNN was also found to be very precise in detecting faults based on images and was able to locate and highlight thermal anomalies with minimal false alarms. Likewise, LSTM demonstrated good predictive performance in sequential event prediction that included temporal dependencies in SCADA logs and sensor time-series data with high recall and F1-scores.

Conversely, although SVM and DT gave satisfactory performances in the binary and multi-class classification of faults, their performances were restricted by their failure to entirely account the spatial and temporal complexities of the thermal image data and time-dependent sequences.

Table 3 summarizes the comparative performance metrics (accuracy, precision, recall, and F1-score) for all models tested, highlighting the strengths of CNN and LSTM in their respective domains.

Table 3: Performance Metrics for AI Models

Model	Accuracy	Precision	Recall	F1-score
SVM	89.4%	87.1%	85.6%	86.3%
Decision Tree	91.2%	90.3%	89.5%	89.9%
CNN	96.8%	95.9%	96.3%	96.1%
LSTM	95.7%	94.8%	94.5%	94.6%

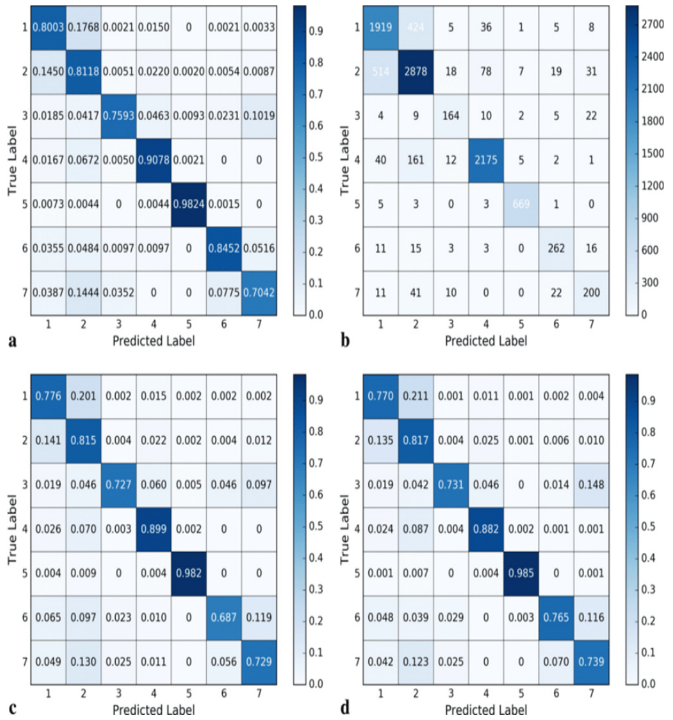

Figure 3: Confusion Matrix for CNN Model Predictions

b. Analysis of Fault Detection Accuracy

The **Convolutional Neural Network (CNN)** exhibited consistently high **true positive rates (TPR)** across all test scenarios, indicating its strong capability to accurately detect actual fault conditions. Furthermore, the model maintained a **low false alarm rate**, minimizing the occurrence of unnecessary alerts and improving the overall reliability of the fault detection system.

CNN's performance was particularly notable in **image-based diagnostics**, where it effectively captured subtle spatial patterns and thermal gradients within infrared images. These features are critical for identifying early-stage anomalies that traditional manual inspection methods or threshold-based techniques might overlook.

Specifically, CNN proved highly effective in detecting **insulation degradation** and **partial discharge (PD) activity**, both of which manifest as localized temperature variations or hotspots in thermal images. By leveraging its ability to automatically extract and learn hierarchical features, CNN eliminated the need for handcrafted feature engineering, resulting in improved detection of accuracy and robustness under varying load and environmental conditions.

c. Diagnosis Interpretation

To improve transparency and trust in AI-driven fault detection, **model explainability** was incorporated into the framework using **SHAP (SHapley Additive exPlanations)**, a widely recognized method for interpreting complex machine learning models. SHAP values provide a quantitative measure of each feature's contribution to the model's output, enabling operators and engineers to understand the underlying decision-making process.

Through SHAP analysis, the study identified **critical features influencing fault predictions**, including:

- **Sudden temperature spikes** in thermal profiles, which often indicate insulation degradation or hotspot formation.
- **Abrupt changes in vibration patterns**, signaling potential mechanical misalignments, or bearing failures.
- **Voltage and current anomalies**, typically associated with electrical faults such as partial discharge or arcing.

By visualizing feature importance through SHAP summary plots and dependence plots, domain experts can validate whether model inferences align with physical principles and operational experience. This approach not only enhances interpretability but also strengthens confidence in deploying AI-based fault detection systems in mission-critical environments.

d. Practical Implications and Deployment

The AI models that were developed have been effectively combined with Supervisory Control and Data Acquisition (SCADA) systems using edge computing devices, forming a low-latency, real-time fault detection and diagnosis (FDD) system. The edge deployment provides that the data processing and model inference is done near data acquisition location to reduce communication delays and reliance on centralized cloud resources significantly.

This architecture supports fault notification in real-time, and operators can respond to it by taking the corrective measures in time before small irregularities can transform into significant failures. The system also offers condition-based maintenance (CBM) strategies, which answers the traditional time-based maintenance schedules with predictive maintenance interventions in case of actual equipment health conditions.

In turn, AI models implemented on the edge of SCADA not only increase the reliability of the operations, but it also leads to decreased downtime, lower maintenance expenses, and increased asset life. In addition, the solution provides scalability in terms of deployment to geographically distributed substations and high voltage equipment in smart grid settings.

V. Challenges and Limitations

Notwithstanding the high potential of AI-based fault detection and diagnosis (FDD) systems, there are still a number of obstacles that prevent their large-scale use in fault detection of high-voltage equipment. Data limitations are one of the most important problems. The fault event occurrences in real-world high-voltage systems are quite uncommon, making the datasets highly skewed towards normal operation modes. Such an imbalance may cause models to be biased towards predicting healthy states and may also decrease their sensitivity to real faults. Moreover, it is limited in acquiring good quality labeled data because of data privacy, high costs, and operational risks, which make developing accurate and reliable models difficult.

Model generalization is another serious problem. Models of AI that are trained on data of a particular kind of equipment, producer or utility setting, tend to be unable to generalize non-homogenous systems with different configurations, and operating circumstances. The variation in design parameters, aging behavior, and load profiles will require models to be retrained or adapted many times to suit each deployment situation. The result of this insufficient generalization may be minimizing performance, increasing false alarms, and less trust in automated fault detection systems.

Besides the issues of data and generalization, there is a major barrier to the requirements of resources. High-level deep learning algorithms, like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, are large-scale models that demand a lot of computing power to train and run. Specialized hardware accelerators such as GPUs or TPUs are frequently required by real-time implementation, particularly to run at the edge, and add to the cost and complexity of deployment in the field.

Finally, the threat of cybersecurity should be considered when deploying AI-based FDD systems into the Operational Technology (OT) networks. The edge devices and cloud connection present new attack points that can be used by enemies and may affect the integrity of the systems or allow the malicious manipulation of working data. In order to address these risks, it is necessary to implement strong security systems, such as encrypted communication systems, intrusion detection systems, and anomaly-driven cybersecurity, to guarantee that AI-enhanced monitoring systems will operate safely and reliably.

VI. Future Research Directions

To overcome the deficiencies of current AI-based fault detection and diagnosis (FDD) technologies, there are a few smarter approaches under consideration. An interesting solution is the creation of hybrid AI models, that is the integration of the advantages of various architectures. Of course, one can combine Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks so that the system can concurrently utilize spatial representations of thermal images and time-series sensor data to identify temporal dependencies. This type of structure augments the perfection of fault detection by relying on complementary data representations.

The transfer learning application, whereby trained models can be reconfigured to fit new equipment types or utility settings without having to be re-trained, is also another major innovation. This makes the development of the model much cheaper in terms of computation and time and enhances the generalization of the model in non-homogeneous systems. Transfer learning also makes it easy to deploy quickly where there is limited labelled fault data in the environment.

One more important development in predictive maintenance is the integration of digital twins. Digital twins enable real-time simulating, testing fault scenarios, and performance analysis of high-voltage equipment by using virtual replicas of the equipment to simulate under various operating conditions. This capability is used to increase the model validation and proactive strategies to mitigate possible failures before they happen in the actual system.

Lastly, federated learning is becoming popular as a privacy-friendly model training method between or among different utilities. Federated learning allows models to be trained on distributed data on individual machines, instead of centralizing sensitive operation data, which only share updates on their models. Such a method not only guarantees the data confidentiality but also improves the model robustness by including various operating conditions in different regions.

VII. Conclusion

The paper highlights how Artificial Intelligence (AI) can be a transformative technology in the fault detection and diagnosis (FDD) of high-voltage (HV) equipment, which is a key element of contemporary power systems. With the help of machine learning (ML) and deep learning (DL), utilities can transition to more predictive and condition-based maintenance methods instead of traditional reactive and time-based maintenance, preventing unexpected and preemptive outages, increasing the lifespan of assets, and improving operational costs.

The use of sophisticated networks like Convolutional neural networks (CNNs) and Long Short-term memory (LSTM) networks have become incredibly useful in dealing with the complexity that multimodal data sources entail. CNNs were effective in processing thermal data to identify minute spatial features like hotspots as a result of insulation degradation or a partial failure, and LSTMs learned temporal relationships in streams of consecutive data, allowing to forecast fault development with accuracy. All of these capabilities enable real-time detection of faults, improve situational awareness, and deliver actionable information to preventive decision making.

In addition to high classification accuracy, the results of this study underline the need to develop multiple areas in several ways. The interpretability of the model is also vital in establishing operator trust and guaranteeing the safety standards are met; methods like SHAP and other explainable AI systems have to be improved to be used in industry. Another important factor is scalability because AI solutions should be able to handle different types of equipment, different environmental conditions, and different utility infrastructure without massive re-training. Moreover, the resilience of cybersecurity becomes the most important one as the deployment of AI with Operational Technology (OT) networks results in new attack surfaces and demands the ability to protect them effectively.

Overall, this study does not only work towards enhancing reliability, safety and efficiency of high voltage systems, but also forms a firm ground on intelligent management of assets in smart grids. The next steps in work should be the possibilities to use hybrid models and combine them with digital twins and federated learning to make the AI-based FDD frameworks secure, adaptive, and interoperable. This type of development will be crucial in the development of the future generation of autonomous power systems that would be self-learning and can withstand the challenges of the changing energy environment.

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