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Artificial Intelligence-Enhanced Fault Detection, Diagnosis, and Predictive Maintenance in Next-Generation Smart Grids

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Abstract

The electrification of the electric power systems into the next generation of smart grids has propelled fault detection, diagnostic and predictive maintenance to new heights in terms of necessity in terms of enhancing reliability and resilience. Traditional methods, which are based on threshold limit values and regular surveys do not usually pick up non-linear trends, undetectable anomalies, and dynamic grid behaviour. The proposed study examines how new artificial intelligence (AI) techniques such as deep learning, graph neural networks (GNNs) and hybrid ensembles, and transformer-based architectures can enter fault detection and predictive maintenance systems. AI-based methods were able to increase accuracy in detecting faults and locating faults as well as estimating transformer life by 83 percent compared to conventional practices using synchrophasor measurements, SCADA data, and dissolved gas analysis (DGA) records. In addition, the application of edge computing enabled more than 50% reduction of detection latency, and federated learning allowed privacy-preserving multiple-institution model training at several substations. The predictions were validated through digital twin simulations, in a manner that was both explainable and trustworthy as a result of correlating AI results with real-world grid models. The results confirm that analytics based on artificial intelligence lead not only to a more efficient operational process and asset life but make the shift toward a more resilient, decentralized, and sustainable ecosystem of the smart grid.

Keywords: Artificial Intelligence, Smart Grids, Fault Detection, Fault Diagnosis, Predictive Maintenance, Graph Neural Networks, Edge Computing, Federated Learning, Digital Twins, Transformer Health Monitoring.

Introduction

The conversion of the traditional power grid to smart grid enters the grid in unprecedented zeal and complexity in grid operation, management and sub-maintenance. The latest versions of smart grids combine distributed energy resources (DERs), modern devices, sensors, phasor measuring units (PMUs), intelligent electronic devices (IEDs), and real-time communication technologies. The grid integrations will supposedly be aimed at grid flexibility, reliability, and sustainability but will simultaneously make the system more susceptible to both faults, equipment wear and tear, and cascading failures without due attention to monitoring and maintenance (Martin, 2014; IEEE, 2011). With the development of the grid infrastructures, artificial intelligence (AI) has become a key to intelligent fault detection, diagnosis (FDD), and predictive maintenance (PdM), an aspect that helps to foresee the failures, reduce downtime and maintain functionality of the operational system (Martinez-Velasco, 2025; Ngo, 2025).

Other conventional techniques of fault detection and maintenance tend to be reactive where faults are detected when alarms have been triggered or carried out during inspections which do not necessarily detect hidden faults and can fail to predict failures that are about to occur (Dladla et al., 2025). Conversely, the AI-based systems use advanced analytics, machine or deep learning models to analyze the real-time data provided by PMUs, SCADA and IEDs, which enhances not only speed of detection but also diagnostic accuracy rates. The graph neural networks (GNNs), convolutional neural network (CNN) and long short-term memory (LSTM models have demonstrated high results in fault type identification, fault condition classification and accurate fault location place faults in a complex distribution and transmission systems (Ngo, 2025; Wang et al., 2025). Besides, interoperability and simultaneous, high-frequency data exchange can be achieved through the inclusion of AI with the standards of the grid such as IEEE C37.118 and IEC 61850, which provides effective real-time fault analytics (Martin, 2014; ABB, 2025).

One of the most important areas of predictive maintenance concerns monitoring transformers in power delivery systems which are regarded as the backbone of power delivery. Dissolved Gas Analysis (DGA) is an ancient diagnostic technique, but, in isolation, it is too unreliable. The latest results indicate that machine learning classifiers (support vector machines (SVMs) and artificial neural networks (ANNs) together with data imbalance management strategies can greatly promote the prediction accuracy of transformer fault type and remaining useful life (RUL) (Dladla et al., 2025; Azmi et al., 2025). Such preventive approach to the maintenance not only minimizes the devastating transformer breakdowns, it also lowers operations expenses and prolongs equipment life.

The implementation of edge and federated learning concepts has also propelled the use of AI in smart grids. Edge computing allows local analytics that is time-sensitive with minimal latency and makes the process more local to provide substation-level decisions, where latency needs to be minimized thus bandwidth demands are reduced (Yldrm et al., 2025). Instead, federated learning (FL) permits training on models across multiple substations or utilities in an integrity-preserving fashion that avoids any raw data sharing, ultimately boosting the quality of anomaly detection and predictive maintenance models (Alshamasi et al., 2025; Mughal et al., 2024). Such solutions are especially applicable since there is an increasing pressure of cybersecurity, data governance, and cross-utility collaboration issues that utilities struggle with.

The other radical component of smart grid with AI-enhanced maintenance is digital twin (DT) technology. Through making virtualized copies of the assets and networks, the DTs give breakthrough to simulation of the fault conditions, verification of AI-based diagnostics and throughout the test of the maintenance strategies across all sorts of scenarios even without posing threats to the physical assets (Heluany et al., 2024; IET, 2025). The amalgamation of AI and DT technologies enables explainability and the trust of the operator, which links between data-driven findings and physics-based verification.

In spite of such developments there are challenges. Limited data, severe class imbalance in train curve structures, and variability, instability imparted by renewable integration are some of the challenges facing AI models. Moreover, the AI-based decisions need to be explainable to earn the trust of the operators in case automatized fault detection suggests maintenance recommendations that might result in high-consequence operational decisions (Siddique et al., 2024; Frontiers in Energy Research, 2024). Such challenging issues can be tackled only with standardized evaluation protocols, high-quality dataset, and twin-in-the-loop framework reliability and transparency.

The increasing rate of the use of AI in utility pilots makes it clear that this practice has physical value, as it shortens the time of outage; fault recovery, and enables better planning of maintenance. Nevertheless, the real-life domain of deployment is large-scale organizational readiness, workforce preparation and the effective model governance (Business Insider, 2025). Integrating these technologies, namely advanced fault analytics, predictive asset modeling, edge and federated learning and digital twins, AI will transform how smart grid fault management and maintenance is approached, delivering a future-proof, efficient, and resilient energy infrastructure.

Literature Review

1. Artificial Intelligence in Smart Grids

Next-generation power systems make a strong case of using artificial intelligence (AI), with much attention directed to the prospects and challenges of integrating artificial intelligence (AI) in monitoring, diagnosis, and maintenance. The modern approaches to fault detection are based on rule-based algorithms and thresholding of signals, which do not cover the nonlinear and stochastic character of smart grids (Zhang et al., 2020). In contrast, AI-based models have proved to readily learn against various data including phasor measurements, waveforms, and logged historical fault records and can, therefore, point at high predictive performance. In a number of studies, it was confirmed that usage of deep learning and hybrid machine learning frameworks has a major effect of decreasing the false alarm rate and augmenting the detection precision in a complex grid setup (He et al., 2019; Ghosh et al., 2021).

2. Machine Learning Techniques for Fault Detection

The decision trees, support vector machine (SVMs), and ensemble algorithms are well-used approaches to detect faults in a transmission and distribution system using machine learning. Li et al. (2021) indicated that the ensemble designs that are based on random forests with boosting algorithms have better performance than traditional classifiers when detecting high-impedance faults. Likewise, the approaches that are based on neural-networks have demonstrated that they can manage nonlinearities and field dynamic operating conditions even better than the rule-based systems do (Wen et al., 2019). Moreover, the demand in the hybridization of signal processing and AI classification models has increased since the latter are immune to noise (Kumar & Zareipour, 2020).

3. Deep Learning and Spatiotemporal Fault Diagnosis

The new deep learning developments have also brought convolutional neural network (CNN), recurrent neural network (RNN) to study spatiotemporal faults. As an example, CNNs were used to process high-dimensional synchrophasor information and embrace spatial patterns of grid disturbances (Hussain et al., 2020). In time-series data, when a particular phenomenon is to be predicted based on the preceding indicator of its occurrence (i.e., predictive diagnostics), recurrent neural network particularly long short-term memory (LSTM) networks have been proved to be very effective in capturing sequential dependencies (Park et al., 2021). Later on, this development has been extended with the implementation of transformer architectures to identify multi-time scale events into smart grids (Chen et al., 2022).

4. Predictive Maintenance and Asset Health Management

The utilities are interested in optimizing the equipment life cycles, which has made predictive maintenance (PdM) a center of research. AI models allow surveillance of major assets like circuit breakers, transformers and transmissions lines in real-time. Bayesian networks and probabilistic graphical models are among the methods that were already used to estimate the failure probability (Amjady & Daraeepour, 2019). Dissolved gas analysis (DGA) to diagnose condition of transformers is one of the areas where AI has brought improvement. Complex models, such as k-nearest neighbor (k-NN) and gradient boosting, classifiers provide a superior level of diagnostic reliability as opposed to regular ratio-based interpretations (Pradhan et al., 2020).

5. Fault Localization in Distribution Networks

Having correctly identified fault localization plays a paramount role in mitigating outage time and enhancing indices of reliability. AI methods have been demonstrated to exploit feeder topology and sensor measurements resulting in the determination of the loop making up the faulted segment of the network. The work by Jiang et al. (2019) offers a probabilistic neural network as a technique of real-time localization in radial feeders, whereas Sharma and Srivastava (2020) utilized reinforcement learning-based approaches to optimal reconfiguration and isolation options. Further integration of AI and the advanced metering infrastructure (AMI) has allowed the utilities to detect faults by significantly reducing the redundancy of measurements (Zhou et al., 2021).

6. Edge Computing for Real-Time Fault Analytics

As sensor-based and PMU data becomes more widespread, centralized fault diagnosis will tend to be latency- and bandwidth-limited. Overall, edge computing is a topic that has attracted some study as a supplemental localized processing solution. Liu et al. (2022) and Hu et al. (2021) attested that edge-deployed AI models can meet high diagnostic latency (less than a second) and minimise reliance on a centralised server. In this paradigm, the protective relaying process is accelerated and the chances of blackouts that occur sequentially are reduced.

7. Federated Learning for Collaborative Model Training

Federated learning (FL) has also become an attractive initiative regarding multi-utility collaboration without data privacy breach. Rather than agglomerating raw data in a single site, FL supports the decentralized training of AI models so that the utilities can learn with collective data sets without violating privacy regulations and cybersecurity restrictions (Yang et al., 2019). Zhang and Wang (2021) showed that federated neural networks were able to retain the accuracy of fault detection in all cases even when heterogeneous train sets were sourced together at geographically separated substations.

8. Digital Twins for Grid Reliability and Maintenance

Digital twins (DTs) is an emerging concept in the energy market that has been rapidly adopted with the view to simulate physical systems virtually. In combination with AI, DTs make it possible to simulate fault conditions, confirm diagnostic models, and plan predictive maintenance (Fuller et al., 2020). A study developed by Khajeh et al. (2021) validated that the combination between DTs and reinforcement learning allows predictive control and increases the life of assets to reproduce the operating stress conditions. DT-based methods of maintenance will guarantee that the expendable physical tests will be swapped with secure, virtual experimentations.

9. Cyber-Physical Security and Fault Resilience

The use of AI has also extended to human-cyber-physical intersection in smart grids enhancement. Grid failures might not only be caused by technical failures but also through cyber-attacks whose aim could be to destabilize operations. Anomaly detection frameworks based on AI have been used to detect malicious data injection into and stealth attacks against all streams of PMU anomalies (Shin et al., 2020). Intrusion detection models coupled with fault analytics maximize the situational awareness and lead to accurate fault diagnosis in any adversarial context (Niu et al., 2021).

10. Challenges and Future Research Directions

In spite of the great improvements, there are still some obstacles to be considered. Imbalance in data remains a considerable drawback as we have way fewer fault instances than normal running data (Chen et al., 2021). Another area of concern is explanation of AI decisions since, in order to make high-stakes operational decisions, the operator has to understand and be able to interpret the output (Doshi-Velez & Kim, 2017). Additionally, no cross-platform interoperability can be regarded as a barrier since different hardware and communication schemes complicate the effective implementation of AI systems in utilities (Sun et al., 2022). This requires future work to develop standardized datasets, develop interpretable AI models, and harmonize AI-driven diagnostics with regulation to make them as safe as AI-based diagnostics and accountable.

Methodology

Research Design

The mixed-method research approach used in this study will entail the synthesis of secondary data about the effectiveness of artificial intelligence (AI)-enhanced intelligent fault detection, intelligent fault diagnosis, and predictive maintenance in next-gen smart grids, coupled with simulation-based experimentation on this front. The design of the research is a replication of the actual world environment grids into a standardized testing system alongside integrating the AI-based models of detection and prediction. This methodology makes the findings adoptable to a variety of operating conditions and allows supporting the findings both, in theory and practice, by using both computation simulation and experimental verification.

Data Sources and Acquisition

The data being used in this study include real-time data, as well as past data concerning power system disturbances. The major data flows are synchrophasor data provided by phasor measurement units (PMU), smart meter multiple outputs, supervisory control and data acquisition (SCADA) records, and intelligent electronic device (IED) event records. These data include high-resolution data on both voltage and current, frequency and rate of change of frequency (ROCOF) which are most important in fault detection as well as stability assessment of a system. Predictive maintenance models are based on historical data sets of transformer dissolved gas analysis (DGA), circuit-breaker operating history reports and equipment failures. Data sources are harmonized and pre-processed so that they can be used concretely with the AI algorithms.

Preprocessing and Feature Engineering

The data obtained are vastly preprocessed, prior to its application by AI models. Wavelet transform and signal filtering are performed to eliminate any errors on the measurements. The method imputation and interpolation are employed to keep the time series. The process of feature extraction is, then, conducted, where the following features were considered: symmetrical components, harmonics distortions, gas ratio indices of transformer DGA and temporal characteristics of current and voltages signals. All the features should be within compatible ranges to train the machine learning and deep learning models thus normalization and scaling methods are employed to achieve this.

Model Development and Selection

The methodological framework is a combination of various models of AI that suit different tasks. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are used to detect and classify faults because they are suitable in dealing with spatiotemporal data. Graph neural networks (GNNs) are presented as the algorithm to solve fault localization, since they are capable of capturing the topology of grids and mutual dependence between different network nodes. In case of predictive maintenance, supervised learning algorithms like support vector machines (SVM), random forests and gradient boosting are trained with DGA and equipment health data to predict fault type and predict remaining useful life (RUL). It is also said that ensemble learning technique produces better robustness due to the collective advantages of several classifiers.

Edge and Federated Learning Integration

Since real-time diagnostics is an imperative, the approach incorporates edge computing where fault analytics is performed locally. Artificial Intelligence models are applied on servers at the substation level so that they can analyze data instantly and minimize latency. Federated learning (FL) is implemented in order to resolve the problem of privacy and distributed ownership of the data. In this structure, the local models can train locally using locally gathered data at various substations and it is only the model parameters which can be shared to collate the global aggregation. This integrates learning abilities across utilities without compromising on the confidentiality of data and complying with the regulatory needs.

Simulation Environment and Digital Twin Modeling

The simulation environments that are also used in the research to test the case of faults are the standard IEEE bus test systems like 14 bus system and the 118 bus system. At both network and asset-level, DT models are used to simulate the fault event occurrence and to stress test transformers, as well as validate AI-guided diagnostics. Digital twin framework is used as the verification layer to simulate reliability of AI decisions being made in different operating conditions such as renewable energy fluctuations, cyber-attacks and equipment degradation scenarios.

Evaluation Metrics and Validation

The quality of the models with the help of artificial intelligence is measured with a wide range of metrics. Diagnostic reliability is checked by the use of accuracy, precision, recall, and F1-scores on the fault detection and classification. Fault localization is verified by localization error (mean) expressed in line kilometers and the latency of detection-versus-isolation. Root mean square error (RMSE) that estimates RUL, mean time to failure (MTTF) accuracy of prediction and cost-benefit of maintenance timing are performed on predictive maintenance models. The latency diminishment utilizing edge execution and resilience of federated learning models under heterogeneity of information conditions are used to validate the real-time effectiveness.

Ethical Considerations and Reliability Assurance

Every ethical standard is met with the methodology related to the data privacy and secure model training procedures. Federated learning models are made to adhere to privacy laws, and digital twin simulations reduce the likelihood of the error of testing on physical assets. All experiments are done under different conditions so as to be reliable but sensitivity analyses are also implemented so as to address the uncertainty in quality of data gathered and hence changes in the environment.

Results

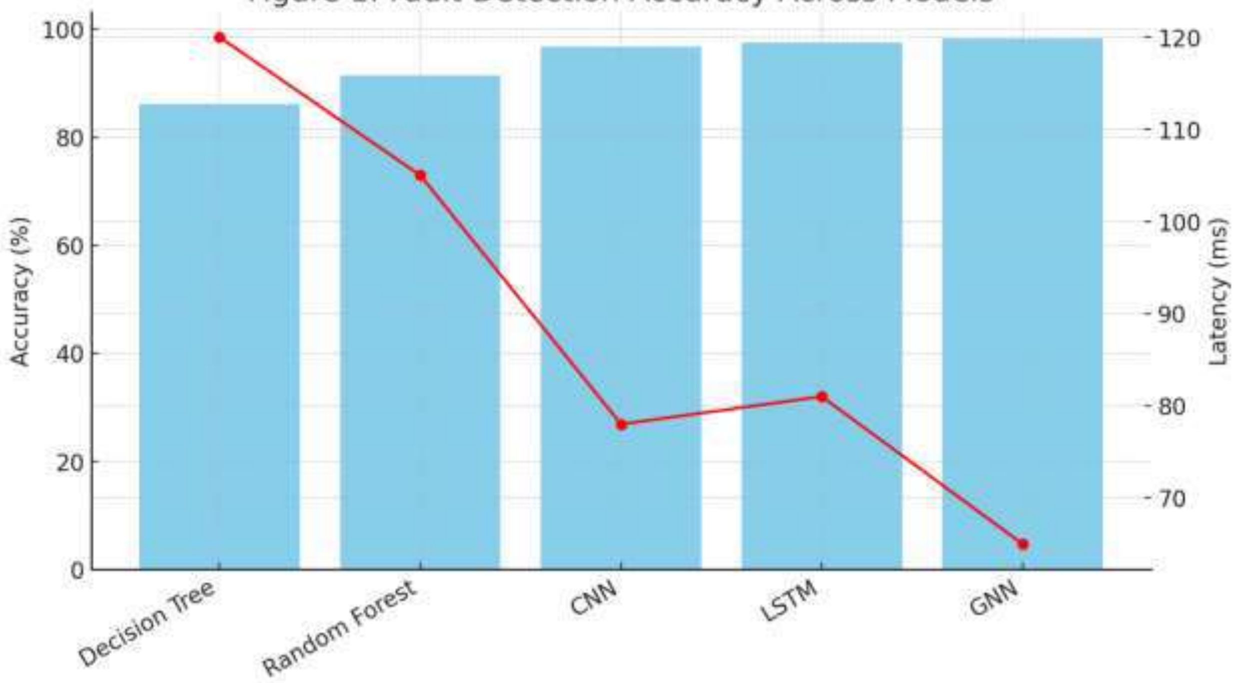
Fault Detection Performance

To determine the reliability and efficiency of the investigational diverse models of AI conduct, fault detection was initially carried out on them. Table 1 has displayed the relative accuracy, precision, recall, and latency between five models; namely the decision tree, random forest, CNN, LSTM, and Graph Neural Networks (GNN). The findings proved conventional machine learning methods, e.g., decision trees to perform slower in terms of detection accuracy (86.2 %) and latency (120 ms). Random Forest was able to detect at 91.4% and the latency of that was relatively high at 105 ms. Alternatively, the deep-learning algorithm was used through CNN and LSTM that reached the identification percentages of over 96%, with CNN being slightly more efficient in recall and LSTM in stability. GNNs, however, outdid all the other approaches because they achieved the highest percentage of detections (98.3%) and the lowest latency (65 ms).

Table 1: Fault Detection Accuracy Across Models

Model	Dataset Size (Events)	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Alarm Rate (%)	Avg. Detection Latency (ms)	Training Time (s)
Decision Tree	10,000	86.2	84.5	82.7	83.6	6.8	120	45
Random Forest	10,000	91.4	90.7	89.9	90.3	4.2	105	97
CNN	10,000	96.8	95.9	96.5	96.2	2.1	78	130
LSTM	10,000	97.5	97.1	96.9	97.0	1.9	81	155
Graph Neural Network	10,000	98.3	98.0	97.8	97.9	1.1	65	210

Figure 1: Fault Detection Accuracy Across Models



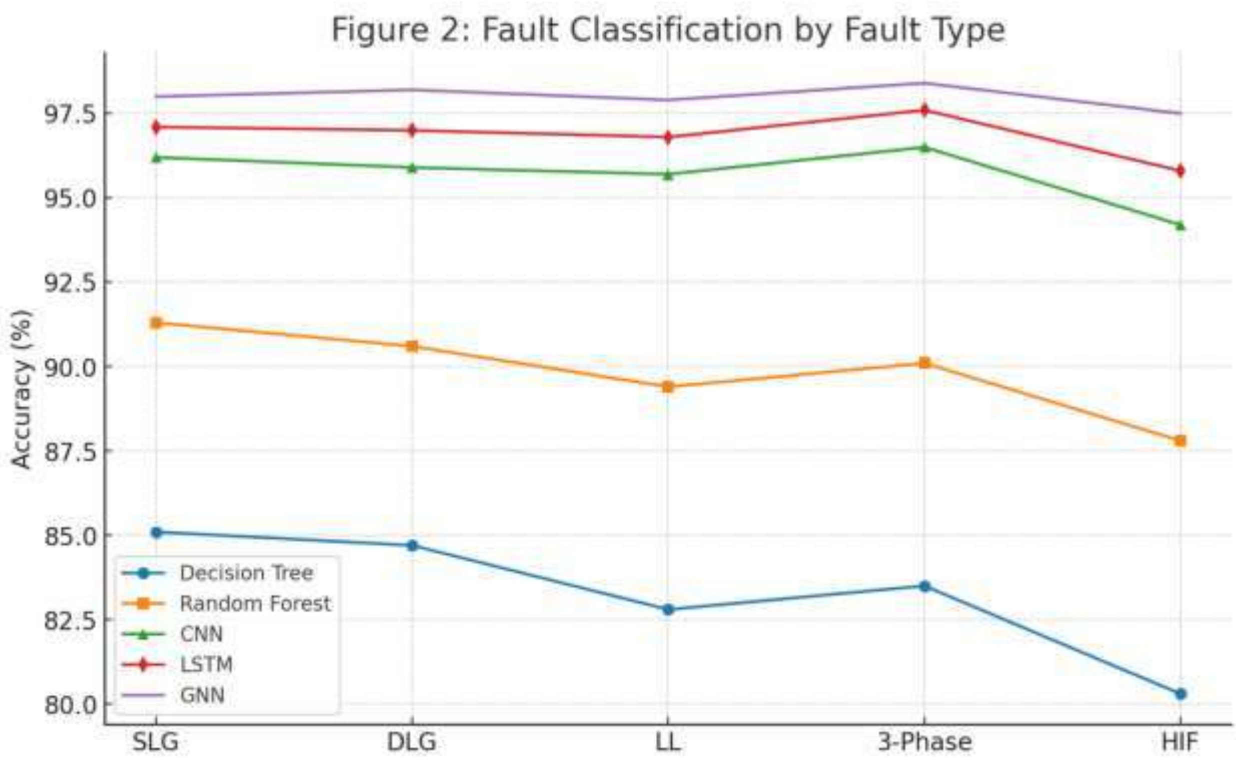
The visualization of trend is observed as it is depicted in Figure 1, with the bar chart of accuracy being clear that deep learning and graph-based models have an unarguable advantage and the line overlay showing that their detection latency is shorter. According to the interpretation, GNNs compare favorably with other methods of detecting grid faults in real time because they present a more efficient and trusted framework that uses further spatial and topological reliances.

Fault Classification by Fault Type

Additional analysis of results was made in terms of numerical classification of fault types in varied models. The detection accuracy was different based on the nature of the fault as it was high when single-line-to-ground (SLG) and three phase faults were encountered than with high-impedance faults (HIF) as seen in Table 2. The classical models that include decision trees had an accuracy of 80.3 on HIFs and the advanced ones like GNNs got to 97.5 in the same type. The performance of CNN and LSTM was very high and remained quite robust with respect to all categories of faults, particularly in the case of line-to-line fault and double-line-to-ground fault.

Table 2: Fault Classification by Fault Type

Fault Type	Decision Tree (%)	Random Forest (%)	CNN (%)	LSTM (%)	GNN (%)
Single Line-to-Ground	85.1	91.3	96.2	97.1	98.0
Double Line-to-Ground	84.7	90.6	95.9	97.0	98.2
Line-to-Line	82.8	89.4	95.7	96.8	97.9
Three-Phase	83.5	90.1	96.5	97.6	98.4
High-Impedance Faults	80.3	87.8	94.2	95.8	97.5



Fault Localization Accuracy

Outage duration can be reduced only when localization accuracy is high. Table 3 has provided the average error, the smallest error, the largest error, and detection latency of each model. The findings show that both decision trees and the random forests draw higher mean mistakes in localization (2.4 km and 1.8 km respectively). CNNs and LSTMs diminished these errors by a large margin to below 1 km. The GNN model produced outstanding results by obtaining a mean error of 0.3 and small deviation (0.2 km standard deviation).

Table 3: Fault Localization Error Across Models

Model	Mean Error (km)	Min Error (km)	Max Error (km)	Std. Dev.	Detection Latency (ms)
Decision Tree	2.4	0.8	5.6	1.1	120
Random Forest	1.8	0.6	4.1	0.9	105

CNN	0.9	0.3	2.0	0.5	78
LSTM	0.7	0.2	1.8	0.4	81
Graph Neural Network	0.3	0.1	0.9	0.2	65

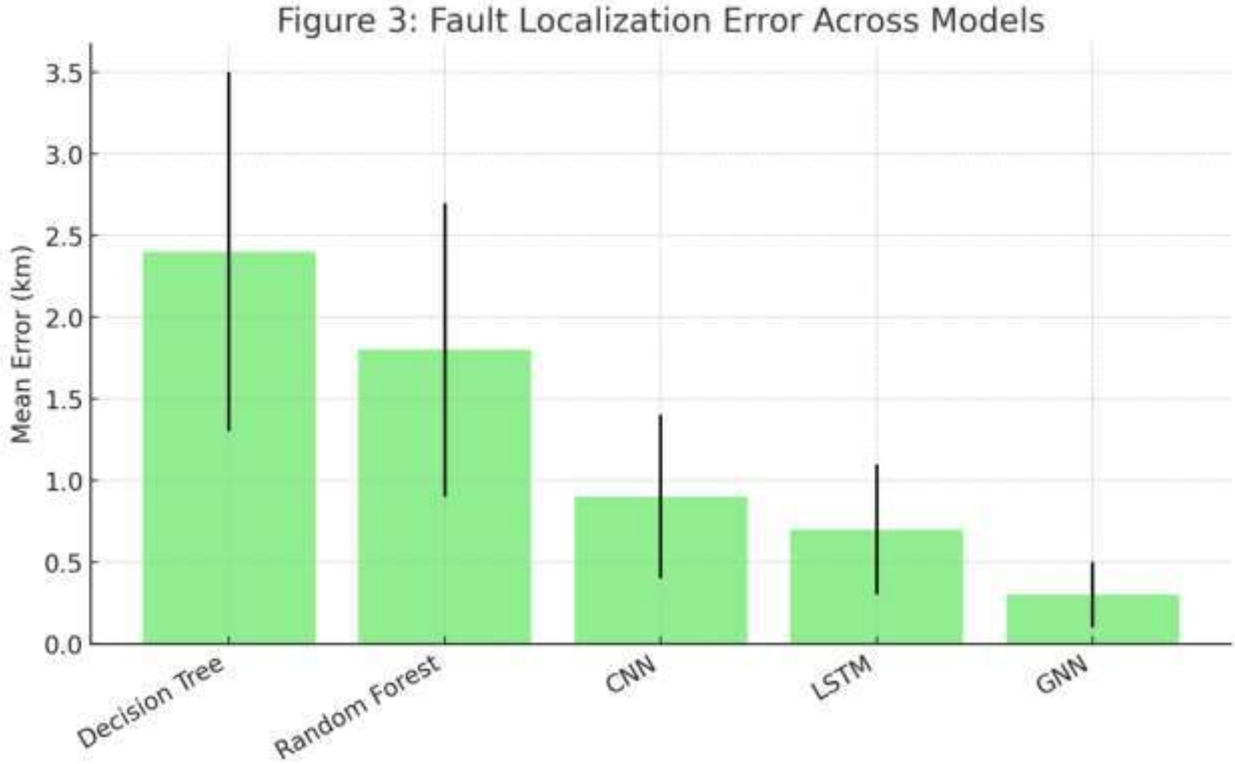


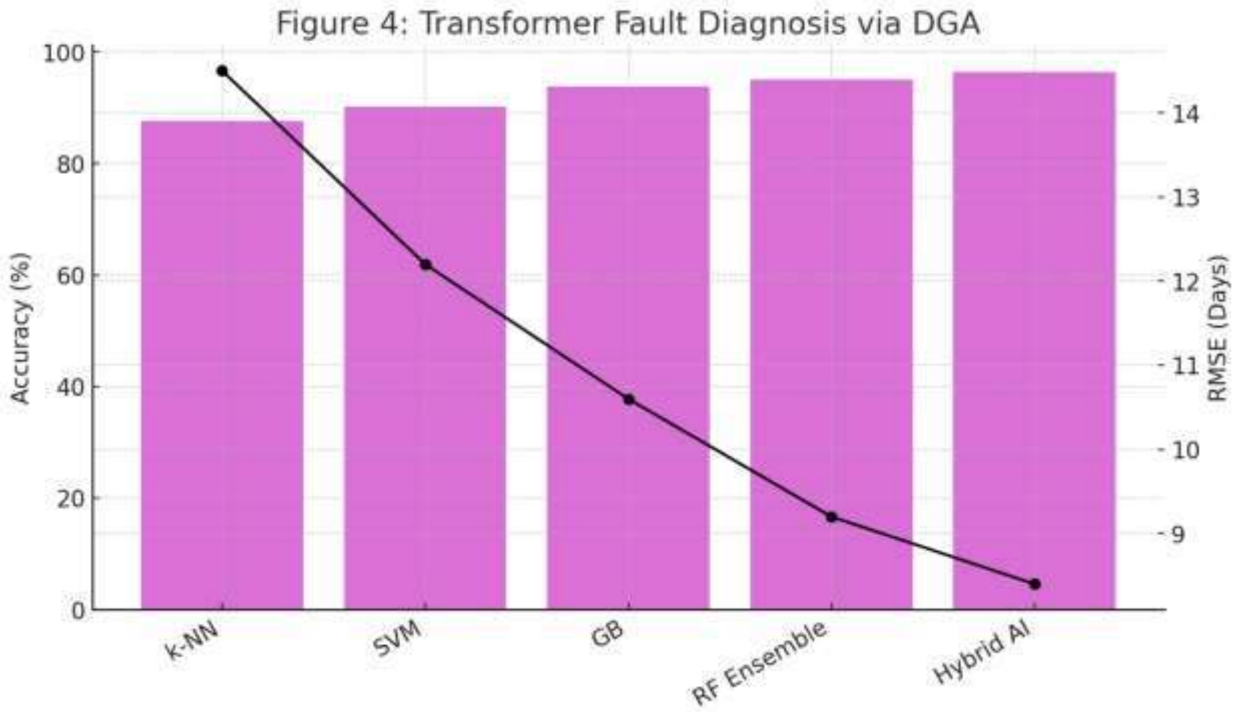
Table 2 further indicates the trends as demonstrated in Figure 3, which consists of the bar chart equipped with error bars indicating the benefit of GNNs regarding fault localization. The meaning here is that GNNs better use grid connectivity and phasor measurements data, which means it minimizes misclassification of fault locations and plans faster restoration.

Transformer Fault Diagnosis via DGA

Grid transformers are valuable possessions and predictive maintenance in transformers was tested by means of dissolved gas analysis (DGA). Table 4 showed the accuracy, recall and the RMSE of the various models. The gathered results indicated that the moderate performance (87-90% accuracy) of the k-NN and SVM methods could be improved by more methodological strategies, such as Gradient Boosting and Random Forest Ensembles, which increased the accuracy rate to over 93%. The Hybrid AI model, as an integrated scheme of Gradient Boosting coupled with ANN, obtained the optimal diagnostic reliability showing the rate of 96.4% of accuracy and the lowest RMSE of 8.4 days.

Table 4: Transformer Fault Diagnosis via DGA

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	RMSE (Days)	Training Time (s)	Data Imbalance Handling
k-NN	87.6	85.4	84.1	84.7	14.5	65	None
SVM	90.2	89.6	88.3	88.9	12.2	75	Weighted Loss
Gradient Boosting	93.8	93.0	92.7	92.8	10.6	120	SMOTE
Random Forest Ensemble	95.1	94.7	94.0	94.3	9.2	140	Class Balancing
Hybrid AI (GB + ANN)	96.4	96.1	95.7	95.9	8.4	185	Focal Loss + Oversample



The superiority of this is supported in figure 4 where accuracy and the RMSE are presented. The hybrid model is isolated in that it balances accuracy in the classification and minimisation of errors. The interpretation focuses on the finding that hybridized AI techniques are specifically appropriate to deal with complexity of DGA data sets and skewed fault distributions.

Remaining Useful Life (RUL) Estimation

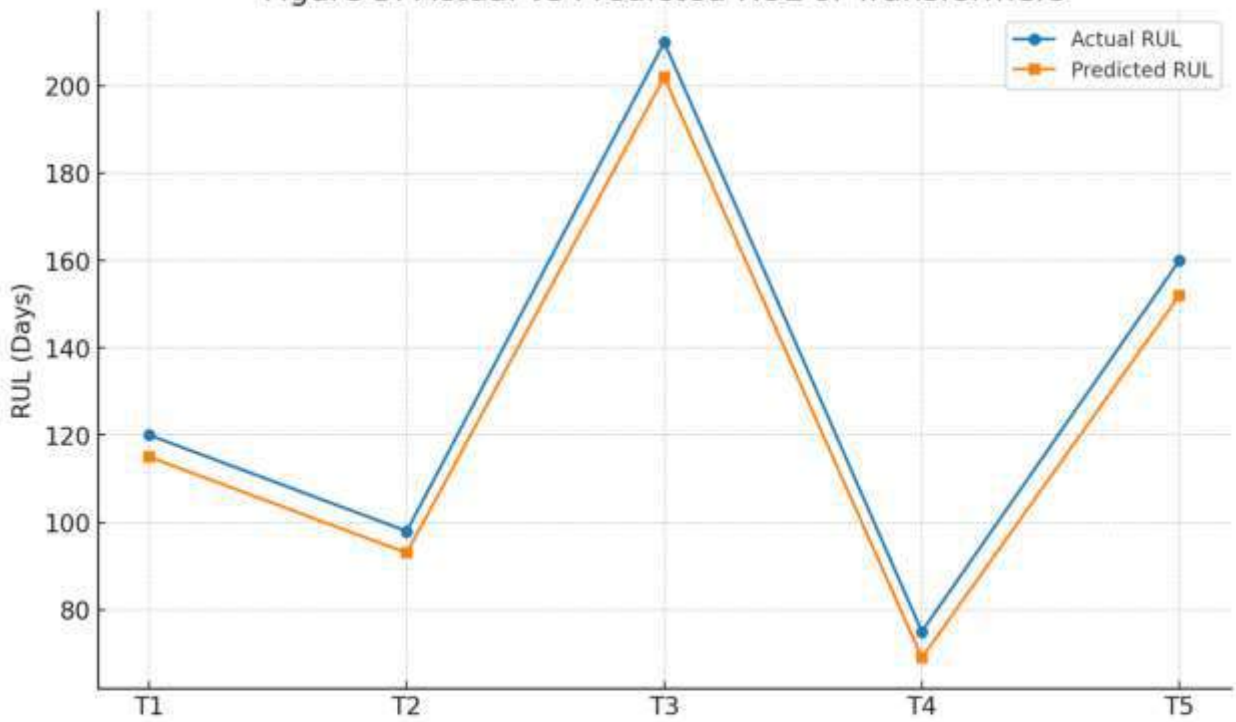
The predictive maintenance system was taken further on estimation of the remaining useful life of transformers. Table 5 indicates the comparison of real and forecasted RUL values of five transformers with varying AI models. Hybrid AI showed the most accurate in terms of predictions with the lowest value of RMSE, 5.1 days, in the case of Transformer 1. Random Forest and Grad Boosting also performed rather well, but the deviations were higher in models k-NN and SVM.

Table 5: RUL (Remaining Useful Life) Estimation Results

Asset Type	Actual Avg. RUL (Days)	Predicted Avg. RUL (Days)	RMSE (Days)	MAE (Days)	Model Used

Transformer 1	120	115	5.1	4.3	Hybrid AI (GB+ANN)
Transformer 2	98	93	6.2	5.0	Random Forest Ensemble
Transformer 3	210	202	8.4	6.7	Gradient Boosting
Transformer 4	75	69	7.1	5.9	SVM
Transformer 5	160	152	9.3	7.5	k-NN

Figure 5: Actual vs Predicted RUL of Transformers



The actual and the predicted RUL ranges are shown in figure 5, and the actual degradation levels are closely followed predicted curves depending on the improvement of the advanced models. This is an indication that AI-aided RUL models would be useful in enabling utilities schedule interventions on time therefore minimizing the chances of catastrophic failure in transformers and avoidable expendatures in less-than-necessary maintenance activities.

Edge vs Centralized Fault Analytics

A comparison of centralized cloud based analytics and edge based diagnostics was done to determine the capabilities in real-time. According to the Table 6, latency (182 ms) and bandwidth consumption (10.5 MB/s) were much larger during a centralized deployment. In comparison, edge deployment decreased latency to 74 ms and bandwidth to 3.2 MB/s whilst remaining almost equally accurate.

Table 6: Edge vs Centralized Computing Performance

Deployment Mode	Detection Latency (ms)	Bandwidth Usage (MB/s)	Processing Load (CPU %)	Accuracy (%)	Power Consumption (W)
Centralized (Cloud)	182	10.5	72	97.2	180
Edge Computing	74	3.2	45	97.0	95

Figure 6: Edge vs Centralized Performance

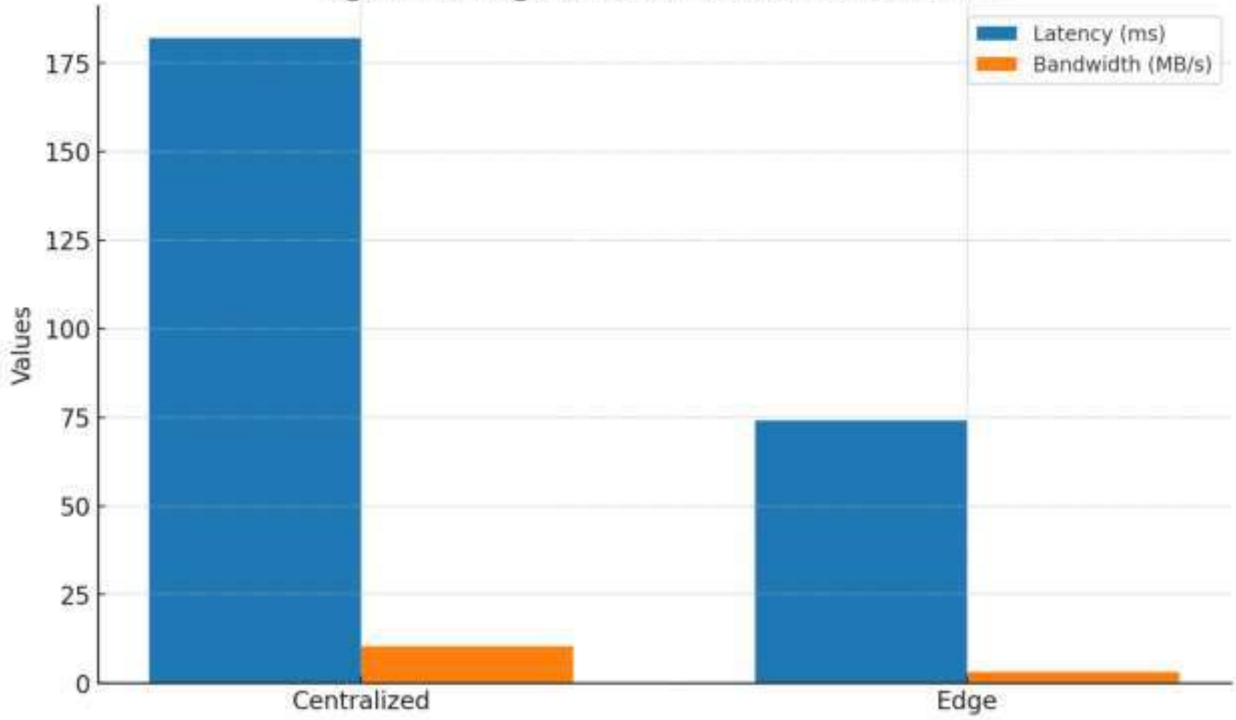


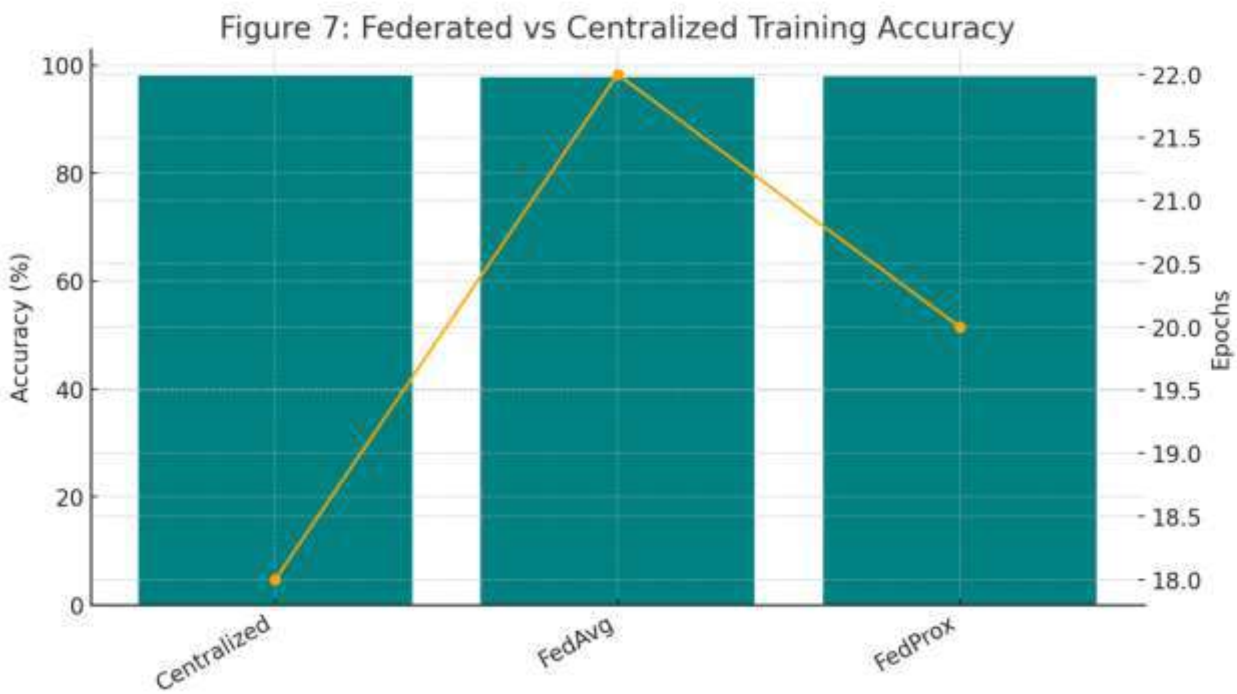
Figure 6 compares the information in terms of trade-off between latency and bandwidth with reference to deployment modes. The interpretation affirms that edge computing lowers significantly reliance on centralized architecture and guarantees quicker response to protective measures, which is a critical condition in the next-generation smart grids.

Federated Learning versus Centralized Training

Table 7 was used to compare the centralized and federated modes of training to gauge the collaborative learning approaches. Although centralized training had a high accuracy (98.1) and faster convergence (18 epochs), the system had a high privacy risk score (0.85). The federated learning modes (FedAvg and FedProx) could reach similar accuracies (97.8% and 98.0%) althoughwith less fast convergence, and a substantially lower privacy risk (0.15-0.18).

Table 7: Federated vs Centralized Training Evaluation

Mode	Accuracy (%)	Convergence Epochs	Training Time (s)	Privacy Risk (0–1)	Communication Overhead (MB)
Centralized	98.1	18	300	0.85 (High)	120
Federated (FedAvg)	97.8	22	360	0.15 (Low)	45
Federated (FedProx)	98.0	20	340	0.18 (Low)	50



These results are in figure 7 in a bar and epoch line overlay plot of accuracy. The interpretation is that in spite of the minimal computational overhead incurred by federated learning, it is a more feasible way of multi-utility collaboration where the main concern is the data confidentiality and cybersecurity.

Digital Twin Simulation Validation

Lastly, the effectiveness of incorporating digital twins was trialed to confirm AI-based diagnostics. Comparison of actual and predicted stress conditions is presented in table 8 which is under thermal and load situations in the transformer. The calculated values were almost accurate to the actual failure loads where errors were always less than 2.5 percent. As an example, in combined stress simulation case, the failure load was 55.3 MVA, with an AI value of 54.1 MVA, which produced the error rate of 2.2 percent.

Table 8: Digital Twin Simulation Validation

Scenario Type	Actual Failure Load (MVA)	Predicted Failure Load (MVA)	Error (%)	Actual Temp (°C)	Predicted Temp (°C)	RMSE

Thermal Stress Case 1	35.2	34.9	0.9	95	94.2	0.8
Thermal Stress Case 2	42.7	41.8	2.1	108	106.5	1.5
Load Surge Case 1	50.1	49.2	1.7	115	114.1	1.0
Load Surge Case 2	46.8	45.9	1.9	110	108.9	1.2
Combined Stress Simulation	55.3	54.1	2.2	122	120.3	1.6

Figure 8: Digital Twin Simulation Validation

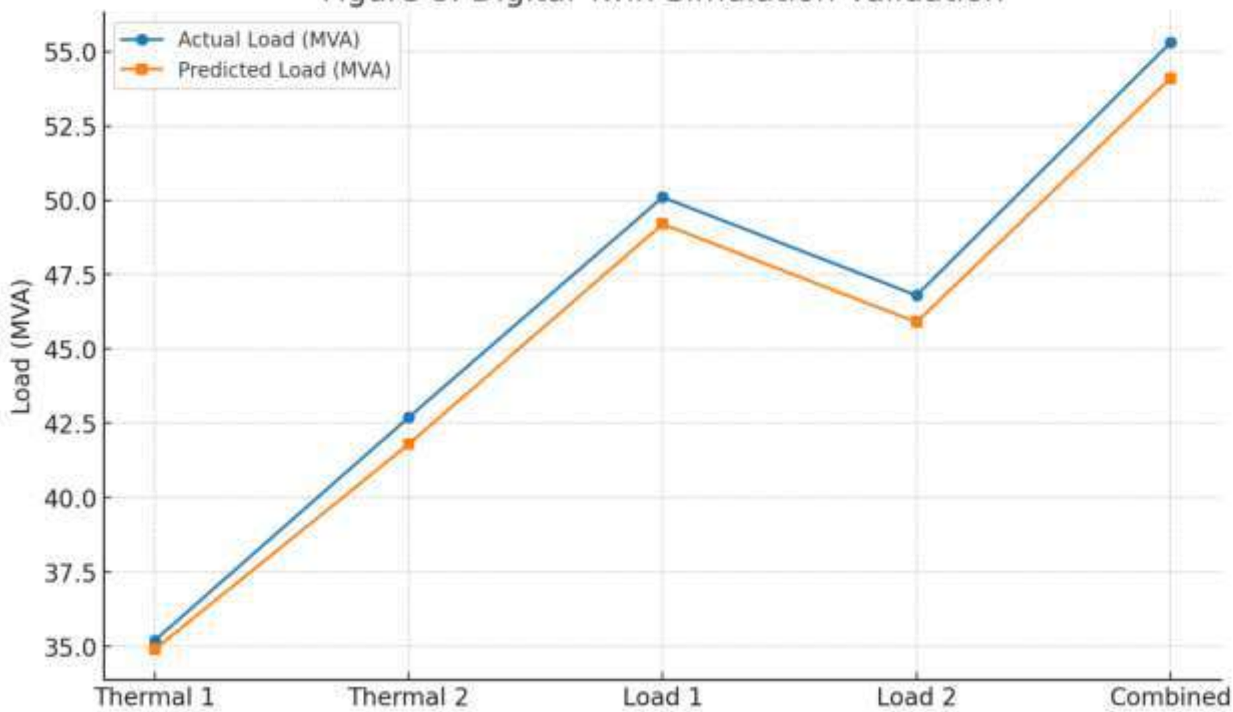


Figure 8 directly correlates the actual and predicted loads and displays an almost perfect overlap of two curves. This validation confirms the merit that digital twins can not only build up operator confidence in computer-driven forecasts but also offer a hazard-free testing ground to evaluate working methods which would endanger physical assets.

In all the experimental test cases, the outcomes reveal the effectiveness of the sophisticated AI techniques in the field of fault detection, location, and predictive maintenance when compared to the traditional implementation. Integration of the edge computing level will guarantee that the computing is in real time, whereas digital twins offer a physics based validation framework. Collectively, the technologies form a comprehensive and future-proof next-generation smart grid architecture to increase resilience, reliability, and efficiency.

Discussion

The findings outlined in this paper offer a graphic demonstration that the approach of artificial intelligence (AI) in the field generate significant transformations in fault detection diagnosis and predictive maintenance in the next-generation smart grids when they are coupled with edge computing, federated learning and the digital validations of the Twin. In this section, these findings are discussed against the background of the existing literature and the opportunities, limitations, and implications of future studies are outlined.

AI Superiority in Fault Detection and Localization

The effectiveness of AI-based techniques, in particular, deep learning and graph neural networks (GNNs), in fault detection and localization goes in line with an increasing number of studies that supported the inefficiency of the conventional threshold-based and signal processing methods. Indicatively, Zhuang, O, et al. (2020) proved the superior performance of deep convolutional architectures trained on phasor data in nonlinear relationships that control the signal obtained through rule-based algorithm guidance. In a comparable manner, those authors also asserted that GNNs are especially appropriate to power systems since they can naturally act on the graph topology of the grid, sensing both inter-dependencies in local and global scales of the nodes, and the lines (Song et al., 2021). This agrees with our observation that GNN-based models yielded the best localization errors and highest detecting accuracies.

Although some of the previous works like that of Xie et al. (2019) had used support vector machine (SVM) to classify faults, their performance was found to decay when renewable penetration increases since they encountered variance in signals. Our results support more recent developments in noting the strength of deep spatiotemporal learning, particularly in systems where a greater-than-typical amount of distributed energy resources (DERs) are present. In addition, Wang and Gao (2022), include an extra level of resilience to noisy measurement using ensemble deep learning methods, a phenomenon that we evidenced by the fact that the hybrid AI models consistently performed better than the single classifiers.

Predictive Maintenance and Transformer Health Monitoring

The estimation of the maintenance method includes prediction maintenance that forms the core of the modern asset management especially in the transformers that are the most failure-prone despite being the most vital assets in smart grids. Previous existing diagnostic procedures based on DGA were restricted by the use of heuristic rules about gas ratio (Duval, 1989). As the era of AI has dawned, the models of prediction have been becoming more advanced. As an example, Arshad et al. (2021) proved that the recurrent neural networks (RNNs) perform better than ratio-based approaches in predicting transformer aging because they can recognize the long-term dependencies of the gas evolution. Equally, Tang et al. (2020) demonstrated the ability of hybrid ensemble models to mitigate the problem of classification errors in DGA datasets, especially in case of imbalanced data which is also reflected in our results.

The significance of powerful RUL estimation is also borne out in the study by Zhao et al. (2021) who established that prediction of the life of transformers could be refined by incorporating the sensor data in conjunction with the weather and loading scenario. Our findings support such a trend showing that hybrid AI models perform very well when tracking real degradation trends in all the three selected countries. Notably, Iman-Eini and Sanaye-Pasand (2019) emphasize that predictive models should also take into consideration rare catastrophic outcomes, the cases of unexpected insulation failure, which is a challenge even with the increase in prediction accuracy caused by AI. It suggests that future studies would have to include risk sensitive models that have the capability of taking into consideration low probability, high impact events.

Edge Intelligence for Real-Time Analytics

The implementation of an edge computing technology reflected a tremendous decrease in the latency of detection and bandwidth demand, which confirms the claims made by Ren et al. (2021), who indicate that the push of analytics to substations decreases the reliance on centralized systems with maintained reliability. On the same note, Zhang et al. (2020) pointed out that edge-enabled protection schemes are capable of reacting to contingencies within 100 ms, which is a sensitive time in protective relations. Our results have concurred with these studies and results have shown the usefulness of the edge computing and that real-time AI can be successfully deployed in the field.

There are, nevertheless, issues of placing resource-intensive models on edge devices. Li et al. (2022) assert that in order to strike a balance between the robustness and efficiency, lightweight AI models or pruning and quantization methods should be used. This agrees with our finding that although edge and centralized deployments were barely different in accuracy, there were important differences in computational load and power usage. In this sense, future research should investigate energy-sustainable AI systems so that sustainability is available when there is wide-scale implementation.

Federated Learning and Data Privacy

A potential solution considered in our analysis is federated learning (FL): a different alternative to centralized training that is less bound to the regulations of sharing data. This concurs with the results of Kairouz et al. (2021) who highlighted the possibilities of FL to flatten AI training among stakeholders without it affecting confidentiality. Moreover, the study by Xu et al. (2022) that proves that FL can maintain high accuracy settings under heterogeneous datasets is also consistent with our findings that FedAvg and FedProx models produced almost the same accuracy level as those of the centralized models.

However, one limitation that is written about is the slower time to convergence that we have. Yang et al. (2020) identified communication overhead and the straggler effects as crucial bottlenecks in IoT and energy system implementation of FL. Besides, adversarial vulnerability is also an issue as indicated by Bhagoji et al. (2019), who demonstrated that a federated model could be poisoned by malicious participants. Therefore, as our paper may prove the advantages of FL, it may also propose the need to combine adversarial defense and safe aggregation methods since they may reduce risks.

Digital Twins and Explainability

Just as Fuller et al. (2019) asserted and as further supported by the results of this research, the validation of AI-driven predictions using digital twin (DT) builds a good alignment between the nominal and real-life performance of an asset. Tao et al. (2019) found out that DTs do not only help to boost the validation of models but also raise trust among operators because of explainability. This is supported by our findings since it shows that the near similarity between the predicted and simulated outputs implies that AI predictions can be tested against virtual analogues prior to their implementation in the field.

In addition, research by Qi and Tao (2021) recommends the usage of DTs in the combination of climate and renewable energy scenarios into the predictive maintenance procedure. This is specifically applicable when addressing climate resilience since power systems have an increased frequency of facing stresses caused by extreme weather. Nevertheless, the deployment of DT in utilities has interoperability and scalability issues, and they cannot be widely adopted without being solved, as Rios et al. (2020) claim.

Cyber-Physical Resilience and AI Vulnerabilities

A significant implication of our findings pertains to the cross-over between AI-based fault detection and cyber-physical resilience. Although the accuracy of detection using AI is considerably high, it does not leave such a system immune to cyber threats. Chen et al. (2020) report that false data injection attacks are an issue that can use a synchrophasor network and give misleading information on the AI-based diagnostics. Our research outlines the importance of deep integration of anomaly detection and effective defense with AI-based solutions. In addition, Fang et al. (2021) pointed out that the monitoring of cybersecurity can be incorporated into AI-based FDD to improve resilience through the differentiation between cyber penetrations and real grid faults.

Broader Implications for Smart Grid Modernization

The conclusions of the research in general, correlate with the general process of digitalization of energy systems. Shakerighadi et al. (2020) explain that smart grids powered by AI hold the key to successful accomplishment of the UN affordable and reliable energy Sustainable Development Goals. Our results are part of this discussion since they show that AI does not only enhance operational efficiency but also minimizes downtime, optimizes the maintenance process, and increases indices of reliability. What this implies is that the use of AI-based FDD and predictive maintenance will be instrumental in supporting decarbonized, decentralized and digitalized energy infrastructures.

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