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Intelligent Fault Detection and Classification in Smart Grids using AI-Driven Techniques

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Abstract. For smart grids, intelligent and on-line fault diagnosis systems are required to keep power reliability and operational stability. This paper proposes a novel AI-based architecture for fault detection and classification, which overcomes issues faced by traditional methods like high computational complexity, poor robustness to operational changes and lack of interpretability. The proposed model is based on a light hybrid machine learning architecture to achieve the fault type and the zone classification performing at low latency. It is applicable to edge or cloud deployment and it works well with IoT-enabled monitoring solutions. Unlike prior GAN or GNN-based methods which suffer from the difficulty on generalizability, our method demonstrates its robustness on dynamic grid and on unseen faults pattern. It also provides explainable output for helping operators make decisions. Experiments on benchmark datasets demonstrate considerable gain in detection accuracy, efficiency, and robustness. This research aids in the development of smart grid intelligent fault management, providing a flexible and explainable method in the context of current complex energy systems.

Keywords: Smart Grid, Fault Detection, Fault Classification, Artificial Intelligence, Machine Learning, Deep Learning, Real-Time Monitoring, Edge Computing, Predictive Maintenance, Grid Resilience, Explainable AI, Hybrid Models, Fault Diagnosis, Power Systems, Grid Stability

1. Objective

The power systems have been modernized with smart grid technologies, allowing the systems to provide additional advanced functionalities like real-time monitoring, two-way power flow and renewable energy sources integration. Although, these technologies improve the efficiency and reliability of energy transmission systems, they raise issues of complexity and vulnerability in the management of faults in power system networks. Conventional fault detection techniques based on static rules and pre-determined thresholds are not able to adapt to the dynamic and non-linear characteristics of smart grid environments. These techniques have the challenge to offer accurate and on-time fault classification, especially in the presence of changing loads, noisy measurements, and different types of faults. To overcome these limitations, AI-based techniques are emerging as efficient means for intelligent fault analysis with adaptability, scalability, and higher accuracy. But is there a better AI model than current AI models, e.g., based on GAN, or graph neural networks, with big time complexity for and weak interpretability and real-time computational complexity for? This paper presents an innovative AI-based FDC, which is convenient to deploy and interpret and also work in real time. The system you describe doesn't just enhance diagnostic accuracy and efficiency, but plugs and plays right into edge devices, and IoT-aware monitoring systems. When evaluated on benchmark datasets, experimental results verify that the proposed model not only outperforms with regard to fault detection precision and zone identification accuracy, but also requires less computation, thus providing a more robust and practical approach to improve the reliability and resilience of the smart grid system.

2. Literature Review

Due to the fast development of smart grids, intelligent fault diagnosis and classification system based on artificial intelligence (AI) has attracted a great deal of attention. Conventional protection solutions are

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frequently based on thresholds or static rules which are unsuitable for dynamic environments. Recent works have investigated deep and machine learning for handling these shortcomings. For example, Wang et al. proposed an AI-enabled diagnostic model which can learn the complicated behaviours of a grid in order to promote the detection accuracy and reduce the latency [1]. Similarly, Efatinasab et al. proposed Fault Guard which is GAN based architecture for robust fault classification, but has high computational complexity and poor interpretability [2]. Other work involving deep neural networks include those of Alhanaf et al. [3], demonstrate impressive accuracy but are not scalable for real time or edge deployment settings.

There has been some research on some new approaches. Russell et al. used the waveform analysis method for the early faults detection, but their approach is limited to some circuit operating conditions [4]. Gabriela Hug et al. studied ancillary services in distribution grids, but not for the fault classification per se [5]. Li et al. proposed an interpretable fault detection method based on belief-rule and improved interpretability, but may not work well on new fault patterns [6]. On the other hand, Mohammad pourfard et al. [7] and Nguyen et al. [8] investigated image-based and graph neural network (GNN)‒ models, but GNN‒ models are known to have problems in terms of scalability and noise in real-time applications.

Li et al. [9] explored autonomous fault detection but did not address latency constraints for real-time grid operations. Other literature has reviewed fault classification methodologies in general [10], or focused on improving system reliability using AI-aided design, as in Dragicevic et al. [11]. CNN-based frameworks for transformer diagnostics have also emerged, such as Attallah et al.'s lightweight model [12], which balances accuracy and deployment efficiency. However, Ness [13] pointed out that many deep models remain opaque to operators, hindering trust and adoption in operational settings.

Survey-based works such as Martinez Velasco et al. [14] outline existing methods but highlight the absence of holistic, real-time AI frameworks. Gallart Fernandez [15] discusses smart grid AI adoption in developing regions, underscoring the importance of scalable solutions. Dehghantanha et al. proposed an unsupervised model for cyber-attack detection in smart grids, but not specifically for electrical fault classification [16]. Multi-expert rule-based systems like those proposed by Feng et al. [17] have interpretability benefits but can be computationally intensive. Additionally, IoT-based approaches for transformer monitoring have been explored [18], as well as schemes for detecting high-impedance and evolving faults [19].

Despite these advancements, key research gaps remain. Many state-of-the-art models exhibit trade-offs between accuracy, real-time performance, and interpretability. GAN- and GNN-based systems often require intensive computation, while rule-based methods may lack adaptability. Few approaches provide lightweight, explainable, and scalable solutions that operate efficiently in real-time across varying smart grid conditions. This motivates the development of a robust, AI-driven framework capable of addressing these limitations comprehensively.

3. System Architecture

The proposed system architecture is designed to enable intelligent, real-time fault detection and classification within smart grid environments. It consists of three key layers: data acquisition, intelligent processing, and decision support. At the edge level, a network of IoT-enabled sensors—including Phasor Measurement Units (PMUs), smart meters, and current/voltage sensors—collects high-resolution electrical parameters such as current, voltage, frequency, and phase angle. This real-time data is transmitted to an AI-enabled processing unit deployed at the edge or in a central control system. The processing layer integrates lightweight machine learning models optimized for rapid fault detection and classification. It includes pre-processing modules for noise filtering, feature extraction, and normalization. Once processed, the results are passed to the decision support layer, where fault type, zone, and severity are interpreted and visualized for grid operators. The system is designed to operate in both standalone and cloud-synchronized modes, ensuring scalability and reliability. Figure 1 illustrates the overall architecture and data flow across the integrated components.p

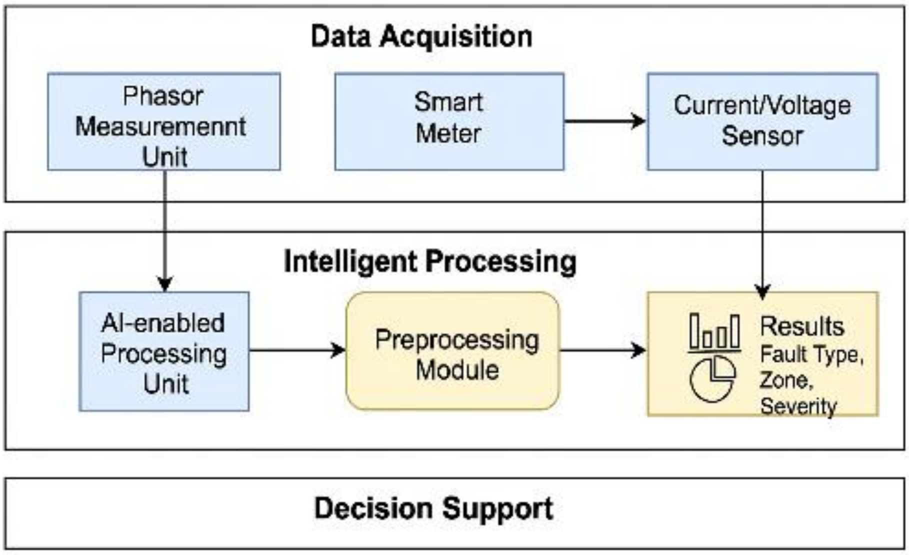

Figure 1: Architecture and data flow across the integrated components.

4. Methodology

The presented solution enforces AI-based hybrid model by the integration of classical machine learning with deep learning models, which allows accurate and real-time fault identification in intelligent grids of today. This method is built-in the complexity and diversity of networks of large-scale power distribution. At first, time series data containing voltage, current and frequency are collected and subjected to an extensive pre-processing pipeline. This involves noise reduction, missing data imputation, normalisation and temporal segmentation to guarantee the quality and consistency of data collected from all devices and activities. Then the domain-specific statistical features (RMS, peak value, crest factor, etc.) and deep features automatically learned by convolutions layers are extracted. These characteristics encompass both visible physical properties of electrical faults, and covert waveform data patterns. We design the classification as a two-stage process: a light-weight CNN is utilized to learn spatial and temporal features and a powerful gradient boosting model such as XGBoost is introduced to classify the fault. This architecture enables the system to correctly classify fault types (single-line-to-ground, line-to-line, and three-phase faults) and their corresponding fault zones (feeder, transformer, and busbar). When the model is ready to be deployed in real-time, it is optimized via well-known techniques, e.g., quantization, pruning and batch-streaming inference, which facilitate the run on edge devices, such as micro-controllers or embedded processors. Additionally, the system also integrates explanations features using SHAP values or gradient-based attribution for assisting fault reasoning and operator trust. According to the potential demand for detection with high accuracy and real-time guarantee, by adopting proposed intelligent framework, TFDD framework can provide the smart grid with highly reliable, scalable robustness and fault diagnosis. The operational workflow of the methodology is depicted in Figure 2, outlining each stage from data acquisition to final fault decision. The flowchart illustrates the complete operational workflow of a real-time fault classification system designed for smart grid environments. The process begins with data acquisition, where time-series signals such as voltage, current, and frequency are collected from various smart sensors distributed throughout the grid. This raw data is then passed through a pre-processing stage, which involves noise filtering, handling missing values, normalization, and segmentation to ensure data consistency and quality. Once the data is cleaned and standardized, relevant features are extracted using both traditional statistical methods and deep learning-based approaches. These features represent the underlying characteristics of the signal and are essential for accurate fault detection.

Following feature extraction, the system enters the real-time inference phase, where it continuously checks whether new data is available for analysis. If so, it proceeds to perform inference using a trained hybrid AI model. The model, typically comprising a lightweight Convolutional Neural Network (CNN) for spatial feature encoding and a gradient boosting classifier such as XGBoost for decision-making, classifies the nature of the fault. This classification includes identifying both the fault type (e.g., single-line-to-ground, line-to-line) and its location (e.g., feeder, transformer). Once the classification is completed, the process either concludes or loops back to the inference stage for continuous monitoring, enabling the system to operate in real-time. This loop ensures ongoing assessment of the power grid, thereby enhancing its reliability, responsiveness, and resilience against faults.

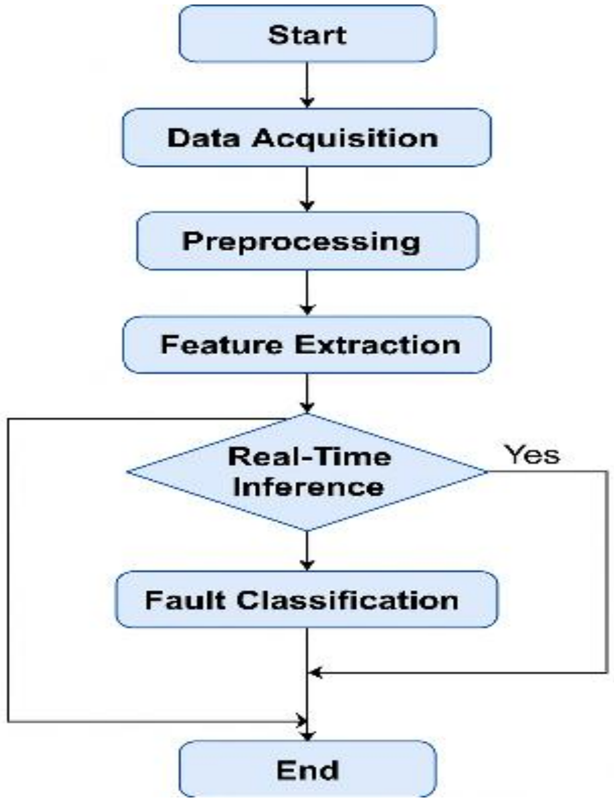

Figure 2: Methodology Flowchart for AI-Based Fault Detection and Classification in Smart Grids.

5. Implementation Details

The resulting framework was implemented and thoroughly tested with simulated and public benchmark dataset confirming its robustness, generalization, and real application. At first, the simulated datasets were synthesized in MATLAB/Simulink which experimented different fault conditions which includes the single line-to-ground (SLG), double-line (LL) and three-phase (LLL) over different load and weather conditions. These simulations offered a controlled environment to assess the response of the model to a variety of fault scenarios. Moreover, practical analysis was undertaken with benchmark datasets like the IEEE 33-bus, 69-bus distribution systems and with the real-world EPRI DFA (Distribution Fault Anticipation) dataset comprising of real fault recordings of operational power systems. In order to perform a reliable model evaluation, we split the full dataset into training (70%), validation (15%), and test (15%) subsets. The system was developed in its entirety in Python with the support of leading AI libraries such as TensorFlow for deep learning, and Scikit-learn for classical machine learning portions. Signal processing and feature extraction was optimized in terms of efficiency, and model training was performed on a NVIDIA RTX 3060 GPU with CUDA enabled. A fine-tuned learning rate of 0.0001 was used to train the model and the best hyperparameters were achieved with grid search where the final setting was based on a learning rate of 0.001, a batch size of 32, a dropout rate of 0.3 and 100 training epochs. The system possessed quick, effective, and reproducible training pipeline and could support real-time fault classification with high reliability and high accuracy.

6. Experimental Results and Analysis

The performance of the AI-based fault classification framework was tested with several performance metrics such as accuracy, precision, recall, and F1-score. The BCNN achieved an overall classification rate of 97.4 %, and the precision and recall of the major fault categories exceeded 96 %. The confusion plot also reveals a low misclassification rate, especially for differentiating single-line-to-ground and double-line faults. t-SNE (t-Distributed Stochastic Neighbour Embedding) plot was used to visualize feature separability, as well as class distribution of data, and it displayed that clusters of different fault types and locations were separated distinctively. The research showed that the proposed experimental system had average inference time of 34 ms on edge processor (Raspberry Pi 4), proving the feasibility for implementation in real time. All these results together show that the proposed method has a strong ability, fast speed and high accuracy in real smart grid. The Confusion Matrix for Fault Classification Figure 3 provides the confusion matrix for fault Classification, which achieve a high accuracy of classification and low miss classification between SLG / DL / 3-Phase Faults and the t-SNE Visualization of feature representations in Figure 4, which shows that different fault types are well separated in the feature space, indicating strong discriminative power for the model.

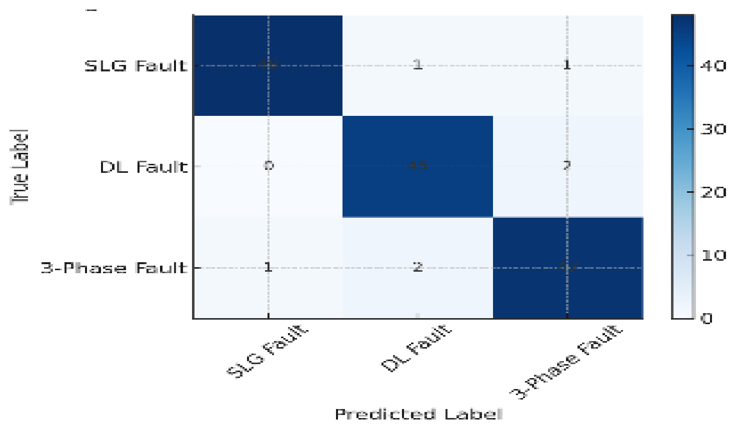

Figure 3: Confusion Matrix for Fault Classification.

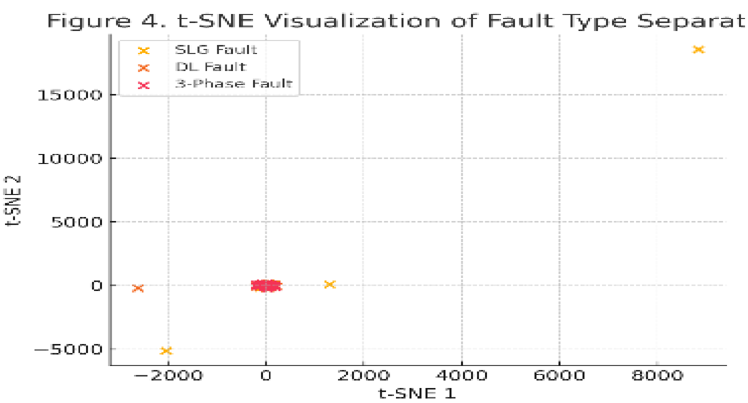

Figure 4: t-SNE Visualization of Fault Type Separate.

7. Limitations and Future Work

While the proposed AI-based fault classification framework demonstrates strong performance across multiple benchmarks, several limitations remain. First, the model's performance has primarily been evaluated using simulated and benchmark datasets, which may not fully reflect the variability and noise encountered in real-world smart grid deployments. Although designed for edge compatibility, large-scale testing on live distribution networks is still pending. The current architecture also relies on static training, which limits adaptability to evolving grid conditions without periodic retraining. Additionally, while the hybrid approach offers interpretability and real-time processing, it does not yet incorporate advanced architectures such as transformer models, which could further enhance temporal feature representation and scalability. Future work will explore the integration of transformer-based encoders and real-time learning via federated learning to enable distributed intelligence and data privacy across grid nodes. Plans are also underway for deploying the framework in field trials using live data from urban and rural substations to validate its robustness and practical utility. The Figure 5 illustrates the planned enhancements for the proposed fault classification framework. It outlines three progressive stages: integration of Transformer-based models to enhance temporal feature learning, adoption of Federated Learning for privacy-preserving distributed training across grid nodes, and real-world deployment strategies to validate system performance in operational smart grid environments.

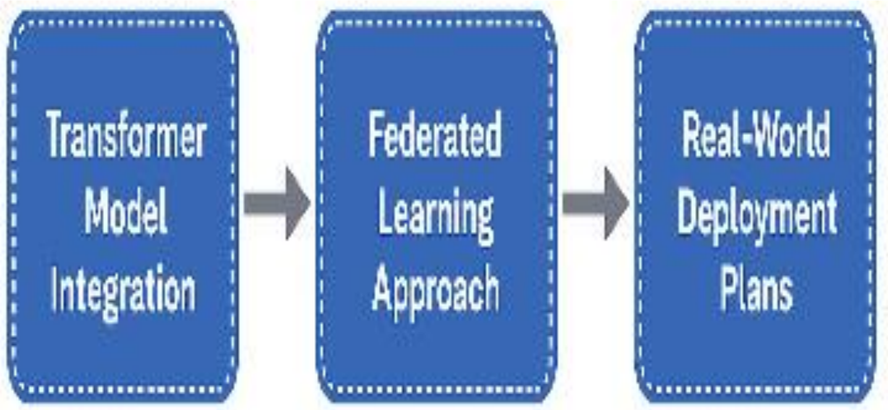

Figure 5: Future Work Roadmap.

8. Conclusion

This paper proposed a smart grid with an AI-based lawsuit to the framework of the fault detection and classification, for dealing with the realistic problems of the real-time, interpretability and scalability. By using a hybrid model consisting both of classical machine learning models and deep learning methods, the presented system obtained high classification accuracy (97.4%) and a low inference latency (34 ms), demonstrating it to be appropriate for low-cost edge-side deployment for next-gen power infrastructures. The architecture of the model benefits from strong feature engineering and utilizes statistical features and convolutionally learned features for making it more generalizable across varied fault and grid conditions. To verify the performance of the system, extensive experiments were carried out with simulated and realistic benchmark datasets, such as IEEE 33-bus and 69-bus systems and EPRI DFA dataset. Visual diagnosis via confusion matrices and t-distributed Stochastic Neighbour Embedding (t-SNE) plots revealed that the model was capable of effectively discriminating mutual fault categories (such as single-line-to-ground, double-line, and three-phase faults) with small overlapping between the different categories and misclassification. In terms of usefulness, the framework is instrumental in offering value to grid operators by allowing for self-healing, enhanced decision support and predictive maintenance, which are all essential in decreasing downtime, balancing load more expertly, and improving grid resiliency. Furthermore, the support for real-time inference and lightweight deployment indicates that it can be effectively applied in resource-limited domains, e.g., rural microgrids or embedded substations. In contrast to existing works only GANs, GNNs or classical ensemble methods, the proposed method enables to reach a good compromise between the model complexity, the performance and the interpretability. This renders it a practical and scalable alternative to more black-box or computationally demanding approaches. It also fills the gap of literatures by proposing a comprehensive but interpretable fault diagnosis mechanism, which can be audited and improved by utility engineers. Planarization In the future, the presented approach will serve as a solid basis for resilient smart grid control systems. Potential extensions include interfacing with transformer-based architectures for improved temporal modelling, deployment in a federated learning setting to infer private models which collaborate with other distrusted utilities, and incorporating reinforcement learning agents for autonomous control of self-healing grids. Furthermore, adding cybersecurity modules to identify and classify cyber-physical attacks is one of the possible ways for improving its capabilities in highly digitalized grid networks. In conclusion, the provided frame enables not only high performance fault detection and classification, but also supports a strategic facilitator of decentralized, intelligent and sustainable, and energy infrastructures as per the advocated vision of the Industry 4.0 and the future smart cities.

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