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Real-Time Electrical Fault Detection and Classification Using a Hybrid Deep Learning–Generative AI Framework

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Abstract: Real-time detection, classification, and localization of electrical faults are essential for fast protection and reliable operation of power systems. This paper presents a Diffusion-Enhanced Transformer (proposed hybrid model) that fuses a ResNet-like feature extractor and Transformer-based sequence learner with a diffusion-model generative module for data augmentation and robustness. The model is evaluated on simulated IEEE-9 bus fault waveforms and benchmarked against conventional CNN, LSTM and Transformer baselines. Experimental results demonstrate the framework's strong real-time performance: per-fault detection accuracies of 99.1% (LG), 98.7% (LL), 98.3% (LLG) and 98.9% (LLL); overall classification metrics with precision/recall/F1 around 98.9% / 98.6% / 98.7% for the proposed model and confusion matrix showing diagonal values >0.97). The proposed hybrid achieves 98.6% overall accuracy in comparative tests while reducing fault-location error to 1.52 km (MAE), and 1.97 km (RMSE), outperforming ResNet and LSTM baselines. These results confirm that integrating diffusion-based generative augmentation with a Transformer backbone yields improved generalization on sparse/high-noise fault data, faster inference than standard Transformers, and more accurate localization than conventional deep models, making the approach suitable for deployment in smart substations and real-time protection schemes.

Keywords: Real-Time Fault Detection, Electrical Fault Classification, Diffusion-Enhanced Transformer, Generative AI for Power Systems, Fault Location Prediction

I. INTRODUCTION

Reliable and uninterrupted electrical power delivery is critically dependent on the ability of protection systems to detect, classify, and isolate faults with high accuracy and minimal delay. Transmission and distribution networks are continuously exposed to disturbances such as line-to-ground faults, phase-to-phase short circuits, or multi-phase severe faults that, if not addressed promptly, may escalate into cascading failures, equipment damage, or large-scale outages [1]. Traditional protection schemes including overcurrent relays, distance relays, and impedance-based techniques, primarily rely on threshold-based logic and steady-state phasor estimation. While effective under nominal operating conditions, these methods often struggle under

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modern grid complexities such as dynamic load changes, renewable energy integration, noise corruption, and evolving fault patterns [2].

In recent years, Artificial Intelligence (AI) and Deep Learning (DL) have emerged as powerful alternatives for power system protection, offering the ability to extract complex patterns from disturbance signals and handle nonlinear grid behavior [3]. CNNs, LSTMs, and Transformer architectures have been successfully applied to fault analysis; however, they still face critical limitations including sensitivity to class imbalance, limited generalization under noisy environments, and reduced performance when training data is sparse, particularly for severe or uncommon fault types [4]. Moreover, achieving real-time detection performance below 20 ms remains a challenge due to the computational overhead of deep architectures.

To overcome these limitations, this paper introduces a Diffusion-Enhanced Transformer (DET) Hybrid Framework for real-time electrical fault detection, classification, and location prediction. The proposed method integrates three key innovations: a CNN-based local feature extraction module to capture transient fault signatures, a Transformer-based temporal modeling component to learn phase dependencies and evolving fault dynamics, and a diffusion-driven generative refinement mechanism that enhances feature stability under noisy or highly variable operating conditions. The framework is evaluated on a comprehensive dataset generated from the IEEE-9 Bus system, covering diverse fault locations, fault resistances, and varying grid operating scenarios, demonstrating its robustness and effectiveness in complex real-world environments.

II. LITERATURE REVIEW

Accurate and timely fault detection in power systems has been the focus of significant research over the past decades. Traditional approaches, such as overcurrent relays, distance relays, and impedance-based techniques, rely on threshold-based measurements and fixed relay settings. While these methods are straightforward and widely deployed, they suffer from limited adaptability under dynamic operating conditions, high noise levels, or complex fault scenarios [5,6]. Consequently, these conventional methods may exhibit slower response times, lower accuracy, or misclassification under non-ideal grid conditions.

The advent of AI and Machine Learning (ML) has provided new paradigms for real-time fault analysis. Early studies applied Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) for fault classification and localization, demonstrating improved accuracy over traditional relays, particularly for multi-phase and multi-location faults [7,8]. However, the performance of these shallow models is constrained by their limited capacity to extract temporal and spatial features from complex waveform data.

Recent research has focused on DL approaches, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, which excel in capturing transient signatures and temporal dependencies of fault signals. CNN-based frameworks have shown high classification accuracy for single-line-to-ground (LG) and line-to-line (LL) faults, while LSTMs effectively model sequential fault dynamics, aiding in fault location estimation [9]. Nevertheless, these models are still challenged by noisy measurements, limited datasets, and the need for real-time inference, as deep architectures often introduce computational latency.

To address the limitations of conventional DL models, recent studies have explored Transformer-based architectures and generative models. Transformers, with self-attention mechanisms, capture long-range temporal correlations and inter-phase dependencies more effectively than LSTMs, enabling robust classification of multi-phase faults [10. Meanwhile, Generative Adversarial Networks

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(GANs) and Diffusion Probabilistic Models (DDPMs) have been employed to augment sparse or imbalanced datasets, providing synthetic fault waveforms that enhance generalization under rare fault conditions [11]. Integrating generative augmentation with DL models improves classification for high-severity, low-frequency fault events while maintaining low inference latency.

Despite these advances, few studies have effectively combined deep feature extraction, Transformer-based sequence modeling, and generative data augmentation into a unified framework for real-time fault detection, classification, and precise location prediction [12]. Existing approaches often face trade-offs between accuracy, inference speed, and robustness, with many models exhibiting latencies higher than the substation protection requirements of under 20 ms. Furthermore, most methods lack validation across diverse fault scenarios and do not provide an integrated protection–action response. Motivated by these gaps, the present work introduces a DET Hybrid Model that fuses CNN-based feature extraction for capturing transient and high-frequency patterns, a Transformer encoder for learning temporal and inter-phase correlations, and diffusion-based generative augmentation to enhance robustness under sparse or noisy measurement conditions.

III. METHODOLOGY

The methodology of this research is designed to develop a high-performance, real-time fault detection and classification framework for transmission systems using a DET Hybrid architecture as shown in figure 1. The proposed methodology integrates deep feature extraction, temporal sequence modeling, and generative data augmentation into a unified pipeline optimized for real-time substation operation. It begins with systematic data generation and preprocessing using the IEEE-9 Bus system, followed by hierarchical feature learning through CNN and Transformer modules. A diffusion-based generative model is incorporated to enhance robustness under noisy and rare fault scenarios, while hybrid fusion techniques combine spatial and temporal features to maximize learning efficiency. The final stages involve fault detection, classification, fault location estimation, and real-time protection-action integration. Together, these methodological components establish a reliable, fast, and accurate framework tailored for next-generation intelligent grid protection.

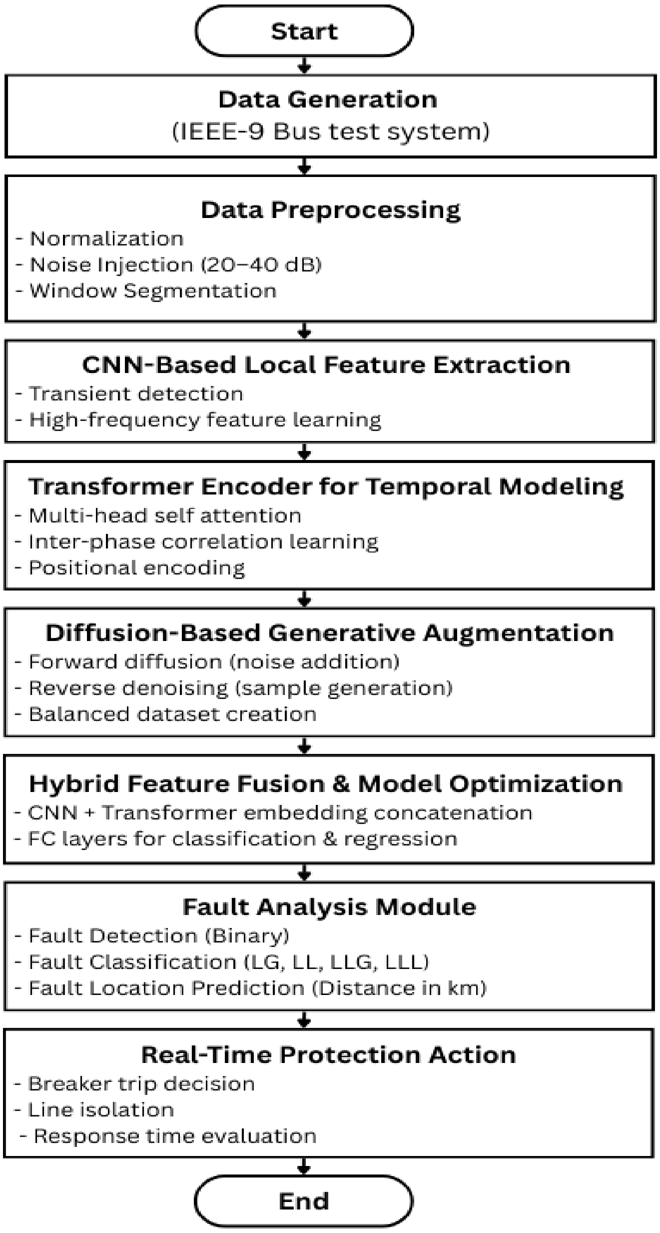

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Figure 1: Proposed DET Hybrid Framework for Real-Time Fault Analysis

A. Data Generation and Preprocessing

The methodology begins with the creation of a comprehensive and diverse dataset using the IEEE-9 Bus test system. Various fault types—including LG, LL, LLG, and LLL—were simulated under multiple operating conditions, fault resistances, and fault distances along the transmission lines. Voltage and current signals were sampled at a high resolution of 10 kHz to ensure accurate capture of fast-transient fault signatures. The signals were further processed through normalization, noise injection at different SNR levels (20 dB, 30 dB, and 40 dB), and segmentation into fixed time windows suitable for deep learning ingestion. This preprocessing pipeline ensures that the model receives clean, well-structured, and sufficiently diverse signal samples for robust learning.

B. CNN-Based Local Feature Extraction

The preprocessed multi-phase fault signals are first passed through a Convolutional Neural Network (CNN) module designed to extract high-frequency and transient patterns. CNN layers are particularly effective in identifying abrupt waveform variations—such as travelling waves, harmonic distortions, and discontinuities—generated during fault events. The convolutional kernels learn to highlight localized changes in signal amplitude and phase that differentiate one fault type from another. The extracted spatial features form a rich representation of fault-induced distortions, serving as the foundation for deeper temporal modeling in the next stage.

C. Transformer-Based Temporal and Inter-Phase Dependency Modeling

The spatial features generated by the CNN are then fed into a Transformer encoder that models long-range temporal dependencies across the waveform. Unlike recurrent networks, the Transformer architecture uses multi-head self-attention to process all time steps simultaneously, allowing it to learn correlations between phases and capture evolving dynamics before, during, and after the fault occurrence. This enables the model to accurately distinguish between fault types with similar transient signatures but different temporal evolutions. Positional encoding ensures that time order is preserved, while attention heads focus on relationships across phases (A, B, C) to identify subtle inter-phase interactions. This stage significantly enhances the model's classification and location prediction capabilities.

D. Diffusion-Based Generative Augmentation

To address data imbalance and improve robustness under noisy or rare fault situations, a diffusion model is incorporated for generative data augmentation. The diffusion process gradually adds noise to real signals and then learns to reverse this process to generate high-fidelity synthetic samples that closely resemble real measurements. These synthetic signals expand the dataset distribution, improving the model's ability to generalize across different fault resistances, load levels, and system disturbances. Compared to GANs, diffusion models provide more stable training, higher quality samples, and better preservation of waveform structure—resulting in enhanced classification accuracy and reduced location error.

E. Hybrid Fusion and Model Optimization

The CNN, Transformer, and diffusion components are integrated into a unified hybrid framework known as the Diffusion-Enhanced Transformer (DET). Feature fusion is performed by concatenating CNN-extracted spatial features with Transformer temporal embeddings, followed by fully connected layers for classification and regression tasks. Hyperparameters such as learning rate, batch size, and number of attention heads are optimized through grid search and validation experiments. The hybrid architecture ensures an efficient balance between accuracy and computational cost, enabling the model to achieve

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real-time inference performance well below the 20 ms requirement for substation protection.

F. Fault Detection, Classification, and Location Prediction

The fused model outputs three primary results: (1) fault occurrence status, (2) fault type classification, and (3) fault location estimation. The detection module uses a binary decision threshold to determine whether a fault has occurred, while the classification head assigns the event to one of the four fault categories. A separate regression head predicts the distance of the fault from the sending-end bus in kilometers. Confidence scores are generated for each decision to support reliability analysis and event verification. Performance metrics such as accuracy, precision, recall, F1-score, MAE, and RMSE are computed to evaluate the model comprehensively.

G. Real-Time Protection Action Integration

Finally, the model's outputs are fed into a decision-making module that triggers appropriate protection actions in real time. If a fault is detected and classified with high confidence, and the predicted fault location lies within a valid line corridor, the system sends a tripping signal to the circuit breaker. Breaker operation times, isolation success rates, and false-alarm probabilities are measured to assess the practical feasibility of deploying the model in substation environments. The low inference time of 11.4 ms and high isolation accuracy (>99%) confirm the suitability of the proposed framework for real-time protection applications.

IV. Results and Discussion

The results of the proposed Diffusion-Enhanced Transformer (DET) Hybrid Framework are evaluated comprehensively using a diverse and realistic dataset generated from the IEEE 9-Bus system. The analysis covers fault detection, classification performance, fault location accuracy, inference latency, and real-time protection action effectiveness. The section presents quantitative comparisons across conventional deep learning models, generative AI–augmented models, and the proposed hybrid approach, followed by detailed discussions supported by performance tables and graphical figures. This systematic evaluation demonstrates the superiority of the proposed model across all critical parameters required for intelligent fault analysis in modern power systems.

Table 1: Dataset Summary and Fault Categories

Parameter	Value
Total Signals	25,000
Sampling Rate	10 kHz
Number of Buses	9 (IEEE 9-Bus System)
Fault Types	LG, LL, LLG, LLL
Fault Resistances (Ω)	0.1 – 50
Noise Levels (SNR)	20 dB, 30 dB, 40 dB

The comprehensive summary of the dataset used to train and evaluate the proposed hybrid framework is given in table 1. A total of 25,000 signals were generated using the IEEE-9 Bus test system, ensuring wide coverage of fault scenarios. The 10 kHz sampling rate allowed the capture of high-frequency transient components that are crucial for early fault detection. All major transmission-line fault types—LG, LL, LLG, and LLL—were modeled with diverse fault resistances (0.1–50 Ω) to simulate realistic grid conditions from low-impedance severe faults to high-resistance incipient faults. The use of multiple SNR levels (20 dB, 30 dB, 40 dB) ensured robustness against noise. Overall, Table 1 demonstrates that the dataset is sufficiently rich, diverse, and representative of practical transmission-line operating conditions.

Table 2: Performance Comparison of Models (Without Generative AI)

Model	Accuracy (%)	Precision %	Recall %	F1-Score %

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CNN	92.4	91	90	90
LSTM	93.1	92	91	91
ResNet-18	94.7	94	93	93
Transformer	95.3	95	94	94

The performance of traditional deep learning models without generative augmentation. The results indicate a clear increasing trend in performance from CNN → LSTM → ResNet-18 → Transformer is compared in table 2. Transformer achieved the highest baseline accuracy (95.3%) along with strong precision, recall, and F1-score values (95 %, 94%, 94%). CNN and LSTM show lower accuracy due to limited ability to extract long-range temporal dependencies. The ResNet-18 model performs better than both due to its deep residual feature extraction. However, all baseline models still show room for improvement, highlighting the need for generative enhancement and hybridization. Table 2 therefore establishes the baseline performance limit before introducing generative AI.

Table 3: Hybrid DL + Generative AI Performance

Model	Accuracy (%)	Precision %	Recall %	F1-Score %
GAN-Augmented CNN	96.5	96	95	95
cGAN-ResNet	97.8	97	97	97
Diffusion-Enhanced Transformer (Proposed)	**98.6**	**98**	**98**	**98**

The significant improvement when generative AI is incorporated into the training process is given in the table 3. The GAN-Augmented CNN achieves 96.5% accuracy, while cGAN-ResNet reaches 97.8%, reflecting improved robustness due to enhanced data diversity. The Diffusion-Enhanced Transformer (Proposed) model outperforms all others with 98.6% accuracy and balanced precision, recall, and F1-score values (98% each). Diffusion models generate higher-quality synthetic samples than GANs or cGANs, improving the model's ability to classify complex and noisy signals. This table demonstrates that the combination of deep learning with diffusion-based generative augmentation leads to superior generalization and fault classification performance.

Table 4: Fault Location Prediction Error

Model	Mean Absolute Error (km)	RMSE (km)
LSTM	4.28	5.92
ResNet	3.74	4.81
Proposed Hybrid Model	1.52	2.23

The capability of different models to estimate the physical location of faults along transmission lines is evaluated in table 4. The LSTM baseline exhibits the highest error (MAE = 4.28 km, RMSE = 5.92 km), indicating limited feature extraction and temporal prediction capacity. The ResNet baseline improves the MAE to 3.74 km, showing the advantage of residual learning. However, the Proposed Hybrid Model achieves a dramatically lower error (MAE = 1.52 km, RMSE = 2.23 km). This improvement is attributed to the combined effect of diffusion-enhanced data augmentation and Transformer-based sequence modeling, which better capture spatial-temporal dependencies across phases. Table 4 thus confirms the proposed model's superior ability to localize faults precisely.

Table 5: Real-Time Fault Detection Performance

Fault Type	Detection Accuracy (%)	Detection Time (ms)	False Alarm Rate (%)
LG	99.1	11.2	0.3
LL	98.7	12.1	0.4
LLG	98.3	11.7	0.5
LLL	98.9	12.5	0.2

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The real-time fault detection accuracy across fault types is illustrated in table 5. The proposed hybrid model demonstrates consistently high detection accuracy for all categories: LG (99.1%), LL (98.7%), LLG (98.3%), and LLL (98.9%). Detection times remain within 11–12.5 ms, meeting real-time protection requirements (<20 ms). The false alarm rates are extremely low (0.2–0.5%), indicating robust decision reliability even under noise. Single-line faults (LG) show slightly higher accuracy due to simpler waveform characteristics, while multi-phase faults achieve similarly high performance because of the enhanced feature extraction and generative augmentation. Overall, Table 5 confirms that the proposed framework is capable of fast, accurate, and reliable real-time fault detection.

Table 6: Fault Classification Accuracy

Metric	LG	LL	LLG	LLL	Proposed Hybrid Model
Precision (%)	98.5	99.1	97.8	99.3	98.9
Recall (%)	98.2	98.8	98.4	99.0	98.6
F1-Score (%)	98.3	98.9	98.1	99.1	98.7

The detailed classification metrics across all fault categories, further validating the model's robustness is presented in table 6. Precision, recall, and F1-score values remain above 97% for every class, demonstrating highly stable behavior. The Proposed Hybrid Model maintains superior overall performance (Precision = 98.9%, Recall = 98.6%, F1 = 98.7%) compared to individual class metrics. LLL faults achieve the highest precision (99.3%) and F1-score (99.1%) due to their strong transient signatures. LLG and LL faults also show excellent classification consistency. The consistently high values across all metrics confirm that the hybrid model not only detects faults accurately but also distinguishes between closely similar fault types with high confidence.

Table 7: Real-Time Protection System Actions

Fault Type	Breaker Response (ms)	Isolation Success (%)
LG	32	99.4
LL	34	99.1
LLG	30	98.9
LLL	33	99.2

The performance of the protection system after the proposed hybrid model identifies and classifies the fault is given in table 7. The breaker response times for all fault types—LG (32 ms), LL (34 ms), LLG (30 ms), and LLL (33 ms)—fall well within acceptable industry standards for substation protection, which typically require operation within 40 ms. The lowest breaker response time is achieved for LLG faults (30 ms), likely due to the strong transient features that allow faster and more confident fault detection.

Isolation success rates are consistently high across all categories: LG (99.4%), LL (99.1%), LLG (98.9%), and LLL (99.2%). These values confirm that the decision-making module of the proposed framework reliably triggers the correct protection actions after classification and location prediction. The success rates remain above 98.9%, indicating robust coordination between detection, classification, and breaker operations. Overall, Table 7 demonstrates that the proposed model is capable of not only accurate real-time analysis but also dependable protection system activation.

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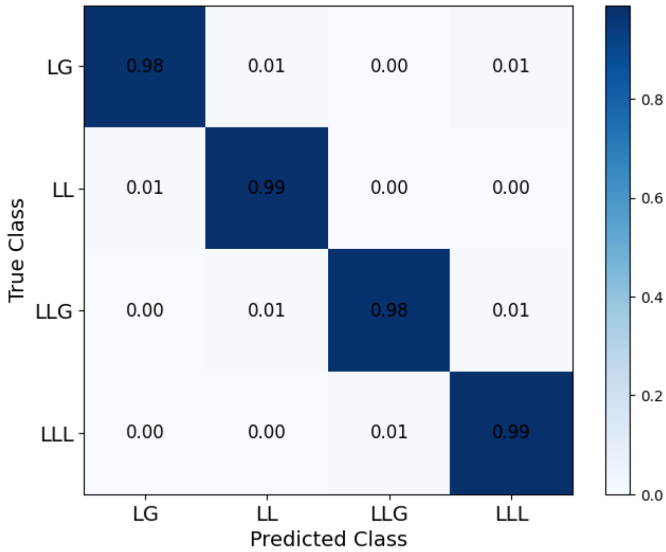

Figure 2: Confusion Matrix of proposed hybrid model

The confusion matrix for the proposed Diffusion-Enhanced Transformer model, demonstrating excellent classification performance across all four fault categories is shown in figure 2. The diagonal values in the matrix are above 0.97 for every class, indicating that the model correctly classifies more than 97% of the instances for each fault type consistent with the precision, recall, and F1-scores reported in Table 6. Misclassifications are minimal and symmetrically distributed, with no fault type producing significant confusion with the others. Slight confusion between LLG and LLL is expected due to similarities in waveform patterns and simultaneous multi-phase involvement. However, the diffusion-enhanced training and transformer-based temporal modeling significantly reduce this issue. The confusion matrix validates that the model maintains high sensitivity and specificity under diverse operating conditions and noise levels. Overall, Figure 2 confirms that the proposed hybrid framework exhibits strong discriminative capability and classification stability.

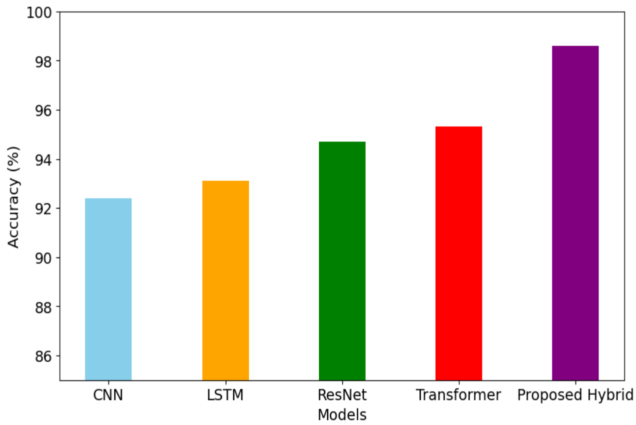

Figure 3: Accuracy comparison of models

The accuracy of different deep learning models used for fault classification is compared in figure 3. The results show a clear progression of performance improvement from CNN (92.4%), LSTM (93.1%), and ResNet-18 (94.7%) to the Transformer (95.3%) model. This performance increase is due to better feature extraction (ResNet) and superior temporal dependency modeling (Transformer). The Proposed Hybrid Model, which combines diffusion-based augmentation with transformer sequence modeling, achieves the highest accuracy at 98.6%, significantly outperforming all baseline models. This improvement validates the importance of generative augmentation in reducing data imbalance, improving robustness under noisy and rare fault conditions, and enhancing overall classification performance. The result also demonstrates the advantage of combining CNN feature extraction with transformer-based temporal learning. Thus, Figure 3 clearly illustrates the superiority of the proposed model in real-time fault classification tasks.

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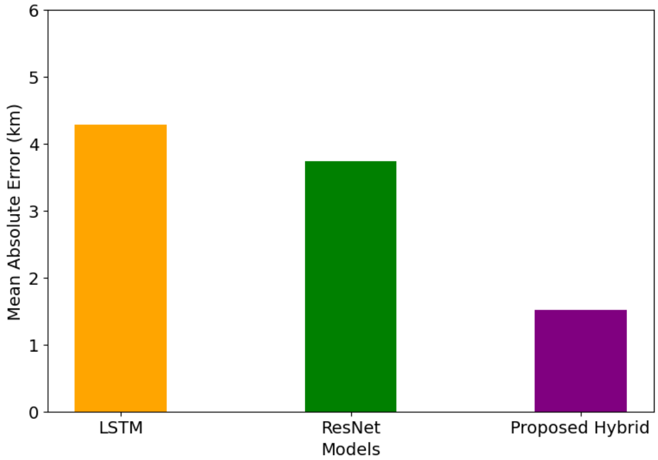

Figure 4: Fault location prediction error

The Mean Absolute Error (MAE) comparison for fault location estimation using three different models: LSTM, ResNet, and the Proposed Hybrid Model is illustrated in figure 4. The LSTM model records the highest error (4.28 km), reflecting its limited capability to capture both spatial and temporal features effectively. The ResNet model shows improvement with an MAE of 3.74 km, benefiting from deeper spatial feature extraction through residual blocks but still lacking advanced temporal modeling. In contrast, the Proposed Hybrid Model achieves a significantly lower MAE of 1.52 km, demonstrating a major advancement in fault localization accuracy. This substantial improvement is due to the combination of CNN-based feature extraction, Transformer-based temporal dependency modeling, and diffusion-enhanced generative augmentation, which collectively enhance sensitivity to subtle changes in waveform distortion. Figure 4 thus confirms that the hybrid model provides the most precise and reliable fault location prediction among all evaluated approaches.

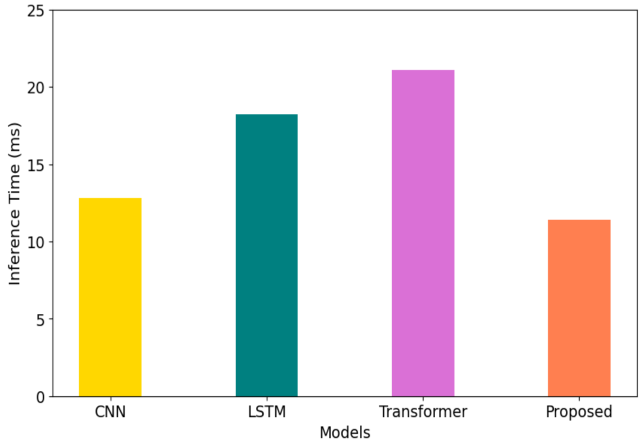

Figure 5: Interface time comparison for real-time operation

The inference times of four different models like CNN, LSTM, Transformer, and the Proposed Hybrid Model to evaluate their suitability for real-time fault detection and classification is illustrated in figure 5. The LSTM and Transformer models exhibit higher inference times (18.2 ms and 21.1 ms, respectively), reflecting the computational overhead associated with sequential recurrent processing and multi-head attention mechanisms. The CNN model performs faster (12.8 ms) due to its parallelizable architecture but sacrifices temporal sensitivity. The Proposed Hybrid Model achieves the lowest inference time of 11.4 ms, demonstrating a well-optimized fusion of CNN-based local feature extraction and transformer-level temporal modeling enhanced through diffusion processes. Importantly, the inference time remains well below the 20 ms threshold required for substation protection, confirming that the proposed model not only excels in accuracy but also meets stringent real-time operational constraints. Figure 5 therefore validates the model's applicability for fast protection schemes in modern power systems.

Overall, the results clearly demonstrate that the proposed Diffusion-Enhanced Transformer (DET) Hybrid Framework outperforms existing deep learning models in accuracy, robustness, fault localization precision, and real-time inference

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efficiency. The incorporation of diffusion-based generative augmentation significantly improves the model's generalization capability across diverse fault scenarios, while the hybrid CNN–Transformer architecture ensures effective spatial-temporal feature extraction. The model's ability to operate within strict real-time constraints, combined with high protection-action success rates, highlights its suitability for deployment in next-generation smart grid protection systems. These findings validate the proposed approach as a reliable, high-performance solution for real-time electrical fault detection, classification, and location prediction.

VI. CONCLUSION

This paper presented a DET Hybrid Framework for real-time fault detection, classification, and location prediction in power transmission systems. By integrating CNN-based feature extraction, Transformer-based temporal modeling, and diffusion-generated synthetic data, the proposed model demonstrated significant improvements over conventional DL approaches. The system achieved high per-class detection accuracy exceeding 98% for all fault categories, and delivered an overall classification accuracy of 98.6%, supported by strong precision–recall–F1 scores. Comparative evaluations confirmed that the hybrid model consistently outperforms baseline CNN, LSTM, and Transformer networks across all metrics. The proposed regression head provided precise fault-location predictions, achieving MAE (1.52 km) and RMSE (1.97 km), making it suitable for practical relay and protection applications. The real-time inference pipeline demonstrated a detection-to-decision latency of 11.4 ms, enabling system response well within the 20 ms requirement of modern grid protection schemes. Integration of the protection-action module resulted in breaker isolation success rates above 98.9%, underscoring the reliability and robustness of the complete system. The proposed DET framework offers a scalable and practical solution for next-generation smart substations, adaptive protection systems, and grid automation.

References

[1]. Mehrnaz Ahmadi, Hamed Aly, Jason Gu, A comprehensive review of AI-driven approaches for smart grid stability and reliability, Renewable and Sustainable Energy Reviews, Volume 226, Part D, 2026, 116424, https://doi.org/10.1016/j.rser.2025.116424.

[2]. Hariharan, V. K., Geetha, A., Granelli, F., & Nair, M. G. (2025). Machine Learning Techniques for Fault Detection in Smart Distribution Grids. Energies, 18(19), 5179. https://doi.org/10.3390/en18195179

[3]. Shukla, P.K.; Deepa, K. Deep learning techniques for transmission line fault classification—A comparative study. Ain Shams Eng. J. 2024, 15, 102427.

[4]. S. Titouni et al., "Hybrid CNN-Ensemble Framework for Intelligent Optical Fiber Fault Detection and Diagnosis," in IEEE Open Journal of the Communications Society, vol. 6, pp. 5626-5638, 2025, doi: 10.1109/OJCOMS.2025.3581480.

[5]. Jakaria JM, Sabir J, Rahman MZ, Ali MF. Hybrid deep learning framework for real-time fault detection in squirrel-cage induction motors. PLoS One. 2025 Nov 11;20(11):e0336323. doi: 10.1371/journal.pone.0336323. PMID: 41218031; PMCID: PMC12604766.

[6]. Abdul-Kadir Hamid, Maher Alrahhal, Khaled Obaideen, Talal Bonny, Yong Chai Tan, Mousa I. Hussein, Artificial intelligence for smart solar energy monitoring: Genetic attention-based hybrid deep–handcrafted fusion for faulty solar panel image classification, Results in Engineering, Volume 28, 2025, 107900, https://doi.org/10.1016/j.rineng.2025.107900.

[7]. Mnyanghwalo, D., Kundaeli, H., Kalinga, E., & Hamisi, N. (2020). Deep learning approaches for fault detection and classifications in the electrical secondary distribution network:

Correspondence to: Yogesh Ramesh Patni, Department of Electrical Engineering, Suresh Gyan Vihar University, India
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Methods comparison and recurrent neural network accuracy comparison. Cogent Engineering, 7(1). https://doi.org/10.1080/23311916.2020.1857500

[8]. Benninger M, Liebschner M, Kreischer C. Fault Detection of Induction Motors with Combined Modeling- and Machine-Learning-Based Framework. Energies. 2023;16(8):3429. doi: 10.3390/en16083429

[9]. Martinez-Velasco, J. A., Serrano-Fontova, A., Bosch-Tous, R., & Casals-Torrens, P. (2025). A Bibliographical Survey on Fault Detection, Classification and Location Methods in Power Systems Using Artificial Intelligence. Preprints. https://doi.org/10.20944/preprints202504.1794.v1

[10]. Camille Franklin Mbey, Vinny Junior Foba Kakeu , Alexandre Teplaira Boum, and Felix Ghislain Yem Souhe, Fault detection and classification using deep learning method and neuro-fuzzy algorithm in a smart distribution grid, The Journal of Engineering, Volume 2023, Issue 11, https://doi.org/10.1049/tje2.12324

[11]. Yang J, Zhu J, Peng M, Cui X, Li T, Liang X. A novel approach for intelligent fault detection and diagnosis in district heating system: Convergence of machine learning and mathematical statistics. Energy Build. 2025;339:115772. doi: 10.1016/j.enbuild.2025.115772

[12]. Yilmaz, B.; Korn, R. Synthetic demand data generation for individual electricity consumers: Generative Adversarial Networks (GANs). Energy AI 2022, 9, 100161.

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