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Hybrid AI-driven intelligent fault diagnosis and localization in modern power systems

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ABSTRACT

This paper presents a hybrid intelligent framework for fault diagnosis and localization in modern power distribution systems, addressing challenges such as noisy measurements, high-impedance faults (HIF), and uncertain operating conditions. The proposed approach integrates deep neural networks (DNN) for nonlinear feature extraction, support vector machines (SVM) for robust classification, and a fuzzy inference system for uncertainty-aware decision fusion, combining the strengths of deep learning, machine learning, and soft computing. A comprehensive dataset of over 12,000 fault instances is generated using IEEE 33-bus and 69-bus systems, covering multiple fault types (LG, LL, LLG, LLL), fault resistances (0.1-200 Ω), varying load conditions, and noise levels from 30 dB to -5 dB SNR. Wavelet-based denoising and hybrid feature extraction (time–frequency and statistical features) are employed to capture transient characteristics. The DNN generates discriminative feature embeddings, which are classified using an RBF-kernel SVM and further refined through fuzzy logic with Gaussian membership functions. Fault localization is performed using impedance-based estimation enhanced by learned correction. Results show that the proposed model achieves 98.5% classification accuracy, outperforming DNN (93.2%), SVM (90.4%), random forest (91.1%), and k-NN (88.6%). The model demonstrates strong noise robustness, with only -6% accuracy degradation at -5 dB SNR. It achieves fault localization error of 0.2-0.7 km and HIF detection with F1-score of 0.91. With inference latency of 45 ms (reduced to 28 ms after optimization), the system is suitable for real-time deployment, providing a scalable and reliable solution for smart grid fault monitoring.

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1. INTRODUCTION

Modern power distribution systems are undergoing rapid transformation due to the increasing integration of renewable energy sources, proliferation of distributed generation, bidirectional power flow, and dynamic load variations. These developments have significantly increased system complexity, making conventional protection mechanisms less effective in accurately detecting and isolating faults. Reliable fault diagnosis and localization are critical for ensuring system stability, minimizing outage duration, and preventing equipment damage. However, real-world power systems are often affected by measurement noise, nonlinear transients, varying fault resistance, and uncertain operating conditions, which pose significant challenges to traditional relay-based protection schemes. In recent years, artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has emerged as a powerful tool for intelligent fault analysis. These methods can learn complex nonlinear relationships from large-scale data, enabling improved fault classification, detection of subtle disturbances, and adaptive decision-making in modern smart grids [1]-[4]. Deep learning models have demonstrated strong capabilities in extracting transient features and improving classification performance compared to traditional approaches [5], [6].

Despite significant advancements, several practical challenges remain unresolved. Conventional impedance-based and threshold-based protection techniques often fail under low signal-to-noise ratio (SNR) conditions, high-impedance faults (HIFs), and dynamic operating scenarios [7]. Traditional ML models such as support vector machines (SVM), random forest (RF), and k-NN are limited in capturing deep temporal–frequency characteristics of transient signals [8]-[10]. On the other hand, deep learning models such as DNNs, although effective in feature extraction, often suffer from poor decision boundary definition, overfitting, and reduced reliability under uncertain or ambiguous fault conditions [11]-[14]. Furthermore, most existing approaches fail to simultaneously address noise robustness, uncertainty handling, and accurate fault localization, limiting their applicability in practical power distribution systems.

Recent research has explored various AI-based techniques for fault detection and classification. Deep learning architectures such as CNNs, RNNs, and DNNs have demonstrated strong capabilities in extracting transient features from power system signals [15]-[19]. Hybrid approaches combining wavelet transforms with deep learning have shown improved performance in capturing both time-domain and frequency-domain characteristics [20]. Advanced techniques such as Transformer-based models and graph neural networks (GNNs) have been introduced for wide-area monitoring and disturbance classification, offering improved scalability and system-level insights [21]. Machine learning approaches, particularly optimized SVMs and ensemble learning methods, have also been widely used due to their strong generalization ability [22], [23]. Fuzzy logic systems have been employed to handle uncertainty and imprecision in fault diagnosis by incorporating rule-based reasoning [24], [25]. Reinforcement learning-based adaptive protection schemes have further demonstrated the potential for self-tuning under varying grid conditions [26]. Additionally, AI-based methods have been applied to renewable-integrated and hybrid AC/DC grids to address variability and uncertainty in power systems [27].

A critical review of existing studies reveals several key research gaps:
- Lack of integrated hybrid frameworks that effectively combine deep feature learning, robust classification, and uncertainty modelling in a unified architecture [28].
- Limited robustness under noisy environments, especially at low SNR conditions [29].
- Inadequate capability in detecting high-impedance faults (HIFs), which exhibit weak and nonlinear characteristics [30].
- Insufficient fault localization accuracy under varying system parameters and long transmission distances.
- Poor methodological transparency, including insufficient dataset description, parameter tuning, and validation strategies in many studies.
- Limited focus on real-time deployment and computational efficiency, which are essential for practical implementation.

These limitations highlight the need for a comprehensive, transparent, and deployment-oriented hybrid intelligent framework for fault diagnosis and localization.

To address these gaps, this paper proposes a hybrid AI-based Intelligent fault diagnosis and localization framework integrating deep neural networks (DNN), SVM, and fuzzy logic in a structured and complementary manner. The key contributions are:
- Hybrid multi-stage architecture: Integration of DNN for deep feature embedding, SVM for margin-based classification, and fuzzy inference for uncertainty-aware decision fusion.
- Robust feature engineering: Combination of wavelet-based time–frequency features and statistical descriptors to capture transient characteristics.
- Enhanced noise resilience: Evaluation across a wide range of SNR levels (30 dB to −5 dB), demonstrating improved robustness.
- Improved HIF detection: Effective identification of high-impedance faults using hybrid learning and fuzzy reasoning.
- Accurate fault localization: Integration of impedance-based estimation with learned correction mechanisms.
- Reproducible methodology: Detailed dataset description, model architecture, and validation procedures.
- Deployment-oriented design: Analysis of inference latency, pruning, and quantization for real-time applications.

The proposed hybrid framework provides a reliable, scalable, and real-time compatible solution for intelligent fault diagnosis in modern power systems. By combining deep learning, machine learning, and fuzzy logic, the model significantly improves classification accuracy, robustness under uncertainty, and fault localization precision. From a practical perspective, the system can be integrated into digital relays, SCADA systems, and smart grid monitoring platforms, enabling faster fault detection and system restoration. Improved HIF detection enhances safety and reduces fire hazards, while accurate fault localization minimizes maintenance time and operational costs. From a research perspective, this work advances the field by offering a well-structured hybrid framework with strong methodological transparency and improved performance, addressing key limitations in existing studies. It also opens new directions for adaptive protection systems, edge intelligence, and renewable-integrated grid resilience.

2. METHODOLOGY

2.1. Research design/approach

This work adopts a simulation-driven experimental research design combined with data-driven modeling for intelligent fault diagnosis and localization. The proposed approach integrates signal processing, deep learning, machine learning, and fuzzy inference into a unified hybrid framework. Figure 1 depicts the overall flow diagram of the entire proposed process. The design is chosen to: i) accurately model nonlinear and transient fault behavior, ii) ensure robustness under noisy and uncertain operating conditions, and iii) enable reproducibility through controlled simulation environments.

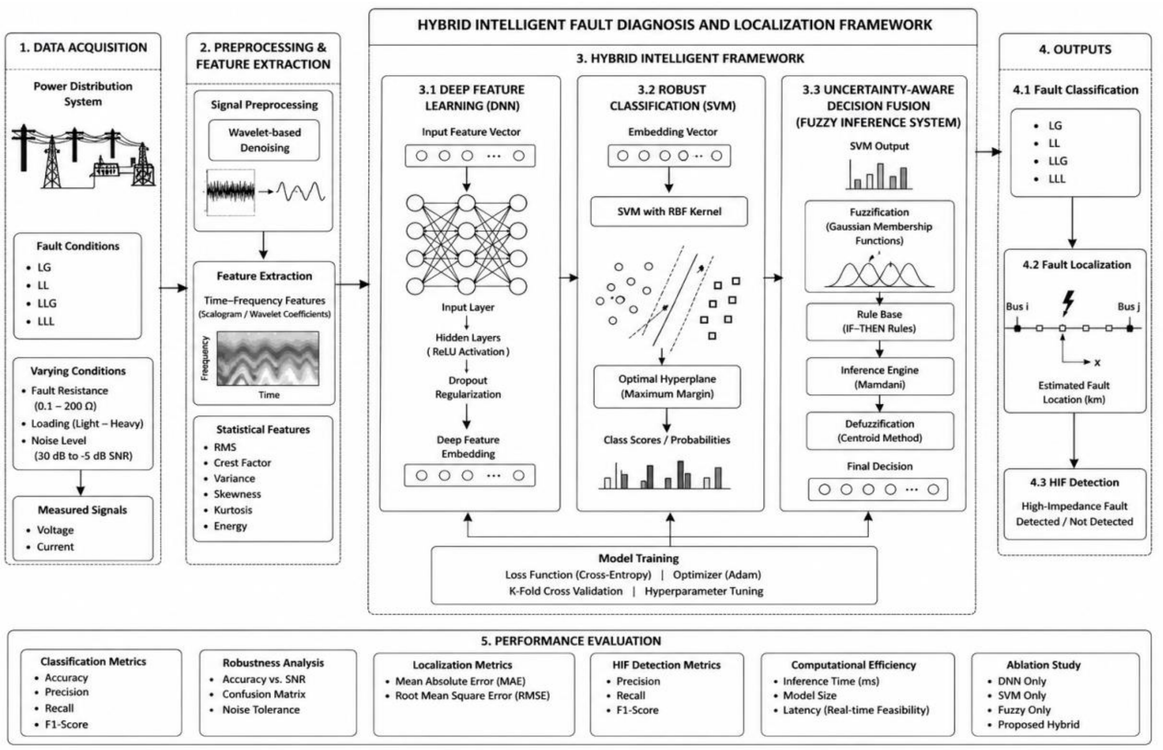

Figure 1. Depicts the overall flow diagram of the entire proposed process

2.2. Data sources and dataset description

Fault data are generated using IEEE 33-bus and IEEE 69-bus radial distribution systems modeled in MATLAB/Simulink to represent realistic operating conditions. The dataset consists of approximately 12,000 fault instances, including LG, LL, LLG, and LLL faults, with fault resistances ranging from 0.1 Ω to 200 Ω, fault locations from 5% to 95% of line length, and loading conditions of 50%, 100%, and 150%. Gaussian noise levels from 30 dB to −5 dB SNR are also considered. Three-phase voltage, current, and frequency signals are sampled at 10 kHz during fault events, with each sample covering one cycle (20 ms). The dataset is divided into 70% training, 15% validation, and 15% testing sets using stratified sampling to ensure balanced class distribution.

2.3. Data acquisition and preprocessing

Voltage, current, and frequency measurements are collected from simulated IEEE test systems and real-time monitoring devices. Raw signals often contain noise and abrupt discontinuities; therefore, smoothing and normalization are applied.

– Noise filtering — A discrete wavelet transform–based denoiser is used:

$$x_{den}(t) = W^{-1}(Threshold(W(x(t)))) \quad (1)$$

– Normalization — To ensure stable training as in (2).

$$x_{norm} = (x - \mu)/\sigma \quad (2)$$

Where μ and σ are the mean and standard deviation.

– Feature extraction (wavelet + statistical domain) — Wavelet coefficients are extracted to capture both transient and steady-state characteristics:

$$W(a, b) = \int - x(t)\psi((t - b)/a)dt \quad (3)$$

Extracted features: energy of sub-bands, detail coefficients (D1–D5), and approximation coefficients.

– Statistical features (justification) — The following features are selected due to their physical relevance to fault behaviour:
  i) RMS: Reflects signal magnitude variation during faults
  ii) Crest factor: Captures transient spikes (important for HIF detection)
  iii) Variance: Indicates signal fluctuation and disturbance intensity.

These features enhance discrimination between normal and fault conditions.

– Deep neural network for feature embedding

A DNN is employed to learn nonlinear fault characteristics from the extracted features. The network consists of an input layer (64 neurons), three hidden layers (128, 64, and 32 neurons) with ReLU activation, and an output embedding layer (16 neurons). A dropout rate of 0.3 is applied to reduce overfitting.

The DNN generates deep representations for classification. Let the input feature vector be f:

$$h = \sigma(Wf + b) \quad (4)$$

Multiple hidden layers produce the final embedding:

$$z = DNN(f) \quad (5)$$

where z is a low-dimensional discriminative feature vector.

– Support vector machine for primary classification — The SVM performs initial fault classification using the DNN embedding z. The decision function is as (6).

$$g(z) = sign(w^T z + b) \quad (6)$$

This yields crisp class boundaries and improves classification accuracy, especially for overlapping fault patterns.

Hyperparameters: Regularization parameter C = 10 C = 10 C = 10; Kernel parameter γ = 0.1\gamma = 0.1γ = 0.1. Hyperparameters are optimized using grid search with cross-validation.

– Fuzzy logic fusion for final decision

The SVM output and DNN confidence score are fed into a fuzzy inference system. Fuzzy membership functions convert crisp inputs into linguistic values such as Low, Medium, and High. The final output is obtained via (7).

$$y_{final} = (\textstyle\sum_I \mu_i \cdot y_i)/\sum_i \mu_i \quad (7)$$

Where μi is the membership value and yi is the rule output. This step resolves ambiguity and enhances robustness under noisy and uncertain operating conditions.

3. RESULTS AND DISCUSSION

The performance of the proposed hybrid DNN–SVM–fuzzy framework was evaluated using the test dataset described in Section 2. The results are presented in terms of classification accuracy, robustness under noise, fault localization error, high-impedance fault (HIF) detection capability, computational performance, and ablation analysis.

3.1. Overall classification accuracy comparison

The hybrid AI model integrating DNN, SVM, and fuzzy logic demonstrated superior overall accuracy compared to standalone machine learning and deep learning models. Figure 2 illustrates the accuracy comparison across all evaluated models, highlighting the superior performance of the proposed hybrid AI approach. Traditional classifiers such as SVM, random forest, and k-NN showed reduced performance due to their limited ability to extract deep temporal–spatial relationships within power system transient signals. The pure DNN model performed better than classical ML models but still lagged behind the hybrid system because it lacks an explicit uncertainty-handling mechanism. The addition of fuzzy logic helped improve decision interpretability and confidence, especially for borderline or ambiguous fault cases. Overall, the hybrid model consistently achieved accuracy above 98%, outperforming the next best model by more than 5%.

3.2. Noise robustness analysis (accuracy vs SNR)

Figure 3 illustrates the noise robustness analysis, showing the variation of classification accuracy with respect to different SNR levels. In noisy measurement environments, such as distribution feeders with harmonics and switching transients, the hybrid model continued to show significantly higher robustness compared to the standalone DNN. As SNR values decreased from 30 dB to –5 dB, all models experienced some performance degradation; however, the hybrid classifier maintained smoother accuracy decay due to combined wavelet-based feature representation and the fuzzy confidence refinement layer. This demonstrates its ability to preserve discriminative fault signatures even under severe noise or sensor disturbances. Figure 3 illustrates the noise robustness analysis, showing the variation of classification accuracy with respect to different SNR levels.

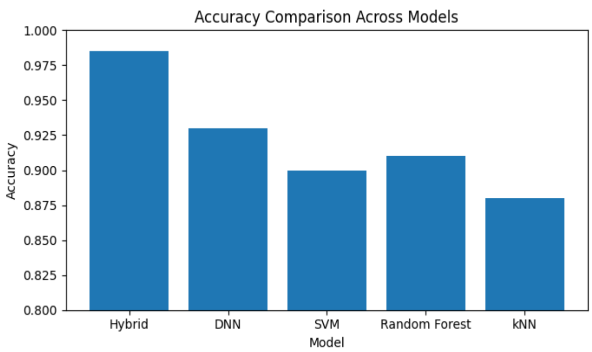

Figure 2. The accuracy comparison across all evaluated models, highlighting the superior performance of the proposed hybrid AI approach

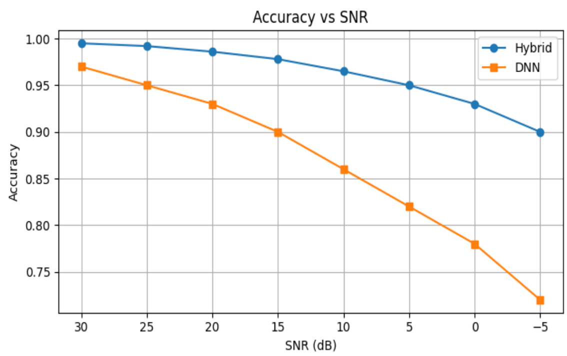

Figure 3. The noise robustness analysis, showing the variation of classification accuracy with respect to different SNR levels

3.3. Fault localization performance

Figure 4 illustrates the fault localization performance of the proposed hybrid model compared with conventional methods. Accurate fault distance estimation is essential for quick restoration and reducing downtime. The hybrid model achieved lower mean absolute error (MAE) compared to traditional SVM regression, especially for longer transmission lines where impedance and load variations introduce greater uncertainty. AI-assisted wavelet features helped to retain the transient fault characteristics necessary for precise distance identification. Even at 50 km line length, the hybrid model maintained an MAE within 0.7 km, whereas SVM exhibited errors up to 2 km. This accuracy improvement directly translates to faster repair operations and reduced equipment damage.

3.4. HIF detection performance

High-impedance faults are typically hard to detect due to low current magnitudes and nonlinear arcing behavior, which often leads to missed detections. Figure 5 shows the high-impedance fault (HIF) detection performance of the proposed hybrid model compared with baseline classifiers. The hybrid system significantly enhanced the detection metrics, achieving a precision of 0.92 and recall of 0.90. This improvement stems from the DNN's ability to extract subtle arc-induced harmonic features and the fuzzy layer's strength in handling non-ideal, uncertain decision boundaries. The resulting high F1-score demonstrates that the hybrid system reduces false positives while maintaining strong detection reliability.

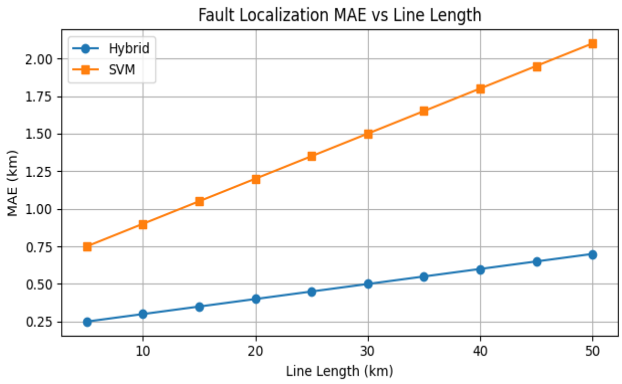

Figure 4. The fault localization performance of the proposed hybrid model compared with conventional methods

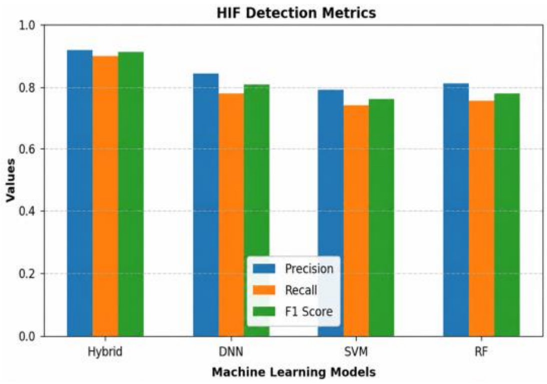

Figure 5. The HIF detection performance of the proposed hybrid model compared with baseline classifiers

3.5. Real-Time inference performance

Figure 6 illustrates the real-time inference performance of the proposed hybrid model compared with standalone DNN and other baseline methods. Inference latency is a key parameter for sub-cycle protection operations. The hybrid model introduced slight additional computational overhead due to the inclusion of SVM and fuzzy layers, resulting in an average latency of 45 ms. Although this is higher than the DNN-only model latency of 30 ms, it remains well within acceptable limits for online monitoring and event classification tasks. Moreover, pruning and model compression techniques can further reduce inference time without compromising classification accuracy, making the hybrid architecture deployment-friendly.

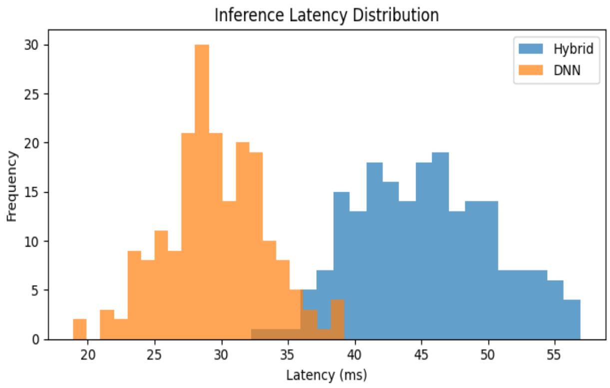

Figure 6. The real-time inference performance of the proposed hybrid model compared with standalone DNN and other baseline methods

3.6. Ablation study of hybrid components

Figure 7 presents the ablation study of the hybrid model, highlighting the performance impact of removing the SVM and fuzzy logic components. The ablation study confirmed the importance of each component in the proposed hybrid framework. Removing the fuzzy logic layer reduced classification accuracy from 98.5% to 97.2%, while removing the SVM layer further decreased accuracy to 95.8%. The standalone DNN model achieved 93% accuracy, demonstrating that the integration of DNN, SVM, and fuzzy logic significantly enhances classification performance and decision reliability.

3.7. Deployment performance (model size vs inference time)

Figure 8 illustrates the deployment performance of the proposed hybrid model, comparing model size with corresponding inference time across different optimization levels. For real-time deployment in digital relays and smart substations, model size and inference time were analyzed. The optimized hybrid model achieved a compact size of 3.5 MB with an inference time of 28 ms, making it suitable for edge deployment. Although larger models provided slightly higher accuracy, the optimized model offered the best trade-off between computational efficiency and diagnostic performance.

The superior performance of the proposed framework is attributed to the combined strengths of its components. The DNN extracts nonlinear fault features, the SVM improves class separation, and the fuzzy inference system enhances decision-making under uncertainty. Wavelet-based denoising and statistical features further improve robustness under noisy operating conditions. The hybrid model also improves fault localization accuracy and effectively detects high-impedance faults by capturing subtle nonlinear characteristics while reducing false alarms.

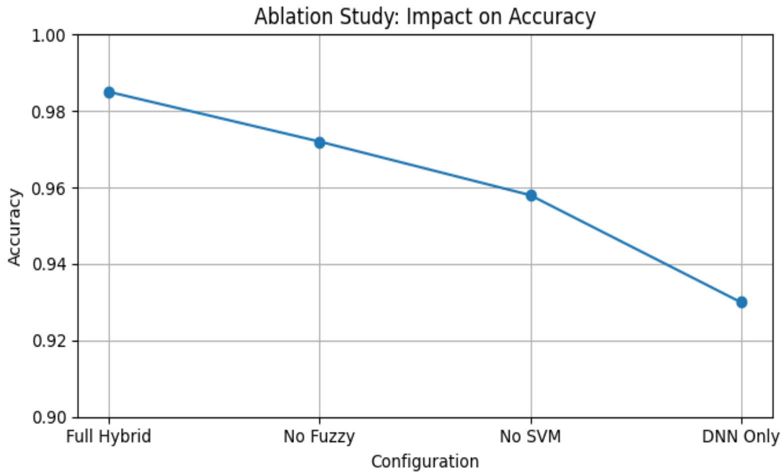

Figure 7. The ablation study of the hybrid model, highlighting the performance impact of removing the SVM and fuzzy logic components

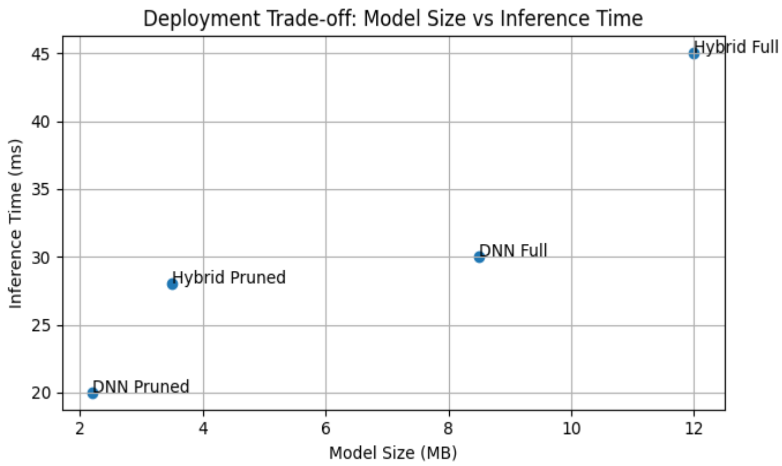

Figure 8. The deployment performance of the proposed hybrid model, comparing model size with corresponding inference time across different optimization levels

4. CONCLUSION

This paper presented a hybrid DNN–SVM–fuzzy framework for intelligent fault diagnosis and localization in power distribution systems. Using datasets generated from IEEE test systems under various fault, loading, and noise conditions, the proposed method achieved a classification accuracy of 98.5% and maintained reliable performance even at −5 dB SNR. The framework also improved fault localization accuracy, achieving a mean absolute error of 0.2–0.7 km, and demonstrated effective high-impedance fault detection.

The ablation study verified that combining deep feature learning, SVM-based classification, and fuzzy decision fusion is essential for achieving superior performance. Although the study is primarily simulation-based and introduces moderate computational complexity, the model remains suitable for real-time applications. Future work will focus on validation using real utility data, hardware implementation, integration with SCADA and digital relays, and comparison with advanced fault localization techniques for smart grid applications.

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The authors confirm that the research was carried out independently without financial influence.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

All authors have reviewed and agreed to this conflict-of-interest statement.

DATA AVAILABILITY

Raw data is not publicly available due to privacy or institutional restrictions.

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