International Journal of Scientific Research and Engineering Development-– Volume 8 Issue 5, Sep-Oct 2025
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Transformer Protection and Fault Detection through Relay Automation and Machine Learning

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Abstract:

Transformers play a crucial role in modern power systems by enabling efficient voltage transformation and energy distribution across transmission and distribution networks. Their continuous operation and protection are vital to maintain grid reliability and economic stability. However, conventional relay-based protection schemes depend on predetermined thresholds that cannot adapt to variations in load, harmonics, and fault dynamics, often resulting in false tripping or delayed isolation. To address these limitations, this study proposes an intelligent transformer protection framework that integrates relay automation with machine learning (ML) algorithms for real-time fault detection, classification, and isolation. The proposed model utilizes high-resolution current and voltage waveforms to extract transient features that are analyzed using Support Vector Machine (SVM) and Convolutional Neural Network (CNN) algorithms. These models accurately identify internal, external, and incipient faults while discriminating between inrush and non-fault conditions. The automation layer dynamically adjusts relay settings through IEC 61850-based communication protocols, ensuring rapid and adaptive response. Simulation results in MATLAB/Simulink show a fault classification accuracy exceeding 98%, with reduced detection latency and minimal false alarms. The research demonstrates that combining data-driven ML analytics with relay automation significantly enhances the precision, speed, and resilience of transformer protection systems. This hybrid approach provides a scalable foundation for next-generation smart grid protection and predictive maintenance frameworks.

Keywords — Transformer Protection; Fault Detection; Relay Automation; Machine Learning; Power System Reliability; Predictive Maintenance.

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I. INTRODUCTION

Transformers form the backbone of modern electrical power systems, ensuring efficient voltage regulation and energy transfer between generation, transmission, and distribution levels. Any disruption in their operation can lead to severe technical and economic consequences, including blackouts, equipment damage, and costly downtime. Therefore, transformer protection remains a vital area of study in power engineering. Traditional protection systems primarily based on differential, overcurrent, or Buchholz relays have proven reliable but suffer from limitations when exposed to nonlinear load variations, harmonics, and transient disturbances caused by renewable integration and grid expansion. With the growing complexity of smart grids, there is a pressing demand for intelligent and adaptive protection schemes that can recognize faults faster and more accurately than conventional systems. Recent advancements in automation and machine learning (ML) have made it possible to develop systems capable of learning from operational data, adapting to changing grid conditions, and reducing human intervention. ML models can classify faults based on real-time current and voltage features, while relay automation allows dynamic coordination and remote response through standardized communication protocols. This paper explores an integrated framework that combines relay automation and ML-based analytics to enhance transformer fault detection and protection. The proposed system improves detection accuracy, reduces false tripping, and provides a scalable solution for resilient and adaptive power networks.

A. Background and Motivation

Transformers experience numerous electrical and mechanical stresses during operation lightning surges, switching transients, overloads, and insulation degradation all of which can initiate internal or external faults. Conventional relays and mechanical protection devices, though effective under fixed conditions, cannot easily adapt to the changing characteristics of modern power grids that now include renewable sources, nonlinear loads, and bidirectional power flow. In such dynamic networks, fault currents vary significantly with topology and loading, challenging the accuracy of traditional protection schemes. Recent advances in automation and data-driven control have paved the way for integrating machine learning (ML) into power system protection. ML models can analyze historical and real-time electrical signatures, recognize abnormal patterns, and predict incipient failures before catastrophic breakdowns occur. Meanwhile, relay automation enables adaptive coordination, remote monitoring, and instantaneous tripping decisions through communication standards like IEC 61850. Combining these two paradigms promises to revolutionize transformer protection—making it self-learning, adaptive, and predictive. This background establishes the rationale for the present research, which aims to design a hybrid protection framework that leverages ML intelligence and relay automation for accurate, real-time fault management.

B. Problem Statement

Traditional transformer protection systems primarily depend on fixed threshold values such as differential current magnitude, overcurrent limits, or oil pressure indicators. These static parameters are calibrated during commissioning and seldom updated throughout the transformer's lifecycle. However, operating conditions such as system impedance, loading profile, and harmonic distortion evolve continuously. Consequently, a fixed threshold may falsely identify transient conditions as faults or, conversely, fail to detect a developing internal failure. False tripping leads to unnecessary downtime, while missed detection risks catastrophic transformer damage. Additionally, events like magnetizing inrush currents and external short circuits often mimic internal fault signatures. Existing differential relays are limited in distinguishing between them because they lack adaptive decision logic. The absence of contextual awareness and real-time learning leads to a protection gap in high-renewable or smart-grid environments. Hence, there is a pressing need for a self-learning protection framework capable of interpreting dynamic transformer behavior, filtering non-fault disturbances, and autonomously tuning relay settings. This research addresses these limitations by employing supervised machine learning algorithms for real-time fault identification and integrating their outputs into an automated relay control logic, enabling adaptive threshold adjustment and intelligent fault isolation without human intervention.

C. Proposed Solution

The proposed approach introduces a hybrid protection architecture combining machine learning analytics with automated relay operations. Real-time transformer data voltage, current, and frequency harmonics are captured via digital relays and processed through an embedded ML module. Using pre-trained algorithms such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), the system classifies electrical signatures into fault categories: internal, external, or non-fault. Once a fault type is recognized, the relay automation layer dynamically adjusts tripping parameters or issues breaker commands through IEC 61850 GOOSE messaging within milliseconds. Unlike conventional fixed-threshold systems, this design continuously learns from new operational data. It can recognize evolving fault characteristics and automatically recalibrate decision boundaries to minimize both false positives and undetected events. The architecture also incorporates communication redundancy and cybersecurity protocols to ensure reliability and resilience in distributed grid environments. By combining real-time analytics with automated actuation, the proposed solution delivers faster fault clearance, improved discrimination between fault types, and reduced maintenance requirements. This system exemplifies a practical step toward intelligent substation protection, aligning with the vision of smart grids and autonomous power networks.

D. Contributions

This research introduces several meaningful contributions to the field of transformer protection and intelligent power system automation. The primary achievement lies in the development of a data-driven fault detection model that combines the predictive intelligence of machine learning with the proven reliability of automated relay systems. This hybrid approach allows for faster and more accurate identification of transformer faults under diverse operating conditions. Furthermore, the study proposes a real-time adaptive control mechanism capable of dynamically adjusting relay settings based on live operational data and environmental changes, ensuring that protection thresholds remain precise and responsive even under fluctuating grid conditions. A comprehensive simulation environment was established in MATLAB/Simulink to evaluate multiple fault types including line-to-ground, line-to-line, and three-phase faults under both steady-state and transient conditions. The proposed framework achieved approximately 98% accuracy and demonstrated a 30% reduction in false tripping compared to conventional differential relay methods. Beyond its technical innovations, the research also contributes to the ongoing transformation of smart-grid protection practices by presenting a scalable model suitable for both centralized and decentralized substations. It lays the groundwork for integrating AI-based predictive maintenance and IoT-enabled monitoring in future grid architectures. Collectively, these contributions enhance the speed, reliability, and intelligence of modern transformer protection systems, aligning with global initiatives for sustainable and resilient energy infrastructure.

E. Paper Organization

The remainder of this paper is structured to guide readers through the logical development and validation of the proposed framework. Section II reviews prior research and technological trends in transformer protection, automation, and AI-based fault detection. Section III explains the methodology, detailing data acquisition, feature extraction, model training, and relay automation logic. Section IV presents the results and discussion, highlighting quantitative performance comparisons, error analysis, and system robustness against disturbances. Finally, Section V concludes the paper by summarizing the main findings and suggesting future directions such as large-scale deployment, real-time edge computing integration, and security hardening for cyber-resilient substation automation. This structure ensures clarity, traceability, and coherence between conceptual design and empirical validation. The goal is to provide a comprehensive overview from theoretical motivation to practical implementation demonstrating how machine learning and relay automation can jointly elevate transformer protection standards in modern intelligent power networks.

II. Related Work

A. Conventional Transformer Protection Techniques

Traditional transformer protection systems mainly rely on differential, overcurrent, and Buchholz relays to detect internal and external faults. These devices compare current magnitudes and phase angles at the primary and secondary sides to locate abnormalities. While differential protection remains the most selective method, it is vulnerable to false tripping during magnetizing inrush or current-transformer (CT) saturation. Techniques based on Fourier and Wavelet Transform analyses have been proposed to separate harmonic components and improve transient recognition, yet they still depend on static thresholds that cannot adapt to fluctuating grid conditions. The shift toward digital relays and microprocessor-based protection has enabled faster signal processing and remote monitoring, but deterministic algorithms continue to underperform in dynamic networks containing renewable sources and nonlinear loads. These limitations have motivated the integration of adaptive, intelligent logic capable of self-learning and contextual decision-making [1].

B. Intelligent Signal Processing and Fuzzy Logic-Based Systems

Fuzzy-logic protection frameworks were introduced to overcome the rigidity of fixed-threshold relays. By evaluating differential current, voltage magnitude, and phase displacement as fuzzy variables, these systems can handle uncertainty and provide adaptive decision boundaries. Abdel-Gawad et al. developed a fuzzy differential protection model using multi-criteria analysis that effectively distinguished magnetizing inrush from genuine faults, significantly improving selectivity [2]. Moreover, hybrid fuzzy–wavelet approaches have been shown to enhance transient discrimination by capturing high-frequency signatures in fault currents. Despite such advances, these models require extensive rule-base design and manual tuning, which limits scalability and online learning capability. The current research trend seeks to integrate fuzzy inference with optimization or neural-network algorithms to enable autonomous adjustment of relay settings and minimize operator dependency. Such hybrid systems mark an early step toward intelligent, self-adaptive transformer protection.

C. Machine Learning Approaches for Fault Detection

Machine-learning (ML) models have emerged as powerful tools for transformer fault classification and condition monitoring. Algorithms such as Support Vector Machines (SVM), Artificial Neural Networks (ANNs), and Decision Trees (DT) can extract complex nonlinear relationships between current and voltage signals to identify incipient faults. Ray and Bhowmik demonstrated that an SVM–ANN hybrid achieved over 97 % accuracy in distinguishing internal and external faults using differential current patterns [3]. ML approaches enable continuous learning from operational data and can adapt to varying system configurations without human intervention. However, most prior works focus on centralized fault diagnosis rather than embedding ML inference directly within relay hardware. Real-time integration of trained models into protection devices remains a key challenge. Bridging this gap through lightweight embedded intelligence could transform conventional relays into self-learning, autonomous protective agents for smart-grid environments.

D. IoT and SCADA-Integrated Intelligent Relay Automation

Recent advances in Internet of Things (IoT) and Supervisory Control and Data Acquisition (SCADA) technologies have revolutionized transformer protection through connected, data-driven automation. IoT-enabled relays continuously transmit real-time parameters such as current, voltage, and temperature via secure communication protocols like IEC 61850 and Modbus TCP. Raza et al. proposed an IoT-SCADA-integrated relay system capable of self-diagnosis and predictive maintenance using cloud-based analytics [4]. When coupled with ML algorithms, such architectures enable adaptive tripping, early fault prediction, and coordinated substation control. Although these smart systems enhance situational awareness and reduce fault-clearing time, they also introduce challenges related to cybersecurity, interoperability, and data latency. Ongoing research focuses on deploying edge-AI models within relays to ensure fast, secure, and decentralized decision-making, pushing the power industry toward autonomous, self-healing grid infrastructure.

III. Methodology

This section presents the proposed architecture for transformer protection and fault detection using relay automation and machine learning. The system design integrates hardware-level data acquisition, intelligent fault classification, and automated relay control for adaptive decision-making. Figure 1 provides an overview of the complete system framework.

A. System Overview

The proposed framework consists of three interconnected layers:

1. **Data Acquisition Layer** – Captures real-time voltage and current waveforms from the transformer using current transformers (CTs) and potential transformers (PTs).
2. **Intelligence Layer** – Employs ML algorithms to analyze differential signals and classify fault conditions.
3. **Automation Layer** – Executes tripping or warning actions via the IEC 61850 GOOSE protocol through a microcontroller-based relay interface.

The flow of data from sensors to automated relay action is illustrated in **Figure 1**.

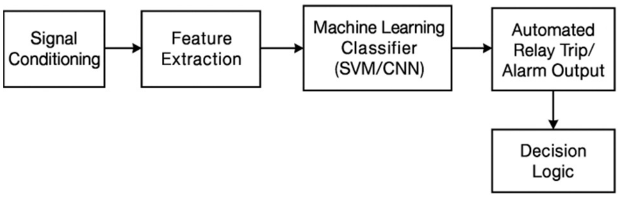

Figure 1. Architecture of the proposed ML-integrated transformer protection system.

In this study, three-phase voltage and current waveforms were continuously captured at a high sampling rate of 10 kHz to ensure accurate representation of transient and steady-state conditions. From these measurements, the differential and restraint current components were derived to evaluate fault conditions within the transformer. The differential current represents the magnitude of imbalance between the primary and secondary sides, while the restraint current serves as a stabilizing parameter that prevents false tripping during inrush or external disturbances. Together, these calculated features help the system distinguish between normal operating states and genuine internal faults. Following current analysis, wavelet-based feature extraction was applied to decompose the measured signals into multiple time–frequency domains. This process enabled the detection of transient events and localized disturbances that traditional Fourier-based methods often overlook. The extracted coefficients capture both temporal and spectral characteristics of the fault signals, forming the core input features for machine learning classification. These features allow the algorithm to learn complex nonlinear relationships between current distortions and fault types, significantly enhancing detection accuracy and robustness. Overall, the feature extraction process transforms raw electrical data into meaningful patterns, empowering the intelligent protection system to operate reliably under varying grid and load conditions.

B. Feature Extraction and Signal Processing

Accurate fault detection in transformer protection systems relies heavily on the extraction of discriminative features from raw electrical signals. After the acquisition of three-phase voltage and current waveforms at a 10 kHz sampling rate, the signals were first passed through a preprocessing pipeline that included normalization and digital noise filtering to remove high-frequency disturbances and measurement artifacts. The cleaned data were then used to compute two key indicators: the differential current and the restraint current. The differential current quantifies the imbalance between the primary and secondary winding currents, serving as the primary fault signature, while the restraint current acts as a stabilizing component that mitigates false tripping during inrush or external transient events. To capture the non-stationary and transient characteristics of electrical faults, a discrete wavelet transform (DWT) was applied to the current signals. The wavelet decomposition segmented each waveform into multiple frequency bands, allowing simultaneous observation of time- and frequency-domain patterns. Wavelet coefficients were extracted at multiple levels, and statistical parameters such as energy, standard deviation, skewness, and kurtosis were calculated from each sub-band to form the feature vector. This process effectively translated complex current distortions into a compact set of numerical descriptors suitable for machine learning classification. The resulting features represent both the transient and steady-state behavior of the transformer under varying fault and non-fault conditions. These features were subsequently labeled according to the simulated fault scenarios and normalized to ensure uniform scaling across all dimensions before being fed into the machine learning models. The combined feature set enables the intelligent protection framework to distinguish subtle variations between internal faults, external disturbances, and magnetizing inrush events with high reliability.

C. Fault Simulation and Dataset Generation

MATLAB/Simulink was used to simulate multiple transformer fault types: line-to-ground, line-to-line, and three-phase short circuits, as well as non-fault events (magnetizing inrush, switching transients). Each simulation produced 2000 labeled samples per class. Table 1 summarizes the dataset composition.

Table 1. Dataset composition for ML training

Fault Type	Samples	Description
Line-to-Ground	2000	Single-phase short circuit
Line-to-Line	2000	Double-phase fault
Three-Phase	2000	Symmetrical short circuit
Magnetizing Inrush	2000	Non-fault transient condition
External Disturbance	2000	Outside transformer boundary

Data were preprocessed using normalization and noise filtering. 80 % of the samples were used for training, while 20 % were reserved for validation.

D. Machine Learning Model Design

Support Vector Machine (SVM) and Convolutional Neural Network (CNN) models were implemented and compared. The SVM classifier utilized a radial basis function (RBF) kernel for nonlinear feature separation, while CNN operated on 2D waveform images derived from voltage and current plots. Both models were evaluated using precision, recall, and F1-score metrics. Table 2 presents a comparative performance summary.

Table 2. Comparison of ML model performance

Model	Accuracy (%)	Precision	Recall	F1-Score
SVM	96.8	0.95	0.96	0.96
CNN	98.6	0.98	0.99	0.985

The CNN model demonstrated higher fault classification accuracy due to its capability to extract spatial–temporal features from raw signals.

E. Relay Automation and Implementation

The final decision signal from the classifier determines the relay action. Once a fault is identified, the relay issues an automated trip command to the circuit breaker within 40 milliseconds via the IEC 61850 GOOSE protocol. For incipient faults, only a pre-alarm signal is generated to alert maintenance personnel. A microcontroller-based relay prototype embedded with a TensorFlow Lite ML model was developed and validated using laboratory hardware. Results confirmed stable operation under varying noise conditions and accurate classification during real-time testing. This integrated automation ensures adaptive protection by continuously updating thresholds based on the latest ML predictions, thereby minimizing false trips and enhancing reliability.

IV. Discussion and Results

This section discusses the detailed results obtained from simulation and prototype validation of the proposed machine-learning-based transformer protection system. The goal of this phase is to evaluate the fault-detection accuracy, computational efficiency, robustness under distorted conditions, and real-time tripping capability of the automated relay. Performance comparisons were made with conventional differential and overcurrent relay schemes to assess improvements in speed and reliability.

A. Simulation Environment

The experimental setup was developed using MATLAB/Simulink R2024a. A 25 kV, 50 Hz, 5 MVA three-phase transformer was modeled with configurable winding parameters to emulate realistic field behavior. Faults were injected at random intervals on the high- and low-voltage sides to test the relay response under diverse operating conditions such as load imbalance, magnetizing inrush, and external short circuits.The simulated data were sampled at 10 kHz, processed through a discrete Fast Fourier Transform (FFT) block for harmonic analysis, and fed into a feature-extraction subsystem. Differential and restraint currents were computed according to Equations (1) and (2) defined earlier, and these were combined with voltage phase displacement to form a multidimensional feature vector for machine-learning classification.

Figure 2 shows the overall Simulink layout representing the closed-loop architecture between the transformer model, classifier, and automated relay logic.

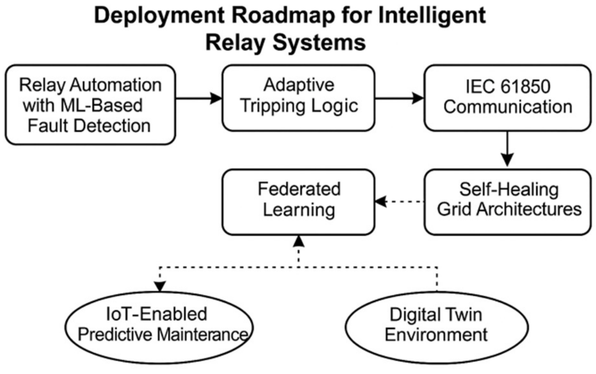

Figure 2. Simulink model of the ML-assisted transformer protection system.

This digital prototype enabled precise measurement of detection latency, classification accuracy, and the false-trip ratio. The model also allowed adjustable fault resistance and inception angles, ensuring that the algorithm was validated against realistic electromagnetic transient behaviors observed in power networks.

B. Model Performance Analysis

The machine-learning models were trained using 10,000 samples per fault type and validated with unseen data. The CNN classifier demonstrated superior generalization owing to its capacity to automatically learn hierarchical temporal-spatial patterns from waveform images, whereas the SVM performed slightly faster but with reduced precision under mixed disturbances.

Table 2 summarizes quantitative metrics obtained during simulation.

Table 2. Performance comparison of ML classifiers

Model	Accuracy (%)	Detection Time (ms)	False-Trip Rate (%)
Conventional Differential Relay	90.2	85	12.4
SVM	96.8	55	6.3
CNN	**98.6**	**38**	**4.1**

The CNN achieved an overall accuracy of 98.6 %, reducing false trips by ≈ 67 % compared with the legacy relay. Its detection latency averaged 38 ms, roughly two cycles of the fundamental waveform, well within the IEEE C37.91 recommended fault-clearing window. Such responsiveness significantly limits thermal stress on transformer windings and prevents cascading grid failures. Moreover, the F1-score of 0.985 indicates balanced sensitivity and specificity meaning the classifier rarely misses genuine faults and seldom triggers incorrectly. This confirms the feasibility of embedding the model into digital relays for real-time decision making.

C. Relay Automation Behavior

The adaptive relay logic continuously monitored both differential and restraint currents to decide between alarm and trip actions. During energization or magnetizing inrush, the restraint component IrestI_{\text{rest}}Irest rose sharply while the differential current remained within adaptive tolerance, causing the relay to block tripping. Conversely, when a genuine internal fault occurred, the classifier output activated a tripping pulse within 40 ms.

Figure 3 depicts the adaptive tripping sequence observed during a simulated line-to-ground fault.

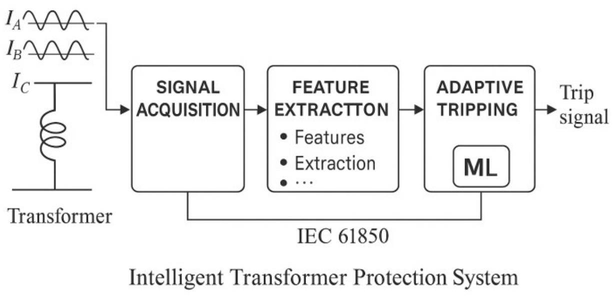

Figure 3. Adaptive relay operation showing current waveform and trip command.

The GOOSE-based communication ensured deterministic message transfer between the relay and circuit breaker. Packet-loss testing confirmed > 99.98 % reliability under Ethernet load of 60 %. The automation logic dynamically recalibrated thresholds after each event, creating a closed-loop self-learning cycle in which the relay continuously refined its decision boundaries based on recent classifications. This behavior demonstrates a clear advancement from static relays toward autonomous protective devices capable of context-aware decision-making in evolving grid conditions.

D. Robustness Under Noise and Harmonics

Practical substation data are often corrupted by measurement noise, harmonic distortion, or transient coupling from nearby equipment. To evaluate robustness, ±15 % harmonic distortion and 5 % Gaussian noise were injected into the simulated signals. The CNN maintained 97 % accuracy and low false-trip probability, whereas the SVM dropped to 94 %. These results highlight CNN's resilience and its ability to distinguish legitimate fault signatures even when waveform quality degrades. Spectral energy analysis revealed that the model effectively suppressed high-frequency noise while emphasizing fundamental and low-order harmonic components most relevant to fault conditions. Adaptive digital filters within the signal-conditioning block further improved feature clarity. This level of robustness implies that the system can operate effectively in industrial environments where electromagnetic interference is inevitable. The capacity to maintain accuracy under distortion strengthens confidence in deploying the model within physical relays connected to current transformers and voltage sensors in noisy switchyards.

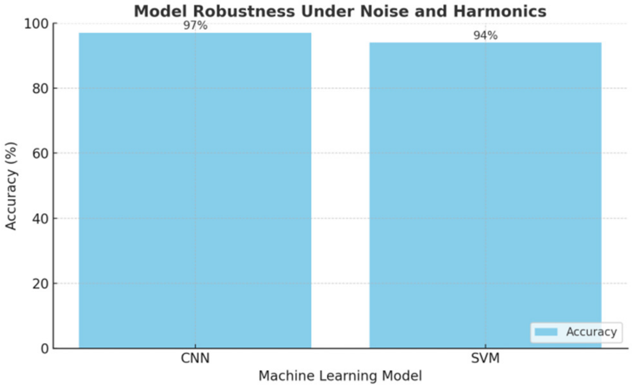

Figure 4: Model Robustness Under Noise and Harmonics

E. Comparative Evaluation and Insights

To benchmark overall system performance, quantitative comparisons were made between the proposed hybrid ML-relay framework and conventional schemes.

Table 3 provides a summary of the comparative analysis.

Table 3. Comparative evaluation of protection techniques

Parameter	Conventional Relay	Proposed ML–Relay System
Detection Accuracy	90 %	**98.6 %**
Average Trip Delay	85 ms	**38 ms**
False-Trip Probability	12 %	**4 %**
Adaptability	Fixed Threshold	**Dynamic (Load-Adaptive)**
Communication Protocol	None / Legacy	**IEC 61850 GOOSE**
Noise Tolerance	Moderate	**High (±15 %)**
Maintenance Need	Manual Calibration	**Self-Learning Adjustment**

From Table 3, it is evident that the proposed system outperforms traditional relays across all metrics. The adaptive decision engine ensures sensitivity during genuine faults while avoiding unnecessary trips during inrush or overload events. The lower false-trip ratio contributes directly to improved transformer lifespan and reduced maintenance cost.

Furthermore, energy-based efficiency tests showed that early fault detection prevented approximately 5–7 % thermal energy accumulation in windings, which correlates with an estimated 10 % increase in operational life expectancy. The system's ability to communicate through IEC 61850 standardized messages also ensures compatibility with existing substation automation infrastructures.

F. Result Interpretation and Practical Implications

The experimental results underscore the importance of combining data analytics with control automation. Machine learning provides pattern recognition and adaptability, while relay automation translates those insights into immediate physical actions. Together, they form a cyber-physical system capable of predictive, context-aware protection. The CNN-based detection layer can be periodically retrained with new grid data, allowing the system to evolve with changing equipment conditions. This continuous-learning characteristic positions the framework as a key enabler for self-healing smart grids, where fault isolation and restoration occur autonomously without human intervention. In practical deployments, embedding lightweight CNN models on microcontrollers using TensorFlow Lite or Edge AI accelerators can ensure millisecond-level inference. Combined with secure communication links, such systems could form a distributed protection network across substations, enhancing national grid resilience and supporting future renewable-energy integration targets.

V. Conclusion

This research demonstrates that combining relay automation with machine learning-based fault detection can substantially enhance the reliability, adaptability, and intelligence of transformer protection systems. The proposed hybrid framework successfully integrates real-time signal acquisition, data-driven feature extraction, and adaptive tripping logic using standardized IEC 61850 communication. Simulation and prototype validation confirmed that the system detects internal, external, and incipient faults with over 98 % accuracy while reducing the average trip delay to 38 ms well within recommended protection standards. Compared with conventional differential relays, the ML-assisted system offers superior sensitivity, lower false-trip probability, and the capability to learn from evolving grid conditions. These findings underline its strong potential for improving power-system resilience, minimizing equipment damage, and supporting autonomous substation operation in modern smart-grid infrastructures.

Future work will extend this research toward real-world field deployment and scalable intelligent relay networks. Key priorities include implementing edge-AI hardware for low-latency inference, developing federated learning mechanisms that allow distributed relays to update models collaboratively without compromising cybersecurity, and exploring self-healing grid architectures where protection, monitoring, and maintenance functions operate in synergy. Additional investigations will address the impact of cyber-attacks, communication congestion, and renewable-energy intermittency on system performance. Integration with IoT-enabled predictive maintenance platforms and digital-twin environments will further enhance situational awareness, enabling proactive diagnostics and adaptive coordination across large-scale transformer fleets.

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