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Development of an Artificial Intelligence System for Insulation Condition Assessment in Generators

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Abstract

Partial Discharge (PD) analysis plays an important role in assessing the insulation condition of electrical generators. Conventional analysis of Phase-Resolved Partial Discharge (PRPD) patterns relies heavily on expert interpretation, which is time-consuming and leads to inconsistent results. This research presents an automated PRPD pattern classification system using a deep learning-based artificial intelligence (AI) approach on the CiRA CORE platform. Two Convolutional Neural Network (CNN) models, YOLOv4-tiny and YOLOv7-tiny, were trained on 100 PRPD images with a 90:10 training-testing split. The models achieved mean Average Precision (mAP) at IoU 0.5 of 81.77% and 84.97% for YOLOv4-tiny and YOLOv7-tiny, respectively. Further evaluation used 80 PRPD test images benchmarked against three human experts. The AI system outperformed the experts in both accuracy and speed. YOLOv7-tiny achieved 85.8% accuracy in 10 minutes, while YOLOv4-tiny achieved 79.5% in 12 minutes. Human experts averaged 50% accuracy and required 50.66 minutes. The proposed system reduces analysis time and reliance on expert judgement while improving diagnostic accuracy, supporting a more efficient predictive maintenance strategy for the power generation industry.

Keywords
Artificial Intelligence, CiRA CORE, Deep Learning, Generator, Partial Discharge

1. Introduction
In the power generation sector, the sustained operability of electrical generators is a fundamental requirement, as any erosion of their functional integrity has a direct impact on the reliability of energy supply and grid continuity. While there are numerous subsystems that influence the longevity of generators, the stator winding insulation system is particularly critical. This insulation experiences progressive deterioration as a result of the compounding effects of electrical field stress, thermally induced expansion and contraction, and vibrational mechanical loading. If left unaddressed, this deterioration may result in dielectric breakdown and unscheduled operational interruption, which impose significant financial burdens on utility operators (Stone 2014). Partial discharge monitoring (PD) has been institutionalized as a standard diagnostic protocol within condition-based maintenance frameworks for rotating high-voltage equipment in recognition of this risk.

The current approach to evaluating insulation conditions is based on the acquisition and interpretation of Phase-Resolved Partial Discharge (PRPD) patterns. These two-dimensional graphical representations plot the discharge magnitude against the instantaneous phase angle of the applied alternating voltage cycle. These visualizations encode specific morphological signatures that correspond to distinct categories of insulation degradation, thereby allowing trained practitioners to infer both the type and severity of the defect (IEC 60034-27 2012; Butdee and Techaumnat 2022). This interpretive process is, however, impeded by several systemic deficiencies that collectively erode maintenance efficiency, despite its diagnostic utility. The most significant issues include the scarcity of domain-specialized personnel capable of conducting reliable PRPD analysis, the inherent subjectivity in visual pattern recognition when done manually, and the protracted reporting cycles that delay actionable maintenance decisions. These inefficiencies, which are well-known forms of operational waste that are in conflict with the principles of lean manufacturing and impede the scalability of predictive maintenance programs, have been documented in recent surveys of AI-assisted maintenance applications (Chomklin et al. 2023).

The present study capitalizes on the transformative potential of computational image analysis and Artificial Intelligence (AI) to surmount these deeply ingrained constraints. Systems that are capable of autonomous, high-throughput feature extraction and pattern classification from complex visual inputs have been produced as a result of advancements in Deep Learning, particularly the development and ongoing refinement of Convolutional Neural Networks (CNNs). These systems have demonstrated performance metrics that consistently surpass or rival those of human expert benchmarks in a wide range of industrial inspection domains (Saengsiangfa and Deelertpaiboon 2021; He et al. 2025). This research aims to develop an automated PRPD pattern classification system by utilizing You Only Look Once (YOLO) object detection algorithms within the CiRA CORE platform, a low-code AI environment that was developed in Thailand and is specifically designed for industrial deployment contexts (CiRA CORE 2026; Redmon et al. 2016). The system will be built upon this foundation. The study aims to create a diagnostic workflow that is more objective, reproducible, and faster than traditional expert-dependent methods by integrating these elements. This will provide power plant operators with a robust, evidence-based instrument for monitoring insulation condition and making informed maintenance decisions.

1.1 Objectives

The principal objectives of this research are as follows:

- To create an automated process for evaluating the insulation condition of generators on the CiRA CORE platform using Artificial Intelligence (AI).
- To develop and evaluate deep learning models for the classification of signal patterns associated with partial discharge.
- To evaluate the performance of the AI system that has been developed in terms of accuracy and analysis time in comparison to the conventional expert-based assessment method.
- To develop a prototype framework for the integration of the CiRA CORE platform into a predictive maintenance system for power facilities.

2. Literature Review

This research integrates concepts from electrical engineering, industrial operations management, and artificial intelligence. The literature review is structured to cover the foundational knowledge in each of these domains.

2.1 Partial Discharge (PD) and PRPD Analysis

Partial Discharge is a well-established indicator of insulation degradation in high-voltage equipment like generators. PD events can be categorized into several types based on their physical origin, such as internal discharges, slot partial discharges and discharges in the end-winding. Each type produces a distinct signature when plotted against the AC voltage phase, creating a Phase-Resolved Partial Discharge (PRPD) pattern (IEC 60034-27 2012). The visual interpretation of these patterns allows experts to identify the nature and location of the insulation defect. For instance, PRPD patterns from internal voids are typically symmetrical, while those from delamination between the conductor and insulation are asymmetrical, with negative pulses having higher amplitudes (Ardila-Rey et al. 2020). The international standard IEC 60034-27 provides a comprehensive guide to stylized examples of these patterns, which serves as a foundational reference for both human experts and the training of AI models.

2.2 Deep Learning for Industrial Applications

The rapid advancement of Artificial Intelligence (AI), particularly within the domain of Deep Learning, has introduced transformative capabilities for addressing intricate problems that once demanded human cognitive intervention. At its core, Deep Learning leverages multi-layered Artificial Neural Networks (ANNs) to autonomously extract and internalize complex patterns embedded within large-scale datasets, eliminating the need for manual feature engineering (Saengsiangfa and Deelertpaiboon 2021).

Among the architectural variants within the Deep Learning paradigm, the Convolutional Neural Network (CNN) stands out as a foundational framework engineered specifically for visual data processing. Through a hierarchical learning mechanism, CNNs progressively capture spatial representations ranging from elementary primitives such as edges and contours to more sophisticated structural configurations, including object geometries and compositional arrangements. This multi-scale feature learning capacity renders CNNs particularly well-suited for tasks involving object detection and category discrimination (Butdee and Techaumnat 2022). Consequently, CNN-based systems have been widely adopted across manufacturing and engineering sectors, with notable implementations in automated defect identification on Printed Circuit Boards (PCBs) (He et al. 2025) and vision-based quality assurance within automotive production environments (Saengsiangfa and Deelertpaiboon 2021).

Nevertheless, industrial deployment scenarios frequently impose stringent latency requirements that necessitate inference at near-instantaneous speeds. This operational constraint has driven the evolution of detection frameworks that retain CNN as a computational backbone while substantially enhancing processing throughput, culminating in the development of the YOLO family of algorithms as a direct response to these industrial demands.

2.3 YOLO-Based Detection Framework and the CiRA CORE Platform

Building upon the representational power of CNNs, the "You Only Look Once" (YOLO) algorithm represents a paradigm shift in the field of real-time object detection. Unlike conventional multi-stage detection pipelines that sequentially propose candidate regions prior to classification, YOLO reformulates detection as a unified regression problem, enabling the simultaneous localization and identification of multiple objects within a single forward propagation pass (Redmon et al. 2016). This architectural efficiency yields a substantially improved inference speed without disproportionate sacrifice in predictive accuracy, making YOLO particularly well-suited for time-critical applications in industrial environments (Redmon et al. 2016; Lv et al. 2025). As a result, YOLO has emerged as a preferred computational solution in scenarios where rapid and reliable visual decision-making is operationally essential (Lv et al. 2025).

To further reduce the technical barriers associated with deploying YOLO-based systems in practice, the CiRA CORE platform, an AI development environment engineered in Thailand, provides an accessible, low-code infrastructure tailored for building and operationalizing object detection applications. By employing a modular, block-based programming interface, the platform empowers engineers and applied researchers with limited software development expertise to configure and deploy AI-driven inspection systems without extensive coding proficiency (CiRA CORE 2026). The practical efficacy of this platform has been substantiated through a range of domain-specific investigations, including the automated classification of knee osteoarthritis severity from radiographic imaging (Pongsakonpruttikul et al. 2022) and the interpretive analysis of colorimetric pesticide detection kits within agricultural monitoring contexts (Jantawong et al. 2024). Collectively, these applications underscore the platform's adaptability and operational readiness for complex diagnostic and industrial inspection tasks.

2.4 Related Works

Recent studies have increasingly demonstrated the potential of AI in various diagnostic and inspection fields. CNNs have been successfully applied to classify PRPD patterns, showcasing the viability of deep learning for this task (Butdee and Techaumnat 2022). Research on PCB defect detection highlighted the superiority of deep learning over traditional machine vision in terms of accuracy and speed (He et al. 2025). In the agricultural sector, the CiRA CORE platform with a YOLOv8 model was utilized to read pesticide test kit results, achieving over 92% accuracy and reducing human error (Jantawong et al. 2024). Similarly, a YOLOv3-tiny model on CiRA CORE was developed to assist physicians in classifying knee osteoarthritis from X-rays, achieving accuracies of 85–86.7%

(Pongsakonpruttikul et al. 2022). These studies collectively validate the efficacy of AI (CNN/YOLO) and the readiness of the CiRA CORE platform for tackling complex image-based analysis tasks across diverse industries. This research builds upon these foundations by applying a similar methodology specifically to the insulation assessment of electrical generators.

3. Methods

This research employs a systematic approach to develop, train, and validate an AI-based system for PRPD pattern classification, following the workflow illustrated in Figure 1.

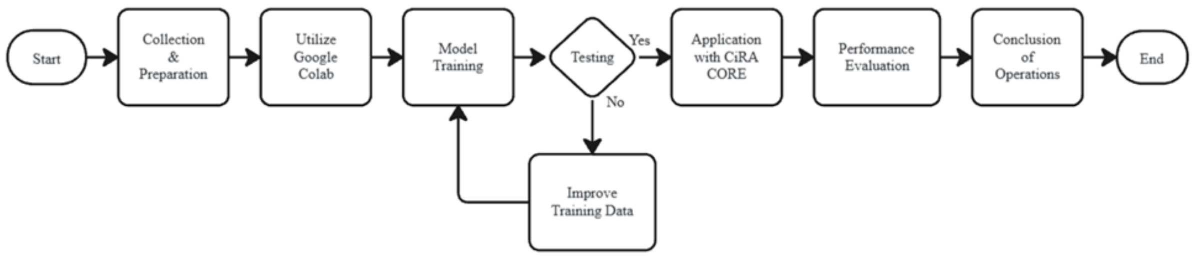

Figure 1. Proposed research methodology workflow.

3.1 Data Collection and Preparation

A comprehensive dataset is crucial for training a robust deep learning model. The initial dataset consisted of 100 PRPD images collected from three primary sources to ensure variety and relevance, as illustrated in Figure 2:

- International Standards: Stylized PRPD patterns from IEC 60034-27.
- Manufacturer Guides: Example patterns from the user manuals of PD testing equipment.
- Field Data: Real-world PRPD images from generator tests, which were verified and labeled by human experts.

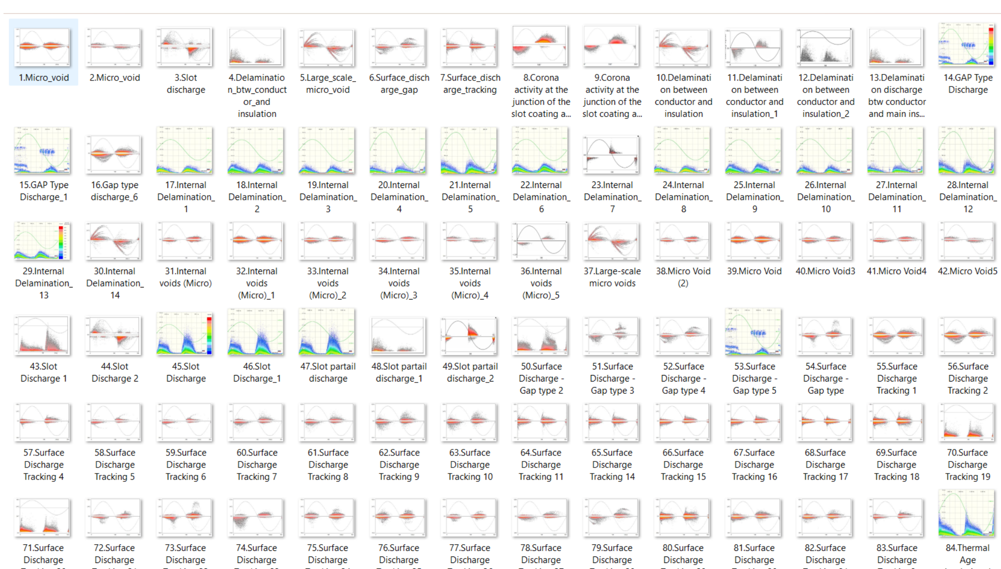

Figure 2. PRPD images

3.2 Model Development and Training

For this investigation, two lightweight YOLO-based architectures, namely YOLOv4-tiny and YOLOv7-tiny, were selected as the primary detection frameworks for comparative evaluation. The adoption of these compact model variants was justified by their inherent capacity to maintain a favorable equilibrium between inferential throughput and classificatory precision, rendering them particularly well-suited for deployment within resource-constrained computational environments. All model training procedures were conducted utilizing CiRA Deep Train Colab, a cloud-based training tool developed and operated upon the Google Colaboratory infrastructure, which provides accessible GPU-accelerated model optimization without requiring local hardware resources (CiRA CORE 2026). The computational acceleration was facilitated through the integrated T4 Graphics Processing Unit (GPU) available within the Colaboratory environment, enabling efficient iterative weight adjustment throughout the training phase. The overall training configuration and procedural workflow employed in this study are illustrated in Figure 3.

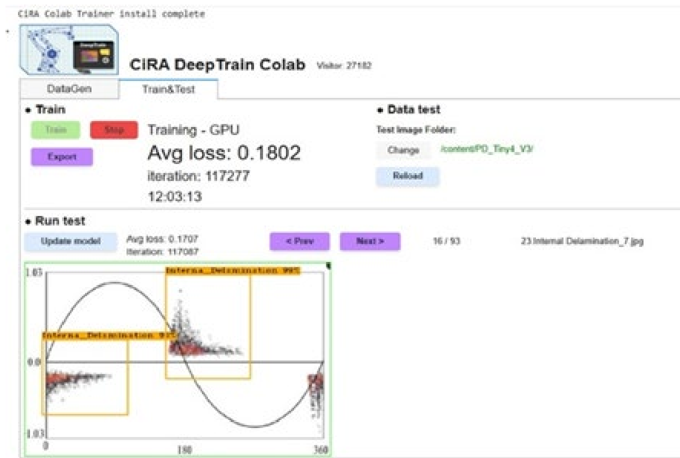

Figure 3. CiRA Deep Train Colab

With regard to training duration and convergence behavior, the YOLOv4-Tiny model completed its optimization process in approximately 12 hours, attaining a final average loss value of 0.1802. In contrast, the YOLOv7-tiny model, owing to its more advanced architectural complexity, necessitated a substantially longer training period of approximately 24 hours, ultimately converging to a final average loss of 0.5972. In both cases, training was sustained until the average loss metric exhibited consistent stability at a sufficiently low threshold, serving as an empirical indicator that each YOLO model had acquired a robust capacity to discriminate among the distinct morphological classes of PRPD patterns present in the dataset. A comprehensive summary of the training outcomes for both models is presented in Table 1.

Table 1. Summary of model training performance

Model	Average Loss	Iterations (cycles)	Training Duration (hours: minutes: seconds)
YOLOv4-tiny	0.1802	117,277	12:03:13
YOLOv7-tiny	0.5972	161,677	23:46:46

3.3 System Implementation and Evaluation

The trained models were deployed on the CiRA CORE platform to create an automated analysis system. The system was designed with a node-based architecture, consisting of four main modules, as illustrated in Figure 4:

- Data Acquisition Module: Inputs PRPD images into the system via a webcam or image file upload.
- AI Inference Engine: Utilizes the DeepDetect node, which contains the trained YOLO model, to analyze the input image and classify the PRPD pattern.
- Logic Control and Visualization: Displays the classification result on the user interface.
- Remote Notification System: Uses the TGNotify node to send the analysis results, including the image and classification, as a Telegram message to designated users, enabling on-site decision-making, as illustrated in Figure 5.

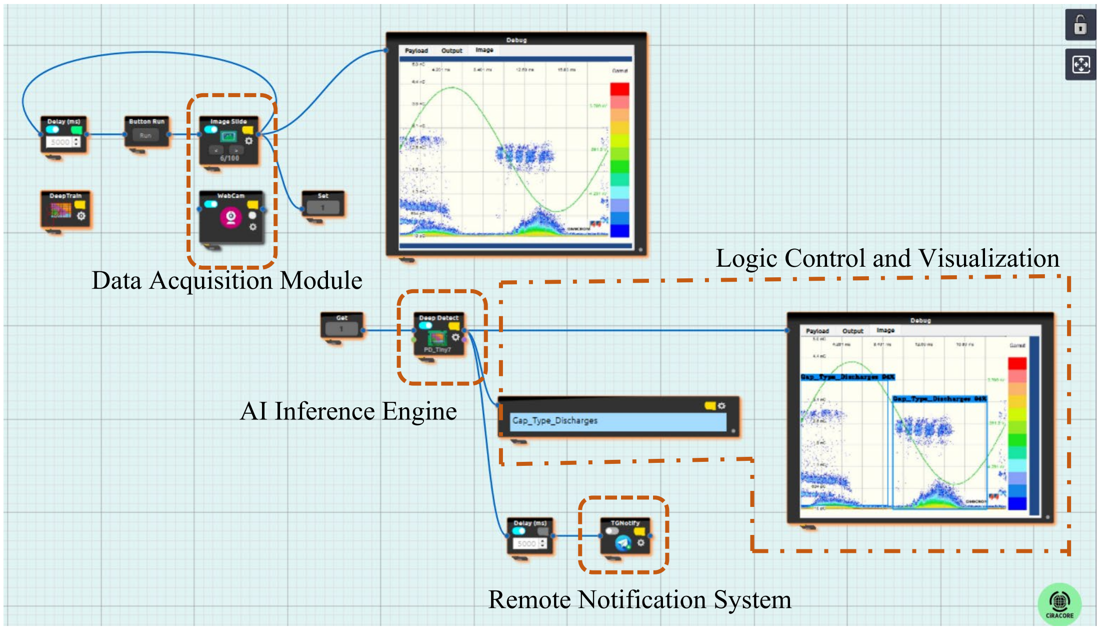

Figure 4. System architecture on CiRA CORE Platform

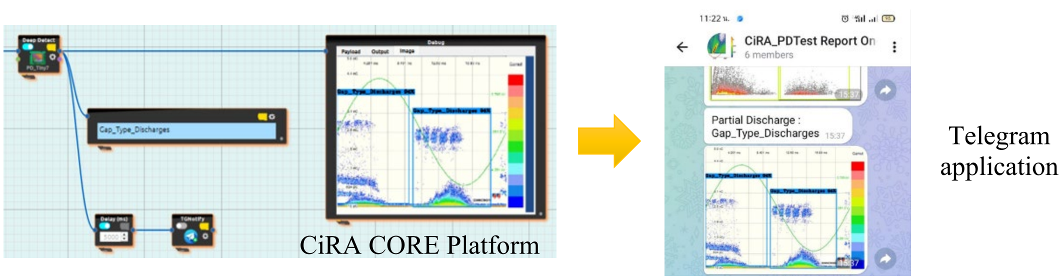

Figure 5. The resulting image and PRPD classification message delivered via the Telegram application.

3.4 Performance Evaluation
A two-stage evaluation was conducted. First, the intrinsic performance of the trained models was assessed using the mean Average Precision (mAP) metric on the test dataset (Redmon et al. 2016; Lv et al. 2025). Second, a comparative study was performed to benchmark the AI system against human experts. A separate test set of 80 PRPD images was prepared. Three human experts with experience in PD analysis were asked to classify each image. The same set of images was then processed by the AI system using both the YOLOv4-tiny and YOLOv7-tiny models. The performance of each (human experts and AI models) was measured based on two key metrics: Accuracy (the percentage of correct classifications) and Analysis Time (the total time taken to classify all 80 images) (Chomklin et al. 2023).

4. Data Collection
The dataset underpinning this investigation was assembled and preprocessed in accordance with the procedural specifications outlined in the research methodology. The foundational corpus consisted of 100 PRPD images, encompassing a representative range of partial discharge fault categories derived from two complementary sources: internationally recognised testing standards and field measurement records that had undergone rigorous verification by qualified engineering personnel. Following initial collection, this dataset was partitioned into a training subset comprising 90 images (90%) and a held-out test subset of 10 images (10%), designated for preliminary model validation.

To facilitate a robust final evaluation of the developed AI system, a separate and independent test collection of 80 PRPD images was subsequently prepared. This evaluation dataset was administered concurrently to two distinct assessment channels: manual classification performed independently by three practising engineers with established expertise in partial discharge analysis and automated processing through the AI-based YOLO classification system. By subjecting both the human evaluators and the AI models to an identical image set under equivalent experimental conditions, a direct and unbiased performance comparison was rendered possible. The cumulative time required by each individual expert and the deployed YOLO model to complete the full classification of all 80 images was systematically recorded as a primary performance metric.

5. Results and Discussion

5.1 Numerical Results

The detection efficacy of the optimized model architectures, YOLOv4-tiny and YOLOv7-tiny, was subjected to comprehensive quantitative assessment via a specialized evaluation pipeline. Performance indices were obtained by the CiRA CORE platform's integrated DeepEval scoring mechanism, utilizing its EvalDetect function, which analyzed the AI-trained picture library to provide objective assessments of detection accuracy and overall classification reliability. The benchmarking technique was implemented on a curated test collection of 100 annotated images, with the Intersection over Union (IoU) overlap criterion set at a threshold of 0.5 to delineate the boundary conditions for successful positive detections. The trade-off between Precision and Recall for each assessed architecture was depicted as a graphical curve, with Precision on the vertical axis and Recall on the horizontal axis, facilitating a systematic comparison of both model configurations, as illustrated in Figure 6.

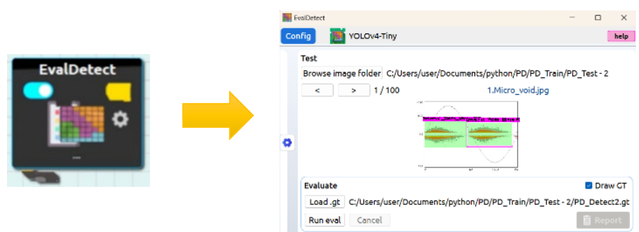

Figure 6. Model Performance Evaluation

The numerical outcomes of this benchmarking experiment indicated that both architectural configurations achieved substantial classification accuracy across all PRPD fault pattern categories. Among the two candidates, YOLOv7-tiny exhibited a slight but persistent performance advantage, attaining a mean Average Precision (mAP) of 84.97%, whereas YOLOv4-tiny registered a marginally lower mAP of 81.77%, as depicted in Figure 7.

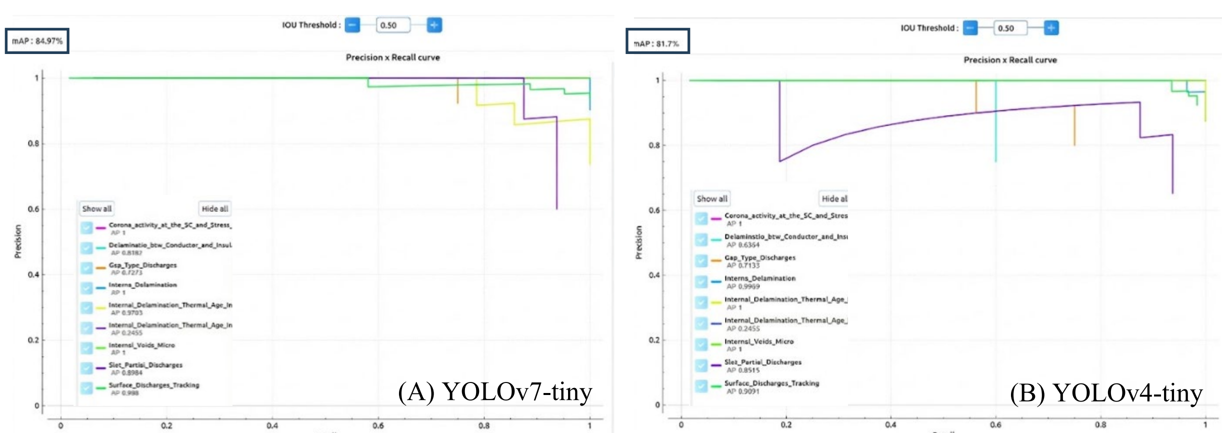

Figure 7. Precision x Recall curves for both models

The comparative study against human experts provided more compelling insights. The AI-based system demonstrated superior performance in both accuracy and speed (He et al. 2025; Saengsiangfa and Deelertpaiboon 2021). The

YOLOv7-tiny model achieved the highest accuracy at 85.8%, followed by the YOLOv4-tiny model at 79.5%. In stark contrast, the three human experts achieved an average accuracy of only 50%. In terms of time, the AI system was significantly faster. The YOLOv7-tiny and YOLOv4-tiny models completed the analysis of 80 images in 10 and 12 minutes, respectively. The human experts, on average, required 50.66 minutes to complete the same task. These results are summarized in Tables 2 and 3.

Table 2. Performance AI System

AI System				
Item	Analysis Duration	Correct Interpretations	Average Processing Time	Diagnostic Accuracy
	(minutes)	(out of 80 images)	(minute/image)	(%)
	(A)	(B)	(A)/80 images	(B/80 images) *100%
YOLOv7-tiny				
Test 1	10	70	0.125	87.5
Test 2	10	68	0.125	85.0
Test 3	10	68	0.125	85.0
Mean Average	10	68.66	0.125	85.8
YOLOv4-tiny				
Test 1	11	65	0.137	81.2
Test 2	14	62	0.175	77.5
Test 3	11	64	0.137	80.0
Mean Average	12	63.8	0.14	79.5

Table 3. Performance Human Experts

Human Experts				
Item	Analysis Duration	Correct Interpretations	Average Processing Time	Diagnostic Accuracy
	(minutes)	(out of 80 images)	(minute/image)	(%)
	(A)	(B)	(A)/80 images	(B/80 images) *100%
Expert 1	48	38	0.60	47.5
Expert 2	46	26	0.575	32.5
Expert 3	58	56	0.725	70.0
Mean Average	50.66	40	0.633	50.0

5.2 Graphical Results

The performance gap between the AI system and human experts is visualized in Figures 8 and 9. Figure 8 clearly illustrates the superior accuracy of both YOLO models compared to the human average. Figure 9 highlights the dramatic reduction in analysis time achieved by the AI system, processing the entire test set approximately five times faster than the human experts.

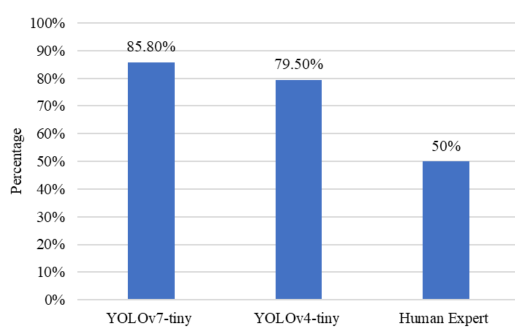

Figure 8. Accuracy Comparison

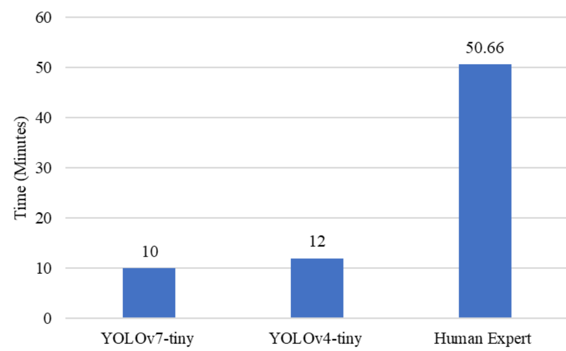

Figure 9. Analysis Time Comparison

5.3 Proposed Improvements

The results strongly indicate that the developed AI system is a viable and superior alternative to the conventional manual process. The system not only improves diagnostic accuracy but also drastically reduces the lead time for analysis from nearly an hour to just 10-12 minutes. This eliminates the "waiting" waste associated with queuing for an expert, a core principle of Lean thinking (Womack and Jones 2003). By providing rapid, on-site preliminary analysis via Telegram, the system empowers maintenance teams to make faster, data-driven decisions. The role of the human expert is transformed from a routine analyst into a verifier for complex or ambiguous cases, allowing their valuable experience to be utilized more effectively. This streamlined workflow introduces a new standard for PRPD analysis that is faster, more consistent, and less dependent on individual skill levels. While the current accuracy of 85.8% is a significant improvement, further enhancements can be achieved by expanding the training dataset with more diverse, real-world examples and exploring more advanced models like YOLOv8.

6. Conclusion

This research successfully developed and validated an artificial intelligence system for the automated assessment of generator insulation conditions based on PRPD pattern analysis. By implementing YOLOv4-tiny and YOLOv7-tiny models on the CiRA CORE platform, the study demonstrated that an AI-driven approach can significantly outperform traditional human expert analysis in both accuracy and speed. The YOLOv7-tiny model achieved an accuracy of 85.8% in just 10 minutes, compared to the human experts' average of 50% accuracy in over 50 minutes.

The findings confirm that the proposed system effectively addresses the key limitations of the conventional process, such as time-consuming bottlenecks, subjectivity, and inconsistency. By automating the classification task, this system provides a rapid, standardized, and reliable diagnostic tool that supports a lean and efficient predictive maintenance strategy. The integration with a remote notification system like Telegram further enhances its practical utility, enabling immediate feedback to on-site personnel. Future work will focus on expanding the training dataset and exploring newer model architectures to further improve accuracy and robustness for real-world deployment in the power generation industry.

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