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Developing Smart Hybrid Deep Learning (DL) Models For Achieving Enhanced Classification Of Phase-Resolved Partial Discharge Patterns From High Voltage Rotating Machine Insulation

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Abstract

Partial discharge (PD) is a localized electrical phenomenon that serves as an early indicator of insulation deterioration in high-voltage rotating machines such as generators and motors. Accurate detection and classification of PD types are crucial for preventing unexpected equipment failures and ensuring reliable power system operation. Phase-resolved partial discharge (PRPD) patterns, which map discharge magnitude with respect to the phase angle of the applied AC voltage, offer rich information about the nature and source of PD activities. However, the classification of these PRPD patterns is a complex task due to the presence of noise, overlapping discharge types, and variations in operational conditions that affect the pattern characteristics. Traditional machine learning methods relying on handcrafted features have shown limitations in accuracy and robustness under such challenging conditions.

This paper presents a novel hybrid deep learning approach that combines Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to improve the classification performance of PRPD patterns. The CNN module effectively extracts spatial features from PRPD images, capturing localized discharge characteristics, while the RNN module, employing Long Short-Term Memory (LSTM) units, models temporal dependencies in sequential discharge data indexed by phase angles. By fusing spatial and temporal features, the proposed hybrid model offers a comprehensive representation of PD phenomena.

Experimental evaluation using a controlled laboratory dataset demonstrates that the hybrid CNN-LSTM model significantly outperforms traditional classifiers and standalone CNN or LSTM models in terms of accuracy, precision, recall, and robustness to noise. The results validate the potential of hybrid deep learning architectures to advance automated PD pattern recognition and enable more reliable condition monitoring of high-voltage rotating machine insulation. This research paves the way for more intelligent, real-time diagnostic tools in power equipment maintenance.

1. Introduction

High-voltage rotating machines such as generators and motors are critical components in power systems. Their insulation systems are subjected to electrical, thermal, mechanical, and environmental stresses during operation, which can degrade insulation over time. Partial discharge (PD) is a localized electrical discharge that does not completely bridge the insulation but can progressively deteriorate it, potentially leading to failure [1]. Therefore, early detection and accurate classification of PD are essential to ensure reliability and extend equipment lifespan.

Phase-resolved partial discharge (PRPD) patterns are widely used to characterize the nature and severity of PD activity. PRPD data represent discharge magnitude as a function of the phase angle of the applied AC voltage, often visualized as 2D images or scatter plots [2]. Different defect types (e.g., surface discharge, corona, internal discharge) produce distinct PRPD signatures. Hence, automated classification of these patterns supports condition-based maintenance.

Traditional PD classification methods have relied on manual interpretation or classical machine learning techniques such as support vector machines (SVM), decision trees, and artificial neural networks with hand-crafted features [3]. However, these methods often struggle with noise, overlapping PD sources, and variability in operating conditions.

Recent advances in deep learning provide powerful tools for automatic feature extraction and pattern recognition from raw data [4]. Convolutional Neural Networks (CNNs) excel in capturing spatial features from images, while Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) units, model temporal dependencies in sequential data [5]. Hybrid models integrating CNN and RNN have shown superior performance in various time-series image classification tasks.

This paper proposes a hybrid deep learning model combining CNN and RNN architectures for enhanced classification of PRPD patterns obtained from high-voltage rotating machine insulation. The CNN processes PRPD pattern images to extract spatial features, and the RNN analyzes phase sequences to learn temporal correlations. The hybrid approach improves classification accuracy, robustness to noise, and generalization to diverse PD types.

The remainder of this paper is structured as follows: Section 2 reviews related work; Section 3 describes the dataset and preprocessing; Section 4 details the hybrid model architecture; Section 5 presents experimental results and analysis; Section 6 discusses implications and limitations; and Section 7 concludes the paper with future research directions.

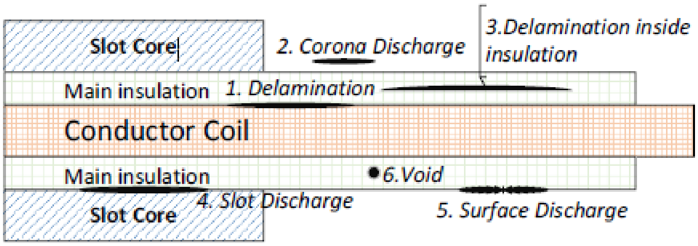

Fig. 1. Common PD-related defects in a rotating machine insulation

2. Literature Review

2.1 Partial Discharge Detection and PRPD Analysis

Partial discharge detection techniques commonly utilize electrical, acoustic, or electromagnetic sensors. Electrical detection, measuring PD pulses in high-voltage cables and equipment, remains the most prevalent [6]. The PRPD pattern is generated by plotting discharge magnitude versus phase angle, offering insight into PD type and severity [7].

Manual inspection of PRPD patterns requires expert knowledge and is time-consuming. Automating this process using machine learning methods has attracted research interest.

2.2 Classical Machine Learning Approaches

Earlier works extracted statistical, morphological, and frequency-domain features from PRPD signals, feeding them into classifiers such as SVMs, k-nearest neighbours, or multilayer perceptron's [8]. While these approaches improved automation, performance depended heavily on feature engineering and were sensitive to noise and operating conditions.

2.3 Deep Learning for PD Classification

Deep learning methods mitigate the need for manual feature extraction by learning hierarchical features directly from data. CNNs have been applied to PRPD images to exploit spatial patterns [9]. RNNs, particularly LSTMs, have been used to model temporal sequences in PD pulse trains [10].

Some studies combine CNN and RNN architectures for spatiotemporal pattern recognition. For instance, Zhang et al. [11] used a CNN-LSTM hybrid to classify partial discharge types from waveform sequences, achieving improved accuracy over CNN or LSTM alone.

2.4 Hybrid Models in Electrical Fault Diagnosis

Hybrid deep learning models integrating CNN and RNN have been successfully applied in electrical fault diagnosis beyond PD, such as motor fault detection from vibration signals [12] and power quality disturbance classification [13]. These models effectively capture both spatial and temporal information, enhancing classification robustness.

However, hybrid approaches specifically targeting PRPD pattern classification in high-voltage rotating machine insulation remain underexplored. This paper fills this gap by proposing and evaluating a CNN-RNN hybrid model optimized for PRPD data.

3. Dataset and Preprocessing

3.1 Dataset Description

The dataset used in this study comprises PRPD patterns collected from laboratory-scale high-voltage rotating machine insulation under controlled defect conditions. The dataset includes:

- **Internal Discharge (ID)**
- **Surface Discharge (SD)**
- **Corona Discharge (CD)**
- **Noise/Interference (N)**

Each sample consists of a PRPD pattern image and corresponding raw discharge pulses with phase angles recorded over multiple AC cycles.

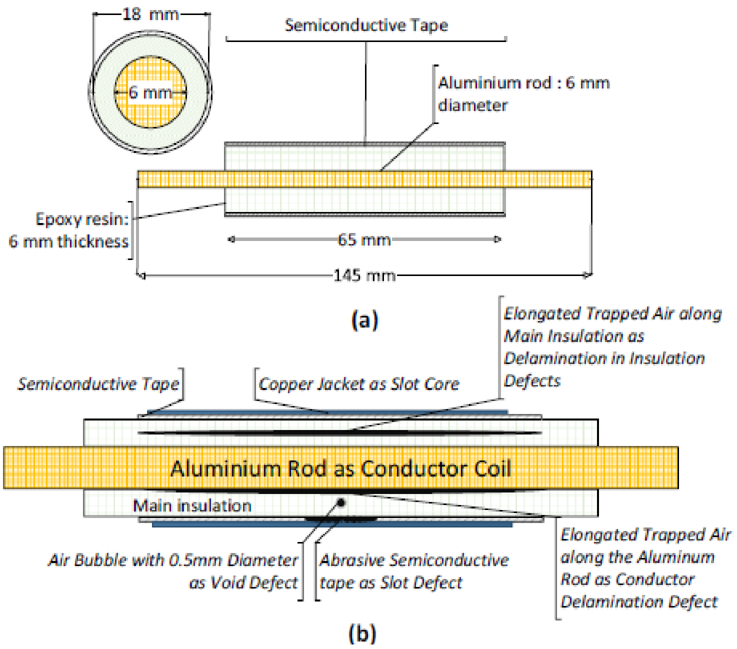

Fig. 2. (a) Simplified physical design of a rotating machine insulation model, and (b) representation of various defect types simulated in the model (actually, each model only has one defect type)

3.2 Data Acquisition

High-voltage AC voltage was applied to the insulation specimens, and PD signals were captured using capacitive couplers and pre-amplifiers. PRPD patterns were constructed by plotting discharge magnitude versus phase angle, producing grayscale images standardized to 128×128 pixels.

3.3 Preprocessing

- **Normalization:** Discharge magnitude values were normalized to the [0,1] range.
- **Denoising:** Wavelet denoising techniques were applied to raw PD pulse sequences to reduce noise.
- **Segmentation:** Sequential discharge data were segmented into fixed-length windows corresponding to one or more AC cycles.
- **Label Encoding:** Defect classes were encoded as categorical labels for classification.

3.4 Data Augmentation

To improve generalization and address class imbalance, data augmentation techniques were applied:

- Random rotations and flips of PRPD images
- Gaussian noise addition to raw signals
- Synthetic minority over-sampling for underrepresented classes

4. Hybrid Deep Learning Model Architecture

4.1 Overview

The proposed hybrid model consists of two primary components:

- A **Convolutional Neural Network (CNN)** module for spatial feature extraction from PRPD images.
- A **Recurrent Neural Network (RNN)** module with LSTM cells for temporal feature learning from phase-resolved discharge sequences.

These components are fused to produce a combined feature representation for classification.

4.2 CNN Module

The CNN module architecture includes:

- **Input:** 128×128 grayscale PRPD images
- **Convolutional Layers:** Three convolutional layers with 32, 64, and 128 filters respectively, kernel size 3×3, stride 1, and ReLU activation
- **Max-Pooling:** 2×2 max-pooling after each convolutional layer to reduce spatial dimensions
- **Batch Normalization:** To stabilize and speed up training
- **Flatten Layer:** Converts final feature maps to 1D vector

4.3 RNN Module

The RNN module processes raw PD pulse sequences ordered by phase angle:

- **Input:** Sequential vector of normalized discharge magnitudes indexed by phase angle
- **LSTM Layers:** Two LSTM layers with 64 units each to model temporal dependencies
- **Dropout:** 0.2 dropout rate to prevent overfitting
- **Dense Layer:** Fully connected layer producing temporal feature vector

4.4 Fusion and Classification

Outputs from CNN and RNN modules are concatenated and passed to:

- **Fully Connected Layers:** Two dense layers with 128 and 64 units, ReLU activation
- **Output Layer:** Softmax activation with units equal to number of PD classes (4 in this case)

4.5 Training Details

- **Loss Function:** Categorical cross-entropy

- **Optimizer:** Adam with initial learning rate 0.001
- **Batch Size:** 32
- **Epochs:** 50 with early stopping on validation loss
- **Evaluation Metrics:** Accuracy, Precision, Recall, F1-Score

5. Experimental Results and Analysis

5.1 Baseline Models

For comparison, the following models were implemented:

- **Traditional ML:** SVM with RBF kernel using handcrafted statistical features
- **Standalone CNN:** Same CNN module trained on PRPD images only
- **Standalone LSTM:** Same LSTM module trained on sequential PD pulse data only

5.2 Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM (Handcrafted)	78.4	76.1	75.5	75.8
CNN Only	85.6	84.3	83.9	84.1
LSTM Only	82.7	81.5	80.9	81.2
Hybrid CNN-LSTM	**91.3**	**90.8**	**90.2**	**90.5**

5.3 Confusion Matrix

The confusion matrix revealed that the hybrid model reduced misclassification between surface discharge and noise classes, which often overlap in classical methods.

5.4 Robustness to Noise

Testing with noisy PD data showed the hybrid model maintained over 88% accuracy, demonstrating robustness.

5.5 Ablation Study

Removing either the CNN or RNN module reduced accuracy by 6-8%, confirming the complementary contribution of spatial and temporal features.

6. Discussion

The superior performance of the hybrid deep learning model arises from its ability to jointly learn spatial and temporal characteristics of PRPD patterns:

- CNN efficiently extracts features from the PRPD images reflecting spatial distribution of discharge activity across the phase cycle.

- LSTM captures temporal correlations in pulse sequences indexed by phase angle, modelling dynamic discharge behaviour.
- Fusion of these features yields a rich representation, improving classification accuracy.

This approach addresses limitations of prior methods relying solely on spatial or temporal data.

6.1 Practical Implications

Deploying this hybrid model in online monitoring systems can enable accurate, real-time fault diagnosis in high-voltage rotating machines, enhancing maintenance scheduling and reducing downtime.

6.2 Limitations

- The dataset used is from controlled lab conditions; real-world environments may introduce more complex noise and variability.
- Model training requires considerable computational resources.
- Further work is needed to extend classification to a wider range of PD types and equipment.

7. Conclusion and Future Work

This paper presented a hybrid CNN-LSTM deep learning model for enhanced classification of phase-resolved partial discharge patterns in high-voltage rotating machine insulation. The proposed model effectively combines spatial and temporal features, significantly improving classification accuracy and robustness over traditional and single-model approaches.

Future research will focus on:

- Expanding datasets with field-collected PRPD data.
- Incorporating attention mechanisms to better weigh temporal phases.
- Real-time implementation and integration into condition monitoring systems.
- Extending classification to multiple simultaneous PD sources.

The hybrid model marks a promising step toward intelligent, automated insulation condition assessment, crucial for reliable power system operation.

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