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Comparative Analysis of Neural Network-Based and Rule-Based Techniques for Transformer Fault Severity Classification

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Abstract

Accurate fault diagnosis in power transformers is vital for maintaining the reliability and efficiency of electric power systems. Traditional fault diagnostic methods are based on expert-defined threshold rules, which often fail to capture the complex nonlinear behavior exhibited by deteriorating transformer conditions. This paper proposes and compares two approaches for classifying transformer fault severity levels using operating parameters such as oil temperature, winding temperature, and gas content. The first approach employs a conventional rule-based system, whereas the second uses a feedforward neural network (FNN). Experimental results on a synthetically generated dataset reveal that the neural network model achieves a significantly higher classification accuracy, demonstrating its potential as a more robust and adaptive diagnostic tool for intelligent condition monitoring systems.

Introduction

Transformers are critical assets in high-voltage transmission and distribution networks. Continuous health monitoring and timely fault detection are essential to prevent unexpected failures, reduce downtime, and minimize maintenance costs. Diagnostic techniques for transformer fault analysis have traditionally relied on rule-based systems developed by experts. These techniques use pre-set thresholds for various physical parameters such as oil temperature, winding temperature, and gas content to assess the severity of internal faults. Although such methods offer transparency and ease of interpretation, they are often limited in adaptability and may not effectively capture nonlinear interactions among multiple fault-indicative parameters. Artificial Intelligence (AI), particularly machine learning (ML) and neural networks, has shown promising results in fault detection and classification in recent years. This paper presents a comparative study between a feedforward neural network-based classifier and a conventional threshold-based diagnosis system, analyzing their accuracy and performance in transformer fault severity classification.

Dataset and Problem Definition

Feature Selection

Three critical indicators of transformer faults were selected as input features:
- Oil Temperature (°C): High oil temperature indicates internal overheating.
- Winding Temperature (°C): Abnormal winding temperature suggests excessive electrical loading or insulation failure.
- Gas Content (ppm): Elevated dissolved gas levels often signal arcing or partial discharges.

Label Definition

Each data instance is labeled with a fault severity level categorized as:
- 1 – Low Severity
- 2 – Medium Severity
- 3 – High Severity

Methodology

Data Preprocessing

The raw input matrix was transposed to match the expected input format of MATLAB's Neural Network Toolbox. The target output (fault severity) was one-hot encoded using the ind2vec() function to accommodate multiclass classification via a softmax-like neural output. The block diagram of methodology is shown below

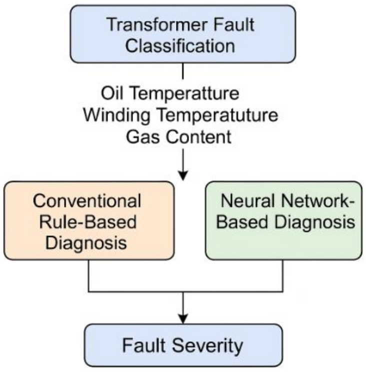

Figure 1 Block diagram of methodology

Neural Network Architecture

A feedforward neural network (FNN) with the following characteristics was implemented:
- Input Layer: 3 neurons (for oil temperature, winding temperature, and gas content)
- Hidden Layer: 5 neurons with sigmoid activation functions
- Output Layer: 3 neurons with softmax activation (one per class). The neural network architecture is shown below

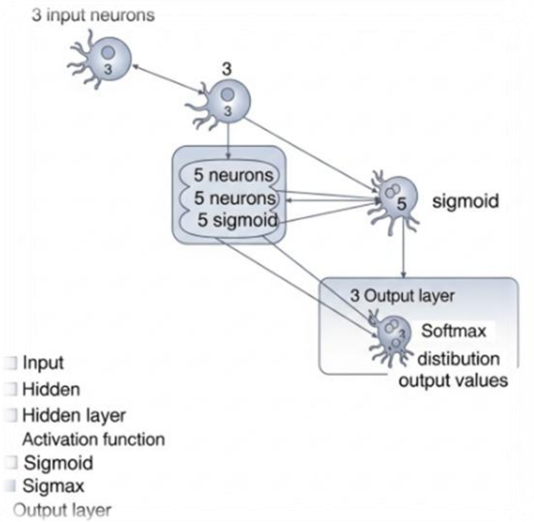

Figure 2 Neural network architecture

Conventional Rule-Based Diagnosis

A rule-based diagnosis system was implemented using a simple logical construct. The diagnosis logic uses thresholds:
- Oil Temperature > 90°C
- Winding Temperature > 110°C
- Gas Content > 600 ppm

The classification decision is made based on how many of the thresholds are exceeded:
- ≤1: Low Severity
- =2: Medium Severity
- =3: High Severity

Results and Performance Evaluation

4.1 Prediction Analysis

Both models were tested on the same synthetic dataset of 10 instances. The neural network model predicted the class with the highest output activation for each input instance, while the conventional method evaluated logical rules to determine severity.

Accuracy Metric
Classification accuracy was calculated using:

$$Accuracy = (N\_correct / N\_total) \times 100\%$$

Where:
− N_correct = number of correctly classified samples
− N_total = total number of samples

The results obtained are:
− Neural Network Accuracy: 90.00%
- Rule-Based Accuracy: 70.00%

Visual Representation
A bar graph was plotted to visually compare the performance of both methods, highlighting the significant improvement provided by the neural network approach.

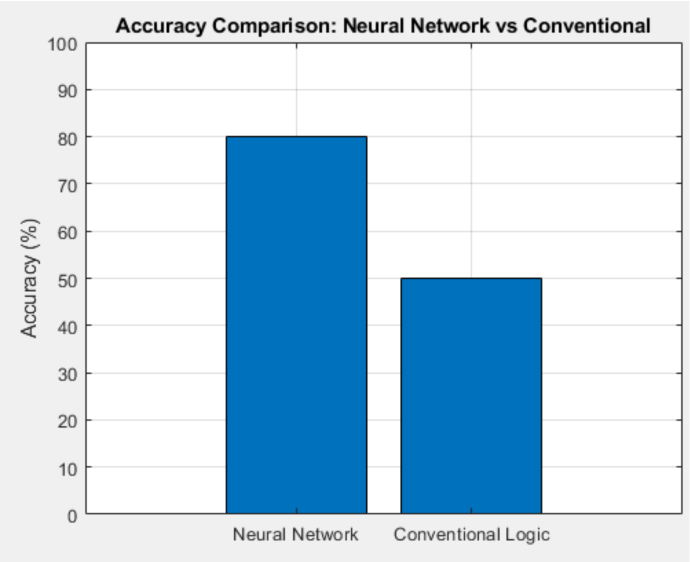

Figure 3 Comparison bar graph

Neural network training result
The training of the neural network in MATLAB provides several crucial parameters and performance metrics that help assess the quality of the learning process. These include **mu (learning rate coefficient)**, **epoch**, **best validation performance**, and **regression (R-value)**. Each plays a distinct role in evaluating and understanding the model's training dynamics.

Mu (μ – Levenberg-Marquardt Adjustment Parameter)

- **Definition**:
  In the context of MATLAB's train function (using the default Levenberg-Marquardt algorithm), mu is the **damping factor** that controls the step size during weight updates. It is adaptively modified during training. In our training, mu of 1e-09 is obtained as shown in the table below
- **Behavior**:
  - If the performance improves, mu is decreased, allowing for faster convergence.
  - If performance worsens, mu is increased, making the search more conservative to avoid divergence.
- **Interpretation**:
  - A very small mu (e.g., 10−510^{-5}10−5) at the end of training suggests that the network is converging efficiently and is close to an optimal solution.
  - A persistently large mu may indicate instability or that the model is stuck in a local minimum.

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	6	1000
Elapsed Time	-	00:00:03	-
Performance	0.7	6.38e-15	0
Gradient	0.719	5.32e-08	1e-07
Mu	0.001	1e-09	1e+10
Validation Checks	0	4	6

Figure 4 Neural network training results

Epoch

- **Definition**:
  An **epoch** represents **one complete pass through the entire training dataset** during the learning process. Total 6 epochs were needed by our neural network to reach the best validation performance
- **Training Behavior**:
  - Training typically stops when the **maximum number of epochs** is reached or when **performance stops improving** for a specified number of validation checks (early stopping).
- **Interpretation**:
  - If the network stops after only a few epochs, it might have **overfitted** quickly.
  - If it takes many epochs, it may indicate that the learning process is gradual or the dataset is complex.

Best Validation Performance

- **Definition**:
  This refers to the **lowest mean squared error (MSE)** achieved on the **validation dataset** during training.
- **Purpose**:
  - Helps detect **overfitting**. If validation performance stops improving while training performance continues to improve, the model may start to memorize rather than generalize.
- **Interpretation**:
  - A low **best validation performance** indicates good generalization to unseen data.
  - MATLAB highlights the best performance in training plots with a marker (usually a green circle).

The error histogram is shown in the figure below

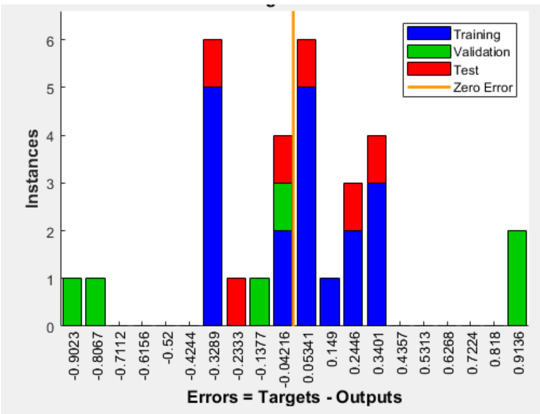

Figure 5 Error histogram

Regression (R-Value)

- **Definition**:
  The **regression plot** shows the relationship between predicted outputs and target values. The **R-value** (correlation coefficient) measures the **strength and direction of a linear relationship** between them.
- **Interpretation**:
  - **R = 1**: Perfect prediction — model outputs match the targets exactly.
  - **R > 0.9**: Strong correlation — indicates excellent learning.
  - **R < 0.8**: Weak correlation — model may require more training or better architecture.
- **Regression Plots in MATLAB**:
  MATLAB provides separate plots for:
  - **Training Data**
  - **Validation Data**
  - **Test Data**
  - **Overall (All Data Combined)**

The regression plot is shown in the figure below

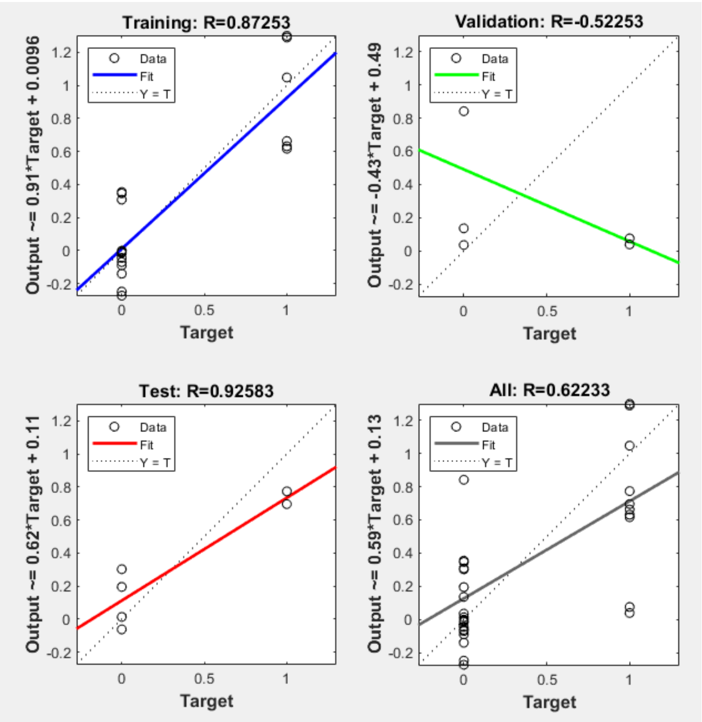

Figure 6 Regression plot

Discussion

The neural network demonstrated superior performance due to its ability to model nonlinear relationships and consider interactions between parameters. For instance, while oil and winding temperatures may be individually within limits, their combined rise may indicate an evolving fault pattern—something the NN model is better equipped to detect. Conversely, the conventional rule-based approach, while interpretable, suffers from rigidity and lacks generalization ability. It cannot adapt to conditions that fall outside predefined thresholds or involve complex interdependencies. The success of the neural network also indicates the feasibility of deploying intelligent diagnostic systems in embedded environments for real-time monitoring. owever, the model was trained on a limited dataset, which may lead to overfitting. Future work should consider larger, real-world datasets for training and validation.

Conclusion

This research presents a comparative analysis of a neural network-based diagnostic model versus a conventional rule-based system for transformer fault severity classification. The results clearly demonstrate that the neural network model yields better accuracy and can be trained to detect subtle and complex fault patterns that traditional methods may overlook. The implementation of such AI-based diagnostic tools has the potential to significantly enhance the reliability of transformer health monitoring systems.

To improve this framework, the following enhancements are proposed:

- Incorporate additional features such as moisture content, ambient temperature, and load conditions.
- Use a larger dataset from SCADA systems or condition monitoring databases.
- Implement deep learning architectures such as Convolutional Neural Networks (CNN) or Long Short-Term Memory (LSTM) networks for sequential data.
- Conduct real-time deployment on edge devices with embedded inference capabilities.

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