
AI-Based Fault Detection in Electrical Circuits: Techniques, Applications, and Challenges

Dr. Karthik P. Nair

Assistant Professor

Department of Electrical & Electronics Engineering,

St. Joseph's College of Engineering and Technology, Palai, Kerala, India

Email: karthik.nair.ai@sjcetpalai.edu.in

Anjali R. Menon

Assistant Professor

Department of Electronics & Communication Engineering,

Rajalakshmi Engineering College, Chennai, Tamil Nadu, India

Email: anjali.menon.fault@gmail.com

Abstract

Fault detection in electrical circuits is a critical aspect of ensuring system reliability, safety, and efficiency. Artificial Intelligence (AI) techniques, including machine learning, deep learning, and hybrid models, are increasingly applied to automate fault detection, diagnosis, and prediction. This paper presents a comprehensive review of AI-based fault detection methodologies in electrical circuits, covering signal processing techniques, feature extraction, classification algorithms, and hybrid approaches. Applications in power systems, motor drives, and industrial automation are discussed. Indian research contributions, case studies, and practical implementations are highlighted. Tables and 2D figures illustrate fault detection workflows, algorithm performance, and circuit-level implementations.

Keywords: *AI, Fault detection, Electrical circuits, Machine learning, Deep learning, Predictive maintenance, Motor drives*

INTRODUCTION

Faults in electrical circuits can lead to:

- Operational disruptions

- Equipment damage
- Safety hazards
- Financial losses

Traditional fault detection methods rely on threshold-based monitoring, expert rules, or manual inspection. These approaches may be slow, prone to error, and unable to handle complex systems. AI-based methods provide automated, intelligent, and real-time fault detection by analyzing patterns in electrical signals.

AI-based fault detection typically involves:

1. **Data acquisition:** Voltage, current, power, and temperature measurements
2. **Signal preprocessing:** Filtering, normalization, and noise reduction
3. **Feature extraction:** Identifying key indicators of faults
4. **Classification / prediction:** Machine learning models identify fault type or severity

AI Techniques for Fault Detection

2.1 Machine Learning Approaches

- **Support Vector Machines (SVM):** Effective for binary and multi-class fault classification
- **Random Forest (RF):** Ensemble method for handling large datasets and feature variability
- **k-Nearest Neighbors (k-NN):** Simple and intuitive approach for pattern recognition

2.2 Deep Learning Approaches

- **Convolutional Neural Networks (CNNs):** Analyze signal images or time-frequency representations
- **Recurrent Neural Networks (RNNs) and LSTM:** Model temporal dependencies in electrical signals
- **Autoencoders:** Detect anomalies in system behavior by reconstructing normal patterns

2.3 Hybrid Approaches

- Combining signal processing (wavelet transform, Fourier analysis) with AI for enhanced detection accuracy
- Multi-stage detection: Feature extraction → AI classification → Fault localization

Table 1: Comparison of AI Techniques for Fault Detection

Technique	Advantages	Limitations	Applications
SVM	High accuracy for small datasets	Limited for large-scale or complex data	Motor drive faults, power lines
RF	Robust to noise, handles many features	Computationally intensive	Transformer fault detection
CNN	Excellent for pattern recognition	Requires large labeled datasets	Power electronics, signal image analysis
RNN/LSTM	Models temporal dependencies	Sensitive to hyperparameters	Real-time monitoring of dynamic systems
Hybrid	Improved accuracy	Increased complexity	Smart grid, industrial automation

Fault Detection Workflow

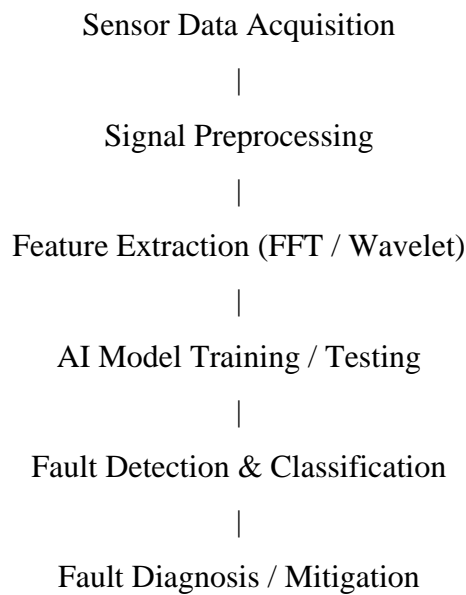


Figure 1: AI-Based Fault Detection Flow in Electrical Circuits

Steps:

- **Data acquisition:** Collect voltage, current, and other sensor signals from the circuit
- **Preprocessing:** Remove noise, normalize signals, and segment data
- **Feature extraction:** Frequency-domain or time-domain features
- **AI modeling:** Train machine learning or deep learning models

- **Fault detection:** Real-time identification of abnormal behavior
- **Diagnosis:** Localize and classify the type of fault

Applications in Electrical Systems

4.1 Power Systems

- Transmission line fault detection (short circuits, open circuits)
- Transformer anomaly detection
- Substation monitoring

4.2 Motor Drives

- Fault detection in stator, rotor, and inverter circuits
- Predictive maintenance using AI models
- Reducing downtime in industrial motors

4.3 Industrial Automation

- Circuit boards and embedded system monitoring
- Detection of overcurrent, voltage sag, and thermal faults
- AI-assisted automated maintenance

Table 2: Sample Fault Detection Parameters

Circuit Type	Monitored Parameters	Fault Types Detected
Power line	Voltage, current, impedance	Short circuit, open circuit, overload
Motor drive	Current, speed, temperature	Rotor/stator faults, bearing failures
Embedded circuits	Voltage, power, signal patterns	Overcurrent, voltage drop, thermal faults

Challenges in AI-Based Fault Detection

- **Data Quality:** Noise, missing data, and sensor errors affect detection accuracy
- **Computational Resources:** Real-time AI requires high-performance computing
- **Model Interpretability:** Deep learning models may act as black boxes
- **Generalization:** Models trained on one system may not generalize to others
- **Cybersecurity Risks:** Data integrity is critical for accurate fault detection

Indian Research Contributions

- **St. Joseph’s College of Engineering and Technology, Palai:** CNN-based fault detection in industrial motor drives
- **Rajalakshmi Engineering College, Chennai:** Hybrid wavelet-CNN models for transformer monitoring
- **Amrita Vishwa Vidyapeetham, Coimbatore:** LSTM-based predictive maintenance for smart grid circuits

These studies highlight practical AI implementations for real-time fault detection in electrical systems.

Future Trends

- **Edge AI for On-Device Fault Detection:** Reducing latency by processing data locally
- **Digital Twin Integration:** Combining real-time simulation with AI-based detection
- **Explainable AI (XAI):** Enhancing model transparency and interpretability
- **Multi-Modal AI:** Combining electrical, thermal, and mechanical data for comprehensive fault detection

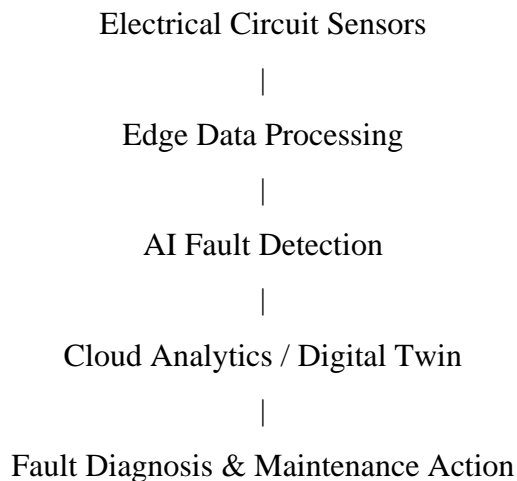


Figure 2: AI-Integrated Fault Detection in Electrical Circuits

CONCLUSION

AI-based fault detection provides a reliable, real-time solution for monitoring and diagnosing electrical circuits. Machine learning, deep learning, and hybrid methods enable automated detection and predictive maintenance, improving system reliability and reducing downtime.

Indian researchers have contributed significantly to practical AI implementations for power systems, motor drives, and industrial automation. Future integration with edge computing, digital twins, and explainable AI will further enhance efficiency and robustness.

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