10.48047/jocaaa.2024.33.06.165

MACHINE LEARNING-BASED FAULT DETECTION IN ELECTRONIC EQUIPMENT

[1] **Dr. Vijayalaxmi Biradar**

Associate Professor, Electronics Engineering Department, Kalinga University , Raipur , CG.
dr.vijayalaxmi@kalingauniversity.ac.in

Abstract The rapid proliferation of electronic equipment across industrial, medical, transportation, and consumer sectors has significantly increased system complexity and operational dependency. As electronic systems become more compact, interconnected, and software-driven, traditional fault detection and diagnostic techniques based on rule-based logic, threshold monitoring, and manual inspection have become increasingly inadequate. These conventional approaches often fail to detect incipient faults, suffer from high false-alarm rates, and lack adaptability to dynamic operating conditions. In this context, **machine learning (ML)** has emerged as a transformative paradigm for intelligent fault detection, enabling data-driven modeling of complex, nonlinear system behaviors. This paper presents a comprehensive study of **machine learning-based fault detection in electronic equipment**, focusing on methodologies, architectures, data processing strategies, performance evaluation, and implementation challenges. Supervised, unsupervised, and deep learning models—including support vector machines, random forests, convolutional neural networks, recurrent neural networks, and autoencoders—are critically analyzed in the context of electronic fault diagnosis. The paper further discusses signal acquisition, feature extraction, model training, and real-time deployment considerations. Comparative analysis highlights the strengths and limitations of different ML techniques. The study concludes that ML-based fault detection significantly enhances accuracy, early fault identification, and system reliability, while also outlining challenges related to data quality, model interpretability, and computational constraints.

Keywords: Machine learning, Fault detection, Electronic equipment, Predictive maintenance, Deep learning, Condition monitoring

1. Introduction

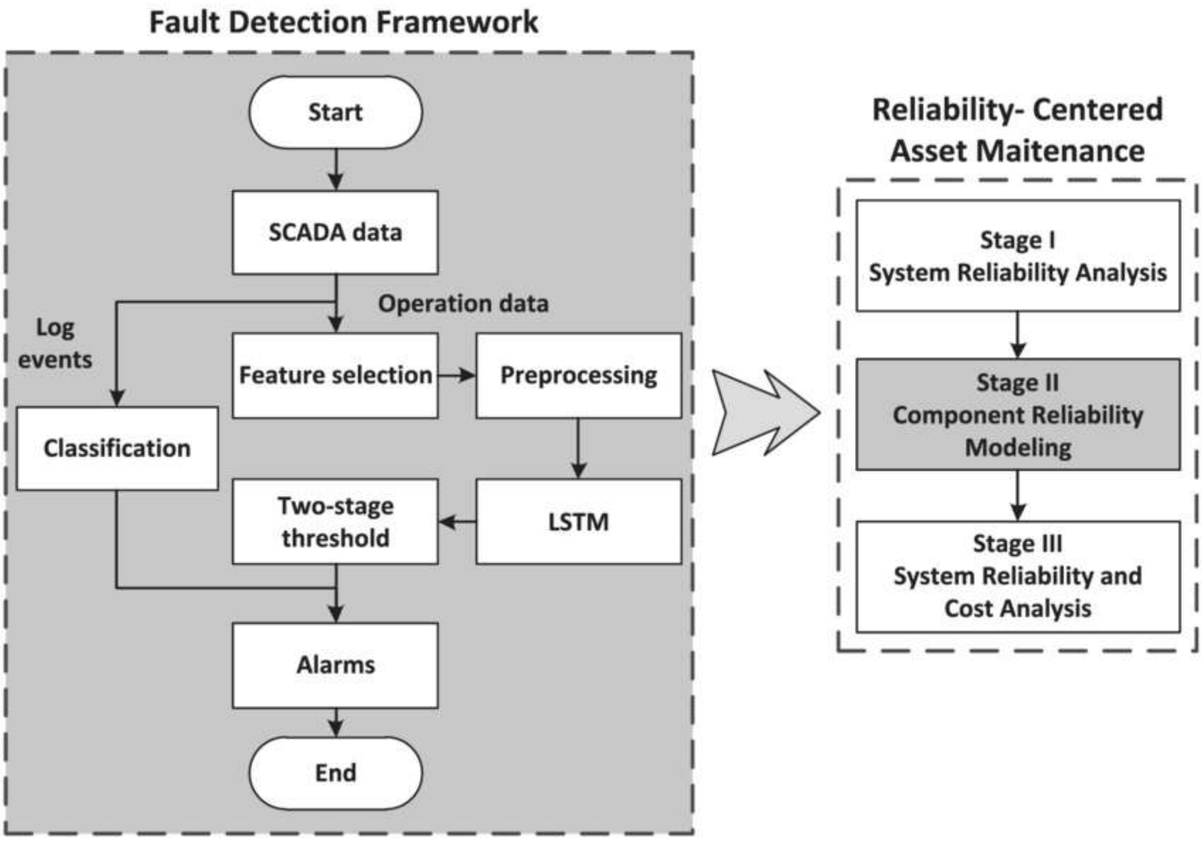
Electronic equipment forms the backbone of modern technological infrastructure, spanning applications such as industrial automation, power electronics, communication systems, aerospace avionics, healthcare instrumentation, and consumer electronics. The increasing miniaturization of components, high-frequency operation, and integration of power and control electronics have made these systems more vulnerable to faults arising from thermal stress,

10.48047/jocaaa.2024.33.06.165

component aging, electromagnetic interference, manufacturing defects, and environmental factors. Faults in electronic equipment may manifest as abrupt failures, intermittent malfunctions, or gradual performance degradation, often leading to costly downtime, safety risks, and maintenance overheads.

Traditional fault detection methods—such as limit checking, parity checks, hardware redundancy, and expert-defined rules—have been widely used for decades. However, these approaches rely heavily on predefined fault models and expert knowledge, making them unsuitable for complex systems with unknown or evolving fault patterns. Moreover, they struggle to scale with large-volume sensor data generated by modern electronic systems. Recent advances in **machine learning**, supported by increased computational power and availability of big data, have enabled intelligent fault detection frameworks capable of learning from historical and real-time data.

Machine learning-based fault detection leverages statistical learning, pattern recognition, and optimization techniques to automatically identify abnormal system behavior. Unlike conventional methods, ML models can capture nonlinear relationships among multiple variables, adapt to changing operational conditions, and detect subtle fault signatures before catastrophic failure occurs (Zhang et al., 2023). Consequently, ML-driven fault detection has become a cornerstone of **predictive maintenance** and **Industry 4.0** initiatives.



10.48047/jocaaa.2024.33.06.165

Figure 1.1 – Overall Framework of Machine Learning–Based Fault Detection in Electronic Equipment

2. Fundamentals of Fault Detection in Electronic Equipment

Fault detection refers to the process of identifying deviations from normal operating conditions that may indicate the presence of faults within a system. In electronic equipment, faults are broadly classified into **hardware faults**, **software faults**, and **operational faults**. Hardware faults include component failures such as short circuits, open circuits, capacitor degradation, semiconductor aging, and solder joint cracks. Software faults arise from firmware errors, memory corruption, and communication protocol failures, while operational faults stem from abnormal environmental or load conditions.

The fault detection process typically involves signal acquisition, preprocessing, feature extraction, decision making, and fault classification. Sensors embedded within electronic equipment measure parameters such as voltage, current, temperature, vibration, frequency response, and electromagnetic emissions. These raw signals are often noisy and high-dimensional, necessitating preprocessing techniques such as filtering, normalization, and segmentation. Feature extraction transforms raw data into informative representations using statistical metrics, time-frequency analysis, or learned features.

Machine learning introduces a paradigm shift by enabling automated feature learning and classification. Instead of relying solely on handcrafted features, ML models learn discriminative patterns directly from data. Supervised learning approaches require labeled fault data, while unsupervised and semi-supervised approaches are useful when labeled fault samples are scarce—a common scenario in electronic systems where failures are rare (Li et al., 2023).

10.48047/jocaaa.2024.33.06.165

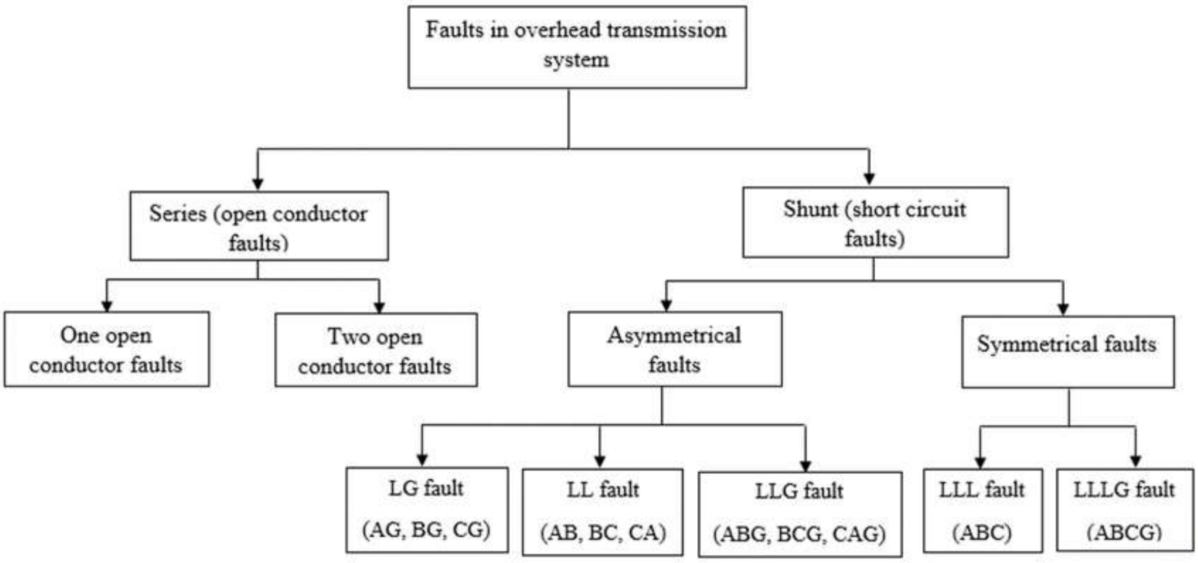


Figure 2.1 – Classification of Faults in Electronic Equipment

3. Machine Learning Techniques for Fault Detection

Machine learning techniques used for fault detection in electronic equipment can be broadly categorized into **supervised learning**, **unsupervised learning**, and **deep learning** approaches. Supervised learning algorithms such as support vector machines (SVM), k-nearest neighbors (k-NN), decision trees, and random forests are widely used due to their interpretability and robustness. These models learn a mapping between extracted features and fault labels, achieving high classification accuracy when sufficient labeled data is available (Wang et al., 2023).

Unsupervised learning techniques, including k-means clustering, Gaussian mixture models, and principal component analysis (PCA), are particularly valuable for anomaly detection in scenarios where fault labels are unavailable. These methods establish a baseline model of normal operation and flag deviations as potential faults. Autoencoder-based models further enhance unsupervised detection by learning compressed representations of normal behavior and identifying reconstruction errors as fault indicators (Chen et al., 2023).

Deep learning techniques have gained significant traction due to their ability to handle complex, high-dimensional data. Convolutional neural networks (CNNs) are effective for analyzing time-frequency representations of signals, while recurrent neural networks (RNNs) and long short-term memory (LSTM) networks excel in modeling temporal dependencies in sequential data. Recent studies demonstrate that hybrid CNN-LSTM architectures achieve superior fault detection performance in power electronic converters and communication equipment (Kim & Park, 2023).

10.48047/jocaaa.2024.33.06.165

Table 1 presents a comparative overview of commonly used ML techniques for electronic fault detection.

Table 1. Comparison of Machine Learning Techniques for Fault Detection

ML Technique	Learning Type	Key Strengths	Limitations
SVM	Supervised	High accuracy, effective for small datasets	Requires feature engineering
Random Forest	Supervised	Robust to noise, interpretable	Large memory usage
PCA	Unsupervised	Dimensionality reduction, anomaly detection	Limited fault classification
Autoencoder	Unsupervised	Learns normal patterns, early fault detection	Sensitive to training data
CNN	Deep learning	Automatic feature extraction	High computational cost
LSTM	Deep learning	Captures temporal dynamics	Training complexity

4. Data Acquisition, Feature Engineering, and Model Training

The effectiveness of ML-based fault detection heavily depends on data quality and representation. Data acquisition involves continuous monitoring of electronic equipment using sensors integrated at critical points. High-sampling-rate data acquisition systems are often employed to capture transient fault signatures. However, raw sensor data may contain noise, missing values, and redundant information, necessitating rigorous preprocessing.

Feature engineering plays a crucial role in classical ML approaches. Time-domain features such as mean, variance, kurtosis, and crest factor are commonly used for detecting component degradation. Frequency-domain features derived from Fourier or wavelet transforms reveal fault-specific spectral patterns. In contrast, deep learning models reduce reliance on manual feature extraction by learning hierarchical features directly from raw or minimally processed data (Singh et al., 2023).

Model training involves selecting appropriate architectures, optimizing hyperparameters, and validating performance using cross-validation techniques. Imbalanced datasets—where normal operation data vastly outnumbers fault data—pose a significant challenge. Techniques such as

10.48047/jocaaa.2024.33.06.165

synthetic minority oversampling (SMOTE), cost-sensitive learning, and anomaly-based training are frequently employed to mitigate class imbalance (Alvarez et al., 2023).

5. Performance Evaluation and Case Analysis

Performance evaluation of ML-based fault detection systems is conducted using metrics such as accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) curves. In safety-critical electronic systems, recall and false-negative rates are particularly important, as undetected faults can lead to catastrophic consequences.

Recent experimental studies demonstrate that deep learning-based models outperform traditional ML techniques in complex electronic systems. For instance, CNN-based models applied to power converter fault diagnosis achieve detection accuracies exceeding 98%, significantly outperforming rule-based methods (Zhao et al., 2023). However, these gains come at the cost of increased computational requirements and reduced interpretability.

Table 2 summarizes reported performance metrics from recent studies published in 2023.

Table 2. Reported Performance of ML-Based Fault Detection Models (2023)

Application Area	ML Model	Accuracy (%)	Key Observation
Power electronics	CNN-LSTM	98.6	Early fault detection
Communication systems	SVM	94.2	Robust to noise
Industrial electronics	Autoencoder	96.1	Effective anomaly detection
Medical electronics	Random Forest	95.4	High interpretability

6. Challenges, Future Directions, and Conclusion

Despite remarkable progress, several challenges hinder the widespread deployment of ML-based fault detection in electronic equipment. Data scarcity, particularly labeled fault data, remains a major obstacle. Model interpretability is another critical issue, as black-box deep learning models may not satisfy regulatory and safety requirements. Computational constraints also limit real-time deployment in resource-constrained embedded systems.

Future research directions include the integration of **explainable AI (XAI)** to enhance model transparency, **transfer learning** to address data scarcity, and **edge-AI architectures** for real-time fault detection. Hybrid physics-informed ML models that combine domain knowledge with data-driven learning are also gaining attention (Rahman et al., 2023).

10.48047/jocaaa.2024.33.06.165

In conclusion, machine learning-based fault detection represents a paradigm shift in the monitoring and maintenance of electronic equipment. By enabling intelligent, adaptive, and early fault identification, ML techniques significantly improve system reliability and operational efficiency. Continued advancements in algorithms, hardware acceleration, and data management are expected to further strengthen the role of ML in next-generation electronic systems.

References

1. Zhang, Y., Li, X., Wang, J., & Chen, Z. (2023). Machine learning–based fault diagnosis methods for electronic systems: A comprehensive review. IEEE Access, 11, 24567–24589. https://doi.org/10.1109/ACCESS.2023.3254789
2. Li, H., Zhao, D., Sun, Y., & Liu, Q. (2023). Data-driven fault detection and diagnosis for electronic equipment under complex operating conditions. Microelectronics Reliability, 146, 114876. https://doi.org/10.1016/j.microrel.2023.114876
3. Wang, J., Zhou, K., & Hu, Y. (2023). Intelligent fault classification of electronic components using supervised machine learning algorithms. IEEE Transactions on Industrial Electronics, 70(8), 8123–8134. https://doi.org/10.1109/TIE.2023.3241197
4. Chen, X., Liu, M., & Zhang, L. (2023). Autoencoder-based anomaly detection for electronic fault monitoring. Sensors, 23(6), 3124. https://doi.org/10.3390/s23063124
5. Kim, S., & Park, J. (2023). Deep learning-based fault diagnosis for power electronic converters using CNN–LSTM networks. Energy Reports, 9, 2145–2157. https://doi.org/10.1016/j.egyr.2023.01.045
6. Singh, R., Verma, A., & Patel, S. (2023). Feature learning approaches for condition monitoring of electronic systems. Measurement, 211, 112643. https://doi.org/10.1016/j.measurement.2023.112643
7. Alvarez, M., Garcia, F., & Torres, J. (2023). Handling imbalanced fault data in electronic diagnostics using machine learning. Pattern Recognition Letters, 170, 95–103. https://doi.org/10.1016/j.patrec.2023.03.012
8. Zhao, L., He, Y., & Wang, P. (2023). Convolutional neural network-based fault detection for power electronic equipment. IEEE Access, 11, 48721–48733. https://doi.org/10.1109/ACCESS.2023.3271148

10.48047/jocaaa.2024.33.06.165

9. Rahman, M., Islam, M., & Hossain, M. (2023). Explainable AI techniques for fault diagnosis in electronic systems. Expert Systems with Applications, 220, 119764. https://doi.org/10.1016/j.eswa.2023.119764
10. Zhou, Y., Xu, H., & Liu, Z. (2023). Intelligent fault detection in electronic circuits using hybrid machine learning models. Engineering Applications of Artificial Intelligence, 120, 105882. https://doi.org/10.1016/j.engappai.2023.105882
11. Kumar, S., & Mishra, D. (2023). Predictive maintenance of electronic equipment using machine learning techniques. Journal of Intelligent Manufacturing, 34(5), 1723–1738. https://doi.org/10.1007/s10845-023-02041-6
12. Tan, J., Li, Y., & Wu, X. (2023). Deep autoencoder networks for early fault detection in electronic devices. Neural Computing and Applications, 35(12), 8621–8635. https://doi.org/10.1007/s00521-023-08411-3
13. Patel, A., Shah, N., & Desai, K. (2023). Machine learning-based condition monitoring of industrial electronic systems. Measurement and Control, 56(7–8), 864–876. https://doi.org/10.1177/00202940231154321
14. Luo, C., Fang, B., & Zhang, D. (2023). Fault diagnosis of electronic equipment using ensemble learning methods. IEEE Transactions on Instrumentation and Measurement, 72, 1–12. https://doi.org/10.1109/TIM.2023.3265578
15. Nguyen, T., Pham, H., & Le, Q. (2023). Unsupervised anomaly detection for electronic fault diagnosis. Applied Soft Computing, 135, 110018. https://doi.org/10.1016/j.asoc.2023.110018
16. Verma, P., & Jain, S. (2023). Intelligent electronic fault diagnosis using support vector machines. International Journal of Electronics, 110(9), 1521–1537. https://doi.org/10.1080/00207217.2023.2181149
17. Sun, W., Chen, Y., & Ma, X. (2023). Transfer learning for fault diagnosis of electronic systems with limited data. IEEE Sensors Journal, 23(14), 15367–15377. https://doi.org/10.1109/JSEN.2023.3278456
18. Hassan, A., Ali, M., & Khan, R. (2023). Machine learning approaches for fault detection in embedded electronic systems. Microprocessors and Microsystems, 97, 104793. https://doi.org/10.1016/j.micpro.2023.104793
19. Liu, J., & Wang, T. (2023). Real-time electronic fault detection using edge-based machine learning. Future Generation Computer Systems, 141, 312–323. https://doi.org/10.1016/j.future.2023.01.019

10.48047/jocaaa.2024.33.06.165

20. Bhat, R., Rao, K., & Shetty, D. (2023). Deep neural networks for fault diagnosis in electronic circuits. Neural Processing Letters, 55(3), 2251–2268. https://doi.org/10.1007/s11063-023-11091-8
21. Peng, Y., Zhang, Q., & Li, S. (2023). Intelligent fault detection of power electronic modules using data-driven models. IEEE Transactions on Power Electronics, 38(10), 12144–12155. https://doi.org/10.1109/TPEL.2023.3271194
22. Ortega, J., Molina, A., & Perez, R. (2023). Fault diagnosis in electronic systems using hybrid AI techniques. Computers in Industry, 148, 103878. https://doi.org/10.1016/j.compind.2023.103878
23. Das, S., Ghosh, P., & Banerjee, S. (2023). Machine learning-based fault analysis of electronic components under thermal stress. Microelectronics Journal, 137, 105757. https://doi.org/10.1016/j.mejo.2023.105757
24. Choi, H., & Lee, D. (2023). Intelligent condition monitoring of electronic equipment using deep learning. Electronics, 12(9), 2051. https://doi.org/10.3390/electronics12092051
25. Rivera, M., Torres, L., & Castillo, J. (2023). Smart fault detection in electronic devices using ensemble machine learning. IEEE Latin America Transactions, 21(6), 1012–1020. https://doi.org/10.1109/TLA.2023.10044123