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ARTIFICIAL INTELLIGENCE TECHNIQUES FOR FAULT DETECTION IN ELECTRONIC SYSTEMS: A REVIEW

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Abstract :

In order to function safely and reliably, electrical systems used in power electronics, communication, industrial control, and consumer applications must be able to detect faults. As systems become more complex and data quantities increase, traditional fault detection methods based on thresholds, rules, and analytical models usually fail to function properly when conditions are not linear or change. Artificial intelligence (AI) tools have evolved into outstanding data-driven solutions for automatic defect identification. This review paper provides an overview of AI-based fault detection techniques for electrical systems, which include machine learning, deep learning, and unsupervised anomaly detection methods. Common defect types, data acquisition and feature processing procedures, performance evaluation metrics, and major application areas such as printed circuit boards, power electronic systems, integrated circuits, electric drives, and embedded systems are discussed. The benefits of AI-based techniques, such as early defect detection and increased dependability, are highlighted, along with significant challenges related to data availability, processing needs, and model interpretability. Future research directions include edge intelligence, explainable AI, and hybrid data-driven models.

Keywords : Artificial intelligence; Fault detection; Electronic systems; Machine learning; Deep learning; Anomaly detection

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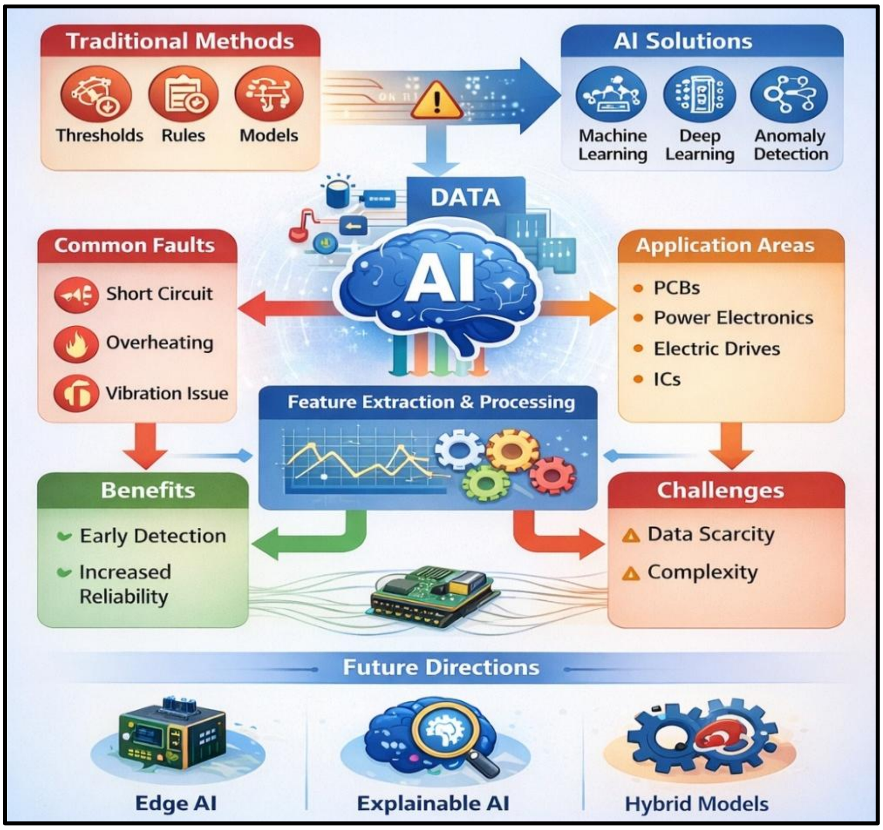
Graphical Abstract :



Introduction :

Electronic systems are essential components of modern technology, with applications ranging from industrial automation to power systems, communication networks, transportation, healthcare, and consumer electronics. Advances in microelectronics have enabled compact and highly integrated systems, but greater complexity makes them more susceptible to failure, raising concerns about reliability and maintenance [i, ii] Manufacturing defects, component aging, thermal stress, ambient conditions, and electromagnetic interference may lead to faults. Common faults include permanent issues like open and short circuits, transient faults generated by unstable connections, and dynamic faults induced by progressive changes in component characteristics. Early detection of faults is challenging because fault indicators are frequently weak, nonlinear, and hidden by noise, especially in complex systems. [iii, iv]

Traditional fault detection methods, such as threshold-based monitoring, rule-based systems, and model-based processes, are useful in simple systems but have limitations in modern applications. These methods depend on precise models, expert knowledge, and manual feature extraction, but their performance degrades under nonlinear behavior, changing operating conditions, and unknown fault conditions [v, vi]. AI provides a data-driven approach to fault detection. Machine learning procedures identify fault patterns directly from data, whereas deep learning techniques extract features from raw signals and time-series data. These methods have shown higher accuracy and flexibility in predictive maintenance, power system monitoring, and circuit testing [vii, viii]. Deep learning-based anomaly detection is beneficial when labelled fault data is limited, as it simulates typical system behaviour and detects anomalous variations. However, issues such as data availability, computational cost, model generalization, and interpretability exist [ix, x].

This paper provides an overview of AI-based fault detection in electronic systems, including typical defect types, limitations of traditional methods, and new machine learning, deep learning, and anomaly detection techniques.

Faults and Traditional Fault Detection Approaches :

Electronic systems experience various faults that affect reliability and performance. Common fault types include permanent faults such as open and short circuits, intermittent faults caused by loose connections or environmental effects, and parametric faults resulting from aging and thermal stress. Soft or incipient faults develop gradually and are difficult to detect early, while timing, thermal, and signal-related faults are critical in high-speed electronic systems. This basic fault classification helps describe fault behaviour and supports the selection of suitable detection methods [xi, xii, xiii, xv]

Traditional fault detection approaches rely on threshold-based monitoring, rule-based systems, hardware redundancy, and model-based diagnosis. Threshold methods compare measured signals with fixed limits, whereas rule-based techniques use expert knowledge for fault identification. Model-based approaches detect faults by comparing measured outputs with values estimated from mathematical models using residual analysis [xi, xiv]. Although effective for well-understood systems, these methods depend strongly on accurate models and prior knowledge and are sensitive to noise, uncertainties, and nonlinear behaviour. As a result, their effectiveness is limited in modern complex electronic systems [xii, xv, xvi].

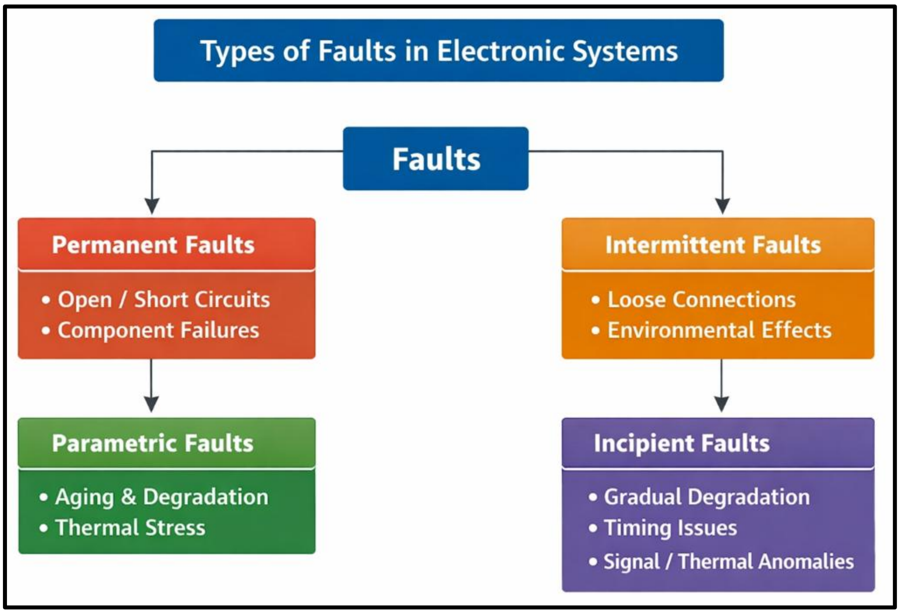


Figure 1. Classification of faults in electronic systems and their typical characteristics.

Artificial Intelligence Techniques for Fault Detection :

Artificial intelligence (AI) techniques play an important role in fault detection for electronic and industrial systems because they can learn complex patterns from large amounts of sensor data and adapt to varying operating conditions. Unlike traditional model-based methods, AI-based approaches are data-driven and can effectively handle nonlinearity, noise, and uncertainty. Recent studies report improved diagnostic accuracy and early fault detection using AI in applications such as rotating machinery, power electronics, embedded systems, and industrial monitoring [xvii, xviii, xix] based on data availability and application needs, AI techniques for fault detection are generally classified into classical machine learning, deep learning, unsupervised or anomaly detection, and hybrid and explainable approaches.

Classical machine learning methods are widely used due to their simplicity and low computational cost. Techniques such as support vector machines, k-nearest neighbours, decision trees, random forests, and logistic regression rely on manually extracted features from time-domain, frequency-domain, or time–frequency analysis. These methods show good performance for well-defined fault conditions and stable operating environments but depend heavily on expert-designed features and prior knowledge, which limits their scalability and generalization for complex systems [xvii, xix]

Deep learning techniques overcome these limitations by enabling end-to-end learning directly from raw data. Convolutional neural networks are commonly applied to vibration signals, current signatures, acoustic data, and inspection images, while recurrent neural networks and long short-term memory models effectively capture temporal dependencies in time-series data [xviii]. Auto encoder-based models further enhance fault detection by learning compact representations of normal system behaviour and identifying faults through reconstruction errors [xx, xxi]. Despite their high accuracy, deep learning models require large labelled datasets, significant computational resources, and suffer from limited interpretability [xxii]

Unsupervised and anomaly detection methods are particularly useful when labelled fault data are scarce. These approaches learn normal operating behaviour and detect deviations as potential faults. One-class classifiers and auto encoder-based methods are widely used, while recent transformer-based architectures improve anomaly detection by capturing long-range dependencies in multivariate time-series data [xxiii, xxiv]. However, these methods may generate false alarms under changing conditions, and threshold selection remains challenging.

Hybrid and explainable AI approaches aim to improve robustness and trust by combining data-driven models with physical knowledge or interpretability techniques. Physics-informed and federated learning frameworks enhance generalization, data privacy, and reliability, while explainable AI methods such as SHAP and attention mechanisms help interpret model decisions and support practical deployment [xxv, xxvi, xxvii].

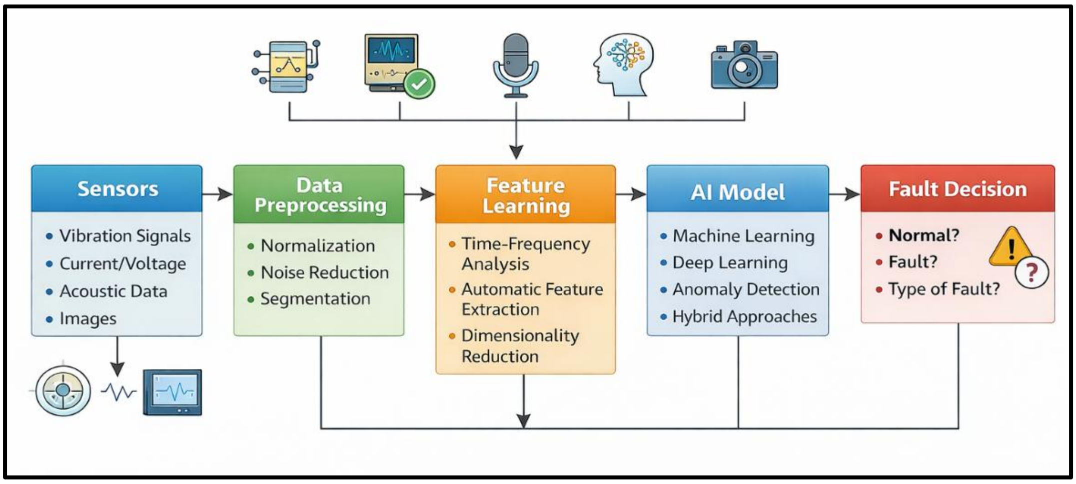


Figure 2. Block diagram of an AI-based fault detection framework

Table 1. AI techniques used for fault detection

AI Techniques	Methods	Features	Limitations
Classical machine learning	Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), Decision Tree (DT), Random Forest (RF), Logistic Regression (LR)	Low cost; handcrafted features	Feature dependence; poor generalization
Deep learning	Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Autoencoder (AE)	End-to-end learning; high accuracy	Large data; high computation; low interpretability
Unsupervised / anomaly detection	One-Class Classifier, Autoencoder (AE), Transformer	No labels required; normal-pattern learning	False alarms; threshold sensitivity
Hybrid & explainable AI	Physics-informed models, Federated Learning, SHapley Additive exPlanations (SHAP), Attention	Robust; interpretable; privacy-aware	Model complexity; implementation effort

Data, Features, and Evaluation :

AI-based fault detection relies on data collected from electronic systems. Common signals include voltage and current waveforms, which reflect operating conditions and electrical faults. Thermal and infrared data are used to detect overheating and abnormal power losses, especially in power electronics and printed circuit boards. Vibration and acoustic signals are widely applied in rotating machines to identify mechanical faults, while optical and infrared images support surface defect detection and component inspection [xvii, viii, iii]. Raw sensor data often contain noise and redundant information, making pre-processing necessary. Typical steps include normalization, filtering, resampling, and window-based segmentation. Noise reduction techniques such as smoothing filters and wavelet de-noising are commonly applied, while data balancing methods help address limited fault samples [v]. Feature extraction converts signals into fault indicators. Time-domain features describe signal amplitude behaviour, frequency-domain features capture fault-related spectral information, and time–frequency features are effective for non-stationary signals. Dimensionality reduction techniques such as principal component analysis reduce redundancy and computational cost [xxviii]. Model performance is evaluated using accuracy, precision, recall, F1-score, confusion matrices, and false alarm rate [xxix]

Applications :

In printed circuit board (PCB) inspection, AI-based fault detection is used to identify solder joint defects, missing components, short circuits, and thermal anomalies. Machine learning and deep learning models analyse electrical test data and optical or infrared images to improve inspection accuracy and reduce manual testing effort [xvii, viii]. For power electronic systems, AI techniques are applied to detect faults in converters, inverters, and power semiconductor devices using voltage, current, and thermal signals. These methods support early fault detection and predictive maintenance in renewable energy systems and electric vehicles [xxix, xvii]. In IC and VLSI systems, AI-based fault detection focuses on identifying manufacturing defects, timing faults, and aging-related degradation. Machine learning models analyse test vectors and signal responses to improve fault coverage and reduce testing time in complex circuits [v]. Electric motors and rotating machinery widely use AI-based fault detection to identify bearing faults, rotor defects, and misalignment. Vibration and current signals are commonly analysed using deep learning and anomaly detection methods to enable condition-based maintenance [viii, iii] In embedded systems, lightweight AI models are deployed for real-time fault detection in sensors, actuators, and communication modules. Edge-based fault detection improves system reliability while reducing data transmission and computational overhead in industrial and IoT applications [i]

Conclusion and Future prospects :

This review has presented an overview of artificial intelligence based fault detection techniques for electronic systems, covering fault types, data processing methods, AI models, and key application areas. AI-based approaches offer clear advantages over traditional methods, including early fault detection, higher diagnostic accuracy, adaptability to complex and nonlinear systems, and reduced reliance on precise physical models. However, their practical deployment is still limited by challenges such as data scarcity and labelling effort, high computational requirements, model generalization under changing conditions, and limited interpretability. Future research is expected to focus on edge and real-time fault detection, explainable and trustworthy AI models, hybrid data-driven and physics-based approaches, and efficient learning methods that can operate with limited data. Addressing these challenges will be essential for the wider adoption of AI-based fault detection in reliable and safety-critical electronic systems.

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