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PERFORMANCE EVALUATION OF MACHINE LEARNING ALGORITHMS FOR FAULT DETECTION AND DIAGNOSIS IN ELECTRONIC SYSTEMS

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Abstract- Modern electronic systems are becoming increasingly complex due to the integration of advanced components across industrial automation, electric vehicles, renewable energy, telecommunications, medical equipment, and other applications. This complexity increases the risk of component degradation, abnormal operation, and system failure, creating a need for reliable and early fault detection and diagnosis. Conventional threshold-based and model-based diagnostic methods may have limitations under varying operating conditions, component ageing, noise, and incipient faults. Machine learning (ML) provides an intelligent data-driven approach by learning relationships between electrical and physical measurements such as voltage, current, temperature, impedance, vibration, and frequency-domain characteristics and different system health conditions. This review discusses the application of supervised, unsupervised, and deep-learning approaches, including Support Vector Machine, k-Nearest Neighbour, Decision Tree, Random Forest, Artificial Neural Network, XGBoost, CNN, LSTM, and hybrid models for electronic-system fault diagnosis. The importance of data cleaning, feature extraction, feature selection, cross-validation, and appropriate train–test splitting is emphasized to improve model reliability and prevent data leakage. Model performance should be evaluated using multiple parameters, including accuracy, precision, recall, F1-score, Matthews correlation coefficient, AUROC, computational cost, robustness, and generalization. The review further highlights Explainable AI, transfer learning, digital

twins, edge AI, sensor fusion, and physics-informed ML as emerging approaches for developing transparent, adaptive, and real-time diagnostic systems. Overall, effective fault-diagnosis models should be selected according to the electronic system, fault characteristics, data availability, computational resources, and required interpretability rather than relying solely on classification accuracy.

Keywords: Electronic Systems; Fault Detection; Fault Diagnosis; Machine Learning; Deep Learning; Support Vector Machine; Artificial Neural Network; Feature Extraction; Explainable AI; Physics-Informed Machine Learning; Real-Time Diagnosis.

I. INTRODUCTION

Modern electronic systems are fundamental components of industrial automation, electric vehicles, renewable-energy systems, telecommunications, medical equipment, consumer electronics and aerospace systems. The increasing integration of electronic components has improved functionality and efficiency but has simultaneously increased system complexity. A failure in an electronic component can propagate through interconnected subsystems and result in degraded performance, unexpected shutdown or complete system failure. Therefore, early detection and accurate diagnosis of faults are essential for maintaining system reliability, safety and availability.

Traditional fault detection methods commonly use threshold-based monitoring, mathematical models, circuit analysis, signal processing and expert-defined diagnostic rules. These methods can perform effectively when system behaviour is well understood and operating conditions remain relatively stable. However, practical electronic systems frequently operate under changing loads, temperatures, supply conditions and component ageing. Consequently, fixed thresholds and simplified models may produce false alarms or fail to detect incipient faults.

Machine learning has emerged as an important approach for fault detection because ML algorithms can identify patterns directly from measured data. Electrical quantities such as voltage, current, impedance, temperature, vibration, switching characteristics and frequency-

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domain responses can be used as input variables. The ML model then learns the relationship between these measurements and different health conditions.

Recent research confirms the growing role of ML and AI in fault diagnosis. A 2025 review of Industry 4.0 fault detection and diagnosis emphasized real-time fault detection, while recent reviews have highlighted the increasing integration of ML, deep learning, digital twins and knowledge-based approaches.

For electronic circuits specifically, recent research has demonstrated the effectiveness of supervised ML for soft-fault diagnosis. Dieste-Velasco reported that ANN and SVM achieved test accuracies of 97.92% and 97.22%, respectively, for soft-fault diagnosis in a Sallen-Key band-pass filter, while Random Forest showed evidence of overfitting despite higher training accuracy. This illustrates an important point: **the best-performing algorithm should not be selected using training accuracy alone**.

II. FAULT DETECTION AND DIAGNOSIS IN ELECTRONIC SYSTEMS

Fault detection refers to determining whether an electronic system is operating normally or abnormally. Fault diagnosis goes one step further by identifying the type, location or severity of the fault.

For example, an electronic converter may exhibit normal operation, an open-switch fault, a short-switch fault, capacitor degradation or sensor failure. A diagnostic system should ideally distinguish among these conditions.

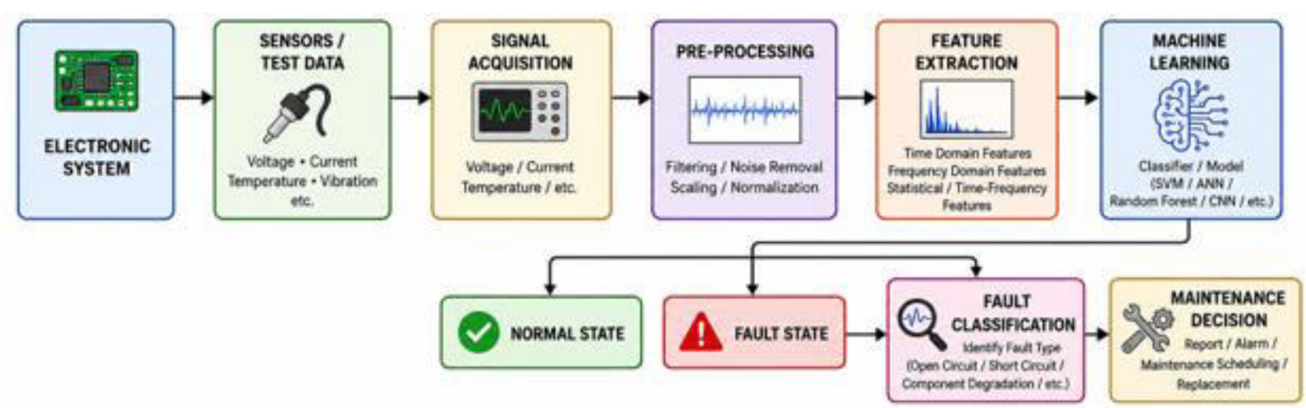

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Figure 1. General concept of electronic-system fault diagnosis

III. TYPES OF FAULTS IN ELECTRONIC SYSTEMS

Electronic-system faults can broadly be divided into **hard faults and soft faults**.

Hard faults generally produce substantial changes in electrical behaviour. Examples include open circuits, short circuits and complete component failures. Soft faults are more difficult because the component continues to operate but its parameters deviate from their nominal values.

For example, a resistor designed to have a resistance of 10 kΩ may gradually change to 10.8 kΩ. The circuit can still function, but its performance may be degraded. Such faults may remain undetected by conventional threshold-based methods.

Table 1. Major fault categories in electronic systems

Fault category	Example	Typical effect	Diagnostic difficulty
Open-circuit fault	Broken connection	Loss of current path	Moderate
Short-circuit fault	Component terminal short	Excess current	Moderate
Soft fault	Resistance/capacitance deviation	Parameter drift	High
Intermittent fault	Temporary connection loss	Unstable operation	Very high
Thermal fault	Excessive temperature	Component degradation	High
Sensor fault	Incorrect measurement	False control signal	High
Switching fault	Semiconductor switch failure	Converter malfunction	High
Ageing fault	Capacitor ESR increase	Reduced efficiency	High

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IV. MACHINE LEARNING ALGORITHMS USED FOR FAULT DIAGNOSIS

Machine learning approaches can generally be classified into supervised, unsupervised and semi-supervised learning.

4.1 Support Vector Machine

Support Vector Machine is a supervised learning algorithm that identifies an optimal separating hyperplane between classes. SVM is particularly suitable for small- and medium-sized datasets and high-dimensional feature spaces.

For electronic-system fault diagnosis, voltage and current features can be supplied to an SVM classifier to distinguish normal and faulty states.

Its major advantages are good generalization, effectiveness with small datasets and robustness in high-dimensional feature spaces. However, performance depends strongly on kernel selection and hyperparameter optimization.

4.2 k-Nearest Neighbour

KNN classifies an unknown observation based on the classes of neighbouring observations. Its implementation is simple and does not require an extensive training phase.

However, prediction can become computationally expensive when the dataset is large. Its performance is also affected by feature scaling and the selection of the value of *k*.

4.3 Decision Tree

Decision Tree models classify observations through a sequence of decision rules.

For example:

Current > Threshold?

YES NO

Voltage high? Temperature high?

Fault A Fault B

Decision Trees are easy to interpret and therefore attractive for engineering

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applications where diagnostic decisions need to be explained.

4.4 Random Forest

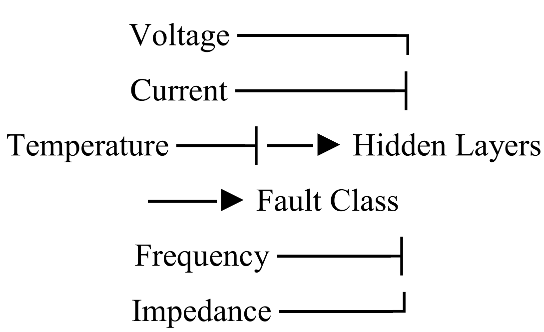
Random Forest combines multiple Decision Trees to improve classification performance and reduce overfitting.

It is particularly useful when several electrical features are available simultaneously.

A major advantage of RF is its ability to handle nonlinear relationships and feature interactions. However, the model may require greater computational resources than an individual Decision Tree.

4.5 Artificial Neural Network

ANN models consist of interconnected computational nodes arranged into input, hidden and output layers.



ANNs can learn highly nonlinear relationships between measured signals and fault conditions.

Recent experimental work on analog-circuit soft faults found ANN to be one of the strongest-performing approaches, reaching 97.92% test accuracy in the investigated circuit.

V. DEEP LEARNING FOR ELECTRONIC-SYSTEM FAULT DIAGNOSIS

Deep learning can automatically learn complex representations from raw or minimally processed data.

CNNs are particularly useful when electrical signals are transformed into images or two-dimensional representations, whereas 1D-CNNs can directly process time-series signals.

LSTM networks are suitable for sequential data because they can capture temporal dependencies.

Recent research has explored lightweight deep-learning networks for online diagnosis of power-electronic converters, demonstrating the increasing emphasis on high-speed and computationally efficient diagnosis.

Recent research also increasingly investigates transfer learning, multimodal learning and hybrid architectures to address limited labelled data and changing operating conditions.

VI. PROPOSED PERFORMANCE EVALUATION FRAMEWORK

The performance evaluation of ML algorithms should not be limited to accuracy. A model with high accuracy can still perform poorly when the dataset is imbalanced or when one fault class is rarely represented.

The proposed evaluation framework consists of the following stages.

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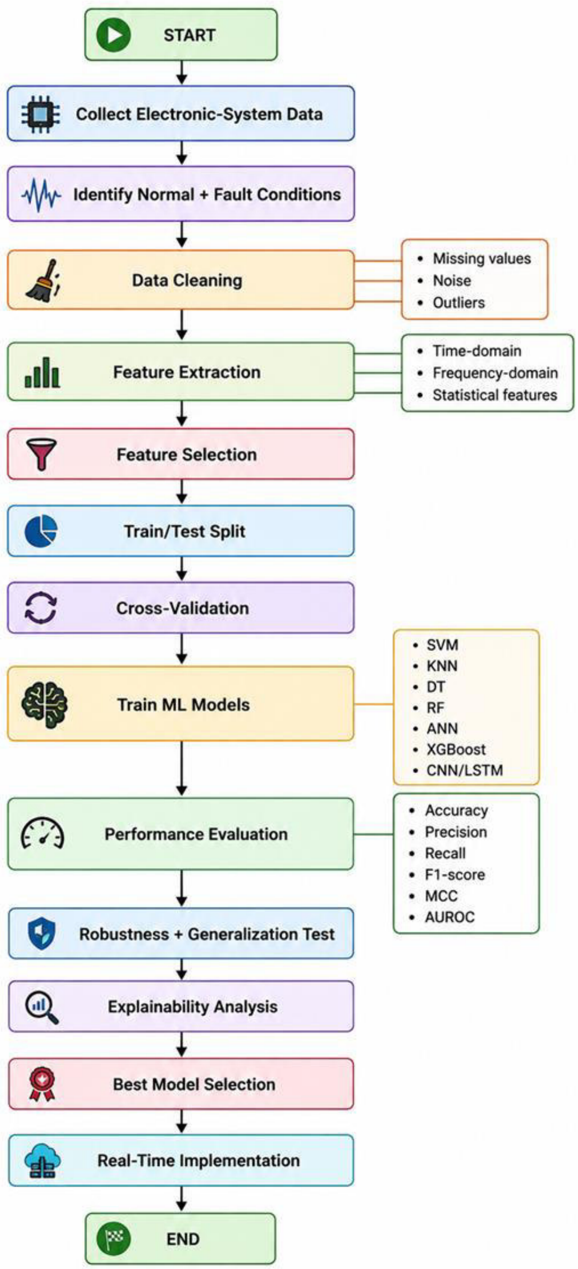

Figure 2. Proposed ML-based evaluation flow chart

VII. DATA ACQUISITION AND FEATURE EXTRACTION

The quality of the training data directly influences ML performance. Electronic-system data can be collected using oscilloscopes, data-acquisition systems, sensors, embedded monitoring systems and simulation platforms.

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Typical input parameters include voltage, current, switching frequency, temperature, impedance and harmonic characteristics.

Table 2. Examples of diagnostic features

Feature type	Examples	Application
Voltage	RMS, peak, mean	Circuit fault detection
Current	RMS, peak, crest factor	Switch/component faults
Temperature	Mean, maximum, gradient	Thermal faults
Frequency	Dominant frequency, harmonics	Oscillatory faults
Time-domain	Mean, variance, skewness	Fault classification
Frequency-domain	FFT amplitudes	Component degradation
Impedance	Magnitude, phase	Interconnect/component faults
Statistical	Kurtosis, entropy	Abnormality detection

Feature selection is important because irrelevant features can increase computational complexity and decrease generalization.

A 2024 study on analog-circuit soft-fault diagnosis used **Boruta feature selection** together with LightGBM to identify efficient features from high-dimensional time- and frequency-domain information.

VIII. COMPARATIVE EVALUATION OF MACHINE LEARNING ALGORITHMS

Table 3. General comparative evaluation

Algorithm	Accuracy potential	Dataset requirement	Interpretability	Computational cost	Suitable application
KNN	Moderate–High	Small–Medium	High	Medium–High during prediction	Simple diagnosis
Decision Tree	Moderate–High	Small–Medium	Very high	Low	Rule-based diagnosis
Random Forest	High	Medium	Medium	Medium	Multiclass faults

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SVM	High	Small–Medium	Medium	Medium	Soft-fault classification
ANN	High	Medium–Large	Low	Medium–High	Nonlinear faults
XGBoost/GBM	High	Medium	Medium	Medium	Structured data
CNN	Very high	Large	Low	High	Signal/image diagnosis
LSTM	Very high	Large	Low	High	Time-series faults
Hybrid CNN-LSTM	Very high	Large	Low	Very high	Complex temporal signals

These values represent general expected characteristics rather than a single experimental dataset. Direct comparison should always use the same dataset, preprocessing procedure and test protocol.

IX. EVIDENCE FROM RECENT STUDIES

Recent literature provides useful evidence for comparing ML approaches.

A 2025 study on soft-fault diagnosis of analog electronic circuits evaluated KNN, Naïve Bayes, Discriminant Analysis, Decision Tree, Random Forest, SVM and ANN. ANN achieved 97.92% test accuracy**,** while SVM achieved 97.22%**.** Random Forest produced 99.39% training accuracy but only 93.06% test accuracy, demonstrating the importance of detecting overfitting.

A 2024 Electronics study proposed Boruta feature selection with LightGBM for analog-circuit soft faults, showing the importance of reducing high-dimensional feature spaces before classification.

Research on electronic interconnects has also investigated learning frequency-domain reflection-coefficient patterns for non-destructive diagnosis. Ensemble learning was used to improve severity classification under noisy conditions.

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For power-electronic converters, recent work has focused on lightweight deep networks for online open-circuit-fault diagnosis, indicating that real-time implementation requires consideration of computational efficiency in addition to classification accuracy.

A 2024 study investigated an Extreme Learning Machine for series arc-fault diagnosis, addressing the challenge of detecting relatively small fault currents.

Recent research in broader industrial systems similarly shows that ML and deep learning can support fault classification, prediction and remaining-useful-life estimation, but generalization and changing operating conditions remain important challenges.

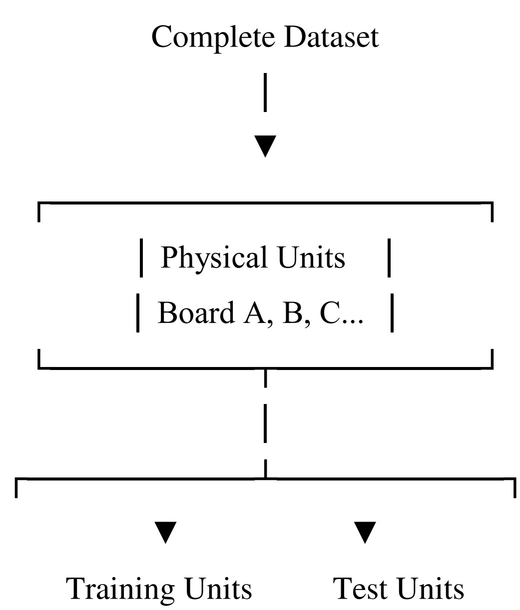
X. IMPORTANCE OF PROPER TRAIN–TEST VALIDATION

One of the most important issues in ML-based fault diagnosis is **data leakage**.

If signals generated from the same physical component are randomly divided between training and testing datasets, the model may see highly similar patterns during training and testing. This can produce artificially high accuracy.

Recent research specifically examining bearing fault diagnosis demonstrated that conventional segment-wise or condition-wise splitting can introduce spurious correlations and inflate performance. The study recommended component-wise splitting to achieve a more realistic evaluation.

The same principle is applicable to electronic-system diagnosis. If multiple measurements originate from the same physical electronic board or component, the training and test sets should ideally be separated by physical unit rather than simply by randomly selected signal segments.



▼

Cross Validation

▼

Model Training

▼

Final Evaluation

Figure 3. Recommended validation strategy

XI. OVERFITTING AND GENERALIZATION

Overfitting occurs when an ML algorithm learns the training data too closely and performs poorly on unseen data.

This problem is particularly important in electronic fault diagnosis because laboratory datasets may contain controlled experimental conditions that do not represent real industrial environments.

For example, a model may achieve 99% training accuracy but only 90% test accuracy. Such a model should not automatically be considered superior to another model with 95% training accuracy and 95% test accuracy.

Therefore, the following should be evaluated:

- Training accuracy
- Validation accuracy
- Independent test accuracy
- Cross-validation performance
- Confusion matrix
- MCC
- AUROC
- Robustness against noise
- Performance under different loads
- Performance under different temperatures
- Performance on unseen physical components

XII. EXPLAINABLE AI IN FAULT DIAGNOSIS

A major limitation of advanced deep-learning models is their black-box nature. In safety-critical electronic systems, engineers may need to understand why a particular fault has been identified.

Explainable AI (XAI) methods such as SHAP, LIME, feature importance and saliency analysis can provide information regarding the variables contributing to a prediction.

Recent 2026 literature specifically reviews XAI for industrial fault detection and diagnosis and emphasizes transparency and trust as important requirements for practical AI deployment.

For example, an XAI system might indicate:

Predicted fault: Capacitor degradation

Contribution:

XIII. HYBRID AND PHYSICS-INFORMED MACHINE LEARNING

Purely data-driven ML approaches may require large quantities of labelled fault data. However, fault data are often limited because deliberately damaging expensive electronic equipment is impractical.

Physics-informed machine learning offers an alternative by combining physical knowledge with data-driven models.

A 2026 systematic review reports increasing use of physics-informed AI for electrical systems and highlights its potential for improving data efficiency, interpretability and robustness in applications including digital twins and fault detection.

Physical Knowledge

↓

| Physical Model |

↓

Sensor Data ──► ML Model ◄── Training Data

↓

Fault Prediction

↓

Physics Consistency Check

↓

Final Diagnosis

Figure 4. Hybrid physics-informed ML framework

XIV. 14. APPLICATION OF ML IN DIFFERENT ELECTRONIC SYSTEMS

Table 4. Applications

Electronic system	Measured signal	Typical fault	ML approach
Analog circuit	Voltage/current	Parameter deviation	SVM, ANN, RF
Power converter	Current/voltage	Open/short switch	CNN, ANN
Transformer	Gas concentration	Internal fault	RF, SVM, DL
Circuit breaker	Current waveform	Mechanical/electrical fault	CNN/DL
PCB	Image	Component/assembly defect	CNN
Interconnect	Reflection coefficient	Structural defect	Ensemble ML
Battery electronics	Voltage/current/temperature	Degradation	ML/DL
Electric motor drive	Current/vibration	Bearing/winding fault	CNN, LSTM
Industrial equipment	Multisensor data	Multiple faults	Hybrid ML

XV. FUTURE PERSPECTIVES

The future of electronic-system fault diagnosis is expected to involve increasingly integrated AI systems.

One important direction is **edge AI**, where models are deployed directly on embedded processors. This can reduce communication latency and enable real-time diagnosis.

Another direction is **transfer learning**, which can allow models trained on one operating condition or circuit to be adapted to another system with less data. Recent research on analog-circuit diagnosis is already investigating transfer-learning architectures involving AlexNet, VGGNet and ResNet.

Digital twins may also become increasingly important because they can generate

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simulated fault data when real fault measurements are limited.

Multimodal systems combining voltage, current, temperature, vibration, images and other sensor signals may provide more robust diagnosis than a single sensor.

Recent literature also identifies knowledge graphs, large language models and physics-based approaches as emerging components of next-generation fault-diagnosis systems.

XVI. CONCLUSION

Machine learning has become an important technology for fault detection and diagnosis in modern electronic systems. The increasing complexity of analog circuits, digital systems, power converters, electronic interconnects and embedded devices has created a need for intelligent diagnostic approaches capable of identifying faults rapidly and accurately.

The literature demonstrates that conventional ML algorithms such as SVM, Random Forest and gradient boosting can provide excellent performance when meaningful electrical features are available, whereas ANN, CNN and LSTM models become particularly advantageous for nonlinear, high-dimensional and sequential data. Recent evidence from analog-circuit research demonstrates that ANN and SVM can achieve test accuracies above 97% for specific soft-fault diagnosis tasks, although performance is strongly dependent on the dataset, feature representation and validation methodology.

Importantly, algorithm performance should not be evaluated solely using accuracy. Precision, recall, F1-score, MCC, AUROC, computational cost, robustness and generalization should also be considered. Proper physical-unit-based data splitting is essential to prevent data leakage and unrealistic performance estimates.

The next generation of electronic-system diagnostics is likely to combine machine learning with explainable AI, transfer learning, digital twins, sensor fusion, edge computing and physics-informed learning. Recent 2026 literature supports this transition from purely black-box data-driven models toward more transparent, adaptive and physics-aware diagnostic frameworks.

Overall, the most appropriate ML model should be selected according to the type of electronic system, fault characteristics,

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dataset size, signal type, computational resources and required level of interpretability, rather than assuming that the most complex deep-learning model will always provide the best practical solution.

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