

Intelligent Fault Diagnosis and Root-Cause Analytics for Renewable Power Converters Using Machine Learning Techniques Effectively

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Abstract: The accelerating integration of renewable energy resources into modern power systems has increased reliance on power electronic converters for efficient energy conversion, grid synchronization, voltage regulation, and power-quality management. However, converters deployed in photovoltaic, wind, and energy-storage systems operate under variable loading, switching stresses, thermal cycling, environmental disturbances, and component degradation, creating complex fault mechanisms that can compromise reliability and energy availability. Conventional fault-diagnosis approaches based on fixed thresholds and predefined physical models often struggle to distinguish interacting faults and identify their underlying causes under dynamic operating conditions. This study investigates an intelligent framework that applies machine learning techniques to fault diagnosis and root-cause analytics in renewable power converters. Electrical, thermal, operational, and switching data are processed to extract discriminative fault signatures and degradation indicators. Supervised and unsupervised learning techniques are employed to detect anomalies, classify converter faults, and associate observed abnormalities with probable root causes. The framework further integrates feature importance and explainable analytics to improve diagnostic transparency. This approach enables earlier fault detection, reduces diagnostic uncertainty, supports predictive maintenance, and improves converter reliability, operational resilience

Keywords: Renewable Power Converters; Intelligent Fault Diagnosis; Root-Cause Analytics; Machine Learning; Predictive Maintenance; Power Electronics

1. INTRODUCTION

1.1 Renewable Energy Expansion and the Growing Dependence on Power Converters

The transition from conventional generation toward renewable electricity has increased the deployment of photovoltaic, wind, battery-energy-storage, and distributed generation systems across modern electrical networks [1]. Unlike conventional synchronous generation, many renewable resources require power electronic interfaces to transform variable electrical outputs into forms compatible with loads, storage devices, and utility grids [3]. Power converters consequently perform voltage transformation, DC–DC conditioning, DC–AC or AC–DC conversion, and maximum power extraction from variable renewable sources [2]. Grid-connected converters additionally regulate active and reactive power, maintain synchronization, control voltage, and contribute to power-quality management [5]. In battery-integrated systems, bidirectional converters coordinate charging and discharging while enabling energy to move between storage, renewable sources, loads, and grids [4]. Converter performance has therefore become increasingly important to renewable-system availability, controllability, efficiency, and stability.

1.2 Converter Reliability and Fault-Diagnosis Challenges

The central position of converters also creates a significant reliability concern because their components operate under repeated electrical, thermal, and environmental stresses. Semiconductor switches experience rapid switching transitions and temperature fluctuations, while capacitors, gate drivers, sensors, and interconnections deteriorate under prolonged operation [6]. Variable renewable generation

introduces changing loading conditions that can intensify thermal cycling and complicate separation of normal transients from emerging abnormalities [3]. Environmental exposure, including humidity, dust, vibration, and elevated temperature, can accelerate degradation, particularly in converters deployed under demanding field conditions [7]. Grid disturbances and abnormal voltages impose additional stresses capable of initiating or accelerating component failure [5]. Converter faults can consequently interrupt energy conversion, reduce generation availability, degrade power quality, increase maintenance expenditure, and potentially propagate disturbances into connected equipment or wider electrical networks [8].

1.3 Limitations of Conventional Fault-Diagnosis Approaches

Conventional converter diagnosis commonly employs protection thresholds, mathematical models, spectral or signal analysis, residual generation, and expert-defined rules for identifying abnormal operating conditions [2]. These approaches remain valuable when fault signatures and system parameters are clearly understood. Their effectiveness can decline, however, when converter behavior becomes nonlinear or operating conditions vary substantially [7]. Fixed thresholds may confuse load or renewable-resource variations with actual faults, while model-based approaches can become sensitive to parameter uncertainty and modelling errors [9]. Multiple interacting faults further produce overlapping symptoms that complicate deterministic diagnosis. Predefined rules are similarly constrained when degradation patterns differ from anticipated fault scenarios or evolve gradually during operation [6].

1.4 Research Aim, Scope, and Contributions

This study develops an integrated machine-learning framework for intelligent diagnosis and root-cause analytics in renewable power converters. The framework combines multi-source condition data, signal preprocessing, feature engineering, machine-learning inference, and diagnostic interpretation to distinguish normal variability from genuine converter abnormalities [4]. Fault detection first establishes whether observed behavior deviates from acceptable operation, whereas fault classification determines the likely fault category and localization identifies the affected component or subsystem [9]. Root-cause analytics extends diagnosis by examining the physical, electrical, thermal, environmental, or operational mechanisms responsible for the observed failure [8]. By separating these analytical stages, the proposed approach moves beyond fault recognition toward actionable diagnostic intelligence capable of supporting targeted maintenance, reducing diagnostic uncertainty, and improving converter reliability across variable renewable-energy operating conditions [1].

2. RENEWABLE POWER CONVERTER FAULT MECHANISMS AND DIAGNOSTIC SIGNATURES

2.1 Converter Components and Failure-Prone Subsystems

Renewable power converters comprise interconnected electrical, electronic, thermal, and control subsystems whose failure mechanisms differ according to function and operating stress. IGBTs and MOSFETs perform high-frequency switching and therefore experience electrical overstress, switching losses, and junction-temperature fluctuations [10]. Gate drivers control semiconductor operation but remain vulnerable to supply abnormalities, isolation deterioration, and control-signal failures. DC-link capacitors experience voltage ripple and thermal ageing, while inductors and transformers are exposed to magnetic, insulation, and winding stresses [6]. Current and voltage sensors introduce measurement dependencies that directly influence converter control and protection. Connectors and solder joints experience mechanical and thermomechanical fatigue, whereas cooling systems determine whether semiconductor temperatures remain within acceptable limits [12]. Control circuitry coordinates switching, protection, synchronization, and reference tracking. Consequently, converter reliability reflects interactions among components exposed to different electrical, thermal, mechanical, environmental, and operational stresses [8].

2.2 Semiconductor Switching Faults

Power semiconductor faults are particularly consequential because switches directly regulate converter current and voltage. Open-circuit faults prevent an IGBT or MOSFET from conducting when commanded, producing phase-current distortion, output imbalance, reduced power transfer, and abnormal harmonic content [7]. Short-circuit faults create uncontrolled current paths that can generate rapid thermal

stress and require immediate protection to prevent destructive damage [11]. Gate-driver abnormalities may produce missing pulses, incorrect timing, insufficient gate voltage, or unintended switching states. Progressive semiconductor degradation can additionally increase conduction losses, switching losses, or thermal resistance before catastrophic failure occurs [13]. These conditions alter switching waveforms, phase currents, DC-link behavior, output voltage, and junction temperature. Monitoring relationships among these variables can therefore distinguish abrupt switching failures from progressively developing semiconductor abnormalities under changing converter operating conditions [9].

2.3 Passive-Component and Sensor Faults

Passive components can deteriorate gradually and produce symptoms that resemble switching or control abnormalities. DC-link capacitor ageing commonly involves capacitance reduction and increasing equivalent series resistance, which can increase voltage ripple, heating, and instability [14]. Inductor faults may arise from insulation deterioration, winding abnormalities, core degradation, or saturation, altering current ripple and filtering performance [10]. Measurement systems introduce another diagnostic challenge because current and voltage sensors can develop bias, gain errors, drift, noise, or complete signal loss [12]. Communication faults may similarly delay, corrupt, or interrupt measurements supplied to controllers. Because control algorithms respond directly to sensed information, inaccurate measurements can generate abnormal switching commands or regulation errors, making sensor faults appear similar to genuine power-stage failures [8].

2.4 Thermal, Environmental, and Ageing-Related Degradation

Converter degradation is frequently cumulative rather than instantaneous. Repeated thermal cycling produces expansion and contraction within semiconductor packages, solder layers, bond wires, connectors, and interfaces, progressively weakening their structural integrity [6]. Junction-temperature variations can accelerate semiconductor ageing, particularly where renewable generation repeatedly changes converter loading. Humidity and condensation may promote corrosion and insulation deterioration, while dust accumulation can obstruct cooling paths and reduce heat dissipation [13]. Mechanical vibration can weaken connections, solder joints, and mounted components, particularly in wind-energy applications [11]. Over extended operation, these mechanisms interact with electrical loading and environmental exposure. Accumulated stress therefore creates degradation trajectories that may precede observable converter failure [14].

2.5 From Fault Causes to Observable Diagnostic Signatures

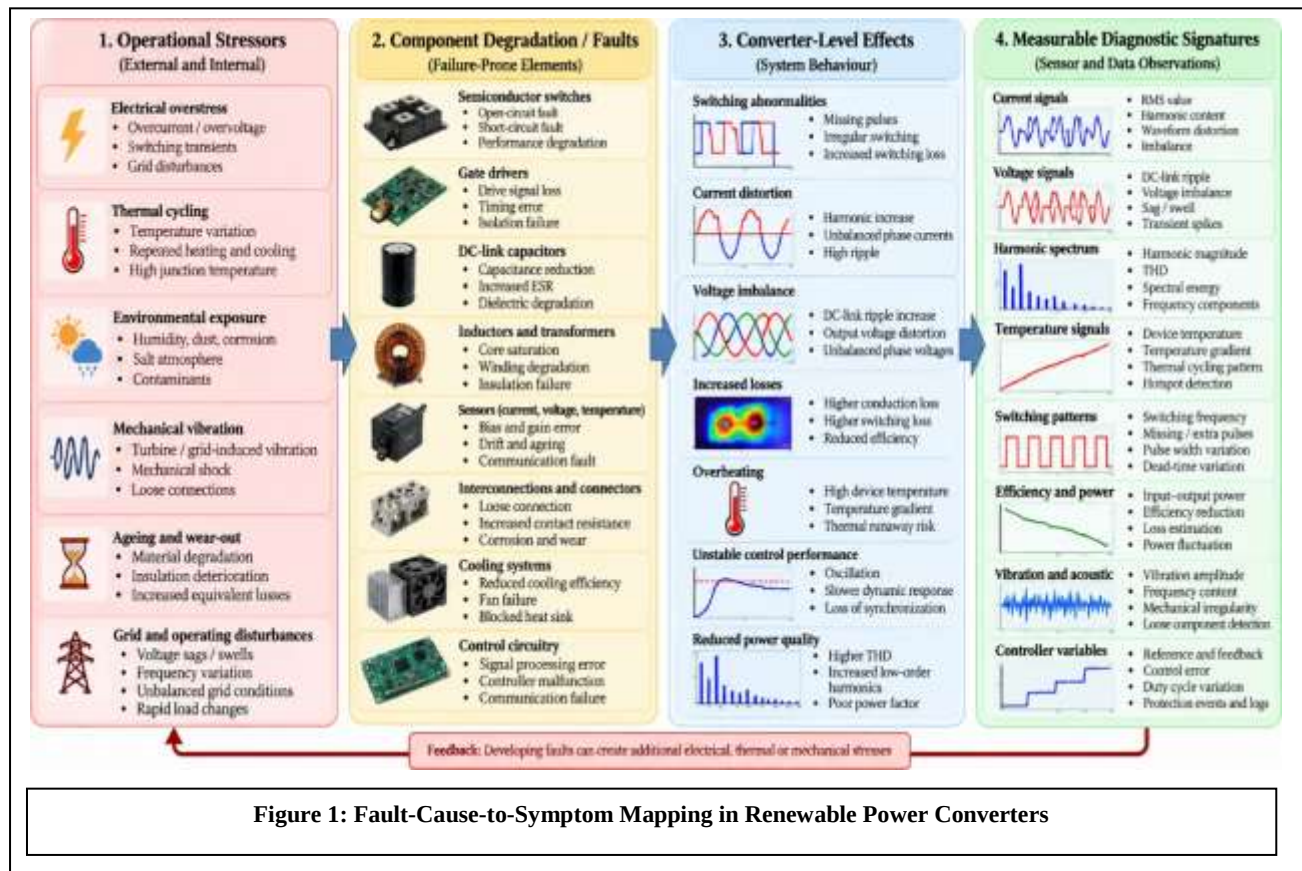
Underlying faults become diagnosable when their physical effects alter measurable converter behavior. Semiconductor abnormalities can change current symmetry, voltage

waveforms, switching transitions, harmonic content, and temperature [9]. Capacitor degradation may appear through increased DC-link ripple and reduced filtering effectiveness, while sensor faults can create inconsistent measurements and unexpected controller responses [12]. Thermal or cooling abnormalities may produce rising temperature without corresponding load increases. Efficiency reduction can indicate growing conduction or switching losses, whereas vibration can reveal mechanical deterioration [13]. Combining current, voltage, harmonics, switching frequency, temperature, power-quality indicators, efficiency, vibration, and controller behavior therefore creates diagnostic signatures linking observable symptoms with potential fault mechanisms [7].

measurements characterize conversion efficiency and waveform degradation [16]. Vibration sensing can expose mechanical deterioration in connections, cooling assemblies, or associated electromechanical equipment. Environmental variables, including ambient temperature and humidity, provide operating context for interpreting degradation [18]. Controller references, error signals, protection states, and fault/event logs further connect physical measurements with control actions and recorded abnormalities [15].

3.2 Signal Preprocessing and Data Quality

Raw condition-monitoring signals require preprocessing before reliable diagnostic patterns can be extracted. Measurements acquired from different sensors should be synchronized so that electrical, thermal, mechanical, and



3. DIAGNOSTIC DATA ACQUISITION AND FAULT FEATURE ENGINEERING

3.1 Multi-Source Converter Condition Monitoring

Reliable fault diagnosis begins with condition data capable of capturing complementary aspects of converter behavior. Current and voltage measurements reveal electrical imbalance, switching abnormalities, ripple, and transient responses, while temperature measurements provide evidence of semiconductor losses, cooling deterioration, and thermal stress [13]. Switching states and gate signals indicate whether commanded semiconductor behavior corresponds with actual converter response. Power and harmonic distortion

controller events correspond temporally [17]. Filtering and denoising can suppress measurement interference while preserving fault-related transients. Normalization prevents variables with larger numerical ranges from disproportionately influencing learning algorithms [14]. Missing observations require appropriate handling, while abnormal measurements should be distinguished from genuine fault-induced outliers. Resampling can establish consistent temporal resolution across heterogeneous sensors, and segmentation divides continuous operation into diagnostic windows [19]. Preprocessing should nevertheless avoid removing weak degradation signatures. Noise-robust preparation is therefore essential for maintaining

diagnostically meaningful information under practical operating conditions.

3.3 Time-, Frequency-, and Time-Frequency-Domain Features

Feature engineering converts processed measurements into representations that expose fault-related characteristics. Time-domain features such as mean, root-mean-square value, variance, peak magnitude, skewness, and kurtosis describe waveform amplitude, dispersion, and impulsiveness [15]. Frequency-domain analysis can identify harmonic components, sidebands, dominant frequencies, and spectral energy associated with switching or component abnormalities. Fast Fourier Transform methods provide efficient conversion of stationary signal segments into spectral representations [20]. However, converter faults frequently produce transient and nonstationary behavior whose frequency characteristics vary with time. Wavelet transforms and related time-frequency methods can localize short-duration disturbances while preserving information about their spectral content [17]. Combining features from several domains can therefore distinguish faults producing similar time-domain waveforms but different spectral or transient characteristics, providing richer inputs for subsequent machine-learning diagnosis [16].

3.4 Feature Selection and Dimensionality Reduction

Large feature sets can contain redundant, noisy, or weakly informative variables that increase computational cost and encourage model overfitting. Correlation analysis can identify highly related features whose simultaneous inclusion provides limited additional information [18]. Information-based selection methods can retain variables exhibiting stronger relationships with fault classes, while discriminative approaches prioritize features that separate operating conditions effectively. Principal component analysis can transform correlated measurements into fewer dimensions while preserving substantial variance within the dataset [14]. Selection should nevertheless maintain physically meaningful indicators needed for diagnostic interpretation. An effective procedure therefore balances dimensionality reduction, computational efficiency, classification performance, and retention of features capable of explaining converter abnormalities [20].

3.5 Fault Dataset Construction and Class Imbalance

Diagnostic learning requires datasets representing both normal operation and credible fault conditions. Labels can originate from controlled laboratory fault injection, maintenance records, historical event logs, or verified field failures [19]. Synthetic data may supplement rare conditions when destructive faults cannot be repeatedly produced experimentally. Nevertheless, healthy observations commonly outnumber failure samples substantially, creating class imbalance that can bias models toward normal operation [13]. Training, validation, and testing data should therefore preserve meaningful fault representation while remaining

appropriately separated to prevent information leakage and overly optimistic estimates of diagnostic generalization [17].

Table 1. Converter Fault Types, Root Causes, Observable Signatures, and Candidate Diagnostic Features

Fault type	Component	Potential root cause	Observable symptoms	Sensor/data source	Candidate ML features
Open-circuit fault	IGBT/MOSFET	Gate failure, bond-wire damage, semiconductor degradation	Current distortion, phase imbalance, reduced output power	Phase current, output voltage, gate signals	RMS current, current imbalance, harmonic amplitudes, waveform statistics
Short-circuit fault	IGBT/MOSFET	Electrical overstress, insulation breakdown, erroneous switching	Rapid overcurrent, voltage collapse, temperature rise	Current, voltage, protection signals	Peak current, transient energy, rate of current change
Gate-driver fault	Gate-driver circuit	Supply failure, isolation degradation, control-signal error	Missing or irregular switching pulses	Gate signals, switching states, current	Pulse duration, switching frequency, missing-pulse count
Capacitor degradation	DC-link capacitor	Thermal ageing, dielectric deterioration	Increased voltage ripple, heating, unstable DC-link voltage	DC-link voltage, temperature	Ripple RMS, spectral energy, ESR-related indicators
Inductor fault	Filter inductor	Winding damage, saturation, insulation deterioration	Increased current ripple, filtering deterioration	Current, temperature	Ripple magnitude, harmonic, spectral components

Fault type	Component	Potential root cause	Observable symptoms	Sensor/data source	Candidate ML features
Sensor fault	Current/voltage sensor	Bias, gain error, drift, communication failure	Incorrect feedback, control deviation, inconsistent measurements	Sensor outputs, controller variables	Residual error, bias estimate, variance, cross-sensor inconsistency
Cooling-system fault	Fan/heat sink	Fan degradation, obstruction, poor thermal contact	Progressive overheating under normal loading	Temperature, power, fan status	Temperature gradient, thermal rate of change, load-temperature correlation
Connection degradation	Solder joints/connectors	Thermal cycling, vibration, corrosion	Intermittent operation, increased resistance, localized heating	Voltage, temperature, vibration	Voltage drop, temperature variation, vibration statistics

4. MACHINE LEARNING FOR INTELLIGENT FAULT DETECTION AND CLASSIFICATION

4.1 Fault Diagnosis as a Hierarchical Learning Problem

Intelligent converter diagnosis can be structured as a hierarchy in which each analytical stage answers a different reliability question. Anomaly detection first distinguishes normal operation from behavior indicating a potential fault [16]. Fault localization subsequently identifies the component or subsystem associated with the abnormality, while classification determines whether the condition represents an open-circuit fault, sensor error, capacitor degradation, or another failure mode [21]. Severity estimation establishes the extent of deterioration and its operational significance. Root-cause inference then investigates the underlying mechanism responsible for the diagnosed condition [18]. Treating these tasks as interchangeable can produce incomplete conclusions because recognizing an abnormal signal does not necessarily identify its location, severity, or initiating cause.

4.2 Supervised Machine-Learning Methods

Supervised learning is appropriate when converter observations are accompanied by reliable labels identifying normal conditions and known fault classes. Support vector machines can establish decision boundaries between fault categories in high-dimensional feature spaces and remain effective with moderately sized datasets [20]. Decision trees provide interpretable classification rules based on diagnostic features, whereas random forests combine multiple trees to improve robustness and reduce sensitivity to individual training samples [22]. K-nearest neighbors assigns observations according to similarity with previously labeled operating conditions, making classification dependent on representative feature distributions. Logistic classifiers provide probabilistic class estimates and relatively transparent relationships between input variables and diagnostic outcomes [17]. Ensemble approaches combine predictions from several learners to improve stability where fault patterns overlap. These techniques can use current, voltage, thermal, harmonic, and controller-derived features to learn mappings between observed converter behavior and predefined fault conditions when sufficiently representative labeled data are available [23].

4.3 Unsupervised and Semi-Supervised Fault Detection

Real converter datasets frequently contain extensive normal operating records but comparatively few verified failures. Unsupervised methods address this limitation by identifying structures or unusual observations without requiring complete fault labels [19]. Clustering can group measurements with similar operating characteristics and expose observations that depart from established patterns. Anomaly-detection methods similarly model expected behavior and flag substantial deviations as potential faults [24]. One-class approaches can learn boundaries surrounding healthy operating data, making them useful where representative examples of every possible failure cannot be obtained [21]. Semi-supervised learning combines limited labeled observations with larger quantities of unlabeled converter data. These approaches can improve diagnostic coverage, although detected anomalies still require engineering interpretation because unfamiliar but legitimate operating conditions may resemble genuine faults [18].

4.4 Neural and Deep-Learning Approaches

Neural approaches are particularly useful where relationships between converter measurements and fault states are nonlinear and difficult to represent through manually defined rules. Artificial neural networks can learn mappings between engineered features and fault categories through interconnected processing layers [22]. Convolutional neural networks extend this capability by extracting localized patterns from current or voltage waveforms, spectral representations, and time-frequency images, reducing dependence on manually selected features [20]. Recurrent architectures can model sequential dependencies within converter measurements and are therefore suited to faults

whose signatures evolve across time. Autoencoders learn compressed representations of input data and can support anomaly detection by identifying observations that reconstruct poorly relative to learned normal patterns [24]. Deep models can integrate electrical, thermal, vibration, and controller information to capture complex interactions among diagnostic variables. However, their performance depends strongly on dataset size, representativeness, computational resources, and appropriate model design [23]. Increased predictive capability must therefore be balanced against interpretability and deployment requirements.

4.5 Model Training, Validation, and Generalization

Reliable diagnostic performance requires evaluation on observations not used to construct the model. Training data support parameter learning, validation data guide model selection and hyperparameter adjustment, and independent test data estimate generalization [17]. Cross-validation can provide additional evidence where available fault samples are limited. Excessive model complexity can cause overfitting, producing strong training performance but unreliable predictions under new operating conditions [21]. Evaluation should therefore include changes in renewable input, converter loading, temperature, grid conditions, and measurement noise. Models trained at restricted operating points may incorrectly interpret legitimate variations as faults [19]. Transfer across operating conditions or converter configurations consequently requires testing rather than assuming diagnostic relationships remain unchanged [24].

4.6 Diagnostic Performance Metrics

No single metric adequately characterizes fault-diagnosis performance. Accuracy measures the overall proportion of correct predictions, while precision indicates how frequently predicted faults are genuine [23]. Recall measures the proportion of actual faults successfully detected, and specificity quantifies correct recognition of healthy conditions. The F1-score balances precision and recall where class distributions are uneven [16]. False-alarm rate is operationally important because excessive alarms reduce confidence and create unnecessary inspections. Detection latency determines whether faults are identified sufficiently early for protective or maintenance action [22]. Confusion matrices reveal which fault categories are repeatedly misclassified, while computational requirements determine real-time feasibility. High accuracy can remain misleading when abundant healthy observations conceal poor recognition of rare, safety-critical faults [24].

5. MACHINE-LEARNING-ENABLED ROOT-CAUSE ANALYTICS

5.1 Distinguishing Fault Detection, Diagnosis, and Root-Cause Analysis

Intelligent condition assessment requires clear separation between fault detection, diagnosis, and root-cause analysis because each addresses a different analytical question.

Anomaly detection determines whether observed converter behavior deviates significantly from expected operation [22]. Diagnosis subsequently interprets the abnormality by identifying the affected component, subsystem, or recognized fault class [25]. Root-cause analysis extends beyond these outputs to determine the mechanism that initiated the failure, which may involve electrical overstress, thermal deterioration, control malfunction, environmental exposure, manufacturing weakness, or progressive ageing [27]. Consequently, detecting distorted current does not establish why distortion developed. Effective root-cause analytics must connect measured symptoms with component condition and underlying failure mechanisms to support corrective intervention [23].

5.2 Causal Relationships between Stressors, Components, and Symptoms

Root-cause reasoning requires relationships among operational stressors, component degradation, and observable converter responses to be considered collectively. Repeated thermal cycling can progressively weaken semiconductor interconnections, increasing electrical resistance and localized heating before functional failure occurs [24]. Electrical overstress may damage switching devices or insulation, whereas capacitor ageing can increase equivalent series resistance and subsequently amplify DC-link ripple and temperature [28]. Controller abnormalities can produce inappropriate switching commands that generate current distortion even when semiconductor devices remain physically healthy. Conversely, deteriorating switches can produce similar control errors because feedback systems attempt to compensate for abnormal power-stage behavior [26]. Thus, identical symptoms may originate from different mechanisms, while a single initiating mechanism may produce several downstream symptoms. Root-cause models must therefore evaluate causal consistency across stress history, component condition, controller behavior, and measured responses [29].

5.3 Feature Importance and Explainable Machine Learning

Machine-learning predictions become more useful for root-cause analysis when diagnostic decisions can be related to specific measurements. Feature-importance techniques can identify whether current imbalance, harmonic magnitude, temperature rise, DC-link ripple, switching irregularity, or another variable contributes strongly to a predicted fault [25]. Interpretable models such as decision trees can expose explicit diagnostic rules connecting measured conditions with classifications, while sensitivity analysis determines how predictions change when particular inputs vary [27]. For more complex models, feature-attribution mechanisms can estimate the relative contribution of individual measurements to specific diagnostic outputs [23]. Explanations should also remain physically plausible; for example, a thermal-failure prediction should be supported by temperature, loading, or loss-related evidence rather than unrelated correlations [28]. Explainability therefore connects statistical predictions with

engineering reasoning and strengthens the evidential basis for identifying credible root causes.

5.4 Temporal and Sequential Root-Cause Analysis

The sequence in which abnormalities emerge provides information that static classification can overlook. Precursor signals such as gradually increasing temperature, rising voltage ripple, changing harmonic content, or intermittent switching irregularities may occur before a converter reaches an explicit fault state [26]. Temporal models can examine these trajectories and determine whether deterioration developed progressively or resulted from a sudden disturbance [29]. Event logs can similarly establish whether protection activation followed an overcurrent condition, controller error, temperature excursion, or grid disturbance. Distinguishing initiating events from downstream consequences is essential because later symptoms may dominate measured data after failure propagation [24]. Sequential root-cause analysis therefore reconstructs how converter condition evolved, allowing machine-learning outputs to be interpreted within the chronological development of the failure [22].

degradation, for example, can increase semiconductor temperature, accelerate ageing, alter switching characteristics, and eventually produce secondary electrical abnormalities [28]. Similarly, sensor bias can distort controller feedback, causing inappropriate switching actions that increase stress on otherwise functional components [25]. A capacitor fault may destabilize the DC link and subsequently affect inverter current regulation and output power quality. Diagnostic systems that assume one fault at a time can therefore misidentify secondary symptoms as independent root causes [27]. Multi-fault reasoning should evaluate relationships among simultaneously abnormal variables and identify plausible propagation pathways between components. Separating initiating faults from consequential failures enables maintenance teams to address the mechanism responsible for the cascade rather than merely replacing components exhibiting downstream damage [29].

5.6 Confidence-Aware Root-Cause Decision Support

Root-cause conclusions should communicate uncertainty rather than presenting every machine-learning prediction as definitive. Diagnostic confidence can reflect model probability, data quality, agreement among diagnostic

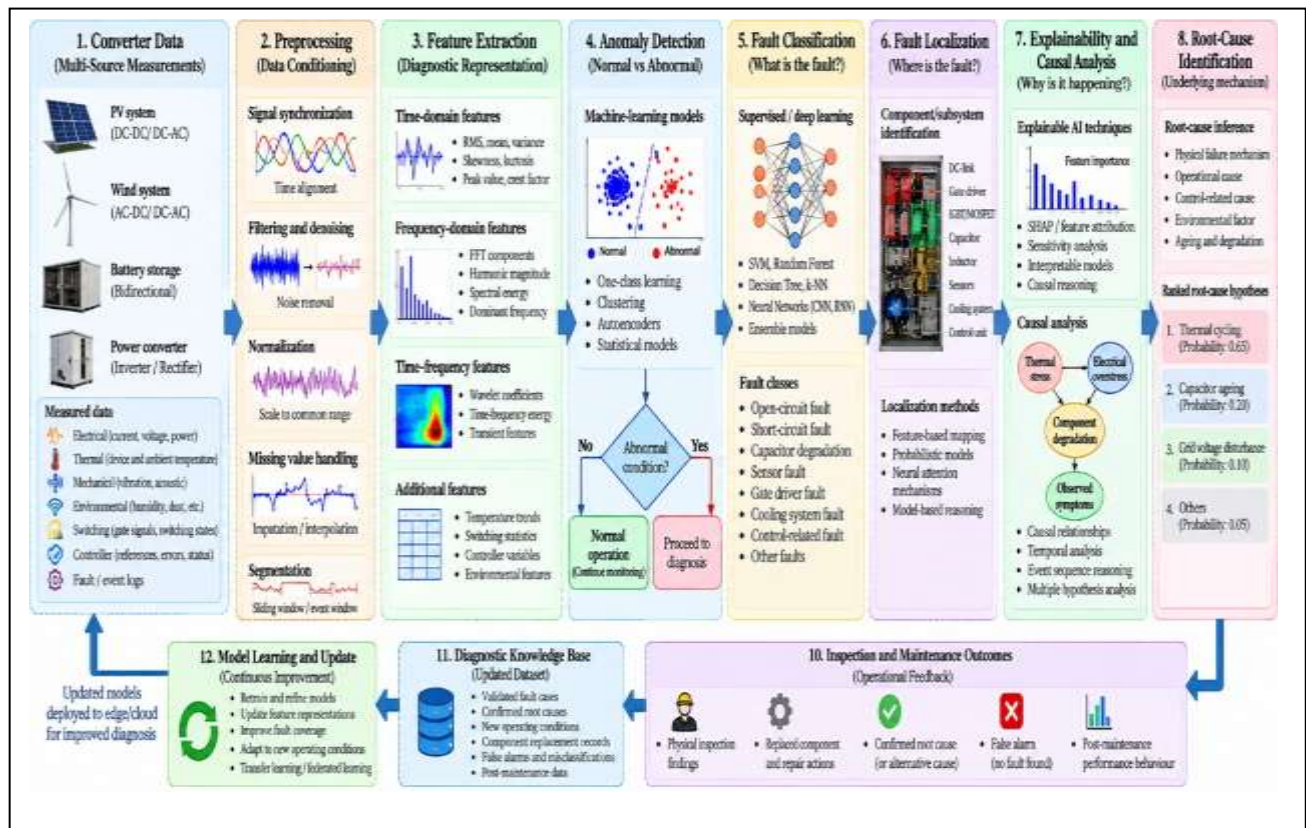


Figure 2: Machine-Learning-Enabled Fault Diagnosis and Root-Cause Analytics Framework

5.5 Multi-Fault and Cascading-Failure Reasoning

Practical converter failures may involve multiple interacting abnormalities rather than isolated component faults. Cooling

methods, and consistency between predicted causes and observed symptoms [23]. Where evidence supports several mechanisms, the system can present competing root-cause hypotheses together with their supporting indicators and uncertainty levels [26]. Low-confidence cases should trigger

additional measurements, inspection, or engineering review rather than automatic maintenance decisions. Human specialists can then assess operating history and physical evidence unavailable to the model [28]. Confidence-aware decision support therefore combines computational inference with engineering judgment while reducing inappropriate interventions arising from uncertain predictions [24].

6. INTEGRATED INTELLIGENT FAULT-DIAGNOSIS FRAMEWORK

6.1 Real-Time Monitoring and Diagnostic Pipeline

An operational intelligent diagnostic framework begins with continuous monitoring of electrical, thermal, mechanical, environmental, switching, and controller variables during converter operation [27]. Sensors transmit measurements to an edge acquisition layer where signals are synchronized, filtered, normalized, and segmented before diagnostic processing. Relevant time-, frequency-, and time-frequency-domain features can then be generated from each observation window [30]. Machine-learning models evaluate these representations continuously or when predefined triggering conditions occur, allowing abnormalities to be identified with limited diagnostic delay [32]. Detected deviations initiate subsequent classification and root-cause analysis rather than immediately generating maintenance conclusions. The pipeline ultimately converts raw converter measurements into structured alerts and diagnostic reports containing sufficient contextual information for operators to distinguish genuine component deterioration from transient renewable-energy operating variations [29].

6.2 Hierarchical Fault Decision Architecture

Diagnostic decisions should progress hierarchically so that increasingly specific conclusions are supported by preceding evidence. Anomaly detection first determines whether converter behavior remains within learned normal boundaries [31]. When an abnormality is confirmed, localization identifies the affected component or subsystem, followed by classification of the probable fault mode [28]. Severity assessment evaluates the extent of degradation and its potential operational consequences. Root-cause analysis then integrates diagnostic features, operating history, stress conditions, and temporal relationships to identify the most plausible initiating mechanism [34]. The resulting evidence supports maintenance recommendations proportional to diagnostic confidence and fault criticality. This hierarchy prevents isolated abnormal measurements from being interpreted prematurely as definitive component failures [30].

6.3 Edge, Cloud, and Hybrid Diagnostic Deployment

Deployment location influences diagnostic latency, computational capability, communication dependence, and

scalability. Edge processing enables measurements to be analyzed close to the converter, supporting rapid detection and protective responses without continuous network connectivity [33]. Cloud platforms can provide greater computational capacity for historical analysis, large-scale model training, fleet-level comparison, and computationally intensive model optimization [29]. However, cloud-dependent diagnosis can introduce communication latency, bandwidth requirements, and data-security considerations. A hybrid architecture can therefore perform time-critical preprocessing and inference locally while transmitting selected diagnostic information for deeper cloud analysis [35]. Updated models can subsequently be returned to edge devices, combining responsive local diagnosis with broader analytical learning [31].

6.4 Diagnostic Outputs and Maintenance Decision Support

Diagnostic outputs should communicate actionable evidence rather than presenting a fault label alone. Reports can identify the probable fault, affected component, estimated severity, likely root cause, diagnostic confidence, and measurements supporting the conclusion [32]. Where uncertainty remains, alternative explanations can be presented for engineering evaluation. Maintenance recommendations can then prioritize immediate shutdown, targeted inspection, component replacement, continued observation, or scheduled intervention according to risk [28]. Connecting diagnostic evidence with maintenance priorities reduces unnecessary component replacement while helping operators respond rapidly to conditions capable of escalating into consequential failures [34].

6.5 Continuous Learning from Operational Outcomes

Maintenance activities provide valuable evidence for improving subsequent diagnosis. Confirmed component failures, inspection findings, replaced parts, false alarms, and identified root causes can be incorporated into diagnostic datasets as verified outcomes [30]. Post-maintenance measurements can further establish whether intervention removed the detected abnormality. These feedback data enable models to refine class boundaries, update fault representations, and identify previous misclassifications [35]. Continuous learning consequently transforms operational experience into diagnostic knowledge, allowing the framework to adapt as converter components age, operating conditions change, and additional failure patterns become available [33].

7. PERFORMANCE EVALUATION, PRACTICAL CHALLENGES, AND FUTURE DIRECTIONS

7.1 Multi-Dimensional Evaluation Framework

Evaluation of intelligent converter diagnosis should extend

representative environmental, loading, and grid conditions,

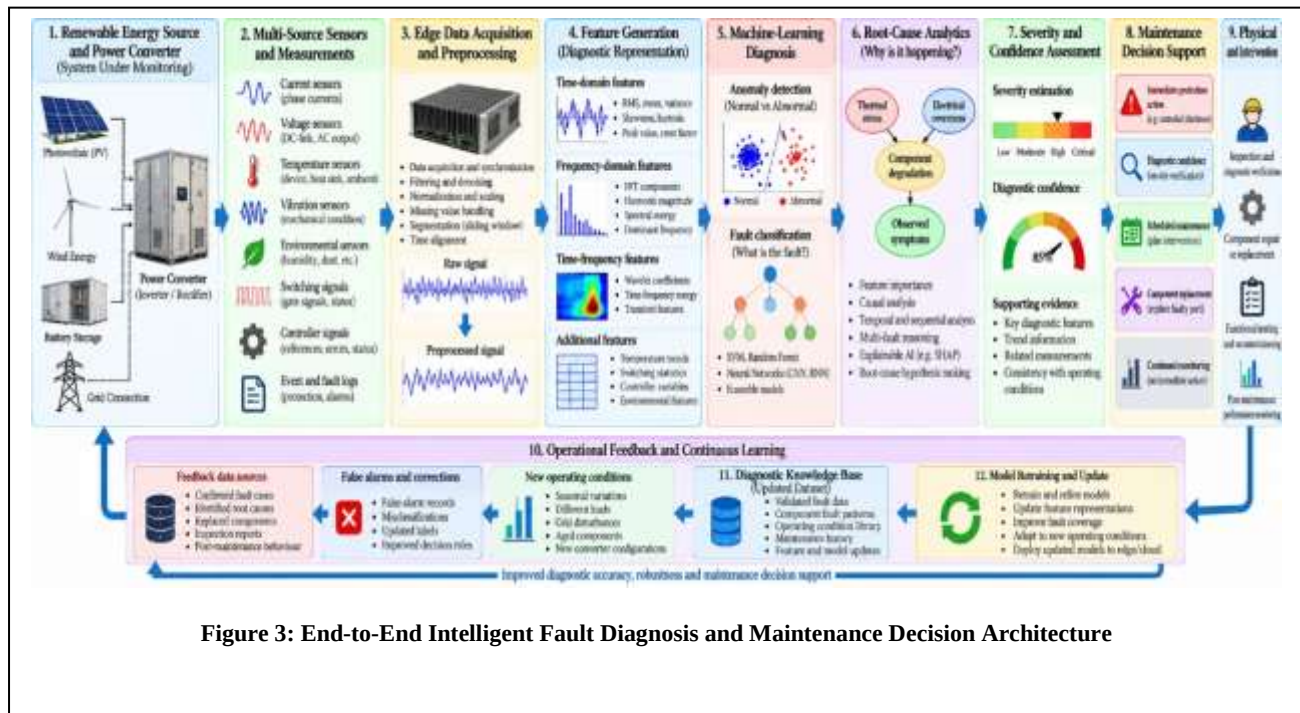


Figure 3: End-to-End Intelligent Fault Diagnosis and Maintenance Decision Architecture

beyond classification accuracy because operational effectiveness depends on several interacting performance dimensions. Fault coverage determines whether the system recognizes diverse component failures, while false-alarm rate measures unnecessary interventions generated during healthy operation [26]. Detection latency establishes whether abnormalities are identified early enough for protective or maintenance action. Root-cause accuracy evaluates whether diagnosed failures are connected correctly to their initiating mechanisms [31]. Robustness indicates stability under noise and changing operating conditions, whereas computational efficiency determines real-time feasibility [28]. Interpretability establishes whether diagnostic conclusions can be understood and verified by engineers. Scalability additionally measures whether models can accommodate increasing sensor volumes, converter populations, and heterogeneous renewable installations [33].

7.2 Robustness under Variable Renewable Operating Conditions

Renewable converters operate under substantial variability that can resemble genuine fault behavior. Photovoltaic irradiance fluctuations alter input voltage, current, power, and converter operating points, while changing wind speeds produce comparable variations in wind-energy systems [29]. Load transitions, grid disturbances, switching changes, and ambient-temperature variation can further modify measured diagnostic signatures without indicating component failure [32]. Models trained under restricted conditions may therefore classify legitimate transitions as abnormalities or overlook faults occurring at unfamiliar operating points. Robust diagnosis requires training and validation across

together with contextual variables that enable machine-learning models to distinguish expected operating variability from degradation-related changes [27].

7.3 Data Scarcity, Fault Imbalance, and Model Transferability

Obtaining representative failure data remains difficult because destructive converter faults are relatively infrequent and cannot always be induced safely in operational systems. Laboratory fault injection provides controlled observations but may not reproduce progressive field degradation accurately [30]. Consequently, datasets frequently contain substantially more healthy than faulty samples, creating class imbalance and biased learning [26]. Converter-specific datasets introduce an additional limitation because switching frequencies, topologies, component ratings, control strategies, and sensor configurations differ between installations. Models transferred between converters may therefore encounter domain shifts that alter learned feature distributions [34]. Effective transfer requires adaptation and validation rather than assuming that diagnostic relationships learned from one converter remain universally applicable.

7.4 Explainability, Reliability, and Human-in-the-Loop Diagnosis

Highly complex models can produce accurate classifications while providing limited explanation for their decisions. Such black-box predictions can reduce engineering trust where diagnostic outputs trigger costly component replacement or converter shutdown [31]. Explainable mechanisms should therefore identify influential measurements, supporting symptoms, uncertainty, and plausible causal relationships.

Reliability additionally requires validation against independently confirmed faults rather than predictive performance alone [28]. Human oversight remains particularly important for uncertain or consequential diagnoses. Engineers can combine algorithmic evidence with inspection findings, maintenance history, and contextual knowledge unavailable to the model before authorizing intervention [33].

7.5 Deployment Constraints and Cyber-Physical Considerations

Practical deployment must account for computational and cyber-physical limitations. Embedded processors may restrict model complexity, while communication latency can undermine time-critical cloud-based diagnosis [27]. Sensor deterioration or communication loss can also compromise diagnostic data quality. Connected diagnostic platforms introduce cybersecurity concerns because manipulated measurements or model inputs could produce misleading conclusions [32]. Data integrity, secure communication, interoperability, and compatibility with existing converter controllers and energy-management systems are therefore essential. Deployment architectures must balance computational sophistication with latency, reliability, security, and integration requirements [30].

7.6 Future Research Directions

Future research can increasingly combine data-driven diagnosis with physical converter knowledge. Digital twins and physics-informed machine learning can constrain predictions using expected system behavior, while transfer and self-supervised learning may reduce dependence on extensively labeled fault datasets [34]. Federated learning offers opportunities for collaborative model improvement without centralizing sensitive operational data. Explainable AI, multimodal sensing, and edge intelligence can strengthen diagnostic transparency and responsiveness [29]. Integrating fault diagnosis with prognostic models and remaining-useful-life estimation could further shift maintenance from reactive intervention toward condition-informed failure prevention [33].

Table 2. Performance Dimensions, Evaluation Metrics, Practical Challenges, and Diagnostic Objectives

Evaluation dimension	Metric	Diagnostic significance	Practical challenge	Desired outcome
Fault detection	Accuracy, recall, sensitivity	Measures successful recognition of abnormal converter states	Rare faults and changing operating conditions	Reliable early fault recognition

Evaluation dimension	Metric	Diagnostic significance	Practical challenge	Desired outcome
Fault coverage	Number/proportion of detectable fault classes	Determines diagnostic breadth across converter components	Insufficient examples of uncommon failure modes	Broad component and fault-mode coverage
False alarms	False-positive rate, specificity	Indicates unnecessary fault warnings during healthy operation	Normal renewable variability can resemble faults	Minimal unnecessary intervention
Detection speed	Detection latency, inference time	Determines suitability for real-time protection and maintenance	Computational complexity and communication delays	Timely diagnosis before fault escalation
Root-cause identification	Root-cause accuracy, causal consistency	Evaluates identification of the initiating failure mechanism	Similar symptoms can originate from different causes	Credible causal diagnosis
Robustness	Performance under noise and operating variation	Measures diagnostic stability in realistic environments	Irradiance, wind, temperature, load, and grid variability	Stable performance across operating conditions
Computational efficiency	Processing time, memory and processor utilization	Determines feasibility of embedded or edge implementation	Resource-constrained converter controllers	Efficient real-time inference
Interpretability	Explanation fidelity, feature relevance	Supports engineering verification of predictions	Complexity of deep-learning models	Transparent and defensible diagnosis

Evaluation dimension	Metric	Diagnostic significance	Practical challenge	Desired outcome
Transferability	Cross-domain performance degradation	Measures generalization between converter systems	Different topologies, ratings, sensors, and control strategies	Adaptable diagnosis across installations
Scalability	Processing throughput, device/model capacity	Assesses expansion across converter fleets	Increasing data volumes and heterogeneous assets	Fleet-level diagnostic capability

8. CONCLUSION

The growing integration of renewable energy has increased dependence on power electronic converters for efficient, controllable, and reliable energy conversion. This study has demonstrated that converter reliability depends on understanding relationships among component failure mechanisms, operating stresses, measurable condition signatures, and intelligent diagnostic interpretation. Multi-source monitoring of electrical, thermal, mechanical, environmental, switching, and controller variables provides the foundation for detecting emerging abnormalities before they develop into consequential failures.

Importantly, fault detection, classification, localization, and root-cause identification represent distinct but interconnected diagnostic functions. Detecting abnormal behavior does not necessarily identify the affected component, while correctly classifying a fault does not establish the physical or operational mechanism responsible for its occurrence. Integrating signal preprocessing, feature engineering, supervised and unsupervised learning, explainability, temporal analysis, and causal reasoning enables conventional monitoring to evolve toward intelligent diagnostic decision support. Such integration can provide maintenance personnel with fault identity, component location, severity, probable root cause, diagnostic confidence, and supporting evidence. Consequently, intelligent diagnosis can enable earlier intervention, reduce unplanned downtime, improve converter availability, support targeted maintenance, and strengthen renewable-energy-system resilience. Wider implementation, however, requires improved real-world fault datasets, model transferability, interpretability, computational efficiency, uncertainty management, and rigorous validation across variable operating environments.

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