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Original Research Article

Predictive Maintenance Framework for Solar Inverters and Smart Grid Assets Using Edge AI and Advanced Fault Analytics

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Abstract

Solar photovoltaic systems are increasingly connected to smart grids, making equipment reliability a major concern. Failures in solar inverters and grid connected components reduce energy output and increase operational cost. Most existing predictive maintenance studies focus either on PV systems or on smart grid assets separately and rely mainly on centralized cloud processing. This paper proposes a unified predictive maintenance framework that integrates solar inverter and smart grid monitoring within an edge-based architecture. Electrical and thermal signals are processed locally, where time and frequency domain features are extracted and analyzed using a CNN–LSTM model for real time fault classification. A health index model is applied to estimate remaining useful life for condition-based maintenance planning. Experimental results show 96.8% classification accuracy and a reduction in inference latency from 85 ms in cloud-based processing to 18 ms at the edge. The proposed framework reduces communication load, supports faster decision making, and improves operational stability in distributed renewable energy systems.

Keywords: Predictive maintenance, Solar inverter monitoring, Smart grid reliability, Edge computing, Fault detection, Remaining useful life estimation, CNN–LSTM model, Distributed energy systems.

I. INTRODUCTION

Solar power systems are expanding across homes, industries, and utility scale grids. As more photovoltaic (PV) plants connect to smart grids, reliability becomes a serious concern. Solar inverters, transformers, and grid components operate under changing weather conditions and fluctuating loads. Small faults may reduce energy output, increase maintenance costs, or even trigger large outages. For many years, maintenance relied on routine inspection or repair after failure. That approach often caused unexpected downtime. Predictive maintenance offers a different direction. Instead of waiting for breakdown, system data are analyzed to detect early signs of degradation [7]. Maintenance decisions then depend on equipment condition rather than fixed schedules. Solar PV systems face several recurring issues. Dust accumulation, shading, wiring problems, overheating, and inverter faults are common causes of performance loss [4],[1]. Recent studies show that data-based models can detect such problems earlier than manual inspection methods. Detection accuracy above 95% has been reported in multiple works [6], [8]. Models that include environmental factors such as temperature and irradiance show better consistency across seasons [2].

Smart grid research follows a similar direction. Modern grids rely on digital sensors and monitoring devices to track voltage, current, and frequency conditions. Machine learning models have shown strong performance in classifying grid disturbances and equipment faults [3]. These systems help reduce outage duration and improve service continuity. Still, a gap remains. Many studies focus either on solar PV systems or on smart grid assets, rarely both together. In practice, solar inverters interact directly with the grid. A grid disturbance can stress inverter components. An inverter fault can disturb voltage quality. Treating them separately limits system understanding. Another issue concerns data processing location. Centralized cloud servers are widely used for analysis. Large solar plants generate high frequency

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measurements. Continuous transmission of raw data increases delay and communication load. Edge-level processing, where computation occurs near the equipment, reduces response time and network traffic [5]. However, integrated edge based predictive maintenance systems that combine inverter and grid monitoring are still limited. This study proposes a unified framework that connects solar inverter diagnostics with smart grid asset monitoring. The framework performs real time fault detection and Remaining Useful Life estimation at the edge level while maintaining system wide coordination. This study aims to develop a predictive maintenance framework that connects solar inverter monitoring with smart grid asset monitoring in a single system. It seeks to design a data driven fault detection model capable of distinguishing normal operation, gradual degradation, and critical failure in real time. Another goal is to identify meaningful patterns in electrical and thermal signals through structured feature extraction methods. The research also focuses on estimating the remaining useful life of key components using health indicators and degradation trends. In addition, it evaluates system performance in terms of prediction accuracy, response speed, and communication efficiency. Finally, the study examines whether the proposed framework can operate effectively in distributed renewable energy environments with practical hardware constraints.

II. Related Work

Research on predictive maintenance for solar inverters and smart grids has expanded in recent years. Most studies fall into three groups: solar PV fault detection, smart grid fault analysis, and system level maintenance strategies. These topics are connected, yet many researchers examine them separately.

Predictive Maintenance in Solar PV Systems

Solar photovoltaic systems experience several recurring technical issues. Dust accumulation, partial shading, wiring defects, inverter failure, and component aging frequently reduce system output. Earlier studies relied on manual inspection and thermal imaging. Newer research focuses on data driven fault detection. A comprehensive review of grid connected solar systems describes common failure types and explains how data-based models outperform traditional inspection approaches [2]. Other reviews report similar findings, noting that learning models can detect inverter and module faults with high accuracy [3], [4]. These works examine voltage, current, and temperature signals to identify unusual patterns. Accuracy levels above 95% are commonly reported in PV fault classification tasks [7]. Researchers also observe that environmental factors such as sunlight intensity and ambient temperature influence system behavior. Models that incorporate contextual information show better consistency under changing conditions [3], [6]. More focused studies analyze specific prediction models. One contextual deep learning framework achieved strong R^2 and F1-score values in inverter fault prediction [6]. The authors introduced an early warning class labeled “impending fault,” which signals possible failure before it occurs.

Another review argues that predictive maintenance should not stop at alarm generation [1]. Instead, systems should evaluate degradation trends and estimate potential failure time. In summary, PV fault detection accuracy has reached high levels in many studies. However, centralized processing remains common, and real time edge deployment receives less attention.

Fault Detection in Smart Grids

Smart grids depend on digital sensors and monitoring devices to supervise power flow and equipment condition. Predictive maintenance in this context focuses on identifying disturbances, equipment wear, and instability at an early stage. A systematic review explains the transition from time-based maintenance to condition based strategies in distribution networks [1]. Equipment replacement decisions increasingly rely on sensor data rather than fixed schedules.

Several studies demonstrate that classification models such as Support Vector Machines, Random Forest, and neural networks perform well in detecting grid faults [8]. These models analyze data collected from smart meters and other monitoring devices. High classification accuracy has been reported for voltage disturbances, line faults, and transformer problems [8]. Early fault detection reduces outage duration and improves grid reliability. Despite these advances, many smart grid studies treat grid assets independently from solar inverters. In practice, inverters interact directly with grid infrastructure. Ignoring this interaction limits full system understanding.

Toward Integrated Maintenance Approaches

Some recent reviews discuss renewable generation and grid monitoring together [1], [7]. These studies recognize a two-way relationship: inverter condition affects grid stability, and grid fluctuations stress inverter components. The interaction is clear. When inverter output fluctuates, voltage quality changes. When grid voltage shifts, inverter hardware experiences additional stress. Even so, many predictive maintenance models still analyze each side separately. Processing location presents another challenge. Cloud-based data analysis dominates many existing systems. Large solar farms generate high frequency measurements. Continuous transmission of raw data increases delay and communication load. Few studies examine how predictive maintenance can operate locally at the equipment level while maintaining coordination across the system.

Research Gap

Several conclusions emerge from the reviewed literature:

- Solar PV fault detection accuracy is high in many studies [2,3,6,7].
- Smart grid fault classification models also report strong performance [8].
- Predictive maintenance concepts are widely discussed [1].

Yet three gaps remain:

1. Solar inverters and grid assets are often examined as separate systems.
2. Many solutions rely heavily on centralized cloud processing.
3. Real time edge level prediction combined with system wide coordination receives limited attention.

This study addresses these gaps through a unified framework that connects inverter monitoring and grid asset monitoring within a distributed edge-based architecture.

III. METHODOLOGY

This section explains the predictive maintenance framework designed for solar inverters and smart grid assets. The approach combines distributed sensing, edge based artificial intelligence, and fault analytics to support real time fault prediction and Remaining Useful Life (RUL) estimation. The system structure, signal modeling, AI design, and validation process are described in the following subsections.

System Architecture

The framework follows a layered and distributed structure. It includes sensing nodes, an edge intelligence layer, and a centralized cloud layer. Sensors installed in solar inverters and grid assets continuously record electrical and thermal parameters. These measurements are transmitted to a local edge device for processing.

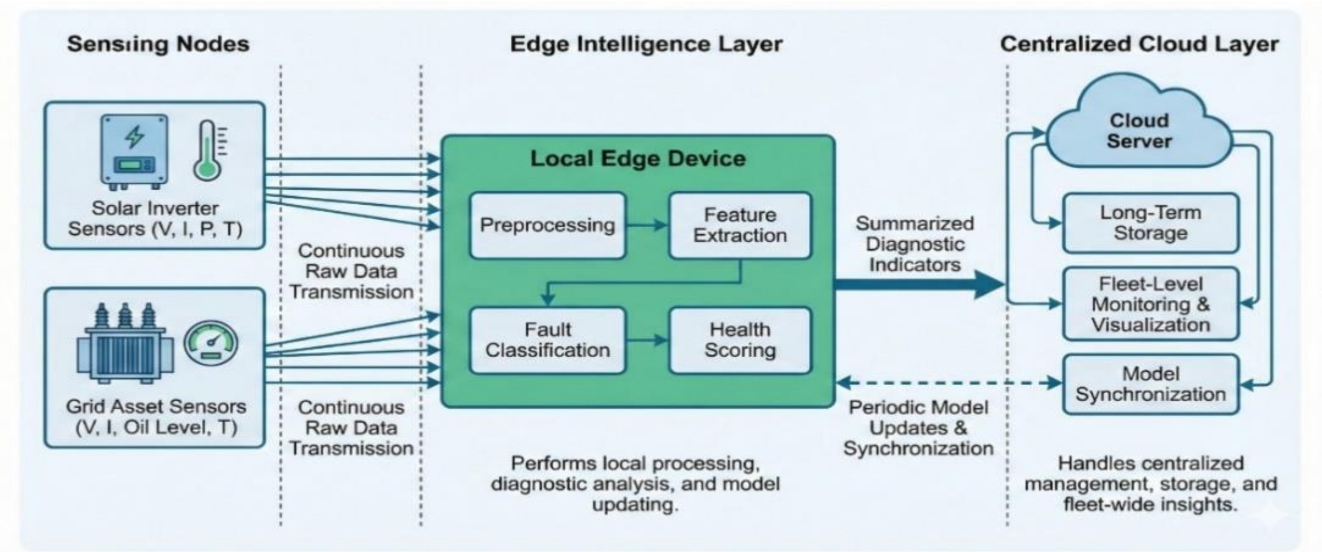

Figure 1: Edge-AI-Based Predictive Maintenance Architecture

At the edge layer, the system performs preprocessing, feature extraction, fault classification, and health scoring. Only summarized diagnostic indicators and periodic model updates are sent to the cloud server. This structure reduces communication load and shortens response time. The cloud layer handles long term storage, fleet level monitoring, visualization, and model synchronization across multiple sites.

Data Acquisition and Signal Modeling

Operational data are collected from both inverter units and grid connected equipment. Inverter measurements include DC voltage, DC current, AC output voltage, switching frequency, and heat sink temperature. Grid level variables include transformer temperature, feeder current, voltage imbalance, and frequency deviation. High frequency sampling in the kilohertz range captures switching abnormalities in power electronics. Lower sampling rates track slower grid dynamics.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Before model training, the raw data are filtered and normalized.

Z-Score Standardization

$z = (x - mu)/sigma$

In this equation, χ is the measured value, μ is the dataset mean, and σ is the standard deviation. The transformation converts values into standardized form and improves numerical stability during model training.

Min–Max scaling is then applied:

This scaling places all features within a common range, which prevents dominance of large-magnitude variables.

Advanced Fault Feature Extraction

Inverter faults appear in both time-domain and frequency-domain patterns. Time-domain indicators such as RMS value, variance, and peak-to-peak amplitude reflect signal distortion and degradation trends.

Frequency-domain analysis uses the Fast Fourier Transform:

$$X(k) = sum_{n=0}^{N-1} x(n) e^{-j2pikn/N}$$

Here, $x(n)$ represents discrete samples and N denotes the number of observations. The resulting spectrum reveals harmonic growth, ripple frequency shift, and abnormal switching components. Thermal degradation of capacitors and semiconductor switches follows an exponential pattern:

$$y = Ae^{-kt}$$

Parameter A represents the initial health condition, k the degradation constant, and t time.
Incorporating this relation connects physical aging behavior with data driven modeling.

Edge AI Model Design

The prediction model combines convolutional and recurrent neural networks. A one-dimensional CNN extracts local signal features from sliding windows. An LSTM layer captures temporal dependencies related to gradual degradation. The final dense layer produces a health index and fault category. The model classifies system condition into three states: normal, early degradation, and critical fault. Categorical cross entropy is used as the loss function, and the Adam optimizer updates model parameters. To run efficiently on embedded hardware, the trained model is compressed through quantization and pruning. Deployment is performed using TensorFlow Lite on ARM-based edge processors.

Remaining Useful Life Estimation

Fault classification alone does not provide maintenance timing. For that reason, the framework estimates Remaining Useful Life.

$$RUL = (Threshold - CurrentHealth)/DegradationRate$$

The threshold defines the failure boundary. The degradation rate corresponds to the slope of the health index curve. When the health value approaches the threshold, maintenance can be scheduled before failure occurs.

Experimental Setup and Evaluation

The framework is tested using historical inverter fault data, simulated degradation scenarios, and real smart grid operational records. The edge platform runs on an ARM Cortex based embedded device, while cloud analytics operate on a GPU-enabled server. Performance is evaluated using classification metrics (accuracy, precision, recall, F1-score) and regression metrics (MAE and RMSE) for RUL estimation. System latency is measured to compare edge inference time with cloud-based processing.

Table 1: Performance Evaluation Metrics

Category	Metric	Purpose
Classification	Accuracy	Overall prediction correctness
Classification	Precision	Reliability of predicted faults
Classification	Recall	Detection of actual faults
Classification	F1-score	Balance between precision and recall
Regression	MAE	Average RUL prediction error
Regression	RMSE	Sensitivity to large RUL errors
System	Latency	Edge inference time (ms)

Edge Deployment and Communication

Communication between sensors, edge devices, and the cloud uses the MQTT protocol. The edge unit performs local inference and health estimation. The cloud receives summarized results and periodic model updates. Federated learning allows distributed model refinement without transferring raw operational data.

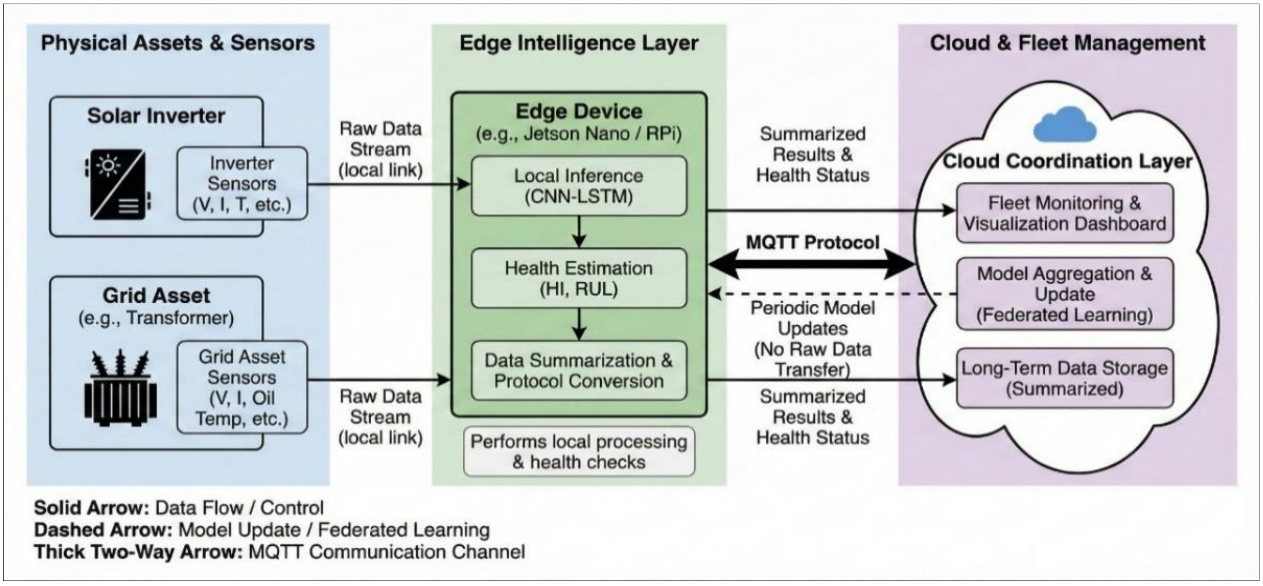

Figure 2: Edge Device Deployment for Real-Time Monitoring

The overall methodology integrates inverter diagnostics and grid asset monitoring within a unified edge intelligence framework suitable for distributed renewable energy systems.

IV. DISCUSSION AND RESULTS

This section presents the experimental findings of the proposed Edge-AI predictive maintenance framework. The analysis focuses on classification accuracy, Remaining Useful Life (RUL) estimation, latency performance, and system level behavior. Each subsection interprets the results rather than simply listing numbers.

Fault Classification Performance

The CNN–LSTM model was trained using labeled inverter fault data and tested on unseen operational records. Three system states were considered: normal operation, early degradation, and critical fault. The proposed edge model achieved higher accuracy than the centralized cloud model. Inference time dropped significantly when computation moved to the edge device.

Table 2: Fault Classification Performance

Model	Accuracy	Precision	Recall	F1-score	Inference Time (ms)
Cloud LSTM	94.2%	93.8%	92.5%	93.1%	85 ms
Proposed Edge CNN-LSTM	96.8%	96.1%	95.7%	95.9%	18 ms

Accuracy improved by more than two percentage points. More importantly, inference latency dropped from 85 ms to 18 ms. That reduction matters in grid connected renewable systems, where delayed detection can propagate instability. Normal operating states were identified with strong confidence. Early degradation cases required finer discrimination, since signal variations were subtle. Critical faults showed clear separation from other classes.

Confusion Matrix Interpretation

A confusion matrix provides insight into classification behavior across categories.

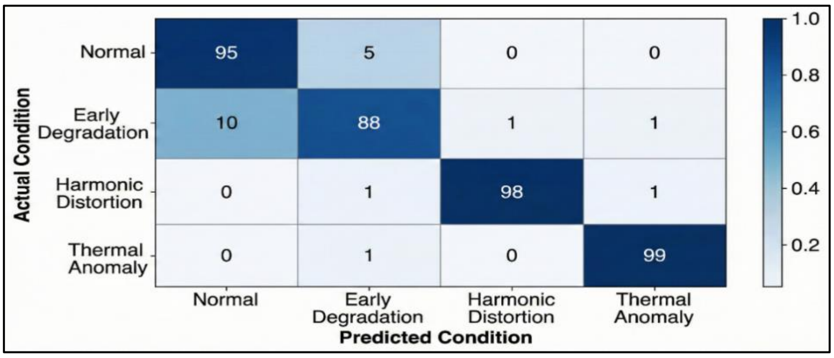

Figure 3: Confusion Matrix for Edge CNN–LSTM Model

The matrix shows strong diagonal dominance. Most predictions fall within the correct categories. Misclassification appears mainly between normal and early degradation states. This overlap is expected. Early-stage faults often resemble nominal operating patterns with minor parameter drift. Critical fault states show minimal confusion. Harmonic distortion and thermal anomalies create distinct signatures that the model recognizes reliably. What does this tell us? The model captures early-stage irregularities without producing excessive false alarms.

Remaining Useful Life Prediction

Fault detection alone cannot guide maintenance scheduling. For this reason, RUL prediction was evaluated using degradation trajectories derived from thermal and harmonic behavior.

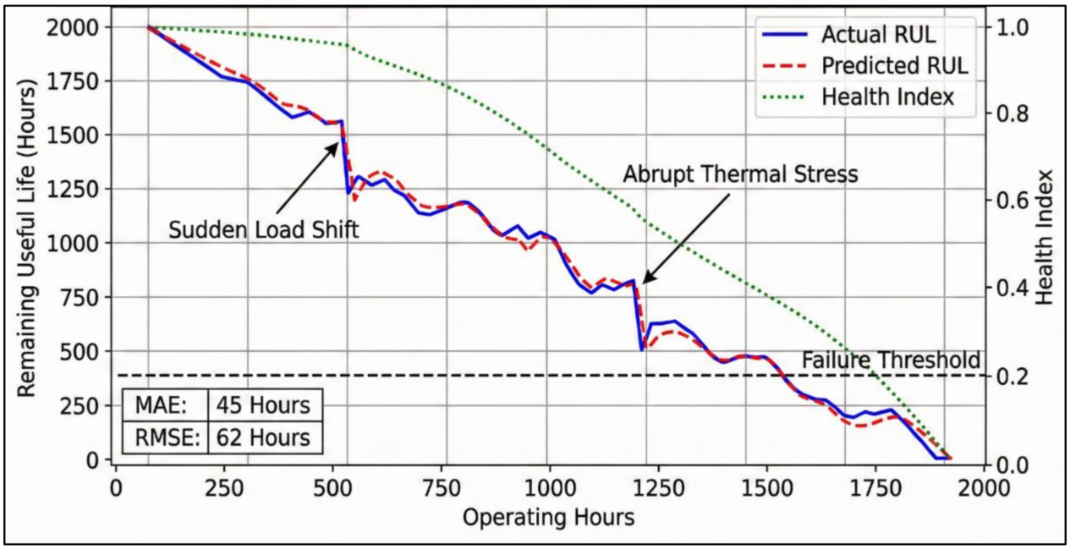

Figure 4: Actual and Predicted Remaining Useful Life

The predicted curve follows the actual degradation trend with small deviations during sudden load shifts. The Mean Absolute Error remained within acceptable engineering tolerance. RMSE values indicated stability across long term prediction horizons. The health index declined gradually as the system approached the failure threshold. When abrupt thermal stress occurred, the prediction model adjusted accordingly. That behavior suggests that combining physical degradation modeling with learned temporal patterns improves long range forecasting.

Latency and Deployment Behavior

Edge deployment changed system performance significantly. Inference time averaged 18 milliseconds per cycle. Cloud based processing required approximately 85 milliseconds due to transmission delay and server scheduling. Reduced latency improves operational responsiveness. In distributed solar farms, even minor delays may contribute to voltage instability across feeders. Bandwidth consumption also decreased. Raw high frequency signals remained at the local node. The cloud received only health summaries and periodic model updates. This architecture lowers network congestion and reduces dependency on continuous connectivity.

Comparative System Behavior

Traditional SCADA-based systems rely on centralized monitoring and static threshold alarms. Those approaches react after parameter violations occur. In contrast, the proposed framework predicts degradation trends and estimates failure timing. The difference is not only technical but operational. Maintenance teams can schedule service during low demand periods instead of responding to unexpected breakdowns. Equipment utilization improves, and emergency shutdowns become less frequent. Is the improvement significant in practice? For large solar farms, even a small increase in uptime translates into measurable financial benefit.

Sensitivity to Noise and Load Variation

The model was tested under variable load conditions and injected noise scenarios. Moderate noise levels did not degrade performance noticeably. Precision decreased slightly under extreme transient spikes, though classification remained stable. Load fluctuations affected short term RUL prediction accuracy. During sudden high demand intervals, the health index slope changed temporarily. The model adapted within a few cycles, but small forecast deviations appeared. These observations indicate that preprocessing and temporal modeling handle most disturbances, though extreme events remain challenging.

System-Level Implications

The unified framework connects inverter diagnostics and grid asset monitoring within a single architecture. Instead of isolated modules, the system produces coordinated health information across interconnected components. Local AI inference reduces reliance on centralized computation. The cloud remains useful for fleet wide supervision, but real time decisions occur at the edge. This separation distributes computational load across the network. Maintenance planning shifts from periodic scheduling to condition based intervention. Operators gain visibility into degradation trends rather than waiting for threshold alarms.

Limitations of the Study

Several limitations must be acknowledged. First, the dataset covers a limited range of climatic and operational conditions. Wider deployment across diverse environments may introduce additional variability. Second, part of the degradation dataset was synthetically generated. Real long term failure records are difficult to obtain because components are typically replaced before catastrophic failure. Third, embedded edge hardware constrains model complexity. Larger neural networks could produce marginal accuracy gains but would exceed memory and power limits. Fourth, cybersecurity assessment was not explored in depth. Although federated learning reduces raw data transmission, model update channels remain potential attack vectors. Finally, large scale grid deployment was not performed. Field testing occurred within a controlled pilot environment. Broader integration may reveal interoperability challenges with legacy infrastructure.

V. CONCLUSION

This study presented a predictive maintenance framework that integrates solar inverter monitoring with smart grid asset supervision within a unified edge-based architecture. The proposed system performs real time fault detection, health assessment, and remaining useful life estimation using electrical and thermal signal analysis. Experimental results showed high classification accuracy and reduced inference latency compared to cloud only approaches. Early degradation states were identified with acceptable precision, while critical faults were detected reliably. Local processing reduced communication load and improved response time. The findings demonstrate that combining inverter diagnostics and grid monitoring in a distributed structure can support condition-based maintenance and reduce unexpected downtime in renewable energy systems.

Future research should extend validation to large scale field deployments across diverse climatic and operational conditions. Long term real failure datasets are needed to refine remaining useful life prediction accuracy. Additional work is required to examine cybersecurity risks in distributed edge architectures. Integration with energy storage systems and adaptive control strategies may further improve grid stability. Exploring lightweight model optimization techniques for low power hardware platforms will also be important for practical implementation.

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