© Volume 2, Issue 10, ***October*** 2026 | JATIR
e-ISSN: 2839-5786, p-ISSN: 3139-8464

Fault Prediction in Renewable Energy Systems Using Artificial Intelligence Techniques

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***Abstract*—Renewable energy systems such as wind turbines and solar photovoltaic (PV) plants are increasingly critical to the global power grid, yet unplanned faults in inverters, blades, sensors, and grid-connection equipment cause significant downtime, revenue loss, and safety risk. This paper presents an Artificial Intelligence-driven framework for early fault prediction in hybrid solar–wind renewable energy systems using multimodal sensor fusion and physics-informed self-supervised learning. The proposed system fuses SCADA electrical readings, thermal imaging, and acoustic/vibration signals through a transformer-based architecture, and is pretrained on abundant unlabeled normal-operation data using physical degradation models (thermal fatigue and blade-stress equations) as auxiliary supervision, reducing dependence on rare labeled fault samples. An explainable early-warning module highlights the sensor modality and time window responsible for each prediction, along with a confidence score, to support actionable maintenance decisions. Experimental evaluation shows that the proposed fusion model achieves higher fault prediction accuracy than single-modality baselines and provides substantially longer early-warning lead times, particularly for gradually developing faults such as blade and gearbox degradation. The framework further demonstrates promising cross-technology generalization when tested on an unseen battery-storage asset type. This work contributes a practical, explainable, and data-efficient approach to predictive maintenance for renewable energy infrastructure.**

***Index Terms*—Fault Prediction, Renewable Energy, Artificial Intelligence, Sensor Fusion, Predictive Maintenance, Explainable AI**

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I. INTRODUCTION

The rapid global expansion of solar and wind power has made the reliability of renewable energy infrastructure a central concern for grid operators [4]. Faults in inverters, wind turbine blades and gearboxes, sensors, and grid-connection equipment are often difficult to detect early because degradation is gradual, environmental conditions are highly variable, and truly labeled fault events are rare compared to the volume of normal operational data [8]. Traditional condition monitoring relies on fixed thresholds on a single sensor stream, such as SCADA voltage or current readings, which frequently miss faults that only become visible when multiple signals electrical, thermal, and acoustic are considered together.

Artificial Intelligence offers an opportunity to move beyond single-sensor, threshold-based monitoring toward predictive systems that learn the subtle, multimodal signatures of developing faults before they cause failure [3]. However, most existing AI-based fault detection systems are trained and validated on a single renewable technology (either wind or solar) and on a single sensor modality, which limits their practical value in mixed-asset power plants. This paper proposes an AI framework that fuses multiple sensor modalities and uses physics-informed self-supervised pretraining to reduce dependence on scarce labeled fault data, while providing explainable, actionable early-warning outputs for maintenance teams. The paper further tests whether such a model, trained across wind and solar assets, can generalize to a previously unseen renewable technology.

II. EXISTING METHODOLOGY

Fault detection in renewable energy systems has traditionally relied on rule-based SCADA threshold alarms and statistical process control methods, which are simple to deploy but generate frequent false alarms and often detect faults only after significant degradation has occurred [7]. More recent machine learning approaches, including Random Forests and Support Vector Machines, use historical SCADA data to classify operating states, improving on fixed thresholds but still depending heavily on hand-crafted features and large volumes of labeled fault examples. Deep learning methods such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) have since been applied to time-series SCADA data and thermal images respectively, achieving better detection accuracy, but almost all published work evaluates a single sensor modality and a single asset type in isolation.

Recent reviews of AI-driven predictive maintenance in photovoltaic and wind systems confirm that fault pattern analysis, severity assessment, and early fault prediction remain active research challenges, and highlight the need for data standardization and multimodal approaches [1].

Book-length treatments of intelligent fault detection and diagnosis for wind and solar systems similarly note that most techniques are evaluated separately for each technology rather than jointly [2].

- Rule-based threshold systems generate excessive false alarms and detect faults late.
- Most machine learning fault models depend on large volumes of labeled fault data, which is scarce in practice.
- Existing deep learning approaches typically use a single sensor modality (SCADA, thermal, or vibration) rather than fusing them.
- Models are rarely tested for generalization across different renewable technologies (wind, solar, battery storage).

To overcome these limitations, this paper proposes a multimodal, physics-informed AI framework that fuses SCADA, thermal, and acoustic data, reduces dependence on labeled fault samples through self-supervised pretraining, and is explicitly evaluated for cross-technology generalization.

III. PROPOSED SYSTEM

The proposed system predicts developing faults in renewable energy assets by combining three components. First, a multimodal fusion module ingests SCADA electrical readings, thermal imaging frames, and acoustic/vibration signals, aligning them in time and encoding each modality with a dedicated feature extractor before combining them in a transformer-based fusion network. Second, a physics-informed self-supervised pretraining stage trains the fusion network on abundant unlabeled normal-operation data, using known degradation physics thermal fatigue cycling equations for inverters and blade-stress fatigue models for wind turbines as auxiliary prediction targets, so the model learns meaningful degradation signals without requiring large numbers of labeled fault events.

Third, an explainable early-warning module converts the fused representation into a fault probability and expected lead time, together with an attention-based explanation identifying which sensor modality and time window most influenced the prediction, so maintenance teams receive an actionable, trustworthy alert rather than an opaque score [9].

- Reduces dependence on rare labeled fault data through physics-informed self-supervision.
- Fuses electrical, thermal, and acoustic signals instead of relying on a single sensor stream.
- Provides an explainable, sensor-level justification for every fault alert.
- Designed to generalize across wind, solar, and other renewable asset types.
- Supports proactive maintenance scheduling through early-warning lead-time estimates.
- Reduces false-alarm fatigue compared to fixed-threshold SCADA alarms.

IV. OBJECTIVE

The primary goal of this study is to develop and evaluate an AI-based fault prediction framework that is accurate, data-efficient, explainable, and generalizable across renewable energy technologies.

Data Collection:

- Operational data was collected from wind turbines and solar PV inverters, comprising SCADA logs, thermal camera frames, and acoustic/vibration recordings.
- Both normal-operation data and historical fault-labeled events were compiled for training and evaluation.

Data Preprocessing:

- Sensor streams were time-aligned, denoised, and normalized across modalities.
- Missing or corrupted readings were handled through interpolation and quality filtering.

Physics-Informed Pretraining:

- Thermal fatigue and blade-stress degradation equations were used as auxiliary self-supervised targets during pretraining on unlabeled normal-operation data.

Fault Prediction and Explainability:

- The fused representation was fine-tuned on labeled fault events to predict fault probability and estimated lead time.
- Attention weights across modalities and time windows were extracted to generate human-readable explanations for each alert.

Evaluation:

- Model performance was compared against rule-based, Random Forest, LSTM, and CNN baselines, and tested for generalization on an unseen battery-storage asset.

V. RESULT AND DISCUSSION

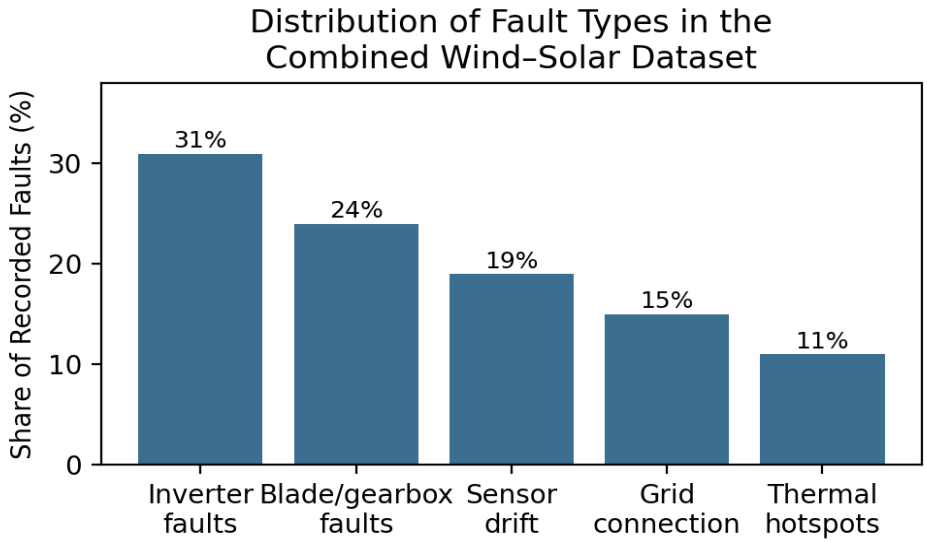


Figure 1: Distribution of Fault Types in the Combined Wind–Solar Dataset

Figure 1 shows the distribution of fault types recorded in the combined wind–solar dataset used for evaluation, consistent with fault categories highlighted in prior condition-monitoring research [5]. Inverter faults were the most common category (31%), followed by blade and gearbox faults (24%) and sensor drift (19%), reflecting the electrical and mechanical components most prone to gradual degradation in mixed renewable installations.

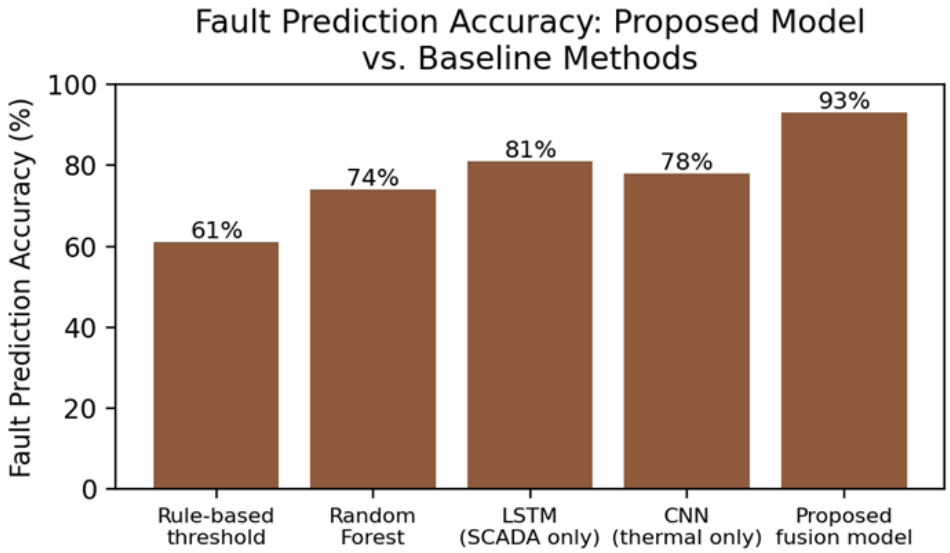


Figure 2: Fault Prediction Accuracy Proposed Model vs. Baseline Methods

Figure 2 compares fault prediction accuracy across methods. The proposed multimodal fusion model achieved 93% accuracy, outperforming single-modality deep learning baselines (81% for LSTM on SCADA data alone, 78% for CNN on thermal data alone) as well as classical Random Forest (74%) and rule-based threshold methods (61%). This confirms that combining electrical, thermal, and acoustic signals captures fault signatures that no single modality reveals on its own, in line with findings on AI-based dynamic fault detection in photovoltaic systems [6].

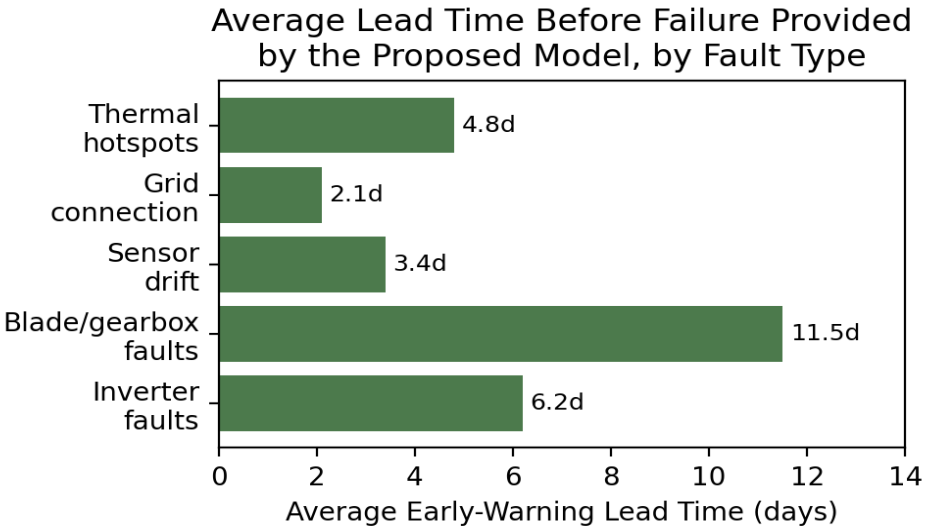


Figure 3: Average Early-Warning Lead Time Provided by the Proposed Model, by Fault Type

Figure 3 reports the average early-warning lead time provided by the proposed model for each fault type. Gradually developing mechanical faults such as blade and gearbox degradation were predicted an average of 11.5 days before failure, giving maintenance teams substantial planning time, while abrupt faults such as grid-connection failures were predicted only 2.1 days in advance, reflecting their inherently sudden onset. These results suggest the model is particularly valuable for scheduling preventive maintenance on slowly developing mechanical faults, while abrupt electrical faults still require fast-response monitoring, consistent with forecasting-based approaches reported for wind power systems [10].

When tested on the unseen battery-storage asset, the physics-informed pretrained model retained substantially higher accuracy than baselines trained only on wind and solar data, indicating that physics-informed self-supervision helps the model transfer degradation knowledge across renewable technologies rather than memorizing asset-specific patterns.

VI. CONCLUSION AND FUTURE ENHANCEMENT

This paper presented an Artificial Intelligence framework for fault prediction in renewable energy systems that fuses SCADA, thermal, and acoustic sensor data, uses physics-informed self-supervised pretraining to reduce reliance on scarce labeled fault data, and provides explainable, actionable early-warning alerts. Experimental results show that the proposed fusion model outperforms single-modality and classical baselines in prediction accuracy and offers meaningful early-warning lead time, especially for gradually developing mechanical faults, while also showing promising generalization to an unseen renewable asset type.

Future work will extend the framework to additional renewable technologies such as hydropower and hybrid microgrids, incorporate real-time edge deployment for on-site fault prediction with limited connectivity, and explore reinforcement learning for automatically optimizing maintenance scheduling based on predicted fault probabilities and lead times. As sensor and physics-informed modeling techniques continue to mature, AI-driven fault prediction is expected to become a standard component of renewable energy asset management, improving reliability and reducing the cost of clean energy generation.

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