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Next Generation Solar Photovoltaic Monitoring Systems: A Scoping Review on Techniques, Technologies, Usability and Security Issues

Ahmed Mohammed[a,e], Ranjit Singh Sarban Singh[b*], Saad Aslam[a], Yan Chiew Wong[c], T. Joseph Sahaya Anand[d] & Muhammed Kabir Ahmed[e]

[a]*Department of Smart Computing and Cyber Resilience, Faculty of Engineering and Technology, Sunway University, 47500, Selangor, Malaysia,*

[b]*Research Centre for Human-Machine Collaboration (HUMAC), Faculty of Engineering and Technology (FET), Sunway University, 47500, Selangor, Malaysia*

[c]*Fakulti Teknologi dan Kejuruteraan Elektronik dan Komputer, Universiti Teknikal Malaysia Melaka (UTeM), 76100 Durian Tunggal Melaka, Malaysia*

[d]*Department of Physics, School of Computing, MIT Vishwaprayag University, Solapur, 413255, India*

[e]*Department of Computer Science, Faculty of Science, Gombe State University, 760253, Gombe, Nigeria*

[*]*Corresponding author: ranjits@sunway.edu.my*

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ABSTRACT

The global transition toward renewable energy has positioned solar photovoltaic (PV) systems as a cornerstone of sustainable power generation. This transition is creating an urgent need for a robust and intelligent monitoring solutions. This scoping review systematically examines peer-reviewed studies published between 2020 and 2025, employing the PRISMA-ScR framework to ensure a transparent and structured process of identifying, screening, and synthesizing relevant literature. The analysis highlights progress across four key dimensions. Techniques such as machine learning (ML), deep learning (DL), signal processing, and statistical modelling demonstrate high accuracy in fault detection, predictive maintenance, and performance forecasting. Technologies including Internet of Things (IoT), unmanned aerial vehicles (UAVs), edge computing, and blockchain enable real-time monitoring, remote automation, and secure data handling. Usability considerations such as interface design, scalability, cost-effectiveness, and responsiveness remain underexplored, with few systems developed through user-centered approaches. Security emerges as the weakest area, with most systems offering little protection against critical threats such as false data injection, spoofing, or unauthorized access. The review identified six persistent research gaps; inadequate security frameworks, insufficient user-centered design, scalability versus cost trade-offs, lack of standardization, limited intelligent automation, and underutilized prescriptive analytics. These gaps highlight the need for integrated approaches that go beyond technical performance improvement to ensure resilience, affordability, and user adoption. By addressing these challenges, next-generation PV monitoring systems can become more secure, user-centric, scalable, and capable of autonomous operation and optimization, thereby enhancing the reliability, affordability, and long-term sustainability of global solar energy infrastructures.

Keywords: Solar photovoltaic monitoring; fault detection techniques and technologies; predictive maintenance; machine learning; usability and security

INTRODUCTION

The global demand for clean and sustainable energy has positioned solar PV technology as a pivotal solution for both small- and large-scale power generation (H. A. Kazem et al. 2024). PV modules operate by converting incident solar radiation into electrical energy, with current commercial technologies achieve a maximum efficiency of around 22.8% (A. M. Elbreki et al. 2020)., with many systems operating between 15% and 17%. This relatively low efficiency underscores the importance of optimizing performance across all aspects of PV deployment.

Despite the numerous advantages of PV systems including ease of installation, minimal maintenance, and clean energy generation (W. Priharti et al. 2019; M. E. A. Lopez et al. 2012), their efficiency and reliability are highly dependent on continuous monitoring and maintenance. Performance degradation, environmental conditions, partial shading, dust accumulation, and equipment faults can significantly impair output. As such, real-time data collection on key parameters such as voltage, current, temperature, and irradiance is essential to detect anomalies, perform diagnostics, and enable timely maintenance actions (P. M. Badave et al. 2017; F. Shariff et al. 2014). Modern PV monitoring reduces the need for manual inspection, thereby mitigating safety risks and reducing operational costs (M. Ş. Kalay et al. 2022).

This paper presents a scoping review aimed at examining the techniques and technologies, usability, and security concerns in contemporary solar PV monitoring systems. Drawing on studies published between 2020 and 2025, the review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) framework to ensure a structured and transparent process. PRISMA-ScR provides a standardized approach for identifying, selecting, and charting relevant studies, enabling the review to systematically map current trends, highlight limitations, and propose directions for future research. Unlike traditional systematic reviews that focus narrowly on intervention effectiveness, PRISMA-ScR is particularly suited for mapping broad and heterogeneous evidence, making it ideal for capturing the diverse methods and technologies in PV monitoring.

BACKGROUND AND MOTIVATION

Solar PV systems have become essential components of global renewable energy strategies. As installations grow in scale and complexity, the need for intelligent monitoring systems becomes critical. Monitoring ensures maximum performance, early faults detection, and optimizes operations and maintenance.

SCOPE AND OBJECTIVES

This review explores recent studies on solar PV monitoring systems published between 2020 and 2025 using PRISMA-ScR framework. The objectives are to: (i) examine monitoring techniques and technologies, (ii) evaluate usability features and limitations, (iii) assess security practices and concerns, and (iv) identify existing gaps and propose future research opportunities.

RESEARCH QUESTIONS

1. What are the current techniques and technologies used in solar PV monitoring systems?
2. How usability aspects like cost-effectiveness, user interfaces, and scalability are addressed?
3. To what extent security and privacy measures are integrated into these systems?
4. What are the existing gaps and future research opportunities that can be identified?

METHODOLOGY

SEARCH STRATEGY AND SELECTION PROCESS

A comprehensive keyword-based search was conducted in March 2025 across six major digital libraries: IEEE Xplore, ACM Digital Library, ScienceDirect, Wiley Online Library, Springer, and SAGE. Tailored search strings included terms such as “solar PV,” “monitoring,” “fault detection,” “predictive maintenance,” “AI,” “IoT,” “machine learning,” and “blockchain.”.

In total, 4,248 studies were retrieved. After removing duplicates and applying predefined inclusion criteria (peer-reviewed journal articles, full-text availability, English language, 2020–2025 publications, PV-related focus), and exclusion criteria (non-PV focus, inaccessibility, non-peer-reviewed content), 63 articles were selected. Figure 1 illustrates the PRISMA chart summarizing this process.

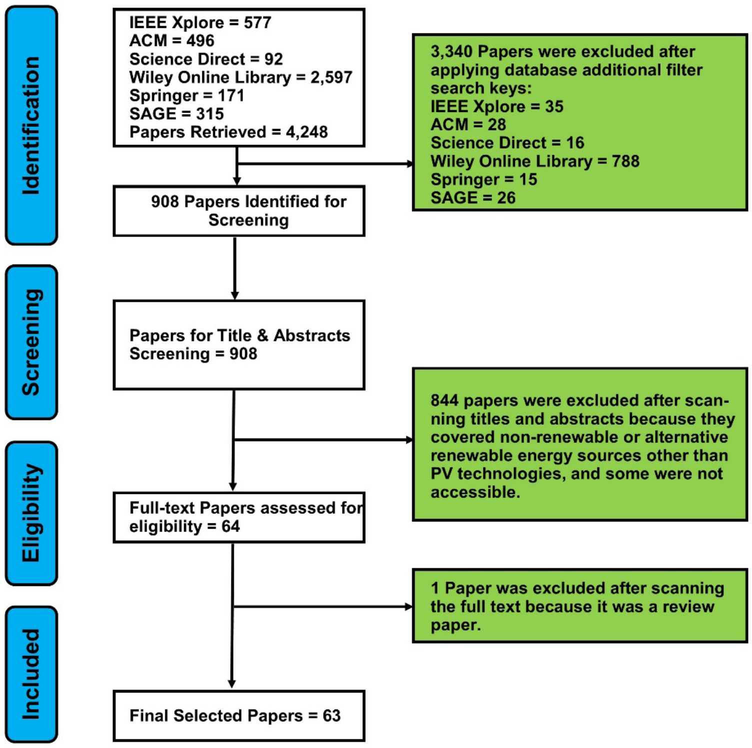

FIGURE 1. PRISMA chart summarizing the study selection process

THEMATIC ANALYSIS AND KEYWORD MAPPING

A keyword frequency and thematic trends were examined across the selected literature. A Wordcloud in Figure 2 visualizes the most frequent terms such as "System," "Photovoltaic," "fault detection," "machine learning," "IoT," "monitoring," and so on. These terms highlight the convergence of machine learning, and IoT in PV monitoring research.

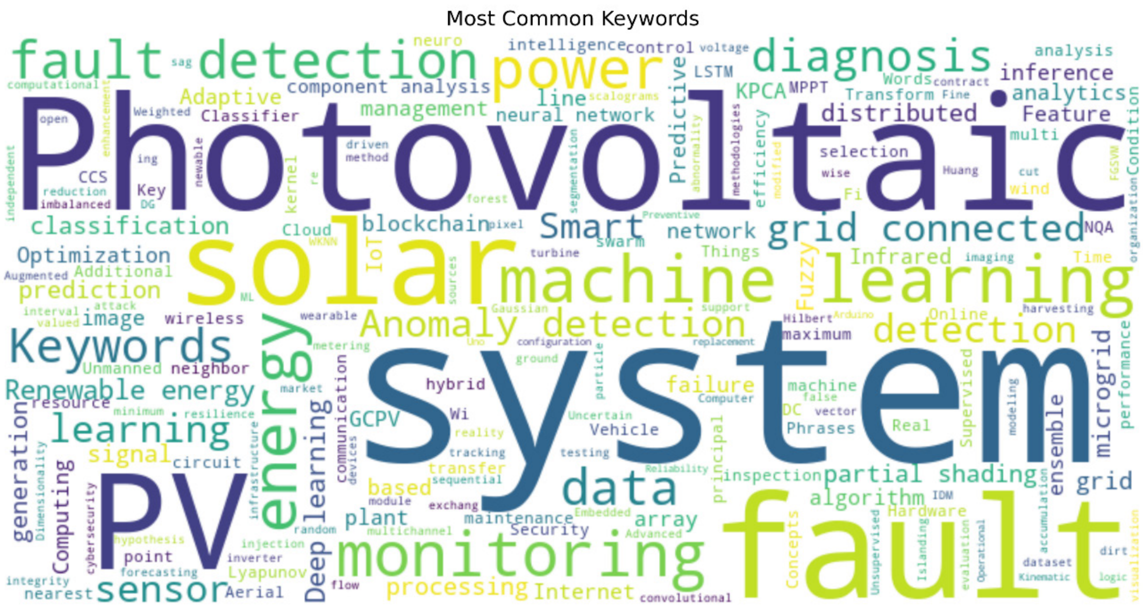

FIGURE 2. Wordcloud showing the frequencies of the selected papers' Keywords.

Thematic evolution shows clear progression from traditional monitoring techniques to intelligent, predictive systems. Earlier research emphasized basic sensor-based diagnostics, while recent studies integrate ML/DL, and IoT architectures to enable real-time fault detection, and predictive maintenance.

Figure 3 presents the proportional distribution of studies from 2020 to 2025, highlighting the rapid growth of interest in advanced PV monitoring technologies.

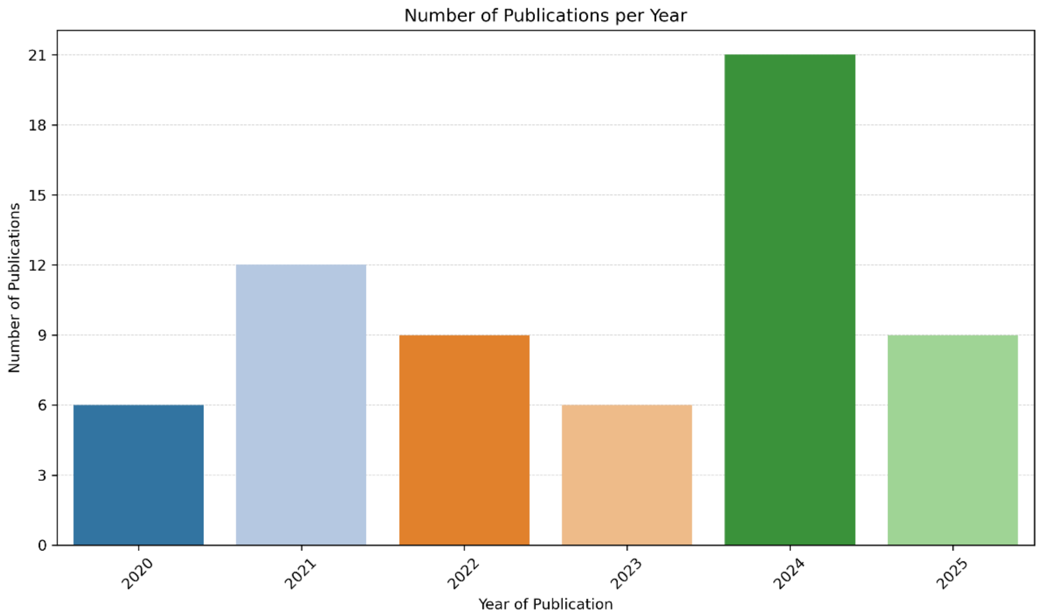

FIGURE 3. Distribution of related studies published from 2020 to 2025

TECHNIQUES AND TECHNOLOGIES IN PV MONITORING

In this review, a distinction was made between techniques (analytical and computational methods such as ML, DL, signal processing, and statistical approaches) and technologies (hardware and software infrastructures such as IoT, UAVs, edge computing, and blockchain). This separation helps clarify why methods that directly enhance monitoring accuracy, usability, and security were prioritized over purely economic or market-driven models.

MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

J. Zwirtes et al. (2025) evaluated five ML models for PV fault detection using voltage, current, temperature, and irradiance data. Data normalization enabled cross-system generalization, with ANN performing best on System 1 and SVM on System 2. The study effectively distinguished faults from partial shading and dirt accumulation but did not address scalability, response time, or user interface considerations.

K. Dhibi et al. (2021) proposed a hybrid FDD approach for grid-connected PV systems using ensemble learning with KPCA and RKPCA for feature extraction. Validated on simulated faults, the RKPCA-based method achieved near 100% classification accuracy and reduced computation time by over 50% compared to conventional techniques.

K. Dhibi et al. (2022) introduced interval-based ML FDD methods for grid-connected PV systems using ensemble learning with interval kernel PCA. The approach improved fault classification accuracy (up to 100%), recall, and precision, while reducing computation time and storage compared to traditional single-valued methods.

H. P. Hwang et al. (2021) developed a hybrid ML framework using infrared imaging and temperature analysis to detect PV module faults. All methods showed high accuracy, with the hybrid approach achieving an average accuracy of 0.992 and up to 0.994 in some tests.

M. Feng et al. (2021) developed SunDown, a fault detection system for residential solar arrays using per-panel generation data and ML models. It achieved a MAPE of 2.98% and detected anomalies with over 97% accuracy, reaching up to 99.13% for specific fault types.

N. Yamin and G. Bhat (2023) proposed an ML-based framework to predict solar energy and optimize energy allocation for battery-powered IoT devices. Their model achieved a 3.4 J MAE, 80% PICP, and near-optimal energy allocations within 2.5 J of an Oracle, with low execution time and minimal energy overhead.

I. A. Saifi et al. (2024) enhanced fault detection in grid-connected PV systems using ML, comparing FRT criteria and applying FGSVM and WKNN with Wavelet Transform. FGSVM achieved 94.9% accuracy, outperforming WKNN (92.5%), with improved fault classification and condition monitoring.

Z. Kang et al. (2024) proposed a fault early warning model for smart grid equipment, including PV systems, using multi-sensor information fusion with SVM for diagnosis and D-S evidence theory for decision fusion. Validated on the PEDL dataset, it achieved over 99% prediction accuracy and superior goodness of fit for warnings, integrating GIS for intuitive fault location.

A. Javaid et al. (2024) proposed a GPR-based ML method for fault detection, classification, and localization in PV systems. Exponential GPR showed optimal RMSE (363.59–397.1 for PS faults), efficient detection, and fast testing (<1 minute), with noted trade-offs between training time and accuracy.

M. Abbas and D. Zhang (2021) developed a PV fault detection system using an ANFIS approach, showing that the Subtractive Clustering (SC) method outperformed Grid Partitioning. The ANFIS-SC model achieved high accuracy with R = 0.9989, RMSE = 0.0383, and $R^2 = 0.9978$, confirming its effectiveness.

A. Teta et al. (2024) proposed a fault diagnosis framework for grid-connected PV systems by converting time-series data into 2D images for MobileNet and using an ensemble of SVM, RF, and DT. It achieved 97.36% accuracy on noiseless and 91.67% on noisy data, outperforming 1D-CNN and baseline models in precision, recall, and error rate.

S. Voutsinas et al. (2023) developed a lightweight ML algorithm using logistic regression with cross-validation for early PV fault detection based on irradiance and temperature data. It achieved 97.11% accuracy with minimal resource usage of 8 ms per prediction and 180 KB RAM.

V. Singh and R. Beniwal (2025) proposed a cost-effective ML-based fault detection method for grid-connected PV systems using KNN and ANN with ANOVA-based feature selection. The enhanced KNN achieved near-perfect accuracy (F1 score of 1), outperforming PCA in reducing complexity and cost.

N. Yang and H. Ismail (2022) proposed a robust intelligent learning algorithm using random forest (RF) and modified independent component analysis (MICA) for PV fault detection in cases of imbalanced data. The RF-MICA method effectively detects faults with high accuracy, handling data imbalances better than traditional approaches.

A. Hichri et al. (2024) proposed and validated an SSA-SML framework for fault diagnosis of PV systems by selecting the most relevant features and classifying a range of fault types with very high accuracy and efficiency. The SSA-based SML approach achieved high diagnostic accuracy (average greater than 99%) and reduced computation time compared to PCA and KPCA methods.

D. Marangis et al. (2024) developed a data-driven approach for real-time fault detection and predictive maintenance in PV plants, combining ML and trend forecasting. The system achieved 3–5% nRMSE in performance simulation, 96.9% fault detection sensitivity, 92.9% predictive alert sensitivity, and 99.4% overall warning accuracy.

S. R. K. Joga et al. (2024) proposed a fault detection method for PV arrays using SBCT-based time-frequency analysis combined with ML classification. It outperforms wavelet transforms in detecting faults like open circuit, short circuit, and partial shading, achieving up to 99.5% accuracy and robust fault localization.

E. A. Refaee (2022) applied ML to classify solar system performance and detect early faults using sensor data from Saudi installations. Tree-based models like J48 and RF achieved top accuracy (98.85%) and F-score (0.978), outperforming SVMs and confirming their suitability for PV fault detection.

B. Basnet et al. (2020) developed an intelligent fault detection model for PV systems using a PNN to classify fault types based on electrical parameters. The approach demonstrated superior prediction accuracy compared to traditional methods, effectively identifying faults like short circuits and shading with high reliability in simulated and real datasets.

A. Patel et al. (2022) developed a prototype datalogger for small-scale PV systems using IoT and ML to monitor and forecast power output. Linear regression, enhanced with temperature and humidity data, outperformed polynomial regression and case-based reasoning in prediction accuracy and cost efficiency.

I. S. Ramírez et al. (2021) developed a UAV-based PV monitoring system using radiometric sensors, IR remote sensing, and ML. It achieved 100% fault detection, 96% fault identification accuracy, and around 95% accuracy with ANN and statistical methods for fault cell prediction.

U. Farooq et al. (2025) applied ML for half-hourly solar power forecasting, using anomaly detection and detailed data analysis. Comparing two plants, they achieved forecasting accuracies of 0.97% and 0.61–0.62% using GB classifiers and linear regression, aiding improved grid integration.

R. Elazab et al. (2024) developed a supervised machine learning model using regression techniques (e.g., NNs, GPR) to mitigate solar power uncertainty in microgrids through irradiance prediction. The NN model achieved RMSE of 61.79 and R^2 of 0.9, integrated into an energy management system for high economic accuracy.

Y. Liu et al. (2025) proposed a hierarchical quantitative prediction model for PV power generation depreciation expenses, using matrix task prioritization to account for uncertainty risks. The model leverages ML techniques to forecast depreciation costs based on operational data, achieving high accuracy in expense prediction and enabling proactive financial planning for PV system maintenance. Validated on real-world datasets, the approach demonstrated robust performance with low error rates, supporting improved economic efficiency in large-scale PV monitoring systems. However, the study did not address user interface design or cybersecurity measures, limiting its immediate applicability to real-time monitoring platforms.

C. B. Lema et al. (2024) proposed a KPCA-based method for diagnosing single and simultaneous PV faults using I-V curve analysis. Validated via Matlab/Simulink, it achieved 93.33% accuracy for partial shading, 100% for open/short circuits, and 81.81% for combined faults, effectively distinguishing normal from faulty conditions.

M. U. Ali et al. (2024) proposed a hybrid feature extraction method using global and local features from IR images of PV panels, combined with an optimized b-IHHO algorithm for feature selection. The approach achieved ~98.41% accuracy, reduced features to 47, and enabled fast, robust classification of normal, hotspot, and defective panels.

F. Aziz et al. (2020) conducted a comparative study on PV fault diagnosis using deep learning, converting electrical data into 2D scalograms and applying AlexNet for feature extraction. The CNN-based method achieved 73.53% accuracy on noiseless and 70.45% on noisy data, outperforming traditional techniques and showing strong noise robustness.

S. A. Zaki et al. (2021) proposed a DL-based method for faults classification in PV systems, utilizing NNs to analyze electrical signals and classify common faults. The approach achieved high classification accuracy, demonstrating robustness in various operating conditions.

A. Stojkovic et al. (2025) proposed a lightweight deep learning framework using LSTM and LSTM with attention, optimized via DGPSO, for PV power forecasting. Tested on real-world datasets and deployed in a TinyML environment, it achieved low MSE scores (e.g., 0.007297 and 0.001812), showing high accuracy and low latency suitable for embedded applications.

H. Wang et al. (2021) devised a DETS that leverages IoT sensor data, blockchain ledgering, and predictive LSTM algorithms to optimize distributed energy trading and reduce total energy consumption costs using an MCMF formulation. The proposed solution is practical, achieves a lower cost of power energy consumption, and supports efficient scheduling and payment clearing in distributed energy markets based on experimental results with real data.

A. Syamsuddin et al. (2024) used an LSTM-AE model trained on SCADA data for predictive maintenance in PV systems. The model detected anomalies effectively, supporting early failure prediction, with test errors of MSE = 10.95, RMSE = 3.30, and MAE = 2.76.

S. O. Obatola and T. Junjie (2024) developed a data-driven framework combining advanced preprocessing, DL, and hybrid optimization for fault detection in grid-connected PV systems. It achieved 98.71% accuracy, with high sensitivity (0.97), specificity (0.9915), and F1-score (0.9688), outperforming traditional methods.

T. Khatib et al. (2021) proposed LSTM and GRU models to predict PV output current every second for a week using just half a day of training data. GRU showed slightly better accuracy and lower computational cost, with RMSE and MBE within acceptable limits, proving effective under uncertain conditions.

M. Dong et al. (2021) introduced ISEE, an edge computing and CNN-based framework for real-time solar panel defect detection. It achieved 93.75% accuracy on the verification set and improved automation and efficiency while reducing operational costs.

S. Wang et al. (2025) proposed an attention-based LSTM model for security monitoring and fault detection in renewable energy systems. Using real-world solar and wind data, the model outperformed traditional IDS and defense methods, achieving higher accuracy and detection performance.

S. Ikemba et al. (2024) used LSTM to assess solar energy potential in five southeastern Nigerian cities with NASA weather data. Enugu showed the highest potential (6.25 kWh/day), and Awka had the highest demand. The LSTM model outperformed traditional methods with an MSE of 0.01 and R^2 of 0.92, supporting its reliability for solar forecasting and investment planning.

D. Liu et al. (2025) proposed a hybrid network traffic anomaly detection method for PV power plants, combining EMD, and deep learning models to effectively monitor and secure the communication networks within renewable energy systems. The study demonstrates that the proposed anomaly detection framework outperforms current state-of-the-art approaches in terms of resilience, speed, and identification accuracy.

E. K. Ukiwe et al. (2024) developed a deep learning approach using VGG-16 with transfer learning and a GAP layer for hotspot detection in infrared images. The model achieved 99.98% accuracy with the Adam optimizer (learning rate 0.0001), effectively identifying minute and multiple hotspots in substation equipment.

L. Bommes et al. (2022) proposed a fault detection method for PV modules using IR images and a DL model with supervised contrastive loss and k-NN classification. The approach adapts to domain shifts, achieving AUROC scores of 73.3%–96.6% and classification rates of 79.4% (normal) and 77.1% (anomalous), outperforming cross-entropy classifiers.

S. N. Venkatesh et al. (2023) proposed a deep learning-based fault detection method for PV modules using CNNs to extract features from aerial images in a cloud computing framework. The model achieved up to 98.66% accuracy in binary and multiclass fault classification, with low computational complexity and fast processing times suitable for large-scale deployments.

A. Procházka et al. (2024) used advanced signal processing and ML to analyze power time series from east/west-oriented PV panels. By calculating a symmetry coefficient (mean 1.013, SD 0.041), they identified healthy panel behavior and detected timing differences in peak power between panel orientations.

C. Saiprakash et al. (2024) proposed a PV fault detection framework using the Stockwell Transform and ML algorithms to classify faults like open-circuit, short-circuit, and partial shading. It achieved 99.61% accuracy on simulated data and 98.12% on experimental data, outperforming traditional methods with high sensitivity and specificity.

ML dominates PV fault detection research. Algorithms such as SVM, RF, KNN, GPR, and ANFIS are widely used, achieving fault classification accuracies up to 98%. DL methods, including CNNs, LSTMs, and GRUs, extend these capabilities to infrared image analysis, short-term forecasting, and anomaly detection. Hybrid approaches (CNN + scalogram features, MobileNet + ensembles, attention-enhanced LSTMs) show growing robustness by achieving up to 100% in accuracy, even in noisy data conditions as shown in Table 1.

TABLE 1. Key Studies Using ML/DL Techniques for PV Monitoring

Reference	Technique	Accuracy/Other Metrics	Strength	Limitation
J. Zwirtes et al. (2025)	ANN, SVM	High (98%)	Robust detection of shading vs. dirt faults	Scalability concern
K. Dhibi et al. (2021)	Hybrid ML (KPCA/RKPCA)	~100%	High accuracy, reduced computation	No security focus, UI not provided
K. Dhibi et al. (2022)	Interval ML + Ensemble	100%	High recall, precision, reduced storage	No UI provied and security concern
H. P. Hwang et al. (2021)	Hybrid ML + IR imaging	99.2–99.4%	Combines thermal and visual features	Cost and security not reported
A. Teta et al. (2024)	MobileNet + Ensemble	97.4%	Robust to noise, low-resource	No UI provided, weak security
S. Voutsinas et al. (2023)	Lightweight ML	97.1%	Low cost, minimal resource use	Lacked security
V. Singh & R. Beniwal (2025)	KNN + ANN	~100%	Cost-effective, simple	Security concern
M. Abbas & D. Zhang (2021)	ANFIS-SC	$R^2 = 0.998$	High accuracy, efficient clustering	No UI provided, security concern
A. Javaid et al. (2024)	GPR-based ML	RMSE = 364–397	Fast testing, accurate fault localization	High training time
F. Aziz et al. (2020)	CNN (scalogram features)	73–70%	Noise robust	Low accuracy
A. Stojkovic et al. (2025)	LSTM + Attention	MSE < 0.01	Real-time TinyML deployment	Computationally heavy
S. Wang et al. (2025)	Attention LSTM	High	Effective for security monitoring	Scalability weak
D. Liu et al. (2025)	Hybrid DL for network anomaly detection	High	Strong resilience, speed	Accuracy metrics not provided
E. Ukiwe et al. (2024)	VGG-16 Transfer Learning	99.9%	Detects minute hotspots	High cost, no UI provided
S. N. Venkatesh et al. (2023)	CNN (aerial images + cloud)	98.7%	Low complexity, fast processing	Cloud dependency, no security focus

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B. Basnet et al. (2020)	PNN	High	Accurate fault classification	Limited to specific fault types, scalability concern
Z. Kang et al. (2024)	SVM + multi-sensor fusion	>99%	High resilience, GIS integration	Weak on small faults, data dependency
N. Yang & H. Ismail (2022)	RF + MICA	High	Robust to data issues	Computationally intensive, no scalability
S. A. Zaki et al. (2021)	DL	High	Robust fault identification	Huge data requirements, no security focus
R. Elazab et al. (2024)	Regression ML (NN, GPR)	$R^2 = 0.9$	Simplifies inputs, high interpretability	Data quality dependent
Y. Liu et al. (2025)	ML + Matrix Task Prioritization	High	Accurate expense forecasting, proactive planning	No security focus

SIGNAL PROCESSING AND STATISTICAL APPROACHES

A. Procházka et al. (2024) applied advanced signal processing and ML to analyze power time series data from east/west-oriented PV panels. Using filtering, feature extraction, and a symmetry coefficient, they identified distinct feature clusters and confirmed healthy panel behavior (mean coefficient 1.013 ± 0.041). The study also detected differences in peak power timing between panel orientations.

I. U. Khalil et al. (2020) compared mathematical models and fault detection techniques to enhance PV system reliability and efficiency. MBD and RDM showed robust performance with faster detection times. The study emphasized that method selection should align with fault type and conditions, with some configurations achieving up to 98% detection accuracy.

M. E. C. D. Rosa et al. (2024) proposed a non-invasive PV cell diagnostic method using 2D wavelet analysis on electroluminescence images. It detected hidden faults at the electrode-cell interface linked to poor soldering and high series resistance, with some cells showing up to 16.3% power loss and 15% efficiency reduction.

I. A. Dahham et al. (2023) investigated the effects of graphene, silica, and natural dust on the performance of monocrystalline, polycrystalline, and thin-film PV modules. Using spectrophotometric analysis for UV absorbance/transmittance, XRD and SEM for crystallinity/reflectance, and lab-scale setups, the study found graphene caused up to 96% power drop due to high UV absorbance and crystallinity, while silica and natural dust showed lower impacts (up to 26.79%) dependent on layer thickness. Thin-film modules exhibited the highest degradation, highlighting dust spectral properties as key to performance losses.

A. Livera et al. (2020) presented a complete methodology for PV data processing and quality verification to enhance performance and reliability analytics. The standardized procedures address common field measurement issues like outliers and gaps, ensuring data integrity for accurate monitoring and fault identification in operational PV systems.

A. Livera et al. (2022) developed failure diagnosis and trend-based performance loss routines for detecting and classifying incidents in large-scale PV systems. The methods accurately identify underperformance causes like faults or degradation, using statistical analysis to classify events with high precision in field data.

Signal processing approaches such as Wavelet Transforms and Stockwell Transforms capture transient faults that conventional techniques miss. Statistical methods, including RDM and MBD aid predictive maintenance and system reliability enhancement as shown in Table 2.

TABLE 2. Signal Processing and Statistical Approaches

Reference	Technique	Accuracy/Result	Strength	Limitation
A. Procházka et al. (2024)	Signal Processing + Symmetry Coefficient	High	Distinguishes east/west PV behavior	Cost, security concern
I.U. Khalil et al. (2020)	MBD, RDM	98%	Robust, fast	Scalability concern
C. Saiprakash et al. (2024)	Stockwell Transform + ML	99.6%	Robust under noisy data	High cost, no UI provided
M. E.C.D. Rosa et al. (2024)	Wavelet Electroluminescence	>90%	Non-invasive diagnostics	Expensive, security concern

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A. Livera et al. (2020)	Data processing + quality verification	High data integrity	Standardized, improves analytics	No real-time focus
A. Livera et al. (2022)	Trend-based performance losses	High classification	Accurate incident detection	Data-dependent, Security concern
I. A. Dahham et al. (2023)	Spectrophotometric + XRD/SEM	Power drop up to 96% (graphene)	Identifies dust spectral impacts	Lab-scale only, no real-time monitoring focus

IOT AND EDGE COMPUTING

S. Ghosh et al. (2021) developed an IoT-based power monitoring framework using ANFIS for optimizing hybrid solar-wind energy generation. Integrating WSN and Matlab/Simulink, the system achieved 99.74% efficiency, improved power extraction, load management, and energy sharing.

N. Yamin and G. Bhat (2023) proposed an ML-based framework for predicting solar energy and optimizing energy allocation in battery-powered IoT devices. Their model achieved a 3.4 J MAE, 80% PICP, and near-optimal energy allocations within 2.5 J of an Oracle, with low execution time and minimal energy overhead.

H. Wang et al. (2021) devised a DETS that leverages IoT sensor data, blockchain ledgering, and predictive LSTM algorithms to optimize distributed energy trading and reduce total energy consumption costs using an MCMF formulation. The proposed solution is practical, achieves a lower cost of power energy consumption, and supports efficient scheduling and payment clearing in distributed energy markets based on experimental results with real data.

C. K. Rao et al. (2025) developed a low-cost IoT-based solar PV monitoring system using sensors and microcontrollers for real-time data collection, cloud storage, and remote display. It effectively monitored parameters like voltage, current, and temperature, with peak power at 29.85 W, panel temperature at 28.19°C, and an average data transmission time of 53.02 seconds.

M. Bouzguenda et al. (2022) developed a cost-effective Arduino-based remote monitoring system for off-grid PV setups. It uses secure DMZ routing, multiple data access methods, and accurate sensors, achieving 98% accuracy with only 2% error and meeting IEC-61724 standards at a total cost of US$96.

A. B. Owolabi et al. (2023) assessed the performance of four grid-connected solar PV technologies under similar environmental conditions in Nigeria, evaluating metrics like efficiency, reliability, and output. The study highlighted variations in performance, providing insights into cost-effective deployment in tropical regions.

B. M. Ali et al. (2025) proposed sustainable strategies for preventive maintenance and replacement in PV power systems, focusing on enhancing reliability, efficiency, and economic performance. The approach integrates data-driven predictive maintenance techniques with cost-optimization models to schedule maintenance and replacements, minimizing downtime and operational costs. Validated through simulations, the strategy achieved significant improvements in system uptime and energy yield, with up to 15% cost savings compared to traditional maintenance approaches. However, the study lacks details on real-time monitoring interfaces and cybersecurity measures, limiting its applicability to interconnected PV systems.

M. Ghafoor et al. (2024) developed an automated IoT-based solar panel cleaning system with real-time monitoring and remote cloud control. It improved the efficiency of a 30W panel by 30%, with an average response delay of just 2 seconds.

M. Dong et al. (2021) introduced ISEE, an edge computing and CNN-based framework for real-time defect detection in solar panels. It achieved 93.75% accuracy on the verification set, enhancing automation and reducing operational costs in PV production.

B. H. Hameed and S. Kurnaz (2024) proposed a low-cost PV monitoring system using long-range wireless communication and AI-based predictive analytics. It achieved 97.65% accuracy, operated at 0.5W power, covered 10 km, and cost around $200 to implement.

Y. Cheddadi et al. (2020) developed a low-cost IoT-based PV monitoring system using ESP32 and sensor fusion to measure irradiance with a lux meter. It enables real-time data collection, cloud storage, and visualization via Grafana, providing efficient monitoring and timely alerts.

M. Z. Mohd Ashhar and C. H. Lim (2023) developed an amphibious mobile solar power generator with an ultra-water filtration system for disaster relief, featuring a hybrid PV system (2.88 kW from 12 panels) with battery storage and a generator for ~25 kWh/day. The system includes a Solar monitoring platform for real-time and historical data on production/consumption via mobile/web interfaces, enabling efficient deployment in inaccessible areas with simulations showing 93.9% solar fraction.

IoT systems provide low-cost, distributed, and cloud-integrated solutions for real-time monitoring. Edge computing supports localized processing, reducing latency in decision-making. Several works highlight low-cost IoT platforms (Arduino, ESP32), wireless communication, and cloud dashboards (Grafana, ThingSpeak) as shown in Table 3.

TABLE 3. IoT and Edge Computing Applications

Reference	Approach	Accuracy	Strength	Limitation
S. Ghosh et al. (2021)	IoT + ANFIS Hybrid	99.7%	Efficient hybrid generation monitoring	Security concern
C.K. Rao et al. (2025)	IoT + Cloud Dashboard	High	Real-time monitoring, proactive alerts	Security concern
M. Bouzguenda et al. (2022)	Arduino + Secure Routing	98%	IEC-compliant, cost = $96	Limited sensor resolution
M. Ghafoor et al. (2024)	IoT + Automated Cleaning	+30% efficiency	Integrated cleaning and monitoring	Security concern
B.H. Hameed & S. Kurnaz (2024)	IoT + Long-range Wireless	97.6%	Low power (0.5W), 10 km range	Some vulnerabilities remain
Y. Cheddadi et al. (2020)	ESP32 + Grafana	High	Open-source, modular	Security concern
M. Dong et al. (2021)	Edge Computing + CNN	93.8%	Real-time defect detection	Security concern
M. Z. Mohd Ashhar & C. H. Lim (2023)	IoT + Mobile PV Monitoring	High	Innovative dual-purpose design, Practical and scalable solution	Limited to mobile/off-grid, no advanced analytics

UAVS, SCADA, AND BLOCKCHAIN

M. Ghiasi et al. (2021) proposed a resilient approach for smart DC microgrids by combining Hilbert Huang Transform-based FDIA detection with blockchain-secured data exchange. The system detects FDIA in under 5 ms with over 96% accuracy across simulated scenarios, ensuring both reliability and security.

UAVs enhance PV fault inspection with infrared imaging, achieving near-perfect accuracy. SCADA systems remain essential for industrial-scale monitoring. Blockchain has been introduced to ensure transparency and data integrity, though often at higher costs as shown in Table 4.

TABLE 4. UAVs, SCADA, and Blockchain Applications

Reference	Technology	Accuracy	Strength	Limitation
I. S. Ramírez et al. (2021)	UAV + IR Imaging + ML	95–100%	High detection accuracy	Security concern
H. P. Hwang et al. (2021)	UAV + Thermal Analysis	99%	Hybrid IR + temp-based detection	High cost, Security concern
M. Ghiasi et al. (2021)	Blockchain + FDIA Detection	>96%	<5ms detection, secure	High cost, UI not provided
H. Wang et al. (2021)	IoT + Blockchain + LSTM	High	Secure energy trading	Expensive integration, accuracy not detailed
S. Ahmad et al. (2024)	Blockchain Monitoring	High	Resilient to single point failures	High cost, accuracy not detailed

S. Manna et al. (2023) introduced LRMRAC for rapid and ripple-free MPPT in PV systems under varying conditions. Validated in simulations and real-time, it achieved 99.07–99.96% tracking efficiency and convergence in less than 3.8 ms, outperforming traditional methods.

S. Singh et al. (2023) demonstrated the use of a Solar-PV inverter for mitigating oscillations in power systems, employing BFO-based intelligent MPPT control for DC-link voltage management. Simulations showed reduced settling time and improved stability under faults, with optimized controller gains enhancing overall system reliability.

Simulation and programming environments provide the backbone for algorithm design and validation. MATLAB/Simulink is widely used for MPPT simulations and synthetic fault generation, while Python supports ML/DL model development and analytics. Cloud visualization platforms (Grafana, Adafruit IO) offer operator dashboards.

USABILITY

Usability plays a decisive role in solar PV monitoring systems because it directly affects how effectively operators, technicians, and even non-expert users can interact with monitoring tools. The literature reveals varied emphasis on user interface design, scalability, cost-effectiveness, responsiveness, and overall user satisfaction.

Several studies implemented dashboards for real-time monitoring, typically displaying operational parameters such as voltage, current, power, irradiance, and fault indicators (C. K. Rao et al. 2025; Y. Cheddadi et al. 2020; A. Syamsuddin et al. 2024; D. Marangis et al. 2024). However, the level of sophistication varied widely, while some offered customizable cloud-based visualization (Grafana, ThingSpeak), others lacked clear usability testing. Several studies failed to report any user interface at all, highlighting a gap in user-centered design.

Scalability was more commonly addressed, often through modular hardware and cloud-based data handling (A. Teta et al. 2024; C. K. Rao et al. 2025). Yet, many studies acknowledged limitations in extending designs from small residential to industrial-scale systems. Cost-effectiveness was another recurring theme: Arduino- and ESP32-based systems demonstrated affordability and ease of implementation (M. Bouzguenda et al. 2022; A. Patel et al. 2022), while UAV-based and high-end thermal imaging solutions significantly increased deployment costs.

Responsiveness in terms of real-time fault detection was frequently claimed but often fell short. Systems that relied on heavy computational techniques or had weak communication pipelines introduced delays that could compromise timely decision-making (J. Zwirtes et al. 2025; A. Procházka et al. 2024; C. Saiprakash et al. 2024). Very few studies explicitly evaluated user satisfaction, though exploratory work on augmented reality (A. Oulefki et al. 2024) indicates future potential in user engagement as shown in Table 5.

TABLE 5. Usability Analysis of PV Monitoring Studies

Reference	UI Type	Scalability	Cost-Effectiveness	Responsiveness	Strength	Weakness
C. K. Rao et al. (2025)	Cloud-based dashboard	✓	✓	✓	Real-time remote monitoring with seamless visualization	Limited security integration
Y. Cheddadi et al. (2020)	Grafana-based visualization	✓	✓	✓	Open-source, modular, affordable	Lacks advanced user-centric design
A. Syamsuddin et al. (2024)	SCADA-based	✓	✓	✓	Predictive maintenance enabled	Expensive, UI not user-centric
D. Marangis et al. (2024)	Predictive alert dashboards	✓		✓	Accurate forecasting, early warnings	No prescriptive analytics, Not affordable to small scale PV installation
A. Oulefki et al. (2024)	AR visualization for maintenance	✓		✓	Innovative, immersive, role-specific support	High cost, No accuracy/security integration
M. Bouzguenda et al. (2022)	Web-based simple interface	✓	✓	✓	Low-cost, IEC-compliant	Limited processing capability
A. Patel et al. (2022)	Datalogger dashboard	✓	✓	✓	Affordable, easy to implement	No user-centric design
J. Zwirtes et al. (2025)	Not reported		✓		High detection accuracy	Lacked UI design, poor scalability, no real-time response
A. Procházka et al. (2024)	Not reported	✓			Strong analytical methods	Weak user interaction, not cost-effective

C. Saiprakash et al. (2024)	Not reported	Robust time-frequency analysis	No UI design, delayed response, computationally expensive
A. B. Owolabi et al. (2023)	Not reported	Real-world performance insights	Location-specific, no explicit UI implementation
B. M. Ali et al. (2025)	Not reported	Cost-efficient maintenance, high reliability	No real-time UI, lacks security integration

SECURITY

Security and data integrity remain underexplored dimensions in solar PV monitoring systems. While monitoring accuracy and reliability receive significant attention, few studies consider cybersecurity threats despite increasing system interconnectivity. Unsecured, grid-connected PV systems are vulnerable to attacks such as FDI, spoofing, or unauthorized access, which could lead to masked faults, financial loss, or even grid instability.

Most studies only briefly mention encryption or secure transmission, while only a handful directly address cyber-resilience. Ghiasi et al. (2021) applied Hilbert-Huang Transform with blockchain integration for rapid (< 5 ms) false data injection detection. Wang et al. (2021, 2025) proposed blockchain and LSTM-based methods for anomaly detection and secure energy trading, demonstrating practical benefits but incurring high costs. Liu et al. (2025) advanced traffic anomaly detection using hybrid DL, significantly improving resilience. Syamsuddin et al. (2024) explored sequential hypothesis testing to counter integrity attacks in microgrids.

Despite these innovations, very few frameworks are standardized or tested on a scale. Blockchain-based systems remain expensive and complex to deploy, while anomaly detection approaches require extensive labeled datasets. The lack of comprehensive security frameworks, combined with an absence of systematic evaluation against adversarial threats, makes current PV monitoring solutions vulnerable as shown in Table 6.

TABLE 6. Security Analysis of PV Monitoring Studies

Reference	Threat Addressed	Defense Method	Resilience	Scalability	Weakness
M. Ghiasi et al. (2021)	False Data Injection (FDI)	Hilbert-Huang Transform + Blockchain	>96% accuracy, <5 ms detection	✓	Relies solely on blockchain, costly
S. Ahmad et al. (2024)	Grid resilience, tampering	Blockchain-based decentralized monitoring	Secure, tamper-proof	✓	High cost, no accurate metrics
D. Liu et al. (2025)	Network anomalies	Hybrid DL + Empirical Mode Decomposition	High speed, robust anomaly detection	✓	Accuracy not fully reported
H. Wang et al. (2021)	Secure energy trading	IoT + Blockchain + LSTM forecasting	Cost optimization, secure clearing	✓	High cost of blockchain integration
S. Wang et al. (2025)	Intrusion, IDS improvement	Attention-based LSTM	High accuracy, robust detection	X	Limited scalability
A. Syamsuddin et al. (2024)	Data integrity attacks	Sequential Hypothesis Testing	Low computational cost, effective early detection	X	No accurate metrics
M. Zakir et al. (2022)	Fault & FDI detection	Hardware + Diode network	Fast response (~44 µs)	✓	Low generalizability
Mohammadi et al. (2022)	General data integrity	ML anomaly detection	Secure data validation	X	Limited adoption, not standardized

ANALYSIS AND DISCUSSION

The reviewed literature demonstrates remarkable progress in solar PV monitoring systems, yet it also reveals fragmentation across techniques, technologies, and application priorities. This section integrates findings across usability, security, scalability, and system intelligence, highlighting how these elements interrelate to shape the current state and future of PV monitoring.

Techniques such as machine learning and signal processing have proven highly effective in fault detection and performance forecasting. ML/DL models achieve impressive diagnostic accuracy, with some exceeding 99% in detecting anomalies, shading, or dirt accumulation. Signal processing complements these approaches by capturing transient anomalies often missed by conventional methods. Yet, these techniques rarely integrate security or usability features, leaving monitoring systems accurate in detection but limited in usability and security.

Technologies like IoT, UAVs, blockchain, and edge computing provide the infrastructure necessary to implement these techniques at scale. IoT devices and cloud platforms enable real-time, distributed monitoring, while UAVs offer powerful imaging capabilities. Blockchain and edge computing further enhance system resilience and responsiveness. However, their adoption raises trade-offs: UAVs and thermal cameras improve detection but at high cost; blockchain provides security but adds latency and complexity; edge computing supports low-latency decisions but demands resource optimization. Thus, the technological ecosystem is diverse but uneven, with adoption patterns strongly tied to context and resource availability.

Usability emerges as a crucial yet underdeveloped dimension. Systems with high diagnostic accuracy often neglect user interfaces or scalability, resulting in tools that perform well in controlled settings but lack real-world accessibility. Dashboard-based interfaces using Grafana or web applications improve usability but often miss user-centered design principles. Non-expert users, such as residential PV owners or maintenance technicians, remain underserved. Responsiveness also suffers in many cases, with delays in real-time monitoring undermining system reliability. In practice, usability directly shapes the perceived value of technical accuracy.

Security remains the weakest link across the reviewed literature. Only a handful of studies explicitly address data integrity, FDI attacks, or cyber-resilience. This oversight is particularly concerning given the increasing network connectivity of PV infrastructures. Without robust security frameworks, monitoring systems risk becoming points of vulnerability that attackers could exploit to mask faults or manipulate grid data. The disconnection between accuracy-driven research and security-driven design represents a structural gap in the field.

Scalability and cost-effectiveness represent a persistent tension. High-accuracy solutions often rely on expensive technologies, while affordable IoT-driven systems sometimes sacrifice accuracy or responsiveness. Studies that integrate lightweight ML models with IoT platforms suggest promising middle grounds, but systematic frameworks for balancing scalability and performance remain absent. This trade-off underscores the importance of interoperability and standardization, which would allow components and platforms to be mixed and matched without losing functionality.

Finally, integrated implications reveal that future PV monitoring systems must combine accuracy, usability, security, and scalability rather than advancing them in isolation. The convergence of ML/DL with IoT and edge computing shows clear potential for real-time, secure, and user-friendly systems. Yet to achieve this, research must move from siloed performance benchmarks toward holistic frameworks that evaluate systems in terms of operational reliability, resilience to cyber threats, accessibility to non-expert users, and economic feasibility.

The analysis shows that while solar PV monitoring has advanced significantly in technical sophistication, its true impact will depend on integrating accurate techniques with enabling technologies, user-centered usability, robust security, and scalable architectures. This interrelation transforms monitoring systems from diagnostic instruments into resilient, intelligent infrastructures capable of supporting the global transition to renewable energy.

GAP AND FUTURE RESEARCH DIRECTIONS

This review highlights significant advancements in solar PV monitoring systems through the integration of machine learning, deep learning, IoT, and other emerging technologies. However, several critical gaps remain. Addressing these gaps is essential to ensure monitoring systems evolve from diagnostic tools into secure, scalable, user-friendly, and autonomous infrastructures.

Security remains a fundamental gap as most studies still rely on basic encryption, with little emphasis on robust defense frameworks. FDI and spoofing attacks are rarely addressed (M. Ghiasi et al. 2021; S. Ahmad et al. 2024; D. Liu et al. 2025). This is a critical weakness because unsecured, grid-connected PV systems are prime targets for cyber-attacks that could mask faults, damage equipment, cause financial losses, or even destabilize local grids.

Future research should investigate AI-based intrusion detection tailored for PV monitoring, blockchain-based decentralized architectures for tamper-proof data management (H. Wang et al. 2021), and federated learning approaches that allow privacy-preserving analytics across distributed PV networks (S. Wang et al. 2025).

Usability challenges also remain underexplored, even though, dashboards and real-time interfaces are common (A. Procházka et al. 2024; A. Teta et al. 2024; M. Dong et al. 2021), many lack intuitive, user-friendly design suitable for non-expert users. Weaknesses in responsiveness, clarity, and interpretability have been noted (J. Zwirtes et al. 2025; C. Saiprakash et al. 2024). Future systems should adopt human-centered design principles, integrating adaptive visualizations, role-specific insights, and interactive tools such as augmented reality (AR) for guided maintenance (A. Oulefki et al. 2024), which are key to improving user satisfaction.

Scalability and cost-effectiveness represent another research trade-off. Although many systems claim scalability such as (S. Ghosh, 2021; A. Teta et al. 2024; C. K. Rao et al. 2025), high performance often depends on expensive UAVs, thermal cameras, or high-end sensors, restricting widespread adoption in resource-constrained environments (K. Dhibi et al. 2021; Y. Cheddadi et al. 2020). Recent studies suggest edge computing and optimized sensor configurations as potential solutions (S. Chandrasekharan et al. 2021). Therefore, future research should focus on lightweight, affordable architectures that maintain diagnostic accuracy without imposing prohibitive costs.

A lack of standardization and interoperability is also evident. The absence of shared data formats, communication protocols, and evaluation benchmarks restricts integration across platforms and impedes fair comparison of performance (A. Procházka et al. 2024; S. Ahmad et al. 2024; D. Liu et al. 2025). Establishing open standards would facilitate compatibility, support third-party integration, and enable benchmarking across diverse PV systems.

Intelligent automation is another underdeveloped area. While ML and DL models are widely applied, most remain conventional. Advanced approaches such as reinforcement learning for adaptive control, hybrid models merging physics-based simulation with data-driven learning, and federated learning for secure distributed training remain underexplored (K. Dhibi et al. 2021; A. Teta et al. 2024; S. O. Obatola and T. Junjie, 2024; A. Hichri et al. 2024). These methods promise greater interpretability, robustness, and adaptability, especially for detecting rare or overlapping fault conditions (Y. Liu et al. 2025; C. B. Lema et al. 2024).

Finally, prescriptive decision-making is largely overlooked. Most systems stop at diagnosis or prediction, without offering actionable maintenance or operational recommendations. Only a few studies address intelligent scheduling or prioritization of components (A. Syamsuddin et al. 2021; B. M. Ali et al. 2025; D. Marangis et al. 2024). To fully realize the potential of PV monitoring, future systems must incorporate prescriptive analytics to enable proactive scheduling, component prioritization, and autonomous optimization.

So, this review identifies at least six critical research gaps: security, usability, scalability/cost-effectiveness, standardization, intelligent automation, and prescriptive decision-making. Addressing these gaps will be essential to building the next generation of PV monitoring systems, ones that are secure, user-centric, scalable, interoperable, and capable of autonomous decision-making. Such improvements will enhance the resilience, affordability, and long-term impact of solar energy infrastructures worldwide.

CONCLUSION

This review synthesized recent advancements in solar PV monitoring, focusing on techniques, technologies, usability, and security. Machine learning and deep learning methods dominate fault detection and performance forecasting, while IoT platforms provide the backbone for real-time monitoring. Complementary technologies such as UAV-based imaging, edge computing, and blockchain are emerging to improve inspection, responsiveness, and trust. Together, these advances illustrate the rapid evolution of PV monitoring toward intelligent, data-driven infrastructures.

Yet the analysis reveals that progress remains uneven. Accuracy-focused methods often neglect usability and security, leaving non-expert users underserved and systems exposed to cyber risks. Scalability and affordability remain tense, with high-performance solutions dependent on costly hardware, while low-cost systems face limitations in responsiveness and robustness. Standardization across platforms is limited, impeding interoperability and comparative benchmarking. Most notably, monitoring remains diagnostic in scope, with few systems progressing toward prescriptive decision-making and autonomous optimization.

This review identifies six critical research gaps: (1) insufficient security frameworks beyond basic encryption, (2) limited user-centered design for interfaces and user satisfaction, (3) unresolved trade-offs between scalability and cost-effectiveness, (4) lack of standardization and interoperability, (5) underexplored intelligent automation through reinforcement or hybrid learning, and (6) minimal adoption of prescriptive analytics for operational decision support. Addressing these gaps will require integrative solutions that embed accuracy within secure, scalable, and user-centered architectures.

Looking ahead, the next generation of PV monitoring systems must transcend siloed advancements by integrating robust security, immersive usability, cost-aware scalability, interoperable standards, and autonomous decision support. Such systems will not only detect and diagnose faults but also prescribe actions, adapt dynamically, and ensure resilience against emerging cyber and operational risks. Achieving this vision is essential to build trustworthy, accessible, and intelligent monitoring infrastructures that strengthen the global transition toward sustainable solar energy.

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DECLARATION OF COMPETING INTEREST

None.

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