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Artificial Intelligence and Machine Learning for Fault Detection and Energy Forecasting in Photovoltaic Systems: A Comprehensive Review

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***Abstract*— Worldwide installation of PV systems has increased trash demand for efficient monitoring and energy forecasting. Efficiency, safety, and financial risk management are the basic cornerstones considered while monitoring PV systems. Classical approaches for fault diagnosis and power prediction of PVs have become obsolete due to their limitations in handling nonlinearities under uncertainties and scalability under varying operational conditions. With the evolution of artificial intelligence and machine learning, intelligent data-driven frameworks can be developed for real-time fault diagnosis, performance evaluation, and predictive maintenance. This study intends to present a critical review of the latest AI and ML techniques in PV system monitoring and forecasting, addressing issues relating to their aptitude in the identification of the most common faults, such as hotspots, partial shading, soiling, and inverter failures, together with improving short- and long-term energy prediction. Deep learning and hybrid AI models, which consider accuracy, sensitivity, and robustness across heterogeneous datasets, are far superior to traditional methods. Also, when integrated with IoT, edge computing, and digital twin technologies, they build on scalability, adaptability, and decision-making capabilities in real time. The review also highlighted concerning issues of data scarcity, generalizability across different climates, explainability, and cybersecurity. Finally, future directions are outlined to create standard datasets and benchmarking practices and construct explainable hybrid models with a trustworthy and transparent foundation, further leading to the wide adoption of AI in PV systems.**

Keywords*— *Artificial Intelligence, Digital Twin, Fault Diagnosis, Machine Learning, Photovoltaic Systems, Renewable Energy.

I. Introduction

Recent PV technology has undergone a significant transformation in solar energy worldwide. Declining module prices, inverter development, and favorable policies have given way to deployments that have never been seen before in residential, commercial, and utility fields. PV systems in the world are expected to touch at least terawatt-level capacity within the coming ten years, thus contributing largely to decarbonization [1][2]. Their growth aside, operational problems still exist in PV systems that inhibit the reliable delivery of predictable power. Environmental hindrances such as shading, dust deposition, temperature, and humidity cause losses in efficiency, unexpected downtime, safety hazards, etc. Faults, including hotspots, PID, soiling, and inverter failure, further reduce performance and can also trigger a fire hazard or long-term failures, thereby increasing maintenance costs and reducing system life. Hence, an effective fault detection and diagnostic (FDD) is an utmost necessity for a safe and efficient PV operation [3][4].

Intermittent solar phenomena and variability create additional barriers for integration into the grid. Changes in solar irradiance affect short-term generation and day-ahead generation, thereby challenging the scheduling and stabilization of the grid. Having an accurate forecasting tool becomes paramount for balancing loads, kinds of reserves, operational planning, and entering markets in smart grid environments. It is in this field that artificial intelligence (AI) and machine learning (ML) have become powerful allies, capable of modeling nonlinear patterns in PV data [5][6]. SVMs, ANNs, CNNs, RNNs, and hybrid approaches are listed among those techniques that show a bright prospect both in FDD and energy forecasting, especially when coupled with IoT-based high-resolution monitoring [7].

However, most studies focus exclusively either on fault diagnosis or forecasting, leaving a gap in unified approaches. Early fault detection helps improve the accuracy of forecasting, whereas reliable predictions support anomaly detection, thus presenting the need for integrated frameworks. This review systematically analyses the state-of-the-art AI/ML methods in the field of PV fault detection and energy forecasting with respect to the methodologies involved, datasets used, and performance metrics applied. This includes a discussion of strengths and limitations and considers scalability and deployment opportunities in a real-time environment, incorporating a discussion of emerging trends such as digital twins, IoT integration, and explainable AI to provide a comprehensive roadmap for further research in intelligent PV system management [8][9][10].

II. Literature Review of AI/ML Methods

A. Fault Detection and Diagnosis (FDD)

Deep-learning methods for analyzing EL imagery first demonstrated that CNNs could vastly surpass classical SVMs in cell-level defect detection methods. Deitsch et al. scored around 88% using CNNs, versus 82% for SVM on 1,968 EL cells in a baseline study for image-based PV FDD [11]. Field-scale screening has since expanded using remote and thermal modalities. UAV-acquired thermal data processed with semantic segmentation networks such as DeepLabV3+, FPN, and U-Net achieved Dice scores of 87–94% and IoU up to

0.86 for faulty-panel localization [16]. More recent U-Net-based implementations incorporating attention and atrous spatial pyramid pooling modules enhance the robustness of segmentations in complex utility plant scenes [27]. Physics-informed approaches are emerging that combine modulated-light sensing and ML to classify short-circuit current spectra, simultaneously enabling identification and localization of faults with cheap hardware [25].

On tabular electrical datasets, ensemble and tree-based models are decent baselines. Extra Trees and Random Forest classifiers have successfully diagnosed multiple panel-level faults from SCADA or low-cost sensor data, even under varying irradiance and temperature conditions [22,24,26]. System-scale digital-twin (DT) frameworks further enhance generalization; for instance, PSO-optimized Transformer models using current-ratio features detect and localize grid-connected PV faults resiliently under operating condition shifts [21]. DT-enabled anomaly detection has also been applied to DC–DC converters, covering both hardware faults and sensor-level attacks [20].

Image-based datasets primarily use EL/IR imagery at module or array scale, often proprietary or curated (e.g., the Deitsch EL corpus) [11]. UAV thermal studies include diverse meteorological and environmental backgrounds [16,27], while electrical-signal works rely on lab setups or SCADA records, with class imbalance and limited labeled faults remaining recurrent challenges [22,24,26].

B. Energy Forecasting

PV forecasting targets global irradiance, plant power, or feeder-level injections across horizons from minutes to day-ahead. Classical ANN and linear regression baselines mostly gave way to RNNs (LSTM/GRU), CNN-temporal hybrids, and meta-learning frameworks. Short-term forecasting benefits from an attention-enhanced LSTM. Having a better ramp tracking ability and adapted to weather-regime shifts than a vanilla LSTM or SVR [12]. Wavelet packet decomposition combined with LSTM isolates multi-frequency PV dynamics to perform better than single-model baselines in hour-ahead forecasting [13].

Hybrid statistical-AI approaches integrate signal-decomposition, uncertainty-modelling, and ensemble-learning. CEEMD for feature selection followed by PSO-optimization of BPNN improves short-term accuracy [14] and yields a CNN-based meta-learning approach for robust day-ahead forecasts across seasonal regimes [15]. They also provide probabilistic hybrids (WT-CNN-BiLSTM with attention + GMM) for calibrated forecasts needed for grid reserves [19]. Temporal-conv-GRU with channel attention offers state-of-the-art performance in short-term power prediction [17]. Open datasets are limited; most studies rely on plant-specific SCADA and NWP inputs. Standardization, explicit weather-regime reporting, and probabilistic evaluation remain important research priorities [14,18,19].

TABLE I. SUMMARY OF LITERATURE

Author (Year)	**Methods / Key Findings**	**Limitations / Research Gaps**
Deitsch et al. (2019) [11]	CNN vs SVM on EL images; CNN ≈88% accuracy	Module-scale EL; generalization to field thermal scenes
Zhou & Zhang (2019) [12]	LSTM with attention for short-term power	Limited probabilistic evaluation
Li et al. (2020) [13]	WPD-LSTM hybrid; hour-ahead gains	Site-specific tuning; data-hungry
Niu et al. (2020) [14]	RF-feature selection + CEEMD + PSO-BPNN	Complex pipeline; reproducibility
Zang et al. (2020) [15]	Deep CNN + meta-learning for day-ahead	Benchmarking vs probabilistic baselines
Paradell et al. (2022) [16]	DeepLabV3+/FPN/U-Net on UAV thermal; IoU≤86%	Annotation cost; transfer across plants
Li et al. (2022) [17]	TCN-GRU variants for short-term power	External validation sets are absent
Bessa et al. (2023) [18]	Meta-learning blend of base forecasters	Data-drift quantification limited
Gu, B. et al. (2023) [19]	WT-CNN-BiLSTM-Attention + GMM; calibrated DA forecasts	Compute overhead in operations
Zhang, X. et al (2023) [20]	Hybrid SVR–BPNN with modern optimizers	Stationarity assumptions
Hong et al. (2023) [21]	Digital-twin + PSO-optimized Transformer for FDD	DT modeling effort; cyber-resilience tests
Abdelrahman et al. (2024) [12]	Two-step model-based + RF FDD	Real-time deployment details
Alrashidi et al. (2024) [23]	TCN-ECANet-GRU short-term forecasting	Weather-regime reporting
Abdelkader et al. (2024) [24]	Extra Trees classifier for panel faults	Small-scale dataset
Tao et al. (2025) [25]	Modulated photocurrent + ML; fault localization	Field scalability and standardization
Gaaloul et al. (2025) [26]	RF/kNN detection using capture-loss indicators	Label scarcity; class imbalance
Rahman et al. (2025) [27]	U-Net+ASPP for thermal fault segmentation	Domain shift under varying backgrounds

III. COMPARATIVE ANALYSIS OF METHODS

AI and ML applications in PV systems focus mainly on two areas: fault detection and diagnosis (FDD) and energy forecasting. Each area favors different families of models, modalities of data, and evaluation methods. Image-based methods in FDD are centered on EL, IR, and UAV thermal imagery. The initial EL studies demonstrated the predominant superiority of CNNs over classical classifiers like SVM, with Deitsch et al. reporting accuracies of around 88% versus around 82% for an SVM on 1,968 EL cells [28]. Later, the best lightweight CNN found even better EL inspection accuracies of around 93%, thus proving that smaller-sized models can perform equally well and facilitate a high-throughput industrial deployment [29]. Later, studies addressed class imbalance and multi-class defects with deeper backbones, special loss functions, and data augmentation to improve robustness beyond simple binary defect detection [30][32].

At the plant level, UAV thermal inspection and semantic segmentation networks, like U-Net, FPN, or DeepLabV3+, have been described as yielding IoUs of up to ~0.86 in the localization of defects at the string level [33]. Recent advancements (2024–2025) incorporate attention and ASPP modules on U-Net variants for better generalization against different backgrounds, tiny hotspots, and domain shifts [39],[40],[41]. Lightweight detectors focused on edge deployment further push the ideals of efficiency alongside that of accuracy [8]. On the other hand, electrical-feature classifiers, such as random forests and decision trees, are still to be considered competitive in low-sensor environments due to their speed and interpretability; however, under variations in irradiance and temperature or overlapping faults, their performances tend to drop [33],[38],[42],[43].

In energy forecasting, in the short- to medium-term horizons, recurrent architectures such as LSTM and GRU dominate. Hybrid models incorporating wavelet and multi-resolution decomposition with LSTM denoise and increase hour-ahead accuracy compared to single-model baselines [31]. The ramp tracking and robustness at utility scale are further increased by the Attention-LSTM and the TCN-GRU variants [30],[39]. Day-ahead forecasting is aided by meta-learning, ensemble techniques, and decomposition techniques such as IVMD/CEEMD for non-stationary signals [36],[37]. More recent Transformer-hybrid and probabilistic models help calibration and regime generalization [39],[41]. Neural networks from the RNN, TCN, and Transformer families are among the best at modeling nonlinear temporal dependencies and incorporating exogenous inputs; nevertheless, they also suffer from the problem of data shift and require explainability for operational deployment.

Essentially, CNN/U-Net families are designed to localize faults spatially, whereas RNN/GRU/Transformer families are used for temporal forecasting. Integration strategies that combine image-based FDD with temporal forecasting are now becoming best practices for PV analytics.

TABLE II. COMPARATIVE SUMMARY

Study (Year)	Task / Method	Dataset	Metric / Accuracy	Context
Deitsch et al., Solar Energy (2019) [28]	EL FDD; CNN vs SVM	1,968 EL cells	Acc ≈88% (CNN)	Factory/module QA.
Jin et al., Energy (2019) [29]	EL FDD; lightweight CNN	EL cell dataset	Acc ≈93%	Factory EL screening.
Tang et al., (2020) [30]	EL FDD; deep CNN w/ augmentation	EL multi-class	vs baselines (multi-class)	Robust to class imbalance.
Li et al., (2020) [31]	WPD – LSTM forecasting	Utility plant power	RMSE vs LSTM/SVR	Hour-ahead decomposition.
Sharma et al. (2020) [32]	EL FDD; CNN classification	EL images	Acc vs trad. features	Multi-defect classification.
Li et al., Sensors (2022) [34]	Short-term forecasting; DL	Plant SCADA	MAE/RMSE vs persistence	7.5 – 15-min horizons.
Zhang et al., (2022) [35]	IR hotspot FDD; lightweight CNN	IR video → frames	Acc reported; edge-friendly	Low-cost, embedded.
Bessa et al., (2023) [36]	Meta-learning blend (DA)	Multi-site	MAE vs single models	Day-ahead adaptation.
Wang et al. (2023) [37]	IVMD – DL hybrid (ST)	Utility plant	RMSE/MAE	Noise-robust short-term.
Liu et al. (2024) [38]	EL FDD; improved U-Net	EL images	F1/IoU vs baselines	Handles tiny cracks.
Sousa et al. (2024) [39]	LSTM short-term forecasting	Open EDP/plant data	60-min MAE	Public dataset eval.
Zhang et al. (2024) [40]	Probabilistic ST forecasting (decomp + Vine Copula)	DKASC	Calibrated CRPS	Uncertainty for reserves.
Rahman et al. (2025) [41]	IR FDD ; U-Net + ASPP	Thermal imagery	IoU/F1 ↑ vs U-Net	Robust to background.
Chen et al. (2025) [42]	LSTM – Transformer hybrid (ST)	Multi-plant	MAE/RMSE ↓	Regime-aware short-term.

For fault detection and diagnosis (FDD), either CNN or U-Net outperforms the other when utilizing image and infrared data for precise location determination, particularly with UAV incorporation. Conversely, with low-rate electrical signals, ensemble tree methods are more competitive when supplemented by physics-based features such as string current imbalances or thermal deviations. Decomposition-based hybrids act as a reasonable solution for robustness under non-stationarity for energy forecasting. In FDD and forecasting integration, a promising approach can be made through the inclusion of fault-aware states into predictive models, affording more accurate de-rated deterministic and probabilistic forecasts for grid operation [33] [38-42].

IV. PERFORMANCE EVALUATION

For evaluating AI and ML model performance in photovoltaic (PV) fault detection and energy forecasting, metrics must be carefully chosen, as robustness needs to be verified through real-world deployment requirements. For fault detection, common metrics are accuracy, sensitivity (recall), specificity, and F1-score. For instance, on PV plant data from 16 days of a grid-tied system, when comparing results for KNN, Logistic Regression, Decision Tree, and Naïve Bayes, KNN achieved 99.2% precision and 99.7% AUC-ROC for fault detection with respect to short circuits and shading [43]. Similarly, the KNeighbors meta-learner optimized by DBFLA for fault detection gave accurate results detected by 96.07% accuracy, 96.30% precision, and 96.08%

TABLE III. PERFORMANCE EVALUATION IN LITERATURE STUDIES

Study (Year)	Application & Method	Metrics Reported	Key Result
Chouder et al. (2024) [43]	Fault detection: KNN vs others	Precision, AUC-ROC	KNN: 99.2% precision, 99.7% AUC
Massi et al. (2023) [44]	Fault detection: DBFLA-optimized KNN	Accuracy, Precision, F1	~96% across metrics
Sharma et al. (2022) [45]	Forecasting: LSTM vs CNN-LSTM	RMSE, MAE	CNN-LSTM outperforms LSTM significantly
Khan et al. [46]	Forecasting: attention-LSTM	RMSE, MAE, R^2	RMSE/MAE ↓ up to 29%, R^2 ↑ 31%
Arab at al. (2020) [47]	Forecasting: LSTM with GHI	RMSE, MAE	RMSE ≈0.524 kW; MAE ≈ 0.303 kW
Wang et al. (2022) [48]	Forecasting: hybrid LSTM-GRU	RMSE, MAE, R^2	RMSE=10.63; MAE=2.0; R^2=0.999
Mekki et al. [49]	Forecasting: multimodal vision-language	RMSE, MAE	RMSE ↓ 5 – 7%, MAE ↓ 6 – 9.5%
Muniraj et al. [50]	Forecasting: CNN-LSTM hybrid	RMSE, MAE	Consistently better across horizons
Zhao et al. (2021) [51]	Forecasting: LSTM vs persistence	RMSE skill score	LSTM outperforms persistence
Riganti et al. (2020) [52]	Forecast forecasting: LSTM vs RNN	RMSE, MAE, R^2	LSTM is superior across metrics
Peng et al. (2021) [53]	Fault detection: IR images CNN	F1, IoU	High localization accuracy; efficient
Marquez et al. (2021) [54]	Fault detection: UAV IR segmentation	IoU	IoU ~0.86
Xie et al. (2022) [55]	Fault detection: improved U-Net	F1, IoU	F1/IoU improved
Esposito et al. (2023) [56]	Fault detection: U-Net + ASPP	F1, IoU	Enhanced under real-world scenes
AlShahrani et al. (2025) [57]	Forecasting: CNN-LSTM autoencoder	RMSE, MAE	Best performance across 0.5–2 h horizons

F1-score, showing the influence of optimization methods in increasing detection accuracy [44].

In PV energy forecasting, regression-based metrics such as RMSE, MAE, MAPE, and the coefficient of determination (R^2) are normally applied for error measurement. The comparative investigation informs that hybrid setups like CNN-LSTM do better than standalone LSTM in both short- and long-term horizons by always delivering a lower RMSE and MAE [45]. LSTM attention models also reduced RMSE and MAE by up to 29% and increased R^2 by 31% under adverse weather conditions [46]. Other inputs, such as global horizontal irradiance, meanwhile, were found to enhance forecasting accuracy (RMSE $\approx$0.524 kW, MAE $\approx$0.303 kW) [47]. Hybrid LSTM-GRU models applied to minute-level PV data yielded an RMSE of approximately 10.63, an MAE of roughly 2.0, and an R^2 of approximately 0.999, outperforming individual models [48]. The multimodal PV-VLM framework, which merges imagery and textual inputs, improved RMSE and MAE by ~5% and 6%, respectively. Transfer experiments resulted in a further 7% improvement in RMSE and a 9.5% improvement in MAE [49].

Studies benchmarked in the literature have always placed CNN-LSTM and attention-based architectures as top performers in terms of accuracy with robustness across seasonal and site variations [50][51]. Scalability and real-time applicability are still important; optimized DBFLA-KNN and hybrid LSTM-GRU models provide computational efficiencies required for near-real-time implementation [44],[48]. Overall, these AI methods can bring significant advances in fault detection and forecasting energy output. There is a pressing need for standardized metrics, benchmark comparisons, and scalable solutions for practical PV applications.

V. Challenges and Future Research Directions

Even with several breakthroughs attained in AI- and ML-based methods for PV fault detection and prediction, several key challenges remain. A major limitation is the inability to access labeled fault datasets. Usually, real-world PV installations do not maintain comprehensive annotated data, which is needed for supervised learning strategies to generalize. Synthetic and augmented datasets offer a partial solution but they are unable to replicate the entire gamut of variations of operating conditions [49][50].

Another challenge is set to be the ability to generalize across different climates, seasons, and PV technologies. Models perform well in one geographical or technological set but recognize fast drops in performance when deployed elsewhere owing to the difference in irradiance pattern, temperature dynamics, and system topologies, thus forging a need for domain-adaptive and transfer learning frameworks.

Explainability also has to be carried out in a landscape where safety-critical PV systems are involved. Current deep learning models are frequently operated as black boxes, which is providing limited insights into decision-making processes [51][52].

In addition, the growing reliance on IoT-enabled monitoring raises the cybersecurity issues. These systems are more and more exposed to adversarial attacks and tampering with the data. In order to go into reliable deployment, strong encryption, a resilient edge-based architecture, and secure data pipelines are considered basics [53][54][55].

For making the company get faster, the next research should go in concrete directions. For one thing, the setting up of large-scale open-source benchmark datasets is highly needed. All produced PV fault datasets are either proprietary or limited in some way, giving scant chance to reproduce and compare the work. Community-based ventures that collect EL, IR, UAV thermal imagery, and SCADA data from various environments would set up a base like ImageNet was for computer vision. Well-founded standardized protocols for annotation and shared repositories will guarantee clearer transparency and comparable data.

Second, domain adaptation and transfer learning strategies remain a maximum priority to guarantee model robustness across regions and technologies. Unsupervised domain adaptation, few-shot learning, and cross-plant validation are some of such approaches, which will provide strength to generalization and also lessen the costs of labeling.

Thirdly, integrating explainable AI in PV fault detection and prediction frameworks is of utmost importance. Methods like Grad-CAM, LIME, and SHAP provide excellent explanation tools (visual in some cases or feature level) capable of building user trust concerning automated decisions. Hybrid PV systems that could merge some physics-informed models with various approaches to XAI will thus provide the required accuracy and interpretability.

Fourthly, digital twins integrated with IoT-based monitoring bring prospects for adaptive and predictive PV management. These real-time digital twins can simulate a fault scenario so that they can be used for continuous model updating. Considering additional attributes of cross-PV plant model forming, federated learning frameworks would be implemented in the future as well.

Fifth, security, and robustness shall remain the desiderata. Adversarial robustness testing, secure edge-AI deployments, and intrusion detection systems must be embedded within the AI monitoring pipelines to protect critical energy infrastructure.

Our Perspective is, beyond these directions, we emphasize the underexplored but crucial intersection of cybersecurity and AI-driven PV monitoring. Framing cyber-resilience as a research priority alongside explainability and domain adaptation positions AI not only as a predictive tool but also as part of a secure and trustworthy energy infrastructure. Furthermore, we argue that fault-aware forecasting frameworks, where early fault detection directly informs energy prediction, represent a next-generation research direction. This integrated approach has not been systematically emphasized in prior reviews but is essential for reliable grid-level integration of solar power.

VI. Conclusion

The reviewed literature highlights how artificial intelligence and machine learning have been able to transform PV fault detection and energy forecasting methods. AI-based methods consistently offer accuracy, sensitivity, and robustness that are significantly higher than those obtained via traditional statistical and rule-based approaches, depending on the dataset and operating conditions imposed. The developments impact PV system reliability and safety, making it more efficient, thereby facilitating the integration of the smart grid and sustainable energy infrastructure.

Considering the scalability and real-time application, an introduction is made to IoT monitoring using an edge-AI digital twin methodology for PV predictive and adaptive management. Challenges such as the availability of limited labeled datasets, lack of generalization, and cyber risks, however, are open to research.

Future progress requires standardized datasets, concurrent benchmarking practices, and hybrid explainable models that offer the best compromise between predictive power and interpretability. Developments along these lines are crucial for AI applications used in PV energy systems to gain trust and transparency and be widely adopted [56][57].

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