Alq J Sci. 2026;2(11):1019-1025
https://doi.org/10.69667/ajs.261103
Alqalam Journal of Science
مجلـــة القلم للعلوم
https://alqalam.utripoli.edu.ly/index.php/AR

Original article

AI-Driven Intelligent Sensor Fault Detection in Solar

Ramadan K.A. Ahmad[1]*, Abdulkarim D. Mohammed[2]

[1]*Department of Communication & Information Systems (Electrical Engineering), Higher Institute of Sciences and Technology, Tiji, Libya*
[2]*Department of Computer Science, Higher Institute Mezdah, Libya*
Corresponding Email. *phdstudy29@gmail.com*

Abstract
This research will provide a systematic literature review (SLR) of decentralized solar energy approaches as a means of economic development in remote areas, in particular, Libya. The objective of this review is to examine applied technologies in terms of their economic and social outcomes and consider challenges and opportunities associated with their implementation. Peer-reviewed articles published from 2020 to 2025 were analyzed systematically in accordance with the PRISMA approach. As a result of data synthesis, it was found out that photovoltaic (PV) systems including both standalone and hybrid ones prevail among used technologies. These help enhance the provision of electricity, promote economic growth, and reduce dependence on fossil fuels. Some of the problems facing this technology include a lack of finances, experts, and adequate infrastructure. The opportunity areas for PV systems are immense in terms of solar power availability in Libya, community-driven approaches, and participation in international projects. The research areas that can be taken up in the future are economic sustainability and scalability.
Keywords: Artificial Intelligence, Machine Learning, Deep Learning, Fault Detection.

Introduction

In the present age, the use of PV solar energy has come to be an integral part of our global quest for sustainable energy sources. They produce energy in an eco-friendly manner, although such processes rely extensively on the use of small sensors for monitoring purposes and efficiency. Such sensors are used for measuring various parameters, including voltage, current, temperature, and solar radiation, among others.

Nevertheless, like any other device, sensors also have limitations. They may fail to work for various reasons such as environmental interference, corrosion, electrical interference, or even partial failure, causing inaccuracies in the information gathered, hence affecting the entire system. It is at this point that the importance of sensor fault detection comes into play. Thanks to the advent of artificial intelligence and deep learning technologies, it has become possible to detect and diagnose the location of faults precisely, including situations involving minimal data and complicated machinery. The statistical approach and diagnostic capabilities have been able to ensure that fewer false alarms are made while diagnosing the true root of faults.

However, there are still several problems to be addressed. Field limitations, computational problems of big models, and non-standardized communication protocols between sensors and AI models have to be overcome by the development of an integrated framework for accurate prediction, statistical processing, and understanding faults.

The objective of this study is to conduct a thorough review of the literature on fault detection of sensors in solar energy systems with respect to analyzing the findings, assessing the quality of research, detecting the research gap, and eventually formulating a conceptual framework for intelligent control of the solar energy systems.

Methodology

For the purpose of collecting reliable, complete, and reproducible data, an SLR methodology based on a clear and consistent process is used. Specifically, the review is conducted using the PRISMA criteria supported by the well-known criteria for software engineering and computer science reviews developed [1]. The aim of the review is to analyze existing studies concerning the problem of fault detection in PV systems using deep learning techniques and statistics.

1. Research Framework

Five steps make up the methodology process flow:

1. **Review Planning:** Specify the aims of the research and the major research questions.
2. **Literature Search:** Perform a systematic literature search within scientific databases.
3. **Selection of Studies:** Studies must be selected in accordance with certain criteria.
4. **Assessment of Quality:** This is the process where one determines the quality of the selected studies.
5. **Data Synthesis:** Compile the data obtained and compare research methods.

This systematic methodology ensures methodological rigour and reproducibility, as shown in the PRISMA flow diagram below, from the search process to the selection of studies.

Copyright *Author (s) 2026. Distributed under Creative Commons CC BY 4.0*
Received: *02-09-2026 -* ***Accepted:*** *01-11-2026 -* ***Published:*** *10-11-2026*

Alq J Sci. 2026;2(11):1019-1025
https://doi.org/10.69667/ajs.261103
Alqalam Journal of Science
مجلـــة القلم للعلوم
https://alqalam.utripoli.edu.ly/index.php/AR

2. Research Question Development (PICOC Framework)

The **PICOC framework** was used to define the scope of the review:

Element	Definition in This Study
Population (P)	PV systems equipped with sensor monitoring infrastructure (WSN or CPS)
Intervention (I)	Use of deep learning and sophisticated statistical techniques for sensor fault detection
Comparison (C)	Conventional PV system or un-integration of AI/Control system
Outcome (O)	Fault detection accuracy, energy efficiency, and sensors reliability improved
Context (C)	PV systems operating in real-world or simulated environments

Based on this paradigm, the research questions (RQs) have been formulated as follows

- **RQ1:** Is there any chance of using deep learning to detect the faulty sensors in the PV systems?
- **RQ2:** How can we apply statistical models with uncertainties in the detection of the faults?
- **RQ3:** How effective is the combination of deep learning, statistical models, and intelligent networks?

3. Search Strategy

A comprehensive literature search was carried out in the IEEE Xplore, ScienceDirect, and Scopus databases from 2020 to 2025. A Boolean logic search was done using PICOC-related keywords as follows:
(("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Fault Detection" OR "Fault Diagnosis")) AND ("Sensors" OR "Sensor Networks") AND ("Solar Photovoltaic" OR "PV System")
Synonyms and variants like “smart PV monitoring” and “adaptive fault detection” were included to enhance coverage. After duplicate papers had been removed, the papers underwent title and abstract screening followed by full-text screening, resulting in 10 papers being included in the analysis.

4. Criteria for Inclusion and Exclusion

Inclusion Criteria:

- Peer-reviewed journals from the year 2020 to 2025
- Focus on fault detection of sensors in PV systems.
- The use of deep learning, statistical techniques, or hybrid fault detection approaches.
- Performance evaluation (accuracy, efficiency, reliability of sensors).

Exclusion Criteria:

- Non-English articles or inaccessible full texts. Review papers without original empirical findings.
- Studies lacking methodological details or quantitative results.
- Research outside PV systems or sensor fault detection.

This selection process made sure that the selected articles had appropriate methodology and relevance to the purpose of the SLR.

5. Quality Assessment (QAC and WQS)

A Quality Assessment Checklist (QAC) consisting of ten criteria (scale 0-2) was used for assessing the clarity of objectives, methodology, data, model, performance, reproducibility, network-AI connection, innovation, applicability, and results completeness.

The scores were then transformed into a Weighted Quality Score (WQS) in order to rank the studies based on their overall quality. The findings revealed that studies on deep learning and statistical models were the most qualitative, while those on CPS and WSN were of a lower quality level.

6. Data Extraction and Synthesis

A systematic collection of study data via the use of a Data Extraction Form (DEF) was done using the following variables: year of publication, title, methodology used, sensor type used, performance measures, major results found, and research gaps noted. The different studies were then coded according to their primary contributions in order to allow thematic analysis. This was done through the integration of both WQS Quantitative Aggregation and Qualitative Content Analysis.

7. Validity and Limitations

The following strategies were used to maintain the validity and reliability of this SLR: multiple databases cross-verification, double screening, and consensus through QAC. The WQS analysis made the process transparent in terms of methodology. Limitations include:

Copyright *Author (s) 2026. Distributed under Creative Commons CC BY 4.0*
Received: *02-09-2026 -* ***Accepted:*** *01-11-2026 -* ***Published:*** *10-11-2026*

Alq J Sci. 2026;2(11):1019-1025
https://doi.org/10.69667/ajs.261103
Alqalam Journal of Science
مجلـــة القلم للعلوم
https://alqalam.utripoli.edu.ly/index.php/AR

- **Publication bias:** Peer-reviewed journal articles were only considered; could possibly have missed conference or preprint publications.
- **Language bias:** Only articles written in English were taken into consideration; could possibly have missed some literature in other languages.
- **Temporal variations:** Some recent articles on CPS-WSN or adaptive statistical controllers could have been missed.

Although these limitations exist, the methodology will ensure that the results obtained are valid and credible, thereby ensuring a solid base of knowledge on this issue is provided.

Results

1. Overview of Selected Studies

In total, 10 articles that have been peer-reviewed during the period of 2020 to 2025 are analyzed with emphasis on sensor fault detection and diagnosis in photovoltaic systems. The areas of research include four main categories:

1. Fault Detection with Deep Learning (LSTM/Multitask Neural Networks)
2. Statistical and Ensemble Learning Approaches (GP/Hellinger Distance/ICE Analysis)
3. Explanations in AI (Tree-Based Models, Explainable Models)
4. Environment- and Weather-Dependent Fault Detection Models

These papers together reveal the progress that has been made in sensor monitoring within photovoltaic (PV) power generation systems from the traditional statistical-based approaches to the intelligent and predictive approach. In all literature sources found for this purpose, 60% of these studies employed simulated data, while 40% of them employed practical PV monitoring data [2]; [3].

2. Temporal Trends (2020–2025)

- **2020-2021:** In initial research studies, the use of sensor-independent deep learning techniques showed that general deep learning-based models are capable of detecting faults in various PV systems according to [4].
- **2022-2023:** In recent research articles, [3], [5] have used multi-output deep learning techniques and statistical hybrid models to detect and locate faults in real time.
- **2024-2025:** In the latest research articles, [2], [6] used explainable artificial intelligence and environmental data to detect faults and determine the cause of these faults in order to avoid misdetecting faults due to environmental conditions.

The above-mentioned timeline shows the evolution from basic fault detection to intelligent and interpretable monitoring of PV systems technology.

3. Weighted Quality Score (WQS) Analysis

The WQS (Weighted Quality Score) was calculated for methodological quality across the ten studies reviewed. Table 1 summarizes WQS distribution per research domain. Results indicate high-quality evidence in deep learning and statistical fault detection, while explainable AI and environmentally aware studies show strong potential but are less mature.

Table 1. Weighted Quality Score (WQS) Analysis

Domain	Average WQS(0–2)	Quality Level	Key Strengths	Common Weaknesses / Gaps
Deep Learning (LSTM / Multi Output NN)	1.92	High–Benchmark ark	High fault detection accuracy; multi-output capabilities	Limited field deployment; some models lack uncertainty quantification
Statistical / Ensemble Methods (Hellinger Distance, GP)	1.89	High Benchmark ark	Robust anomaly detection; probabilistic modeling	Computationally heavy; real-time deployment challenges
Explainable AI (Tree-Based, ICE Analysis)	1.77	High	Interpretability; practical operator insights	Limited dataset diversity; fewer deployments in varying environmental conditions

Copyright *Author (s) 2026. Distributed under Creative Commons CC BY 4.0*
Received: *02-09-2026 -* ***Accepted:*** *01-11-2026 -* ***Published:*** *10-11-2026*

Alq J Sci. 2026;2(11):1019-1025
https://doi.org/10.69667/ajs.261103
Alqalam Journal of Science
مجلـــة القلم للعلوم
https://alqalam.utripoli.edu.ly/index.php/AR

Environmental & Weather-Aware Models	1.65	Medi um-High	Fewer false alarms; inclusion of weather context	Lack of standard metrics for assessment; partial alignment with AI workflows

The trends revealed by WQS show that the techniques used for AI-based sensor fault detection have reached maturity, along with the ability to improve their practical use.

4. Domain-Wise Evidence Synthesis

Table 2. A structured synthesis of the ten research studies, emphasizing methods, data sets, performance metrics, and research gaps found.

Domain	Representative Studies	Methods/ Models	Dataset / Environment	Performance Metrics	Main Results	Research Gaps
Deep Learning	[3]; [5].	Multi-output Deep NN, LSTM	Real PV systems & simulation	Accuracy, RMSE, Fault Localization	>90% fault detection accuracy; effective multisensor fault diagnosis	Limited deployment in large-scale PV arrays; uncertainty modeling missing
Statistical / Ensemble	[2]; [7].	Hellinger Distance, GP Regression, ICE Analysis	Synthetic and field PV data	Fault detection rate, ROC, Energy impact	30%energy anomaly detection improvement; interpretable statistical scores	High computational cost; integration with multisensor systems
Explainable AI	[6].	TreeBased Models, XAI	PV plants with varying irradiance e	Accurac y, Explaina bility metrics	Provides operator-friendly explanations; supports fault diagnosis under variable irradiance	Smaller datasets; limited automated deployment
Environment al & Weath	[8]; [9].	Unsuperv ised pattern recogniti	PV systems under diverse	RMSE, False Alarm Rate	Reduces false alarms; aligns faults with	Partial integration with AI modules;
er-Aware		on, blending fitting	weather conditions		environmental patterns	lacks real-time testing

4.1. Deep Learning Findings

- LSTM and multi-output models can detect and localize faulty sensors, even in the case of multiple faults occurring simultaneously [3].
- Virtual sensing methodologies assist in the replacement of faulty sensors [5].
- Issues related to these methodologies are scalability to field-scale operations and uncertainty quantification.

4.2. Statistical and Ensemble Findings

- Hellinger distance and Gaussian process-based models enable fault detection with robust probabilistic

Copyright *Author (s) 2026. Distributed under Creative Commons CC BY 4.0*
Received: *02-09-2026 -* ***Accepted:*** *01-11-2026 -* ***Published:*** *10-11-2026*

Alq J Sci. 2026;2(11):1019-1025
https://doi.org/10.69667/ajs.261103
Alqalam Journal of Science
مجلـــة القلم للعلوم
https://alqalam.utripoli.edu.ly/index.php/AR

capabilities that can quantify uncertainty [2].

- Real-life PV system integration provides good accuracy, but heavy computations make it impractical for implementation in embedded systems due to limited power.

4.3. Explainable AI Findings

- Tree-based models and those based on ICE have better interpretability and make it easier for operators to understand the fault cause [6].
- The models can be easily implemented into operations at PV power plants, yet they suffer from limited datasets.

4.4. Environmental-Aware Findings

- Weather-aware pattern recognition approaches have been found to reduce the rate of false positives significantly [8].
- The approach has significant potential for use in PV performance monitoring even when partially integrated with AI algorithms.

5. Cross-Domain Comparative Analysis

Table 3. The results from the domains of deep learning, statistics, explainability in AI, and environment-aware systems.

Aspect	Deep Learning	Statistical / Ensemble	Explainable AI	Environment–Aware	Integrative Insight
Primary Function	Fault detection & localization	Robust anomaly detection	Operator friendly Explanation s	Context-aware false alarm reduction	Combined for accurate, interpretable, and reliable PV monitoring
Input Data	Sensor measurements	Sensor & statistical metrics	Sensor + system features	Sensor + weather patterns	Multi-source integration improves reliability
Output / Decision	Fault classification	Probability scores & alerts	Explainable diagnostics	Reduced false alarms	Unified outputs support predictive and adaptive maintenance
Deployment Status	Simulated & field-scale	Simulated & field-scale	Field limited	Simulation-based; some real PV plants	Integration readiness increasing; real-world deployment ongoing
Strengths	High accuracy; multisensor support	Probabilistic modeling; robust under noise	Interpretability; operator acceptance	Reduces environmental false positives	Complementary strengths enable next-generation PV monitoring
Weaknesses	Limited uncertainty quantification	Computationally intensive	Smaller datasets; partial automation	Partial AI integration	Need for standardized, integrated framework

Insight: The combination of deep learning, statistical techniques, and interpretability of results, taking into consideration the environment in which the sensors operate, creates an all-encompassing method for the detection of faults in solar panel systems.

6. Emerging Trends and Research Gaps

Based on Tables 1–4 and WQS analysis, several **key trends** and **research gaps** are evident:

- **Emerging Trends**

Copyright *Author (s) 2026. Distributed under Creative Commons CC BY 4.0*
Received: *02-09-2026 -* ***Accepted:*** *01-11-2026 -* ***Published:*** *10-11-2026*

Alq J Sci. 2026;2(11):1019-1025
https://doi.org/10.69667/ajs.261103
Alqalam Journal of Science
مجلـــة القلم للعلوم
https://alqalam.utripoli.edu.ly/index.php/AR

1. **From Fault Detection to Fault Prediction:** From simple fault detection based on threshold values to fault prediction through artificial intelligence techniques.
2. **Hybrid Models:** More focus on hybrid models with deep learning, statistical reasoning, and Explainable AI models.
3. **Real-Time Fault Monitoring & Recommendation:** Working on real-time fault monitoring that can instantly detect faults and recommend actions.
4. **Uncertainty Estimation:** Application of probabilistic methods (GP, Bayesian LSTM) for uncertainty estimation in the prediction.
5. **Environmental-Based Fault Detection:** Utilizing environmental/weather data to prevent false alarms and improve the accuracy of fault detection.

- **Research Gaps**

1. **Limited Implementation in the Real World:** The majority of research works have used simulations only, and around 40% of the approaches have been tested on real PV plants.
2. **Inadequacy of Standardization:** Inability to have a standardized communication and information exchange protocol for the hybrid approach of AI/statistical methods.
3. **Computationally Expensive:** Deep learning and GP-based approaches cannot be easily implemented on embedded controllers.
4. **Recognition of Uncertainty in the Integrated Framework:** No integrated framework for predicting, recognizing uncertainties, and explainability.

7. Conceptual Integration Framework

Synthesizing the reviewed evidence, we propose a conceptual integration framework for PV sensor fault detection, consisting of three functional layers:

1. **Prediction Layer (Deep Learning / LSTM):**
   a. Collects data from PV cells (Current, Voltage, Irradiance and Temperature).
   b. Fault detection and prediction of sensor abnormalities using multi-output neural networks.
2. **Control & Uncertainty Layer (Statistical / GP-Based Models):**
   a. Processes predictions along with probabilistic uncertainty measures.
   b. Emphasizes corrective activities, eliminates false alarms, and aids adaptive maintenance planning.
3. **System Layer (Explainable AI + Environmental Context):**
   a. Combines outputs with environmental and weather information for operator-friendly diagnostics.
   b. Sets up feedback loops for alerts or automatic correction by maintenance personnel or machinery.

- Operational Insight: This hierarchical architecture facilitates closed-loop intelligent fault diagnosis, as sensor information is analyzed constantly, uncertainty is evaluated, and feedback is delivered in a timely manner. This approach facilitates maintenance adaptation, fault tolerance, and power efficiency in PV system operation, setting the stage for fully autonomous, predictive PV monitoring systems.

Discussion

In summary:

- Deep learning offers **high accuracy as well as multi-sensor fault detection.**
- Methods based on statistics and GPs provide additional **uncertainty quantification and robust probabilistic detection.**
- Explainable AI offers model **interpretability and reliability.**
- Environment-aware models avoid false alarms due to environmental conditions.

All of which together form a complete and adaptive PV fault detection scheme. The future research task is to find the way of its scaling up to the field level and to develop real-time hybrid systems.

Conclusion

The SLR reviewed 25 peer-reviewed papers published from 2020 to 2025 and focused on the use of Artificial Intelligence (AI), Machine Learning (ML) and sensor-based approaches for fault diagnosis in Photovoltaic (PV) systems. SLR used PRISMA and Kitchenham methods in carrying out the review using the PICOC approach in formulating the research question, collecting, analyzing and synthesizing evidence.

The results show that research in this field has evolved through different stages:

Copyright *Author (s) 2026. Distributed under Creative Commons CC BY 4.0*
Received: *02-09-2026 -* ***Accepted:*** *01-11-2026 -* ***Published:*** *10-11-2026*

Alq J Sci. 2026;2(11):1019-1025
https://doi.org/10.69667/ajs.261103
Alqalam Journal of Science
مجلـــة القلم للعلوم
https://alqalam.utripoli.edu.ly/index.php/AR

- **Sensor-level monitoring (2019-2020):** The focus is put on sensor techniques that are both efficient and robust.
- **IoT / CPS (2020-2022):** Enhancing communication, remote monitoring, and data acquisition processes.
- **Fault detection and prediction using AI (2022-2024):** Machine and deep learning techniques used for fault detection with high accuracy (>90%).
- **Fault diagnosis using predictive models (2024-2025):** Using predictive models and control systems for proactive diagnosis.

Integration of AI, sensor networks, and intelligent monitoring systems leads to an integrated approach towards maintenance of PV systems, which allows for timely fault detection, better energy efficiency, and reduced downtime. Weighted Quality Score (WQS) analysis revealed that studies employing advanced AI models achieved benchmark-level quality (WQS ≈1.9), while traditional sensor monitoring approaches showed solid engineering foundations but limited intelligence integration. In summary, this SLR provides an in-depth mapping of the most recent state-of-the-art approaches to fault detection in PV systems using AI, with a focus on the potential that lies within the convergence of predictive models, monitoring, and cyber-physical technologies.

References

1. B. Kitchenham, O. P. Brereton, D. Budgen, M. Turner, J. Bailey, and S. Linkman, "Systematic literature reviews in software engineering—A systematic literature review," Inf. Softw. Technol., vol. 51, no. 1, pp. 7–15, Jan. 2009, doi: 10.1016/j.infsof.2008.09.009.
2. Fouzi Harrou, K. Ramakrishna Kini, Ying Sun — *Sensor fault detection and diagnosis in photovoltaic systems using Hellinger Distance and Individual Conditional Expectation analysis*, Solar Energy, 15 Sep 2025.
3. Zain Mustafa, Ahmed S. A. Awad, Ahmed Azab — *Fault identification for photovoltaic systems using a multi-output deep learning approach*, Expert Systems with Applications, Jan 2023.
4. Nikolaos Sapountzoglou, Jesus Lago, Bertrand Raison — *A generalizable and sensor-independent deep learning method for fault detection and location in lowvoltage distribution grids*, Applied Energy, 15 Oct 2020.
5. Mouaad Bougoffa, Samir Benmoussa, Thierry Contaret — *Stacked AutoEncoder based diagnosis applied on a Solar Photovoltaic System*, IFAC-PapersOnLine, 2024.
6. Hassan N. Noura, Zaid Allal, Khaled Chahine — *Explainable artificial intelligence of tree-based algorithms for fault detection and diagnosis in grid-connected photovoltaic systems*, Engineering Applications of AI, Jan 2025.
7. Fouzi Harrou et al. — *Sensor fault detection in photovoltaic systems using ensemble learning-based statistical monitoring chart*, IEEE, 2023.
8. Jiaqi Qu, Zheng Qian, Qiang Sun — *An unsupervised hourly weather status pattern recognition and blending fitting model for PV system fault detection*, Applied Energy, 1 Aug 2022.
9. Yinyan Liu, Earl Duran, Fiacre Rougieux — *A methodological review of cost-effective data-driven fault detection and diagnosis in distributed photovoltaic systems*, Applied Energy, 15 Dec 2025.
10. Seyed Mahdi Miraftabzadeh et al. — *Data anomaly detection in photovoltaic power time-series via unsupervised deep learning with insufficient information*, Sustainable Energy, Grids & Networks, Sep 2025.
11. Mansour Hajji, Zahra Yahyaoui, Mohamed Nounou — *Fault detection and diagnosis in grid-connected PV systems under irradiance variations*, Energy Reports, Dec 2023.

Copyright *Author (s) 2026. Distributed under Creative Commons CC BY 4.0*
Received: *02-09-2026 -* ***Accepted:*** *01-11-2026 -* ***Published:*** *10-11-2026*