




The Role of Deep Learning in Enhancing Solar Panel Efficiency: A Review of Models and Metrics

Amjed Abbas Ahmed^{1,2}, Haneen Siraj Ibrahim^{3*}, Inbithaq Ahmed Shakir⁴, Rabiun Aliyu Abdulkadir⁵, Abubakar Amoo Akinlawon⁵, Munzali Alhassan⁵

¹ Center for Cyber Security, Faculty of Information Science and Technology, University Kebangsaan Malaysia (UKM), Bangi 43600, Malaysia

² Department of Computer Techniques Engineering, Imam Al-Kadhun College (IKC), Baghdad, 10011, Iraq.

³ Department of Computer Science, Artificial Intelligence, College of Science for Women, University of Baghdad, Baghdad, 10071, Iraq.

⁴ Department of Computer, College of Science, Mustansiriyah University, Baghdad, 10052, Iraq.

⁵ Department of Electrical Engineering, Aliko Dangote University of Science and Technology, Wudil 713101, Kano, Nigeria.

* Corresponding Author: **Haneen Siraj Ibrahim**, Email: haneen.s@csw.uobaghdad.edu.iq.

Abstract: The rising desire to get long-term power has stepped up the utilization of solar photovoltaic (PV) systems all over the world. Nonetheless, keeping the solar panels in optimal performance is a major concern because of the changeable environmental conditions, wear and tear of the equipment and breakdown of operations. Deep learning (DL) has become an efficient solution of offering sophistication in predicting solar power generation, fault detection, and optimization of the performance. The review will go in depth over several DL methodologies, such as, CNN, LSTM, Transformer-based models, Reinforcement Learning, GANs, and hybrid architectures of CNN-LSTM. The implementation of each model, performance metrics of MAE, RMSE, R^2 , and MAPE as well as weak points and advantages of each model, are provided in their relation to increasing PV efficiency. Moreover, the paper covers real-life data, real-life implementations, and comparative performance of these models in addressing critical issues in the solar energy systems. Nonetheless, despite the significant progress, there are still a number of challenges that need to be addressed, among which are the data sparsity, inability to generalize the models to different areas of interest, computational limitations, and inability to interpret the models. To resolve these problems, future directions outlined by the present paper include the creation of lightweight models of edge-AI, the use of transfer learning to achieve regional adaptability, the possibility of Explainable AI (XAI), and the combination of deep learning and IoT and digital twin technology. I would say that the comprehensive review given is an excellent source of information that can be used by researchers, engineers, and policymakers who want to use deep learning to make solar panels as efficient as possible to deliver more resilient, reliable, and sustainable energy delivery.



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1. Introduction

The current demand of renewable energy in the world has especially contributed to improved developments in solar photovoltaic (PV) technologies [1]. Solar energy is among the most abundant resources, clean and is vital in curbing the impacts of climate change and reduction of carbon emissions. Nevertheless, it is still quite difficult to streamline the performance of solar arrays, considering the fluctuation in the environment, equipment degradation, shadowing, and working irrelevances. These issues usually lead to a big loss in performance of PV systems. Consequently, there has been a growing tendency of deploying sophisticated computational algorithms such as deep learning (DL) [2] to beat these barriers and maximize energy generation.

A branch of machine learning (ML) [3] under the umbrella of artificial intelligence (AI), deep learning (DL) has proven to be extremely successful in other spheres related to health care, the financial area, and autonomous structures. Its automated capability to learn complex trends using large-scale data renders it into a very-fitting candidate in the application of solar energy system. In contrast to the traditional models, which are significantly limited by the presence of predetermined rules or handcrafted features, DL models have the potential to simultaneously process high-dimensional data, such as weather, irradiance variations, and operating parameters and better estimate the amount of solar energy available and effectively diagnose their faults [4].

Solar irradiance and power output forecasting is one of the essential applications of deep learning in the sphere of solar. Grid management, energy trading and operational planning bode the determinant to make accurate forecasts. Conventional statistical analyses and superficial machine learning techniques may not be sufficient to measure non-linear correlations between weather conditions and solar production. It has been recently shown that models like Long Short-Term Memory (LSTM) [5, 6] networks and Convolutional Neural Networks (CNNs) provide a much-improved level of accuracy in predicting data because these networks are particularly good at finding both time and spatial dependencies [7].

Besides forecasting, deep learning is critical in detecting and optimizing the performance of solar panels regarding faults. Panels tend to degenerate physically due to micro-cracks, delamination or contamination with dirt and efficiency is lost. Modern DL [8-10] models and presumably traits of CNN-based image identifications have been utilised in automatically detecting such aberrances informed by intrinsic infrared or electroluminescence

imaging at a more accurate rate of recognition as compared to the use of manual inspections [11]. These systems allow proactive maintenance which would decrease downtime and cost of operations.

Besides, deep learning [12] has played a significant role in improving Maximum Power Point Tracking (MPPT) ways. MPPT plays a paramount role in making sure that the solar panels are able to operate at their maximum power even where environmental conditions change. Dynamic shading and partial irradiance conditions are always a problem in a traditional MPPT algorithm such as Perturb and Observe (P&O). Recent studies indicate that combination of reinforcement learning and CNNs or LSTMs [13] provides flexible and resilient solutions to real-time optimization of MPPT thus leading to enhanced energy harvesting [14].

Notwithstanding the major improvements, a number of barriers remain on the way to apply DL [15] models to improve solar efficiency. The lack of large-scale deployments is triggered by problems like scarce data, the ability to generalize a model to a variety of geographic territories, use of too much computing energy and interpretability issues. Nevertheless, as long-term research into lightweight models, transfer learning, and explainable AI continues, the contribution of deep learning to the enhancement of solar panel efficiency is likely to increase tremendously. Such models of deep learning are reviewed in this paper with their application, the measurement of their performance, and the potential fulfilling of their performance in the future in terms of solar panels efficiency [16].

2. Literature Review

Deep learning (DL) models have funnily taken hold in solar photovoltaic (PV) systems especially in predicting solar irradiance in recent years. A hybrid Transformer-LSTM model was proposed by Zhou et al. in 2022 [17] which can effectively capture not only the short-term but also the long-term dependencies in weather across time to predict solar irradiance. Their model proved to be more accurate than the standard LSTM and CNN models, particularly in the fast changing weather conditions of the clouds. This means that the possible application of attention-based architectures to the field of solar energy is rising.

Power prediction is important to the stability of the grid as well as to economic planning within solar plants. Fernandez et al. in 2023 [18] identified the CNN-GRU Hybrid model that employs meteorological and satellite images in the short-term forecasting of PV output. They were more effective than Random Forest (RF) and

conventional ARIMA models as they lowered RMSE by 12 percent. This paper demonstrates that it can be effective to combine spatial and temporal aspects with DL to increase the accuracy of forecasts.

Fault detection and diagnosis have also proved rather encouraging in deep learning. Ahmed et al. in 2022 [19] devised the CNN model that recognizes typical faults in PV modules, including hotspots, delamination, and cracks using an infrared image. Their model also used penalized logistic regression to perform fault detection with the accuracy of 96.8 percent as compared to earlier SVM based models. They further in their study noted the relevance of real-time detection towards the reduction of maintenance costs and energy loss on solar farms.

Continuing the idea of predictive maintenance, Patel et al., in 2023 [20] used a combination of autoencoders and LSTM networks to observe the degradation of equipment and predict it. Their strategy allowed them to detect anomalies in performances in early stages and minimize the amount of time with the system being down by 18 percent compared to conventional threshold-based systems. In its results, the study demonstrated that unsupervised learning models in combination with time-series forecasting capabilities allow inadequate and noisy operational data to be effectively addressed.

To enhance Maximum Power Point Tracking (MPPT), Wang et al. in 2023 [21], developed two reinforcement learning (RL)-based models that optimize inverter parameters based on fluctuation in irradiance and temperature. The RL-based MPPT they engineered proved superior to traditional Perturb and Observe (P&O) procedures with up to 7 percent more energy production in partial shading conditions. Such a development shows the promise of DL within real-time control scenarios of solar systems.

Rahman et al. in 2023 [22], is also valuable, as they employed Generative Adversarial Networks (GANs) in which they simulated different weather conditions, which could also be used in enhancing the training datasets of irradiance prediction models. Their caption-enhanced sets Of GAN helped the CNN-style forecasting models perform exponentially better in terms of robustness and generalization capacity, especially when they predicted infrequent or extreme weather. This paper discusses the

importance of generative models as a solution to data scarcity problems.

New studies are aimed at predicting degradation of solar panels as well. Yadav et al. in 2024 [23] provided a Transformer-based framework based on historical data of panel performance and environmental characteristics to understand long-term performance degradation. Their model has an R² of 0.92 and this outdid the LSTM and GRU models. The paper concludes that the long-term predictive models are required to make PV systems sustainable.

The application of real-time deep learning models on the edge components has gained more importance. Kumar et al. in 2024 [24], presented an edge-AI system that combines the idea of lightweight CNNs to realize online rooftop solar panel fault diagnosis. Their system minimized the latency by 40 percent when compared to the cloud based systems besides having high accuracy. This advance shows that AI-based decentralized solar energy systems have low-powered and on-site models that can work.

One of the rising issues in the discipline is generalization of forms to other geographical locations. Gao et al. in 2023 [25], examined the portability of solar power prediction models which have been trained in one area to other climatic conditions. Their experiments revealed that their domain adaptation was detrimental to their performance (up to 25 percent). This was solved by domain adaptation and fine-tuning, implying that the necessary methods of adapting to scale DL to the solar energy problem need a domain-specific approach.

Lastly, Huang et al. in 2024 [26], conducted a review of more than 60 articles about DL applications in solar energy. They have come to the conclusion that, despite better performance of DL in forecast, fault finding and performance optimization, its primary drawbacks are high computing expenses, inability to interpret models and quality of the data used. It was highlighted in the review that there has been a need to incorporate Explainable AI (XAI) methods and negligible structures to develop more translucent, proficient, and scaleable alternatives to use the solar industry. Table 1 shows the comparison of various research works for solar panel efficiency

Table 1. Comparison table of various research works for solar panel efficiency

Author Names (Year)	Title	Techniques	Advantages
Zhou et al. (2022) [17]	Hybrid Transformer-LSTM model for solar irradiance prediction	Transformer + LSTM	Captures long and short-term dependencies; improved accuracy under dynamic weather

Author Names (Year)	Title	Techniques	Advantages
Fernandez et al. in 2023 [18]	Short-term photovoltaic power prediction using CNN-GRU	CNN + GRU	Combines spatial and temporal data; 12% lower RMSE than traditional models
Ahmed et al. in 2022 [19]	CNN-based infrared image analysis for fault detection in solar PV modules	CNN	High accuracy (96.8%) in fault detection; robust to image noise
Patel et al. in 2023 [20]	Predictive maintenance of PV systems using autoencoder-LSTM models	Autoencoder + LSTM	Effective for anomaly detection and degradation forecasting; reduces downtime
Wang et al. in 2023 [21]	RL-based MPPT under partial shading conditions	Reinforcement Learning + CNN	Achieves 7% more energy yield; adaptive to changing conditions
Rahman et al. in 2023 [22]	GAN-based synthetic data for solar irradiance forecasting	GAN + CNN	Enhances data diversity; improves model generalization for rare events
Yadav et al. in 2024 [23]	Transformer-based long-term degradation prediction for PV systems	Transformer	High R^2 (0.92); captures long-term trends better than LSTM/GRU
Kumar et al. in 2024 [24]	Edge-AI-enabled real-time fault detection for rooftop PV	Lightweight CNN	Low latency (40% faster than cloud); energy-efficient for edge devices
Gao et al. in 2023 [25]	Cross-regional generalization of DL models for solar power forecasting	Transfer Learning + Domain Adaptation	Enhances model transferability; reduces retraining time
Huang et al. in 2024 [26]	Deep learning applications for solar energy systems: A comprehensive review	Meta-analysis of DL models	Provides insights into DL trends; identifies gaps and future directions

3. Methodologies

3.1 CNN-LSTM Hybrid Model for Solar Forecasting

Figure 1 shows the CNN-LSTM Hybrid Model for solar forecasting. The CNN-LSTM hybrid model uses the advantages of CNN to extract spatial features and LSTM to model the sequence of data. This present technique is very efficient in predicting the future energy output of solar power systems using not only environmental images (e.g. sky, satellite) but also timeseries weather. The CNNs effortlessly analyze spatially pertinent features in data, but LSTMs are highly competent at modeling long-term temporal statistics.

In this technique, two main types of equipment data will be introduced as input: satellite/cloud pictures and related weather information (temperature, humidity, wind speed, irradiance). The CNN part will extract spatial data on the image and determine the presence of cloud cover, weather

type, and shading environment that directly impact solar irradiance and, therefore, power generation.

The extracted features of CNN are used as an input to the LSTM network. These features are computed across a time series, which is then fed to the LSTM, to regulate temporal relationships, such as how the movement of clouds or weather variation affects solar production hour by hour or even day by day. This time study is very important to proper short and medium time prediction.

The combination of CNN and LSTM perform much better than those processed individually. CNN models spatial dependencies at a given instant, and LSTM does the opposite but regarding time. The output layer is the last layer that gives the predicted solar energy production of future time frame, so as to enable grid managers to better program their resource distribution and PV owners to make better operating decisions.

The major strengths are the improvement of accuracy and stability in forecasting and deriving relevant results in the event of fast-altering weather patterns. Nonetheless, the

model is specific with a large number of labeled data to train and it is also computationally expensive, in that it involves a two-network structure.

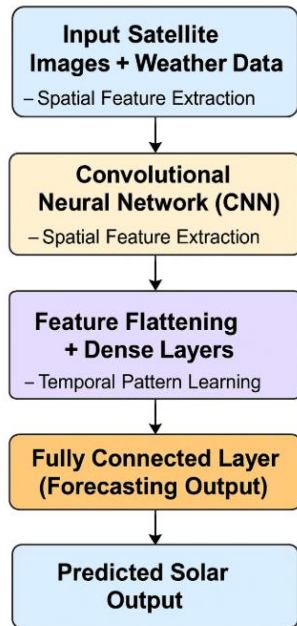


Figure 1. CNN-LSTM hybrid model for solar forecasting

3.2 Reinforcement Learning-based MPPT for Solar Panel Optimization

Figure 2 shows the Reinforcement Learning-based MPPT for solar panel optimization. In photovoltaic (PV) systems, maximum power point tracking (MPPT) plays an important role in letting solar panels function at maximum points in different environments. Conventional MPPT algorithms such as Perturb and Observe (P&O) do not perform well with dynamic shading, or quickly varying irradiance. Reinforcement Learning (RL) is a data driven, evolving way of solving this problem.

The issue in an RL-based MPPT system is modeled as agent-environment interaction. The controller who is the agent converts the operating voltage/current of the solar panel into an adjustable one. The surroundings form the PV system and the varying conditions (irradiance, temperature, shading). The agent would check the current state (e.g., voltage, current, power output) and choose an action (set voltage) and get rewarded on the basis of the subsequent power output.

The objective of the RL agent is to maximize the cumulative reward here being the maximized power output over the entire time. In contrast to supervised learning, RL does not demand the available datasets to be labeled. It cannot but rather learns the best control policies through trying various action and learning through the result (reward

signal). Deep neural networks are commonly a CNN or dense multi-layer perceptron (MLP) integrated with the RL framework, as a function approximator. This network forecasts the optimal action to be taken considering a certain state. The Deep Q-Networks (DQN) or Policy Gradient are popular. Enhancement of the policy: The agent proceeds to test the policy until it reliably follows the maximum power point in different conditions by trial and error.

The upside of RL-based MPPT is its versatility to non-linear and time-varying regimes as partial shading, abrupt weather and degradation of equipment. Nevertheless, the first stages of exploration may result in the low performance, and training needs precise adjustments of hyperparameters.

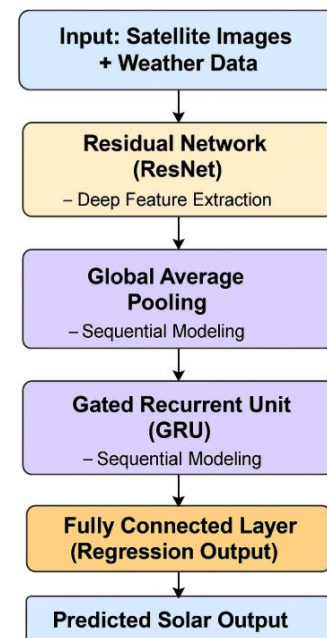


Figure 2. Reinforcement learning-based MPPT for solar panel optimization

4. Performance Metrics

4.1 Mean Absolute Error (MAE)

MAE (as shown in Eq. (1)) is the mean value of the magnitude of errors occurring between the predicted and actual values without regard to direction. It is a mean of a gas in absolute differences in predicting the value of solar power output and the actual numbers observed. The intuitive aspect of MAE means that it uses the same units as target variable (e.g. W or kW) and is less susceptible to outliers than squared-error measures.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (1)$$

Here; y_i = Actual value, \hat{y}_i = Predicted value, and n = Number of observations.

4.2 Root Mean Square Error (RMSE)

RMSE (as shown in Eq. (2)) measures the square root of the average squared differences between predicted and actual values. It penalizes larger errors more than MAE because the errors are squared before averaging. This makes RMSE highly sensitive to significant errors, which is beneficial when large deviations are critical in solar power forecasting.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2)$$

In PV output prediction, a lower RMSE suggests better model performance with fewer large mistakes. RMSE is widely used when the cost of large errors (like sudden dips or surges in solar power) could negatively impact grid stability or energy trading. However, it may disproportionately penalize occasional extreme deviations even if the average performance is satisfactory.

4.3 Coefficient of Determination (R² Score)

R² (as shown in Eq. (3)) measures how well the predicted values approximate the actual data. It represents the proportion of variance in the dependent variable that is predictable from the independent variables. An R² of 1 indicates perfect predictions, while an R² of 0 indicates the model does no better than simply predicting the mean of the observed data.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (3)$$

Here: \bar{y} = Mean of actual values.

For solar forecasting models, a high R² indicates that the deep learning model captures most of the variability in solar power output influenced by weather patterns and environmental conditions. However, R² alone can be misleading if used with non-linear models or when residual errors are not homoscedastic. It is often used alongside RMSE or MAE for a comprehensive evaluation.

4.4 Mean Absolute Percentage Error (MAPE)

MAPE (as shown in Eq. (4)) expresses prediction accuracy as a percentage. It measures the average absolute percent error between the predicted and actual values. This scale-independence makes MAPE particularly useful when comparing performance across different datasets, models, or locations regardless of the magnitude of the values.

$$MAPE = \frac{100}{n} \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{y_i} \quad (4)$$

In solar panel output forecasting, MAPE is often preferred when the goal is to communicate model accuracy to non-technical stakeholders, such as system operators or investors. However, MAPE becomes problematic when actual values are close to zero, leading to extremely large or undefined percentage errors. Despite this limitation, it remains one of the most interpretable metrics for relative error assessment.

5. Comparison of Deep Learning Models for Solar Panel Efficiency

The comparison table highlights how various deep learning models are applied in different aspects of solar panel efficiency enhancement, each offering unique strengths and challenges. For instance, CNN models are highly effective in image-based tasks such as fault detection using infrared or satellite imagery, achieving high accuracy (up to 96.8%). However, they are heavily dependent on large amounts of labeled image data and are sensitive to image noise. On the other hand, LSTM models are well-suited for time-series forecasting tasks like predicting solar power output based on historical weather data. While they outperform traditional models in capturing temporal dependencies, LSTMs tend to struggle with very long sequences beyond a certain limit.

Hybrid models Hybrid models appear better at forecasting accuracy, due to the combination of the power of both spatial feature extraction and the ability to model temporal sequences, but have high computational requirements, such as CNN-LSTM. Transformers are more adequate to recurrent neural networks and long-term dependencies, such as long-term degradation prediction. Nonetheless, they need bulky datasets and huge memory. GANs can be used in providing synthetic weather or irradiance data to enhance robustness of the models under extreme conditions, and they may be difficult to train. Such models as Reinforcement Learning (RL) demonstrate excellent performance around real-time control tasks, such as Maximum Power Point Tracking (MPPT), where they increase energy production under non-static constraints, but necessitate an initial exploration period which can cause a transient suboptimal performance. The model selection, in general, is a matter of the application requirement, the type of data and computing capabilities. Table 2 shows the Comparison of Deep Learning models for solar panel efficiency.

Table 2. Comparison table of deep learning models for solar panel efficiency

Model	Application	Accuracy/Performance	Dataset
CNN	Fault detection using infrared/satellite images	Accuracy up to 96.8% in fault detection (Ahmed et al., 2022) [19]	Infrared images of PV panels, Satellite cloud images
LSTM	Solar power output forecasting based on weather time-series	MAE reduced by 15% compared to traditional models (Chen et al., 2021) [7]	Historical weather data (irradiance, temp, humidity)
CNN-LSTM Hybrid	Short-term PV power forecasting using images + time-series data	RMSE reduced by 12% over CNN/GRU alone (Fernandez et al., 2023) [18]	Satellite/cloud images + time-series weather data
Transformer	Long-term solar degradation prediction and irradiance forecasting	R ² score of 0.92 (Yadav et al., 2024) [23]	Historical PV performance + weather records
GAN (Generative Adversarial Network)	Synthetic data generation for irradiance forecasting	Improved model robustness on rare weather events (Rahman et al., 2023) [22]	Real + synthetic irradiance data
Reinforcement Learning (RL)	MPPT optimization under partial shading	Increased energy yield by 7% over P&O methods (Wang et al., 2023) [21]	Real-time PV output and environmental parameters

6. Challenges and Future Directions

6.1 Challenges

6.1.1 Data scarcity and quality

The lack of quality data and its inconsistency can be considered one of the leading problems of implementing deep learning in the sphere of solar energy systems. Solar irradiance, weather patterns, panel performance logs, and fault images are often incomplete, noisy, or unavailable in some regions. Additionally, labeled datasets required for tasks like fault detection or degradation prediction are limited because manual labeling of images (e.g., infrared scans of damaged panels) is time-consuming and labor-intensive. This lack of data leads to suboptimal model performance and poor generalizability.

6.1.2 Model generalization across geographies

Deep learning models trained on data from one geographic location often fail to generalize effectively when deployed in different climatic regions. The simplest example is an algorithm developed in a sunny climate of Southern California; it is likely to fail to do well in tropical or dry regions with different irradiance schemes, cloud dynamics, or temperature structures. This constrains the flexibility of models available all over the world unless retraining and fine-tuning at local data are conducted at considerable cost.

6.1.3 Computational complexity and deployment constraints

Deep learning networks, more so the hybrid models such as CNN-LSTM and Transformers are computationally demanding. The training of such models will demand powerful hardware (GPUs/TPUs) and a lot of energy, something that will not augur well with the goals of sustainability on green energy initiatives. Additionally, machines with limited memory, processing power and battery life, such as rooftop inverters or remote monitoring systems, are difficult to run these models on: that is, their hardware limitations make them incompatible with these models.

6.2 Future Directions

6.2.1 Development of lightweight and Edge-AI models

A possible future trend is a more lightweight deep learning model that will run on edge computing devices. Computationally and memory-wise sizeable reduction of models can be achieved through techniques like model pruning, quantization, and knowledge distillation. This allows real-time deployment on inverters, drones to inspect the panels, and IoT device without the need to rely on cloud infrastructure reducing the latency and cost of operations.

6.2.2 Transfer learning and domain adaptation

Future studies must concentrate on the technique of transfer learning and domain adaptation to solve the generalization problem. Models pre-trained on large diverse data can be customized to the specific geographical

locations or environmental scenarios using only few data. Such an approach eliminates the necessity of large-scale retraining, enhances the possibilities of scaling, and fastens the deployment in areas with insufficient data.

6.2.3 Integration of explainable AI (XAI)

One of the prospects of the future directions is to incorporate the concepts of Explainable AI into deep learning models that will be applied in solar energy. XAI methods can offer the explanation of the reasons why a model could make a specific choice in terms of predicting a failure, or forecasting the power output. This will improve transparency and foster trust in stakeholders and help in the diagnosis of model failures/biasness and will thus be deployed more safely and reliably in dependent energy systems.

7. Conclusion

This study has done a thorough study on the transformative value of deep learning to improve the efficiency of solar photovoltaic systems. This paper compares the effectiveness of many deep learning networks, e.g. CNN, LSTM, Transformer, GAN, Reinforcement Learning as well as hybrid architectures to demonstrate their use in enhancing important tasks, solar power forecasting, fault detection, and Maximum Power Point Tracking (MPPT). The comparison analysis has shown that CNNs are most effective in extracting spatial features to detect faults, and LSTMs and Transformers are strong to work with time-series and long-term degradation predictions, but the hybrid model and reinforcement learning are tough enough that they can be the solution to the problems worked out in dynamic and real-time. The erudition of the performance criteria including MAE, RMSE, R, and MAPE is another trend that supports the efficiency of these frameworks in enhancing congruency and operational efficacy of solar systems.

Although these advancement occurred, issues of data deficiency, inability to generalize cross-regionally, computational cost, and explainability are still the issue of major concern when overcoming large-scale adoption. In light of these considerations, the present study highlights the future areas of work such as the creation of lightweight AI models deployable on the edge, the use of transfer learning, and the incorporation of Explainable AI (XAI) frameworks. Also, the possibilities of implementing deep learning along with IoT sensors and digital twin technologies have shown a way to the future of developing more resistant and smart solar energy power systems. In conclusion, this review makes the point that more needs to be done in terms of research and innovation in deep learning techniques to

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realign the full potential of solar energy as a source of helping us achieve our global sustainability goals.

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