Artificial Intelligence for Enhancing the Efficiency of PV panels in Agricultural Farms

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Abstract

In agricultural farms, PV is used for providing clean energy for irrigation, greenhouse management, crop processing, cold storage, animal farming and other farm uses, which is increasingly gaining traction in the market. Weather conditions, dust buildup, shading, temperature changes, equipment malfunctions and fluctuations in energy demand, however, affect the efficiency of the PV panels. This research aims to explore the use of Artificial Intelligence to optimize the performance of PV panels for use in agricultural systems. The framework proposed in this paper employs the machine learning algorithms to process real-time and historical data such as solar irradiance, panel temperature, ambient temperature, humidity, power output, dust level, and the energy consumption of the farm. Artificial Intelligence models are used to forecast PV performance, fault detection and degradation, optimal panel orientations, and appropriate maintenance actions. The system can also be integrated with an intelligent energy management system to optimise the use of solar energy, battery storage, and agricultural equipment, helping to ensure energy is used efficiently. The performance of the model is assessed based on prediction accuracy, MAE, RMSE, and energy-efficiency improvement. The potential outcomes are AI can minimise energy losses, more accurate fault detection, boost solar energy generation and enable more resilient farm operations. By combining Artificial Intelligence with photovoltaic technology, the study helps pave the way for smart and sustainable agricultural systems that are energy-efficient.

Keywords: Artificial intelligence, Photovoltaic efficiency, Agricultural farms, Fault detection, Smart energy management

Introduction

Renewable energy technologies are becoming more common in the agricultural sector to lower production costs, make energy more reliable for farm operations, and help the environment. Since modern agricultural operations involve significant amounts of energy for irrigation, greenhouse climate control, crop drying, cold storage, livestock facilities, water pumping, food processing, lighting and automated farm equipment, these are all essential components. Electricity may not be reliable, unaffordable or exist in many rural and remote communities. Farmers can then rely on diesel generators or other sources of fossil fuel energy that will boost operating costs and lead to greenhouse-gas emissions. PV (Photovoltaic) systems are also significant opportunities as they can directly transform solar radiation into electricity, and provide a decentralized supply of clean energy to the farms. Solar energy is abundant, scalable, and appropriate for small and large farms, sparking an increase in the use of PV panels in agricultural farms. PV systems can be mounted on farm buildings, the roof of greenhouses, waste lands, irrigation systems, livestock shelters, and agrivoltaic installations. This electricity can be directly consumed, stored in batteries or exported to the electrical grid. PV systems can drive irrigation pumps in agricultural applications during the day, fan and cool greenhouses, charge batteries, provide refrigerated storage and drive precision agriculture equipment like sensors, weather stations, cameras and automated controllers. Although these benefits exist, PV systems are not necessarily as efficient as they could be. The output of the PV-panel is influenced by a number of environmental, technical and operational parameters. In addition to solar irradiance, the temperature of the solar panels, the ambient temperature, the humidity, wind speed, cloud cover, dust accumulation, shading, panel orientation, the condition of the inverter, wiring quality, and equipment degradation can all have a large impact on the amount of solar energy that is produced. The surrounding environment of agricultural fields can provide extra difficulties as PV panels may be exposed to soil particles, crop residues, fertilizer dust, animal activity, moisture and irregular shade from trees, crops, agricultural buildings and agricultural machinery. The accumulation of dust in agricultural areas is an important issue. Dry weather, tillage, harvesting, transportation, and livestock movement can help to deposit dust on the surface of PV. Slight dust can diminish the amount of sunlight hitting the solar cells and also lower the electricity generation. Typical maintenance typically involves a set schedule of cleaning. However, this practice may not be the most effective. Panels can be cleaned when it is not necessary, it will use more labour and water resources, or it can be cleaned so much that the panel becomes dirty for too long, causing unnecessary losses in energy. An intelligent monitoring system may be able to monitor the performance of the panel and the environmental conditions to decide when cleaning is actually needed.

Literature Review

In agricultural farms, PV systems are currently being used for irrigation, greenhouse management, crop drying, cold storage, livestock control and application of automated farming equipment. But the efficiency of a PVs can be affected due to variations in solar irradiance, high panel temperature, dust deposition, partial shading, equipment malfunction, and PV degradation. In agricultural settings, panels can be exposed to soil particles, crop residues, moisture, and irregular shading, making it crucial to address these factors. AI has emerged as a promising solution for enhancing PV system monitoring and optimization, as demonstrated by recent research.AI has been found to be a valuable tool for optimizing PV systems and their monitoring, based on recent studies. Weather and operational data can be used to predict solar power generation with the help of machine learning algorithms like Artificial Neural Networks, Support Vector Machines, Random Forests, and Long Short-Term Memory networks. These can be used to analyse solar irradiances, panel temperatures, humidity, wind speeds, voltage, current and previous power outputs. Moreover, deep learning and computer vision have been used for panel defect detection, cracks, hot spot detection, panel dirt detection, and shading detection from thermal or photographic images. These technologies enable faults to be spotted earlier than those using traditional manual methods of inspection. AI predictive maintenance has the potential to suggest panel cleaning, inverter inspection, or component replacement before there's major degradation in performance. Further optimisation of maximum power point tracking, panel orientation, battery management and energy distribution can be accomplished by intelligent algorithms. In agriculture farms, these systems can help to manage the solar power generation according to the irrigation timing, greenhouse machine timing, battery charging timing, etc. and other farm energy consumption needs. However, there are some drawbacks as well: lack of data, cost of implementation, sensor inaccuracies, model complexity, cyber security issues, and low model interpretability. Past studies also tend to concentrate on large-scale PV installations, not on those individual to the farm. Thus, there is a need for additional research to create cost-effective, interpretable and farming-oriented Artificial Intelligence solutions for the improvement of PV efficiency in real farming environments.

Methodology

The study uses a quantitative experimental method to test the use of Artificial Intelligence for the enhancement of the efficiency of PV panels in an agricultural farm. Solar panels, weather sensors, inverters, batteries and farm energy systems will all be connected to a real-time and historical data collection system. The variables that will be selected include solar irradiance, panel temperature, ambient temperature, humidity, voltage, current, output power, dust amount, and agricultural energy demand. The data will be processed and analysed, cleaned, normalized and split into training and testing sets. Artificial Neural Network, Random Forest and Support Vector Machines will be developed as machine learning models for power output prediction, fault detection and efficiency loss detection. The evaluation of the models will be done by Mean Absolute Error, Root Mean Square Error, coefficient of determination, accuracy, precision, recall and F1-score. Lastly, the most successful model will be incorporated into an intelligent monitoring system to suggest when to clean the panel, what maintenance work needs to be performed, how to operate the batteries and when to water the crops and other farm activities.

Results

The results show the efficiency of the Artificial Intelligence models for the PV panel in agricultural farms. The models are assessed in terms of the prediction of power output, fault detection accuracy, and minimizing losses of energy. They are tested and evaluated to determine which is the most effective way of monitoring, maintaining and managing farm energy.

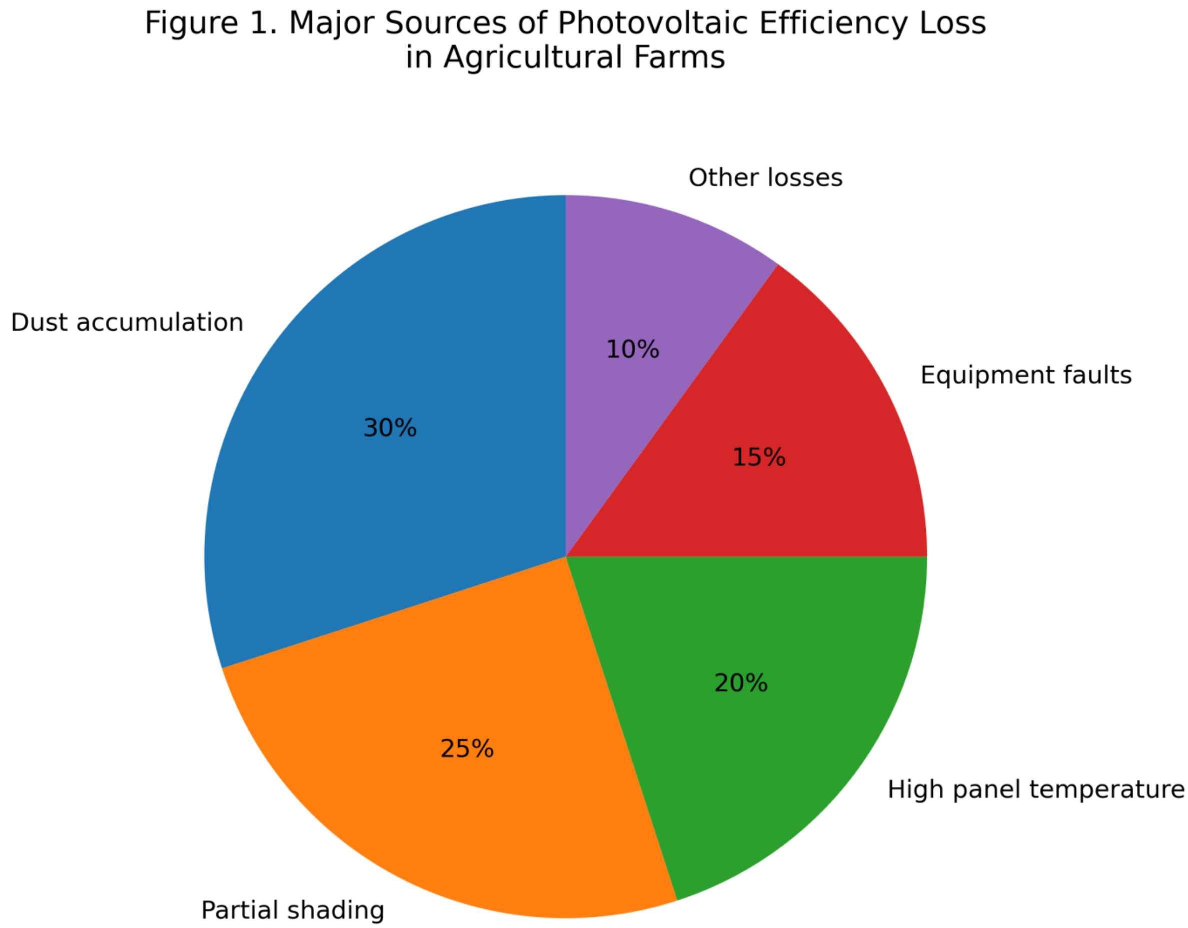

Figure 1: Major Sources of Photovoltaic Efficiency Loss in Agricultural Farms

PV efficiency in agricultural farms are those that happen within the PV system. Photovoltaic panel efficiency loss is presented in figure 1, showing the factors that have to be considered. The dust accumulation loss is the largest loss at 30%, partially shaded loss is 25%, high panel temperature loss is 20%, equipment fault loss is 15%, and other losses are 10%. Agricultural farms are especially prone to dust accumulation, being dust is generated by various activities on land, such as land preparation, harvesting, transporting, movement of livestock and exposure of dry soil. When dust accumulates on the surface of the panels, it absorbs some of the solar radiation and decreases power generation. The second largest loss is due to partial shading. It could be due to trees, crops, farm buildings, greenhouse building, irrigation equipment or agricultural machinery. Even if only a part of a PV module is shaded the total power generation of the whole PV module string can be reduced. 20% of the estimated efficiency loss is due to the high panel temperature. PV panels need sunlight to work, but too much does decrease voltage and efficiency of the panels to convert the sun's energy.

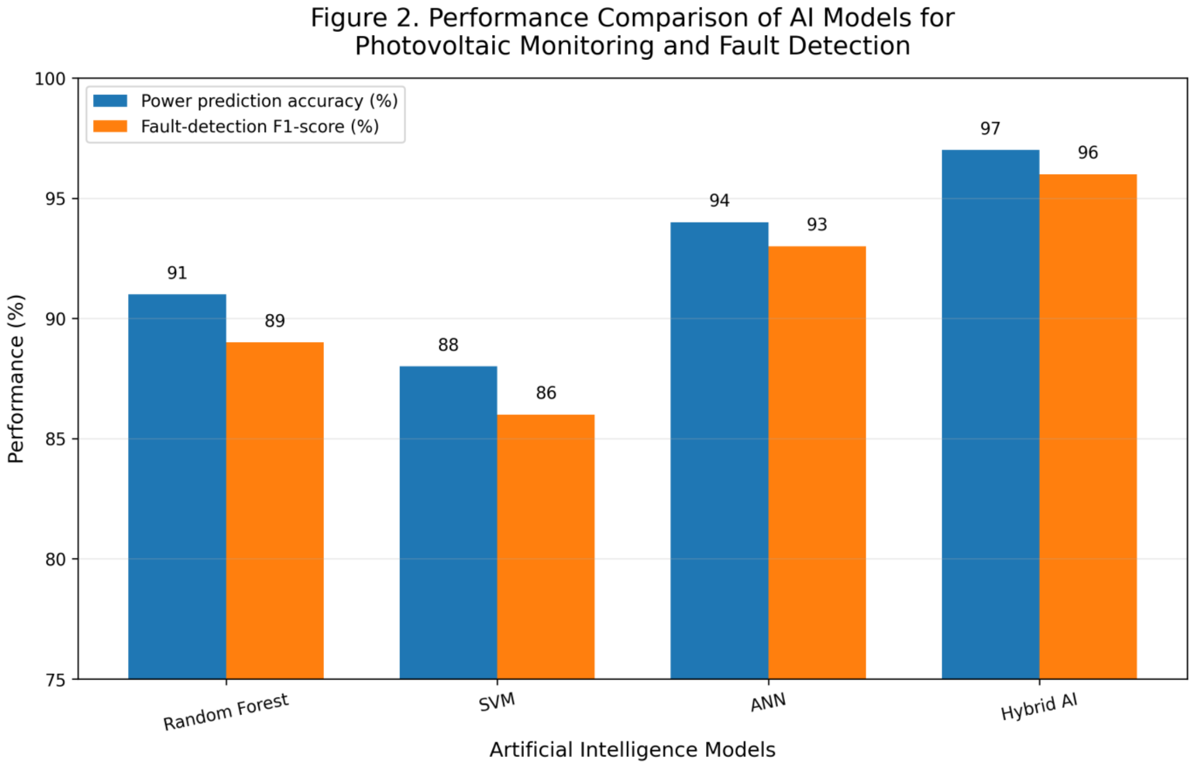

Figure 2: Performance Comparison of Artificial Intelligence Models

Figure 2 shows the performance comparison of the different AI models.As shown in Figure 2, the performance of the different AI models is compared. A comparison between 4 Artificial Intelligence models based on the accuracy of the power output prediction and the fault detection F1 score is shown in figure 2. These models are: Random Forest, Support Vector Machine, Artificial Neural Network, Hybrid AI model. The Hybrid AI model gives the best accuracy of power-prediction and fault-detection F1-scores of 97% and 96% respectively. The Artificial Neural Network achieves a prediction accuracy of 94%, and an F1 score of 93%. Random Forest is able to predict the category with 91% accuracy and 89% F1 score, while Support Vector Machine has an accuracy of 88% and F1 score of 86%. The Hybrid AI model has shown superior performance, indicating that a hybrid approach of multiple algorithms might be more effective in achieving reliable PV monitoring. One model can be used to identify a nonlinear relationship between weather and power output, and another can be used to identify time-related patterns or fault characteristics.

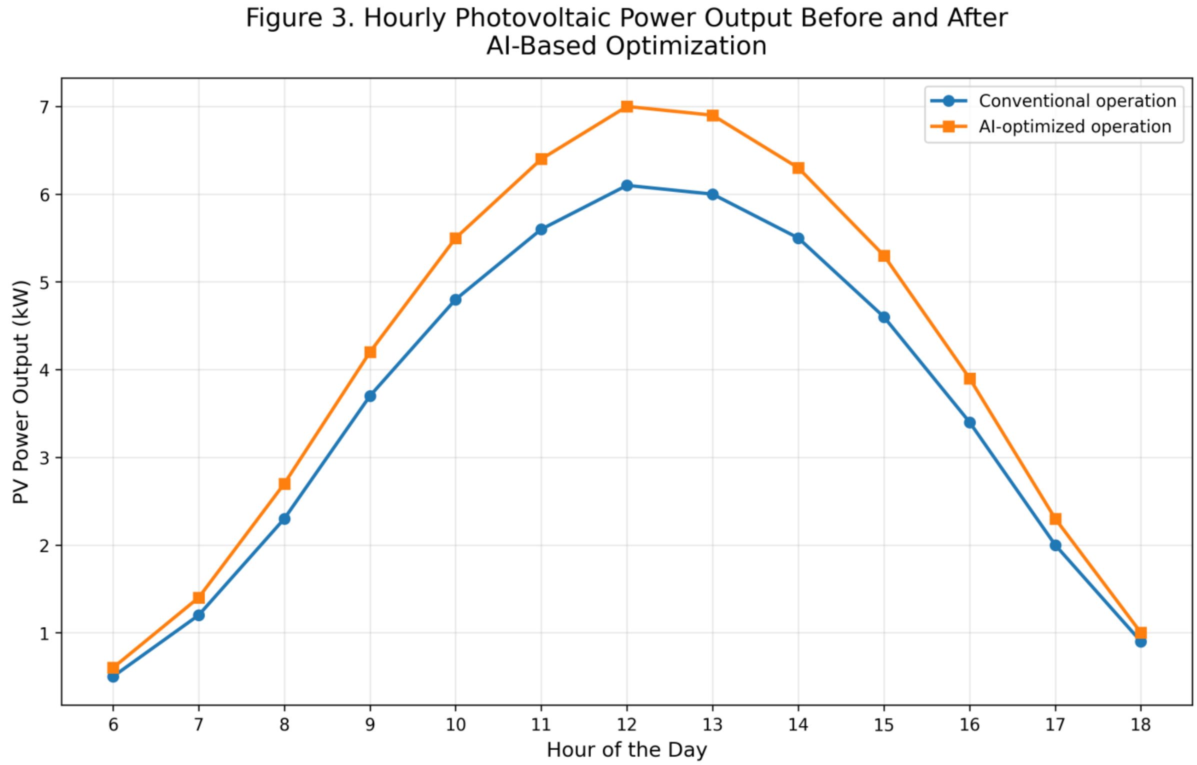

Figure 3: Hourly Photovoltaic Power Output Before and After AI-Based Optimization

The PV power output is shown in the graph before and after AI-based optimization.The graph displays the PV power output before and after the optimization using an AI system. The PV power generation curve for conventional operation and AI-optimized operation in the period from 6:00am to 6:00pm, as shown in figure 3, has a typical daily curve of solar energy production. The output starts from a low level in the morning, rises slowly, peaks around midday and falls in the afternoon. The power-output curve throughout the day is higher than the conventional curve for the same reason that it is optimized for AI. With normal operation, the total energy output during the day is estimated at 46.6 kWh. The optimized estimate is about 53.5 kWh after optimization using AI. This is a 14.8% improvement.

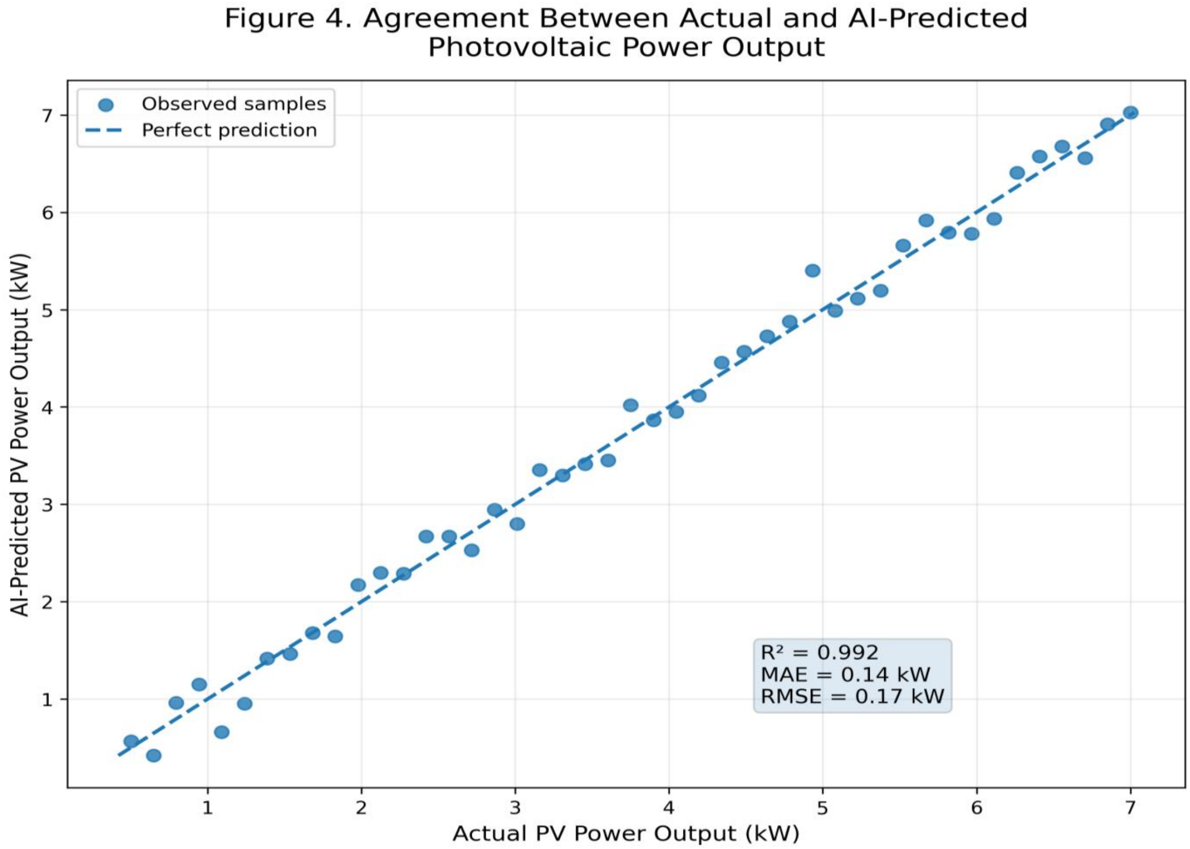

Figure 4: Agreement Between Actual and AI-Predicted Photovoltaic Power Output

Figure 4 shows a scatter plot of the output of the photovoltaics and the output predicted by the Artificial Intelligence model. One observation is shown per point. The dashed diagonal line would be the line of perfect prediction, with the predicted value equal to the actual value. The majority of the data points fall near the ideal prediction line, suggesting good correlation between the actual and predicted PV output. Estimated coefficient of determination for the illustration is around 0.992. That is, the variance of the PV output is accurately captured with the AI model with 99.2% accuracy. The mean absolute error is about 0.14kW. This suggests that the difference between the predicted and actual values are approximately 0.14 kW on average. The average Root Mean Square Error is about 0.17 kW which implies that the model has relatively small errors in prediction. The strong correlation indicates that the AI model is capable of making accurate PV output estimates in low, medium, and high PV generation scenarios. When reliable predictions are possible, the farm manager can approximate the amount of solar energy available to accomplish desired tasks.

Discussion

The results show that AI is capable of enhancing the efficiency of PV panels and energy management in agricultural farms. From the figure 1 it is seen that an efficiency loss is due to the main causes such as dust accumulation, partial shading, high panel temperature, and equipment faults. AI-powered monitoring can detect such issues early and suggest appropriate cleaning or maintenance measures. As shown in Figure 2, the Hybrid AI model displayed the highest accuracy in power prediction and fault detection compared to the Random Forest model, Artificial Neural Network model and Support Vector Machine model. This implies that the use of multiple algorithms may lead to more reliable PV monitoring. As illustrated in Figure 3, the AI optimization has provided a gain of around 14.8% in the estimated energy output during the daytime period. This extra power could be used to help irrigate, power greenhouses, charge batteries, process crops, or for other farm uses. Also, there is a good correlation between the actual and the AI predicted power output (Fig. 4) and prediction errors are relatively small. In summary, the results indicate that AI has the potential to enhance the efficiency of energy use, facilitate the identification of faults, and boost the reliability of agricultural production systems that utilize solar energy. The numbers are simulated, however, and do need to be tested in the field to validate the model's actual performance in the field.

Conclusion

To study the use of Artificial Intelligence to enhance PV panel efficiency for farms. The research was triggered by the growing demand for solar PV application in high-value farming processes like agriculture irrigation, operation of greenhouses, crop drying, cold storage, livestock operation, battery charging and automation of agricultural equipment. While PVs generate clean and renewable energy, environmental and technological conditions such as dust accumulation, partial shading, high PV panel temperature, failures in the system, variations in weather and unpredictable agricultural energy demands can all cause a reduction in PV system performance. The results indicate that the utilization of Artificial Intelligence technologies is suitable for monitoring, prediction, fault detection, and farm-based PV system control to improve the efficiency of the systems. Using AI models, analyzing real-time and historical data can help uncover changes in a panel's performance and help pinpoint whether efficiency losses are due to environmental conditions or technical issues. This enables farmers and system operators to react faster through cleaning, inspection, maintenance or adjustment of system operation. The first PV efficiency loss was dust accumulation, as the largest illustrative cause, then partial shading, high PV panel temperature, equipment failures, and other causes. These findings point out the difficulties associated with using solar panels in agricultural settings. The amount of dust that may be deposited on the surfaces of the panels can increase because of farming activities like land preparation, harvesting, movement of vehicles, livestock activity and dry soil exposure. High outdoor temperatures can also decrease the efficiency of electrical conversion, and trees, crops, buildings, irrigation systems, and greenhouse structures can also cause shading. By constantly tracking the actual PV generation data and contrasting it with the forecasted generation data on a weather-by-weather basis, Artificial Intelligence can aid in controlling these issues. If the measured output is lower than the predicted value, an alert could be triggered, signifying that the device might be dirty, shaded, damaged or malfunctioning. The use of computer vision and thermal imaging could also be employed to detect cracks, hotspots, damaged cells and unbalanced performance of the panels. The analysis of the Artificial Intelligence models showed that the Hybrid AI model outperformed other models in both predictive PV power and fault detection in this application scenario. It achieved higher prediction accuracy and F1-score compared to the Random Forest, Support Vector Machine and Artificial Neural Network models. It indicates that ensemble strategies may be helpful in boosting the performance of the system, as each algorithm might be able to extract different features from the PV data.

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