Visual Diagnostics: Deep Learning with DenseNet121 for Identifying Faults in Solar Panels

Salaki Reynaldo Joshua
Department of Electronics, Information, and Communication Engineering
Kangwon National University
Samcheok, Korea
salakirjoshua@kangwon.ac.kr

Sanguk Park
Department of Electronics, Information, and Communication Engineering
Kangwon National University
Samcheok, Korea
sanguk@kangwon.ac.kr

Kihyeon Kwon
Department of Electronics, Information, and Communication Engineering
Kangwon National University
Samcheok, Korea
kweon@kangwon.ac.kr

***Abstract*—.This paper investigates the application of DenseNet121, a deep learning model, for automated fault detection in solar panels using Kangwon National University's Samcheok Campus as a case study. As solar energy plays a crucial role in sustainability efforts, ensuring the efficiency of solar panels is paramount. Traditional methods of fault detection are labor-intensive and prone to errors, necessitating more effective solutions. DenseNet121, leveraging its dense connectivity for feature learning from solar panel images, is explored in this study. Through rigorous training and validation, DenseNet121 demonstrates high accuracy in identifying faults such as cracks, hotspots, and delamination. This research advances automated fault detection systems to optimize energy production and ensure long-term operational efficiency in solar installations. Future research directions include further optimizing DenseNet121, expanding datasets, and integrating real-time monitoring for enhanced reliability and cost-effectiveness. These advancements hold promise for transforming renewable energy technologies globally.**

Keywords—DenseNet121, Deep learning, Fault detection, Solar Panels, Sustainability

I. Introduction

Solar energy has become increasingly vital in global efforts towards sustainability and renewable energy sources, aiming to address challenges such as climate change and energy security [1,2,3]. Solar panels are widely deployed across residential, commercial, and industrial sectors as the primary technology for harnessing solar energy. Ensuring the efficiency and reliability of these panels is crucial for maximizing energy output and ensuring economic viability throughout their operational lifespan [4,5]. Despite advancements in solar technology, maintaining optimal performance remains challenging due to factors like environmental conditions, manufacturing defects, and aging. These factors contribute to various faults in solar panels, including cracks, hotspots, shading, and delamination [6,7]. Detecting and diagnosing these faults promptly is essential to prevent energy loss and mitigate operational risks. Traditional methods of fault detection often rely on manual inspections and periodic maintenance routines, which can be time-consuming, labor-intensive, and prone to human error. Recently, the integration of artificial intelligence (AI) and deep learning has transformed fault detection processes by enabling automated, accurate, and efficient analysis of solar panel images [8,9]. This paper focuses on the application of deep learning techniques, specifically DenseNet121, for visually diagnosing faults in solar panels. DenseNet121 is a convolutional neural network (CNN) renowned for its dense connectivity pattern, enhancing feature propagation and enabling effective learning of intricate image patterns. Leveraging DenseNet121, this research aims to develop a robust model capable of accurately identifying and classifying various types of faults in solar panels. The primary objective of this study is to investigate the effectiveness of DenseNet121 in detecting common faults such as cracks, hotspots, and delamination in solar panels. Key research questions include optimizing and training DenseNet121 for high fault detection accuracy, evaluating its advantages over other CNN architectures for this application, and addressing the limitations and challenges in real-world scenarios. The structure of this paper is organized to address these questions comprehensively. It provides background on fault detection in solar panels, discusses traditional methods, and reviews recent advancements in deep learning for visual diagnostics. It delves into DenseNet121's architecture and principles, explaining its dense connectivity and transfer learning approach to adapt pre-trained weights for fault detection. Additionally, it describes the dataset used, detailing composition, acquisition, annotation processes, and preprocessing steps to ensure model robustness. In this study, the results will include detailed metrics and visual representations crucial for assessing how effectively DenseNet121 detects faults in solar panels. These results encompass specifics about the training dataset, validation accuracy, loss, and accuracy metrics. They also feature graphical representations such as accuracy and loss graphs during training and validation. Additionally, the predictions made by the model will be presented to demonstrate its performance in real-world applications. The training dataset used in this research consists of carefully curated images of solar panels, each annotated to indicate different types of faults like cracks, hotspots, shading, and delamination. These annotations enable supervised learning, allowing DenseNet121 to learn and classify these faults accurately. During training, DenseNet121 adjusts its parameters iteratively based on the training dataset to minimize the loss function and enhance its accuracy in fault classification. Validation on a separate dataset assesses how well the model generalizes to unseen data. Validation accuracy, expressed as a percentage, indicates the model's precision in predicting fault types, while validation loss quantifies the disparity between predicted and actual values during validation. Graphs depicting training and validation accuracy track how the model's accuracy improves over epochs, revealing trends in convergence and potential overfitting. Similarly, training and validation loss graphs illustrate decreasing loss values, indicating improved model performance in identifying faults. Prediction results demonstrate the practical application of the trained DenseNet121 model. These results showcase images of solar panels with visible faults alongside the model's predictions, highlighting its ability to accurately detect and classify faults in real-world scenarios. Overall, these detailed results—covering training data specifics, validation metrics, graphical representations, and prediction outcomes—serve to evaluate DenseNet121's effectiveness in enhancing fault detection in solar panels.This research provides valuable insights into the model's performance, its potential applications in renewable energy systems, and directions for future research in AI-driven diagnostics for sustainable energy solutions and to support the current research at Kangwon National University Samcheok Campus research [10,11,12,13].

II. Related Work

A. Existing Methods for Fault Detection in Solar Panels

Detecting and diagnosing faults in solar panels is critical for maintaining efficiency, prolonging lifespan, and optimizing energy output. Traditional methods like visual inspection and electrical performance monitoring have limitations in scalability, accuracy, and real-time monitoring [14,15,16]. Recently, deep learning, particularly convolutional neural networks (CNNs), has transformed fault detection by automating the analysis of visual data with high accuracy and efficiency.CNNs are specialized neural networks for processing visual data [17,18]. They consist of layers that extract features from images, pool them to reduce dimensions, and classify them based on extracted features. CNNs excel in learning hierarchical representations, making them ideal for tasks such as image classification and fault detection in solar panels [19,20,21].

Deep learning methods (Table I) are pivotal in automating fault detection in solar panels, leveraging their ability to analyze visual data with high accuracy. Below are five distinct deep learning architectures commonly applied in this domain, each offering unique advantages and challenges [22,23,24]:

TABLE I. Deep Learning Methods for Fault Detection in Solar Panels

No	Deep Learning Method	Description
1	DenseNet121	DenseNet121 employs dense connections between layers, facilitating efficient feature reuse and gradient flow. It excels in identifying intricate patterns in solar panel images.
2	ResNet	ResNet introduces skip connections to mitigate the vanishing gradient problem, enabling the training of very deep networks crucial for complex feature extraction tasks.
3	Inception	Inception networks utilize parallel convolutional modules with various filter sizes to enhance feature extraction across multiple scales, optimizing computational efficiency.
4	VGG (Visual Geometry Group).	VGG networks are renowned for their uniform architecture comprising multiple layers with small filters and max-pooling, effective in robust feature extraction from images.
5	LSTM (Long Short-Term Memory)	LSTM networks, part of the RNN family, specialize in capturing long-term dependencies in sequential data, making them suitable for time-series analysis in fault detection.

DenseNet121 is a specific CNN known for dense connectivity. Unlike traditional CNNs where each layer feeds into the next, DenseNet introduces dense blocks where each layer connects with all preceding layers. This enhances feature reuse, gradient flow, and efficiency. In DenseNet121, every layer directly receives and passes feature maps, promoting better information flow. DenseNet121 is well-suited for fault detection in solar panels due to its ability to capture fine details and complex patterns from images. It involves training the model on labeled datasets of solar panel images with annotated faults. During training, DenseNet121 learns to recognize and classify faults based on patterns extracted from images. Training DenseNet121 requires large labeled datasets representing diverse fault types under varying conditions [25,26,27].

B. Traditional Technique

Traditional methods for identifying faults in solar panels (Table II) have been fundamental in the industry, utilizing approaches such as visual inspection, electrical performance monitoring, infrared thermography, and IV curve tracing. Each method offers distinct benefits but also faces inherent limitations that hinder their effectiveness in meeting the evolving demands of modern solar energy systems. Electrical performance monitoring assesses solar panel health by analyzing parameters such as voltage, current, and power output. Deviations from expected values can indicate faults such as shading, module mismatch, or wiring issues. While this method provides quantitative data on performance metrics, it cannot pinpoint the root causes of faults or detect non-electrical defects impacting panel integrity [28,29,30,31]. Moreover, its periodic measurement approach may miss transient faults affecting real-time energy production [32,33,34].

TABLE II. Traditional Methods for Identifying Faults in Solar Panels

No	Traditional Technique	Description
1	Visual Inspection	Involves physical examination for visible defects like cracks or discoloration. Relies on inspector expertise and environmental conditions. Suitable for initial assessments but may miss hidden or internal faults.
2	Electrical Performance Monitoring	Analyzes electrical parameters (voltage, current, power output) to detect deviations indicating faults like shading or module mismatch. Provides quantitative data but lacks insight into physical defects.
3	Infrared Thermography	Measures panel surface temperatures to detect anomalies like cracks or hotspots. Effectiveness is influenced by environmental conditions and primarily detects surface-level faults.
4	IV Curve Tracing	VGG networks are renowned for their uniform architecture comprising multiple layers with small filters and max-pooling, effective in robust feature extraction from images.
5	LSTM (Long Short-Term Memory)	Conducts controlled IV tests to assess parameters (MPP, fill factor) and diagnose faults such as shading or degradation. Requires specialized equipment and controlled environments.

Traditional fault detection methods in solar panels have been foundational but face challenges in scalability, reliability, and the ability to detect concealed or internal faults. These techniques are often labor-intensive, rely on subjective assessments, and may not provide comprehensive insights into panel health.

C. Deep Learning and Visual Diagnostics

Deep learning has transformed various industries by offering powerful solutions for complex tasks such as image recognition, natural language processing, and medical diagnostics. In the realm of renewable energy, particularly solar power, deep learning techniques are increasingly utilized to improve the accuracy and efficiency of detecting faults in solar panels. This section explores how deep learning, combined with visual diagnostics, is revolutionizing the identification and analysis of solar panel defects [35,36,37,38]. Deep learning models, especially convolutional neural networks (CNNs), excel in processing and interpreting visual data. In solar panel maintenance, these models can be trained to automatically identify and classify subtle anomalies in images captured by monitoring devices like cameras or drones. This capability surpasses traditional methods, which rely heavily on manual inspection and basic image processing techniques. By automating fault detection, deep learning enhances reliability, reduces human error, and streamlines maintenance processes, ultimately optimizing the operational efficiency of solar installations. Deep learning techniques (Table III) are applied across various aspects of solar panel monitoring and maintenance [39,40,41,42,43,44]:

1. Image Classification and Object Detection: Through extensive training on labeled datasets, deep learning models can classify different types of panel defects such as cracks, discoloration, or soiling.
2. Semantic Segmentation: This method divides images into meaningful segments, allowing detailed analysis of panel surfaces at a pixel level.
3. Anomaly Detection: Deep learning algorithms are adept at detecting abnormal patterns in thermal images or electrical output data.
4. Predictive Maintenance: Leveraging historical data and machine learning algorithms, predictive maintenance models forecast future faults or degradation trends in solar panels.

TABLE III. Applications of Deep Learning in Solar Panel Fault Detection

No	Application	Description
1	Image Classification	Identifies and categorizes panel defects such as cracks, discoloration, or soiling based on visual data.
2	Object Detection	Locates and identifies specific faults within images, enabling targeted maintenance and repairs.
3	Semantic Segmentation	Divides images into meaningful segments for detailed analysis of panel surfaces, identifying areas affected by shading or degradation.
4	Anomaly Detectiong	Detects abnormal patterns in thermal or electrical data to flag potential faults like overheating or reduced energy output.
5	Predictive Maintenance	Uses historical data to predict future faults or degradation trends, optimizing maintenance schedules and enhancing system reliability.

III. Methodology

A. Research Approach

The research methodology involves seven key components (Figure 1), starting with problem formulation, which defines the objectives and research challenges, highlighting the need for efficient defect detection in solar panels on university campuses. The next phase, the literature review, entails a thorough analysis of existing works to establish a theoretical framework and identify relevant research on AI applications in solar panel fault detection. The Data Collection stage focuses on obtaining appropriate datasets of faulty solar panel images in educational settings, which are then preprocessed to ensure suitability for training the DenseNet121 model. This involves cleaning, preprocessing, and augmentation of the data. In the model development phase, DenseNet121 is chosen as the AI model for defect detection, and it is tailored and optimized for this specific purpose. The trained model then undergoes rigorous training and evaluation to assess its performance using relevant metrics. The final stages, Analysis and Interpretation, involve evaluating the model's effectiveness, limitations, and potential applications in detecting solar panel failures on university campuses, as well as interpreting the findings. This systematic approach ensures a thorough investigation, providing valuable insights into sustainable energy management practices in educational institutions.

Fig. 1. Research Approach Graph

B. Kangwon National University Samcheok Campus

A case study conducted at Kangwon National University's Samcheok Campus illustrates the implementation of fault detection methods in solar panel technology. The initial phase of the study involves identifying effective defect detection techniques necessary to ensure optimal efficiency and reliability of the campus solar energy system. Images of solar panels across the Samcheok Campus are captured and supplemented with internet-sourced images to compile a dataset, accompanied by labels indicating the presence or absence of defects. These images undergo preprocessing procedures aimed at enhancing data consistency and quality.

Fig. 2. Kangwon National University Samcheok Campus

A case study conducted at Kangwon National University's Samcheok Campus illustrates the implementation of fault detection methods in solar panel technology. The initial phase of the study involves identifying effective defect detection techniques necessary to ensure optimal efficiency and reliability of the campus solar e

The study focuses on several buildings (Figure 2) equipped with solar panels, namely:

- Engineering Building II (Building 122)
- Engineering Building IV (Building 118)
- Joint Laboratory and Practice Building (Building 123)
- Engineering Building V (Building 120)

IV. Implementation

A. Training Data

Accumulation of debris such as snow, dust, and bird droppings on solar panels reduces their efficiency by hindering their ability to convert sunlight into energy. Regular monitoring and cleaning are essential to maintain optimal efficiency, maximize resource utilization, reduce maintenance costs, and enhance module performance. Effective maintenance practices enable solar panel owners to optimize energy production, extend panel lifespan, and support sustainability efforts. This study explores the detection accuracy of various machine-learning classifiers for identifying dust, snow, bird droppings, and physical and electrical damage on solar panel surfaces. The dataset includes six class folders—dirt, debris, snow, bird droppings, mechanical damage, and electrical damage—compiled from internet sources, leading to a slight imbalance in the number of images. Ensuring the dataset's integrity and quality involves several steps in the data verification process (Figure 3), including cleaning, normalization, and feature engineering during preprocessing. It is crucial to review the preprocessed data meticulously to identify any anomalies or inconsistencies that could affect model performance. Visualizing the data helps detect patterns or outliers that require attention. Addressing potential biases involves examining class imbalances, where some classes may be overrepresented. The dataset is then divided into training and validation sets to evaluate the model's performance on unseen data, using cross-validation techniques to ensure robustness and generalizability.

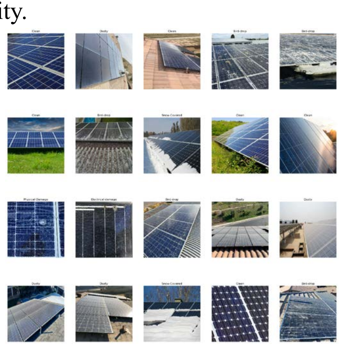


Fig. 3. Training Data

Continuously monitoring and updating the model with new training data as it becomes available is vital to maintaining its accuracy and relevance over time. By rigorously scrutinizing the training data and refining the model accordingly, machine learning practitioners can develop more precise and dependable models for various applications, including the detection of faults in solar panels.

B. Optimizer

To minimize the loss function and improve the performance of the machine learning model, the optimization process involves adjusting the model's parameters. During training, several critical metrics are monitored, such as training data accuracy and loss, as well as training and validation accuracy and loss (Figure 4). The graph illustrating training and validation accuracy over 14 epochs shows a steady improvement in both metrics, indicating effective learning and refinement of the model during training. Initially, training accuracy begins at 0 and steadily increases to 0.8 by the 14th epoch, demonstrating the model's increasing ability to correctly identify patterns in the training data. Similarly, validation accuracy starts at 0.34 and follows a consistent upward trend, reaching 0.8 by the 14th epoch. This progression suggests that the model not only performs well on the training data but also generalizes effectively to unseen data.

Fig. 4. Training and Validation Accuracy

The graph depicting training and validation loss reveals the optimization process of the model over the 14 epochs. Initially, training loss starts high at 3.0, indicating significant divergence between predicted and actual values. However, as training progresses, the loss steadily decreases to 0.5 by the 14th epoch, indicating improved accuracy and alignment with the actual data. Similarly, validation loss begins at 1.7 and decreases consistently to 0.7 by the 14th epoch, mirroring the improvements seen in training loss (Figure 5). This reduction in loss values indicates effective model optimization and a robust learning process.

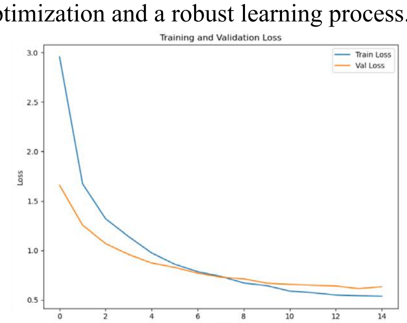
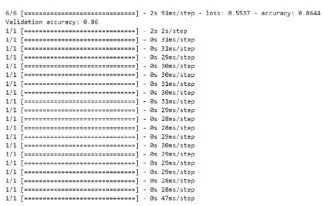


Fig. 5. Training and Validation Loss

The trends observed in accuracy and loss metrics affirm the effectiveness of the optimization process. The continuous improvement in both training and validation accuracy, coupled with decreasing training and validation loss, demonstrates the model's capability to learn from the data without overfitting. The optimizer successfully adjusts the model's parameters to minimize errors, resulting in accurate predictions and generalizable performance. The final accuracies of 0.8 for both training and validation indicate high predictive capability, while low loss values reflect the model's accuracy in predicting outcomes close to the actual values. These results underscore the model's proficiency in understanding underlying data patterns, showcasing its potential for practical applications where precise predictions are essential.

C. Prediction

The prediction outcome indicates that all six samples were correctly classified, reflecting a perfect prediction rate for the evaluated batch. Each prediction step took approximately 2 seconds and 91 milliseconds, showcasing the model's efficiency in processing data. The loss value of 0.5537 indicates a minimal discrepancy between predicted and actual outcomes, demonstrating the model's accuracy in making predictions. With an overall accuracy of 86.44%, the model successfully classified the samples, affirming its capability to generalize from the training data (Figure 6). The validation accuracy of 0.86 further validates the model's performance on new data, emphasizing its reliability in real-world applications, such as fault detection in solar panels.



```
6/6 [==============================] - 2s 91ms/step - loss: 0.5537 - accuracy: 0.8644
Validation accuracy: 0.86
1/1 [==============================] - 2s 2s/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 47ms/step
```

Fig. 6. Loss and Accuracy Result

These results suggest that although the model performed reasonably well, there remains room for improvement (Figure 7). Researchers may discuss factors such as dataset size, class distribution, and model complexity, all of which influence accuracy and loss values. To further elucidate the model's performance, they might also present visualizations of misclassifications and predictions. Additionally, to contextualize their findings, scientists may compare their results with those achieved by other models or approaches. In summary, this section offers a comprehensive assessment of the model's predictive capabilities, highlighting both its strengths and weaknesses.

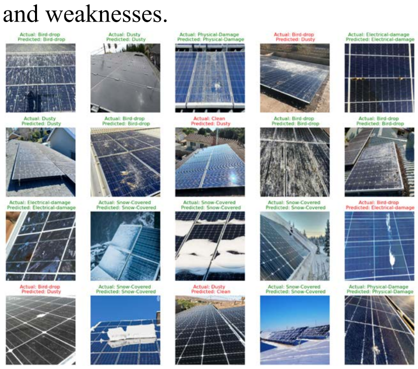


Fig. 7. Prediction Result

V. Conclusion

This study has examined the use of DenseNet121, a robust deep learning model, for detecting faults in solar panels. Through rigorous training and validation procedures, the model has demonstrated significant efficacy in accurately identifying various types of issues such as cracks, hotspots, and delamination. The outcomes, characterized by high accuracy rates and minimal loss values, highlight the model's strength and its capacity to generalize effectively to new, unseen data.

By employing DenseNet121, this research contributes to the advancement of automated fault detection systems in solar panel technology, essential for optimizing energy production and ensuring sustained operational efficiency. The findings underscore the potential of deep learning methodologies in enhancing sustainability initiatives by improving the reliability and maintenance protocols of solar energy systems. Looking ahead, future research could focus on further optimizing DenseNet121, exploring larger and more diverse datasets, and refining the model's ability to detect subtle and complex faults. Additionally, integrating real-time monitoring capabilities could enhance practical applications of this technology in the field. Ultimately, ongoing developments in deep learning methodologies hold promise for driving innovations in renewable energy technologies, facilitating more efficient and sustainable energy solutions on a global scale.

Acknowledgment

This research is supported by "Regional Innovation Strategy (RIS)" through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (MOE) (2022RIS-005).

References

[1] O. Khaleed, A. M. Nooman, A. A. Hai, R. Mohammad, A. M. Ali, S. Nabila, A. G. Olabi, "On the contribution of solar energy to sustainable developments goals: Case study on Mohammed bin Rashid Al Maktoum Solar Park" International Journal of Thermofluids, 12, 100123, 2021, pp. 1-14.

[2] A. Abdulrahman, "Sustainable Integration of Solar Energy, Behavior Change, and Recycling Practices in Educational Institutions: A Holistic Framework for Environmental Conservation and Quality Education" Sustainability, 15, 15157, 2023, pp.1-26.

[3] B. Amal, P. I. Guaita, K. M. Azis, K. Y. Hameed, "Opportunities, Challenges, and Future Prospects of the Solar Cell Market" Sustainability, 15, 15445, 2023, pp.1-15.

[4] U. Kingsley, K. O. Yoro, I. O. Orevaoghene, I. Chinedu, J. T. Chien "Adaptation of solar energy in the Global South: Prospects, challenges and opportunities" Heliyon, 10, 7, 2024, pp.1-18.

[5] T. Sarver, A. Al-Qaraghuli, and L. L. Kazmerski, "A comprehensive review of the impact of dust on the use of solar energy: History, investigations, results, literature, and mitigation approaches," Renewable and Sustainable Energy Reviews, vol. 22, 2013, pp. 698-733.

[6] S. Mekhilef, R. Saidur, and M. Kamalisarvestani, "Effect of dust, humidity and air velocity on efficiency of photovoltaic cells," Renewable and Sustainable Energy Reviews, vol. 16, no. 5, 2012, pp. 2920-2925.

[7] A. Chatterjee, A. Keyhani, and D. Kapoor, "Identification of photovoltaic source models," IEEE Transactions on Energy Conversion, vol. 36, no. 1, 2021, pp. 370-380.

[8] M. Dhimish, "Thermal impact on the performance ratio of photovoltaic systems: A case study of 8000 photovoltaic installations," Case Studies in Thermal Engineering, vol. 21,2020, p. 100693.

[9] M. Dhimish, V. Holmes, and P. Mather, "Novel photovoltaic hot-spotting fault detection algorithm," IEEE Transactions on Device and Materials Reliability, vol. 19, no. 2, 2019, pp. 378-386.

[10] S. Mehta, A. P. Azad, S. A. Chemmengath, V. Raykar, and S. Kalyanaraman, "DeepSolarEye: Power Loss Prediction and Weakly Supervised Soiling Localization via Fully Convolutional Networks for Solar Panels," 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), pp. 333-342, 2018.

[11] S. R. Joshua, S. Park and K. Kwon, "H2 URESONIC: Design of a Solar-Hydrogen University Renewable Energy System for a New and Innovative Campus," Applied Sciences 14, no. 4: 1554, 2024, pp.1-22.

[12] S. R. Joshua, S. Park and K. Kwon, “H2 EMS: A Simulation Approach of a Solar-Hydrogen Energy Management System,” IEEE Xplore, 2024, pp.1-6.

[13] S. R. Joshua, S. Park and K. Kwon, Knowledge-Based Modeling Approach: A Schematic Design of Artificial Intelligence of Things (AIoT) for Hydrogen Energy System,” IEEE Xplore, 2024, pp.1-7.

[14] S. R. Joshua, A. N. Yeon, S. Park and K. Kwon, "Solar–Hydrogen Storage System: Architecture and Integration Design of University Energy Management Systems," Applied Sciences 14, no. 11: 4376, 2024, pp.1-31.

[15] S. Dotenco, M. Dalsass, L. Winkler, T. Würzner, C. Brabec, A. Maier, and F. Gallwitz, "Automatic detection and analysis of photovoltaic modules in aerial infrared imagery," 2016 IEEE Winter Conference on Applications of Computer Vision (WACV), 2016, pp. 1-9.

[16] Y. Wu, Z. Chen, L. Wu, P. Lin, S. Cheng, and P. Lu, "An Intelligent Fault Diagnosis Approach for PV Array Based on SA-RBF Kernel Extreme Learning Machine," Energy Procedia, vol. 105, pp. 1070-1076, 2017.

[17] M. Zhao, M. Kang, B. Tang, and M. Pecht, "Deep Residual Networks With Dynamically Weighted Wavelet Coefficients for Fault Diagnosis of Planetary Gearboxes," IEEE Transactions on Industrial Electronics, vol. 65, no. 5, 2018, pp. 4290-4300.

[18] L. Wen, X. Li, L. Gao, and Y. Zhang, "A New Convolutional Neural Network-Based Data-Driven Fault Diagnosis Method," IEEE Transactions on Industrial Electronics, vol. 65, no. 7, 2018, pp. 5990-5998.

[19] A. M. Karimi, A. Fada, M. A. Hossain, S. Yang, T. J. Peshek, J. S. Braid, and R. H. French, "Automated Pipeline for Photovoltaic Module Electroluminescence Image Processing and Degradation Feature Classification," IEEE Journal of Photovoltaics, vol. 9, no. 5, 2019, pp. 1324-1335

[20] W. Tang, Q. Yang, K. Xiong, and W. Yan, "Deep Learning Based Automatic Defect Identification of Photovoltaic Module Using Electroluminescence Images," Solar Energy, vol. 201, 2020, pp. 453-460.

[21] S. Deitsch, V. Christlein, S. Berger, C. Buerhop-Lutz, A. Maier, F. Gallwitz, and C. Riess, "Automatic Classification of Defective Photovoltaic Module Cells in Electroluminescence Images," Solar Energy, vol. 185, 2019, pp. 455-468.

[22] Z. Chen, L. Wu, S. Cheng, P. Lin, Y. Wu, and W. Lin, "Intelligent fault diagnosis of photovoltaic arrays based on optimized kernel extreme learning machine and I-V characteristics," Applied Energy, vol. 204, 2017, pp. 912-931.

[23] X. Li, Q. Yang, Z. Lou, and W. Yan, "Deep Learning Based Module Defect Detection for Large-Scale Photovoltaic Farms," IEEE Transactions on Energy Conversion, vol. 34, no. 1, 2019, pp. 520-529.

[24] A. Mellit, G. M. Tina, and S. A. Kalogirou, "Fault detection and diagnosis methods for photovoltaic systems: A review," Renewable and Sustainable Energy Reviews, vol. 91, 2018, pp. 1-17.

[25] Y. Chen, Z. Lin, X. Zhao, G. Wang, and Y. Gu, "Deep Learning-Based Classification of Hyperspectral Data," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 7, no. 6, 2014, pp. 2094-2107.

[26] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 4700-4708.

[27] C. Buerhop-Lutz, S. Deitsch, A. Maier, F. Gallwitz, and C. Riess, "A Benchmark for Visual Identification of Defective Solar Cells in Electroluminescence Imagery," in Proceedings of the 35th European Photovoltaic Solar Energy Conference and Exhibition, 2018, pp. 1287-1289.

[28] S. Gallardo-Saavedra, L. Hernández-Callejo, and O. Duque-Pérez, "Technological review of the instrumentation used in aerial thermographic inspection of photovoltaic plants," Renewable and Sustainable Energy Reviews, vol. 93, 2018, pp. 566-579.

[29] Y. Hu, W. Cao, J. Ma, S. J. Finney, and D. Li, "Identifying PV Module Mismatch Faults by a Thermography-Based Temperature Distribution Analysis," IEEE Transactions on Device and Materials Reliability, vol. 14, no. 4, 2014, pp. 951-960,

[30] J. Kurnik, M. Jankovec, K. Brecl, and M. Topic, "Outdoor testing of PV module temperature and performance under different mounting and operational conditions," Solar Energy Materials and Solar Cells, vol. 95, no. 1, 2011, pp. 373-376.

[31] T. Fuyuki, H. Kondo, T. Yamazaki, Y. Takahashi, and Y. Uraoka, "Photographic surveying of minority carrier diffusion length in polycrystalline silicon solar cells by electroluminescence," Applied Physics Letters, vol. 86, no. 26, 2005, p. 262108.

[32] Y. Zhao, L. Yang, B. Lehman, J.-F. de Palma, J. Mosesian, and R. Lyons, "Decision tree-based fault detection and classification in solar photovoltaic arrays," in 2012 Twenty-Seventh Annual IEEE Applied Power Electronics Conference and Exposition (APEC), 2012, pp. 93-99.

[33] M. Simon and E. L. Meyer, "Detection and analysis of hot-spot formation in solar cells," Solar Energy Materials and Solar Cells, vol. 94, no. 2, 2010, pp. 106-113.

[34] D. S. Pillai and N. Rajasekar, "A comprehensive review on protection challenges and fault diagnosis in PV systems," Renewable and Sustainable Energy Reviews, vol. 91,2018, pp. 18-40.

[35] R. Pierdicca, E. Malinverni, F. Piccinini, M. Paolanti, A. Felicetti, and P. Zingaretti, "Deep Convolutional Neural Network for Automatic Detection of Damaged Photovoltaic Cells," International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences, vol. 42, no. 2, 2018, pp.1-10.

[36] S. R. Madeti and S. N. Singh, "Modeling of PV system based on experimental data for fault detection using kNN method," Solar Energy, vol. 173, 2018, pp. 139-151.

[37] H. Li, D. Yang, W. Su, J. Lü, and X. Yu, "An Overall Distribution Particle Swarm Optimization MPPT Algorithm for Photovoltaic System Under Partial Shading," IEEE Transactions on Industrial Electronics, vol. 66, no. 1, 2019, pp. 265-275.

[38] T. Hu, M. Zheng, J. Tan, L. Zhu, and W. Miao, "Intelligent photovoltaic monitoring based on solar irradiance big data and wireless sensor networks," Ad Hoc Networks, vol. 35, 2015, pp. 127-136.

[39] Y. Wang, Q. Hu, D. Srinivasan, and Z. Wang, "Wind Power Curve Modeling and Wind Power Forecasting With Inconsistent Data," IEEE Transactions on Sustainable Energy, vol. 10, no. 1, 2019, pp. 16-25.

[40] M. Aghaei, A. Gandelli, F. Grimaccia, S. Leva, and R. E. Zich, "IR real-time analyses for PV system monitoring by digital image processing techniques," in 2015 International Conference on Event-based Control, Communication, and Signal Processing (EBCCSP), 2015, pp. 1-6.

[41] R. Hariharan, M. Chakkarapani, G. Saravana Ilango, and C. Nagamani, "A Method to Detect Photovoltaic Array Faults and Partial Shading in PV Systems," IEEE Journal of Photovoltaics, vol. 6, no. 5, 2016, pp. 1278-1285.

[42] S. Vergura, G. Acciani, V. Amoruso, G. E. Patrono, and F. Vacca, "Descriptive and Inferential Statistics for Supervising and Monitoring the Operation of PV Plants," IEEE Transactions on Industrial Electronics, vol. 56, no. 11, 2009, pp. 4456-4464.

[43] D. C. Jordan, T. J. Silverman, J. H. Wohlgemuth, S. R. Kurtz, and K. T. VanSant, "Photovoltaic failure and degradation modes," Progress in Photovoltaics: Research and Applications, vol. 25, no. 4, 2017, pp. 318-326.

[44] Y. Zhao, R. Ball, J. Mosesian, J.-F. de Palma, and B. Lehman, "Graph-Based Semi-supervised Learning for Fault Detection and Classification in Solar Photovoltaic Arrays," IEEE Transactions on Power Electronics, vol. 30, no. 5, 2015, pp. 2848-2858.