



Solar Cell Surface Defect Detection Deep Learning: A Comprehensive Survey

¹Amol Salunkhe, ²Dr. B. D. Jitkar

¹M Tech Student, ² Professor

¹Department of Computer Science & Engineering,

¹D. Y Patil College of Engineering & Technology, Kolhapur, India

Abstract: Nowadays due to increase in the awareness of the green and clean energy, the solar cells production increases in lightning speed. So, there is an increasing need for automating the solar cell panel defect detection instead of manual screening. So solar cell surface detection is becoming one of the crucial research areas for providing the reliable and optimistic manufacturing process. Recently the various deep learning frameworks are used for detecting the defects including YOLOv5, Faster R-CNN, and YOLOv6. These techniques are used for addressing the various challenges including accessing the background details, inconsistencies and variable defects. This review paper examines various techniques in the detection of solar cell defect, features extraction techniques, training classifiers, and architectural modifications. It also highlights the various challenges including data imbalance, real time data, use of explainable AI for detecting and interpreting the defects form the solar cells.

Index Terms - Solar Cell Defect Detection, Computer Vision, Deep Learning, YOLOv5, Faster R-CNN, Cross Stage Partial Network, YOLOv6, Deformable Convolution, Industrial Automation, Photovoltaic Inspection.

I. INTRODUCTION

With the growing demand of the renewable energy leads to the rapid development in the photovoltaic (PV) technology. It gives the clean and sustainable energy solution through the solar energy. The solar cell is the key part with the solar energy system which itself ensures the reliability and efficiency of the solar energy system. The solar cells surface often faces challenges of including cracks, scratches and fractures on the surface which can lead to reduction in the efficiency of power generation. So, the defect detection and classification are a core component of the solar cell manufacturing unit.

Earlier for detection of the defect, manual inspection method was used. Some traditional image processing techniques are also used for processing the solar panel images. But these methods fail to detect the defects in the industrial environment having various challenges including lighting variation, noise coming inside the solar cell image background, defect shape recognition, etc. which hampers the large-scale production of the solar cell based on growing demand. In recent years due to advancement in the computer vision and image processing technology with deep learning techniques integration, automates the defects detection and increases accuracy. Models such as R-CNN, YOLOv5, and YOLOv6 shown the excellent results for defect detection using the real environment. Researchers also use the various frameworks including deformable convolutional layers and cross stage partial for enhancing the defect detection process.

Despite these advancements, still they face the various challenges including lack of the well annotated datasets of solar cell, optimization requirement with lightweight models and real time implementation in industry environment. There is also a need of enhancement in deep learning model interpretability which remains an active area of research. This paper provides a review of the various techniques used for solar cell defect detection using deep learning techniques. It analyzes the limitations and challenges identified in the solar cell defect detection area. Section II outlines various techniques proposed by authors, along with their advantages and drawbacks. Section III discusses the challenges in front of the solar cell fault detection for developing a step towards automating the fault detection process.

II. LITERATURE REVIEW

Various researchers are devoted their research for automated detection of the solar cell faults reflecting from traditional manual method to the latest deep learning driven systems as follows –

Rifat Al Mamun Rudro, et al. [1] proposes the deep learning model by integrating InceptionV3 base with U-Net. ImageNet weights are used with Inception V3-Net to enhance the layers. It has two layers; first includes batch normalization and LeakyReLU and second is the Soft-Max output layer. It uses the image segmentation inside the deep learning model for improving the identification accuracy. Further it can be improved by applying the optimization with real-time fault detection. Su, Z. Zhou and H. Chen [2] propose the dataset for detection of the anomaly from the photovoltaic and electroluminescence images. Author includes the 36,543 images including the various types of the defects and backgrounds. It includes the images from the ten different categories with bounding box for 8 faults. The various deep learning algorithms have been evaluated on the dataset. Further this dataset can be evaluated for the many other task including shot detection and classification. Dhritiman Adhya, et al. [3] uses the

three different machine learning algorithms including CatBoost, XGBoost and LGBM for PV fault analysis. This system has been implemented in the Simulink environment with the own dataset. These algorithms reduce the computational time. It further analyzes with the random forest algorithm. These algorithms can be replaced by deep learning techniques for further improvement.

Duranay, Zeynep Bala [4] introduces the fault detection using the deep learning technique. The dataset of 20000 images are utilized with the categorization into 12 classes for the infrared solar images. The classification has been performed using the SVM along with Efficientnet feature extraction technique. The proposed techniques accurately classify the defects into the 12 different categories. Further, optimization can be applied along with the use of data augmentation and generalization. Rohith G, R Rajalakshmi [5] proposes the hybrid deep learning mechanism by combining CNN with the pretrained ViT. It extracts the multi-scale features by reducing time and complexity. It also generalizes the interclass feature extraction mechanism. The model is tested on the balanced solar panel images. It increases the generalization and minimizes overfitting data. Further it can be extended with adding diverse datasets integrating it with the edge computing. Isaac Segovia Ramírez, Fausto Pedro García Márquez, et al. [6] presents the new method of analyzing the image using two CNN to detect the core areas of the ault detection with reduction in the false positive cases. This approach processes the data in autonomous mode whenever it is received using CNN. It uses size, shape and temperature parameters for analysis. This method compared with SVM and ANN which shows the robustness of the technique. It can be further improved by using the edge computing for optimizing the data transfer delay. Tarikua Mekashaw Zenebe, Ole-Morten Midtgård, et al. [7] proposes the ML based fault classification and detection mechanism using the pre-trained CNN. It automatically extracts the features for increase in accuracy and reducing the processing time and memory. The PV array data is used for training. The pretrained CNN includes the data from various deep learning mechanism including, ResNet, EfficientNet, etc. The Pairing with SVM increases the results. Further it can give the focus on the fault localization for reducing cost.

Sampurna Lakshmi P, Sivagamasundari S, Manjula Sri Rayudu [8] uses the ML technique for analyses of the faults based on the power data for the maintenance of solar plants. It processes the data coming from the solar plants and apply the DT-LGB for prediction. The model has been trained to identify the possible faults and predict well in advance. In future it can be applied with the real-time application data. Tareq Salameh, Rasmus Björk, t al. [9] uses the CNN and the transfer learning mechanism for building the new model. It detects the fault on solar PV with consideration of the shading and temperature. The dataset from the Mendely has been tested for different epoch. Transfer learning model shows the promising results. In future the transfer learning can be applied for increasing performance of classification mechanism. Fernando Martinez-Gil, Christopher Sansom, et al. [10] reviews the in-depth analysis of the various techniques used for the maintenance of the solar system. There are many challenges imposed based on the PV and CSP. AI and IoT technology can be used for ease of maintenance process. It also reduces the cost of the maintenance. It gives the UAV for capturing the fault images and failure predication for reducing the downtime. In future various hybrid deep learning mechanism can be used for enhancing the fault prediction.

Abdul-Kadir Hamid, Mena Maurice Farag, et al. [11] proposes the multi-fault classification technique using the combination of the I-V curve and power profile analysis. It combines the CNN and RF for analyzing the fault including cracks, cuts, etc. It gives more result than the CNN. The real-time scalability can be achieved through low computation model integration with IoT and cloud. Further it can be enhanced using the transfer learning, real data, and generalization. Ula Hijawi, Subhash Lakshminarayana, et al. [12] presents the review of the various approaches used for PV defect detection. Author considered IBT and ETT categories. The IBT further categorizes into IRT, EL and LBIC. The ETT has further categorizes into ECM, PLA, TDR and VCM. Various ML and digital processing approaches are considered. It critically analyzes the various defects and its locations. The author discusses the various challenges including monitoring of real time data, availability of the data and efficiency. Further the scope has been given to use ML based models for fault prediction along with fault localization. B. Su, H. Chen and Z. Zhou [13] propose the multi-scale BAFPN architecture for semantic feature layers. With the help of cosine similarity, the importance of each feature has been measured. Objects are detected using the BAF-Detector. It gives good performance for the PV cell image dataset. Further it can be extended by integrating it with IoT.

Hoanh Nguyen, Tuan Anh Nguyen, Nguyen Duc Toan [14] introduce the novel model for fault detection of solar cells. The SMT has been used for enhancement for feature extraction and fusion mechanisms. With the use of self-attention mechanism, it reduces the inference time. The special displacement mechanism improves the recall and precision values. It also combines the various features from various layers for improving accuracy. Further this model can be enhanced with the help of generative models and data augmentation. B. Su, H. Chen, P. Chen, et al. [15] designs the complementary attention network (CAN) mechanism reducing the background noise and highlighting the defects from the images. The output features are extracted from average and max pooling layer. R-CNN used for refinement in the defective regions to improve the accuracy. Proposed mechanism shows better result than the other using solar cell images. Further it can be extended for the generalization. Mustafa Yusuf Demirci, Nurettin Bešli, et al. [16] propose the deep feature v=based model for defect detection and classification. With the help of SVM, RF, KNN and DT the various features are extracted. The mRMR algorithm has been used for coming ML and DL mechanisms. L-CNN has been used for the comparison of the models. Proposed mechanism shows higher accuracy than other models. Further hybrid model can be used for enhancement.

B. Su, H. Chen, K. Liu and W. Liu [17] use the RCAG-Net for achieving defect highlighting, background noise reduction and multi-scale fusion of features. GAP and MLP has been used for reduction of dimensionality and refinement in the features. The channel-wise features are extracted using the filtering mechanism. The system has been tested on the real dataset of the defects, confirms the effectiveness in small defect spot reorganization. Lang, D., Lv, Z. [18] propose the YOLO based mechanism which integrates the Transformer model with attention mechanism for solar PV defect identification. With the help of self-attention features are extracted including spatial and semantic. CCT module sued for extracting the contextual information. It achieves good performance on the real dataset. Further this system can be extended for IoT and hybrid models. X. Xie, H. Liu, Z. Na [19] proposes transformer-based approach used for fault detection. The convolutions are used for extracting context more accurately. CW-MSA used for enlargement of window capacity. The low-level features are merged with the attention based strong features. The proposed DPit detects the fault accurately based on the testing done on elpv dataset. It can be extended using the various deep learning techniques. Sujata P. Pathak, Dr.Sonali Patil, Shailee Patel [20] proposed the novel method for detection of fault using the thermal image processing. The CNN has been used for fault type classification and identify the region of interest of fault. The proposed approach has been tested with other models where ResNet-50 achieves higher performance. It also facilitates the early identification and localization of fault. This can be extended with the use of drones.

III. CHALLENGES

With analysis of the various research literature carried out in the above section, following are the key challenges are identified in front of the solar cell fault detection systems as –

1. Limited availability of the large scale, high quality annotated dataset of the solar cell surface faults which leads to failure in the system in the actual industry environment, imbalanced data and generalization of the model.
2. Increase complexity in the background pattern finding and cracks detection along with pinholes due to their varied nature of shape, size and intensity. The lightening conditions also makes a challenge in front of background extraction.
3. The overlapping defects are still gone unaddressed.
4. Deep learning mechanisms are trained on the specific datasets where it lacks to give performance on the other images.
5. The camera resolution, angle of picture, and illumination can degrade the systems performance.
6. Integration with Explainable AI shall able to enhance the highlighting of the critical defected regions on solar cells. The Explainable AI can be helpful in reducing the misclassification.
7. It needs to apply the transfer learning, data augmentation and cross domain adaptability for improvement
8. Speed of working and accuracy remains the challenge in the real time environment.
9. Need to develop the lightweight, energy efficient models with optimizing the various processed.
10. Need to test the various hybrid and ensemble approaches for the fault detection.

IV. CONCLUSION

The solar cell surface fault detection has got attention of the world due to increasing need and clean energy along with adaption of sustainable solution. The deep learning-based systems proves the evolutionary steps in the photovoltaic quality inspection. Various literature techniques have been reviewed including the YOLOv5, YOLOv6 R-CNN. However, despite of the advantages, these fault detection systems face several challenges including limited annotated dataset availability, generalized model development and matching the trade-off between the accuracy of the model and speed of operation. It also lacks in the interpretability and explainability within the current model. In the future these can be integrated with the IOT for developing the systems for smart inspections, hybrid architecture along with support of the transfer learning. This review is the first step towards the designing the fully automated, reliable and efficient solar cell surface fault detection system. It supports the global vision of clean and sustainable energy production.

REFERENCES

- [1] Rifat Al Mamun Rudro, Kamruddin Nur, Md. Faruk Abdullah Al Sohan, M.F. Mridha, Sultan Alfarhood, Mejdil Safran, Karthick Kanagarathinam, "SPF-Net: Solar panel fault detection using U-Net based deep learning image classification", *Energy Reports*, Volume 12, 2024, Pages 1580-1594, ISSN 2352-4847, <https://doi.org/10.1016/j.egyr.2024.07.044>
- [2] Su, Z. Zhou and H. Chen, "PVEL-AD: A Large-Scale Open-World Dataset for Photovoltaic Cell Anomaly Detection," in *IEEE Transactions on Industrial Informatics*, vol. 19, no. 1, pp. 404-413, Jan. 2023, doi: 10.1109/TII.2022.3162846.
- [3] Dhritiman Adhya, Soumesh Chatterjee, Ajoy Kumar Chakraborty, "Performance assessment of selective machine learning techniques for improved PV array fault diagnosis", *Sustainable Energy, Grids and Networks*, Volume 29, 2022, 100582, ISSN 2352-4677, <https://doi.org/10.1016/j.segan.2021.100582>
- [4] Duranay, Zeynep Bala. 2023. "Fault Detection in Solar Energy Systems: A Deep Learning Approach" *Electronics* 12, no. 21: 4397. <https://doi.org/10.3390/electronics12214397>
- [5] Rohith G, R Rajalakshmi, Dikshithula Sai Manish, Rahul Narasimhan A, "Fusion-Solar-Net for solar panel fault detection", *Results in Engineering*, Volume 27, 2025, 106513, ISSN 2590-1230, <https://doi.org/10.1016/j.rineng.2025.106513>
- [6] Isaac Segovia Ramírez, Fausto Pedro García Márquez, Jesús Parra Chaparro, "Convolutional neural networks and Internet of Things for fault detection by aerial monitoring of photovoltaic solar plants", *Measurement*, Volume 234, 2024, 114861, ISSN 0263-2241, <https://doi.org/10.1016/j.measurement.2024.114861>
- [7] Tarikua Mekashaw Zenebe, Ole-Morten Midtgård, Steve Völler, Berhane Darsene Dimd, "Solar photovoltaic array short circuit fault analysis with machine learning using pre-trained convolutional neural network for feature selection", *Solar Energy Advances*, Volume 5, 2025, 100103, ISSN 2667-1131, <https://doi.org/10.1016/j.seja.2025.100103>
- [8] Sampurna Lakshmi P, Sivagamasundari S, Manjula Sri Rayudu, "IoT based solar panel fault and maintenance detection using decision tree with light gradient boosting", *Measurement: Sensors*, Volume 27, 2023, 100726, ISSN 2665-9174, <https://doi.org/10.1016/j.measen.2023.100726>
- [9] Tareq Salameh, Rasmus Björk, Mohammad Ali Abdelkareem, Abdul Ghani Olabi, "Detecting the faults of solar photovoltaic module due to the temperature and shading effect by convolutional neural network", *International Journal of Thermofluids*, Volume 22, 2024, 100643, ISSN 2666-2027, <https://doi.org/10.1016/j.ijft.2024.100643>
- [10] Fernando Martinez-Gil, Christopher Sansom, Aránzazu Fernández-García, Alfredo Alcayde-García, Francisco Manzano-Agugliaro, "Maintenance techniques to increase solar energy production: A review", *Energy Nexus*, Volume 17, 2025, 100384, ISSN 2772-4271, <https://doi.org/10.1016/j.nexus.2025.100384>
- [11] Abdul-Kadir Hamid, Mena Maurice Farag, Tareq Salameh, Mousa Hussein, "Enhancing fault detection in bifacial photovoltaic systems: a two-stage CNN-RF approach with I-V curve analysis", *Energy Conversion and Management: X*, Volume 28, 2025, 101275, ISSN 2590-1745, <https://doi.org/10.1016/j.ecmx.2025.101275>.
- [12] Ula Hijjawi, Subhash Lakshminarayana, Tianhua Xu, Gian Piero Malfense Fierro, Mostafizur Rahman, "A review of automated solar photovoltaic defect detection systems: Approaches, challenges, and future orientations", *Solar Energy*, Volume 266, 2023, 112186, ISSN 0038-092X, <https://doi.org/10.1016/j.solener.2023.112186>
- [13] B. Su, H. Chen and Z. Zhou, "BAF-Detector: An Efficient CNN-Based Detector for Photovoltaic Cell Defect Detection," in *IEEE Transactions on Industrial Electronics*, vol. 69, no. 3, pp. 3161-3171, March 2022, doi: 10.1109/TIE.2021.3070507.

- [14] Hoanh Nguyen, Tuan Anh Nguyen, Nguyen Duc Toan, "Optimizing feature extraction and fusion for high-resolution defect detection in solar cells", *Intelligent Systems with Applications*, Volume 24, 2024, 200443, ISSN 2667-3053, <https://doi.org/10.1016/j.iswa.2024.200443>
- [15] B. Su, H. Chen, P. Chen, G. Bian, K. Liu and W. Liu, "Deep Learning-Based Solar-Cell Manufacturing Defect Detection With Complementary Attention Network," in *IEEE Transactions on Industrial Informatics*, vol. 17, no. 6, pp. 4084-4095, June 2021, doi: 10.1109/TII.2020.3008021.
- [16] Mustafa Yusuf Demirci, Nurettin Bešli, Abdülkadir Gümüşçü, "Efficient deep feature extraction and classification for identifying defective photovoltaic module cells in Electroluminescence images", *Expert Systems with Applications*, Volume 175, 2021, 114810, ISSN 0957-4174, <https://doi.org/10.1016/j.eswa.2021.114810>
- [17] B. Su, H. Chen, K. Liu and W. Liu, "RCAG-Net: Residual Channelwise Attention Gate Network for Hot Spot Defect Detection of Photovoltaic Farms," in *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1-14, 2021, Art no. 3510514, doi: 10.1109/TIM.2021.3054415.
- [18] Lang, D., Lv, Z. "A PV cell defect detector combined with transformer and attention mechanism". *Sci Rep* 14, 20671 (2024). <https://doi.org/10.1038/s41598-024-72019-5>
- [19] X. Xie, H. Liu, Z. Na, X. Luo, D. Wang and B. Leng, "DPiT: Detecting Defects of Photovoltaic Solar Cells With Image Transformers," in *IEEE Access*, vol. 9, pp. 154292-154303, 2021, doi: 10.1109/ACCESS.2021.3119631.
- [20] Sujata P. Pathak, Dr.Sonali Patil, Shailee Patel, "Solar panel hotspot localization and fault classification using deep learning approach", *Procedia Computer Science*, Volume 204, 2022, Pages 698-705, ISSN 1877-0509, <https://doi.org/10.1016/j.procs.2022.08.084>
- [21] Y. Liu, J. Xu and Y. Wu, "A CISG Method for Internal Defect Detection of Solar Cells in Different Production Processes," in *IEEE Transactions on Industrial Electronics*, vol. 69, no. 8, pp. 8452-8462, Aug. 2022, doi: 10.1109/TIE.2021.3104584.
- [22] Rotimi-Williams Bello, Pius A. Owolawi, Etienne A. van Wyk, Chunling Du, "Photovoltaic module dataset for automated fault detection and analysis in large photovoltaic systems using photovoltaic module fault detection", *Data in Brief*, Volume 57, 2024, 111184, ISSN 2352-3409, <https://doi.org/10.1016/j.dib.2024.111184>
- [23] Tor Atle Solend, Anders Rødningsby, Jonas Moen, "Impacts of infrared thermographic image blurring on UAV inspection efficiency of solar power plants", *Solar Energy*, Volume 299, 2025, 113673, ISSN 0038-092X, <https://doi.org/10.1016/j.solener.2025.113673>
- [24] Irfan Adam Zulfauzi, Nofri Yenita Dahlan, Hathaithip Sintuya, Worajit Setthapun, "Anomaly detection using K-Means and long-short term memory for predictive maintenance of large-scale solar (LSS) photovoltaic plant", *Energy Reports*, Volume 9, Supplement 12, 2023, Pages 154-158, ISSN 2352-4847, <https://doi.org/10.1016/j.egyr.2023.09.159>
- [25] Adel Oulefki, Yassine Himeur, Thaweesak Trongtirikul, Kahina Amara, Sos Agaian, Samir Benbelkacem, Mohamed Amine Guerroudji, Mohamed Zemouri, Sahla Ferhat, Nadia Zenati, Shadi Atalla, Wathiq Mansoor, "Detection and analysis of deteriorated areas in solar PV modules using unsupervised sensing algorithms and 3D augmented reality", *Heliyon*, Volume 10, Issue 6, 2024, e27973, ISSN 2405-8440, <https://doi.org/10.1016/j.heliyon.2024.e27973>
- [26] H. Tella, A. Hussein, S. Rehman, B. Liu, A. Balghonaim, M. Mohandes, "Solar photovoltaic panel cells defects classification using deep learning ensemble methods", *Case Studies in Thermal Engineering*, Volume 66, 2025, 105749, ISSN 2214-157X, <https://doi.org/10.1016/j.csite.2025.105749>
- [27] David Valiente, Fernando Rodríguez-Mas, Juan V. Alegre-Requena, David Dalmau, María Flores, Juan C. Ferrer, "General machine learning models for interpreting and predicting efficiency degradation in organic solar cells", *Expert Systems with Applications*, Volume 296, Part A, 2026, 128890, ISSN 0957-4174, <https://doi.org/10.1016/j.eswa.2025.128890>
- [28] Shiue-Der Lu, Hwa-Dong Liu, Meng-Hui Wang, Chia-Chun Wu, "A novel strategy for multitype fault diagnosis in photovoltaic systems using multiple regression analysis and support vector machines", *Energy Reports*, Volume 12, 2024, Pages 2824-2844, ISSN 2352-4847, <https://doi.org/10.1016/j.egyr.2024.08.074>
- [29] Jinlai Zhang, Wenjie Yang, Yumei Chen, Mingkang Ding, Huiling Huang, Bingkun Wang, Kai Gao, Shuhan Chen, Ronghua Du, "Fast object detection of anomaly photovoltaic (PV) cells using deep neural networks", *Applied Energy*, Volume 372, 2024, 123759, ISSN 0306-2619, <https://doi.org/10.1016/j.apenergy.2024.123759>