ISSN: 0976-9102 (ONLINE)
DOI: 10.21917/ijivp.2024.0460

IMAGE PROCESSING AND CNN BASED MANUFACTURING DEFECT DETECTION AND CLASSIFICATION OF FAULTS IN PHOTOVOLTAIC CELLS

S. Kanthalakshmi[1], S. Maalathy[2] and P. Satheesh Kumar[3]
[1,2]Department of Electrical and Electronics Engineering, PSG College of Technology, India
[3]Department of Electrical and Electronics Engineering, Nachimuthu Polytechnic College, India

Abstract

Renewable energy resources such as solar energy, biomass, tidal, geothermal, and hydroelectric energy are becoming increasingly important due to their potential to mitigate the negative impacts of climate change and reduce our dependence on finite and polluting fossil fuels. Solar power can provide a clean, sustainable, and reliable source of renewable energy. Important component of solar power generation is the silicon panel and its surface quality is highly related to its robustness and power generation efficiency. Cell breakages resulting from micro-cracks, degradation and shunted areas on cells are proven to cause major issues and these affect the photovoltaic module efficiency and performance. Solar cell defect identification is important because defects in solar cells significantly reduce their efficiency, which in turn affects their power output and lifespan. By identifying and classifying defects during the production of these cells, engineers and researchers can improve the quality control of solar cells, leading to more reliable and efficient solar energy systems. The proposed method in this research paper, utilizes image processing operations such as adaptive Gaussian thresholding, horizontal and vertical line extraction morphological operations, Canny edge detection, K- Means clustering and VGG16 convolutional neural network to identify the defects in solar cells and classify them as defective or non-defective during the manufacturing process itself. Once the defects are classified, the classification data is exported to Excel file and the results are visually represented as labelled images. OpenCV and Keras modules in Python are used to perform the image processing operations which contributes to cost-effective, reduced computation and high-precision solution.

Keywords:

Black Core Fault, Broken Gate Fault, Crack Fault, Shunt Fault, Image Segmentation, Adaptive Gaussian Thresholding, K-Means Clustering, Convolutional Neural Network, VGG16

1. INTRODUCTION

Photovoltaic modules consist of a number of solar cells that are electrically connected and laminated in a protective environment. Solar cell images exhibit varying features such as complex heterogeneous background interference, vast number of similar defects, images with high-resolution which are the major challenges in automation of defect detection in these cells. Conventional production is dependent on human visual examination, which is inconsistent, unstable, time consuming and requires huge effort. Non-destructive control means need to be used during the production process in order to retain their structural properties.

Identifying and classifying defects in solar cells can help the researchers to understand the root cause of these defects, which can inform the development of new materials and manufacturing processes that prevent defects from occurring in the first place. Overall, solar cell defect identification and classification play a critical role in improving the quality and efficiency of solar energy systems, helping to meet the increasing demand for clean and renewable energy sources. This section describes about some of the existing reviews on solar cell defect classification using image processing and Deep Learning techniques.

Visual defect detection method which is completely based on multi-spectral deep CNN model has been studied and designed [1]. Features of light spectrum in solar cell color image has been analyzed and observed that a variety of defects showed different features in multiple spectral bands. Though the model enhances the detection results of complex texture background interference features and defect features, they have comparatively high detection rates for dirty cell, thick lines, color difference, paste spot and low detection rates for certain defects such as scratches and broken gates. On analysis, it is found that the area of defects with low detection efficiency is small and linear [1].

Channel-wise attention subnetwork has been connected with spatial attention subnetwork sequentially and a novel complementary attention network (CAN) is designed, which suppresses background noise features adaptively and highlights the defect features. Here, channel-wise attention subnetwork applies convolution operation to concatenate the output features extracted by global max pooling layer and global average pooling layer. CAN has been embedded into region proposal network in faster R-CNN to extract refined defective region proposals and it has been used to construct a novel end-to- end faster RPAN-CNN framework for detecting defects in electroluminescence image. This model shows high detection results for finger interruption, crack and black core defects and has good generality for detecting these defects in solar cell electroluminescence images. But, CAN reduction ratio has been set manually in electroluminescence image defect detection, which is time consuming and requires much effort [2]. In the research paper [3], image processing operations are applied to solar panels in order to detect defects and damaged panels in real time. Here, visual spectrum images are inspected to determine required ROI.

Kirs77ch edge detection technique has been used for defect detection. Image processing operations such as dilation/erosion, thresholding and edge detection have been used for detecting crack faults. Obtained results say that, this method can be used for RGB images, but results in errors due to various factors such as shadows, reflections, snow, dirt, rain[3].

To provide solution for slow speed and low accuracy in electroluminescence image detection, YOLO-based object detection algorithm has been proposed. Backbone's ability to extract deep-level information has been used first. Then, it focuses on the low-level defect information. Next, feature fusion in the Neck part is done using PAN network. It is seen that, single-size feature map output is retained, which reduces the amount of calculation. Interference speed is greater than 35 fps and YOLO-PV has 94.55 percent of average precision on the photovoltaic module data set.

A more efficient feature fusion method and more concise backbone structure to improve efficiency and speed needs to be used [4].

A defect detection method based on Canny and Prewitt operators has been proposed in this paper. Prewitt and Canny operators are used to eliminate the effect of presence of grid- lines in the defect detection of microcracks. Results show that the integrity and purity of the image defect profile has been greatly improved using this method. Clear foreground edge and defect identification accuracy is higher. Misdetection for microcracks that are completely parallel or coincidental with vertical and horizontal gridlines and busbar lines are certain limitations and pattern recognition can't be implemented using this method [5].

Fault diagnosis in the trackers of photovoltaic systems has been done using a new method, based on machine learning approach which is classified into 2 classes namely, supervised and unsupervised. For fault diagnosis, image processing algorithm based unsupervised method has been used to determine the photovoltaic slopes has been proposed. Fault detection is performed, comparing the slopes of several modules. Principal component analysis (PCA) has been used to determine the slope of an object, thereby avoiding the use of a wide range of data and specific sensors. It is highly reliable, even with incomplete images due to reflections. Deviation index has been proposed to differentiate the faulty panels. From the obtained results, it is seen that, PCA can be used in image processing algorithms to determine the slope and detect a fault in the tracker [6].

To provide optimal solution for few of the above-mentioned issues, photovoltaic cells manufacturing defect detection based on image processing and classification of these defects using CNN has been proposed in this research paper.

2. DIFFERENT TYPES OF MANUFACTURING DEFECTS IN PHOTOVOLTAIC CELLS

Following are the different types of manufacturing defects that occur in photovoltaic cells:

2.1 BLACK AREA

Black core faults in solar cells are a type of manufacturing defect that occurs during the fabrication process. They are characterized by a dark, circular or elliptical region in the center of the cell, which is usually surrounded by a lighter ring. Black core is caused by impurities or defects in the silicon material used to make the cell. These defects can significantly reduce the efficiency of the solar cell, as they create a region where the electrical current cannot flow freely. It also causes localized heating. Different types of faults that occur in solar cells is shown in Fig 1.

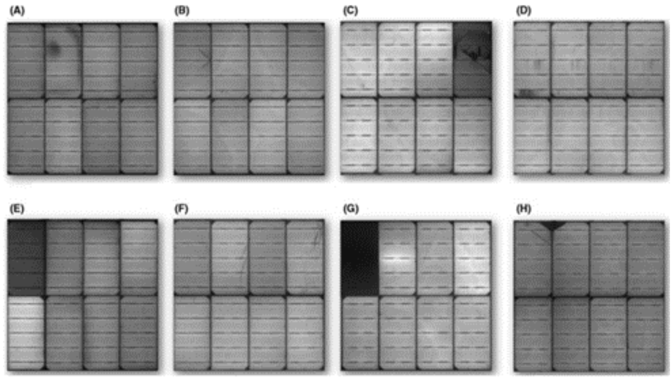

Fig.1. Types of defects in photovoltaic cells (a) Black area (b) Cracks (c) Break (d) Finger failure (e) Low cell (f) Scratches (g) Black cell (h) Broken corner. (i)Shunt faults.

2.2 CRACK FAULTS

Crack faults in solar cells are a common type of manufacturing defect that can occur during the production process or during handling and transportation. These cracks can be caused by a variety of factors, including thermal stress, mechanical stress, and defects in the material used in cell production. Cracks in solar cells can have a significant impact on the performance of the cell. They can reduce the efficiency of the cell by blocking the flow of electrical current, and they can also increase the risk of cell failure over time.

2.3 BREAKS

Breaks in solar cells can occur due to various reasons such as manufacturing defects, transportation, installation, or environmental factors. These breaks can cause a significant reduction in the efficiency of the solar cell, or even render it completely non-functional. Micro- cracks, edge cracks, finger cracks, gridline breaks are some common types of breaks that occur in solar cells.

2.4 FINGER FAILURE

Finger failure in solar cells is a type of manufacturing defect that occurs when the thin metal fingers, that collect the electrical current from the solar cell breaks or become disconnected. These fingers are typically made of silver or aluminum and are printed onto the surface of the cell. Finger failure can occur either due to mechanical stress during the manufacturing process or during handling and transportation or thermal stress caused by exposure to high temperatures during the manufacturing process or operation.

2.5 LOW CELL

A low cell fault in solar cells is a condition where the output voltage of a solar cell is lower than expected, indicating that the cell is not functioning properly. This can be caused by a variety of factors, including damage to the cell, contamination on the cell surface, or problems with the electrical connections between cells in a solar panel.

2.6 SCRATCHES

Scratches in solar cells are physical damages on the surface of the solar cell that can reduce the efficiency of the cell. Scratches can occur during the manufacturing process or during installation and maintenance of the solar panel.

2.7 BLACK CELL

Black cell fault in solar cells is a condition where a solar cell appears black and does not produce any electrical output. This can be caused by physical damage to the cell, such as a crack or break, or by contamination on the surface of the cell that prevents it from absorbing sunlight.

2.8 BROKEN CORNER

Broken corner defect in solar cells is a condition where a corner of a solar cell is physically damaged or broken, which can result in reduced power output and efficiency. This can be caused by mishandling during installation or transportation, or by environmental factors such as hail or wind damage.

2.9 SHUNT FAULTS

A shunt fault in solar cells is a type of defect that can appear when there is an unintended electrical connection between the cell's positive and negative sides. This can lead to a reduction in the cell's overall efficiency and output, as well as potential safety hazards. These faults may appear as dark, irregularly-shaped vertical areas that are distinct from the surrounding bright areas. This is because, the shunt fault effectively bypasses the electrical current that is supposed to flow through the cell, resulting in a localized loss of power.

In the proposed method, image processing operations have been used to detect crack faults, shunt faults, broken gate faults, black core faults in solar cells and VGG16 Convolutional Neural Network has been used to perform defect classification.

3. PROPOSED METHODOLOGY FOR DEFECT DETECTION AND CLASSIFICATION

Following are the steps involved in the proposed method for detection and classification of crack faults, shunt faults, broken gate faults and black core faults in solar cells:

Step1: Converting Electroluminescence Image to grayscale image: Electroluminescence imaging method provides high-resolution images, which helps in the detection of fine level microscopic defects such as finger fault or crack fault for optical investigation using computers. It improves the detection of defects with varying position, size and orientation. In the proposed method, BGR Electroluminescence image is converted to grayscale image.

Step 2: Solar cell segmentation: Adaptive Gaussian Thresholding is applied on the grayscale image obtained in Step1 and the defects, vertical and horizontal bus bar gridlines will be visible as white indications on black background. Contours in the input image are identified and compressed, which helps in reducing memory consumption. Approximation of contour perimeter is done and contours are drawn. Perspective transformation is applied on this image in order to modify the image viewpoint. Top-down representation of the segmented solar cells is obtained by applying Affine transformation and the segmented solar cells are then stored.

Step 3: Morphological image processing for detection of crack faults: Structure element is created for removing horizontal lines in the image through morphology operations applied on the segmented solar cell image. Horizontal lines extracted image is obtained, in which only the crack faults are visible as white marks on a black background.

Step 4: Canny edge detection and contours for highlighting the identified defects: Canny edge detection is a popular image processing technique used for detecting edges in digital images. It has several steps, which include Gaussian smoothing, gradient calculation, non-maximum suppression, double thresholding, and edge tracking by hysteresis.

In the proposed method, Canny edges are detected, and contours are drawn in the horizontal line extracted image to highlight the identified defects as minimum area rotated rectangle, for enhanced visualization of the defects.

Step 5: Morphological image processing for detection of shunt faults: Since shunt faults appear as dark, irregularly shaped vertical areas that appear distinct from the surrounding bright areas, structure element is created for extracting vertical lines in the image through morphology operations, which is applied on the segmented solar cell image. In the obtained result, shunt faults are visible as vertical white marks on a black background. Finally, canny edges are detected, and contours are drawn in this image to highlight the identified defects as mentioned in Step4.

Step 6: Image segmentation using K-Means clustering to detect black core faults and broken gate faults: K-Means clustering is a popular unsupervised machine learning algorithm used for clustering analysis. The algorithm aims to partition a set of data points into K clusters, where each data point belongs to the cluster with the nearest mean. Basic steps of the K-Means clustering algorithm are:

1. Initialize K centroids randomly.
2. Assign each data point to the nearest centroid.
3. Calculate the mean of each cluster.
4. Update the centroid of each cluster to the mean.
5. Repeat steps 2-4 until the centroids no longer move significantly or a maximum number of iterations is reached.

K-Means clustering has been used in the proposed method to segment the image into 2 clusters, based on whether the pixel value is 0 (black) or 1 (white). Finally, the identified defects are highlighted as mentioned in Step 4.

Step 7: Classification of defective and non-defective cells: If defects are not found (no highlighted defects), then it is classified as a non-defective photovoltaic cell and moved to the next stage in the production line. If faults are identified in the cells, then they are classified based on the defects using VGG16 Convolutional Neural Network, as mentioned in Step 8.

Step 8: Faulty cells classification using VGG16 CNN: Convolutional Neural Networks (CNN or ConvNet) are used for image classification and recognition due to its high accuracy. They are complex feed forward neural networks, that is used to detect important features in the image automatically, without human supervision. Its built-in convolutional layer reduces the high dimensionality of images without reducing its information. CNN uses trained datasets to classify the faults in defective solar Cells.

VGG16 is a pre-trained convolutional neural network (CNN) model that is commonly used for image classification tasks. Its architecture consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. Convolutional layers are used to extract features from the input image, while the fully connected layers are used to classify the image into different categories. VGG CNN architecture is shown in Fig.2.

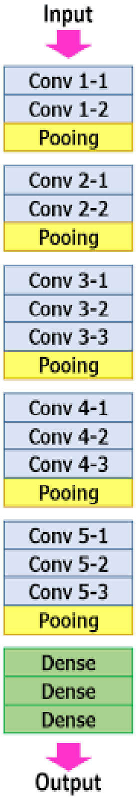

Fig.2. VGG16 CNN Architecture

In the proposed method, parameters such as number of epochs, batch size and image size are set appropriately in order to perform the classification of faults in solar cells. It involves the use of loss function, optimizers and metrics. ReLU activation function is used after each convolutional layer for introducing nonlinearity into the network. Dense is the output layer that contains only 1 neuron which decides the image category and SoftMax activation function has been used in this layer.

Step 9: Logging the classified data in Excel file and labeling the images: Data logging is useful for analyzing the data. The defect classification data is exported to Excel file using Python and the data is available for analysis in the photovoltaic cell manufacturing industries. Also, classified images are labelled and visually presented. Thus, the proposed method has been used to detect the defects in the photovoltaic cells and classify them efficiently using VGG16 Convolutional Neural Network.

4. SIMULATION AND RESULTS

Python is one of the widely used programming languages for performing image processing operations and machine learning. In the proposed method, Python libraries such as OpenCV and Numpy have been used to perform the necessary image processing operations. Keras, a high level neural network library has been used to perform defect classification using VGG16 CNN. Images from Fig.3 to Fig.11 are the results obtained from simulation of the steps 1 to 9 mentioned in Section 3 using Python:

4.1 CONVERSION OF ELECTROLUMINESCENCE IMAGE TO GRAYSCALE IMAGE

Input electroluminescence image has been converted to grayscale image as shown in Fig.3.

Fig.3. EL Image converted to grayscale image.

4.2 SOLAR CELL SEGMENTATION

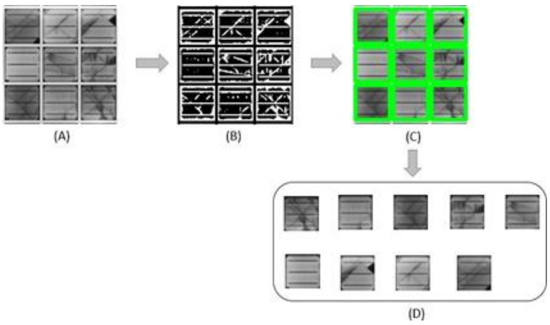

Fig.4. Solar cell segmentation: (a) Grayscale image with 9 cells. (b) Adaptive Gaussian thresholding applied on image. (c) Contour drawn image. (d) Segmented solar cells.

A portion of the grayscale image shown in Fig.3 has been taken and cropped into an image containing 9 cells and segmentation is performed on this image in order to obtain separate cells, as shown in Fig.4.

4.3 MORPHOLOGICAL IMAGE PROCESSING FOR DETECTION OF CRACK FAULTS

On extracting horizontal lines from the edge detected images of segmented solar cells, it is seen that, crack faults appear as white marks on black background, as shown in Fig.5.

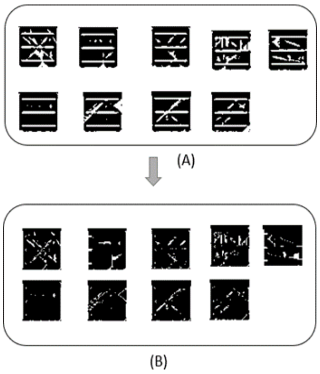

Fig.5. Crack faults detection: (a) Edge detected images (b) Horizontal line removed images showing crack faults.

4.4 CANNY EDGE DETECTION AND CONTOURS FOR HIGHLIGHTING THE DEFECTS

The Fig.6 shows the result of Canny edge detection and contours drawn in the image obtained from Step3. Thus, defects are visually enhanced in this Step.

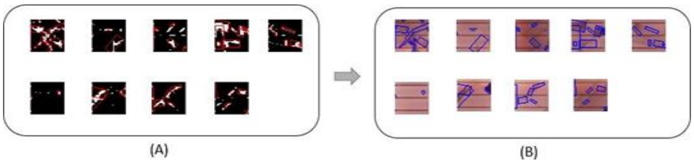

Fig.6. (a) Crack faults highlighted in edge detected images. (b) Crack faults highlighted in segmented solar cells.

4.5 MORPHOLOGICAL IMAGE PROCESSING FOR DETECTION OF SHUNT FAULTS

Other portion of the input image, containing solar cells with shunt faults has been taken in this Step. On extracting Vertical lines from the edge detected images of the segmented solar cells, shunt faults appear as vertical white marks on black background. Canny edge detection is performed on these images and contours are drawn, so as to highlight the shunt faults in the solar cell images, as shown in Fig.7.

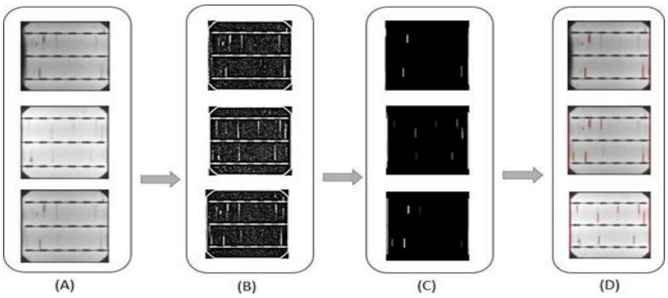

Fig.7. Shunt faults detection: (a) Solar cell images with shunt faults. (b) Edge detected images. (c) Vertical lines in the images indicating crack faults. (d) Shunt faults highlighted images.

4.6 IMAGE SEGMENTATION USING K-MEANS CLUSTERING TO DETECT BLACK CORE FAULTS AND BROKEN GATE FAULTS

Solar cell images with black core faults and broken gate faults have been taken in this Step.

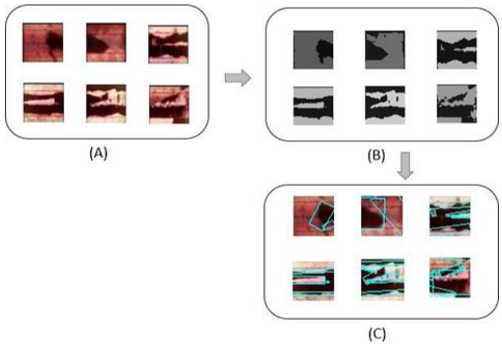

Fig.8. Black core and broken gate fault detection: (a) Solar cell images with black core/broken gate faults. (b) K-Means clustered images. (c) Black core/broken gate faults highlighted images.

K-Means clustering is applied on these images, in order to segment it into clusters and identify the presence of black core or broken gates. Canny edge detection is performed on these images and then, contours are drawn, so as to highlight the black core and broken gate faults in the solar cell images, as shown in Fig.8.

5. CONCLUSION

From the simulation results, it has been observed that, black core faults, broken gate faults, crack faults and shunt faults in solar cells have been identified effectively using this method and can be rejected before moving to the next step in production line. Initially, less computational image processing operations are applied on the solar cells, so as to identify whether the cells are defective or non-defective. Only the defective solar cells are fed to VGG16 machine learning model for further classification, thereby improving the performance and accuracy of the model and avoids more computational machine learning operations on non-defective solar cells, thus saving time and memory. Thus, this research paper focuses on automation of defect detection based on image processing and classification of faults in solar cells based on VGG16 Convolutional Neural Network, which is highly valuable for rejection of defective products and improved quality control in production, thus eliminating the cost of installation of defective products and hence, improves the robustness and efficiency of photovoltaic panels.

REFERENCES

[1] Ying Yi Hong and Rolando A. Pula, "Methods of Photovoltaic Fault Detection and Classification", *A Review, Energy Reports*, Vol. 8, pp. 5898-5929, 2022.

[2] 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," *IEEE Transactions on Industrial Informatics*, Vol. 17, No. 6, pp. 4084-4095, 2021.

[3] Haiyong Chen, "Solar Cell Surface Defect Inspection based on Multispectral Convolutional Neural Network", *Journal of Intelligent Manufacturing*, Vol. 31, No. 2, pp. 453-468, 2020.

[4] A.V. Patel, L. McLauchlan and M. Mehrubeoglu, "Defect Detection in PV Arrays Using Image Processing",

Proceedings of International Conference on Computational Science and Computational Intelligence, pp. 1653-1657, 2020.

[5] Z. Meng and Y. Zhao, "Defect Object Detection Algorithm for Electroluminescence Image Defects of Photovoltaic Modules based on Deep Learning", *Energy Science and Engineering*, Vol. 2022, pp. 810-813, 2022.

[6] T.G. Amaral and A.J. Pires, "Fault Detection in PV Tracking Systems using an Image Processing Algorithm Based on PCA", *Energies*, Vol. 14, No. 1, pp. 7278-7287, 2021.

[7] Arockia Dhanraj and P. Anitha, "An Effective Evaluation on Fault Detection in Solar Panels", *Energies*, Vol. 14, pp. 7770-7782, 2021.

[8] Yifeng Zhang and Biao Zhao, "Research on Image Defect Detection of Silicon Panel Based on Prewitt and Canny Operator", *Frontiers in Physics*, Vol. 9, pp. 701462-701474, 2021.

[9] Q. Ling and N.A.M. Isa, "Printed Circuit Board Defect Detection Methods Based on Image Processing, Machine Learning and Deep Learning: A Survey", *IEEE Access*, Vol. 11, pp. 15921-15944, 2023.

[10] V.S. Bharath Kurukuru, A. Haque and M.A. Khan, "Fault Classification for Photovoltaic modules using Thermography and Image Processing", *Proceedings of International Conference on Industry Applications*, pp. 1-6, 2019.

[11] D.P. Winston, "Solar PV's Micro Crack and Hotspots Detection Technique using NN and SVM", *IEEE Access*, Vol. 9, pp. 127259-127269, 2021.

[12] B. Su, Z. Zhou and H. Chen, "PVEL-AD: A Large-Scale Open-World Dataset for Photovoltaic Cell Anomaly Detection", *IEEE Transactions on Industrial Informatics*, Vol. 19, No. 1, pp. 404-413, 2023.

[13] R. Rajeshkanna and P. Ganesh Kumar, "Fault-Related Feature Discrimination Network for Cell Partitioning and Defect Classification in Real-Time Solar Panel Manufacturing", *Journal of Process Mechanical Engineering*, Vol. 78, No. 2, pp. 1-13, 2023.

[14] N.T.N. Trinh, D.T. Hung, N.H.T. Dat and P.Q. Dung, "Application of Artificial Intelligence in Detecting and Classifying Faults of Solar Panels", *Proceedings of International Conference on Communications and Electronics*, pp. 513-518, 2022.

[15] Hossam A. Abd El-Ghany, Ahmed E. ElGebaly and Ibrahim B.M. Taha, "A New Monitoring Technique for Fault Detection and Classification in PV Systems based on Rate of Change of Voltage-Current Trajectory", *International Journal of Electrical Power and Energy Systems*, Vol. 133, pp. 1-12, 2021.

[16] S. Priya, S. Muruganantham and C. Padma, "Deep Features Based Coral Reef Classifications using Machine Learning", *Journal of Emerging Technologies and Innovative Research*, Vol. 23, No. 1, pp. 1-12, 2020.