 https://doi.org/10.1051/itmconf/20224403065

Performance of fault classification on Photovoltaic modules using Thermographic images.

Ashwini Raorane[1], Dhiraj Magare[2], Yogita Mistry[3]

[1]Department of Electronics Engineering, Ramrao Adik Institute of Technology,Sector 7, Phase I, D. Y. Patil Deemed to be University,
Nerul, Navi Mumbai, Maharashtra, India, E-mail: ashwini.raorane@rait.ac.in
[2]Department of Electronics Engineering, Ramrao Adik Institute of Technology,Sector 7, Phase I, D. Y. Patil Deemed to be University,
Nerul, Navi Mumbai, Maharashtra, India, E-mail: dhiraj.magare@rait.ac.in
[3]Department of Electronics Engineering, Ramrao Adik Institute of Technology,Sector 7, Phase I, D. Y. Patil Deemed to be University,
Nerul, Navi Mumbai, Maharashtra, India, E-mail: yogita.mistry@rait.ac.in

Abstract. In this paper, presents thermal image analysis on Fault Classification (FDC) of Photovoltaic (PV) Module. The traditional manual approach of PV inspection is generally more time-consuming, more dangerous, and less accurate than the modern approach of PV inspection using Thermography Images (TI). The benefit in using (TI) images is that it can be used to quickly establish problematic areas in PV Module and provide various measurement details. Thermal image analysis conducted in this research will contribute to inspect PV module by providing a more accurate and cost-efficient diagnosis of PV faults. To maintain the long-term reliability of solar modules and maximize the power output, faults in modules need to be diagnosed at an early stage. In this research, thermographic images were used to detect faults in PV Module using traditional methods and Deep learning methods are mainly used to identify and classify the type of faults that can happen in PV Module. This method will present and discuss on the fault classification and its performance parameters. The fault detection stage determined whether the PV module has an abnormal condition. In this research, performance metrics of fault classification using Deep Neural Networks (DNNs) models is analyzed, which offers high accuracy for detecting abnormalities in image classification tasks.

Keywords--- Thermal Imaging, fault detection, classification, deep learning, pretrained models

1 Introduction

Photovoltaic (PV) systems, also known as solar panels, are gaining more attention nowadays than ever. The global PV market has grown exponentially from 1992 to 2019, and the market is expected to grow faster in the coming years. According to a market report, Renewables 2019 by IEA (n.d.), the maximum amount of energy produced by renewable energy is estimated to increase by 50% between 2019 and 2024. The IEA addresses that Solar PV accounts for about 60% of the increase.

Utilizing Thermography Images has become an emerging solution for a PV system inspection. (TI) inspect more faster than traditional handheld methods by lying over PV modules and also guaranteeing safety by avoiding dangerous working conditions. Additionally, PV inspection using thermographic images promotes accuracy in detection and classification of anomaly [1]. TI for PV inspection allows us to “assess performance of photovoltaic modules, superseding time-consuming traditional manual methods. This chapter introduces an overall introduction to the research subject. It includes the problem, significance, the purpose, research questions, assumptions, delimitations, and limitations.

Deep learning algorithms have recently been utilised in fault diagnostics of photovoltaic (PV) systems to identify and classify the types of problems that can be detected. As public awareness of climate change grows, the globe is turning its attention to renewable energy sources. Solar energy has managed to come out as a major non-polluting and never ending source of energy in this scenario. Solar energy installations have grown at an exponential rate during the last 10 years [2]. As the world’s reliance on solar energy is increasing, researchers and engineers are naturally concerned about providing reliable and long-lasting solar energy production systems. Because solar modules have a long life span (25-30 years), it is vital to maintain solar energy production systems on a regular basis in order to get the most out of them. Furthermore, fault diagnosis is required in order to maintain an uninterruptible power supply and minimise solar power plant shutdowns.

Traditional methods of PV module’s fault detection with the help of electrical performance measurement are well known. However, these methods have significant drawbacks. Despite an irregular IV characteristic curve of PV panel is a clear sign of problem, its difficult to locate the source or actual location of the fault (Particularly when number of modules installed are large). Therefore, another procedure is required to determine specific location and the nature of issue. The use of IR imaging for PV plant has a number of benefits. A thermal image can clearly show anomalies. Due to the fact that IR imaging is a non-invasive technology, PV panels can be evaluated without disrupting routine operations. Thermal imaging allows you to scan a large number of panels in a short amount of time. In addition to that, IR imaging allows for early fault detection before the system fails completely. As a result, IR imaging provides an easy, quick and dependable means of scanning flaws in solar panels to ensure fault free operation. In this research an automatic detection of anomaly using thermographic images is analysed. In this study a detail analysis of fault detection and classification is studied methodology using deep learning techniques. In this Four different pre-trained of deep Convolutional Neural Network (CNN): Resnet 101, ResNet50, Alexnet and VGG16 were used for transfer learning. In this work, a novel PV thermal image dataset of photovoltaic-thermal-images-dataset based on PV system has carried out for classification of fault [20]. During this project, we have reported three schemes of classifications: Single anomaly, multiple anomaly and contagious string detection is done. The validation accuracy with the help of pre trained model is studies initially. This is often a moderately high accuracy rather than using traditional techniques of the accuracies reported within the literature. Therefore, this research is going to be useful in addition to quickly diagnosing fault using thermographic images and might be helpful to diagnose faults in PV modules. To ensure the reliability and accuracy with high computational speed for long term operation of a PV panel, even minor faults or hotspot formation on a PV panel need to be detected. Out of many kinds of PV module faults, the study focuses on the environmental phenomenon. The performance of PV modules was easily affected as the weather changes and the amount of sunlight was not constant.

The traditional PV system inspection is inefficient, inaccurate, and dangerous. Therefore, the new approach of PV system inspection using thermography images has become a solution in the industry. The thermal image analysis method introduced in this work will help PVS inspection by finding and analyzing the thermal appearances of PV faults and eventually provide meaningful factors for PV inspection using thermography images [10]. The key strengths of these research methods are reliability and accuracy in hot spot detection. This research takes three main steps to conduct a PV module inspection: (i) Thermal data collection for PV module, (ii) Thermal image preprocessing, and (iii) Thermal image data analysis for PV fault detection and classification (FDC). In this research, classification of fault based on deep learning method and traditional machine learning methods will be analysed using imaginary datasets. An intelligent fault detection using thermal image dataset with experimental faults detection and classification with machine learning concept using CNN is studied.

1.2. Organization of paper

We use the CNN architecture for defect detection in this work. In this research, the work is organized as follows. We firstly provide some theoretical background information about the CNN network needed for the Image Analysis in Section II. Literature survey is discussed in section III Then, we briefly describe the thermal images used in our work in Section III. Further on vast literature a solution has come up with proposed methodology in section IV. A deep CNN framework of pretrained model is studied in detail in section V. Based on label dataset a network has analysed using pretrained model in section VI and followed by results and conclusion.

2 Literature Survey

Object-based computer vision (CV) has become a significant technological challenge. There are a few frameworks in this industry, and many developers are looking for a system that can recognize objects quickly and accurately. It is vital to highlight that computer vision is quite beneficial in a variety of fields. Key concepts of the literature study involve PV module inspection, FLIR thermography, fault detection, and classification. The key concepts are present in the concept map in Figure 2. Traditional defect detection approaches need precise operating conditions, which take time, effort, and money. In today's fast-paced environment, innovative tactics and technology breakthroughs are expected to provide rapid results. Advanced and automated fault diagnosis is a procedure that provides immediate results and ensures a longer lifespan for a variety of important PVM components. Hypothesis: This research uses convolutional neural networks (CNN) to conduct fault identification in PVM, successfully classifying different errors based on photos taken by FLIR camera. Pierdicca et al. [20] stated that the utilization of RES, whose application is rising in necessity because of environmental and climatic concerns, as well as the global economy's recovery, will be a major challenge. Renewable energy sources will be the sole option for reducing fossil fuel use and pollution. The amount of allocated PV plants that generate energy has expanded dramatically, and the problem of checking and providing a PV plant has become critical, posing several issues such as efficiency, dependability, safety, and stability. This research describes a unique method for estimating PV cell degradations using DCNNs. Amaral et al. [14] stated that PV power plants currently play a significant part in the production of electricity from renewable sources. The PV modules of these power plants are mounted in trackers to achieve optimal efficiency. However, the trackers' movable construction is prone to failure, putting the required perpendicular position among the PV modules and the smartest moment in the sky in jeopardy. As a result, diagnosing a tracker failure is critical to ensuring optimal energy output. Sensor-based and statistical-based approaches have been investigated; however, they are costly and inefficient. To deal with these issues, a unique technique based on machine learning is presented for defect diagnostics in PV trackers.

3 Design Methodology

Positioning, module identification, defect detection, and defect categorization are the primary hurdles of these tec hniques. The problem of data interpretation still needs to be tackled with these approaches. The high amount of images to be examined is one of the most significant challenges. Mechanized data management intelligent system, using modern signal processing algorithms for

computer vision and capable of identifying single panel frames could be the winning answers for making monitoring more economical and dependable. Deep Convolutional Neural Networks (DCNNs) have been shown to outperform state-of-the-art methods in image classification when compared to widely used machine learning approaches (e.g. Support Vector Machine (SVM), Neural Networks (NN), k Nearest Neighbor (KNN), Decision Tree (DT), Random Forest (RF), Nave Bayes) when dealing with large image collections analysis [26].
They pave the way for total picture interpretation, outper forming existing approaches in terms of accuracy and, in some cases, efficiency, by uncovering many levels of re presentation that can capture the data's more abstract sem antics. One important feature of deep learning's success in image categorization is the usage of convolutional networks. The convolutional layers are the core of DCNN since they learn the feature representations of their input images. By integrating low/mid/high-level features and classifiers in an end-to-end multi-layer, DCNNs have led to a series of advancements for image categorization. DCNNs can automatically extract visual features and categorize them from a vast amount of picture data.

This work describes a novel approach to estimating PV cell degradations using DCNNs, according to research trends. While many scholars have accomplished image classification in the literature, the thermal image dataset is used to illustrate the research work using thermal infrared sensor based on a dataset survey. The tests on the "Photovoltaic Images Dataset" are presented to demonstrate the degradation problem and to thoroughly evaluate the classification approach presented in this study. The DCNN that we choose is based on the VGG19 network architecture, and a typical machine learning technique based on SVM is evaluated and compared for better parameter assessment.

3.1. Infrared Thermograph

The low resolution of IR cameras limits its ability to identify microscopic faults such as microcracks, soiling effect, and hotspots. It has not had an impact on a solar module's photoelectric conversion efficiency. These methods are unable to capture the deep interactions between several parameters, such as particle size, thickness, and coverage, as well as environmental factors (such as sun irradiation and humidity), that are necessary for studying the impact on power loss [2].

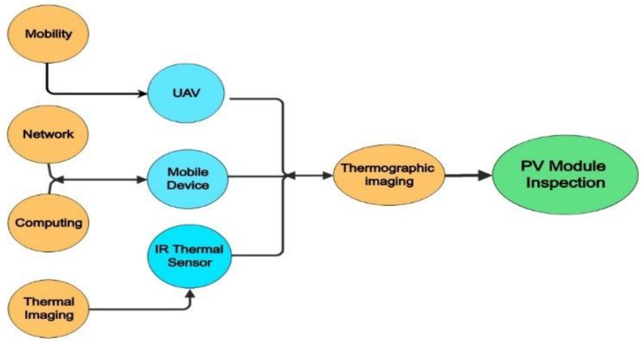

Figure 1. Source of Thermal images for PV Inspection Module

3.2. PV module defects

Identifying defects in PV modules is crucial because these faults can prompt severe power losses and degenerate performance. A single fault in a cell has the potential to spread to other modules near it and result in a complete failure in its functioning. In this work module faults and string and system faults are discussed. For the module faults, there are "hot spots on the cells and for the string and systems faults, "Wiring troubles such as diode defect, frayed wires, charge controller issues, inverter and fuse failures" are among the problems. This research focuses on Hot Spot (HS) phenomenon, which is the primary defect of the PV modules. This phenomenon is a sign of energy loss in PV modules and it is considered as one of the critical faults in PV modules. The leading causes of the hot spots are PV cell failures, partial shadowing, PV cell mismatch, or connection failures in cell links.

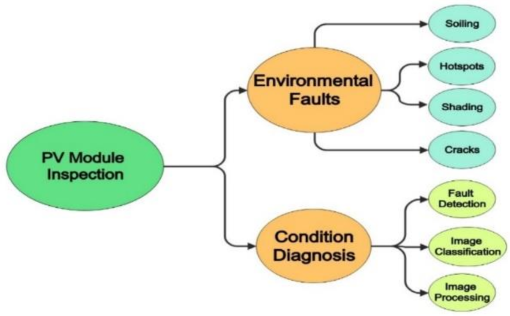

Figure 2. Key concepts of PV Module diagnosis.

3.3. Fault Detection and Classification

This research used a visual method of Fault Detection and classification (FDC) to inspect PV modules. FDC was realized by using Matlab 2021 using deep learning tool box. In this fault detection and classification of thermal images is studied using traditional machine learning techniques and deep learning model. Further comparative analysis is carried out to study deep learning model in future.

Throughout the FDC procedures, the hot spot phenomenon was identified by using image segmentation carrying out binary mask images. With the help of binary mask using image analysis, hotspot are identified and classified in three classes as single hotspot, multiple hotspot and string. This fault are Classifier used in reseach method are support vector machine (SVM) and Pretrained model VGG19. Using this traditional learning and deep learning performance evaluation is carried out. The performance metric like accuracy, precision, recall and F1 score parameters are studied.

3.4. Deep learning

A convolutional neural network (CNN/ConvNet) is a deep neural network used to interpret visual imagery. In neural networks, multiplication is the norm, but in ConvNet, it is the exception. Using a special technique called Convolution, a third function can be generated that describes how one function is modified by another. In mathematics, convolution is the process of combining two functions. One of the most important aspects of deep learning's effectiveness in image categorization is the usage of convolutional structures. The convolutional layers are the core of DCNN since they learn the feature representations of their input images. The DCNN is trained using image labels showing the anomaly in the images in order to provide information regarding cell degradation.. The training is performed with a VGG19 network.

3.5. Data Annotation

A thermographic inspection of a ground-based PV system was conducted on a PV plant with a capacity of around 66 MW in Tombourke, South Africa, for its collection. The “Pv thermal images Dataset” is composed of 3336 images collected as follows: 1007 images with damaged PV cells. This work mainly focuses on damage cell and classification of faults based on three labelled classes is used.

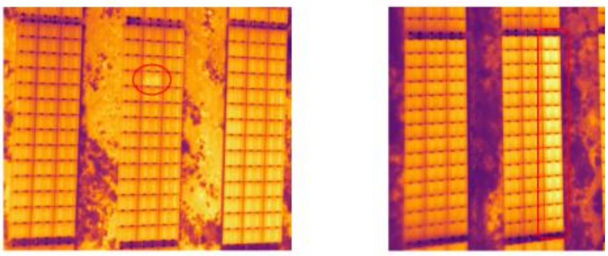

Figure 3. Deep CNN image classification Pipeline

In this Figure no. 3, the thermographic images are studied to identify the hotspot captures on pv array. Based on the mask region using segmentation approach following faults are labeled. Here in this work Three fault are considered to classify the actual predicted class and comment on its model performance.

IV. System Implementation

1. Thermal image input is taken from the FLIR camera from existing data set.
2. Then the Model detects the spot in binary mask using Image segmentation, Identify the Faulty class.
3. After the detection of thermal images, using the Convolution Neural Network (CNN) classifier, the system detects whether single hotspot, multiple hotspot or string features are extracted.
4. Using SVM classifier fault classification is analyzed.
5. Using pretrained model fault classification is analyzed

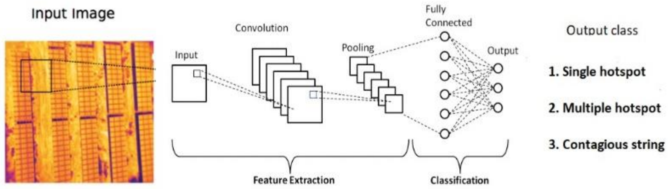

Figure 4. Deep CNN classification Pipeline

Pre-processing:

1. The dataset is divided into two batches: training and validation.
2. Color preprocessing is done with batch normalization.
3. Machine learning and deep learning model has been set up for image classification purposes.
4. A 3x3 convolution filter is used to classify images.
5. Fully connected with softmax layer faults are classified with set of 1000 images

4.1. Performance Evaluation Metrics

The following measures are used to assess the algorithms' performance:

Accuracy: shows the probability of the true predicted value of the class label, which approximates the algorithm's effectiveness.

$$\text{Accuracy}= \frac{Tp+Fn}{Tp+Tn+Fp+Fn} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where tp is the number of true positives and fn the number of false negatives.

Recall is a function of the number of cases that were successfully classified (true positives) and the number of examples that were mistakenly classified (false negatives).

$$\text{Recall}= \frac{Tp}{Tp+Fn} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

Precision is a function of true positives and examples categorized as positives when they aren't (false positives).

$$\text{Precision}= \frac{Tp}{TP+Fp} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

F1-score: is a measure of a test’s accuracy.

F1-score=$\frac{(\beta^2+1)*precision*recall}{\beta^2*precision+recall}$ ……………. (4)

The F1-score is a weighted average of the precision and recall scores. The evaluation of performance parameter will help in greater extend to analyses the model used in classification task.

V. Result and Discussion

In this paper various literature work based on various fault classification methods are discussed and more research based on DNNs have continued to advance, with numerous breakthroughs and advances, and they now offer significant advantages in picture categorization. Computational hardware and capacity have also improved significantly, supporting DNN requirements have been met, and their application has been expanded, thanks to major improvements in computational hardware and capacity. Only the training set will be used to train each classifier. Similarly, the test set is established at the start and is utilized for all tests. The dataset is split into 70 percent training and 30 percent test images. The performance of the traditional learning ad deep learning is studied for the faulty dataset is reported in Table 1. In this comparative analysis of performance parameter on the model has studied.

Learning Model	Accuracy (%)	Precision	Recall	F1-score	Run Time (s)
Machine learning (SVM)	72.54	0.6931	0.562	0.6816	4253
Deep learning (VGG19)	92.0068	0.9694	0.5256	0.6534	3625

Table 1. Evaluation parameter of PV Diagnosis

Table 1 compares the evaluation outcomes for each model, using Equations (1) – (3) to calculate accuracy, precision, recall, and F-measure. A good prediction model requires not only high accuracy but also generalizability. From the network analysis, it is observed that deep learning gives the better performance compared to machine algorithm. Following observations have done as shown below.

1. This has also proved thar training time required to execute process takes longer time compare to machine learning algorithm.
2. Evaluation metrics are usually derived from the confusion matrix) to evaluate classification results, where true positive (TP) means both actual and predicted results are anomaly; true negative (TN) means both actual and predicted results are normal; false positive (FP) means actual results are normal but predicted to be anomaly; and false negative (FN) means actual results are anomaly but predicted to be normal.

6 Conclusion

This research work is studied in detail with experimental dataset to analyse faulty thermal images. The models created for defect detection and classification using Machine learning and Deep learning techniques. The performance of the pretrained models is assessed against the labelled dataset, which holds a set of 1007 images with 3 class labels. The experimental results of the deep learning model are examined in terms of four performance measures such as precision, recall, accuracy, and F1-Score. In the first objective, a comparative study of machine learning and deep learning models for fault classification has been studied and presented.

7 References

[1] HIGUCHI and Tadatoshi BABASAKI, Failure detection of solar panels using thermographic images captured by drone, 7th International Conference on Renewable energy Research and application.

[2] A. Triki-Lahiani, A. Bennani-Ben Abdelghani, and I. Slama-Belkhodja, “Fault detection and monitoring systems for photovoltaic installations: a review,” *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 2680–2692, 2018.

[3]An On-Board Remaining Useful Life Estimation Algorithm for Lithium-Ion Batteries of Electric Vehicles, Faculty of Transportation Engineering, Kunming University of Science and Technology, Kunming 650500, China.

[4] Aicha Djalab1, Mohamed Mounir Rezaoui1, Lakhdar Mazouz1, Ali Teta1 , Nassim Sabri2Robust Method for Diagnosis and Detection of Faults in Photovoltaic Systems Using Artificial Neural Networks, Periodica Polytechnica Electrical Engineering and Computer Science, 64(3), pp. 291–302, 2020

[5] M. Sabbaghpur Arani and M. A. Hejazi, “The comprehensive study of electrical faults in PV arrays,” *Journal of Electrical and Computer Engineering*, vol. 2016, Article ID 8712960, 10 pages, 2016.

[6]Köntges, M., Kurtz, S., Jahn, U., Berger, K., Kato, K., Friesen, T., et al.: Review of failures of photovoltaic modules. In: IEA PVPS Task, p. 13 (2014).

[7] Haque, A., Bharath, K.V.S., Khan, M.A., Khan, I., Jaffery, Z.A.: Fault diagnosis of photovoltaic modules. Energy Sci Eng 7(3), 622–644 (2019).

[8] hao, Q., Shao, S., Lu, L., Liu, X., Zhu, H.: A new PV array fault diagnosis method using fuzzy C-mean clustering and fuzzy membership algorithm. Energies 11(1), 238 (2018).

[9] Dhimish, M., Badran, G.: Photovoltaic hot-spots fault detection algorithm using fuzzy systems. IEEE Trans. Device Mater. Reliab. (2019).
[10] DeepSolarEye: Power Loss Prediction and Weakly Supervised Soiling Localization via Fully Convolutional Networks for Solar Panels, Sachin Mehtal, Amar P. Azad2, Saneem A. Chemmengath2, Vikas Raykar2, and Shivkumar Kalyanaraman, University of Washington, Seattle, WA, USA 2 IBM Research Lab, India.

[11] Power loss due to soiling on solar panel: A review Mohammad Reza Maghami a,b,n , Hashim Hizam a,b , Chandima Gomes a , Mohd Amran Radzi a , Mohammad Ismael Rezadad c , Shahrooz Hajighorbani.

[12] Masoud Alajmi, Sultan Aljahdali, Sultan Alsaheel, Mohammed Fattah, and Mohammed Alshehri Machine Learning as an Efficient Diagnostic Tool for Fault Detection and Localization in Solar Photovoltaic Arrays, College of Computers and Information Technology, Taif University Al-Hawiya, Taif 21974, Saudi Arabia.

[13] J. A. Tsanakas, D. Chrysostomou, P. N. Botsaris, A. Gasteratos, "Fault diagnosis of photovoltaic modules through image processing and Canny edge detection on field thermographic measurements," International Journal of Sustainable Energy (T&F), vol.34, no. 6, 2015.

[14] Amaral, Tito G., Vitor Fernão Pires, and Armando J. Pires. "Fault Detection in PV Tracking Systems Using an Image Processing Algorithm Based on PCA." Energies 14, no. 21 (2021): 7278.

[15] A. Chouder, S. Silvestre, "Automatic supervision and fault detection of PV systems based on power losses analysis," Energy Conversion and Management, vol. 51, pp. 1929-1937, 2010.

[16]Jaffery, Z. A., Dubey, A. K., Irshad, & Haque, A. (2017). Scheme for predictive fault diagnosis in photo-voltaic modules using thermal imaging. Infrared Physics & Technology, 83, 182–187. doi:10.1016/j.infrared.2017.04.015.

[16] T. Takashima, J. Yamaguchi, K. Otani, T. Oozeki, K. Kato, M. Ishida, "Experimental studies of fault location in PV module strings," Solar Energy Materials and Solar Cells, 93 (2009) 1079-1082 [17] D. Riley, J. Johnson, "Photovoltaic prognostics and heat management using learning algorithms," IEEE 38th Conference (PVSC), 2012, pp. 001535- 001539.

[18] P. Ducange, M. Fazzolari, B. Lazzerini, F. Marcelloni, "An intelligent system for detecting faults in photovoltaic fields," 11th International Conference on Intelligent Systems Design and Applications (ISDA), 2011, pp. 1341-1346.

[19] A. Coleman, J. Zalewski, "Intelligent fault detection and diagnostics in solar plants," IEEE 6th International Conference on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS) 2011, pp. 948-953.

[20] Pierdicca, R.; Malinverni, E.; Piccinini, F.; Paolanti, M.; Felicetti, A.; Zingaretti, P. Deep Convolutional neural network for automatic detection of damaged photovoltaic cells. In Proceedings of the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2018 ISPRS TC II Mid-term Symposium "Towards Photogrammetry 2020", Riva del Garda, Italy, 4–7 June 2018; Volume 42.

[21] Christopher Dunderdale1 ;Warren Brettenny1 ; Chantelle Clohessy1 E. Ernest van Dyk2, "Photovoltaic defect classification through thermal infrared imaging using a machine learning approach" Nelson Mandela University; South Africa Statistical Association, DOI: 10.1002/pip.3191, Accepted: 20 August 2019.

[22] Baba M., Shimakage T. and Takeuchi N., "Examination of fault detection technique in PV systems," 35th International Telecommunications Energy Conference, 2013.

[23] Chen Z, Wu L, Cheng S, Lin P, Wu T, Lin W. Intelligent fault diagnosis of photovoltaic arrays based on optimized kernel extreme learning machine and I-V characteristics. Appl Energy. 2017;204:912-931.

[24] Deitsch S, Christlein V, Berger S, et al. Automatic classification of defective photovoltaic module cells in electroluminescence images. Solar Energy. 2019;185:455-468.

[25]. Jaffery ZA, Dubey AK, Haque IA. Scheme for predictive fault diagnosis in photovoltaic modules using thermal imaging. Infrared Phys Technol. 2017;83:182-187.

[26] Pierdicca R, Malinverni ES, Piccinini F, Paolanti M, Felicetti A, Zingaretti P. Deep convolutional neural network for automatic detection of damaged photovoltaic cells. Int Arch Photogramm Remote Sens Spat Inf Sci. 2018;42:893-900.