Fault Detection in aerial images of photovoltaic modules based on Deep learning

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Abstract. Operation and maintenance of photovoltaic (PV) modules are currently the prime concerns of the expanding photovoltaic industry. Unmanned aerial vehicles (UAVs) are applied in the field of inspection and monitoring of faults that occur in a photovoltaic module (PVM). Such inspections can significantly reduce time and human interference to provide accurate classification results. Technological advancements and innovative techniques in the fast moving world expect instantaneous results. Fault diagnosis is one such technique that provides instantaneous results and assures enhanced lifetime of various critical components. This paper presents the fault detection in PVM based on deep learning with the help of aerial images acquired from UAVs. Convolutional neural networks (CNN) are adopted to extract high level features from the images which are classified using the softmax activation function. The feature extraction and fault classification is carried out by using a pre-trained VGG16 network. A total of six test conditions are considered in the study. Burn marks, delamination, discoloration, glass breakage, good panel and snail trail are the several test conditions considered. The classification result for the pre-trained CNN model is exhibited and performance of the model is evaluated.

1. Introduction
Futuristic power generation depends essentially on renewable energy sources. Apart from water and wind energy, solar energy is considered as one of the crucial technologies that supply about two percent of global power demand. Solar energy is harnessed from large solar power plants spread across various geographical regions with an estimated power output of 1GW. Solar farms are constructed with a large number of photovoltaic modules (PVM). The overall power output in solar PVM tends to degrade during their life span due to faults. Ever-changing environmental conditions with an increase in natural hazards make assessing PVM conditions and identifying faults necessary (1). Fault diagnosis is an appropriate technique to determine the faults that occur in a PVM. Several conventional fault diagnosis techniques are available; however, such techniques are time consuming and are limited to single fault detection. Thus, an advanced fault diagnosis technique is the need of the hour. Various authors have suggested the using an image based fault diagnosis technique with the application of unmanned aerial vehicles (UAVs) (2,3). Visual inspection of the acquired aerial images consumes a lot of manpower. Also, the accuracy of fault detection in manual inspection depends highly on the examiners experience and varies with every examiner.

Considering the constraints mentioned above, a reliable, fast and low cost evaluation of PVM is proposed in the present study. An automatic fault diagnosis technique utilizing deep convolutional neural networks (CNN) is employed to classify the PVM faults from the acquired aerial images. Rapid
rise in innovative technologies and fault detection techniques have minimized human interventions in various fields of inspection. Accurate and precise outcomes delivered by the innovative techniques have paved way for the replacement of conventional techniques with automatic approaches. Deep learning technique automatically delivers the classification results in identifying the type of faults. Several literatures have described the use of deep learning in fault diagnosis of PVM which are discussed as follows. A deep learning based approach was performed by Li et.al for automatic detection of faults in large scale PV plants (4). The authors considered six test conditions and overall classification accuracy was found to be 97.9%. The major advantages of deep learning are utilizing pre-trained models or build models from scratch. Several authors in (5–8) have utilized deep learning in the field of fault diagnosis by building models from scratch. Also, various pre-trained models like AlexNet (9), ResNet 50 (10), VGG16 (11) etc have been applied in various image classification applications. Artificial neural networks have been put into use effectively for diagnosing loss in the output power of PVM with the help of power estimation using the sun’s position. Similarly, the condition of PVM is diagnosed using low resolution satellite images with the help of CNN producing higher classification rate exhibits the ability of deep learning based techniques to assess images of PVM (12). In general, CNN require large amount of training data such that the model is trained well to perform classification. Certain challenges persist while using CNN based classifications which are listed as follows.

- Acquisition of good quality sound data is the most challenging task in CNN.
- Multiclass classification requires uniform dataset. Bias in datasets can result in misclassification.
- Nominal hardware is required for performing training and classification.

The above mentioned challenges can be addressed by implementing data preprocessing and data augmentation techniques. Preprocessing image data removes unwanted noise from the image data, thereby creating quality dataset. Data augmentation artificially expands the image dataset such that the model can be trained effectively. Based on the literature survey, the following observations were made.

- The conventional techniques available are confined for identification of a single fault at an instance. Detection of multiple faults with advanced techniques can be considered as an up and coming research interest in the field of fault detection and diagnosis.
- Most of the literatures focus on diagnosis of electrical faults but only a few have reported on visual faults.
- Internet of things and artificial intelligence are the emerging techniques that provides a wide scope in the development of advanced fault detection and diagnosis techniques.
- A combination of several conventional fault detection and diagnosis techniques generally termed as hybrid techniques can be time saving and cost effective with more impact in fault detection and diagnosis.

In the present study, the feasibility of CNN is examined to detect faults in a PVM using aerial images. A pre-trained VGG16 (13) model is used to perform the classification task on the aerial images. VGG16 in comparison with AlexNet contains a number of convolutional layers with smaller filters stacked together to learn and extract complex features from the images provided. The pre-trained VGG16 exhibits better performance compared to other pre-trained models with fewer convolution layer (14). The major advantage of CNN is its ability to work with low resolution and low quality images. A total of six test conditions namely, burn marks, delamination, discoloration, glass breakage, good panel and snail trails are considered. The list of technical contributions made is listed as follows.

- A pre-trained VGG16 model is used to classify various faults from aerial images of PVM.
- Multiple faults are considered.
• Data augmentation technique is used to expand the image dataset.
• Uniform dataset is considered such that misclassification can be reduced.
• The superior classification performance of the model is evaluated with the help of confusion matrix. Softmax is used as classification function.

2. Experimental procedure

2.1. UAV based Data Acquisition and Monitoring System

Unmanned aerial vehicles (UAVs) have been employed in a wide range of fields such as surveillance, security, infrastructure inspection and emergency conditions. In recent years, UAV have been employed in the field of fault diagnosis due to their ability to acquire precise data over large geographical regions in limited time. Conventional visual inspection techniques were performed with the help of skilled inspectors for long period of time. Such methods had certain drawbacks like: (1) large areas require huge man power (2) availability of trained examiners (3) human error rate (4) safety concerns of examiners (5) delayed results (15,16). The above mentioned drawbacks have paved way for innovative methods to perform monitoring on PVM. The world is moving at a fast pace and expects instantaneous results in almost every real time applications. Thus, several researchers and capitalists have suggested the use of UAV as an advanced solution. The overview of UAV based data acquisition and monitoring system is provided in Figure 1. UAV are widely used across the globe for inspection purposes due to the following reasons.

• Minimized danger and health risks for inspectors
• High and in depth data collection
• Faster launch or deployment
• Versatile usage
• Quick and easy accessibility to data
• Inspection of operating machineries and reduces downtime
• Cost effective and Time efficient

Figure 1. Overview of UAV based Data Acquisition and Monitoring System

2.2. Visible faults in a PVM

Extended outdoor operation under varying environmental conditions is the major reason for fault occurrences in a PVM. Faults in a PVM will have a direct effect on the reliability, lifetime and performance. Detection and diagnosis of faults at an early stage will resist the performance degradation of PVM by the application of necessary preventive measures. Figure 2 depicts the most common visible faults that occur in a PVM. Burn marks, delamination, discoloration, glass breakage and snail trail (17–21) are the visible faults considered in the study. A brief description of the visible faults with their cause and effects are presented in Table 1.
Figure 2. PVM visible faults (22)

Table 1. Brief description of visible faults in a PVM

| S.No | Visible Faults     | Reason for fault occurrence                                      | Effects                                      |
|------|-------------------|-----------------------------------------------------------------|----------------------------------------------|
| 1    | Burn marks        | Failure in solder bonds, local heating and ribbon breakage      | Output power loss and Fire hazards           |
| 2    | Delamination      | Loss in adhesion between glass, encapsulant and back cover      | Corrosion                                    |
| 3    | Discoloration     | High exposure to ultraviolet radiation, humidity and heat       | Yellowing and browning of PVM                |
| 4    | Glass breakage    | Thermal stresses, impacts during transportation and installation | Moisture penetration, corrosion and lower irradiance |
| 5    | Snail trails      | Stress induced on micro cracks along edges                      | Accelerated degradation                      |

2.3. Preprocessing and Data augmentation of aerial images

The aerial images collected with the help of UAVs will be of different sizes and resolutions. Further, factors such as external noises, panel reflections, vibrations due to flight motion and other external
factors hinder the quality of images obtained. To improve the resolution of images and provide effective classification of various faults, such disturbances must be removed from the images. Also, larger images cannot be fit into CNN models as it increases the complexity and computational time. Image pre-processing is one technique which helps in solving the aforementioned uncertainties. Noise removal, reshaping and resizing are some of the methods involved in image preprocessing. The pre-trained VGG16 architecture accepts images of size 224x224 pixels. Hence, all the acquired images must be resized to a uniform size that is acceptable by VGG16 architecture. The UAV acquired 100 images for each test condition accounting for a total of 600 images. However, such small custom datasets might be insufficient for training CNN networks and can result in overfitting. Data augmentation is adopted in this study to artificially expand the acquired aerial images dataset. Using this technique, several image transformation functions like rotation, blur, horizontal shift, vertical shift and crop were applied on the acquired images. After the application of data augmentation, the image dataset expanded from a total of 600 images to 3150 images (525 images for each test condition). Table 2 represents the data augmentation functions utilized.

Table 2. Data Augmentation functions

| Transformation functions | Value       |
|--------------------------|-------------|
| Rotation                 | 0° - 180°   |
| (Clockwise, Anticlockwise)|             |
| Flip                     | 90°         |
| (Horizontal, Vertical)   |             |
| Noise                    | Random      |
| Blur                     | Gaussian    |
| Warp                     | 40          |

3. Pre-trained VGG16 CNN Architecture

The VGG16 network architecture was proposed by Karen Simonyan and Andrew Zisserman in the annual ImageNet Large Scale Visual Recognition Challenge (ILSVRC) (13). The architecture contains a stack of 13 convolutional layers, 5 max pooling layers, 3 fully connected layers and 1 output/classification layer. The overall architecture of VGG16 network is depicted in Figure 3.

![Pre-trained VGG 16 architecture](image)

Figure 3. Overview of pre-trained VGG16 model

VGG16 architecture contains a total of 13 convolution layers arranged in a particular designed pattern for classification of images. A kernel of dimension 3 × 3 containing learnable parameters such as A and c are transferred over an image of y pixels to perform the convolution operation that delivers an output x. The movement of the kernel is determined by the stride that commands the kernel to
move either pixel wise or skipping of several pixels. The following equation represents the simple working of the convolutional operation.

\[
x = f(Ay + c)
\]

Convolutional neural networks have the capability to extract features and patterns automatically from the aerial images for discriminating every PVM test condition. Simple features like edges are learnt by the initial convolutional layers that combine with the features extracted by the following convolutional layers resulting in complex features extraction. For every convolution layer passed the image gets resized and is broken down into simpler volume such that the most significant features are extracted. The size of the images depends on the filter size passed through and the stride considered. Each convolution layer contains a non-linear activation function called Rectified Linear Unit (ReLU) that introduces uncertainty (23). Each convolution layer is supported by a max pooling layer to down sample and reduce the size of activation map. The stacked arrangement of convolution layers ends with a classification layer. In the present condition, the convolution layers in the VGG16 architecture are connected to two fully connected layers consisting of 4096 neurons. Additionally, the two fully connected layers are followed by another fully connected layer with 6 neurons representing the number of considered PVM test condition. A final output layer consisting of softmax function performs the classification on the images. A padding of 1 pixel is performed after every convolutional layer to prevent spatial feature of images.

A pre-trained VGG16 model present in deep learning toolbox of Matlab 2020a version is used to perform the classification process. The hyper parameters settings used for fine tuning the VGG16 architecture is displayed in Table 3.

**Table 3. Hyper parameters used for fine tuning VGG16 architecture**

| Hyper parameters       | Values |
|------------------------|--------|
| Number of epochs       | 5      |
| Mini batch size        | 10     |
| Initial learning rate  | 0.0001 |
| Weight learning rate   | 0.003  |
| Momentum               | 0.9    |

4. Results and Discussion

The PVM dataset created was split into two categories namely, training and validation dataset. The split ratio used for the process is 0.8 which means the dataset is split into 80% training data and 20% validation data. The reason for selecting such split is that more training data can make the network learn more features. The validation dataset images are selected in a random order in every PVM condition. Further, the model is compiled using adaptive moment estimation (ADAM) optimizer with a validation frequency of 100 iterations. Figure 4 represents the overall performance of the pre-trained VGG16 model. The plots depict the variation of accuracy and loss for both training and validations sets with respect to the number of iterations. The proposed VGG16 model is initially assessed with the validation dataset prior being adopted for fault classification. The plots show that the training of the pre-trained VGG16 model converges quickly for the validation dataset. The model also exhibits minimum error thereby approving the feasibility of network for fault classification problems. From Figure 4 one can observe that the increase in number of epochs and iterations tends to show a gradual rise in both training and validations accuracy. The trend of training accuracy seems to be quite uniform after 400 iterations and the overall average training accuracy was found to be 98.47%. Faster convergence of network depicts the accelerated learning ability of the network resulting in minimized loss function. The overall validation accuracy of the trained VGG16 network was observed to be 95.40% which is also evident from the confusion matrix depicted in Figure 5.
From Figure 5, one can infer that only one test conditions of PVM namely, good panel has misclassified to a greater extent. The rate of misclassification indicates that the features extracted are not sufficiently trained and requires more amount of training such that the model learns the features well. Out of 630 instances taken into validation, 601 instances are correctly classified and 29 instances are misclassified.

From the confusion matrix it can be observed that good panels are misclassified as faulty panels. The model can be regarded as a better working model, since the good panels are considered as faulty. Such situation gives rise for immediate inspection of the panels. On the other hand, if the model misclassifies faulty panels as good panels then it will lead to a situation of safety concern. Faulty panels being misclassified as good panels are considered dangerous rather than good panels being...
misclassified as faulty panels. In the former case, the need for inspection is eliminated and can result in safety hazards. Based on the obtained results, one can suggest the use of pre trained VGG16 for fault classification problems to be used in real time applications.

5. Conclusion
This paper presented a fault classification model of PVM conditions in aerial images with the help of a pre trained VGG16 model. The outcomes of the present work are listed as follows.

- An effective image preprocessing and data augmentation technique applied in the work is exhibited. The model is trained for a limited number of iterations.

- A multiclass classification is performed for all the conditions and the numerical results confirm that the classification model is more accurate and efficient.

- Typical PVM conditions including burn marks, delamination, discoloration, glass breakage, good conditions and snail trail are considered.

- The results explained that the model produced high classification accuracy of 95.40% in classifying all the PVM conditions.

The exhibited solution can be put into use on a real time basis after enhanced training and various folds of validation. On further development, such kind of models can even be integrated on UAV platform for performing inspection on large scale PVM farms. Automation of inspection techniques with UAVs can minimize human interference, reduce time consumption and eliminate manual errors. Several other pre trained models like ResNet50, GoogLeNet, VGG19 etc can be used for performance comparison in future works.

References
[1] Madeti S R and Singh S N 2018 Modeling of PV system based on experimental data for fault detection using kNN method Sol. Energy 173 139–51
[2] Grimaccia F, Leva S, Dolara A and Aghaei M 2017 Survey on PV Modules’ Common Faults after an O&M Flight Extensive Campaign over Different Plants in Italy IEEE J. Photovoltaics 7 810–6
[3] Grimaccia F, Leva S, Niccolai A and Cantoro G 2018 Assessment of PV Plant Monitoring System by Means of Unmanned Aerial Vehicles Proc. - 2018 IEEE Int. Conf. Environ. Electr. Eng. 2018 IEEE Ind. Commer. Power Syst. Eur. EEEIC/ICPS Eur. 2018 1–6
[4] Li X, Yang Q, Lou Z and Yan W 2019 Deep Learning Based Module Defect Analysis for Large-Scale Photovoltaic Farms IEEE Trans. Energy Convers. 34 520–9
[5] Pierdicca R, Malinverni E S, Piccinini F, Paolanti M, Felicetti A and Zingaretti P 2018 Deep convolutional neural network for automatic detection of damaged photovoltaic cells Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch. 42 893–900
[6] Deitsch S, Christlein V, Berger S, Buerhop-Lutz C, Maier A, Gallwitz F and Riess C 2019 Automatic classification of defective photovoltaic module cells in electroluminescence images Sol. Energy 185 455–68
[7] Tang W, Yang Q, Xiong K and Yan W 2020 Deep learning based automatic defect identification of photovoltaic module using electroluminescence images Sol. Energy 201 453–60
[8] Correa-Jullian C, Cardemil J M, López Droguett E and Behzad M 2020 Assessment of Deep Learning techniques for Prognosis of solar thermal systems Renew. Energy 145 2178–91
[9] Krizhevsky A, Sutskever I and Hinton G E 2017 ImageNet classification with deep convolutional neural networks Commun. ACM 60 84–90
[10] Wen L, Li X and Gao L 2019 A transfer convolutional neural network for fault diagnosis based on ResNet-50 Neural Comput. Appl. 0123456789
[11] Kim K W, Hong H G, Nam G P and Park K R 2017 A study of deep CNN-based classification of open and closed eyes using a visible light camera sensor Sensors (Switzerland) 17
[12] Lu X, Lin P, Cheng S, Lin Y, Chen Z, Wu L and Zheng Q 2019 Fault diagnosis for photovoltaic array based on convolutional neural network and electrical time series graph Energy Convers. Manag. 196 950–65
[13] Simonyan K and Zisserman A 2015 Very deep convolutional networks for large-scale image recognition 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings pp 1–14
[14] Krishnaswamy Rangarajan A and Purushothaman R 2020 Disease Classification in Eggplant Using Pre-trained VGG16 and MSVM Sci. Rep. 10 1–11
[15] Guerriero P, Cuozzo G and Daliento S 2016 Health diagnostics of PV panels by means of single cell analysis of thermographic images EEEIC 2016 - Int. Conf. Environ. Electr. Eng.
[16] Zhang D, Wu F, Li X, Luo X, Wang J, Yan W, Chen Z and Yang Q 2017 Aerial image analysis based on improved adaptive clustering for photovoltaic module inspection 2017 Int. Smart Cities Conf. ISC2 2017
[17] Rajput P, Tiwari G N, Sastry O S, Bora B and Sharma V 2016 Degradation of mono-crystalline photovoltaic modules after 22 years of outdoor exposure in the composite climate of India Sol. Energy 135 786–95
[18] Bouraiou A, Hamouda M, Chaker A, Lachtar S, Neçaibia A, Boutassetta N and Mostefaoui M 2017 Experimental evaluation of the performance and degradation of single crystalline silicon photovoltaic modules in the Saharan environment Energy 132 22–30
[19] Han H, Dong X, Li B, Yan H, Verlinden P J, Liu J, Huang J, Liang Z and Shen H 2018 Degradation analysis of crystalline silicon photovoltaic modules exposed over 30 years in hot-humid climate in China Sol. Energy 170 510–9
[20] Bouraiou A, Hamouda M, Chaker A, Neçaibia A, Mostefaoui M, Boutassetta N, Ziane A, Dabou R, Sahouane N and Lachtar S 2018 Experimental investigation of observed defects in crystalline silicon PV modules under outdoor hot dry climatic conditions in Algeria Sol. Energy 159 475–87
[21] Dolara A, Lazaroiu G C, Leva S, Manzolini G and Votta L 2016 Snail Trails and Cell Microcrack Impact on PV Module Maximum Power and Energy Production IEEE J. Photovoltaics 6 1269–77
[22] S N V and Sugumaran V 2020 Fault diagnosis of visual faults in photovoltaic modules : A Review Int. J. Green Energy 00 1–14
[23] Jiang X, Pang Y, Li X, Pan J and Xie Y 2018 Deep neural networks with Elastic Rectified Linear Units for object recognition Neurocomputing 275 1132–9