Information Sciences Letters

Volume 10
Issue 2 *May 2021*

Article 13

2021

Deep Learning Methods for Solar Fault Detection and Classification: A Review

Rawad Al-Mashhadani
Institute of Sustainable Energy (ISE), Universiti Tenaga Nasional, Selangor 43000, Malaysia, ammar@uniten.edu.my

Gamal Alkawsi
Institute of Sustainable Energy (ISE), Universiti Tenaga Nasional, Selangor 43000, Malaysia, ammar@uniten.edu.my

Yahia Baashar
Institute of Sustainable Energy (ISE), Universiti Tenaga Nasional, Selangor 43000, Malaysia, ammar@uniten.edu.my

Ammar Ahmed Alkahtani
Institute of Sustainable Energy (ISE), Universiti Tenaga Nasional, Selangor 43000, Malaysia, ammar@uniten.edu.my

Farah Hani Nordin
Department of Electrical & Electronic Engineering, Universiti Tenaga Nasional, Selangor 43000, Malaysia, ammar@uniten.edu.my

See next page for additional authors

Inf. Sci. Lett. **10**, No. 2, 323-331 (2021) 323

Information Sciences Letters
An International Journal

http://dx.doi.org/10.18576/isl/100213

Deep Learning Methods for Solar Fault Detection and Classification: A Review

Rawad Al-Mashhadani[1], *Gamal Alkawsi*[1], *Yahia Baashar*[1], *Ammar Ahmed Alkahtani*[1,⋆], *Farah Hani Nordin*[2], *Wahidah Hashim*[3] *and Tiong Sieh Kiong*[1]

[1]Institute of Sustainable Energy (ISE), Universiti Tenaga Nasional, Selangor 43000, Malaysia
[2]Department of Electrical & Electronic Engineering, Universiti Tenaga Nasional, Selangor 43000, Malaysia
[3]College of Computer Science & Information Technology, Universiti Tenaga Nasional, Selangor 43000, Malaysia

Received: 26 Dec. 2020, Revised: 8 April 2021, Accepted: 14 April 2021
Published online: 1 May 2021

Abstract: In light of the continuous and rapid increase in reliance on solar energy as a suitable alternative to the conventional energy produced by fuel, maintenance becomes an inevitable matter for both producers and consumers alike. Electroluminescence technology is a useful technique in detecting solar panels' faults and determining their life span using artificial intelligence tools such as neural networks and others. In recent years, deep learning technology has emerged to open new horizons in the accuracy of learning and extract meaningful information from many applications, particularly those that depend mainly on images, such as the technique of electroluminescence. From the literature, it is noted that this part of the research has not received enough attention despite the importance that researchers have attached to it in the past few years. This paper reviews the most important research papers that rely on deep learning in studying solar energy failures in recent years. We compare deep and hybrid learning models and highlight the essential pros and cons of each research separately so that we provide the reader with a critical overview that may contribute positively to the development of research in this crucial field.

Keywords: Deep learning, data augmentation, electroluminescence, hybrid models, solar defects.

1 Introduction

With the rapid development in the manufacture and use of solar panels, studying their deterioration becomes necessary to allow an appropriate intervention before their final failure. Failure to detect this deterioration may cause several problems, including the loss of solar panels' effectiveness and fatal failure in other extreme cases [1]. The problems of solar panels are identified through several techniques, including electroluminescence (EL) [2,3,4], where special cameras are used to capture the panel images, which enable researchers and technicians to study, troubleshoot or predict faults through the indicators related to each defect. Among these faults, we mention cracks [5,6], corrosion [7,8], delamination [7,9], and others. These faults are identified using several traditional computer vision techniques that make it easier for technical examiners to study these errors on a large scale.

In recent years, deep learning technology models have appeared and have proven to be very effective in studying and detecting solar panels' faults, as they benefit from transfer learning feature that outperforms traditional computer vision methods. Deep learning (DL) is suitable not only to classify failures but also to understand the mechanism through which solar cell defects are detected. Such detection could improve the solar panels' reliability and durability and help manage their deterioration and enhance their performance. However, it is worth mentioning that deep learning power can be tremendous when computers have sufficient ability to interpret data without the deployment of pre-designed algorithms for feature extractions [10].

The importance of solar panels' failure studies has recently increased, branched into several disciplines such as those related to the materials industry or the types of faults and their classifications and their divisions in different kinds. Due to the increase in the number of research articles in this field, we in this paper focus most of our attention on those studies related to deep learning, as they have not received attention commensurate with the number of articles published in them. In this paper, we

* Corresponding author e-mail: ammar@uniten.edu.my

focus most of our attention on those studies related to deep learning. They have not received sufficient attention in the literature than the number of research articles published in this field. Also, to the best of our knowledge, no review has been done on this topic. Thus, we try to review the most significant development in this area and enumerate its shortcomings so that the vision becomes clear to new researchers interested in entering and continuing to research it. We will also put forth some proposals and draw some conclusions to indicate new directions in this important and vital research area.

2 Faults categories of solar cells in EL images

In EL Images, the solar cells emit radiation according to the electron holes reunion during the state of forwarding bias. If there is a crack or any type of fault in the solar cell, the current passage is decreased or hindered during the state of forwarding bias. In EL images, the defects in the solar cell appear comparatively dark due to the reduced radiations. For instance, in Fig.1, the cracking is demonstrated as grey lines.

Other solar cell faults look like dark grey regions in the EL images. For example, silicon material defect, contact forming failure, finger failure, and finger failure along cracks, as shown in Fig.2. Oppositely, the normal solar cells emit more radiations during the state of forwarding bias. It appears brighter in EL images, like the example of "Parallel to busbar" image (upper half) shown in Fig.1.

Cracks can occur due to various reasons. However, the major causes of cracks occur during the manufacturing process [12,13]. There are three causes for the cracks in the manufacturing process [11]: (1) The stress during the soldering causes cracks at the ribbon. This type is the most frequent cracking. (2) Needle pressing on a silicon wafer that is known as a cross crack line. (3) Knocking by something rigid causes cracking at the cell edge. Next to the manufacturing process, cracking may occur because of the thermomechanical loads [13]. Other than that, the branched form of cracks that occurs when the panel is exposed to heavy load often occurs during transportation, panel falling, snow loads, ice pellets, etc. [11].

According to the information presented in Table.1, cracks with their different types are the most common fault targeted in the reviewed studies. Other defects, such as paste spot, dirtiness, interconnection, soiling, and shunt, were covered. The mutual characteristic of all these faults is their appearance in the EL images.

3 Data augmentation operations

The CNN models can integrate the spatial data, but they are not equivariant in rotation and scale transformations. Therefore, the data augmentation should involve rotation

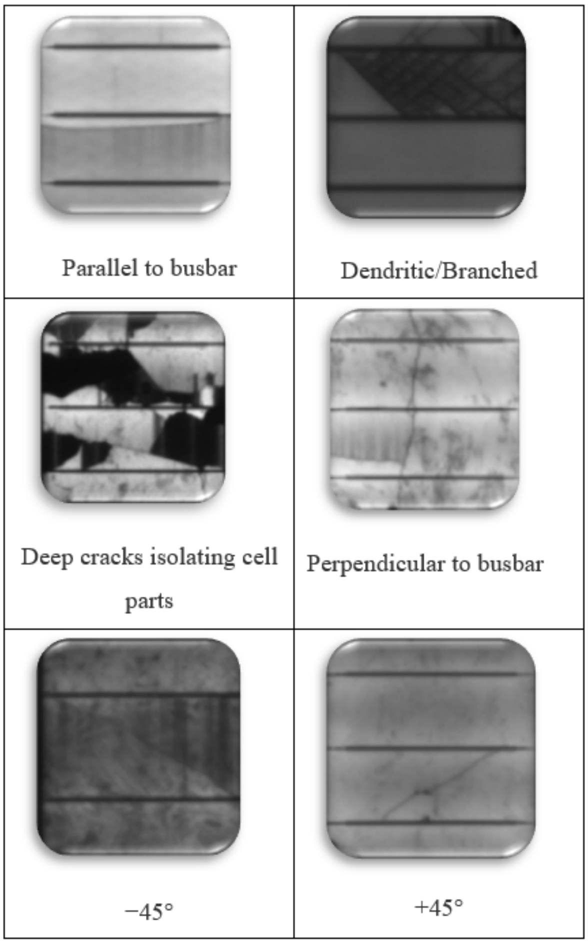

Fig. 1: Cracking orientations presented in EL images of solar cells [11,12].

and scale operations to enhance the networks' generalization [38]. Fawzi, (2016) [39] confirms the importance of data augmentation in deep learning DL methods for two purposes; (1) Data shortage: a small dataset, sufficient for training DL models, especially for multi-level classification. (2) New images (unseen to the model) at which the images are in different forms than the trained images influence the model and lead to wrong results. With data augmentation, it is possible to modify or produce totally new images by capturing necessary characteristics from both images and expanding the training set. For data shortage, applying different transformations with the data augmentation can widely broaden the initial training set.

Recent research work in [40] and [12] developed CNN models for solar defects recognition and confirmed that the models could be improved by applying data augmentation operations. However, a large dataset is required for training to avoid noise. Among the reviewed

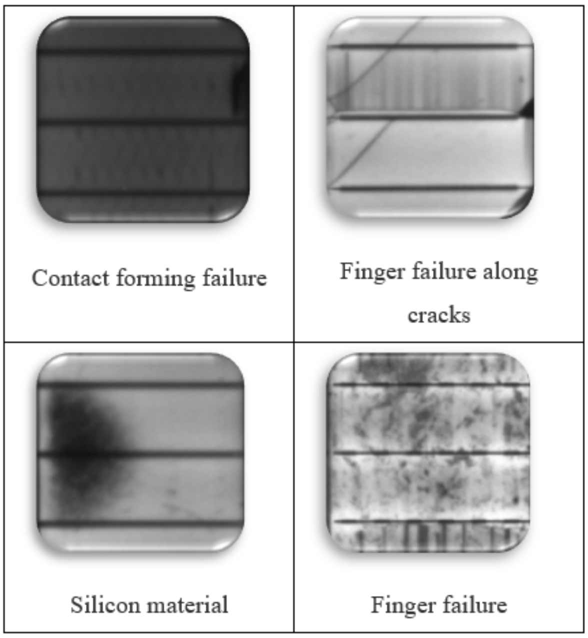

Fig. 2: Other faults in EL images of solar cells [11].

studies, as shown in Table.2, most of the studies implement the data augmentation operation, and the most common operations are flip and rotation.

4 Deep learning models

The implications of the artificial neural networks approach have improved the solar faults detection applications by applying shallow neural networks [41,42,43,44,45,46]. However, in the recent five years, the deep learning approach has emerged as a powerful tool to solve problems related to visual computing and recognition of patterns; this includes object detection, image classification, face recognition, transfer learning, and language processing. Implementing deep learning methods in detecting the defects of solar cells is relatively new [21]. In [16], the authors assessed the automatic detection and classification of the hidden cracks using CNN on a small EL image dataset. It was confirmed that the proposed model could predict the defects of the PC cells with an accuracy of 98.4% using 2000 training steps (25 epochs). The multichannel deep nets and restricted Boltzmann machines were used in [15] for defective cell classification. However, the performance of the model was not stated clearly. Similarly, in [14], they used CNN approach to detect a solar defect, but they focus on the effects of data augmentation and oversampling to process the dataset imbalance. They confirmed that the accuracy of detecting unknown samples could be improved in the implementation of practical detection and classification.

Table 1: Solar cell types in the reviewed studies .

Study	The target of solar cell fault
[14]	Cell cracks
[15]	Cell cracks
[16]	Cell cracks
[17]	Thick lines, broken gates, scratches, paste spot, color differences, and dirty cell
[18]	Material, finger interruption, microcracks, inter-connection, and insulated cells
[19]	Cell cracking and busbar corrosion
[12]	Cracks, shunt faults, finger failure, material defect, and contact forming failure
[20]	Micro-crack, break, finger-interruption
[21]	Cracks, finger-interruption
[22]	Cracks
[23]	Glass breakage, soiling, delamination, discoloration, snail tracks
[24]	Glass breakage, soiling, corrosion, delamination, discoloration, snail trail
[25]	Soiling
[26]	Crack, scratch, broken edge, hot spot, large area damage, surface impurity
[27]	Fault cell
[28]	Cracks
[29]	Crack, broken, unsoldered
[30]	Cracks, fingerprint, black core
[31]	Cracks
[32]	Crystal breakage, dirty, spotted past, scratches, micro-cracks, burned panels
[33]	Micro-crack
[34]	Cracks
[35]	Finger interruption, dislocation pattern
[36]	Soiling
[37]	Cracks

The CNN's outstanding performance was also indicated by [18]. The results showed an accuracy of 88.42% on the dataset, outperforming the SVM model by 6%. Meanwhile, the performance of the method fulfills the requirements of real-time production in terms of speed. This model achieved good results, but the false positive rate remains high, and the classification performance is not up to the expectations. This could be caused by the sameness of the defect characteristics and the complicated background of solar cells.

Similarly, [22] assess the feasibility of three DL methods in detecting solar defects. The results show LeNet architecture (99%) outperforms other architecture GoogleNet (98%), and CifarCNN (50%). But the results still binary.

The CNN model proposed by [12] outperforms the method proposed by [18] with an accuracy rate of 93.02% with minimal resources. The data augmentation operations (rotation, cropping, mirroring, etc.) applied help to increase the model accuracy up to 6.5%. Although they suggested different types of microcracks, the method

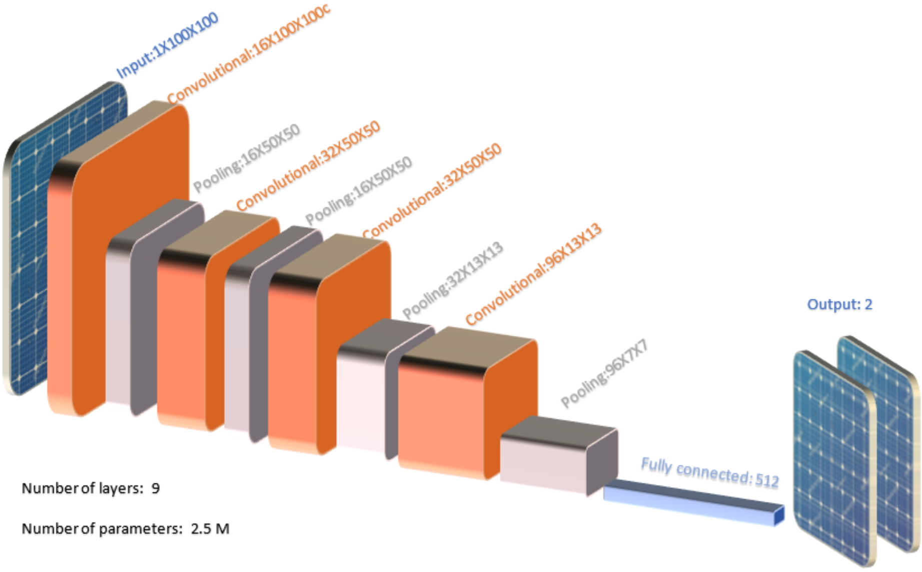

Fig. 3: CNN model developed by [12].

Table 2: Data augmentation operations applied on reviewed studies.

Study	Data augmentation operations
[14]	Flip, rotation, translation, cropping
[15]	NA
[16]	Brightness adjustment, adding blurring, rotation
[17]	NA
[18]	Rotation, translation, flip
[19]	Flip, rotation
[12]	Flip, rotation, cropping
[20]	GAN-based model operation
[21]	Flip, shift, rotation
[22]	NA
[29]	NA
[31]	Rotations, mirroring
[32]	NA
[33]	Flip
[34]	Flip, rotation
[35]	Flip, rotation, brightness and contrast, additive Gaussian noise
[36]	Gaussian noise
[37]	NA

remains two category results. Moreover, this type of method may experience overfitting caused by training samples produced by geometric deformation [20].

An automatic application using multispectral CNN was developed in [17]. The study aimed at detecting the surface of solar with irregular structure and complex background. The proposed CNN model is an effective model for solar faults detection and comprises fifteen conventional layers, nine pooling layers, and two fully connected layers. The results showed that the proposed model had achieved good performance with an accuracy of 94.3%. However, this model can be used to detect small cracks [47].

In [19], Karimi et al. evaluated the automation data analysis pipeline for solar defects recognition using EL images. A comparison of three models (SVM, RF, and CNN) was conducted. The CNN model outperformed other methods with an accuracy rate of 99.42%. However, the result of the application is a binary classification. According to the information presented in Table 3, the CNN model is dominant due to its good performance in image processing in recent years. It outperforms all other previously implemented tools.

Through the eighteen CNN models used, seven models are with a low number of parameters and low number of layers similar to the model developed by [12], as shown in Fig.3.

Out of the eighteen models, there are two models with a low number of parameters and a high number of layers, like the model in Fig.4. The last type of model is with a low number of layers and a high number of parameters.

Through the observations of the models, we can see that the high number of parameters do not depend on the high number of layers but the kernel and the size of fully connected layers. The Electroluminescence (EL) images were dominant across the reviewed studies in terms of the

Table 3: Studies of detecting the defects of solar cells using a deep learning approach.

Study	Model	No. of parameters	Number of layers	Type of image	Performance criteria	Remarks
[14]	VGG-16	0.38 M	21	EL	7.7% (balanced error), 92.3% (balanced accurate)	Considers effects of augmentation and oversampling.
[15]	DBN	4.7M	4	EL	NA	Time-consuming
[16]	CNN	1.1 M	6	EL	98.4%	Small datasets
[17]	CNN	101.2	M	27	RGB 94.3%	Considers only visible defects, not applicable for weak scratch inspection.
[18]	CNN, SVM	34.9 M	24	EL	88.42% (CNN), 82.44% (SVM)	Processing did not distinguish the defect type
[19]	CNN	0.2 M	5	EL	99.43% (SVM), 97.46% (RF), 99.71 % (CNN)	Two-category result
[12]	CNN	2.5 M	9	EL	93.02% Two-category result,	Can suffer from the over-fitting phenomenon.
[20]	CNN	12.9 M	9	EL	Micro-crack (82%), finger-interruption (81%), break (83%)	Two-category result.
[21]	CNN with Attention network & U-net	8.1 M	35	EL	99.3%	Considers hybrid loss and incorporating CNN model with other networks
[22]	CNN (LeNet)	0.06 M	7	EL	99%	Outperforms GoogleNet
[29]	R-CNN & R-FCN	-	-	EL	98.3%	The strategy of hard negative sample mining was used.
[31]	CNN	34.1 M	8	EL	F-measure 98.46%	Fuses steerable evidence filter (SEF) with the function of structural decoupling to filter the input images.
[32]	CNN (AlexNet)	61 M	25	RGB	93.3%.	Two-category result.
[33]	U-Net & Attention mechanism	-	28	EL	IOU (69%) DICE (54%)	Solves the All black issue.
[34]	CNN (ResNet50)	23.5 M	51	EL	98.59%	Used on-field low-resolution EL images.
[35]	CNN (U-Net)	-	-	EL & C-DCR	F1-score is (89%) for dark saturation current density (j0) (82%) for series resistance (Rs)	Introduces smart labeling of defects.
[37]	CNN (ResNet-50)	5.4 M	7	EL	91%	Examines the effect of different parameterizations of the normalized Lp layer on the segmentation performance
[36]	YOLOv3	-	53	RGB	94.5%	Two-category result.

image types. Regarding the detection of the defects, many studies evaluated the cell cracking faults. This is due to the remarkable presence of the defaults in the used images, which enable the different deep learning applications to recognize them. Overall, most of the models achieve an accuracy rate greater than 90%. However, more than 60% of the reviewed models can do two-class classification (Binary classification) to determine either the case is faulty or healthy. It was noticed that the models examining the multi-class classification are less than binary classification. Moreover, the complexity of the two-class classification

Table 4: Studies of detecting the defects of solar cells using hybrid models.

Study	Objective	Model type	No. of layers	No. of Para-meters	Approach	Fault	Performance
[23]	Postprocess	VGG	21	-	SVM	Glass breakage, soiling, delamination, discoloration, snail tracks	90.2% (Tow-class classification) 76.9% (Glass breakage) 84.4% (Soiling) 78.9% (Delamination) 77.3% (Discoloration) 77.8% (Snail tracks)
[24]	Postprocess	CNN	9	25.7 M	SVM	Glass breakage, soiling, corrosion, delamination, discoloration, snail trail	98.1% (average) 96% (glass breakage) 96% (soiling) 97% (corrosion) 98% (delamination) 100% (discoloration) 98% (snail trail)
[25]	Extract features	ResNet	50	-	DnCNN	Soiling	RMSE: 0.69, F-score: 90%
[26]	Extract features and pre-process	GoogLeNet	21	6 M	PCA	Crack, scratch, broken edge, hot spot, large area damage, surface impurity	99.7% (average)
[27]	Extract features	CNN	9	0.37 M	Sliding window scan	Fault cell	88.4% (average)
[28]	Postprocess	VGG-16	21	134.2 M	LRMR	Cracks	F-score :46.8%
[30]	Extract features	CNN	120.87M	BAFPN	Cracks,	fingerprint, black core	Cracks (73.16%), fingerprint (91.3%), black core (100%)
[48]	Extract features	CNN	-	-	ML	Bing	93.7%

models requires more computational resources. Regarding the auto-detection of solar defects, there is still a need for more consolidations via tests to enhance precision and robustness.

5 Hybrid models

The multi-scale identification of defects in the electroluminescence of solar cells is challenging. Many researchers have developed various hybrid models [23,24,27,48] to address this problem. In [30], the authors developed a new attention feature pyramid network (BAFPN) for solar defect detection. The BAFPN is an integration of the region proposal network (RPN) and FPN. In their experiments, 3629 images were included, of which 2129 were detectable. The proposed methods have shown very satisfactory results, indicating that both deep learning and hybrid models have many advantages and offer a practical solution in solar fault detections.

In light of the shortcomings that were highlighted within the current line of industrial production, the substantial detection errors and the limited amount of data were reported. Du et al. [26] proposed a deep CNN to enhance silicon photovoltaic (Si-PV) detection efficiency. In this work, eddy current thermography (ECT) is utilized in order to acquire the infrared thermography (IRT) of various solar cell defects. Other image classifier models such as GoogleNet, VGG-16, and LeNet-5 were also used to detect and classify Si-PV cell faults. Another novel method of detecting microcracks in solar cells through merging the long and short terms features is developed by [28]. In this work, the short-term features represent current knowledge learned from a series of image stacked denoising auto-encoder (SDAE). In contrast, the long-term features represent previous knowledge from a series of natural images that an individual see through CNNs. This work concludes that such a combination of deep features can lead to a better performance in detecting different types of microcracks on the surface of solar cells compared with other methods.

Dust on solar panels is another major problem that can lead to degrading performance, eruption, corrosion, and various defects. Therefore, a new CNNs denoising based on the status of dust accumulation of solar was proposed by [25]. The work concluded that among all the comparisons between various combinations of DnCNNs and VGG-16, ResNet-50, ResNet models, AlexNet, the DnCNN with ResNet-50 model would produce a real-time evaluation of dust accumulation levels. It was also stated that this proposed dust evaluation method

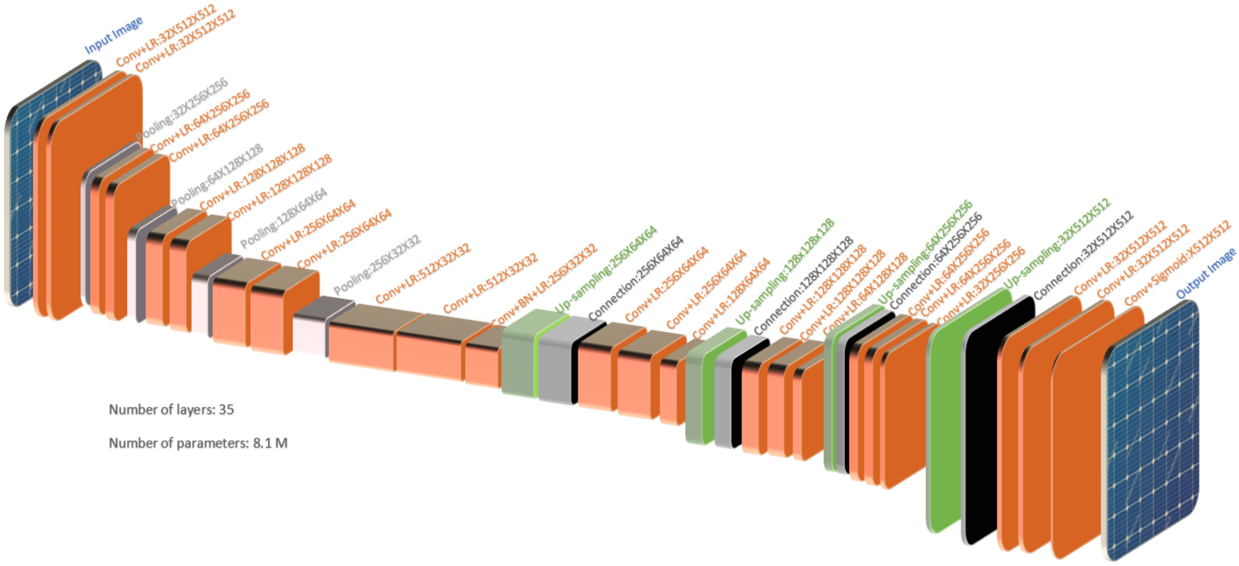

Fig. 4: CNN model developed by [21].

could enhance the accuracy of neural network structure and image quality.

Table 4 summarizes all the work that has used hybridized models for detecting different types of faults regarding the solar. Data such as the main objective, the deep learning model, the approach, the targeted solar defects, and the detection performance were extracted (see table 4).

6 Conclusion

This study presented a review of the deep learning methods applied in solar fault detection. Across all the deep learning methods, it was observed that all the methods are capable of detecting visible defects such as cracks, discoloration, and delamination. In terms of the deep learning approach performance, most of the models achieved good results for classification with accuracy exceeding 90%. However, the other models' performance was lower due to the inappropriate structure of the models or to their ability to separate the input features. However, it should be noted that the results of the hybrid modes showed a better performance than the standard models, and that also depends on the incorporated methods. The data augmentation operations approved in most of the studies their ability to improve the models, and the most commonly used procedures are flip and rotation. Regarding the type of targeted faults, it should be noted that cracks in their different forms are the most common fault targets in the reviewed studies. However, other faults were covered (e.g., paste spot, dirtiness, interconnection, soiling, and shunt).

Concerning applied deep learning models, it was noted that more than 60% of the applications were able to handle two-class classification by identifying whether the module is defective or healthy. However, other studies can do the multi-class classification, but their performance is lower than the two-class applications in terms of accuracy. This indicates the complexity of proper solar fault detections through image processing. In addition, some models are very complex and require more computational resources. Consequently, it is recommended to develop models with suitable architecture and less complexity, as discusses in Section 4. Finally, considering the real-time solar faults detection, the deep learning models showed a good performance, especially for large-scale solar farms. However, it still requires further enhancement in precision and robustness. For future work, it is recommended to explore various deep learning models with different input features and to investigate other hybrid model structures.

Acknowledgement

The authors would like to acknowledge the support of University Tenaga Nasional (UNITEN) under BOLD REFRESH. Also, the authors are grateful to the anonymous referee for the constructive and beneficial comments that improved the present paper.

Conflict of interest

The authors declare that there is no conflict regarding the publication of this paper.

References

[1] M. Santhakumari and N. Sagar, "A review of the environmental factors degrading the performance of silicon wafer-based photovoltaic modules: Failure detection methods and essential mitigation techniques," *Renewable and Sustainable Energy Reviews*, 2019, 110, pp. 83-100..

[2] A. Sinha, O. S. Sastry, and R. Gupta, "Nondestructive characterization of encapsulant discoloration effects in crystalline-silicon PV modules," *Sol. Energy Mater. Sol. Cells*, 2016, 155, pp. 234-242.

[3] C. Mantel et al., "*Machine learning prediction of defect types for electroluminescence images of photovoltaic panels*," Proc. SPIE 11139, Applications of Machine Learning, 1113904 (6 September 2019).

[4] H. R. Parikh et al., "*Enhancement of Electroluminescence images for fault detection in photovoltaic panels*," in 2018 IEEE 7th World Conference on Photovoltaic Energy Conversion, WCPEC 2018 - A Joint Conference of 45th IEEE PVSC, 28th PVSEC and 34th EU PVSEC, 2018.

[5] M. Dhimish and V. Holmes, "Solar cells micro crack detection technique using state-of-the-art electroluminescence imaging," *J. Sci. Adv. Mater. Devices*, 2019, 4(4), pp. 499-508.

[6] H. Chen, H. Zhao, D. Han, and K. Liu, "Accurate and robust crack detection using steerable evidence filtering in electroluminescence images of solar cells," *Opt. Lasers Eng.*, 2019, 118, pp. 22-33.

[7] I. Berardone, J. Lopez Garcia, M. Paggi, Analysis of electroluminescence and infrared thermal images of monocrystalline silicon photovoltaic modules after 20 years of outdoor use in a solar vehicle, *Solar Energy*, 2018, 173, pp: 478-486.

[8] K. Brecl, C. Barretta, G. Oreski, B. Malic, and M. Topic, "The Influence of the EVA Film Aging on the Degradation Behavior of PV Modules under High Voltage Bias in Wet Conditions Followed by Electroluminescence," *IEEE J. Photovoltaics*, 2019, 9, pp. 259-265.

[9] A. Sinha, S. Roy, S. Kumar, and R. Gupta, (2017) *Investigation of Degradation in Photovoltaic Modules by Infrared and Electroluminescence Imaging*. In: Bhattacharya I., Chakrabarti S., Reehal H., Lakshminarayanan V. (eds) Advances in Optical Science and Engineering. Springer Proceedings in Physics, vol 194. Springer, Singapore.

[10] W. Nash, T. Drummond, and N. Birbilis, "A review of deep learning in the study of materials degradation," *npj Mater. Degrad.*, 2018, 2, pp. 37.

[11] M. Köntges et al., "Review of failures of photovoltaic modules," Technical Report UNSPECIFIED, 2014. http://repository.supsi.ch/id/eprint/9645

[12] M. W. Akram et al., "CNN based automatic detection of photovoltaic cell defects in electroluminescence images," *Energy*, 2019, 189, pp.116319.

[13] G. Li et al., "Thermo-mechanical behavior assessment of smart wire connected and busbarPV modules during production, transportation, and subsequent field loading stages," *Energy*, 2019, 168, pp.931-945.

[14] A. Bartler, L. Mauch, B. Yang, M. Reuter, and L. Stoicescu, "*Automated Detection of Solar Cell Defects with Deep Learning*," in 2018 26th European Signal Processing Conference (EUSIPCO), 2018, pp. 2035–2039.

[15] B. Ni, P. Zou, Q. Li, and Y. Chen, "*Intelligent Defect Detection Method of Photovoltaic Modules Based on Deep Learning*," in 2018 International Conference on Transportation & Logistics, Information & Communication, Smart City (TLICSC 2018), 2018.

[16] M. Sun, S. Lv, X. Zhao, R. Li, W. Zhang, and X. Zhang, "*Defect detection of photovoltaic modules based on convolutional neural network*," in International Conference on Machine Learning and Intelligent Communications, 2017, pp. 122–132.

[17] H. Chen, Y. Pang, Q. Hu, and K. Liu, "Solar cell surface defect inspection based on multispectral convolutional neural network," *J. Intell. Manuf.*, 2020, 31, pp. 453–468.

[18] S. Deitsch et al., "Automatic classification of defective photovoltaic module cells in electroluminescence images," *Sol. Energy*, 2019, 185, pp. 455–468.

[19] A. M. Karimi et al., "Automated pipeline for photovoltaic module electroluminescence image processing and degradation feature classification," *IEEE J. Photovoltaics*, 2019, 9, pp.1324–1335.

[20] W. Tang, Q. Yang, K. Xiong, and W. Yan, "Deep learning based automatic defect identification of photovoltaic module using electroluminescence images," *Sol. Energy*, 2020, 201, pp. 453–460.

[21] M. R. U. Rahman and H. Chen, "Defects Inspection in Polycrystalline Solar Cells Electroluminescence Images Using Deep Learning," *IEEE Access*, 2020, 8, pp. 40547–40558.

[22] P. Banda and L. Barnard, "*A deep learning approach to photovoltaic cell defect classification*," in Proceedings of the Annual Conference of the South African Institute of Computer Scientists and Information Technologists, 2018, pp. 215–221.

[23] X. Li, J. Wang, and Z. Chen, "Intelligent fault pattern recognition of aerial photovoltaic module images based on deep learning technique," *J. Syst. Cybern. Inf*, 2018, 16, pp. 67–71.

[24] X. Li, W. Li, Q. Yang, W. Yan, and A. Y. Zomaya, "*Building an Online Defect Detection System for Large-scale Photovoltaic Plants*," in Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, 2019, pp. 253–262.

[25] Y. Tan, K. Liao, X. Bai, C. Deng, Z. Zhao, and B. Zhao, "*Denoising Convolutional Neural Networks Based Dust Accumulation Status Evaluation of Photovoltaic Panel*," in 2019 IEEE International Conference on Energy Internet (ICEI), 2019, pp. 560–566.

[26] B. Du, Y. He, J. Duan, and Y. Zhang, "Intelligent classification of silicon photovoltaic cell defects based on eddy current thermography and convolution neural network," IEEE Trans. Ind. Informatics, 2019, 16(10), pp. 6242-6251.

[27] J. Balzategui et al., "*Semi-automatic quality inspection of solar cell based on convolutional neural networks*," in 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 2019, pp. 529–535.

[28] X. Qian, J. Li, J. Cao, Y. Wu, and W. Wang, "Micro-cracks detection of solar cells surface via combing short-term and long-term deep features," *Neural Networks*, 2020, 127, pp. 132-140..

[29] X. Zhang, Y. Hao, H. Shangguan, P. Zhang, and A. Wang, "Detection of surface defects on solar cells by fusing Multi-channel convolution neural networks," *Infrared Phys. Technol.*, 2020, 108, pp. 103334.
[30] B. Su, H. Chen, and Z. Zhou, "*BAF-Detector: An Efficient CNN-Based Detector for Photovoltaic Solar Cell Defect Detection*," arXiv Prepr. arXiv2012.10631, 2020.
[31] H. Chen, S. Wang, and J. Xing, "*Detection of Cracks in Electroluminescence Images by Fusing Deep Learning and Structural Decoupling*," in 2019 Chinese Automation Congress (CAC), 2019, pp. 2565–2569.
[32] I. Zyout and A. Oatawneh, "*Detection of PV Solar Panel Surface Defects using Transfer Learning of the Deep Convolutional Neural Networks*," in 2020 Advances in Science and Engineering Technology International Conferences (ASET), pp. 1–4.
[33] Y. Jiang, C. Zhao, W. Ding, L. Hong, and Q. Shen, "*Attention M-net for Automatic Pixel-Level Micro-crack Detection of Photovoltaic Module Cells in Electroluminescence Images*," in 2020 IEEE 9th Data Driven Control and Learning Systems Conference (DDCLS), 2020, pp. 1415–1421.
[34] A. Chindarkkar, S. Priyadarshi, N. S. Shiradkar, A. Kottantharayil, and R. Velmurugan, "*Deep Learning Based Detection of Cracks in Electroluminescence Images of Fielded PV modules*," in 2020 47th IEEE Photovoltaic Specialists Conference (PVSC), 2020, pp. 1612–1616.
[35] P. Kunze et al., "*EFFICIENT DEPLOYMENT OF DEEP NEURAL NETWORKS FOR QUALITY INSPECTION OF SOLAR CELLS USING SMART LABELING*," in Presented at the 37th European PV Solar Energy Conference and Exhibition, 2020, vol. 7, p. 11.
[36] J. Wang, B. Zhao, and X. Yao, "*PV Abnormal Shading Detection Based on Convolutional Neural Network*," in 2020 Chinese Control And Decision Conference (CCDC), 2020, pp. 1580–1583.
[37] M. Mayr, M. Hoffmann, A. Maier, and V. Christlein, "*Weakly Supervised Segmentation of Cracks on Solar Cells Using Normalized Lp Norm*," in 2019 IEEE International Conference on Image Processing (ICIP), 2019, pp. 1885–1889.
[38] I. Goodfellow, Y. Bengio, A. Courville, and Y. Bengio, *Deep learning*, MIT press Cambridge, 2016.
[39] A. Fawzi, H. Samulowitz, D. Turaga, and P. Frossard, "*Adaptive data augmentation for image classification*," in 2016 IEEE International Conference on Image Processing (ICIP), 2016, pp. 3688–3692.
[40] M. Koziarski and B. Cyganek, "Image recognition with deep neural networks in presence of noise – Dealing with and taking advantage of distortions," *Integr. Comput. Aided. Eng.*, 2017, 24, pp. 337–349.
[41] Y. Wu, Q. Lan, and Y. Sun, "*Application of BP neural network fault diagnosis in solar photovoltaic system*," in 2009 International conference on Mechatronics and Automation, 2009, pp. 2581–2585.
[42] K.-H. Chao, C.-T. Chen, M.-H. Wang, and C.-F. Wu, "*A novel fault diagnosis method based-on modified neural networks for photovoltaic systems*," in International Conference in Swarm Intelligence, 2010, pp. 531–539.
[43] W. Chine and A. Mellit, "*ANN-based fault diagnosis technique for photovoltaic stings*," in 2017 5th International Conference on Electrical Engineering-Boumerdes (ICEE-B), 2017, pp. 1–4.
[44] S. Laamami, M. Benhamed, and L. Sbita, "*Artificial neural network-based fault detection and classification for photovoltaic system*," in 2017 International Conference on Green Energy Conversion Systems (GECS), 2017, pp. 1–7.
[45] E. Garoudja, A. Chouder, K. Kara, and S. Silvestre, "An enhanced machine learning based approach for failures detection and diagnosis of PV systems," *Energy Convers. Manag.*, 2017, 151, pp. 496–513.
[46] N. Sabri and A. Tlemçani, "*Faults diagnosis in Stand-Alone photovoltaic system using Artificial Neural Network*," in 2018 6th International Conference on Control Engineering & Information Technology (CEIT), 2018, pp. 1–6.
[47] W. Hou, X. Tao, and D. Xu, "Combining Prior Knowledge With CNN for Weak Scratch Inspection of Optical Components," *IEEE Trans. Instrum. Meas.*, 2020, 70, pp. 1–11.
[48] Y. Buratti, A. Sowmya, R. Evans, T. Trupke, and Z. Hameiri, "*End-of-Line Binning of Full and Half-Cut Cells using Deep Learning on Electroluminescence Images*," in 2020 47th IEEE Photovoltaic Specialists Conference (PVSC), 2020, pp. 133–138.