IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 29, No. 6, December, 2024, pp. 2335-2343
Journal homepage: http://iieta.org/journals/isi

Advanced Transfer Learning Technique for Enhanced Detection and Classification of Damaged Solar Cells

Maha Safar Abdulmajed[1*], Yaseen Ahmed Mohammed Alsumaidaee[2]

[1] Department of Laboratory Sciences, College of Pharmacy, University of Tikrit, Tikrit 34001, Iraq
[2] Department of Computer Science, Al Imam Al Adham University College, Baghdad 36001, Iraq

Corresponding Author Email: eng.yassin.ahmed@imamaladham.edu.iq

https://doi.org/10.18280/isi.290621

Received: 21 June 2024
Revised: 4 November 2024
Accepted: 21 November 2024
Available online: 25 December 2024

Keywords:
energy, solar cell, transfer learning, InceptionV3, electroluminescence, image classification, renewable energy, damage detection

ABSTRACT

Solar energy is one of the best-known sources of electricity generation because it is clean; therefore, demand is increasing around the world to fulfill the need for solar photovoltaic panels to produce energy for human use and technological development. However, like any other technological device or machinery, solar panels may break down due to component failure, which is caused by damaged cells in the panel, according to previous research. As a result, identifying such cells is critical for regular panel functioning and ensuring that the panel does not consume more energy than it should. This involves artificial intelligence (AI), which helps in the early stages of identifying impaired cells through electroluminescence photographs of solar panels. This research adopts the transfer learning approach to identify damaged cells with a relatively high degree of accuracy using the InceptionV3 model. We use a dataset of 2624 pictures posted on Kaggle to achieve a clear assembly of the model and fine-tune it accurately. This classification model operates with a striking accuracy of 95.53%, as reflected in InceptionV3. Finally, the findings argue qualitatively the inexhaustible potential to apply transfer learning in identifying and categorizing disparate faulty solar cells that would enhance the performance of solar panels. The effectiveness of adopting AI innovation in discovering damaged cells helps in prompt compensation and ensures minimal interference, allowing an increase in the productivity of the solar panels and an enhancement of durability.

1. INTRODUCTION

The shift from using non-renewable sources of energy to renewable sources of energy is key to the sustainable development of the environment [1, 2]. Renewable energy, energy from natural sources like solar, wind, and hydro energy, has proved to be one of the biggest benefits of green energy as against conventional energy, which usually entails the release of hazardous substances into the environment and exhaustion of resources [3, 4]. Green energy sources help to minimize carbon footprints and global warming. The increased demand and use of renewable energy sources is therefore occasioned by the need to solve environmental concerns and make available energy for future generations [5, 6]. Investing in green energy technologies has been widely encouraged for quite some time now, and this is supported by the fact that as the technology is developed, the costs continue to reduce. For example, sources such as solar energy have come down in price and are more achievable due to enhancements in photovoltaic technologies and materials [7-9].

High-volume solar panel manufacturing and maintenance inspections involve specific assembly processes that require optimal examination techniques [10, 11]. Installing solar panels can, at times, be problematic because of failed parts, as with any other technology or mechanical system as well as Damage to some cells is a common factor that disrupts panel functioning [12]. To address this issue, the next steps typically require a more comprehensive cell examination, which includes a visual inspection to identify any damaged cells. This process can be time-consuming due to the identification of faulty cells and the potential for human error [13, 14]. As a result of the damage found in solar cells, technology has been utilized and developed to create AI, a tool that has the capacity to solve different problems in different fields [15-17]. For the application of AI, a subdomain of machine learning (ML) called deep learning (DL) has shown remarkable results for image classification [18-20]. This makes DL an ideal strategy to handle the detection and inspection of defected solar panels, as described in some studies [21, 22]. Researchers have employed image assessments such as electroluminescence (EL), infrared (IR), and RGB images for the classification of damaged PV cells [23-25]. All these techniques demonstrate that EL inspects PV more efficiently than conventional charge-coupled device (CCD) imaging methodologies [26-28].

Furthermore, authors have confirmed that the use of DL-based algorithms is an intelligent tool for performing many computer vision tasks, including image classification, object detection, recognition, and identifying similarities between two images [29-31].

Several researchers have proposed research propositions for classifying damaged PV cells using a variety of DL paradigms and approaches. For instance, in a work by Chen et al. [32], the authors proposed multispectral CNN networks to classify damaged solar cells based on RGB model images with an accuracy of 94.9%. It offers defect information on an as needed basis but can be expensive and may not be easy to administer.

Similarly, Rahman et al. [33] proposed the use of the U-Net model to identify damaged cells from sequences of EL images, a model that captures details not readily visible in images. The issues are the large data sets and resources required, as well as the fact that these models is computationally intensive. Improvements could be made to the scale of the datasets and the tuning of the models.

In addition, Pierdicca et al. [34] employed transfer learning for the identification of broken and damaged cells using images obtained from the remote sensing system. Still, it demands lots of data and may be uninterpretable. To make the model more comprehensible, future work could focus on data augmentation and explanation.

Cipriani et al. [35] used the VGG16 model and five CNN networks to tell the difference between hotspots and dust objects on PV cells with an accuracy of 98%, even though their model had more layers. The model may not be able to effectively handle other types of defects. Improvements in feature detection and expansion of defect coverage would be the direction of future work.

Akram et al. [36] have proposed a study of distinguishing damaged cells in EL images through a lightweight CNN with an accuracy of 93.02%. The disadvantages of this method include difficulties with data and computation. Here, improvements could be made on points that are related to the use of data and its utilization that do not necessarily require computational processing.

Moreover, Li et al. [37] used DL techniques to perform deep feature extraction for faulty PV cell detection, which may have potential problems associated with a variety of defects. These may include increasing the flexibility in functional learning, which has to do with different types of defects.

On the other hand, Aziz et al. [38] proposed a modification to a pre-trained Alexnet model for faulty detection in PV. Applying it to all types of faults might not yield the same effectiveness. Future work could review and broaden the categories of faults considered.

Li et al. [39] applied deep convolutional neural networks to learn fault pattern features to increase diagnosis accuracy. High- and low-tone image quality problems could arise. Some enhancements could be directed toward managing different conditions.

Girshick et al. [40] introduced a paper using Region-CNN combined with SVM for detection operations. It's highly accurate but complex and resource-intensive.

Despite the advancements in image processing and ML algorithms for defect detection, many approaches fail due to the wide variations in defect appearance and environmental changes. Traditional techniques are sometimes insufficient to distinguish similar anomalies, and they may not be applicable to new forms of damage and degradation.

This is the reason that our experiment is designed to redress those limitations with the help of some advanced transfer learning methods and deep convolutional neural networks (CNN). We are utilizing current model, such as InceptionV3, to identify potential optimization techniques that can improve the accuracy of detection percentages and reduce the likelihood of false positives in defect diagnosis. Thus, this approach goes not only beyond the framework of the development of the method of PV module inspection but also beyond the key objectives of improving the efficiency and reliability of energy-green technologies.

The rationale for this study is the quest for better solutions in inspection practices than those that are currently available. By developing and validating a robust model for solar cell damage detection, we hope to support the sustainable growth of solar energy systems and promote the wider adoption of renewable energy solutions.

The following provides a concise summary of the research objectives and its contributions:

(1) Improve the efficiency and accuracy of detecting damaged solar cells in PV panels, with the primary aim of achieving early detection to prevent potential failures and enhance the overall performance of solar panels.

(2) Introduce the concept of transfer learning with the pre-trained InceptionV3 model for classifying damaged versus normal solar cells. This method uses a publicly available dataset of EL images of solar cells and adds to the dataset using data augmentation techniques to make it bigger and more diverse, which improves the generalization of the model.

(3) Show the importance of the presented approach using the illustrative high level of achieved accuracy, which makes it 95.53%. In this paper, we also do comparisons with other earlier-implemented methodologies in order to put into perspective the main features of the method that is developed here as being better and improved. Furthermore, we avoid using a GPU as a parameter in the research and instead use Google Colab to make GPUs available to a wider audience.

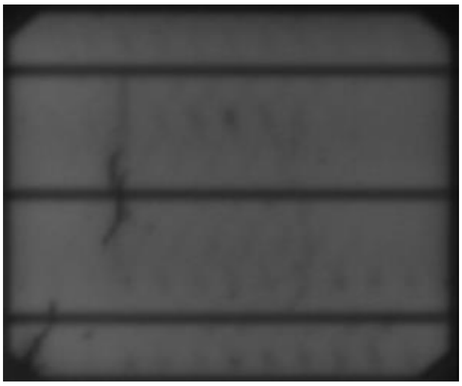
The article's classification is as follows: Introduction: This section includes background information, a literature review, the purpose of the study, and its significance. Methodology: This section provides more details about the strategy used in this work, including the methods for transfer learning, dataset, and the planning of the specific experiments. Results and discussions: We analyze the experimental results, compare the proposed method to existing methods, and then discuss the results. Conclusion: Conclusions and future research directions: The study concludes with a concise summary of the results, highlights the study's contributions to the current knowledge base, highlights the study's practical importance in the relevant field, and offers suggestions for future research.

2. METHODOLOGY

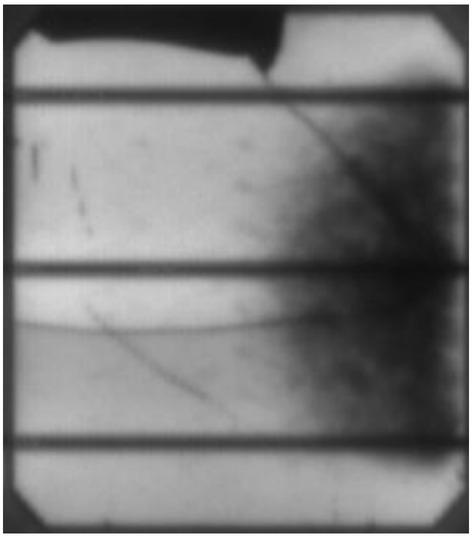
2.1 Dataset

We classified defective solar cells using electroluminescence images from the publicly available Kaggle dataset, "Defective Solar Cells (Electroluminescence Images)" by Philanoe [41]. The dataset includes a total of 2624 images, each with 300x300 pixels in 8-bit grayscale. Figure 1 displays sample images obtained from this database.

Furthermore, we separated the dataset into two independent classes-normal and defective-so that we could use it for training and testing purposes. To be more specific, we used 1177 images from each class for the training segment and 135 images from each class for the testing segment. We further divided the training dataset into training and validation subsets to assess the model's effectiveness and enhance its generalization capabilities. Utilizing this configuration, we conducted an evaluation of the InceptionV3 model, with a particular emphasis on the model's performance on the testing dataset.



(a) Damaged solar cell



(b) Normal solar cell

Figure 1. Samples of the images from the dataset [41]

2.2 Proposed methodology

The model used for the transfer learning technique to detect and classify defected solar cells is shown in Figure 2. The model's objective is to classify a given input image into a normal or damaged class. The utilised model has two important steps: data preprocessing, i.e., normalising the pixels, and data augmentation. The second stage is classification using the InceptionV3 model.

The data preprocessing stage was then further divided into two steps, which are as follows: Normalization and data augmentation. During normalization, we scaled down the image pixels between 0 and 1. The dataset images were multiplied by 1/255 in order to rescale the images. Regarding color normalization, no color balance was necessary as the images were in grayscale. We implemented data augmentation to enhance the robustness of the training dataset. Augmentation strategies comprised (1) rotating pictures by 30 degrees and (2) implementing both vertical and horizontal flipping. The adjustments augmented the dataset by including variables for the model to learn from, thereby enhancing its generalization skills. Figure 3 illustrates examples of the enhanced pictures produced by these processes.

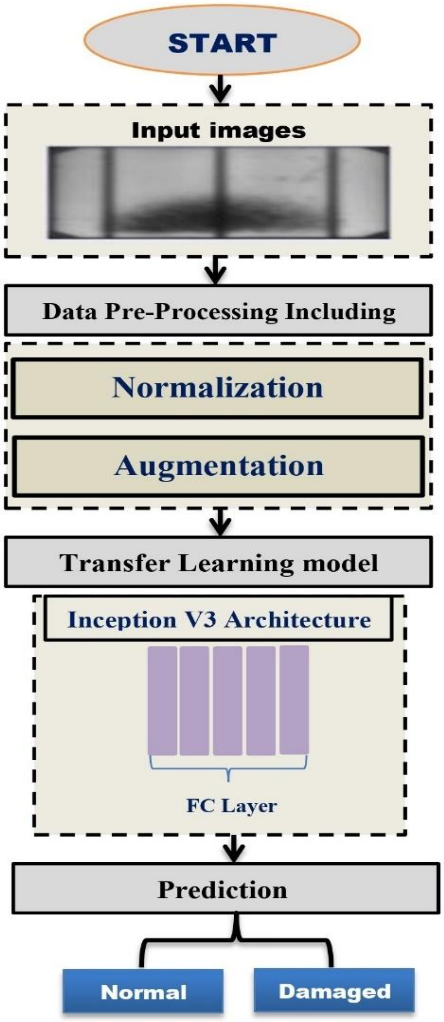


Figure 2. Transfer Learning technique for the classification of solar cells

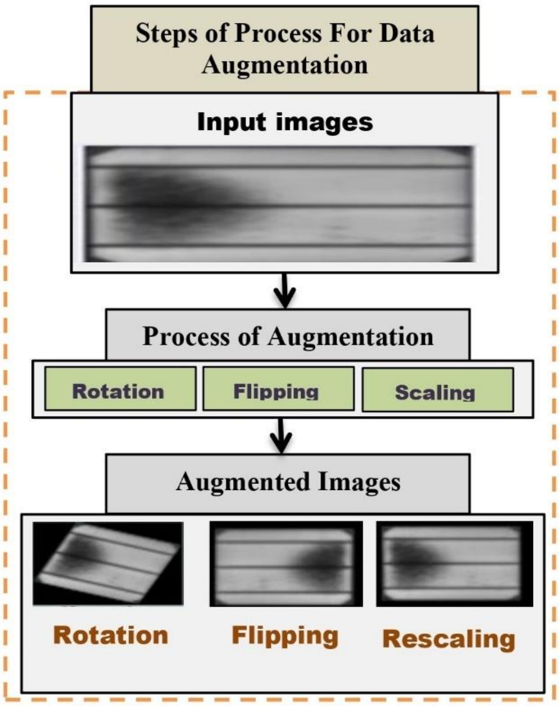


Figure 3. Data augmentation applied to the images

2.3 Transfer learning using InceptionV3

Research has proven that convolutional neural network (CNN) models are superior algorithms for classification and image-processing tasks [42]. However, training these CNN models from scratch is complex due to the limited number of available image data points. The transfer learning (TL) concept is very helpful in such cases. In transfer learning, the knowledge obtained by a DL model trained on a relatively larger dataset is used to do a required task with a comparatively smaller dataset. This study employed pre-trained models named InceptionV3 to distinguish between damaged and normal cells. InceptionV3 is a convolutional neural network that is characteristic of its depth and that was developed to discover multiple scales of info inside input images [43]. This is done through inception modules, in which the filter sizes of 1×1, 3×3, 5×5 is used in parallel which to coarsely and finely detail the images [44].

InceptionV3 includes several enhancements over earlier models [45]:

- Factorized Convolutions: Similarly, to previous models, InceptionV3 does not employ large convolutions but decomposes them into smaller ones thus making the model less complex but not less accurate.
- Auxiliary Classifiers: To enhance the learning of the model and to minimize on overfitting, InceptionV3 has auxiliary classifiers that act as extra outputs.
- Efficient Architecture: The architecture is kept relatively simple, though it is effective in what it does: it minimizes the number of parameters which is important in large scale image classification problems.

Furthermore, we selected InceptionV3 for this study due to its [46, 47]:

- Proven Accuracy: Based on the accuracy analysis of InceptionV3 for large scale image classification, it is considered as a good choice to classify images in complicated manner such as damaged solar cells.
- Transfer Learning Capabilities: The weights which are demonstrated in ImageNet are very helpful for transfer learning and allow to fine tune the model to achievable goal very quickly.
- Balance of Performance and Efficiency: The InceptionV3 model is an optimized model that will provide us with just the same level of powerful and accurate detection while at the same time taking care of the resource use appropriately.

Table 1 displays the architectural descriptions of the InceptionV3 model. This pretrained model, i.e., InceptionV3, is already trained on a large-scale ImageNet dataset. We have added a dense layer to our model to fine-tune the training parameters, utilizing the transfer learning technique. Additionally, we employ a batch normalization layer to eliminate the unassigned neuron weights from the pre-trained models. Finally, the last dense layers in InceptionV3 have been removed, and a new fully connected (FC) layer is inserted with a perceptron value of 2, which represents each class. The hyperparameters play an important role in tuning these pre-trained models.

Table 1. InceptionV3 model parameter overview

Model	Layers	Parameters	Input Layer Size	Output Layer Size
InceptionV3	48	23.9 million	224, 224, 3	2,1

2.4 Fine tuning and hyperparameters

Fine tuning is a crucial step in transfer learning, where the model undergoes training. In this study, we have kept the hyperparameters as follows: images were resized into 224×224, Adam optimizers have been utilized with a momentum of 0.95, weight decay is 0.0005, batch size of 10 is used, and a learning rate of 0.001 has been used with a factor value of 0.7. These hyperparameters were selected after experimenting with various values. Initially, the model faced overfitting issues; however, the chosen parameters significantly alleviated these problems. Specifically, the introduction of weight decay (0.0005) helped to regularize the model and reduce overfitting by penalizing large weights, while the use of dropout and appropriate batch size also contributed to better generalization.

3. RESULTS AND DISCUSSIONS

We evaluate the dataset using the pre-trained InceptionV3 model. A 90:10 training-testing ratio has been used, and train and test dataset details are given in Table 2. The augmented data has been used for the training of proposed models

For the train and valid dataset, the images were resized to 224×224 pixels. We maintained the batch size at 10, and trained InceptionV3 for epoch values of 80. We manually selected the batch size value and the number of epochs through empirical means. The learning rate has been fixed to 0.001 for the training of each model, and the Adam optimizer has been utilized for error minimization purposes. Furthermore, we measured the performance of the InceptionV3 model using metrics like specificity (Spe), sensitivity (Sen), precision (Pre), F1-score, and accuracy (Acc). These metrics were obtained by various parameters of the confusion matrix, such as true positive (TP), true negative (TN), false positive (FP), and false negative (FN) [48]. These metrics have been calculated using Eqs. (1)-(6).

$$\boldsymbol{precision} = \frac{TP}{TP + FP} \tag{1}$$

$$\boldsymbol{Recall} = \frac{TP}{TP + FN} \tag{2}$$

$$\boldsymbol{sensitivity} = \frac{TP}{FN + TP} \tag{3}$$

$$\boldsymbol{specificity} = \frac{TN}{FP + TN} \tag{4}$$

$$\boldsymbol{Accuracy} = \frac{TP + TN}{FP + TP + TN + FN} \tag{5}$$

$$\boldsymbol{F1\ score} = 2 \times \frac{Precision\ x\ Recall}{Precision + Recall} \tag{6}$$

In this study, normal and defective were considered as negative and positive classes, respectively. Thus, the TN and TP represent accurately predicted normal and defective classes. Whereas FN and FP indicate misclassified predicted normal cases and defective cases, respectively.

Furthermore, the performance of InceptionV3 has been compared in terms of parameters such as training loss, validation loss, and validation accuracy at each epoch value. Table 3 presents the results of these parameters. We measured the parameters to identify instances of over-fitting and under-fitting in the trained models. Figure 4 displays the graphs of training loss versus validation loss for each model under study.

For further performance validation, confusion matrices have been generated to classify true positive, true negative, false positive, and false negative values after training. Figure 5 displays the confusion matrices from the test dataset and the loss graphs from the train and valid datasets of the InceptionV3 model.

Table 2. Data splitting details

Classes	Train	Valid	Test
Defected	942	235	135
Normal	942	235	135
Total	1884	470	270

Table 3. Training performance of InceptionV3 model

Model	Epochs	Train Loss	Valid Loss	Train Accuracy	Valid Accuracy
InceptionV3	1	0.712	0.842	69.54	70.23
	.	.	.	.	.
	.	.	.	.	.
	79	0.121	0.132	93.71	93.32
	80	0.112	0.181	95.83	95.65

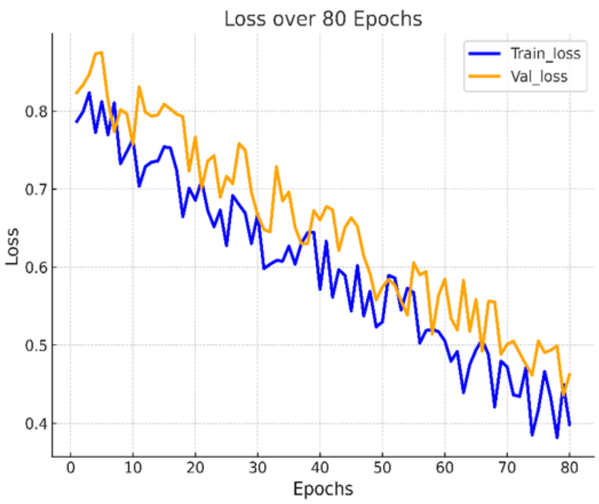


Figure 4. Loss graph for train and valid dataset for the InceptionV3 model

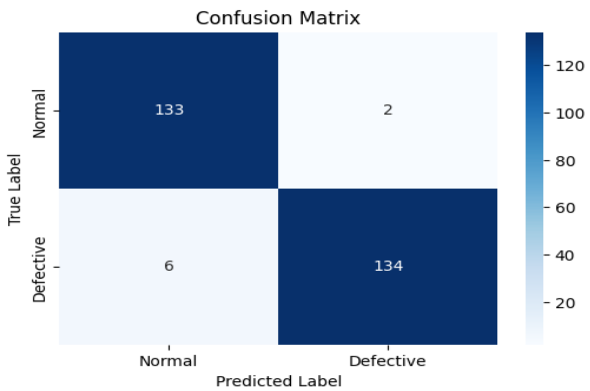


Figure 5. Confusion matrix on test dataset for the InceptionV3 model

Table 4. Performance of InceptionV3 model

Model	Pre	Recall	F1-Score	Sen	Spe	Acc
InceptionV3	95.56	96.27	95.51	96.27	95.59	95.93

Eqs. (1)-(6) have evaluated the performance parameters of the trained models, such as precision, recall, F1 score, sensitivity, specificity, and accuracy, from the numbers obtained through confusion matrices. Table 4 displays the results of these parameters.

3.1 Comparison with different optimizers

Four different optimizers, such as Root Mean Square Propagation (RMSprop), An Adaptive Learning Rate Method (Adadelta), Stochastic gradient descent (SGD), and Adam, which combines the benefits of both Adaptive Moment Estimation (Adam) were used to compare the performance on Iceptionv3 models and evaluation of the optimizer and to select the optimizer that could be the best optimizer applied to the model. The Adam optimizer exhibited promising results among all other optimizers. Therefore, we selected Adam Optimizer for the model's training. The results in Table 5 were calculated using the Adam optimizer.

Table 5. Performance of InceptionV3 model

Model	Optimizer	Pre	Spe	Sen	F1-score	Acc
Inception V3	Adam	96.5	95.5	96.2	0.95	95.9
	SGD	85.0	80	85.2	0.84	89.5
	Adadelta	90.0	93.4	92.9	0.91	91.1
	RMSProp	89.6	88.3	90.7	0.92	92.5

3.2 Comparison with different batch size

Batch size is considered to be one of the important hyperparameters for deep neural networks. This research provides information on the impact of different batch sizes. Table 6 outlines the accuracy of tests conducted on various batch sizes, including 8, 10, and 12. We have observed that a batch size of 10 yields better testing performance. Thus, a batch size of 10 has been kept training the InceptionV3 model.

Table 6. Evaluation of accuracy for varying batch sizes using the InceptionV3 model

Model	Batch Size		
	8	10	12
InceptionV3	85.27%	95.53%	90.25%

3.3 Comparison with other methods

Joshua et al. [49] designed an intelligent method used for detecting the fault in the solar panel at Kangwon National University, Samcheok Campus. By using the deep learning model ResNet-50, the goal of the paper is to find errors and improve the accuracy of data from the university's solar-hydrogen system through data preprocessing. Metrics, general accuracy, and loss specifically indicate its potential for real-time monitoring and maintenance.

However, there are several drawbacks as well: first, the resultant model is less able to detect many sources of fault; second, it also has a restricted variety of faults that are detected, and the used dataset is taken only from a single campus. Painstaking measures such as cross-validation could be implemented, while metrics such as precision and recall could be useful in giving a broader view of the model's evaluation, all in a bid to reduce cases of the model being overfit and thereby underperforming in new data.

Moreover, Kaur et al. [50] used VGG16 in addressing the task of fault detection in PV panels. The model is trained on 885 images across 15 epochs and can correctly classify different faults into the six classes with 86% accuracy. Despite the potential for real-world implementation, there are limitations to the work: the small dataset that we applied the solution to might impact generalization; the machine learning model was trained on a short time span, and while results show that it outperforms other techniques on unseen data after adapting it to a new training set, it remains limited in terms of the time that it has been exposed to.

Additionally, the absence of performance measures like precision, recall, and F1-score for some steps complicates the evaluation of the methods, particularly when dealing with imbalanced datasets. Another adjustment that could potentially yield better results is the change in the learning rate.

Furthermore, Su et al. [51] looked into how supervised learning using CNN and the addition of thermographic images could help classify defects in PV modules. Their CNN achieved 92.5% accuracy for anomaly identification and 78.85% accuracy in defect classification in eight classes. This method is efficient in processing huge amounts of data and detecting outliers, but it is also obstructed by large within-class and between-class variations that decrease the efficiency of defect classification, especially in the case of an unbalanced dataset.

Furthermore, to classify PV panels into different classes, namely healthy, non-faulty hotspot, and faulty, Ali et al. [52] used a fusion of SVM models by using RGB, texture, HOG, and LBP features. Their model demonstrated 92% testing accuracy. It is considered to have the fewest computational requirements and a greater a greater need for storage than any other ML algorithm. However, it relies on specific feature sets that cannot be expanded to encompass other types of defects, and it necessitates a significant number of tests to ultimately identify the optimal features for collaboration [53].

Moreover, Zhang and Yin [54] proposed an improved YOLO v5 model that can solve issues, including complex backgrounds and irregular and differently sized defects in solar cells. The method utilizes deformable convolution, an ECA-Net attention mechanism, and a tiny defect prediction head, resulting in an 89.64%. It has a comparatively low accuracy and a speed of 36.24 FPS. It performs very well in online detection and produces relatively accurate results at different scales. It may have some issues when applied to datasets with different characteristics, and it is computationally intensive.

Therefore, in our paper, InceptionV3 Method was selected because it has better feature extraction and classification performances, with 95.53%. The discrimination accuracy of detecting defects. That is why, when it comes to dealing with defects of different sizes and different characteristics, multi-scale feature extraction in InceptionV3 turns out to be of great use. This method also achieves a balance between error and efficiency, making it the most suitable for the study goals.

3.4 Validate the model using an external dataset

In order to test the generalizability and the solidity of the proposed model, we performed the validation on an external data set. In particular, we work with the "Dust Detection on Solar Panel Using InceptionV3" [55] the dataset presented on Kaggle.ally, we tested the model on the "Dust Detection on Solar Panel Using InceptionV3" by Afroz in the dataset available on Kaggle. This dataset entails images of solar power in diverse states, which include those with dust on the panel and those that don't. In order to achieve this, we utilized an external dataset, distinct from the training data, for our evaluation. This allowed us to assess the generality of the obtained model and its performance on new data, both of which are crucial for a practical solar panel defect detection system. Our method adopts the transfer learning strategy, using the InceptionV3 model as a basis for refinement.

In this work, the InceptionV3 convolutional neural network that was trained on the ImageNet database was fine-tuned to specifically perform the task of identifying defects in solar cells. By fine-tuning, we refine the final layers of the pre-trained model to identify characteristics associated with electroluminescence images of solar cells. This transfer learning technique enhances performance by learning features in limited datasets such as ImageNet [56, 57].

For the external validation, we made sure that the images from the Kaggle dust detection dataset were prepossessed in the same manner as used in the original dataset. We also applied certain data pre-processing techniques, which include resizing the images to 300x300 pixels, scaling the obtained pixel intensities to the range of 0 and 1 by dividing them by 255, and applying data augmentation techniques such as random rotation by up to 30 degrees and horizontal and vertical flipping of the images. These steps were followed in order to avoid influencing and having a bias in the validation process.

To assess the model's performance on the external dataset, basic measures of precision, recall, accuracy, and F1 score values were used. It was shown that when the model foresight its performance on the external Cavin dataset, it achieves rather good values of the metrics that were observed during training and the first tests. This outside opinion supports the idea that the model can successfully generalize to unseen data, indicating that utilizing the transfer learning approach to detect defects on solar panels is viable and still feasible regardless of the different circumstances a solar panel might be under.

4. CONCLUSION

We used transfer learning by using a pre-trained model known as InceptionV3 to detect and classify damaged solar cell EL images. We trained this model on a dataset of 2624 images. Different important parameters, e.g., sensitivity, specificity, F1-score, precision, recall, loss graphs, and confusion matrices, have been measured to determine the accuracy of the model. InceptionV3 displayed an effective result for the classification of the damaged and normal images. The accuracy achieved on InceptionV3 is 95.53%. Various optimizers have been used, and among all the optimizers, the 'Adam' optimizer has been the best.

This study paved the way for the development of effective deep neural networks for accurate early detection of damaged solar cells. We expect the proposed model to perform crucially in the classification problem between damaged and normal solar cells. We can utilize the performance of the suggested model for multiclass solar cell classification tasks in the future.

On the basis of the obtained results connected with

InceptionV3, future studies could be devoted to the optimization of other kinds of deep neural networks (DNNs) that could be hypothetically more effective. For example, ResNet, VGG, and DenseNet all have attributes and architectural makeup that can possibly impact their effectiveness when used in categorizing and detecting damaged solar cells.

Furthermore, there are opportunities to improve model accuracy by utilizing various optimization techniques. Some of the approaches that can be used include more enhanced forms of gradient descent, such as AdamW, learning rate schedules, hyperparameter optimization, such as grid search, or Bayesian optimization. These methods could improve training efficiency as well as model accuracy, which would present an all-encompassing method of model optimization.

REFERENCES

[1] Rahman, A., Farrok, O., Haque, M.M. (2022). Environmental impact of renewable energy source based electrical power plants: Solar, wind, hydroelectric, biomass, geothermal, tidal, ocean, and osmotic. Renewable and Sustainable Energy Reviews, 161: 112279. https://doi.org/10.1016/j.rser.2022.112279

[2] Destek, M.A., Sinha, A. (2020). Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: Evidence from organisation for economic Co-operation and development countries. Journal of Cleaner Production, 242: 118537. https://doi.org/10.1016/j.jclepro.2019.118537

[3] Olabi, A.G. (2016). Energy quadrilemma and the future of renewable energy. Energy, 108: 1-6. https://doi.org/10.1016/j.energy.2016.07.145

[4] Ahmed, Z., Ahmad, M., Murshed, M., Shah, M.I., Mahmood, H., Abbas, S. (2022). How do green energy technology investments, technological innovation, and trade globalization enhance green energy supply and stimulate environmental sustainability in the G7 countries? Gondwana Research, 112: 105-115. https://doi.org/10.1016/j.gr.2022.09.014

[5] Valizadeh, M., ALRubeei, I.R.N., ALRikabi, H.T.S., Abed, F.T. (2022). Enhancing the efficiency of photovoltaic power system by submerging it in the rivers. Telkomnika (Telecommunication Computing Electronics and Control), 20(1): 166-172. http://doi.org/10.12928/telkomnika.v20i1.22460

[6] Kannan, N., Vakeesan, D. (2016). Solar energy for future world: A review. Renewable and Sustainable Energy Reviews, 62: 1092-1105. https://doi.org/10.1016/j.rser.2016.05.022

[7] Al-Shahri, O.A., Ismail, F.B., Hannan, M.A., Lipu, M.H., Al-Shetwi, A.Q., Begum, R.A., Al-Muhsen, N.F.O., Soujeri, E. (2021). Solar photovoltaic energy optimization methods, challenges and issues: A comprehensive review. Journal of Cleaner Production, 284: 125465. https://doi.org/10.1016/j.jclepro.2020.125465

[8] Yao, E., Samadi, P., Wong, V.W., Schober, R. (2015). Residential demand side management under high penetration of rooftop photovoltaic units. IEEE Transactions on Smart Grid, 7(3): 1597-1608. https://doi.org/10.1109/TSG.2015.2472523

[9] Ghasemi-Mobtaker, H., Mostashari-Rad, F., Saber, Z., Chau, K.W., Nabavi-Pelesaraei, A. (2020). Application of photovoltaic system to modify energy use, environmental damages and cumulative exergy demand of two irrigation systems-A case study: Barley production of Iran. Renewable Energy, 160: 1316-1334. https://doi.org/10.1016/j.renene.2020.07.047

[10] Vartiainen, E., Masson, G., Breyer, C., Moser, D., Román Medina, E. (2020). Impact of weighted average cost of capital, capital expenditure, and other parameters on future utility-scale PV levelised cost of electricity. Progress in Photovoltaics: Research and Applications, 28(6): 439-453. https://doi.org/10.1002/pip.3189

[11] Deb, D., Brahmbhatt, N.L. (2018). Review of yield increase of solar panels through soiling prevention, and a proposed water-free automated cleaning solution. Renewable and Sustainable Energy Reviews, 82: 3306-3313. https://doi.org/10.1016/j.rser.2017.10.014

[12] Domanski, K., Alharbi, E.A., Hagfeldt, A., Grätzel, M., Tress, W. (2018). Systematic investigation of the impact of operation conditions on the degradation behaviour of perovskite solar cells. Nature Energy, 3(1): 61-67. https://doi.org/10.1038/s41560-017-0060-5

[13] Park, B., Lehman, D.W., Ramanujam, R. (2023). Driven to distraction: The unintended consequences of organizational learning from failure caused by human error. Organization Science, 34(1): 283-302. https://doi.org/10.1287/orsc.2022.1573

[14] Matusz-Kalász, D., Bodnár, I. (2022). Monitoring and diagnostics of photovoltaic cells by electroluminescence. In 2022 23rd International Carpathian Control Conference (ICCC), Sinaia, Romania, pp. 158-161. https://doi.org/10.1109/ICCC54292.2022.9805888

[15] Alsumaidaee, Y.A.M., Yaw, C.T., Koh, S.P., Tiong, S.K., Chen, C.P., Yusaf, T., Abdalla, A.N., Ali, K., Raj, A.A. (2023). Detection of corona faults in switchgear by using 1D-CNN, LSTM, and 1D-CNN-LSTM methods. Sensors (Basel, Switzerland), 23(6): 3108. https://doi.org/10.3390/s23063108

[16] Paśko, Ł., Mądziel, M., Stadnicka, D., Dec, G., Carreras-Coch, A., Solé-Beteta, X., Pappa, L., Stylios, C., Mazzei, D., Atzeni, D. (2022). Plan and develop advanced knowledge and skills for future industrial employees in the field of artificial intelligence, internet of things and edge computing. Sustainability, 14(6): 3312. https://doi.org/10.3390/su14063312

[17] Johnson, P.C., Laurell, C., Ots, M., Sandström, C. (2022). Digital innovation and the effects of artificial intelligence on firms' research and development-Automation or augmentation, exploration or exploitation? Technological Forecasting and Social Change, 179: 121636. https://doi.org/10.1016/j.techfore.2022.121636

[18] LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. Nature, 521(7553): 436-444. https://doi.org/10.1038/nature14539

[19] Alsumaidaee, Y.A.M., Yaw, C.T., Koh, S.P., Tiong, S.K., Chen, C.P., Ali, K. (2022). Review of medium-voltage switchgear fault detection in a condition-based monitoring system by using deep learning. Energies, 15(18): 6762. https://doi.org/10.3390/en15186762

[20] Sharma, S., Guleria, K. (2022). Deep learning models for image classification: Comparison and applications. In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering

(ICACITE), Greater Noida, India, pp. 1733-1738. https://doi.org/10.1109/ICACITE53722.2022.9823516

[21] Vlaminck, M., Heidbuchel, R., Philips, W., Luong, H. (2022). Region-based CNN for anomaly detection in PV power plants using aerial imagery. Sensors, 22(3): 1244. https://doi.org/10.3390/s22031244

[22] Kurukuru, V.B., Haque, A., Khan, M.A. (2019). Fault classification for photovoltaic modules using thermography and image processing. In 2019 IEEE Industry Applications Society Annual Meeting, Baltimore, MD, USA, pp. 1-6. https://doi.org/10.1109/IAS.2019.8912356

[23] Høiaas, I., Grujic, K., Imenes, A.G., Burud, I., Olsen, E., Belbachir, N. (2022). Inspection and condition monitoring of large-scale photovoltaic power plants: A review of imaging technologies. Renewable and Sustainable Energy Reviews, 161: 112353. https://doi.org/10.1016/j.rser.2022.112353

[24] Buerhop, C., Bommes, L., Schlipf, J., Pickel, T., Fladung, A., Peters, I.M. (2022). Infrared imaging of photovoltaic modules: A review of the state of the art and future challenges facing gigawatt photovoltaic power stations. Progress in Energy, 4(4): 042010. https://doi.org/10.1088/2516-1083/ac890b

[25] Chen, X., Karin, T., Jain, A. (2022). Automated defect identification in electroluminescence images of solar modules. Solar Energy, 242: 20-29. https://doi.org/10.1016/j.solener.2022.06.031

[26] Su, Y., Tao, F., Jin, J., Zhang, C. (2021). Automated overheated region object detection of photovoltaic module with thermography image. IEEE Journal of Photovoltaics, 11(2): 535-544. https://doi.org/10.1109/JPHOTOV.2020.3045680

[27] Schall, J.W., Glaws, A., Doumon, N.Y., Silverman, T.J., Owen-Bellini, M., Terwilliger, K., Uddin, M.A., Rana, P., Berry, J.J., Huang, J., Schelhas, L.T., Kern, D.B. (2023). Accelerated stress testing of perovskite photovoltaic modules: Differentiating degradation modes with electroluminescence imaging. Solar RRL, 7(14): 2300229. https://doi.org/10.1002/solr.202300229

[28] Kumar, M., Kumar, A. (2017). Performance assessment and degradation analysis of solar photovoltaic technologies: A review. Renewable and Sustainable Energy Reviews, 78: 554-587. https://doi.org/10.1016/j.rser.2017.04.083

[29] Voulodimos, A., Doulamis, N., Doulamis, A., Protopapadakis, E. (2018). Deep learning for computer vision: A brief review. Computational Intelligence and Neuroscience, 2018(1): 7068349. https://doi.org/10.1155/2018/7068349

[30] Wang, J., Ma, Y., Zhang, L., Gao, R.X., Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. Journal of Manufacturing Systems, 48: 144-156. https://doi.org/10.1016/j.jmsy.2018.01.003

[31] Krizhevsky, A., Sutskever, I., Hinton, G.E. (2017). ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60(6): 84-90. https://doi.org/10.1145/3065386

[32] Chen, H., Pang, Y., Hu, Q., Liu, K. (2020). Solar cell surface defect inspection based on multispectral convolutional neural network. Journal of Intelligent Manufacturing, 31(2): 453-468. https://doi.org/10.1007/s10845-018-1458-z

[33] Rahman, M.R.U., Chen, H. (2020). Defects inspection in polycrystalline solar cells electroluminescence images using deep learning. IEEE Access, 8: 40547-40558. https://doi.org/10.1109/ACCESS.2020.2976843

[34] Pierdicca, R., Malinverni, E.S., Piccinini, F., Paolanti, M., Felicetti, A., Zingaretti, P. (2018). Deep convolutional neural network for automatic detection of damaged photovoltaic cells. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 42: 893-900. https://doi.org/10.5194/isprs-archives-XLII-2-893-2018

[35] Cipriani, G., D'Amico, A., Guarino, S., Manno, D., Traverso, M., Di Dio, V. (2020). Convolutional neural network for dust and hotspot classification in PV modules. Energies, 13(23): 6357. https://doi.org/10.3390/en13236357

[36] Akram, M.W., Li, G., Jin, Y., Chen, X., Zhu, C., Zhao, X., Khaliq, A., Faheem, M., Ahmad, A. (2019). CNN based automatic detection of photovoltaic cell defects in electroluminescence images. Energy, 189: 116319. https://doi.org/10.1016/j.energy.2019.116319

[37] Li, X., Yang, Q., Lou, Z., Yan, W. (2018). Deep learning based module defect analysis for large-scale photovoltaic farms. IEEE Transactions on Energy Conversion, 34(1): 520-529. https://doi.org/10.1109/TEC.2018.2873358

[38] Aziz, F., Haq, A.U., Ahmad, S., Mahmoud, Y., Jalal, M., Ali, U. (2020). A novel convolutional neural network-based approach for fault classification in photovoltaic arrays. IEEE Access, 8: 41889-41904. https://doi.org/10.1109/ACCESS.2020.2977116

[39] Li, X., Yang, Q., Wang, J., Chen, Z., Yan, W. (2018). Intelligent fault pattern recognition of aerial photovoltaic module images based on deep learning technique. Proceedings of the 9th International Multi-Conference on Complexity, Informatics and Cybernetics (IMCIC 2018), 16: 67-71.

[40] Girshick, R., Donahue, J., Darrell, T., Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of The IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, USA, pp. 580-587. https://doi.org/10.1109/CVPR.2014.81

[41] Philanoe. (2021). Kaggle, Defective Solar Cells (Electroluminescence Images) https://www.kaggle.com/api/v1/datasets/download/philanoe/defective-solar-cells-electroluminescence-images, accessed: Jun. 10, 2024.

[42] Jmour, N., Zayen, S., Abdelkrim, A. (2018). Convolutional neural networks for image classification. In 2018 International Conference on Advanced Systems and Electric Technologies (IC_ASET), Hammamet, Tunisia, pp. 397-402. https://doi.org/10.1109/ASET.2018.8379889

[43] Stefenon, S.F., Yow, K.C., Nied, A., Meyer, L.H. (2022). Classification of distribution power grid structures using inception v3 deep neural network. Electrical Engineering, 104(6): 4557-4569. https://doi.org/10.1007/s00202-022-01641-1

[44] Degadwala, S., Vyas, D., Biswas, H., Chakraborty, U., Saha, S. (2021). Image captioning using inception V3 transfer learning model. In 2021 6th International Conference on Communication and Electronics Systems

(ICCES), Coimbatre, India, IEEE, pp. 1103-1108. https://doi.org/10.1109/ICCES51350.2021.9489111

[45] Biswas, A., Ghosh, S.K., Ghosh, A. (2023). Early fire detection and alert system using modified inception-v3 under deep learning framework. Procedia Computer Science, 218: 2243-2252. https://doi.org/10.1016/j.procs.2023.01.200

[46] Liu, Z., Yang, C., Huang, J., Liu, S., Zhuo, Y., Lu, X. (2021). Deep learning framework based on integration of S-Mask R-CNN and Inception-v3 for ultrasound image-aided diagnosis of prostate cancer. Future Generation Computer Systems, 114: 358-367. https://doi.org/10.1016/j.future.2020.08.015

[47] Dong, N., Zhao, L., Wu, C.H., Chang, J.F. (2020). Inception V3 based cervical cell classification combined with artificially extracted features. Applied Soft Computing, 93: 106311. https://doi.org/10.1016/j.asoc.2020.106311

[48] Kingma, D.P., Ba, J. (2014). Adam: A method for stochastic optimization. arXiv Preprint arXiv: 1412.6980. https://doi.org/10.48550/arXiv.1412.6980

[49] Joshua, S.R., Park, S., Kwon, K. (2024). AI-Driven green campus: Solar panel fault detection using ResNet-50 for Solar-Hydrogen system in universities. In 2024 IEEE 24th International Conference on Software Quality, Reliability, and Security Companion (QRS-C), Cambridge, United Kingdom, pp. 316-325. https://doi.org/10.1109/QRS-C63300.2024.00048

[50] Kaur, G., Sharma, N., Malhotra, S., Devliyal, S., Gupta, R. (2024). Leveraging VGG16 deep learning for photovoltaic panel fault classification. In 2024 2nd World Conference on Communication & Computing (WCONF), RAIPUR, India, pp. 1-5. https://doi.org/10.1109/WCONF61366.2024.10692258

[51] Su, B., Chen, H., Chen, P., Bian, G., Liu, K., Liu, W. (2020). Deep learning-based solar-cell manufacturing defect detection with complementary attention network. IEEE Transactions on Industrial Informatics, 17(6): 4084-4095. https://doi.org/10.1109/TII.2020.3008021

[52] Ali, M.U., Khan, H.F., Masud, M., Kallu, K.D., Zafar, A. (2020). A machine learning framework to identify the hotspot in photovoltaic module using infrared thermography. Solar Energy, 208: 643-651. https://doi.org/10.1016/j.solener.2020.08.027

[53] Rachmanto, R.A., Alfaiz, N.F., Prasetyo, S.D., Bangun, W.B., Juwana, W.E., Arifin, Z. (2024). Modeling future solar and wind energy source applications for power generation at public electric vehicle charging stations in airport parking areas using HOMER-Grid. International Journal of Transport Development and Integration, 8(3): 403-411. https://doi.org/10.18280/ijtdi.080304

[54] Zhang, M., Yin, L. (2022). Solar cell surface defect detection based on improved YOLO v5. IEEE Access, 10: 80804-80815. https://doi.org/10.1109/ACCESS.2022.3195901

[55] Afroz, Kaggle. (2022). Defective Solar Images. Cells Electroluminescence. https://www.kaggle.com/code/pythonafroz/dust-detection-on-solar-panel-using-inceptionv3, accessed: Dec. 17, 2024.

[56] Efendi, S., Nurahmadi, F., Nainggolan, P.I. (2023). The role of recurrent convolutional neural network in IoT for building a security artificial intelligence and home assistance system. International Journal of Safety and Security Engineering, 13(3): 403-408. https://doi.org/10.18280/ijsse.130303

[57] Oreto, C., Biancardo, S.A., Veropalumbo, R., Viscione, N., Russo, F., Abbondati, F., Dell'Acqua, G. (2022). BIM-LCA integration framework for sustainable road pavement maintenance practices. International Journal of Transport Development and Integration, 6(1): 1-11. https://doi.org/10.2495/TDI-V6-N1-1-11