Transfer learning for the classification of the damaged solar cells using pre-trained networks

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ABSTRACT:

Solar energy is one of the primary ways to generate electricity that is both environmentally friendly and has no adverse impacts. Solar panels are needed more than ever before to generate sustainable electricity. It goes without saying that occasionally, faulty components hinder technology or machinery from functioning properly. This also applies to solar panels, which can malfunction for a number of reasons, one of which being a broken panel cell that ultimately results in panel failure. On electroluminescence images taken with solar panels, artificial intelligence is essential for identifying damaged cells as soon as possible. Deep learning's transfer learning principle is useful for classifying damaged solar cells for this purpose. In this work, the pre-trained models ResNet50, VGG16, and InceptionV3 were employed. We also applied the transfer learning approach. We used a publicly accessible dataset from Kaggle, which consists of 2624 photos of solar cells, to train these models. For the aforementioned models, we have presented a thorough analysis and spoken about the model performance in terms of precision, F1-score, sensitivity, specificity, and accuracy. We have achieved an accuracies of 97.40% on ResNet50 model, 97.78% on VGG16 and 95.83% on InceptionV3 model respectively

Keywords:(Artificial intelligence, Transfer Learning)

1. INTRODUCTION

Green energy is one of the needs and demands of our world. One of the main advantages of green energy is that it is environmentally benign and somewhat more affordable than traditional energy sources [1-3]. Solar energy is one of the primary ways to generate electricity that is both environmentally friendly and has no adverse impacts [4-6].

As a result, the market has seen an increase in demand for solar panels that produce sustainable energy [7, 8]. Additionally, a detailed examination of the manufacturing and upkeep procedures is required due to the enormous volume of solar panels produced by robot assembly [9]. It goes without saying that occasionally, faulty components hinder technology or machinery from functioning properly. Similar circumstances apply to solar panels, which can malfunction for a number of reasons, one of which is a damaged panel cell that ultimately results in panel failure. Therefore, one must manually inspect the cell in order to fix this problem, which is inefficient because it needs complexity to check for and identify the damaged cell and also increases the possibility of human error [10-12]. With the development of technology, artificial intelligence, a recent trend, has the potential to solve challenging issues in practically every industry. Deep learning, a subfield of artificial intelligence, is also very helpful for categorising various photographs [13].

Numerous academics have presented their research on the examination and detection of defective solar panels [14, 15]. For the inspection and detection of diseased solar panel cells, electroluminescence (EL), infrared (IR), and RGB images are generally used to classify damage vs. normal solar panel cells [16-18]. According to many research, specialised imaging techniques like electroluminescence (EL) are far more efficient than traditional charge-coupled device (CCD)-based imaging techniques for checking photovoltaics (PV) [19-21]. Additionally, it has been shown that deep learning-based algorithms are among the clever algorithms that help with the resolution of many computer vision-based tasks, such as image categorization, object detection and recognition, and the assessment of image similarity [12, 22-24].

Utilizing imaging techniques based on electroluminescence, we classified the damaged photovoltaic cells using deep learning techniques that are based on convolutional neural networks. Furthermore, we have applied the concept of transfer learning to distinguish between damaged and healthy cells. The classification of the damaged PV cells has been addressed by several academics. According to a study [25] , transfer learning was used to categorise the damaged solar cells. With remote sensing photos serving as the input dataset, they used the pre-trained VGG16 model. A lightweight convolutional neural network was also suggested by the authors of [26] for the categorization of hotspots and damaged areas on solar cells. They had a 93.02% accuracy rate.

Modified U-Net network has been utilized for the classification and identification of damaged cells from solar panel [27]. Similarly, multispectral neural network has been proposed by the authors of [28], and they achieved an accuracy of 94% for the classification solar cells. Deep learning has been used for feature extraction in order to do the classification of damaged parts of solar panels [29]. Alexnet model has been modified by the authors of [30] for the classification of the faulty solar cells. Also, the authors of [31] provided a study while using convoutluional neural network (CNN) for the fault pattern detection. Similar to [31], the authors of [32] utilized five different CNN based networks for the classification of the damaged solar cells, while they achieved a highest accuracy of 98%.

In our study, we tested the convolutional neural network's ability to accurately identify the images of defective solar cells. One of the newest methods, transfer learning, has been used by us. ResNet50, VGG16, and InceptionV3, pre-trained models that we utilised. Furthermore, we took advantage of a dataset that was made public and further divided it into train, valid, and test datasets. Additionally, Google Coolab, which provides momentary free access to GPU, was used to gather the results of this experiment.

2. MATERIALS AND METHODS

2.1. Dataset

Using defective solar cells, the classification of defective solar cells are performed (Electroluminescence Images). The dataset is divided into two categories: "Normal" and "Defective". Total of 2624 images in all, each image of 300x300 pixels are utilized. All 8-bit grayscale images that are being used in this study is available at Kaggle [33]. Figure 1 shows examples of images from the database. Following that, the dataset was divided into training and testing, with 1177 and 135 (defective + normal) photos utilised for each. The evulation of the ResNet50, VGG16, and InceptionV3 models has been carried out using the testing dataset. In addition, the training dataset was divided into the train and valid datasets. The loss graphs presented in section 3 were observed using the train and valid datasets.

2.2. Proposed methodology

The model used for the transfer learning technique to identify and classify defective solar cells is shown in Figure 2. The model's objective is to divide input images into two groups: normal and damaged. Data preparation, which entails improving the data and normalising the pixels, and a second stage, which involves classification using the trained models, are both essential components of the utilised model (i.e., ResNet50, VGG16 and InceptionV3).

(a) (b)

Figure 1. Samples from the dataset [33] (a) Defected solar cell and (b) Normal solar cell.

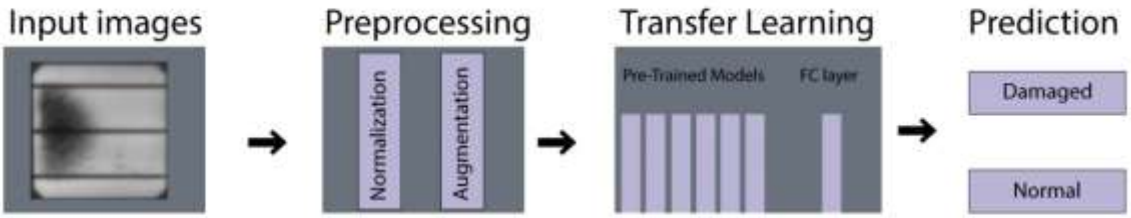


Figure 2. Transfer Learning methodology for the classification of solar cells.

Normalization and data augmentation are the next two processes in the data preprocessing process. During normalising, the picture pixels were shrunk to a range between 0 and 1. The dataset's photos were rescaled by multiplying each one by 1/255. While techniques like 1) a 30 degree rotation, and 2) vertical and horizontal flipping were used to supplement the data. Figure 3 illustrates augmented images.

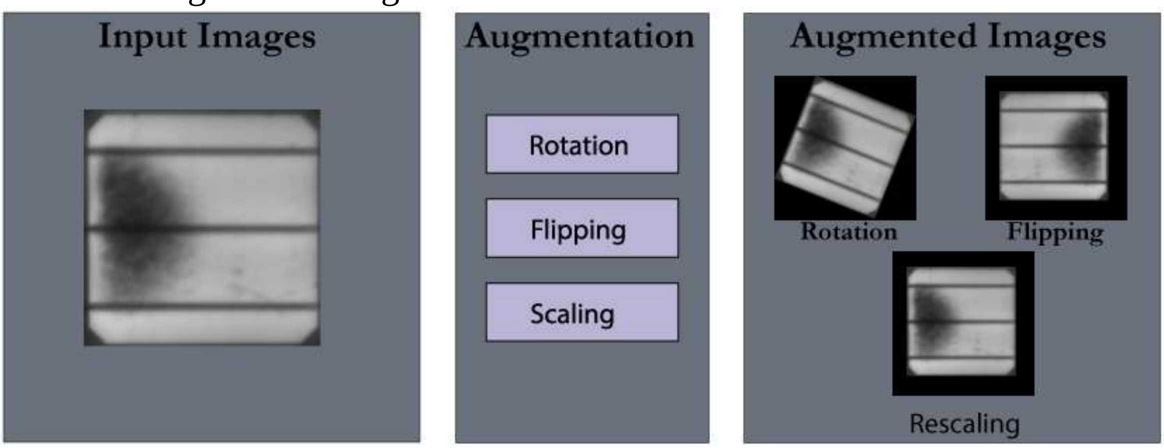


Figure 3. Data augmentation used on the images.

Table 1. Pre-trained models parameter overview

Model	Layers	Parameters	Input layer size	Output layer size
ResNet 50	50	23 million	224, 224, 3	2,1
VGG16	16	135 milllion	224, 224, 3	2,1
InceptionV3	48	23.9 million	224, 224, 3	2,1

2.3. Transfer learning using Pre-trained Models

Convolutional neural network (CNN) models have been shown to be superior for classifying and processing images [34]. However, it is challenging to train these CNN models from scratch because there aren't many picture data sets accessible. With transfer learning, a deep learning model that was trained on a larger dataset can use that knowledge to complete a task with a smaller dataset. In this study, damaged cells and healthy cells were distinguished using pre-trained models from ResNet50, VGG16, and InceptionV3. The architectural descriptions of the ResNet50, VGG16, and InceptionV3 models are shown in Table 1. These pre-trained models have already been trained on an ImageNet dataset. A dense layer has been built to use the transfer learning technique in order to fine-tune the training parameters. To further remove the unassigned neuron weights in the pre-trained models, batch normalisation layer is also used. A new fully connected (FC) layer with a perceptron value of two that represents each class has been introduced in place of the final dense layers in ResNet50, VGG16, and InceptionV3. The hyper parameters are quite important for these pre-trained models.

2.4. Fine tuning and hyperparamters

One of the essential elements on which the model is trained in transfer learning is fine tuning. The image was reduced to 224x224 pixels, Adam optimizers were used, and the following hyperparameters were maintained: momentum was set to 0.95, weight decay was set to 0.0005, batch size was set to 10, and learning rate was set to 0.001 with a factor value of 0.7. Apart from the aforementioned parameters, the model was often having overfitting issues before these parameters were chosen after the model was trained on a variety of values.

3. EXPERIMENTS AND RESULTS

3.1. Experimental Setup and Performance Metrices

The dataset is assessed using the pre-trained models. Table 2 provides information on the train and test datasets and also applies a 90:10 training-to-testing ratio. Utilizing the supplemented data, the suggested models have been trained.

Table 2. Data splitting

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

The images were reduced in size for the train and valid datasets to 224224 pixels. Pre-trained models were only allowed to be trained in batches of 10 with an epochs value of 80. The batch size value and the number of epochs were manually chosen using empirical approaches. For training, the learning rate of each model has been set to 0.001, and the Adam optimizer has been used to lower errors. The success of the Inceptionv3 model has also been evaluated using metrics such as Specificity (Spe), Sensitivity (Sen), Precision (Pre), F1-Score, and Accuracy (Acc). The True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) components of the confusion matrix were varied to produce these measurements. These equations have been computed using Equations (1)-(6) [35].

$$Pre = \frac{TP}{TP+FP} \tag{1}$$

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

$$Sen = \frac{TP}{FN+TP} \quad (3)$$

$$Spe = \frac{TN}{FP+TN} \quad (4)$$

$$Acc = \frac{TP+TN}{FP+TP+TN+FN} \quad (5)$$

$$F1\ score = 2 \text{ x} \frac{Precision\ x\ Recall}{Precision+Recall} \quad (6)$$

In this study, normal and faulty were seen as negative and positive categories, respectively. The normal and defective classes are thus indicated by the TN and TP, respectively. While FN and FP stand for incorrectly classifying expected normal instances and defects, respectively.

3.2. Results and discussions

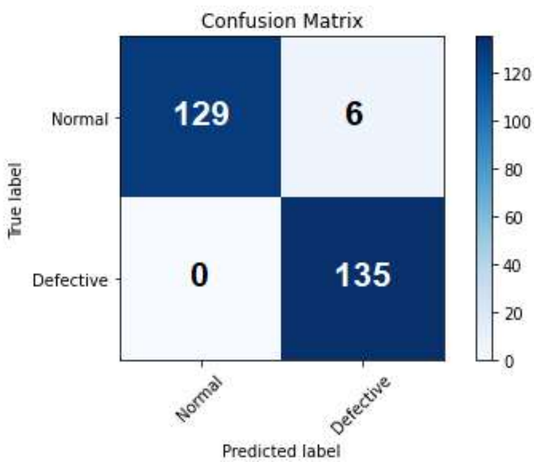
Model performance has been compared in terms of elements like training loss, validation loss, and validation accuracy at each epoch value. The results for these parameters are listed in Table 3. To determine the over- and under-fitting of the training models, the parameters were evaluated. For each model under investigation and training loss.

In order to further confirm performance, confusion matrices have been developed to classify true positive, true negative, false positive, and false negative data after training. On the test dataset, the confusion matrices for the pre-trained model are shown in Figure 4. Equations (1) through (6) have been used to evaluate the trained models' performance metrics using the data produced by confusion matrices, including precision, recall, F1 score, sensitivity, specificity, and accuracy. The results for the parameters that were previously mentioned are shown in Table 4.

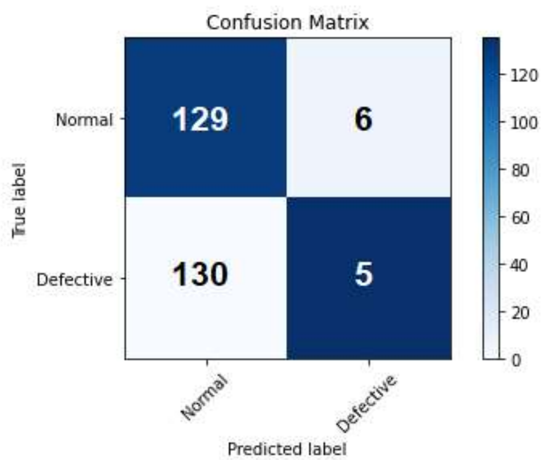
Table 3. Training performance of pre-trained models

Model	Epochs	Train loss	Valid loss	Train accuracy	Valid accuracy
ResNet 50	1 .	0.812 .	0.832 .	68.24 .	71.42 .

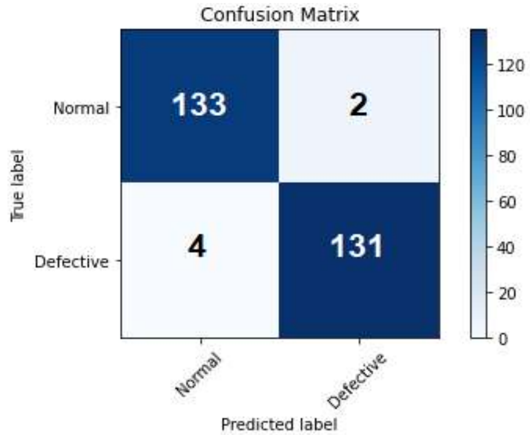
	.	.	.	.	.
	79	0.132	0.123	94.61	93.32
	80	0.131	0.108	94.53	95.63
VGG16	1	0.712	0.794	78.31	73.68
	.	.	.	.	.
	.	.	.	.	.
	79	0.101	0.112	95.23	95.87
	80	0.009	0.102	97.52	96.88
InceptionV3	1	0.712	0.842	69.54	70.23
	.	.	.	.	.
	.	.	.	.	.
	79	0.121	0.132	93.71	93.32
	80	0.112	0.181	95.83	95.65



(a)



(b)



(c)

Figure 4. Confusion metrices achieved on each model for test dataset (a) ResNet50 (b) InceptionV3 (c) VGG16.

Table 4. Performance of the models

Model	Precision	Recall	F1-Score	Sensitivity	Specificity	Accuracy
ResNet 50	97.87	97.82	97.77	97.82	94.07	97.40
VGG16	97.08	96.27	98.52	98.50	97.79	97.78
InceptionV3	95.56	96.27	95.51	96.27	95.59	95.93

3.2.1. Comparison with different optimizers

VGG16 model which outperformed the rest of the models have been tested with various optimizers such as RMSProp, Adadelta, SGD, and Adam, in order to do the comparison of the accuracies on the testing datasetThe Adam optimizer produced the most promising results out of all the optimizers. Thus, Adam optimizer was chosen to train the model. The results in Table 5 were produced using the Adam optimizer.

Table 5. Performance of VGG16 among different optimizer

Model	Optimizer	Precision	Specifity	Sensitivity	F1-score	Accuracy
VGG1	Adam	97.0	96.2	98.5	98.5	97.7

6	SGD	83.0	89.0	95.2	0.89	90.3
	Adadelta	92.3	91.4	92.1	0.92	92.1
	RMSProp	95.6	92.3	94.7	0.94	95.5

3.2.2. Comparison with different batch size

One key hyper-parameter for Deep Neural Networks is batch size, according to experts. This study provides information on the effects of various batch sizes. Table 6 listed the test accuracy results obtained after training on various batch sizes, including 8, 10, and 12. It has been noted that a batch size of 10 results in improved testing performance. Thus all the models has been trained using batches of 10.

Table 6. Testing accuracies on different batch sizes on ResNet50

Model	Batch size		
	8	10	12
VGG16	85.27%	97.78 %	90.25 %

3.2.3. Future work

This discovery has cleared the way for the development of effective deep neural networks that can quickly and precisely identify damaged solar cells. It is anticipated that the suggested model will perform remarkably well in terms of the classification problem between damaged and healthy solar cells. The performance of the suggested model might one day be used to categorise different classes of solar cells. We can also examine the use of optimization approaches with other DNNs in order to propose a potent model.

4. CONCLUSION

Using a pre-trained model, such as ResNet50, VGG16, and InceptionV3, we used transfer learning to recognise and classify images of damaged solar cells. The model was trained using a dataset of 2624 images. A number of important factors, such as sensitivity, specificity, F1-score, precision, recall, loss graphs, and confusion matrices, have been used to assess the model's accuracy. VGG16 was used to demonstrate an effective classification of the damaged and normal images. For VGG16, ResNet50, and InceptionV3, accuracy was reached at a rate of 97.78%, 97.40%, and 95.93%, respectively. The "Adam" optimizer, which was the best of all the optimizers used, was applied to the DNNs.

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