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Automatic Defect Classification of Electro-Luminescence Images of Photovoltaic Modules based on Deep Learning CNN

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Abstract: In recent studies, it has been noticed that to identify the defects in the solar photovoltaic (PV) modules, the manufacturers more rely on the automatic defect detection techniques instead of manual detection of defects in Electroluminescence (EL) images of PV modules. Sometimes the defects are so minute like a small crack such that the manual detection of PV modules cannot easily detect which leads to slow detection and thus involves human error, as a result of which the overall accuracy is affected and hence degrading the performance and quality of modules. The manual detection method is invasive, time consuming and prone to human errors. Automatic defect classifications of EL images of PV modules are much significant these days. Despite of the fact, it is a difficult task to perform automatic classification of defects due to the complexity and inhomogeneity of the crystalline silicon solar cells. The Automatic defect detection is a fast and reliable method to identify the defects from the large dataset. Deep learning is efficient technique to identify these defects with greater accuracy. The present study is carried out for automatic defect classification of EL image dataset of PV modules. In this paper, Alexnet, a pretrained deep learning CNN model has been used to classify EL images into two classes i.e. defected and non-defected and achieved the greater accuracy of 85.16 % with minimum training and validation loss for a learning rate of 0.0001. The proposed research can help the manufacturers to improvise their ventures with less human efforts and highest accuracy of the panels.

***Keywords**:* Solar panel defects, Electroluminescence, Convolution Neural Network, Deep learning, Alexnet.

1. **Introduction**

Solar energy is readily available form of energy and used by the range of technologies. In today's world, apart from wind and water, one of the foremost dependencies will be on solar energy, which has been increased in demand in last recent years. Many researchers, scientists and engineers are continuously working in this field and finding the solutions to use this effectively. The earlier manufacture process relies on manual detection of defects that requires a large amount of manpower which was not guaranteed of accurate results [1]. Solar PV modules are generally protected by an aluminum body and laminated glass sheet. The laminated glass sheet cannot fully protect the mechanical and thermal damage occurring while manufacturing, transportation and handling the PV modules during installation process. If the defects can detect on the surface before installation, it can help the manufacturers to get better performance and can provide an opportunity to repair or replace a faulty cell or part of the panel to avoid total damage [3]. Electroluminescence (EL) imaging is a method which is used to identify the defects in PV modules that provide images at very high resolution and can identify even very small defects too. EL imaging provides accurate quality of small solar film modules in the form of images. EL images that achieve new effects require a reduced amount of energy and time calculation. These EL images can directly show basic defects that cannot be considered for normal modular view, such as hidden cracks, visible heat, dark areas, etc. Currently, most of the solar vendors rely on EL imaging technique that leads to deliberate speed and accuracy. In order to improve the efficiency, we use an efficient technique of automatic defect detection based on deep learning CNN [3]. A dataset of total 2056 EL images of solar PV modules has been taken under test which are classified into two classes. One is defective and other is not defective. In this paper, Alexnet CNN model is used for classification for large dataset of EL images and a highest accuracy of 85.16% is achieved at minimal learning rate.

2. Related works

In this section, some of the proposed methods for automatic defect detection of panel defects has been summarized.

Voulodimos et.al [2] presented a brief overview of deep learning methods such as Convolutional Neural Networks, Deep Boltzmann Machines, Deep Belief Networks, and Stacked Denoising Autoencoders, based on their history, structure, advantages, and limitations is given, which is followed by the description of their applications like object detection, face recognition, action and activity recognition, and human pose estimation. They concluded that CNNs have the capability of learning feature of automatically learning features based on the given data set.

Akram et.al [3] introduced a method based on the convolutional neural network to identify defects in EL images achieved 93.02% results in the solar cell database of Electroluminescence images, the method requires a reduced amount of computational power and time. The paper concluded that the tests showed that the results could be enhanced by increasing the size of the training data. With the availability of large databases, the proposed CNN construction could attain greater accuracy.

Fan et.al [5], investigated the discovery of automatic cracks in roads with deep learning pathways. In this study, a supervised learning approach is proposed, which can address a variety of road conditions. This method is tested on existing information available twice and compared to the five available methods. After training, the model can predict cracks on the edge of the manual labels. The network can learn from the green images without pre-adjustment and produce a satisfactory result.

Ando et. al [8] illustrates the use of a random forest division led to a total specification of 94.7% while using a deep convolutional network resulted in 95.8%. By using the random forest as a deep convolutional network separator, the researchers found a total accuracy of 97.1% better than using neural differentiation networks.

Perez et al [14], developed a model based on a pre-trained VGG-16 classifier with maps to activate the object for automatic detection and construction of structural errors, such as mold, deterioration, and spots, in images. this method used the optimization readings on the VGG-16 network previously trained at ImageNet.

Zhang et.al [16] presented a residual learning framework to ease the training of networks that are significantly better than earlier proposed. They reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. And also provides comprehensive experimental suggestion shows the residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset they evaluate residual nets with a depth of up to152 layers, 8× deeper than VGG nets but still having lower complexity with an error 3.57% on the Image Net test.

Akram et.al [17], presented a case study of electroluminescence of solar photovoltaic panels using an in-depth study method of deep learning CNN. Model is trained for 150 epochs with a batch size of 64 with the training time of 13 hours and 45 minutes.

Bastariet.al, [18] proposed the process consists of two consecutive steps, the first step of vector of elements extracted from the Electroluminescence of photovoltaic cells using a texture analysis process. The second step consists of the integration carried out by a particular Neural Network framework which is suitable for the repair system, because it is faster and has less calculation problems. The results give good performance with effective integration.

Cha et.al [19], proposed a theory-based approach that uses deep convolutional neural networks (CNNs) to detect concrete cracks without counting feature factors. The proposed method showed lower noise levels than conventional methods and provides immature image effects, allowing for differences between sounds and errors. Comparative research has proved that the proposed method gives the best performance and detect cracks in the concrete in the real world.

Pierdicca et. al [21] introduced a method to measure the damage to Photovoltaic cells with DCNNs. This paper provides framework for the data used for DCNN trained cells for cell proliferation, this method provides high accuracy for damage classification. The experiments indicate the problem of degradation and a thorough examination of the strategy presented during this study of the Photovoltaic Infrared Database, which may be a compilation of data.

Deitsch et.al [23] presented a standard SVM and CNN training frame work used to identify malfunctioning solar cells in high-resolution EL images. In mono-crystalline one-day modules, both classifiers do the same, with just a small profit on CNN average. However, the CNN class significantly exceeds the SVM classifier with an accuracy of about 6% of the maximum polycrystalline cell matrix.

Mante et.al [24], proposed a solar cell pathway for error detection in EL images using SVM and RF. Test results shows that simple results were obtained by SVM, which provided 0.997 accuracy and 0.274 memory. The RF model gave 0.967 and the memory was 0.193. Therefore, SVM provided 3% improvement compared to RF accuracy. However, the high accuracy makes both our descriptions (SVM and RF) promise to detect PV panel errors in EL images.

Sun et.al, [25] used the features of the Alexnet status image and extracted the last layer of 4096 Alex-Net model neurons because the image has symbols, and then used the Lib-SVM scene image editing training model and compared the separation method that supports the retrospective model. Test results have shown that DCNN can extract image elements efficiently.

In this paper, Alex net CNN model has been used for transfer learning to train the system for large image dataset to accurately classify the defective solar panels, aiming at good accuracy. Data augmentation is also being done on the available dataset to increase the size of the dataset in order to achieve the higher accuracy. The model is being trained by varying different set of hyper parameters like learning rate, number of epochs etc. and the model with the higher accuracy is considered as the best model for classifying the solar PV images. The Block diagram for the proposed work is shown in fig 1.

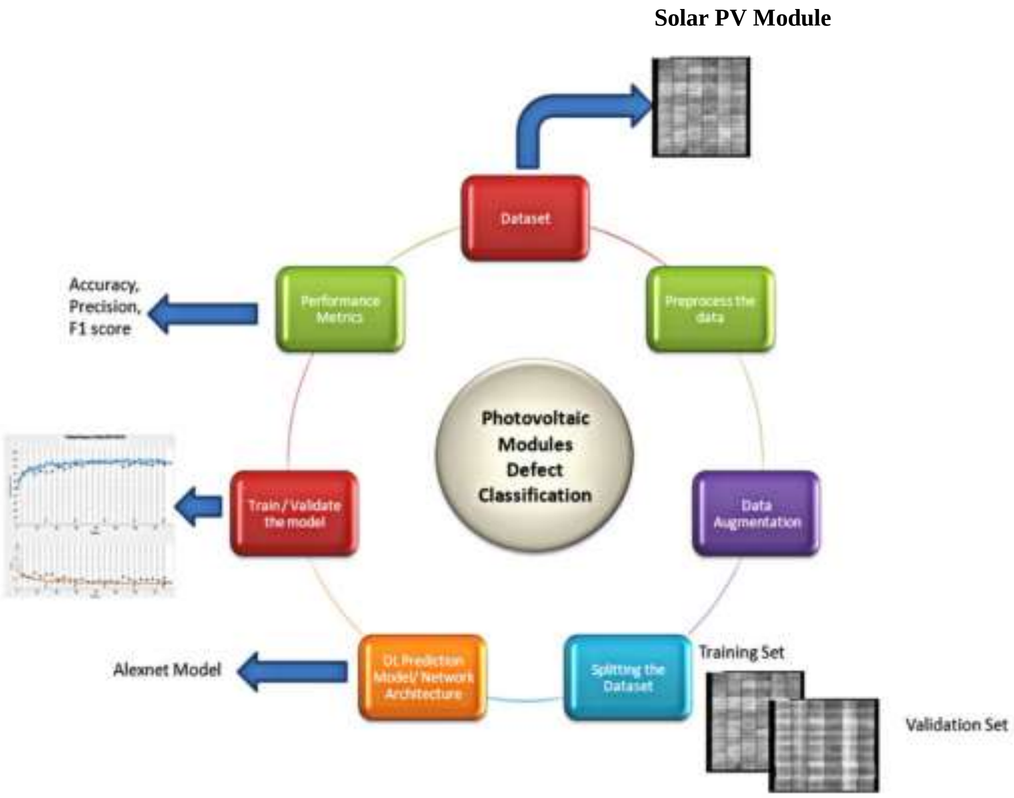
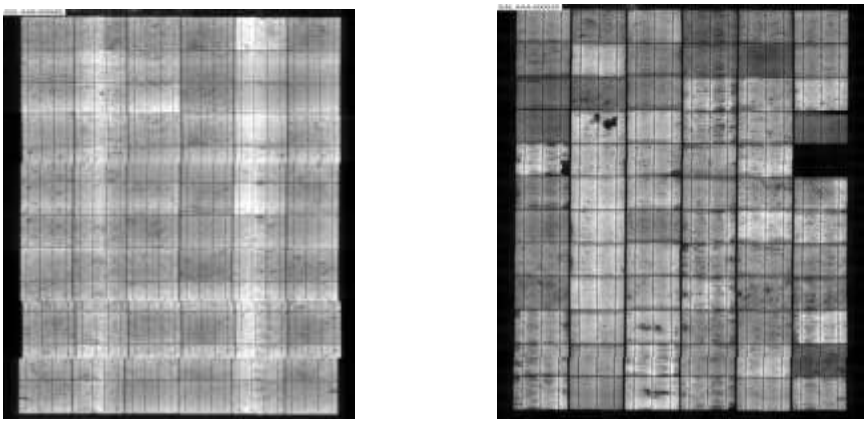


Fig.1 Flow diagram for automatic classification of PV images

3. Material and Methods

3.1 Electroluminescence Imaging

Electroluminescence imaging is commonly used procedure to evaluate the quality of the electrical contacts of solar cells. Electroluminescence builds on an equivalent principle as a light emitting diode. Current is fed into a solar cell and radiative recombination of carriers causes light emission. As an indirect bandgap semiconductor, most of the recombination in silicon occurs through defects [9]. In this detection method, the photovoltaic modules apply the forward bias voltage, due to which the power injects a large amount of non-equilibrium carriers into the photovoltaic module. The large number of non-equilibrium carriers present in the silicon solar cells is injected from the diffusion region recombination to constantly composite luminescence and thus emit photons and hence the result will be displayed after processed by the computer in the dark room. Then, the brightness of the image captured by Electroluminescence is directly proportional to the minority charge density. And, if the minority carrier diffusion length is become low, it means there may be defect present in the solar cell, hence the displayed image becomes dark [30]. An EL inspection of multi crystalline silicon solar cells modules during manufacturing process has carried out on 4000 mw under standard test conditions at cell temperature of 25^0C with the solar irradiation/intensity of 100 milli Watt/cm^2 in the laboratory at solar production division. The real time images dataset is being collected from the laboratory under standard test conditions. Initially the size of dataset was 392 images which is then increased up to 2456 images of broken and non-broken photovoltaic solar cells using data augmentation by flipping and rotating the images. Here, we have 1228 images with broken cells and 1228 images with non-broken cells i.e. normal photovoltaic solar cells. After doing the extensive data augmentation we have a balanced dataset with equal number of images in both classes. The example of normal PV module and broken PV module can be shown in fig 2.



(a) Normal PV module (b) Broken PV module

Fig.2. Examples of normal and broken PV modules

3.2 Convolution Neural Network

Convolution neural network are used for image classification and recognition because of its high accuracy. Deep learning is effectively used as a tool for machine learning, where a neural network is capable of automatically learning features. Deep learning practices neural networks to learn useful representations of features directly from input image data. It provides a framework for designing and implementing deep neural networks with algorithms, pretrained models, and applications. The term 'deep' refers to the no of hidden layers in neural network, traditional neural network only contains two to three hidden layers while deep learning network contains up to 150 hidden network layers. Deep learning models are trained by using large sets of labeled data and neural network architectures that learn features directly from the data without the need for manual feature extraction with greater accuracy. Deep learning requires substantial computing power, the high performance GPUs can have a parallel architecture is efficient for deep learning, which cannot be achieved by a normal CPUs. Training the deep learning model takes time, from days to week. MATLAB with GPU reduces the time required to train the network from days to hours. A simplified architecture of CNN is shown in fig. 3.

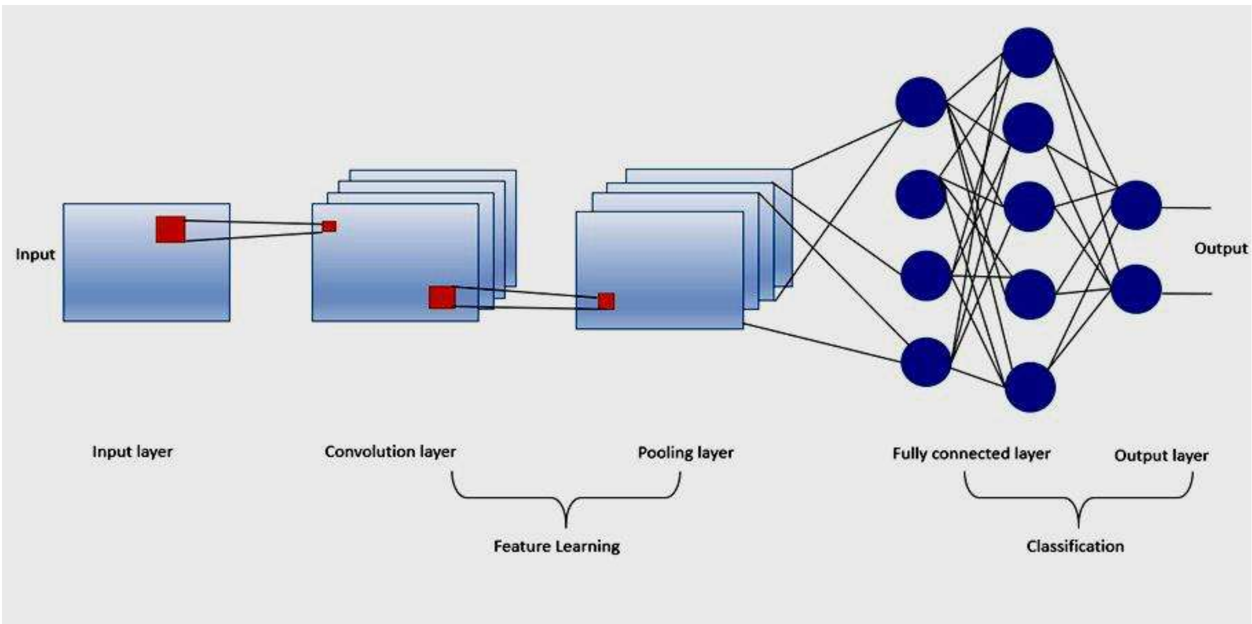


Fig.3. Network Architecture of simple convolutional neural network

3.3 Transfer Learning Using Alexnet

Alexnet is an 8-layer deep convolutional neural network as shown in figure 4. A pretrained network can classify images into 1000 different object categories. As a result, the network has learned rich presentations of various image features. The network has 227-by-227 image input size. The network takes an image as inserting and releasing an object-labeled object and the possibilities for each stage of the object [26]. The addition of data helps to prevent the network from overheating and memorizing the exact details of the training images. If learning rates are too high may results in unstable training process, that's why the learning rates kept small so that the network become stable during training and thus it takes time.

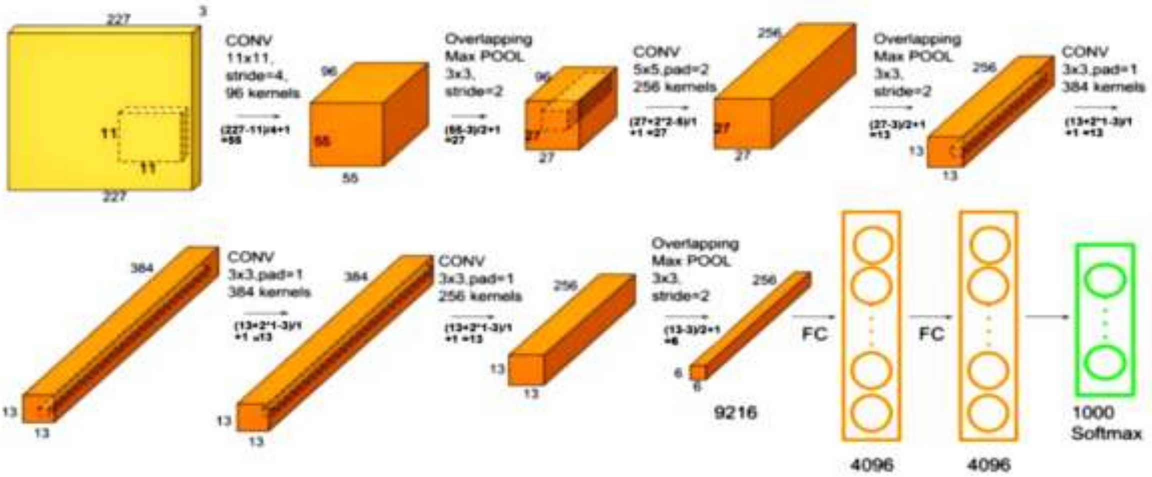


Fig. 4. Schematic of Alex net Architecture [44]

4. Image classification

Image classification is the process of categorizing and labeling groups of pixels or vectors within an image. Mostly, image classification is done by a computer, so, to achieve classification by a computer, the computer must be trained. It never gets sufficient accuracy with the results obtained often, so training is a key to the success of classification. Image classification refers to a process in computer vision that can classify an image according to its visual content. Image classification is a supervised learning problem which defined as a set of target classes such as objects to identify in images and train a model to recognize them using labeled example. CNN is the most popular neural network model being used for image classification problem.

5. Evaluation

5.1 Experimental setup

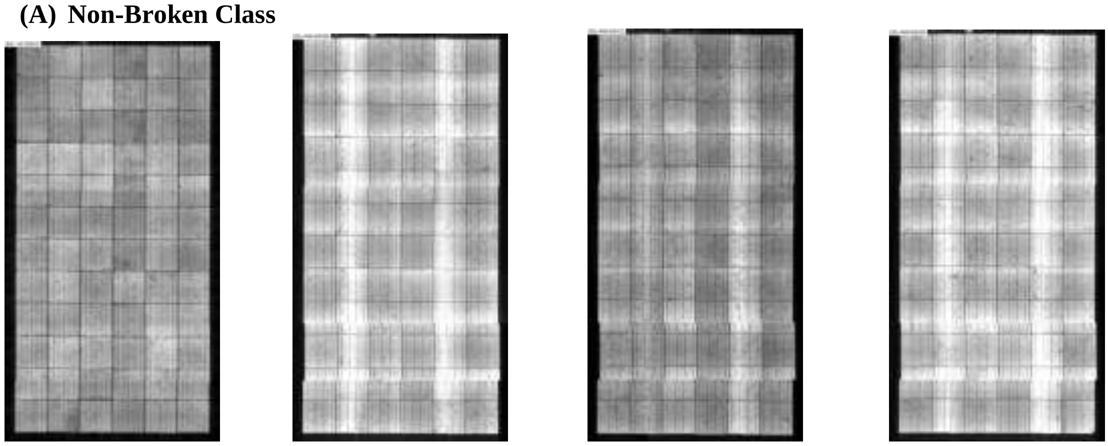
The experimental setup includes both hardware and software specifications. The setup includes an NVIDIA G5 GTX graphics and i7 processor which supports both machine learning and deep learning tools such as training testing and automotive applications in MATLAB. The software here used is Deep learning in MATLAB for training and transfer learning of EL image dataset.

5.2 Experimental analysis

5.2.2 Data set

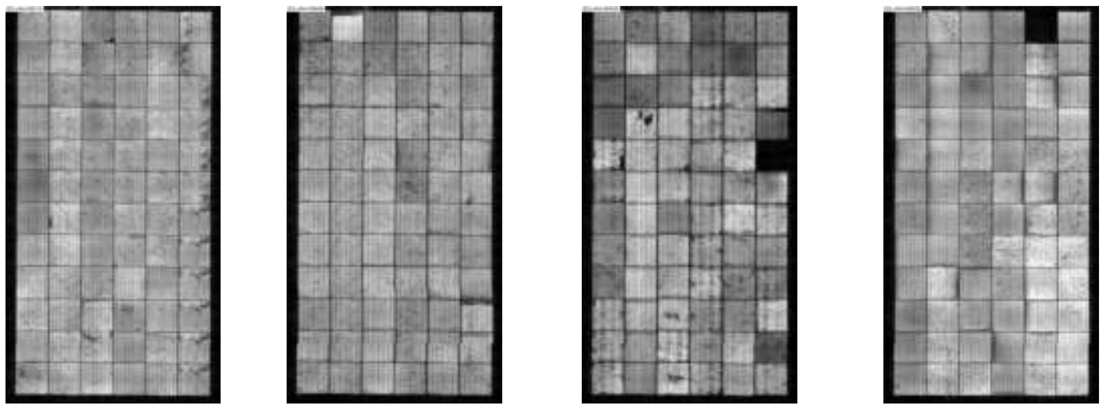
An EL inspection of multi crystalline silicon solar cells modules during manufacturing process has carried out on 4000 mw under standard test conditions at cell temperature of 25^0C with the solar irradiation/intensity of 100 milli Watt/cm2 in the laboratory at solar production division. The real time images dataset is being collected from the laboratory under standard test conditions. Initially the size of dataset was 392 images which is then increased up to 2456 images of broken and non-broken photovoltaic solar cells using data augmentation using flipping and rotation operation. Here, we have 1228 images with broken cells and 1228 images with non-broken cells i.e. normal photovoltaic solar cells shown in the figure 5.

(A) Non-Broken Class



(a) Sample image 1 (b) Sample image 2 (c) Sample image 3 (d) Sample image 4

(B) Broken Class



(a) Sample image 1 (b) Sample image 2 (c) Sample image 3 (d) Sample image 4

Fig. 5. Sample images from non-broken and broken class.

5.2.3 Data Augmentation

Image data enhancement is a way to increase training data size by creating improved versions of images in the dataset. Training deep learning neural network models on more data can result in more dexterous models. Image data augmentation is possibly the most well-known type of data augmentation and involves creating transformed versions of images such as shifts, flips, zooms in the training dataset that belong to the same class as the original image. The augmentation techniques can create variations of the images that can improve the ability of the fit models to generalize what they have learned to new images. It helps prevent the network from overfitting and memorizing the exact details of the training images. To automatically resize the validation images without performing further data augmentation, we can use an augmented image datastore without specifying any additional preprocessing operations.

5.3 Data Training

With transfer learning, we have to preserve the features from the main layer of the pretrained network i.e. the weights of the transferred layer. To reduce the learning rate in the transferred layers, we have to set the initial learning rate to minimum. For transfer learning, we have to keep the features from the primary layers of the pretrained network. To slow down learning in the transferred layers, we set the initial learning rate to a small value. In the previous step, we increased the learning rate factors for the fully connected layer to speed up learning in the new final layers. This combination of learning rate settings results in fast learning only in the new layers and slower learning in the other layers. When performing transfer learning, we need not to train for as many epochs.

5.4 Data validation

Data validation is the process where a trained model is evaluated with a testing data set. The testing data set is a separate portion of the same data set from which the training set is derived. This is carried out after model training. The training set is used to train the model, while the validation set is only used to evaluate the model performance.
Validation within a dataset is accomplished by creating own application-specific validation which can check values in an individual data column during changes and other is by creating own application-specific validation that can check data to values while an entire data row is changing.

6. Results

Following are the experimental results obtained from the transfer learning of Alexnet CNN on the photovoltaic EL image dataset at different learning rates. The train test split is taken into a ratio of 80:20 which means 80% images are being taken for training and 20% for testing. That means, out of the total 2456 images, 492 images have been chosen for validation and remaining 1964 images for training.

The performance of the model is tested with different set of learning rate and for different epochs, it means the network is tuned for the learning rate and the no of epochs for which it is giving the best accuracy. The confusion matrix and the network learning graph for all three learning rates for 50 epochs is shown in fig. 6, 7 and 8 given below.

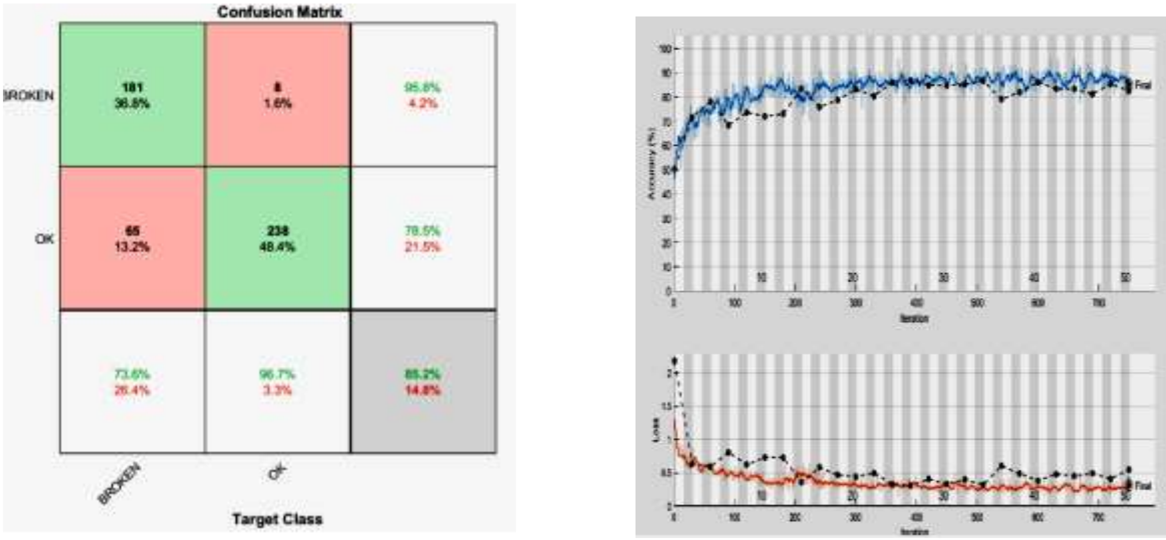


Fig. 6. Confusion matrix, accuracy and training validation loss function graph for a learning rate of 0.0001 and 50 epochs

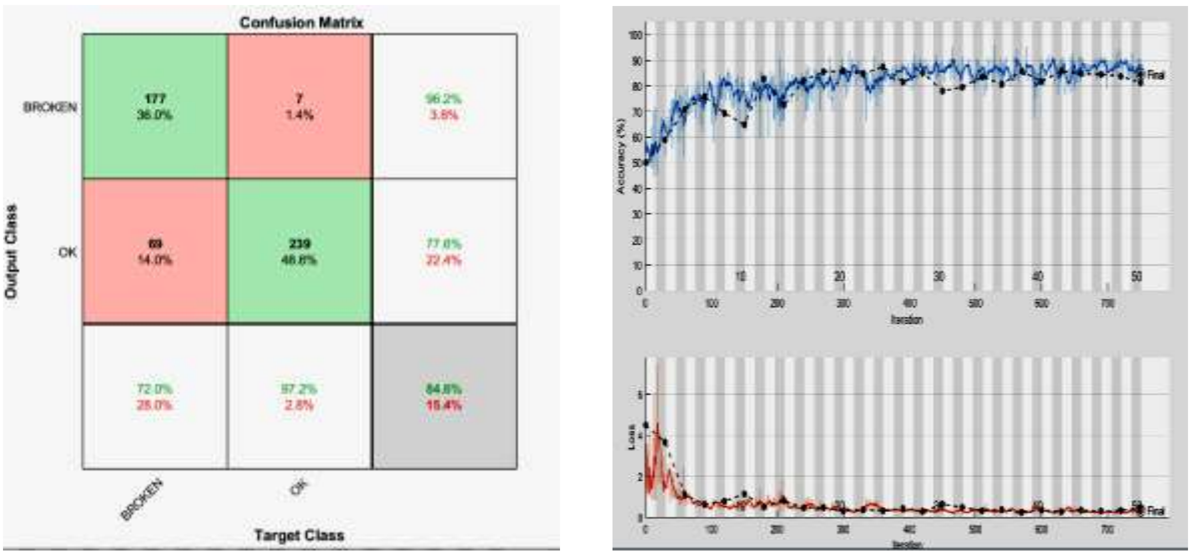


Fig. 7. Confusion matrix, accuracy and training validation loss function graph for a learning rate of 0.001 and 50 epochs

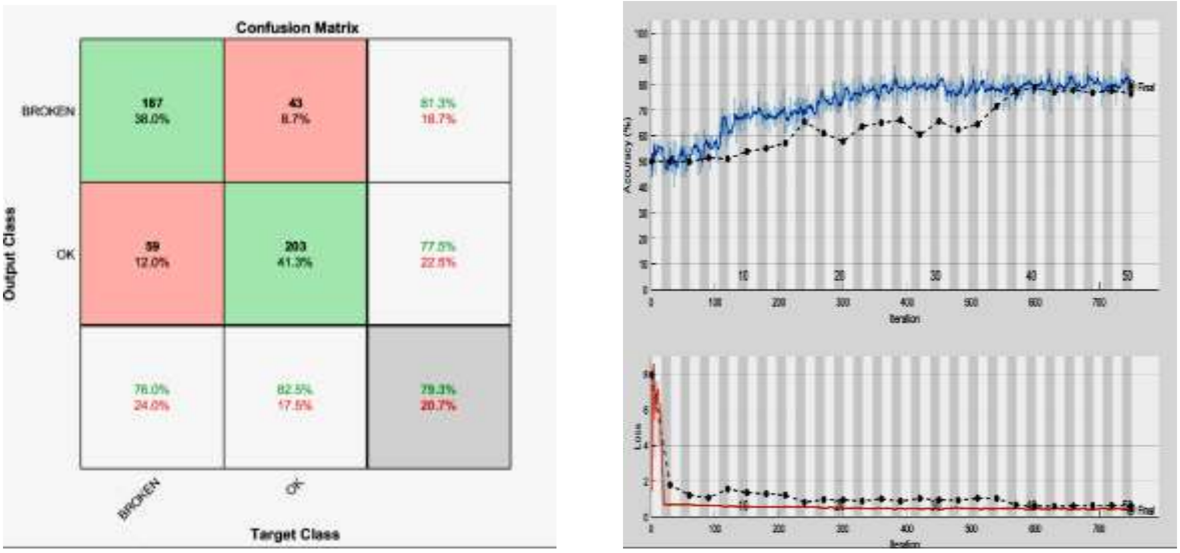


Fig. 8. Confusion matrix, accuracy and training validation loss function graph for a learning rate of 0.01 and 50 epochs

7. Conclusion

From the graphs we have observed that, for a learning rate of 0.01, the highest accuracy achieved is 79.27% for 50 epochs and for learning rate of 0.001 it is achieved as 84.55% for 50 epochs whereas highest accuracy of 85.16% is achieved for a learning rate of 0.0001 respectively. Hence, it is clearly visible that the accuracy of the prediction model will increase if the learning rate of the model is reduced but at the same time, the network training will be slower but that can be taken care of by using a high computational power machine. The only limitation with reducing learning rate is high computational time for training the prediction model.

The detailed results obtained are tabulated below i.e. Table 1. We can see that the maximum accuracy is observed for 50 epochs in all different learning rates graphically in fig 9.

Table1. Model accuracy with varying epochs and learning rate

	learning rate		**learning rate**		**learning rate**	
	0.01		0.001		0.0001	
Sl. No.	epochs	accuracy	epochs	accuracy	epochs	accuracy
1	5	54.07%	5	78.46%	5	80.69%
2	10	65.45%	10	79.47%	10	81.10%
3	20	50.00%	20	79.47%	20	82.93%
4	30	57.52%	30	76.02%	30	82.72%
5	50	79.27%	50	84.55%	50	85.16%

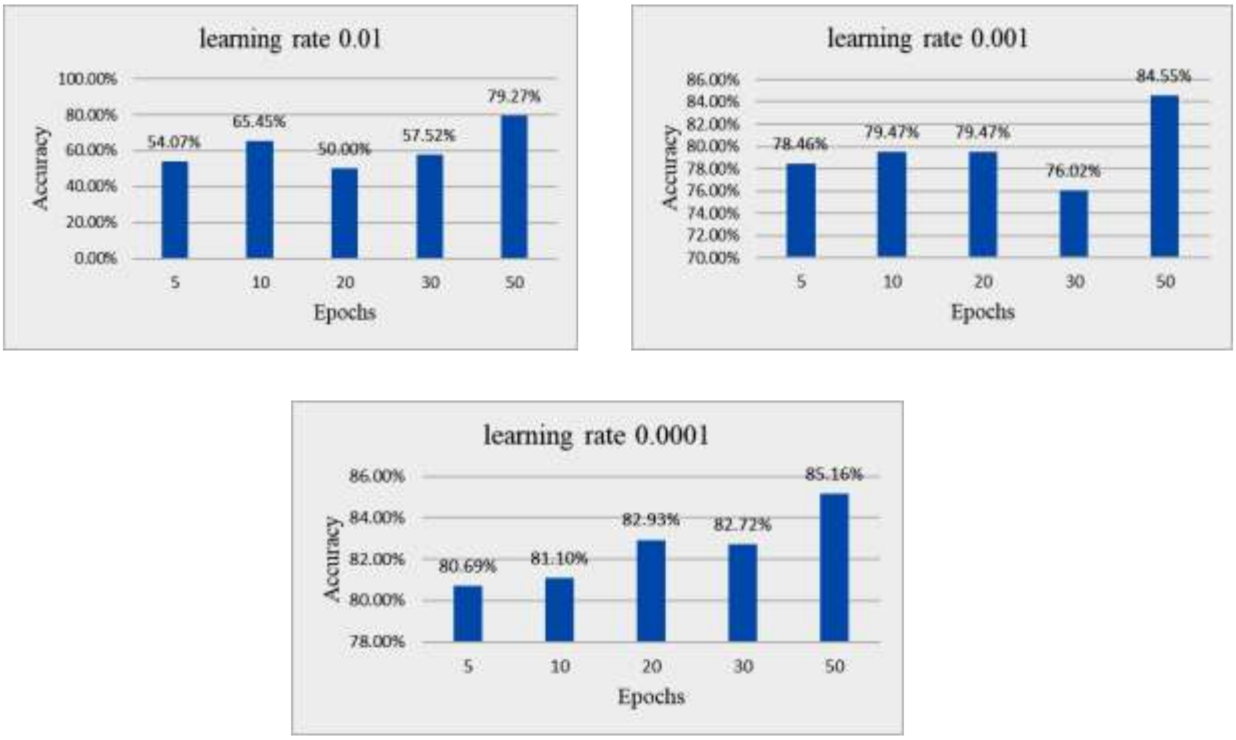


Fig.9. Graphical representation of model accuracy with varying epochs and learning rate

In future, more pretrained models can be used and compared to achieve higher classification accuracy as in this paper, the work is very specific to Alexnet model. Also, in future the work can be extended to classify which particular type of defect is present in the PV image that means extending the work from binary class to multiclass classification.

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