

Research Article

Classification Panel Defects from Infrared Thermal Images Using Deep Neural Networks

**Mabikana Voula Boniface Herve^{1,*} , Mabiala Louboto Antoine Victorien¹,
Nkombo Mazouka Michel¹, M'Passi Mabiala Bernard² **

¹Laboratory of Electrical and Electronic Engineering, National Higher Polytechnic School, Marien NGOUABI University, Brazzaville, Republic of the Congo

²Faculty of Science and Technology, Department of Physics, Marien Ngouabi University, Brazzaville, Republic of the Congo

Abstract

Development research has today, through different technologies, boosted the solar panel manufacturing industry. These technologies allow these solar panels to make the most of solar radiation to produce electricity, and as a result, improve efficiency. These photovoltaic solar panels, whenever they are installed, often have their performance affected by faults and anomalies that lead to a drop in energy efficiency. Many studies have looked into diagnosing, detecting, and locating these faults using algorithms. Building on this research and the experience gained from these systems in operation, several faults have been identified in photovoltaic cells. The goal of this study was to design, based on these different defects, artificial intelligence algorithms to detect, classify, and predict defects on solar panels over time. The model was trained using a neural network with the public database available on GitHub (intended for researchers, public services, solar project developers, and decision-makers). It contains infrared imaging data highlighting anomalies in a photovoltaic solar field. This dataset, made up of 20,000 images, allowed us to create an approximator (neural network) linking the pixels of a thermal image of a photovoltaic module to the presence of defects. During model training, the decrease in training and validation losses shows that this model has learned and can improve its performance. Beyond 20 epochs, the model converges, which means that no additional learning can improve the model's performance. This developed, trained, and validated model was exported to Simulink and allowed us to classify and predict solar panel faults, with an average accuracy of over 95% for some faults and 100% for others.

Keywords

Diagnosis, Panel Defects, Neural Network, Photovoltaic Solar Panels

1. Introduction

The performance of solar panels is strongly influenced by their surface condition; dirt buildup or the appearance of defects

leads to a noticeable drop in energy efficiency [1]. This performance is crucial for maximizing electricity production. Several environmental and technical factors can affect this performance

*Correspondence: Mabikana Voula Boniface Herve (bonifacemabikana@yahoo.fr)

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(changes in sunlight, temperature effects, etc.) [1].

Artificial neural networks (ANNs) are a key part of artificial intelligence and machine learning, offering advanced capabilities to model complex relationships and handle large amounts of data. These systems are especially relevant in the field of renewable energy, where they can be used to optimize photovoltaic system performance and to efficiently detect and classify solar panel defects [2].

The main causes of PV module degradation include gradual power loss, optical losses in the encapsulant, dirt on the front surface of the module, glass breakage, hot spots, degradation of bypass diodes, encapsulant delamination, water accumulation inside the module, etc. [3].

Accelerated degradation tests (for safety, mechanical integrity, and thermal cycling) have been developed by ASTM [4] and IEC [5] to simulate the various modes of degradation in solar modules.

Module efficiency may differ from STC efficiency, primarily due to four meteorological factors (temperature, humidity, irradiance, and wind) [6-9].

In this article, we aim to develop a neural network-based model for the detection, classification, and prediction of defects observed in solar panels during operation. Most manufacturers guarantee a lifespan of approximately 25 to 30 years for solar cells; however, as part of this work, it was not straightforward for us to track the degradation of a solar panel in order to obtain data on its degradation. Therefore, to compensate for the lack of data on solar panel defects, we used publicly available databases on GitHub (accessible to researchers, public agencies, solar developers, and decision-makers). This data consists of infrared imagery.

2. Methodology

A neural network is a collection of interconnected neurons; it is a directed graph. A neural network can be used to solve many artificial intelligence problems.

Formalization of the problem: Consider n input neurons and m output neurons.

Let $X = \{x_1, x_2, \dots, x_p\}$ be a set of p input vectors,

$S_d = \{S_{d1}, S_{d2}, \dots, S_{dp}\}$, a set of p desired outputs, and

$S = \{S_1, S_2, \dots, S_p\}$, the set of outputs actually obtained at the end of the forward propagation of the vectors in the set X .

The pair (X, S_d) forms the basis of the network's learning.

Consider the k^{th} element x_k of the set X ; we denote $X_k = (x_{k1}, x_{k2}, \dots, x_{kp})$ as the components of this vector.

Similarly, we denote:

$S_{dk} = (S_{dk1}, S_{dk2}, \dots, S_{dkm})$, the components of the k^{th} element of the set S_d , and

$S_k = (S_{k1}, S_{k2}, \dots, S_{km})$, the components of the k^{th} element of the set S

We also denote ϕ as the activation function of a neuron (and ϕ' as its derivative) and y_j as the output of neuron j in a hidden layer, such that

$$y_j = \phi \left(\sum w_{ij} e_i - \theta_j \right) \quad (1)$$

where w_{ij} are the weights of the connection between neuron j and neuron i in the previous layer.

Where e_i is the i^{th} input to neuron j ; θ_j is the bias, if any

After presenting the k^{th} example, we minimize the observed quadratic error defined as the difference between the actual output and the desired output:

$$E = \frac{1}{2} \sum \|S_{dk} - S_k\|^2 \quad (2)$$

This error propagates through the network, resulting in a change in the synaptic weights. If the error is less than a chosen threshold, the network is said to converge [10, 11]. The training phase then minimizes the squared error of the entire model by adjusting the weights to reduce the gradient. [12].

This error is then minimized using the gradient method, by updating the weights in the direction indicated by the gradient of E . [12].

The rule for modifying the weights of the connection linking neuron j to neuron i for iteration k is given by:

$$W_{ij}^k = W_{ij}^{k-1} - \alpha \delta_i y_j \quad (3)$$

where

α : the learning rate

δ_i : the error signal of unit i , that is, the contribution of unit i 's input to the squared error observed at the output. This error signal is calculated using the backpropagation principle.

$$\delta_i = (S_i - S_{di}) \phi'(e_i) \quad (4)$$

The calculation of the weights in the last layer depends on the elements in the previous layers. [13].

If i is now considered the index of a hidden neuron and the layer of neurons following unit i is denoted by j , the quadratic error E associated with the presentation of an example depends functionally on the set of all outputs y_j that depend on y_i . In this case, the error signal δ_i is given by:

$$\delta_i = \phi'(e_i) \sum \delta_c W_{ij} \quad (5)$$

2.1. Activation Function

The activation function is a mathematical formula that is applied under certain circumstances. When neurons calculate the weighted sum of the input values, these values are passed to the activation function, which checks whether the calculated value exceeds the required threshold.

If the calculated value exceeds the required threshold, the activation function is triggered to calculate the output value. This output value is then passed to subsequent or preceding layers (depending on the network's complexity), which can help the networks adjust the weights of their neurons.

It can take various forms (linear, nonlinear, sigmoid, etc.),

and it allows for a comparison between the sum and the threshold to validate the output value. The output of the formal neuron can be binary or real.

This output corresponds to a weighted sum of the weights and inputs plus the neuron's bias b . The result of the weighted sum is called the neuron's activation level.

The bias b is also called the neuron's activation threshold [14, 15].

When the activation level reaches or exceeds the threshold b , the argument of f becomes positive (or zero). Otherwise, it is negative [16, 17], and based on this value, an activation function calculates the output value of neuron j .

The activation function defines the state of the neuron based on its total input.

It describes the relationship between the neuron's activation and decision potentials.

The three main stages in the development of a neural network:

- 1) Creation of a database of infrared images showing the main anomalies in solar modules;

- 2) Selection of the neural network architecture;

- 3) Training the network using the database and validating the resulting neural network model.

2.2. Fault Detection Methodology

Observing the various types of degradation in solar panels requires a fairly long period of time [18]. For a solar farm, data related to this degradation can be detected using satellites, drones, and infrared methods [19-21].

This dataset is a collection of labeled data designed to facilitate research and solve problems well-suited to machine learning that may have an impact on the environment.

This dataset consists of 20000 infrared images, each 24 x 40 pixels in size, of solar modules exhibiting various anomalies found in solar farms. This dataset comprises 12 groups (classes) of solar panel images, including 11 classes of different anomalies and one class consisting of solar panels with no anomalies. These 12 image classes are listed in Table 1.

Table 1. Classification of images of different defects.

N °	Class Name	Number of images	Description
0	Single-cell	1877	Hot spot appearing on a square module
1	Multi-cell	1288	Hot spot appearing on a square module within a cell
2	Cracking	941	Cracking on the module's surface.
3	Hot Spot	251	Hot spot on a module
4	Hot-Spot-Multi	247	Multiple hot spots on a module
5	Shading	1056	Sunlight blocked by vegetation, man-made structures, or adjacent rows.
6	Diode	1499	One shunt diode is activated, typically affecting 1/3 of the module.
7	Multi-Diode	175	Several shunt diodes are activated, generally affecting 2/3 of the module.
8	Vegetation	1639	Panels blocked by vegetation.
9	Fouling	205	Dirt, dust, or other debris on the module's surface.
10	Module not connected to the grid	828	The entire module is overheating.
11	No anomalies	10000	Nominal solar module.

This table shows the classification and description of defects in the 20000 infrared images, which are divided into 11 defect classes—ten of which represent specific defect types, while the eleventh class comprises all 10000 defect-free images.

This data was used to develop a model for predicting defects based on the 20000 infrared images of solar panels, categorized into 11 classes as shown in Table 1.

This selection aims to capture a wide range of common conditions that affect the performance of solar panels.

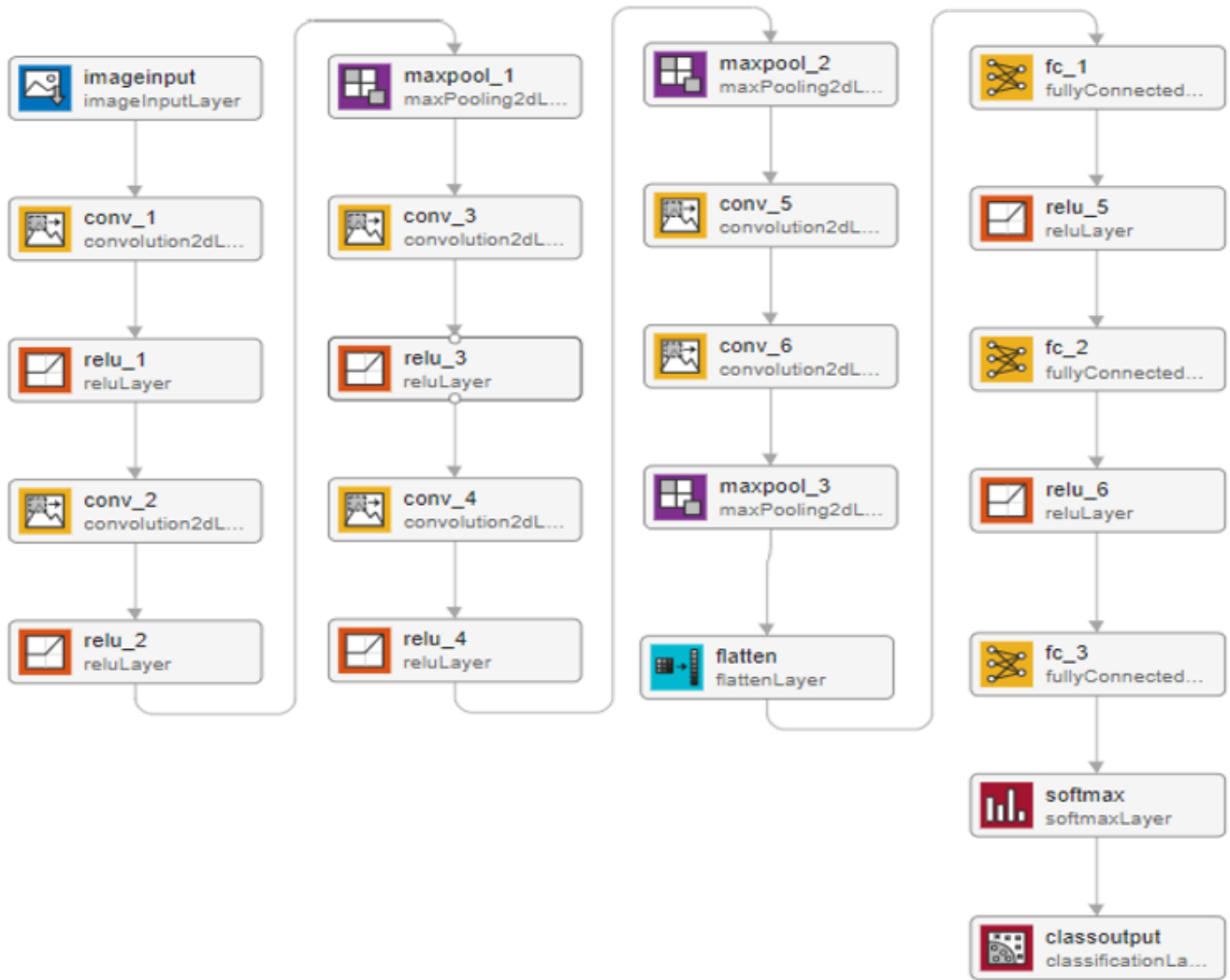


Figure 1. Classification of panel defects using Deep Network Designer (DND).

In MATLAB, a pre-trained TensorFlow model allows for transfer learning, a process that involves using the pre-trained model to refine and adapt it to the problem at hand.

As a result, using Deep Network Designer (DND), we can perform transfer learning either programmatically or iteratively.

The network model is designed for training data using a few lines of MATLAB code and built-in functions that replace, remove, or add layers to any part of the network architecture. Simulink is a block diagram environment used for designing systems with multi-domain models.

Artificial intelligence models are integrated into Simulink to simulate entire systems. Using the TensorFlow model, an AI system reads and classifies the imported images.

The convolutional neural network was created and trained for classification, as this type of network is well-suited for image recognition.

To make predictions, we used an LSTM network that takes

sequence data as input.

Therefore, a large number of annotated images is required to use a CNN for image classification problems. Although there is no formal rule specifying the exact number of images needed to guarantee a minimum level of performance for a CNN, several empirical observations have highlighted the relationship between the complexity of the classification problem to be solved and the size of the training image dataset. Thus, as the number of classes and their variability increase, the number of annotated images required will also increase. [22].

3. Results and Discussion

In this section, we present the simulation results of our model.

Step 1: Designing the network model.

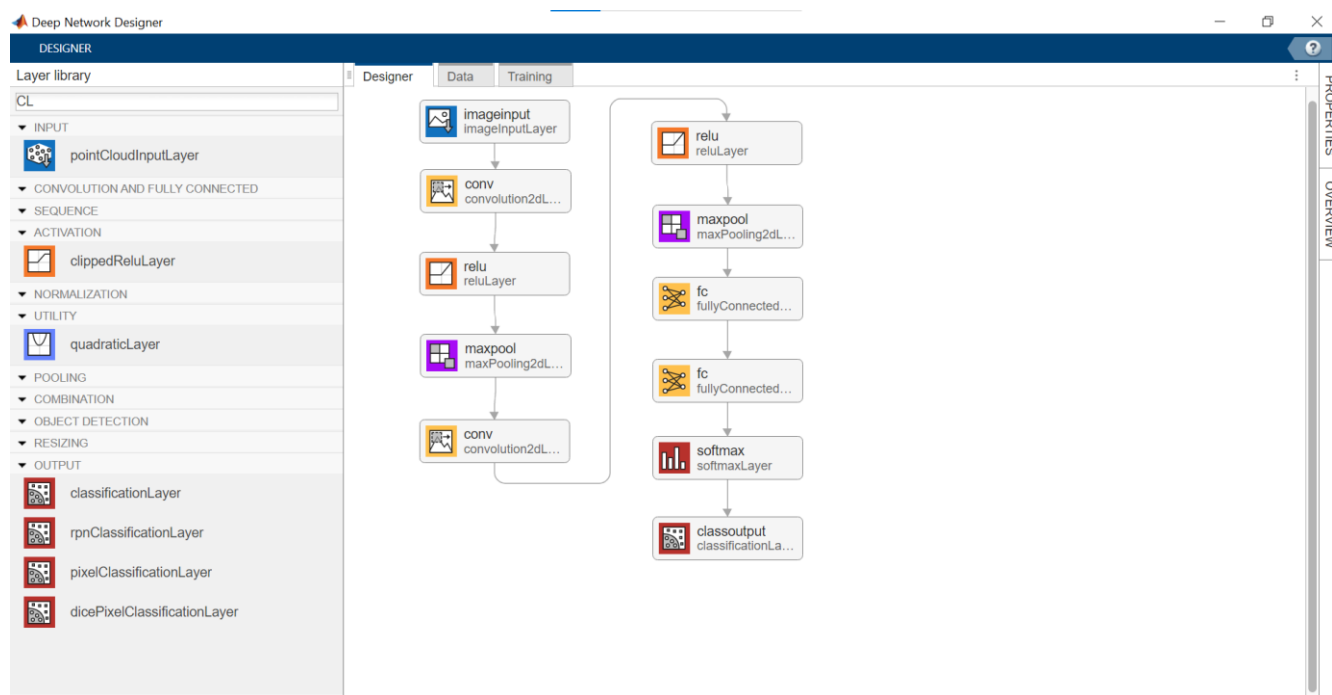


Figure 2. Network model for simulation.

Step 2: Import the data (images)

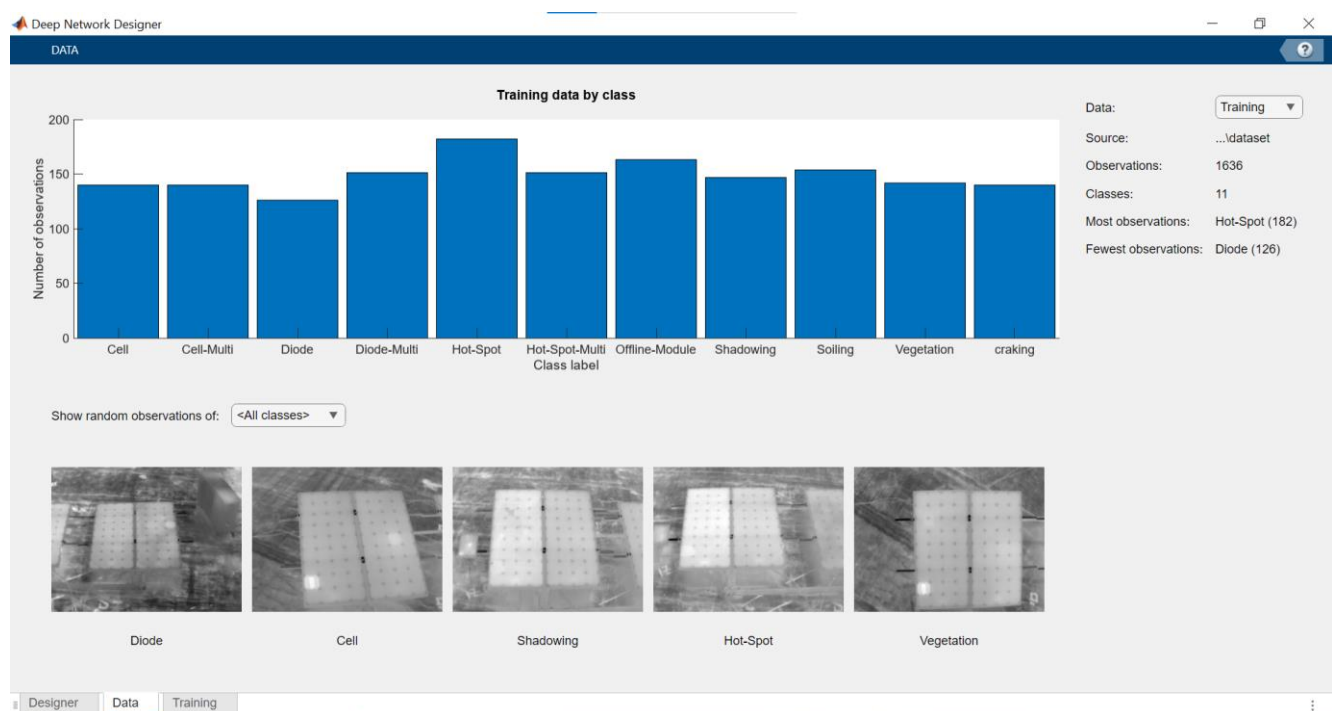


Figure 3. Importing Images.



Figure 4. Data Validation.

Step 3: Training

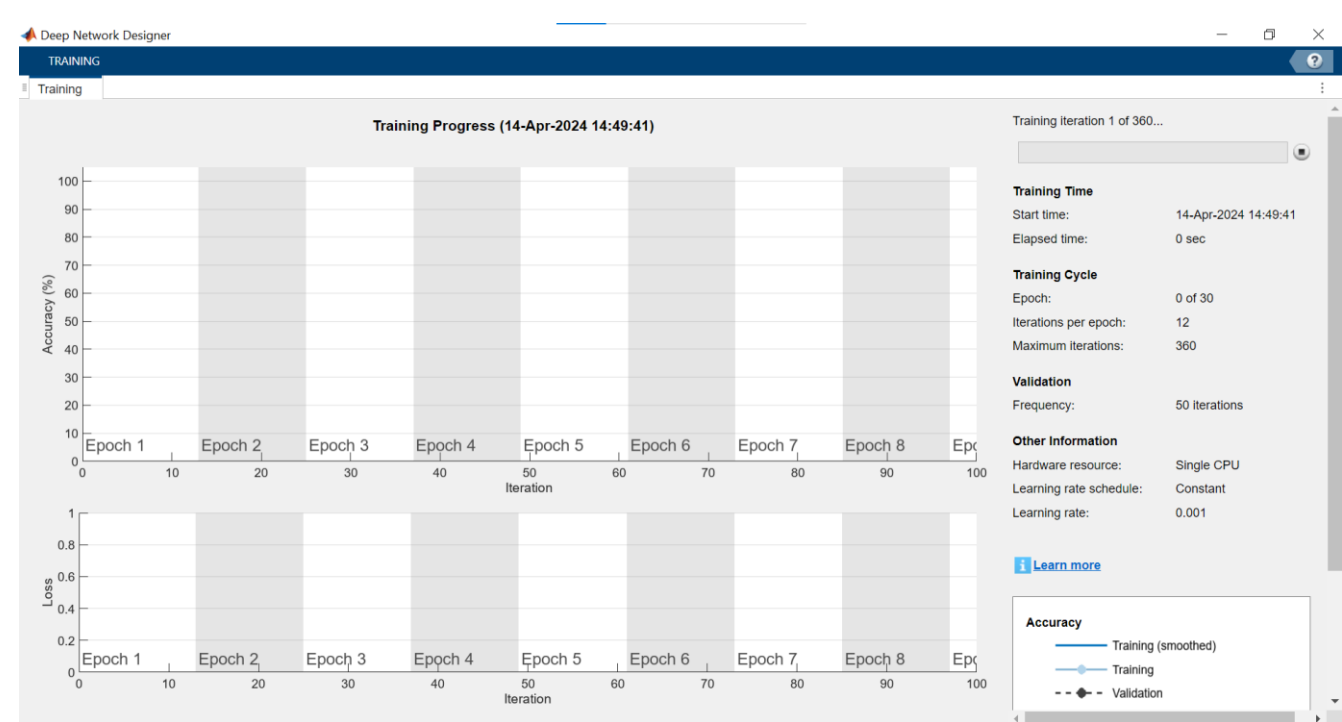


Figure 5. Launching the model for training.

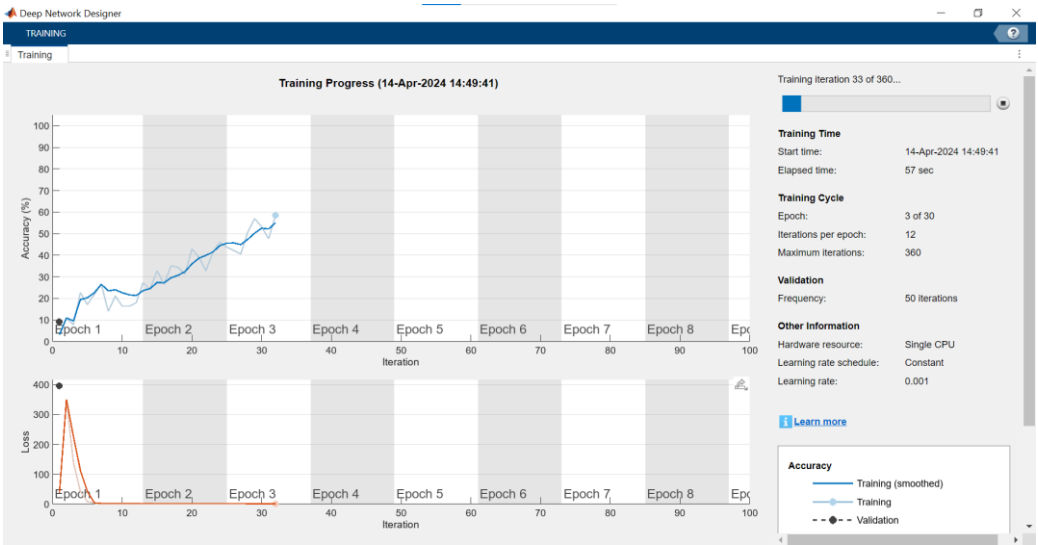


Figure 6. Training Curves.

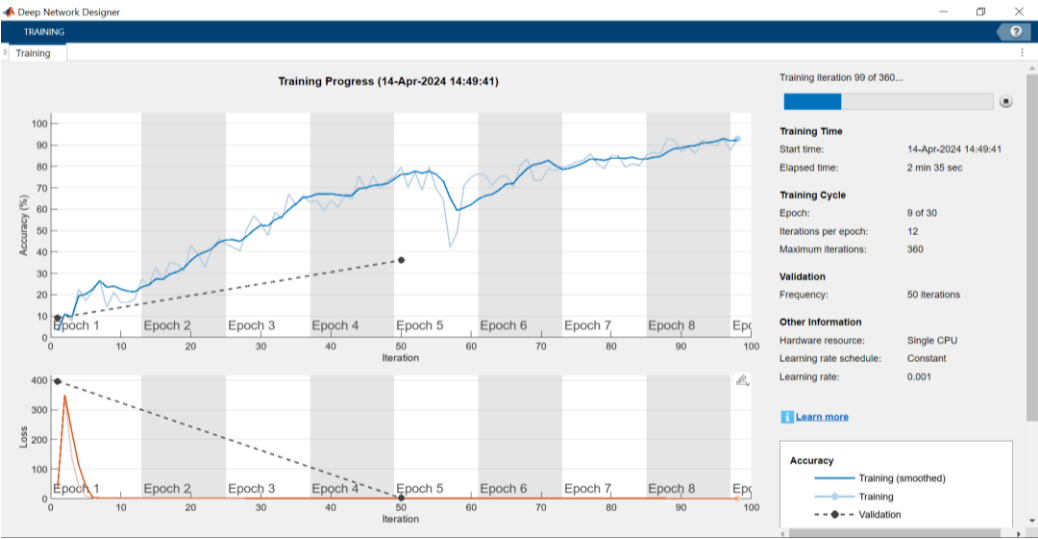


Figure 7. Evolution of the Training Process.

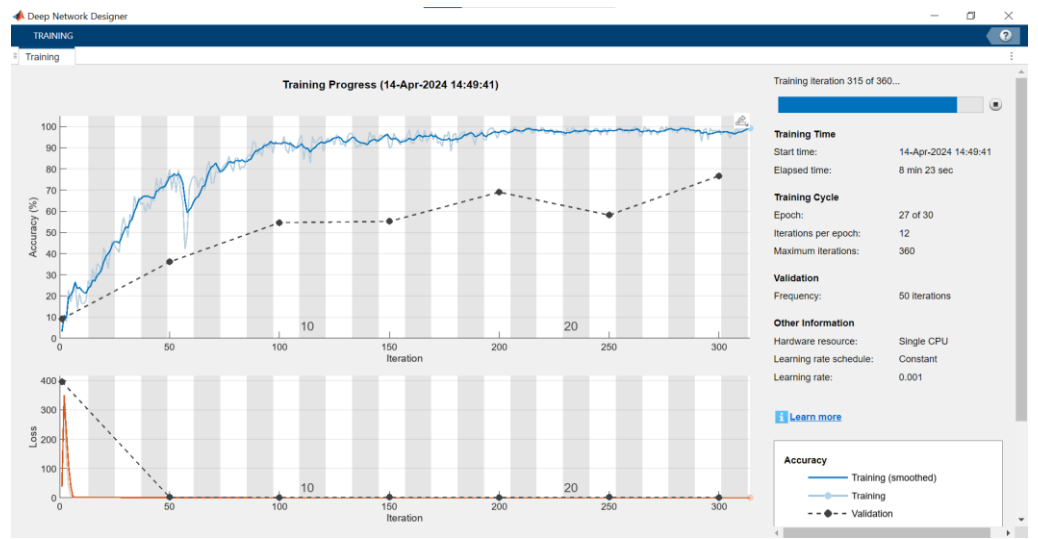


Figure 8. Evolution of the Training Process (continued).



Figure 9. Evolution of the Training Process (continued).

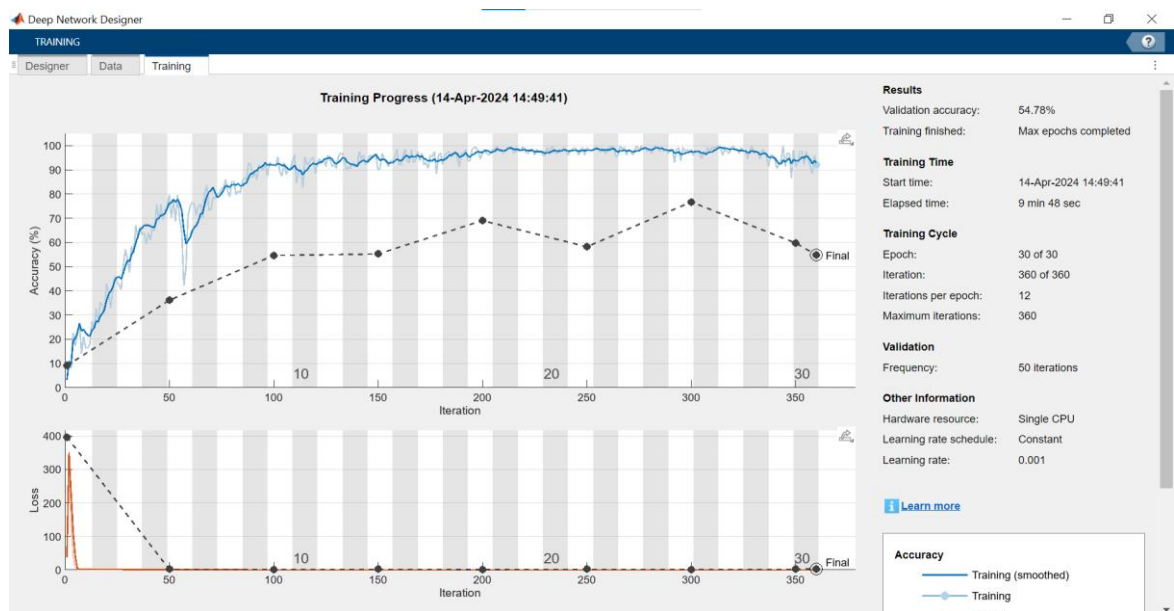


Figure 10. The End of the Training Process.

Defect Identification Tests

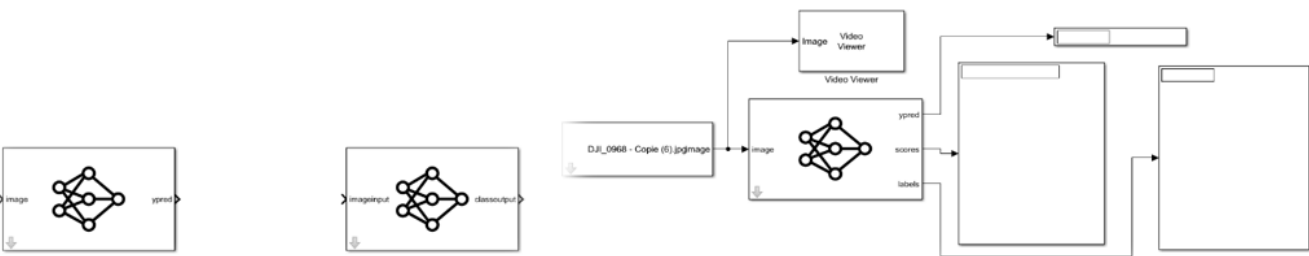


Figure 11. Simulation of the classification system.

Hot spot defect classification test

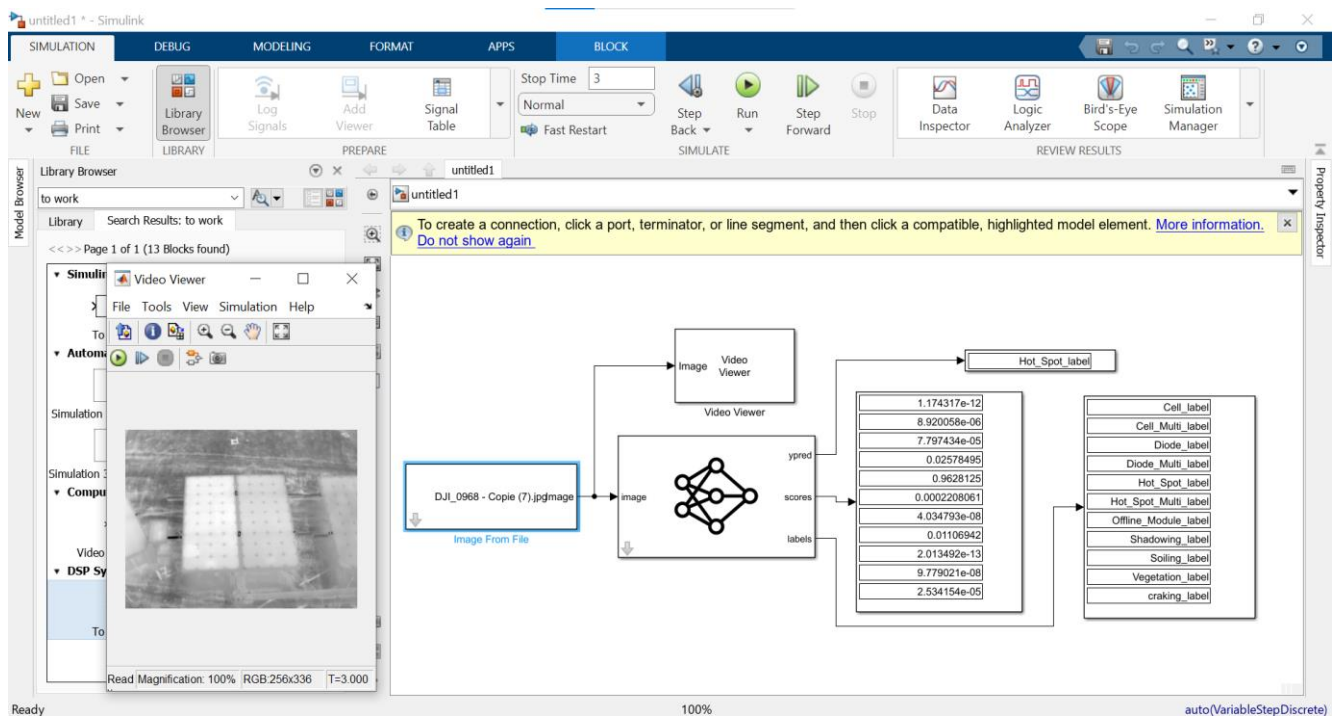


Figure 12. Identification of the Hot Spot Defect.

Diode Fault Classification Test

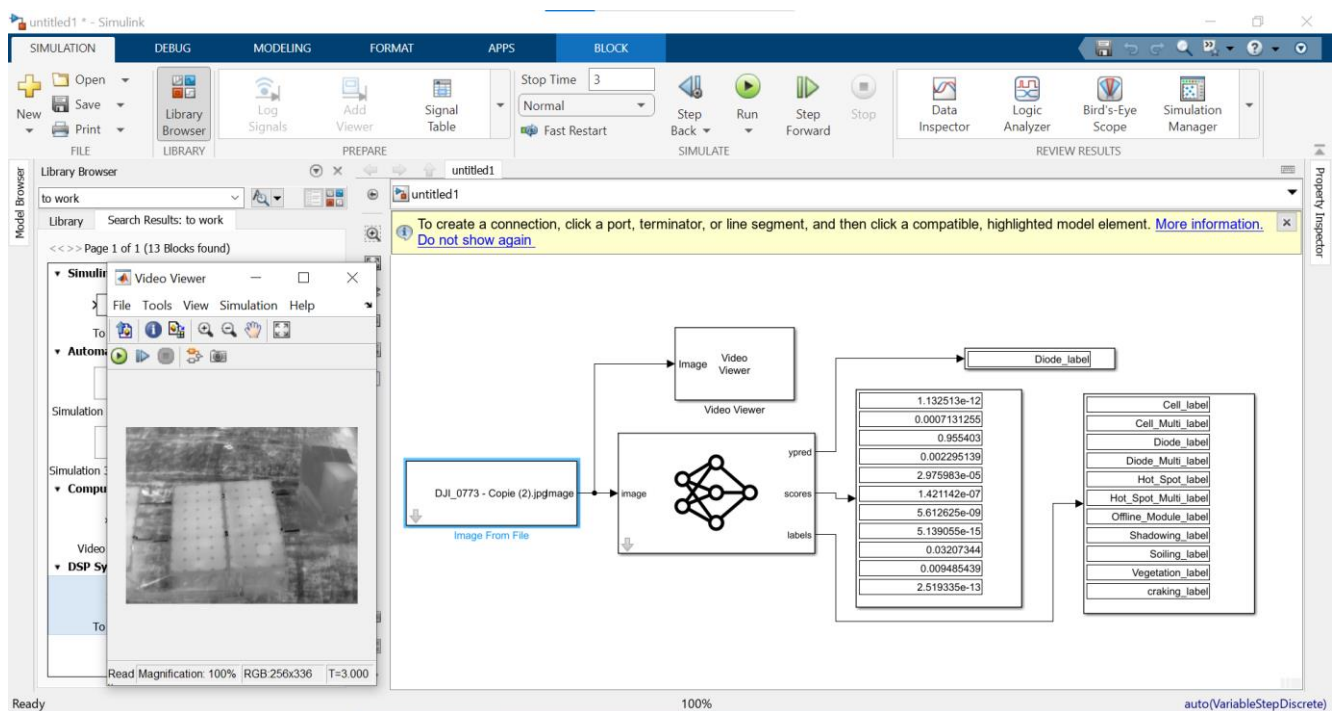


Figure 13. Diode Fault Identification.

Multi-diode Fault Classification Test

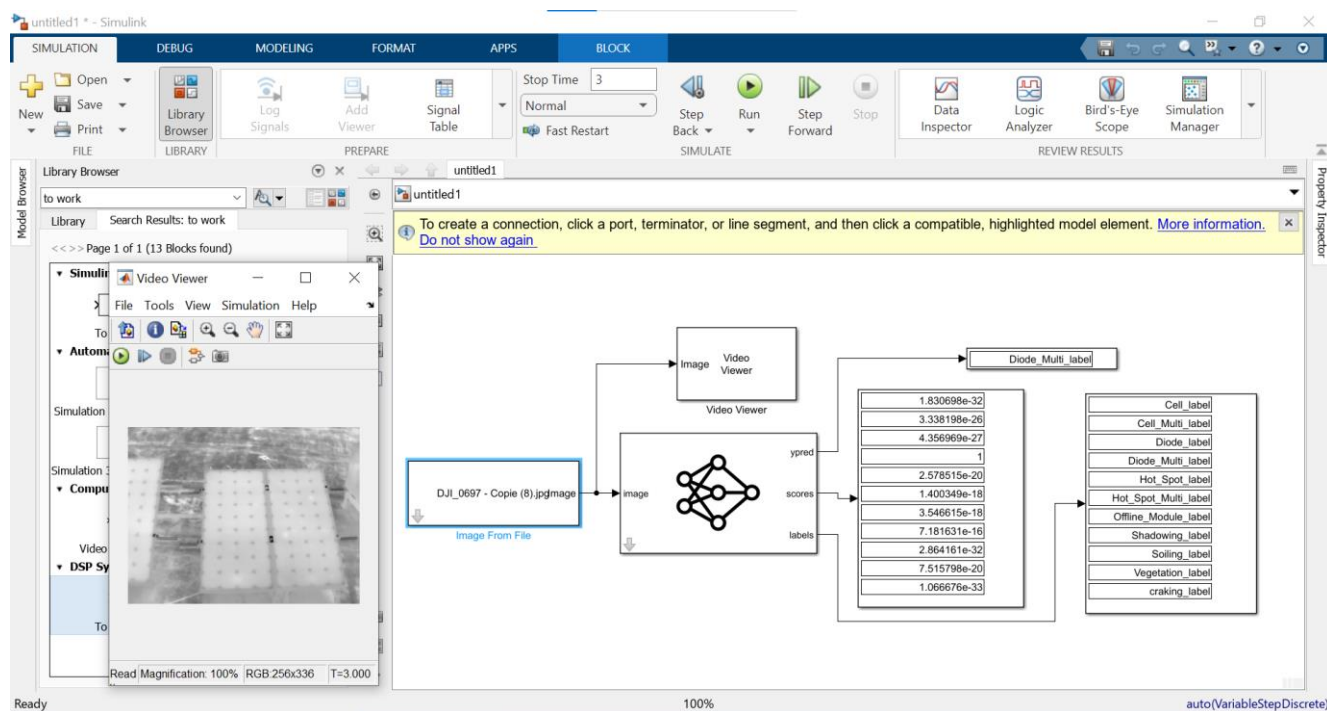


Figure 14. Diode Fault Diagnosis.

The shape of the curves in Figures 5, 6, 7, 8, 9, and 10 reflects the model's learning process, characterized by an increasing trend in accuracy over the course of iterations, with a frequency of 50 iterations out of 360.

This trend indicates that the model is learning information from the images and improving its accuracy, thereby justifying the model's performance. This trend over the course of iterations supports the hypothesis that the number of convolutional layers and the number of iterations are key factors in improving the performance of a convolutional neural network in terms of accuracy and error, on the one hand. On the other hand, as the number of iterations increases, we tend to minimize the classification error.

Based on the verification of this hypothesis, we can confirm that we have a convolutional neural network model that performs well in terms of accuracy, minimizes error, and enables us to classify images.

In terms of accuracy, the results obtained were validated with an accuracy of over 90% and an error rate of less than 5%.

The second part, devoted to testing, focused on the detection and classification of images based on defect type using the convolutional neural network model that was implemented.

The results obtained demonstrate impressive performance in terms of accuracy and robustness, which reinforces the potential for practical applications in predictive maintenance and yield optimization for photovoltaic systems.

Meanwhile, for the classification of solar module defects, a neural network model was designed using a dataset consisting of 20,000 infrared images, each measuring 24x40 pixels, of each module. This model, which was trained, validated, and

exported to Simulink, enabled us to classify and predict defects in solar panels with an accuracy of over 95%. Specifically, 96% for hot spot defects, 95.5% for diode defects, and 100% for multi-diode defects.

4. Conclusion

Among the various deep learning algorithms, we used a convolutional neural network for image classification. In this article, we developed a convolutional neural network model for defect prediction by training it on infrared image data representing different classes of defects recorded during the operation of solar panels. The results of this model are consistent with those reported in the literature. The effectiveness of the designed model allowed us to classify images and predict defects with acceptable accuracy and minimized error.

During training, certain layers slow down information processing, leading to overfitting. To avoid this phenomenon, the dropout method can be used to randomly eliminate neurons. Using this method would help limit marginal effects and enable the network to better generate concepts during training. For the next phase of this work, it would be advisable to conduct an experimental validation of the proposed algorithm using practical tools specific to these techniques.

Abbreviations

STC	Standard Test Conditions
ASTM	American Society for Testing and Materials
ANN	Artificial Neural Networks

DND	Deep Network Designer
LSTM	Long Short-Term Memory
CNN	Convolutional Neural Network

Author Contributions

Mabikana Voula Boniface Herve: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation

Mabiala Louboto Antoine Victorien: Investigation, Methodology, Project administration, Resources

Nkombo Mazouka Michel: Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

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