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Three neural architectures implemented in photovoltaic panel anomaly detection and categorization

Tres arquitecturas neuronales implementadas en la detección y categorización de anomalías en paneles fotovoltaicos

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Solar panels are useful and efficient tools. They need to be kept in excellent working condition, but as time goes by, they suffer from external failures manifested in the environment. Therefore, the need for effective monitoring of such systems is highlighted. Neural models are perfect candidates to perform physical damage recognition. In this case, we compare the performance of three artificial neural networks, the multilayer perceptron, the densely connected neural network, and the ResNet-50 network in this identification problem. What is intended to be obtained from this method is the practical demonstration of the use of neural networks to solve real problems.

Keywords: Anomalies, diagnosis, learning, neural network, solar panels, training, visual inspection

Los paneles solares son herramientas útiles y eficientes. Necesitan mantenerse en excelente estado de funcionamiento, pero a medida que pasa el tiempo, sufren fallos por externos manifestados en el ambiente. Por lo tanto, se resalta la necesidad de hacer un seguimiento efectivo de dichos sistemas. Los modelos neuronales son candidatos perfectos para realizar el reconocimiento de los daños físicos. En este caso, se compara el desempeño de tres redes neuronales artificiales, el perceptrón multicapa, la red neuronal densamente conectada y la red ResNet-50 en este problema de identificación. Lo que se pretende obtener de este método es la demostración práctica del uso de las redes neuronales para solucionar problemas reales.

Palabras clave: Anomalías, aprendizaje, diagnóstico, entrenamiento, inspección visual, paneles solares, red neuronal

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Introduction

The following paper presents one of the applications that can be made based on the anomaly recognition model which aims to categorize the possible aspects that can present a solar panel or a photovoltaic plant using a convolutional artificial neural network, a model specialized in image characterization. In general, we propose a model that can identify the physical states of solar modules, but the internal operating system is irrelevant to this article. The reason why this study is completely necessary is that a visual detection model allows to speed up the inspection that is normally done manually by a technical agent that supervises the state of the panel, therefore it is possible to reduce the inspection time in addition to the cost that this may mean for the owner of the photovoltaic panel.

The characteristics that make solar panels one of the most effective and outstanding energy-generating tools in the world of sustainable development, however, are certain factors that affect the proper functioning of these energy sources over time, not only the complexity of its physical form but also for the efficiency during energy collection. For this reason, it is necessary to recognize each of the situations in which a photovoltaic system is affected due to different factors. It is intended to design a visual recognition system that allows the identification of many of the possible physical, and superficial aspects that a photovoltaic panel may have to predict possible unknown anomalies. This is to minimize the human effort on technical revisions and maintenance that these systems need.

According to (Nomura et al., 2022), solar panels have been implemented with greater intensity since the advent of the environmental initiative with the Paris Agreement of 2016 which proposed the decrease of greenhouse gases, which has caused a high demand in the field of renewable energy collection systems, which positions solar panels as pioneers in the field of environmental care and responsible use of nature for the satisfaction of needs. As these systems are implemented by public entities and independent companies, the common interest in understanding how solar panels work is also awakening. Based on the above it is imminent that to keep a panel working optimally it is necessary to perform proper maintenance and above all be aware of possible failures that this may have in reaction to the environment where it operates, for example in urban areas where a study of degradation during the life cycle of the panel should be performed (Radovanovic & Popovic, 2021). One of the most common failures in photovoltaic panels Power-Voltage (PV) is the production of hot spots according to (Lamb et al., 2022).

Challenges related to the technical performance and reliability of crystalline silicon solar cells in hot desert climates, where the heat and high ultraviolet radiation experienced in the region pose a challenge to optimal performance. A comprehensive analysis of the performance degradation and failure modes of c-Si modules in the Algerian desert climate was previously conducted. Several modules were tested using a visual inspection Intensity-Voltage (IV) tracer. The solar modules have been in the field for a considerable time about 6 to 11 years. The results revealed some defects, such as; physical defects of the material, a decrease in cell shunt resistance, and an increase in the series resistance of the cell they have, this mainly contributed to the drop in power output. In addition, Hot desert climates affect the performance and lifetime of silicon (Kahoul et al., 2021).

On the other hand, an efficient method for PV plant quality monitoring was proposed that combines technologies such as an Unmanned Aerial Vehicle (UAV), using thermal imaging and machine learning so that the systematic inspection of a PV farm can be performed with simultaneous frequency. More emphasis is added to the use of deep neural networks to analyze thermographic images according to (Jumaboev et al., 2022; Masita et al., 2022; Segovia et al., 2022), who confirm that this can be implemented to reduce personnel costs and above all the inspection time normally used by an expert technician. The methods required for the inspection of solar plants are based on current technology such as drones, which are an efficient method to perform preventive and corrective maintenance on solar panels installed in large-scale connected photovoltaic plants. Also, quite a few studies have been conducted to detect anomalies in photovoltaic modules from these thermal images captured by such drones according to (Lin et al., 2014), who also mentions One of the general edge detection techniques, which uses the contrast between the target object and the background of the image to convert the target object into a real meaningful brightness value.

Meanwhile, using the linear relationship, the detailed parts of the image are used to present the location of the object and determine the precise positioning of the target object by linear regression. Among others, there are various image edge inspection methods, which differ in application perspectives. Also, other types of inspection studies can be found and tracked the status of a test object by monitoring through telemetry of a solar panel and corresponding optoelectronic devices, (Lin et al., 2014) mentions the Charge-Coupled Device (CCD) camera, which is triggered by the system proposal and captures the image of the test target in real-time, which is transferred to the system for image filtering, spatial masking, boundary tracing and other means of image processing. Another recognition method, according to (M. Wang et al., 2022; Zhang et al., 2022), suggests a non-clustered convolutional neural network (NPCNN), as a prediction module with the combination of the pattern symmetrized points based on deep learning, which is trained, developed and trained using the processed data to identify nonlinear features; there are other similar methods such as a multi-scale convolutional neural network using transfer learning (Korkmaz & Acikgoz, 2022).

Historical forecast errors are constructed and trained to be corrected by using an error correction module based on a hybrid Wavelet transform (WT) parallel to the K-Nearest Neighbors (KNN) model. In simulations, the proposed method is extensively evaluated on real PV data in Limburg, Belgium, where experimental results show that the proposed hybrid model is beneficial in improving the PV power forecasting performance compared to the benchmark methods (Zhang et al., 2022). At present, several studies have been conducted based on Artificial Intelligence (AI) implemented in the fault detection in PV systems (Eskandari et al., 2023). In addition, pse has implemented neural network models such as U-net neural network accompanied with image detection using true color infrared sensors, this model was applied by (Ahmed et al., 2022; Catalano et al., 2021; Kim et al., 2021; X. Wang et al., 2022), another model using neural networks in three steps by (Tchoketchkebir et al., 2021), which are data feeding step, fault modeling step and decision step.

Other sources of information such as (Prabhakaran et al., 2023) suggest the implementation of models based on multivariate deep learning in real-time, which focuses on physical aspects of the solar panel such as cracks, fissures, among others to detect the location of the defects. A specific algorithm used for detecting faults in solar panels is (Et-taleby et al., 2022). Other previously used methods such as (García et al., 2022) lie in the monitoring of abnormal predictive electrical parameters to alert and stop by automatic disconnection to avoid irreparable failures. Some failures can incur permanent damage and the impact on personnel safety becomes significant, increasing the risk of fire or fatal consequences.

Now, if we go into detail, to ensure the proper functioning of a solar panel, it is necessary to keep away any threat that interferes with its functional process. This is why it is necessary to recognize the possible circumstances in which a photovoltaic system is involved in efficiency mishaps due to its physical state. There are certain factors that directly and indirectly influence solar panels, such as cracking of the panel cells, obstruction of the cells by stains or liquids on the surface of the module, cracks in the metal edges, or unevenness of the panel due to geographical location or destruction of the support base.

The following section presents a broader view of the problem, taking into account the different modules in which it is planned to structure the segmentation of the erroneous physical aspects and consequently the mention of the recognition method without going into further detail. This is followed by the methodological specification proposed to be adopted in the project, to focus it and to obtain a series of conclusions attributed to the adopted solution.

Problem statement

Recognizing the various factors that can impact the performance of solar panel installations is crucial for ensuring their efficient operation. One key aspect to consider is the potential for obstructions on the surface of the panels, which can prevent sunlight from reaching the cells and impede the conversion of solar energy to electricity. Additionally, damage to the panels themselves, such as cracks or breaks in the cells or edges of the modules, can also negatively affect performance.

To address these concerns, a methodology has been developed that utilizes a deep learning model to more effectively and efficiently diagnose issues with solar panels. This model has been chosen for its ability to quickly and accurately identify potential problems, with the ultimate goal of reducing the cost and effort required for ongoing maintenance and supervision.

In detail, the methodology involves the categorization of potential anomalies that may occur in the solar panel environment. This includes issues such as surface obstructions that impede light penetration, as well as damage to the panels themselves, such as cracks or breaks in the cells or edges of the modules.

Once these potential issues have been identified, a deep learning model is used to analyze data and identify any signs of these anomalies. This approach has been chosen for its ability to effectively process large amounts of data and identify patterns that may not be immediately apparent to human observers. Additionally, the deep learning model is expected to be more efficient than other models in terms of diagnostic speed and accuracy.

The ultimate objective of this methodology is to optimize the cost of supervision that the exercise entails. By using the deep learning model to more quickly and accurately identify issues with solar panels, it is hoped that maintenance and repair efforts can be more effectively targeted and managed, resulting in cost savings over time.

Overall, the methodology adopted for this project is designed to recognize the influencing factors in the solar panel installation environment and to effectively diagnose and address any issues that may arise. By utilizing a deep learning model, it is expected that the diagnosis of solar panels will be done in a faster and more effective way, ultimately allowing for more efficient and cost-effective management of solar panel installations.

Methods

The experimental method adopted in this application project is a system based on deep learning. The convolutional neural network mentioned in the introduction is one of the most effective image recognition models, besides being modern, it can generate excellent results, speeding up detection and categorization. Therefore, it is the most attractive model to perform the diagnosis of the solar panel using images taken from it, to categorize the anomalies that appear in the image. To begin with the methodological description, the number of possible categories to be recognized by the system is taken into account; in particular, it is trained with individual output data for each category, i.e. the characteristic parameter cannot belong to two different categories. Furthermore, it must be an abnormal appearance evident to the camera lens with which the panel state is captured for example shown in Fig. 1, Fig. 2 and Fig. 3.

Figure 1

Category of solar panels with crystallization in the cells

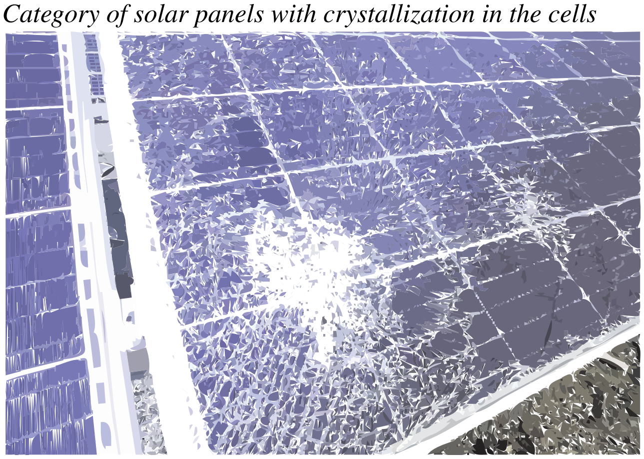


Figure 2

Category of intact solar panels

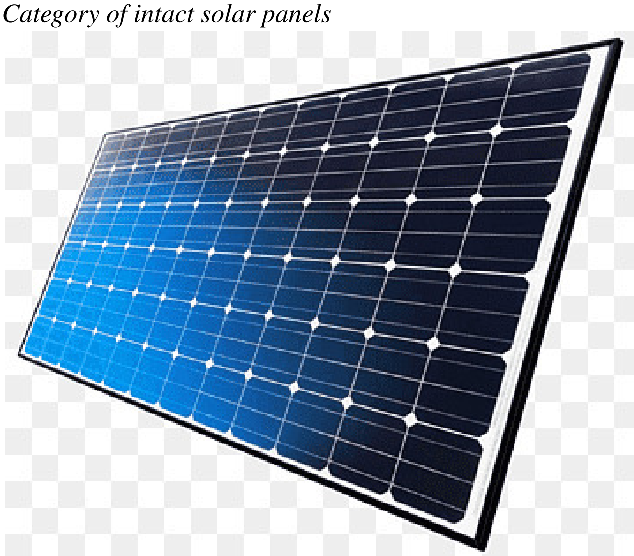


Figure 3

Category of superficially obstructed solar panels

These images have different characteristics and therefore each one belongs to a single category of the model. The neural network must be able to categorize the images correctly, guaranteeing the segmentation of the images according to their anomalies.

To achieve the general objective of this research, four specific objectives have been designated. Each specific objective is related to different activities that, when completed, fulfill each objective. For simplicity, the time at which the activities of each specific objective are carried out will be called phases. The activities to be carried out are detailed below.

Phase 1: Definition and treatment of variables

At the beginning of the procedure, an exhaustive bibliographic review was carried out to validate the importance and to find the technological gaps that are planned to be covered by the project. Likewise, as a result of the bibliographic review, the variables that have been used in similar models are found and the ones that will be used in the neural model can be chosen.

The next step was to choose the neural models to compare their behavior in particular, to conclude the project by selecting the model that most closely resembles the process of characterization of the images of solar panels. For this specific problem, a basic neural model was implemented, i.e. the multilayer perceptron, a model which needs certain adjustments in the parameters of the hidden layers for its correct operation; finally, the densely connected neural network or Dense-Net, which is a recursive network, was implemented. In particular, it emerges as an improvement of the networks with a scheme with greater depth, thanks to the fact that it has a higher convergence speed during training. The idea is that in this network all the neurons of the input layer are connected with all the neurons of the next layer so that each layer uses the parameters of the previous ones, which can be deduced as a better result in terms of efficiency for both training and validation. As for the previous networks, the main task for which they were designed was image recognition, although it should be noted that there are densely connected models designed to perform other types of tasks. Both of the above models are convolutional neural networks adapted for image categorization.

Phase 2: Implementation and training

The next step consisted of the implementation of the respectively selected neural models, adjusting the same database for each network, which contains a sufficient amount of images to perform the training and evaluation of the error behavior and accuracy of the models, based on which the respective comparison and selection are made.

Phase 3: Comparison and selection

In each of the cases of implementation of the selected neural models, it is quite important to highlight the functionality of the model in any percentage, because it is expected to obtain relevant results in each one. As mentioned above, the selection of the model is based on the best performance of the results obtained where the main objective of the project is fulfilled.

Phase 4: Performance analysis of the selected model

Finally, an account of the implemented prediction algorithms was made and after selecting the best-performing model, the results of the neural model and its classification errors were analyzed in detail.

During the implementation of the neural models, certain determining factors were found regarding the proper functioning of the model, such as the number of images in the database, which may be insufficient and incompatible with the structure of the neural network, the differences may also lie in the poor integration of the database along with the structure of the neural network.

Results

In the results section are the plots corresponding to the data yielded by the neural models. Fig. 4 and Fig. 5 show the error and accuracy plots corresponding to the traditional neural model of the multilayer perceptron, used in this case for image categorization. In addition, the respective confusion matrix is added to the model in Fig. 6 and the ROC curve in Fig. 7.

Figure 4

Training accuracy vs. validation accuracy plot

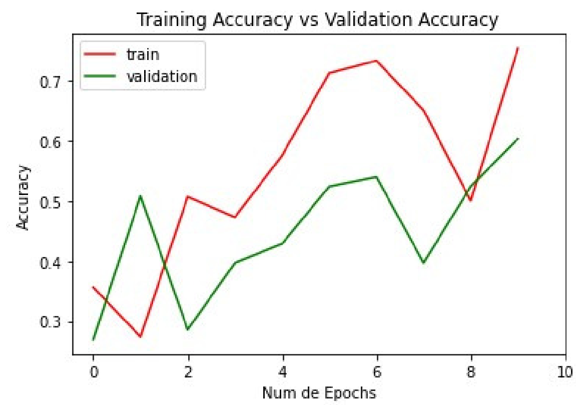
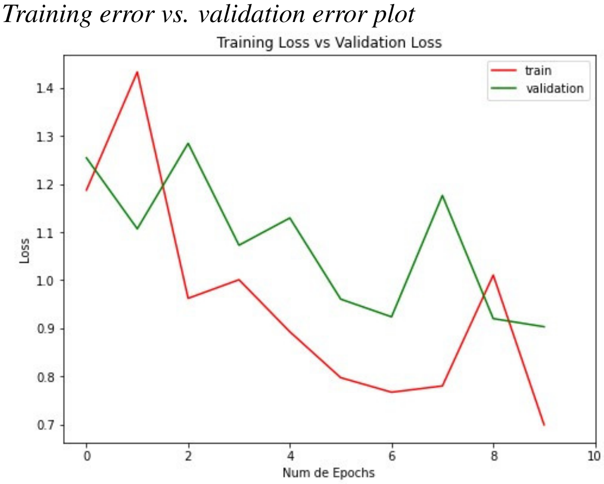


Figure 5

Training error vs. validation error plot



In the accuracy graph the behavior is erroneous but not so far from the result expected by the model, it may be due to the number of images it is recognizing. From the error graph, it can be deduced that it is decreasing with difficulty, over more

Figure 6

Confusion matrix of the multilayer perceptron model

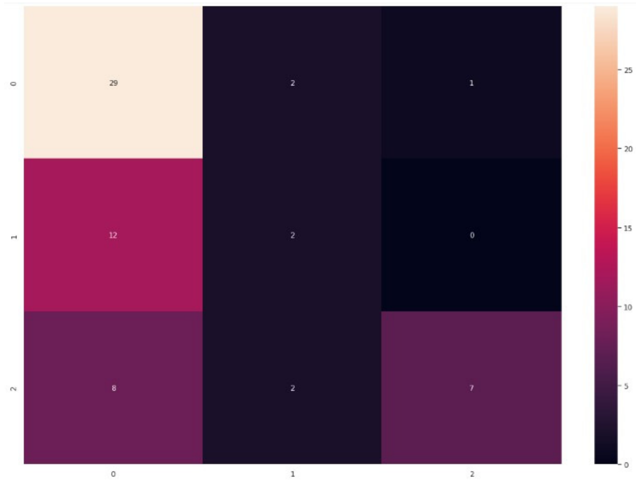
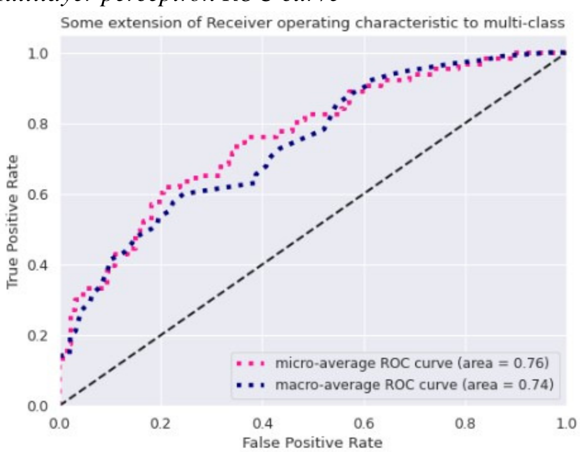


Figure 7

Multilayer perceptron ROC curve



epochs it would be easier to say that the behavior is likely to be correct. The model recognizes twenty-nine images correctly classified in the first category of intact panels, two images in the category of broken panels, and seven in the category of superficially obstructed panels, there is another twenty-five that was added to the wrong categories. The model has more trouble recognizing anomalies in the panels such as crystallization and surface obstruction, contrary to the intact panels which the model has less probability of error in recognizing.

The results for this particular case were not very accurate but neither can we affirm the inefficiency of the model for the moment, on the contrary in the following comparisons we find the evident fact that the other networks do not exceed the performance of the model mentioned above. For the case of the multilayer perceptron the metrics to be evaluated are located in Table 1, which indicate that accuracy in the categorization of the images was obtained between 33% and 88%, in addition, the completeness of the model is appreciated when characterizing the images, which indicates the proportion of the number of images that the model categorized correctly which was 14% in the second category, 41% in the third and 91% in the first category. The third metric is the ratio of accuracy to the completeness, the combined performance of the model can be said to be between 20 and 72%.

Table 1

Table of metrics evaluated for the multilayer perceptron model

	precision	recall	f1-score	support
0	0.59	0.91	0.72	32
1	0.33	0.14	0.20	14
2	0.88	0.41	0.56	17
accuracy			0.60	63
macro avg	0.60	0.49	0.49	63
weighted avg	0.61	0.60	0.56	63

As for the second architecture used to solve this problem, which has been implemented before, it has been a hit or miss in many cases. This convolutional neural network is densely connected which makes it work more efficiently, propagating the error signals to previous layers in a more direct way. In other studies comparing neural classifiers, the densely connected model is found to be at a disadvantage concerning other recognized neural models.

In Fig. 8, Fig. 9, Fig. 10 and Fig. 11 the error and accuracy plots corresponding to the densely connected neural model can be evidenced and the respective ROC curve and confusion matrix are also included. This model particularly presents a disadvantage with the prediction of the images in the respective categories, it can be affirmed with certainty that it is due to the size of the database which is insufficient for the correct execution of the model, even though the results are duly reflected in the article.

From the figures it is evident that the network is not performing optimally and is probably memorizing the images, but is not classifying them as expected, possibly due to overfitting in the composition of the neural network or as mentioned above by the database used in this particular case. The neural network does not fit the data and the categorization error persists, therefore the validation accuracy remains constant and does not climb as it should. The model is classifying all the validation images in the crystallized panel category when thirty-two should belong to

Figure 8

Training error vs. validation error plot

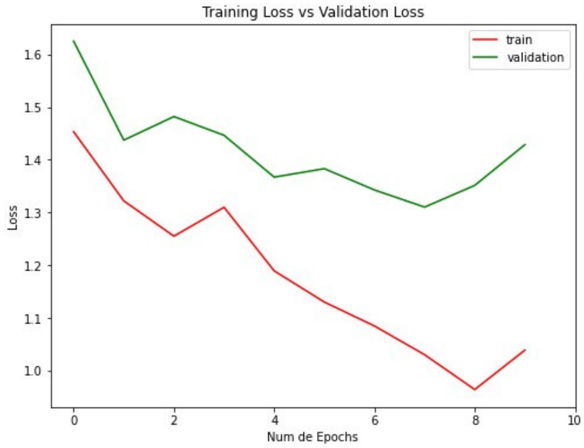


Figure 9

Training accuracy vs. validation accuracy plot

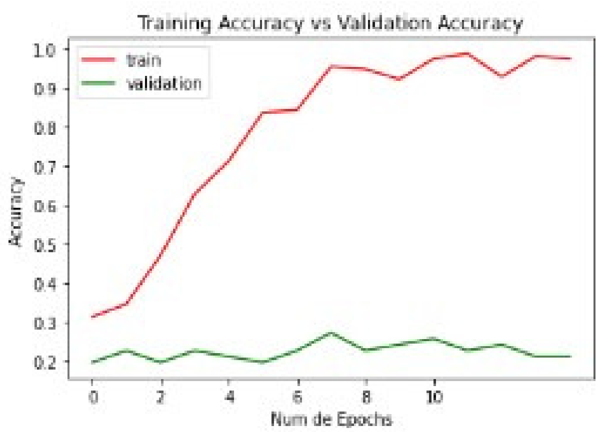


Figure 10

ROC curve of the densely connected model

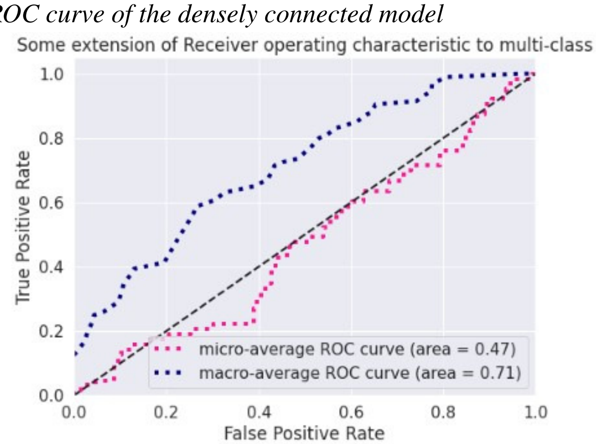
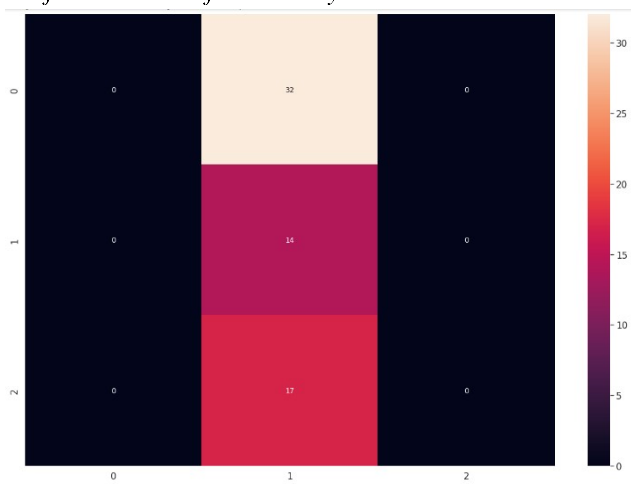


Figure 11

Confusion matrix of the densely connected model



the intact panel category and seventeen to the superficially obstructed category. The ROC curve, although it presents positive points, meaning the correct classifications when recognizing the images, also presents negative indexes, meaning the unification of all the images in a single category.

Table 2 shows the performance of the network during its training and the result as expected, was a failure in terms of classifying the images, which are not being properly categorized by the neural network.

Table 2

Table of metrics evaluated for the densely connected model

	precision	recall	f1-score	support
0	0.00	0.00	0.00	32
1	0.22	1.00	0.36	14
2	0.00	0.00	0.00	17
accuracy			0.22	63
macro avg	0.07	0.33	0.12	63
weighted avg	0.05	0.22	0.08	63

The only metrics obtained with the densely connected model are relapses in the second category of crystallized or broken panels, with accuracy and completeness below the favorable rate, not to mention erroneous data due to the inefficiency of the network for this problem. As a consequence of the above result analysis, the possible selection of the neural network as the solution to the problem of solar panel anomaly classification by imaging is completely ruled out.

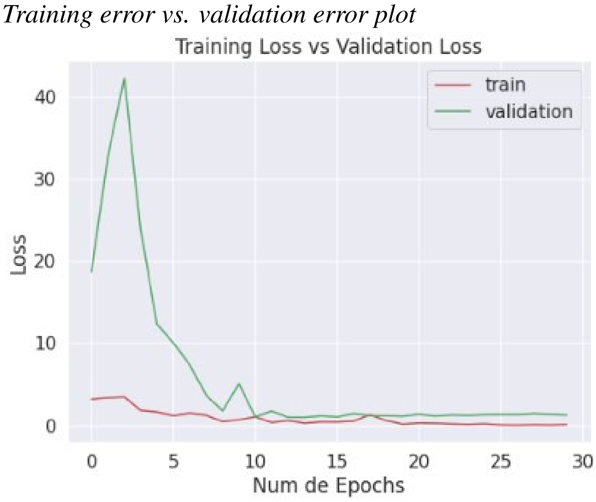
To have a clearer expectation of the problem it was decided to add a different neural architecture, which will be tested with the updated database, followed by scoring the same metrics previously evaluated for all the neural networks under evaluation. The interpretation of the metrics will respond to the objective of this article with the certainty of selecting the most efficient model in the categorization of images based on the problem of the physical state of the solar panels.

The third neural architecture is better known as ResNet-50 network, it is a convolutional neural network with 50 layers deep which not only interacts in the same way as a multilayer perceptron but also sends the original information to all neurons from the first layer to the last layer of the network, to preserve important information across epochs. This network is shown below in the form of results under the constraints of a finite database.

In Fig. 12, Fig. 13, Fig. 14 and Fig. 15 show the actual behavior of the ResNet-50 neural network along with its respective evaluation metrics.

Figure 12

Training error vs. validation error plot



In the figure of the error in the evaluation, the behavior tries to stabilize, reaching a value very close to what it should be, throughout thirty epochs it presents a positive behavior in terms of error decrease. The opposite happens with accuracy, which performs an unstable behavior with no desire to improve increasing through the epochs. The confusion matrix reveals the problem that exists in the case of the superficial obstruction category, the images do not seem to be sufficient and it categorizes them incorrectly, however, the misclassified images may be due to the lack of attention paid by the network to the third category. The ROC curve shows a behavior of mostly positive points, indicating a higher accuracy in classifying the images. Finally, the respective metrics for the ResNet-50 model are shown in

Figure 13

Training accuracy vs. validation accuracy plot

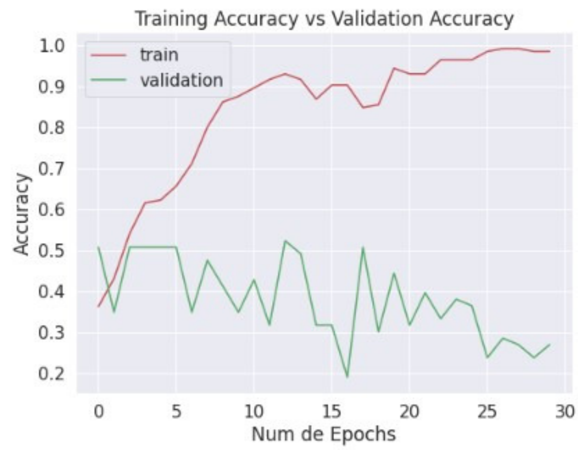


Figure 14

Confusion matrix of the ResNet-50 model

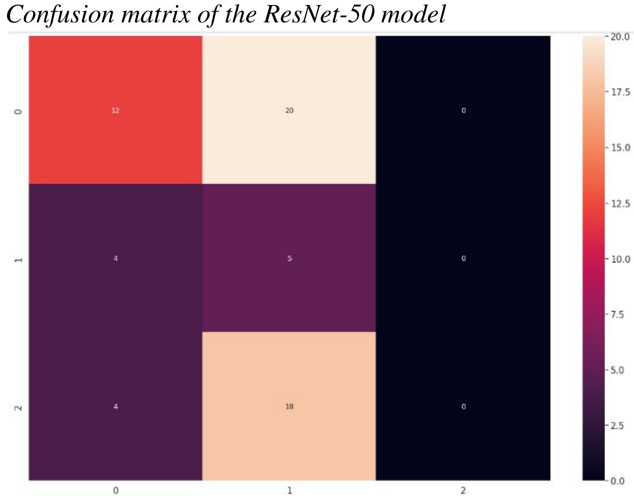


Figure 15

ROC curve of the ResNet-50 model

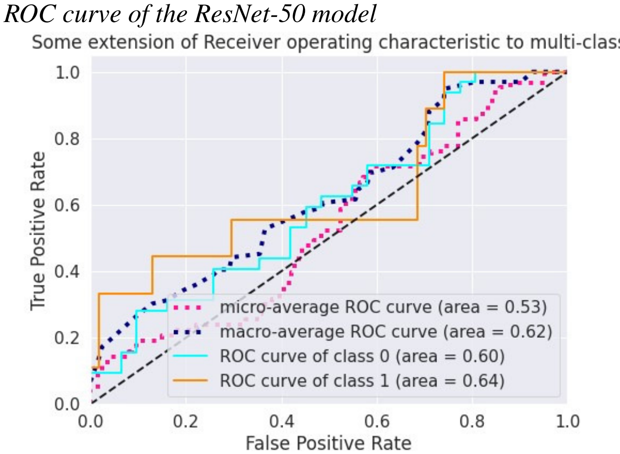


Table 3. According to the table, the accuracy abounds mostly in recognizing the category of intact panels with 60%, and a lower percentage in the category of crystallizations. Completeness is not very good but ranges from 38% to 56% correct categorization. The combined performance does not exceed 50%. The category recognition mishap makes the model very suboptimal for the image classification required to solve the problem.

Table 3

Table of metrics evaluated for the ResNet-50 model

	precision	recall	f1-score	support
0	0.60	0.38	0.46	32
1	0.12	0.56	0.19	9
2	0.00	0.00	0.00	22
accuracy			0.27	63
macro avg	0.24	0.31	0.22	63
weighted avg	0.32	0.27	0.26	63

Conclusion

In summary, of the three architectures evaluated, the traditional neural network or multilayer perceptron model demonstrated the highest performance when considering the number of images used within the selected model. Through an exhaustive analysis, the specific network architecture was chosen, which included 1230 neurons in the first layer and 894 neurons in the hidden layer. Both layers utilized the Rectified Linear Unit (ReLU) as the activation function, and the model was trained over ten epochs.

The results of the neural network showed that a total of 4,883,884 parameters were used, making it the model that used the least input parameters yet still obtained the best result. Even though the behavior of the selected network was not perfect, it did demonstrate a clear learning pattern, where the error was consistently reduced and accuracy increased as the number of evaluated epochs increased.

It is worth noting that the process of selecting the architecture and training the model was not perfect and that there are always trade-offs. However, the model with the highest performance was the one that used the least input parameters and obtained the best result. It is also important to mention that in any machine learning task, the performance of a model is not only dependent on the architecture but also the quality of data and the hyperparameters tuning.

In general it can be concluded that:

- We can appreciate higher performance of the traditional neural network or multilayer perceptron than the densely connected network and the RedNes-50 for this specific recognition problem.
- It can be deduced that the size of the database is essential in terms of the correct operation, which makes the network have such a performance, in addition it is necessary to take into account the correct design of the database, making sure that an image does not correspond to two categories.
- The selection of the neural network suitable for solar panel image classification does not indicate that the other two networks in comparison are inefficient in general. Only in this case, the densely connected networks and ResNet-50 did not perform well, in other studies and in other projects they are pioneering networks in the field of convolutional artificial neural networks.

In conclusion, the traditional neural network or multilayer perceptron model was found to be the most effective architecture when considering the number of images used within the selected model. The specific network architecture chosen had 1230 neurons in the first layer, and 894 neurons in the hidden layer, and utilized the Rectified Linear Unit (ReLU) as the activation function. Although the behavior of the selected network was not perfect, it did demonstrate a clear learning pattern, where the error was consistently reduced and accuracy increased as the number of evaluated epochs increased.

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