Detection and Segmentation of Damaged Photovoltaic Panels Using Deep Learning and Fine-tuning in Images Captured by Drone

Luís Fabrício de Freitas Souza [iD] **, Tassiana Marinho de Castro** [iD]

Lucas de Oliveira Santos [iD]

Universidade Federal do Ceará - UFC, CE

Instituto Federal de Educação, Ciência e Tecnologia do Ceará - IFCE, CE

LAPISCO-Laboratório de Processamento de Imagem, Sinais e Computação Aplicada, (e-mail: coord@lapisco.ifce.edu.br)

{fabricio.freitass, tassiana, lucas.santos}@lapisco.ifce.edu.br

Adriell Gomes Marques [iD] **, José Jerovane da C. Nascimento** [iD] **, Matheus A. dos Santos** [iD]

Guilherme F. Brilhante Severiano [iD] **, Pedro P. Rebouças Filho** [iD]

Instituto Federal de Educação, Ciência e Tecnologia do Ceará - IFCE, CE

LAPISCO-Laboratório de Processamento de Imagem, Sinais e Computação Aplicada, (e-mail: coord@lapisco.ifce.edu.br)

{adriell.gomes, jerovane, matheus.santos, guilherme.brilhante}@lapisco.ifce.edu.br, pedrosarf@ifce.edu.br

Abstract – Energy consumption is a direct impact factor in various sectors of society. Different technologies for energy generation are based on renewable sources and used as alternatives to the consumption of finite resources. Among these technologies, photovoltaic panels represent an efficient solution for energy generation and an option for sustainable consumption. The problem of damaged panels brings numerous problems in energy generation, from the interruption of generation to losses through financial investments. The proposed study presents an efficient model based on deep learning for detection and different models based on fine-tuning for the segmentation of damaged photovoltaic panels. The use of the Detectron2 convolutional network obtained 78% of Accuracy for detection and 95% precision in the detectable panels, also obtaining 99.91% for the segmentation problem of photovoltaic panels in the best-generated model in this study. The proposed model showed great effectiveness for panel detection and segmentation, surpassing works found in the literature.

Keywords – Photovoltaic Panels, Deep Learning for Detection, Panel Segmentation, Detectron2.

1. INTRODUÇÃO

With the rise of renewable energy sources, especially solar energy, as an alternative to the use of fossil fuels and limited energy sources, the so-called photovoltaic plants are on the rise in the energy production market, [1]. These plants use integrated modules on the principle of photon absorption, exciting electrons that flow through the photovoltaic cells, producing electricity, [2]. Thus, the efficiency of solar cells represents the most critical parameter for the establishment of this technology in the market, in which its applicability and substantially improved in recent decades, [3].

Despite their high energy potential, photovoltaic technologies are susceptible to problems that generate their loss of effectiveness. The accumulation of dust and other residues and optical degenerations in the photovoltaic cells, electrical failures, and other unidentified failures can directly impair the functioning of these systems [4]. The maintenance of these malfunctioning equipment involves high costs and the need to identify the defective cells. Usually, specialized technical inspections that demand a long analysis period are necessary, which can cause interruptions in energy generation and become economically unfeasible for recurring reviews [5].

Taking into account the advances achieved by the artificial intelligence algorithms, image recognition technologies have been applied in the most diverse areas, especially in activities that require human attention, such as traffic [6], logistics [7] and maintenance [8] and even in more specific applications, which require a qualified professional, such as metallographic analysis [9] and microscopy [10]. In summary, the use of artificial intelligence in the area of computer vision, especially for Convolutional Neural Networks (CNNS) in image tasks bring high performance and effective solutions [11]. researches such as of Pierdicca et al [12], Espinosa et al [13] and Ge et al [14] have been directing their efforts to develop automatic techniques for detecting failure in photovoltaic cells. To reduce the impact caused by the effects of weather and other failures in energy production so that they are avoided and resolved more easily and with less loss of production, [15]. Studies such as [12] and [16], sought to collect a base of thermal images of a terrestrial photovoltaic system in a photovoltaic plant in Tombourke, South Africa, through thermographic inspections. These works have the proposal of using machine learning techniques and neural networks in the automated detection of damaged cells on solar panels.

So, taking into account the problem of failure detection in photovoltaic panels raised in this section, as well as the positive impacts caused by intelligent systems capable of predicting or pointing out failures in initial states, especially in thermal images. The present study aims to the development of a system for the detection and segmentation of defective photovoltaic panels through the aid of deep Learning techniques optimized with fine-tuning based on digital image processing. As contributions

of this study, these are the use of aerial perspective images obtained by drone, fine-tuning based on low computational cost techniques to improve the results obtained for detectron2 segmentation.

The organization of the research described here is as follows. Section 2 presents some basic concepts and discusses related works, highlighting research that uses the same database used in the developed analyses. Section 3 details the materials and methods used in the project, conceptualizing the main techniques applied and addressing the fundamentals necessary for understanding the theme. Section 4 presents the methodologies applied in the research development. In addition, Section 5 offers the results obtained using the proposed procedures, comparing the metrics obtained with other relevant research in the same area. Section 6 concludes the work with a summary of the project, its consequences, and opportunities for future improvement.

The study of this work aims at the following relevant points within the context of the literature.

- Image capture of photovoltaic panels using a DRONE.

- Detection of photovoltaic panels using deep learning.

- Use of the Detectron2 convolutional network to identify damaged photovoltaic panels.

- Use of fine-tuning methods for segmenting damaged panels.

2. Related Works

Due to the importance of detecting failures in photovoltaic panels for the indices of solar energy production, the literature contains several studies built to detect and predict failures in photovoltaic panels. Through the most varied types of signals, there are data monitoring generation, thermal images, and RGB images. Each type of these signal aims to detect different errors for each scope.

Chen et al [17] used the Random algorithm Forest for line fault detection and diagnosis. Line degradation, open circuit, and partial shading in photovoltaic panel arrays through the voltage of operation, and string chains, thus, seeking to detect faults in photovoltaic panels through the production monitoring. At its best, the authors obtained a mean accuracy of 99% in detecting the pointed faults, demonstrating sat- factors in detecting errors in samples. Nonetheless, it is worth mentioning that the study environment was controlled, made in the laboratory, and the limitations present in the detection of use of operating voltage, not being possible to cover the scope of errors caused by hotspot issues.

The study by Espinosa et al [13] sought to perform the automatic classification of physical failures for photovoltaic plants in RGB images with the help of CNNs for the semantic segmentation and classification of the images. The authors used a set of 345 RGB images captured from a superior perspective. The classification was performed primarily between images with damaged photovoltaic panels and images with photovoltaic panels in perfect condition. Subsequently, in the second stage of classification, the classes change to images with defective photovoltaic panels and failure due to cracks, shadows, and dust. The method obtained average accuracies of around 70% for both problems addressed, demonstrating good initial results. However, the low amount of images used in the model is worth mentioning, which can directly affect the reliability and performance of the model developed, limiting the applicability of the model detection.

The use of drones and mobile robots [18] in inspection applications has been increasingly popular, including some of these robots being able to move autonomous [19]. Aware of this trend, Manno et al [20] developed an automatic method of classifying thermographic images of photovoltaic panels through an open-source CNN. The developed technique also has a pre-processing stage, with the application of filtering based on digital image processing, for the previous noise reduction. The dataset used in the training and testing of the network consists of 1000 images from the most varied capture angles. In its results, the method was able to accuse rates of 90% of accuracy rates in detecting failures with a set of data selected for testing, demonstrating the efficiency of the method and the application of pre-processing. However, it is worth mentioning that the dataset used has a low amount of captured images with a greater distance from the photovoltaic panels, which would consequently improve the technique's applicability with the aid of drones.

Inspired by automatic monitoring applications using aerial imagery, Ramirez et al [21] proposed a new internet-of-things-based technique to perform automatic fault detection through analysis of thermal images directly acquired by aerial inspections. The authors combined two artificial neural networks to detect fault regions; the method can obtain 93% accuracy in detecting hot spots for the dataset used, demonstrating the high capacity of the method for detecting this type of problem, taking into account that the images are thermal. However, other techniques and a new fine-tuning step would be welcome to broaden the discussion and bring more exciting results.

So, motivated by the problem of detecting failures in photovoltaic panels, mainly for the maintenance of production rates and reduction of system maintenance costs, in addition to the methodologies discussed in this section and their respective limitations, the study proposed by this work aims to objective the development of a technique for detecting and segmenting damaged photovoltaic panels through the use of deep learning and fine-tuning for optimized segmentation in images captured by drones. The main contributions of this study are the development of high-performance models for the detection and segmentation of photovoltaic panels, the use of aerial frontal perspective images captured from drones coupled with thermal cameras, and the use of innovative fine-tuning techniques to improve the results obtained.

3. Materials and Methods

This section will discuss the techniques used in the construction of the study method and the dataset used.
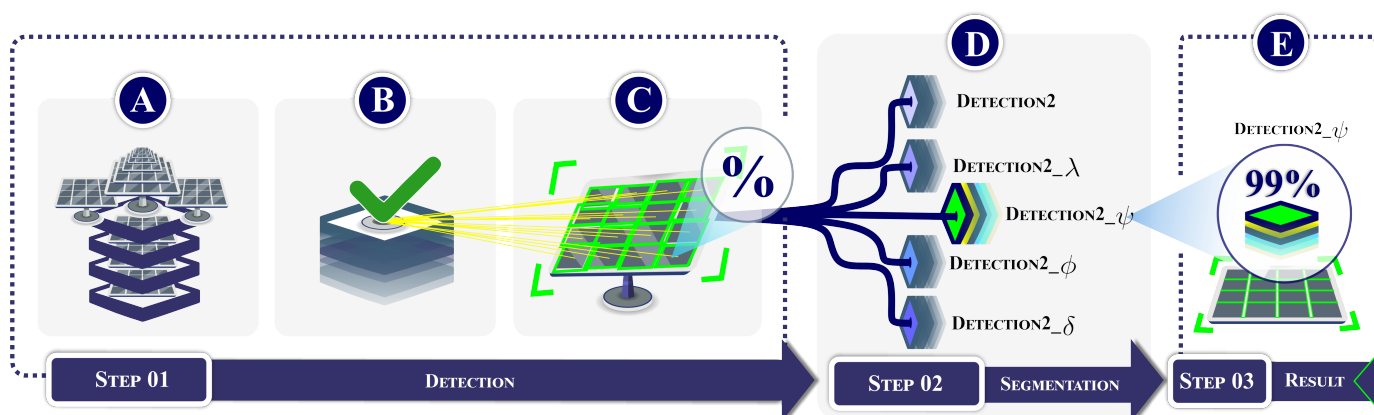
Figura 1: Illustrates the methodology based on deep learning using fine-tuning. Step 01 represents the performance of solar panels detection. Step 02 represents the fine-tuning process to segment the region detected through different models. Finally, Step 03 represents the detection and segmentation results presented, using the models proposed by this study.

3.1 Detection - Detectron2 convolutional network

The Mask R-CNN framework, [22], has created the Detectron2 network through Artificial Intelligence research promoted by Facebook (FAIR). This network model operates in two operating stages, as it has an annotation format in the COCO standard and because the operating mode is similar to the Mask R-CNN. After the due process of training the network, In the first step of Detectron2's operation with applications in two-dimensional signals, the network demarcates the regions of interest with bounding boxes and their respective class, [23]. The demarcations are visually similar to the process of demarcation of Yolo. In the second stage of Detectron2's operation, the bounding boxes demarcated go through a segmentation process by classifying the pixels of their internal region. This classification of the pixels occurs with the extraction of numerous types of deep attributes, resulting in a high segmentation performance, with the output mask well defined, [24].

3.2 Segmentation - Model Fine-tuning

The set of techniques used in the already consolidated Machine and Deep Learning techniques to increase the method's effectiveness concerning classification or segmentation is known as Fine-tuning.

Digital Image Processing is the base for the fine-tuning techniques used in this article. The Mask Generated Result has its edges reprocessed by combining Region Growing, K-means clustering, and Parzen Window techniques to improve the edges of the considered region, the region of interest.

In addition to the segmentation with Detectron2, there was a need to develop four more models for the photovoltaic panel segmentation. The models differ in the fine-tuning technique used on the Detectron2 output.

3.2.1 Detectron2_λ

The Detectron2_λ model uses the morphological dilation operation [25] with a structuring element of order 3x3 on the Detectron2 output to increase the region of interest edges in all directions. The morphological operation of dilatation [26] is applied with a cross structuring element of order 3, uniformly increasing the edges of the region of interest.

3.2.2 Detectron2_ϕ

The second model, Detectron2_ϕ, consists of applying the same morphological dilation operation applied in the previous model, but with a square structuring element of order 3, followed by the application of the contour detection algorithm [27]based on the connection of the edge pixels of the region of interest. Edge detection transforms the image, which results in creating a bounding box around the segmented region. This bounding box is assumed to be the segmented region, resulting in a square segmentation based on the Detectron2 output.

3.2.3 Detectron2_ψ

The third model, Detectron2_ψ, only applies edge detection [] in the region obtained by the Detectron2 output, generating a segmentation result similar to the Detectron2_ϕ model, but with the region of relatively little interest.

3.2.4 Detectron2_δ

Finally, the fourth method, Detectron2_δ, seeks to fine-tune the output of Detectron2 using region growing [28] and k-means clustering [29], clustering, re-segmenting the region of interest with adherence rule of 20 gray levels above and below the centroid gray level calculated from the detectron2 output region. L-means clustering helps segmentation with region growing by reducing the number of groups of color levels in the image. The result of this technique is the homogeneous segmentation of the region of interest.

3.3 Evaluation Metrics

The segmentation metrics in this study are: Accuracy, Specificity, Sensitivity, Positive Predicted Value(PPV), Negative Predicted Value(NPV) and Coefficient Dice [30]

3.4 Statistical Test

Statistical tests are powerful analysis tools used on sets of numerical samples in order to test hypotheses about the distribution of these samples, for example, when indicating whether one sample is, in fact, more significant than the other. It is first necessary to discern whether they are statistically different, taking into account the entire sample and not just the mean and standard deviation [31].

The Kolmogorov-Smirnov test is widely used for statistical classification between two samples. This non-parametric test is based on the maximum distance between the observed and theoretical reference distribution. Thus, it is possible to know whether two distributions of samples of the same size are statistically equivalent through this test. For this test, a reliability value of 95% is typically used, and 99% for more rigorous tests [31].

4 Methodology

This section presents the methodology divided into three steps: Step 01, photovoltaic panel detection; Step 02, segmentation of detected panels; and Step 03, results generated by fine-tuning models.
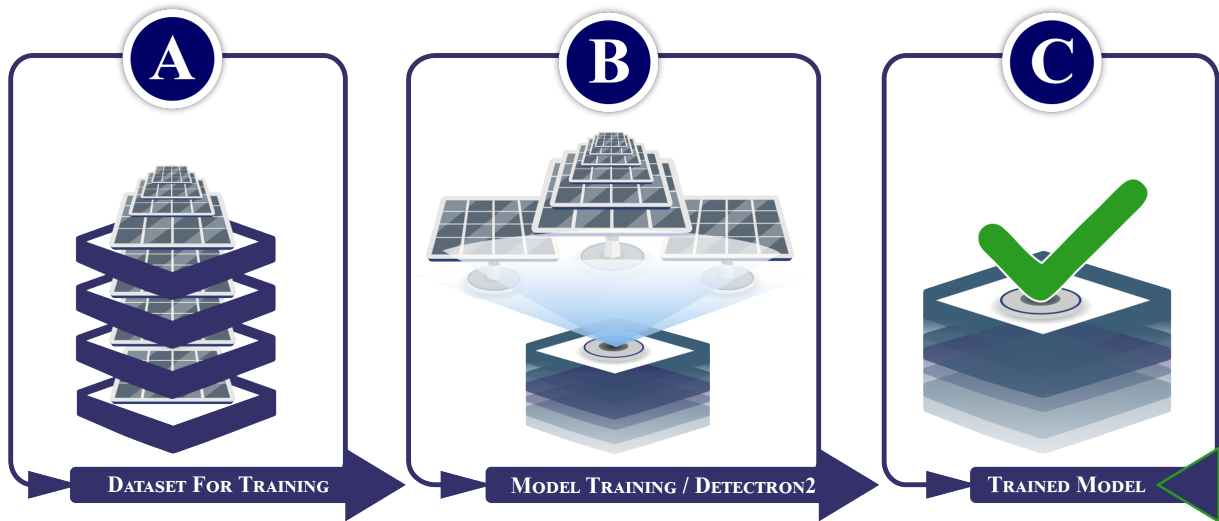

Figura 2: It represents the training of the Detectron2 network, in (A) dataset entry into the network, in (B) Model training, and in (C) the model already training with the images of damaged photovoltaic panels.

Before starting the Steps, the convolutional model is trained with the Detectron2 network, as shown in the figure.2.

Step 01 - In this Step, the detection of the damaged photovoltaic panel is performed based on the training presented in the figure 2. In 1. (A), as shown in the figure 1 starts the detection process with the input image in the model already training. In 1. (B), the trained model processes the input image containing panel images. At the end of this step, the model is output with the image detecting the possible damaged photovoltaic panel. Detectron2 classifies the existing pixels within the bounding boxes detected to obtain the region mask, thus detecting the region of interest. This mask obtained can be used to segment the damaged photovoltaic panel directly.

Step 02 - In this step in Step 02. (D), the convolutional network output serves as an input for the fine-tuning models' stage, generating new results with different models. In addition to the segmentation with Detectron2, there was a need to develop four more models for the photovoltaic panel segmentation. The models differ in the fine-tuning technique used on the Detectron2 output. The models are: (Detectron, Detectron2_λ, Detectron2 _ψ, Detectron2_ϕ, and Detectron2_δ).

The subsection 3.2 describes each model combined with the Detectron2 convolutional network.

Step 03 - After the segmentation process, the results are generated based on the combination of models, and the best model is chosen for the segmentation problem in Step 03.(E), generating the best models for the problem.

5   Results and Discussion

This section is divided into two subsections of results. The first section presents the results and discussion of photovoltaic panel detection. The second section presents the results and discussion of segmentation.

The experiments discussed in this study were developed and tested on a computer with the following configurations: Core i3 with 1.7 GHz, with 8 GB of Ram and ubuntu 20.04 LTS operating system.

5.1   First Results Section (Detection)

The first results section for this study starts at this section. This first approach refers to detecting damaged photovoltaic panels through image processing captured by drones, that is, a top-down perspective. The approach is based on deep learning through the convolutional model detectron2.

Tabela 1: Resultado de imagens com placas solares defeituosa detectadas.

Nº Imagens	Com detecções	Detecções(%)	Acc Total(%)	Acc Parcial(%)
1615	**1329**	**82.34**	**78.82**	**95.78**

The table 1 shows the total number of images of interest used to test Detectron2's prediction and the number of images on which the network was able to perform some object detection. It also shows the quality of detections on the number of hits and the total of images. The use of a medium among all the values obtained for all images, applying zero for the plates where there was no detection, composes the total Acc. The Partial Acc value is related only to 1329, where there is detection by the network. n this sense, the table 1 presents the accuracy results for the detection of photovoltaic panels, which presents damages identified through image capture.

Based on the 1 the detection of the object of interest obtained satisfactory results for the panel images. The results of different accuracy showed a gain of 95%. Or identification, the size of the problem of interest in the image, not obstacles to a problem of interest from different panels in different images in the dataset.

The convolutional network was able to detect 82.34% of the panels, based on learning. Through the bold box, the model efficiently identified regions belonging to the modified panels, that is, the region of interest, previously trained with similar image samples. Of the detected videos, the models found 95% of the location of the panels.

In this way, the convolutional model brought a significant gain for problem-based detection. The Detectron2 convolutional network presented excellent results for detection. The results obtained were possible even considering the reduced number of images used in this experiment. Since, in the case of convolutional models, it is necessary, according to the literature, for a high number of samples to obtain an excellent result in the model's training.

The figure 3 presents different results of the identification of photovoltaic panels, in the image can be seen different panels identified by the convolutional network, presenting different detections in single image capture in a fully automatic way.

Figure 4 presents the detection of the object of interest in detail. In the image, it is possible to identify the object detection on the framing delineation of the object edges, demonstrating the detection model's robustness.

In the image 4, it is possible to notice different photovoltaic panels captured by aerial drone images. The highlighted damaged panel shows an example of possible problems that affect energy production.

5.2   Second Results Section (Segmentation)

Tabela 2: Table of segmentation results of the models developed by this study, using fine-tuning models using Region Growing, k_means clustering, morphological operation of dilatation, and delimitation of borders.

Model	ACC	SPE	SEN	PPV	NPV	DICE
Detectron2	99.91 +/- 0.22	99.98 +/- 0.07	76.04 +/- 18.87	92.54 +/- 17.59	99.92 +/- 0.21	81.77 +/- 18.38
Detectron2_λ	**99.91 +/- 0.23**	**99.97 +/- 0.08**	**85.56 +/- 20.31**	87.27 +/- 17.21	**99.94 +/- 0.21**	**84.60 +/- 18.67**
Detectron2_ψ	99.52 +/- 5.84	99.65 +/- 5.85	48.71 +/- 18.17	**94.64 +/- 21.94**	99.60 +/- 4.65	62.76 +/- 20.42
Detectron2_ϕ	99.55 +/- 5.84	99.63 +/- 5.84	80.25 +/- 27.68	84.13 +/- 20.88	99.77 +/- 3.12	80.13 +/- 24.14
Detectron2_δ	93.56 +/- 13.90	93.69 +/- 13.95	53.80 +/- 30.75	51.39 +/- 46.13	99.85 +/- 0.30	35.89 +/- 33.88

This section presents the results of segmentation using different models. This study used the following models; Detectron2, Detectron2_λ, Detectron2_ψ, Detectron2_ϕ, and Detectron2_δ.

Figure 6 presents the different results of object segmentation. In the image, it is possible to identify the delineation of each proposed model through fine-tuning, post-process of the detectron2 network. In the image, it is possible to identify the model D_λ
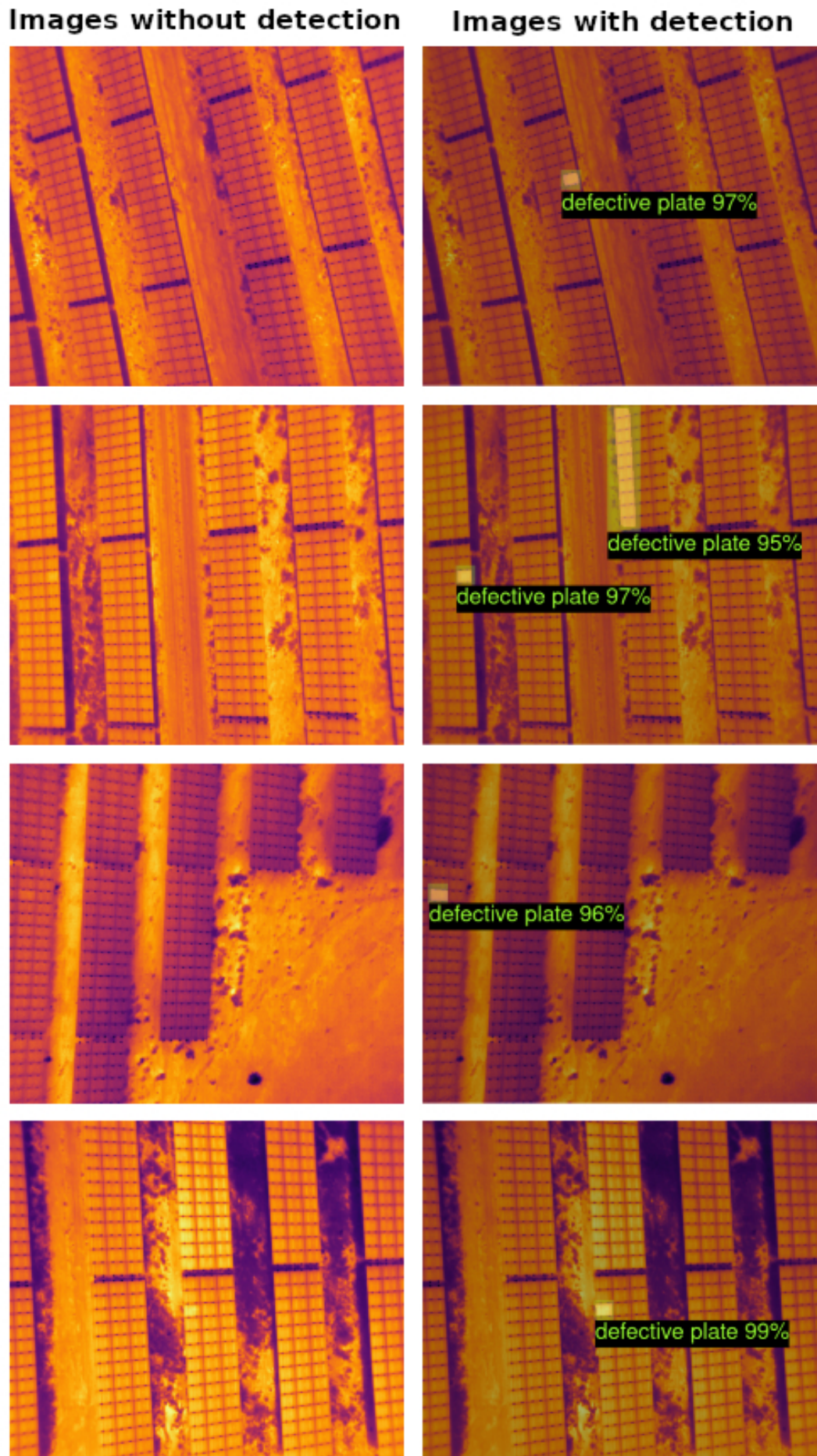
Figura 3: Displays images of photovoltaic panels without the detection of damaged panels, and post-processing detection using the Detectron2 convolutional network.
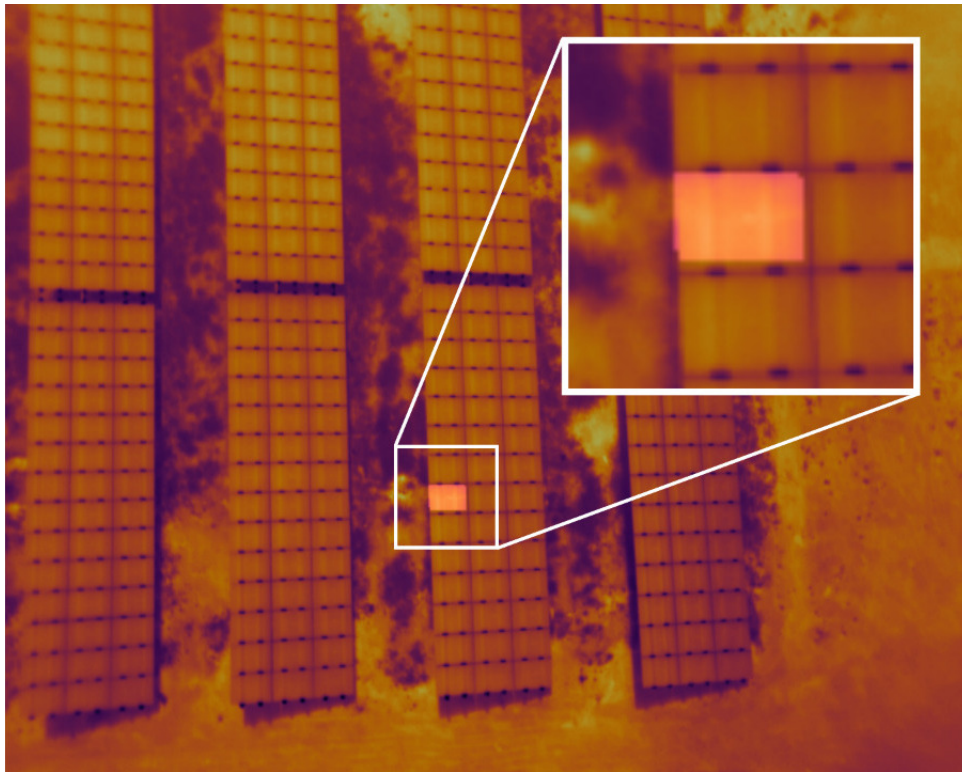
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Figura 4: Displays the image of different photovoltaic panels. In the figure, the result of the damaged panel detection is presented in an enlarged way, based on the training of the Detectron2 convolutional network.

Figura 5: Comparison between our method and Mask R-CNN.
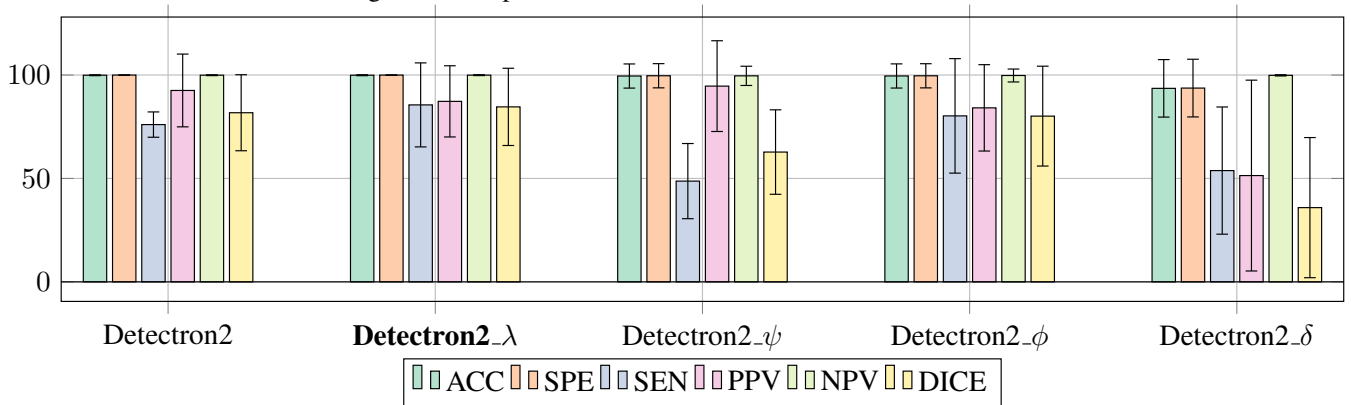
with the result of the best model for segmenting the object of interest. It is worth emphasizing the importance of segmentation for different objects of interest in the image, as it enables different applications for different segmented problems; in the case of photovoltaic panels, the probability of calculating energy generation and counting damaged panels, among other industrial applications, in the area of computer vision and artificial intelligence aimed at monitoring.

Tabela 3: Table of statistical tests, Kolmogorov test

Models	ACC	SPE	SEN	PPV	NPV	DICE
D_λ — D	x	x	x	x	x	x
D_λ — D_ψ	x	x	x	x	x	x
D_λ —D_ϕ	x	x	x	x	x	x
D_λ — D_δ	x	x	x	x	x	x

The table 3 illustrates the results of the Kolmogorov-Smirnov statistical test applied in the comparison of statistical equality between the best segmentation model developed, Detectron_λ, and the other developed models by this study, The result shows
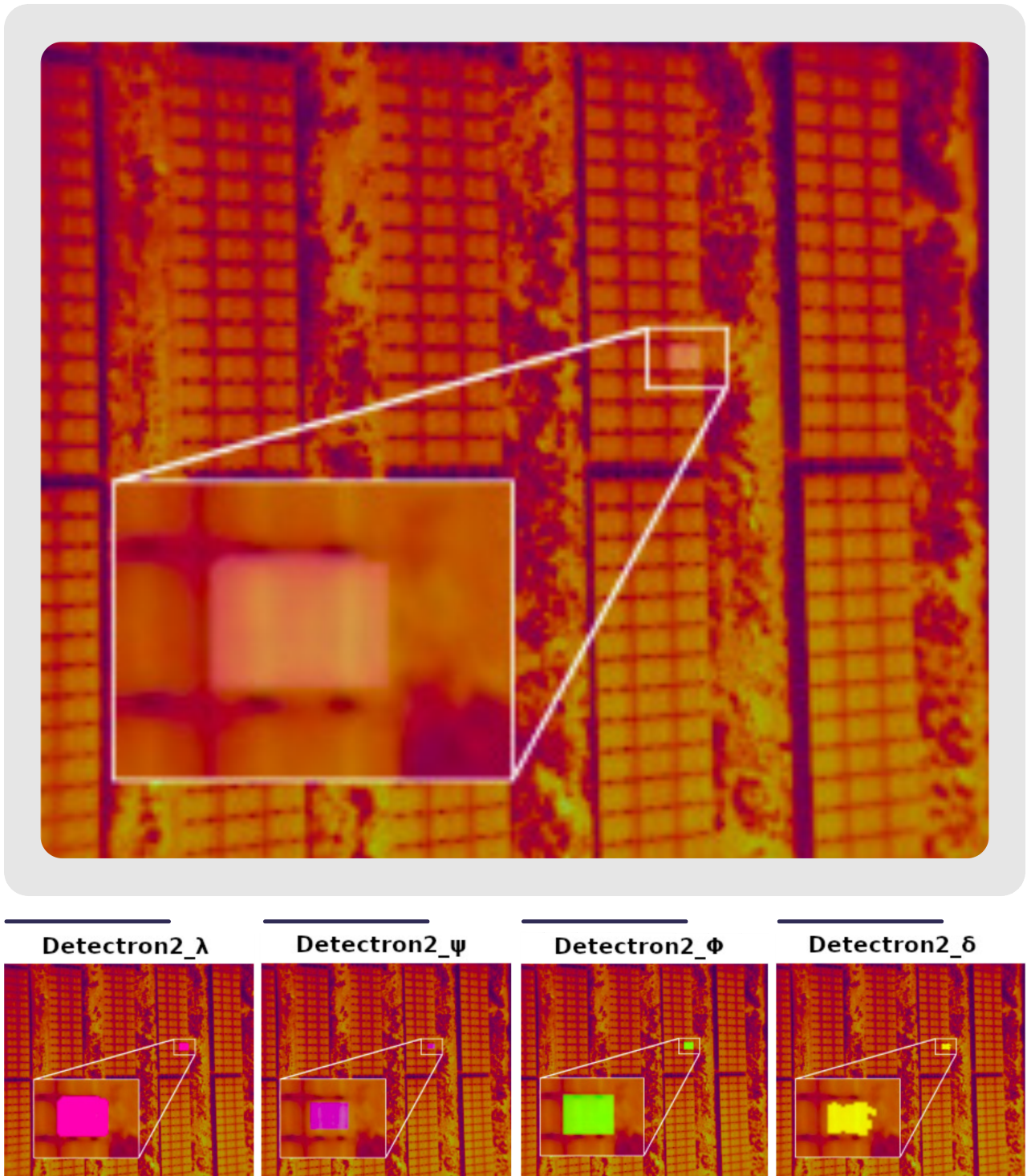
Detectron 2

Figura 6: Fine-tuning results of the different models of photovoltaic panels.

that, for a reliability index of 99%, the Detectron_λ model does not have any statistical equality with the others, making possible its metric comparison and assertion of statistical superiority.

The table 2 presents different models using fine-tuning, using the Detectron2 network together with different fine-tuning techniques based on digital image processing, in order to seek an improvement in the results obtained in the segmentation.

Table 2 illustrates the segmentation results of the five models developed for this approach, showing that the results were generally good, with accuracy rates of 99%. The high model precision indicates the ease of Detectron2 to successfully detect the damaged solar panel from aerial images provided by the drone. However, by this detection evaluation through another optic, such as through the DICE metric use, which measures the overlap of the segmented region concerning the entire region of interest, it

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is noticeable that the result can be improved.

It is worth mentioning that Detectron2 does not focus on object segmentation but its detection, so the edge details of the segmented region end up going unnoticed by the network, in this way, the use of fine-tuning to the improvement of the results obtained is of great help.

The best model developed for the approach, according to the results obtained from the 2 table, was the Detectron2_λ. This model development origin was the morphological operation of dilation, with element order 3 square structuring element. This mask increases the detected region uniformly, that is, in all directions of the region of interest. In this way, the already perfectly positioned region obtained an improvement in the overlap by expanding its edge.

The Detectron2_λ model also showed significant improvements in PPV, with an average of 94.64%, an increase of 2.1% compared to the Detectron2 result. Finally, for the DICE metric, the average obtained was 84.60%, 2.83% higher than the DICE of detectron2.

In short, the Detectron2_λ model obtained the highest metric averages for sensitivity, PPV, and DICE and was numerically equivalent in accuracy, specificity, and NPV, maintaining the excellent result of detectron2. To increase its capacity for real delimitation of the region of interest, the damaged photovoltaic panels in aerial images provided by the drone. More specifically, the improved specificity and PPV metrics indicate an improvement in the delimitation of the edges of the image that are considered the region of interest. The improvement in the DICE metric indicates an improvement in the similarity of the segmented region with the real region's interest in what should be segmented in the image.

In short, the Detectron2_λ model obtained the highest metric averages for sensitivity, PPV, and DICE and was numerically equivalent in the metrics of accuracy, specificity, and NPV. The model maintained the excellent result of Detectron2 and increased its capacity for real delimitation of the region of interest, that is, the damaged photovoltaic panels, in aerial images provided by drone. More specifically, the specificity and PPV metrics improvement indicates a delimitation improvement of the edges of the image that are considered the region of interest. On the other hand, the DICE metric improvement indicates an improvement in the segmented region similarity with the real region of interest, which the image should segment.

The table 2 addresses the metric results adopted in order to measure the segmentation capacity of the models proposed by this study for the detection of damaged photovoltaic panels detected by images captured by drone. The metrics adopted do not only address the method's success rate. The best model developed was Detectron2_λ, with the highest accuracy, Specificity, Sensitivity, NPV and Dice.

6 Conclusion

The proposed study approaches a new model based on deep learning to detect and segment damaged photovoltaic panels. The model used images captured by drone to detect damaged panels and segment them through fine-tuning techniques capable of accurately segmenting the region of interest.

In the first experiment, the convolutional model was the base for detection. The method used reached 78% accuracy in detecting the panels using the Detectron2 network and 95% accuracy in the images detected. The second experiment section carried out different experiments with fine-tuning combinations for the segmentation of photovoltaic panels. The Detectron2_λ model showed the best and most robust model for segmenting damaged panels, with an accuracy of 99.91%. On the other hand, the Detectron2_δ model obtained an accuracy of 93.56%, the worst metric value for this problem. In conclusion, the Detectron2_λ model presented better results in different metrics, such as SEN, NPV, and DICE, equivalent to the other metrics presented in this study.

The proposed study will bring applications using transfer learning to detect and segment photovoltaic panels for future work. Also, perform experiments for different databases, such as images for object detection, vehicular plates, urban signs, and medical images.

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