

UNIVERSIDADE TECNOLÓGICA FEDERAL DO PARANÁ

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**DISPOSITIVO DE BORDA BASEADO EM REDE NEURAL CONVOLUCIONAL
PARA INSPEÇÃO MULTIESPECTRAL DE PAINÉIS FOTOVOLTAICOS**

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**DISPOSITIVO DE BORDA BASEADO EM REDE NEURAL CONVOLUCIONAL
PARA INSPEÇÃO MULTIESPECTRAL DE PAINÉIS FOTOVOLTAICOS**

**Convolutional neural network based edge device for
Multispectral inspection of photovoltaic panels**

Trabalho de conclusão de curso de Tese apresentada como requisito para obtenção do título de Doutor em Ciências do Programa de Pós-Graduação em Engenharia Elétrica e Informática Industrial da Universidade Tecnológica Federal do Paraná (UTFPR).

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CURITIBA

2024



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**DISPOSITIVO DE BORDA BASEADO EM REDE NEURAL CONVOLUCIONAL PARA INSPEÇÃO
MULTIESPECTRAL DE PAINÉIS FOTOVOLTAICOS**

Trabalho de pesquisa de doutorado apresentado como requisito para obtenção do título de Doutor Em Ciências da Universidade Tecnológica Federal do Paraná (UTFPR). Área de concentração: Fotônica Em Engenharia.

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RESUMO

O uso de painéis fotovoltaicos para geração de energia elétrica de forma sustentável vem crescendo em todo mundo. Com isso, grandes plantas solares precisam ser monitoradas de forma a encontrar defeitos com agilidade, evitando longas paradas na geração de energia. Existem várias técnicas para monitorar plantas solares. Algumas delas são inspeção visual, no espectro visível, por termografia infravermelha, aquisição de imagens de fluorescência após excitação do painel por luz ultravioleta. Todas essas técnicas utilizam câmeras para captar imagens do painel para sua posterior análise. Mesmo com tantas técnicas, cada uma delas possuem suas lacunas. Neste trabalho foi desenvolvida uma câmera multiespectral com um para adquirir e classificar imagens de painéis fotovoltaicos em tempo real, utilizando um *edge device* para conectar todo o hardware e processar as imagens. Além disso, um concentrador de luz foi desenvolvido para que inspeções por luz ultravioleta sejam efetuadas de forma eficiente. Neste projeto de pesquisa também foram revisadas técnicas que podem ser utilizadas para melhorar ou esclarecer as técnicas mencionadas auxiliando na inspeção de painéis solares. Em termos de algoritmos computacionais, duas metodologias foram testadas para a inspeção de painéis fotovoltaicos, uma utiliza classificação direta da imagem (sem detecção de objetos) e classifica a imagem adquirida com uma rede neural convolucional e outra técnica utiliza um algoritmo completo que detecta e classifica os painéis solares utilizando também redes neurais convolucionais. Ambas as metodologias apresentaram resultados similares ou melhores que os encontrados na literatura com valores de acurácia superiores a 90% para o caso da metodologia de classificação direta e precisão superior a 86% na metodologia com detecção de objetos. A solução apresentada pode ser uma ferramenta importante para a equipe de manutenção realizar manutenções preventivas, permitindo identificar problemas precocemente e planejar o cronograma de manutenção da planta solar.

Palavras-chave: Painel fotovoltaico; classificação de falhas; redes neurais convolucionais; sistemas embarcados.

ABSTRACT

The use of photovoltaic panels for sustainable electricity generation has been growing worldwide. As a result, large solar plants must be monitored to find defects, quickly avoiding extended shutdowns in energy generation. There are several techniques for monitoring solar plants. Some of them are visual inspection in the visible spectrum, infrared thermography, and the acquisition of fluorescence images after excitation of the panel by ultraviolet light. All of these techniques use cameras to capture images of the panel for later analysis. Even with so many techniques, each of them has its shortcomings. In this work, a multispectral camera was developed to acquire and classify images of photovoltaic panels in real-time, using an edge device to connect all the hardware and process the images. In addition, a light concentrator was developed so that ultraviolet light inspections can be carried out efficiently. This research project also reviewed techniques that can be used to improve or clarify the aforementioned techniques, aiding in the inspection of solar panels. Regarding computational algorithms, two methodologies were tested for inspecting photovoltaic panels. One uses direct image classification (without object detection) and classifies the acquired image with a convolutional neural network. The other technique uses a complete algorithm that detects and classifies solar panels using convolutional neural networks. Both methodologies presented results similar to or better than those found in the literature, with accuracy values above 90% for the direct classification methodology and accuracy above 86% for the methodology with object detection. The presented solution can be an essential tool for the maintenance team to perform preventive maintenance, allowing early identification of problems and planning the maintenance schedule of the solar plant.

Keywords: Photovoltaic panel; fault classification; convolutional neural networks; embedded systems.

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LIST OF ABBREVIATIONS AND ACRONYMS

ABS	Acrylonitrile Butadiene Styrene
AI	Artificial Intelligence
ANN	Artificial Neural Network
AP	Average Precision
CLAHE	Contrast-limited adaptive histogram equalization
CNN	Convolutional Neural Network
DA	Data augmentation
DIP	Digital image processing
DL	Deep Learning
DNN	Deep Neural Network
EC	Edge Computing
EL	Electroluminescence
FN	False Negative
FP	False Positive
FPS	Frames Per Second
FT	Fine Tunning
GAN	Generative Adversarial Network
GPU	Graphical processor unit
GUI	Graphical User Interface
IEA	International Energy Agency
IFPR	Instituto Federal do Paraná
IoU	Intersection over Union
IR	Infrared
IRT	Infrared thermograph
LID	Light induced degradation
mAP	Mean Average Precision
NIR	Near infrared
NLP	Natural Language Processing
O&M	Operation and Maintenance
PV	Photovoltaic
RGB	Red-green-blue
ROI	Region of interest
SVM	Support vector machine
SWIR	Short Wave Infrared
TL	Transfer Learning
TN	True Negative
TP	True Positive
UAV	Unmanned aerial vehicle
UPNA	Universidad Publica de Navarra
UTFPR	Universidade Tecnológica Federal do Paraná
UAV	Unnamed Aerial Vehicle
UV	Ultraviolet
UVF	Ultraviolet Fluorescence
YOLO	You Only Look Once

LIST OF SYMBOLS

I	Electric Current
I_{mpp}	Maximum power point in relation to current
I_{sc}	Short-circuit current
P_{mpp}	Maximum power point
P_{T}	Virtual power point
R_{s}	Series resistance
R_{sh}	Parallel resistance
V	Voltage
V_{mpp}	Maximum power point in relation to voltage
V_{oc}	Open-circuit voltage

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1 INTRODUCTION

Sustainability is one of the main topics in electricity generation globally, and consequently, the Brazilian electricity sector has paid attention to this point (DANTAS; POMPERMAYER, 2018). Even though most of the Brazilian energy matrix comes from sustainable sources (hydroelectric), the search for generation through other sustainable sources is also growing in Brazil (ANEEL, 2024). Another fact that needs attention is the hydrological crisis (DE QUEIROZ *et al.*, 2019), demanding thermoelectric plants to generate energy which are not sustainable. The photovoltaic (PV) generator has been used among many sustainable electrical generators globally (IEA, 2023).

1.1 Motivation

The most significant costs in large solar plants are operation and maintenance (O&M). In order to optimize the maintenance activities, it is necessary to develop innovative techniques (GALLARDO-SAAVEDRA; HERNÁNDEZ-CALLEJO; DUQUE-PÉREZ, 2018). Many parameters can be monitored in PV panels, which can be metrological (temperature) or electric (current and voltage) (MADETI; SINGH, 2017).

Among all the components of a solar plant, failures in PV generators can take longer to repair (GALLARDO-SAAVEDRA; HERNÁNDEZ-CALLEJO; DUQUE-PÉREZ, 2019). Therefore, identifying this fault precisely and quickly results in less downtime in power generation.

Regardless, conventional PV inspections using electrical parameters are limited in fault detection, where fault locations are commonly not found, thus requiring individual PV panel verification (TSANAKAS, John A.; HA; BUERHOP, 2016). Another approach that can help inspect PV panels is image capture, where these images can be from the visible or infrared spectrum (HØIAAS *et al.*, 2022).

Infrared thermography (IRT) images and visual spectrum (RGB) images allow the extraction of information from each PV panel. As the IRT camera captures information about temperature, the RGB camera captures information as the coloration of the PV panel or if the panel is dirty or clear.

Some techniques that capture the PV response to electrical or light stimuli can be applied to capturing PV images. Regarding electrical stimuli, the electroluminescence technique applies a current source. It captures the PV

luminescence through a camera that can capture the near-infrared (NIR) spectrum of about 1150 nm (KÖNTGES *et al.*, 2014).

Two techniques can be applied regarding using lights to stimulate the PV panel. One technique is photoluminescence, where a NIR light (about 800 nm) excites the PV panel, and an image in the same region of the electroluminescence image must be captured (DOLL *et al.*, 2021). Another technique that can be applied is ultraviolet fluorescence (UVF), where ultraviolet light (UV) illuminates the PV panel, and this panel will fluorescence in the visible spectrum (KONTGES *et al.*, 2020). These three techniques involving the PV panel's luminescence are used to search for structural faults in the PV cells, e.g., cracks (DOLL *et al.*, 2021).

With the use of electricity growing, and thus, the growing need for more electricity generation, solar power plants need more space to be installed. Considering this, inspecting these solar plants can be challenging, and using images from multiple spectra can be essential to make a complete inspection of the power plant.

Because inspecting large solar plants requires several hours, several professionals in maintenance, and generating a high volume of collected data, using methodologies that employ computational algorithms can help with this task.

Of various techniques that can be applied to process the captured images, one that has gained focus is artificial intelligence (AI) and, more specifically, to images, Deep Learning (DL) algorithms. One of the most common approaches used in the DL is the convolutional neural networks (CNN) that allow the extraction of multiple image characteristics. Because of these extracted characteristics, the detection and classification of images can be fast and precise in identifying faults in PVs (LI, B. *et al.*, 2021; MEHTA *et al.*, 2017; PAK; KIM, 2017).

Previous works that employ DL with CNN models can be found in the literature. Some works develop the CNN model from scratch. Others use a known base model to build their model. Finally, some use pre-trained CNN models to train only some of the models. The article revision presented by LI, B. *et al.* (2021) shows a range of works using DL techniques to identify defects in solar panels. In this review, two works propose CNN models to classify defects in PVs, the work of (CHEN *et al.*, 2020) and (LI, Xiaoxia *et al.*, 2019). In addition to this review, other works that build their CNN to solve the classification problem are (RICO ESPINOSA; BRESSAN; GIRALDO, 2020) and (CAO *et al.*, 2021).

However, building a CNN is not trivial. Several factors need to be considered for a network to be efficient, both in terms of correct classification and using computational resources. To assist in this process, in the literature, it is possible to verify that several authors use an already known CNN model to address the problem addressed or create their model (AZIS *et al.*, 2022; LI, B. *et al.*, 2021; LI, Xiaoxia *et al.*, 2020b; MORADI SIZKOUHI *et al.*, 2022; WANG, Xiao *et al.*, 2022).

Another technique that can be employed is using previously trained CNN models with a set of images. This technique is known as transfer learning (TL) (PAN; YANG, 2010). In this technique, the CNN model is trained again, but not completely, transferring its previous knowledge. Thus, the model adapts to the new problem that will be addressed, and the computational cost of training will be significantly reduced. Some works that benefit from this technique to evaluate PV plants are found in the literature (DING *et al.*, 2018; NAVEEN VENKATESH; SUGUMARAN, 2021).

In addition to the complexity in developing CNN, another detail that hinders studies and practical implementations of approaches to identify defects in solar panels is the lack of access to real data (GALLARDO-SAAVEDRA; HERNÁNDEZ-CALLEJO; DUQUE-PÉREZ, 2019). This problem with real data occurs because solar plant operators are private or cannot collect and store such information (GALLARDO-SAAVEDRA; HERNÁNDEZ-CALLEJO; DUQUE-PÉREZ, 2019).

Thus, it is possible to observe that most of the works use few images, requiring the application of techniques to increase the volume of data or even use little data in the solutions. This low volume of data, in turn, can limit the generalization of models in a field environment, with more significant variability of defect categories, viewing angles, and different lighting conditions. Thus, there is a need to generate datasets with a large volume of information publicly available, helping find real data, as reported in recent literature (GAVIRIA *et al.*, 2022).

An example of a publicly available dataset of visible spectrum images is presented in (MEHTA *et al.*, 2017) and used in (ZHANG, Wenjie *et al.*, 2021). This dataset consists of more than 46,000 monitoring images of a PV with sand accumulation. Even though this dataset has a large volume of images, since only one panel is monitored, it may not represent the variability in an actual solar plant.

Another example of a dataset is images of snow-covered PVs (OZTURK; HANGUN; EYECIOGLU, 2021). However, it is a dataset with only 395 images, which

limits the generalization previously mentioned and is limited to a single failure that is also different from countries with a hot climate.

Because collecting and selecting images is a time-consuming task, data augmentation (DA) techniques are used, which can be simple image transformations or the use of Generative Adversarial Networks (GAN) to generate a larger dataset from a small volume of images (DING *et al.*, 2018; HAITAO *et al.*, 2021). However, training and developing GAN is also costly, and the results may be far from real images.

1.2 Objectives

This work has general and specific objectives, which will be explained in the following subsections.

1.2.1 General Objective

Develop a camera with multiple image sensors that allows the observation of different spectra of ultraviolet, visible, and infrared light, with its primary use being for the inspection of photovoltaic panels. The camera must be lightweight and use computational algorithms to identify defects.

1.2.2 Specific Objectives

For the proposed general objective to be achieved, specific points must be considered, namely:

- a) Study of photovoltaic panel failures using images from multiple spectra;
- b) Research into image sensors and optical filters be used in lenses to acquire specific parts of the electromagnetic spectrum;
- c) Tests with digital image processing techniques to extract essential features from images acquired by sensor elements;
- d) Creation of image datasets of common faults in photovoltaic panels;
- e) Study of pattern recognition techniques using artificial intelligence to automatically recognize common faults;
- f) e) Embed the solution into an edge device and optimized the computational algorithms to allow real-time inspection of solar panels.

1.3 Justification

Since the return on financial investment of solar plants depends on its lifetime, monitoring these plants with many PVs is still a significant technical and economic challenge (TSANAKAS, John A.; HA; BUERHOP, 2016). Therefore, differentiated methodologies are welcome to reduce this cost and enable constant monitoring of solar plants.

Using UAVs alone to acquire images may not be sufficient. Analyzing a large volume of information can be time-consuming, and some problems may need to be identified by the person analyzing the images. Associated with image capture, digital image processing (DIP) and artificial intelligence (AI) techniques are applied to automatically identify PVs in both visual and thermal images, as well as the most common problems such as snail trails, hot spots, and dirt (DASTOORI *et al.*, 2013; KARIMI *et al.*, 2018; KIM; YOUN; KIM, 2016; LI, Xiaoxia *et al.*, 2017b; QASEM; MNATSAKANYAN; BANDA, 2016; TRIBAK; ZAZ, 2019; TSANAKAS, John A.; HA; BUERHOP, 2016; WU *et al.*, 2017; ZEFRI *et al.*, 2017).

It is observed that most of the networks used in the studies are networks with a large number of parameters, and usually, few comparisons are made between models. The use of large networks requires significant computational power, which limits the application of embedded systems and, consequently, real implementations of the models and application of the technique in the field. Thus, in this work, a broad comparison was made between network models to verify their performance in the problem depicted. This comparison aims to identify possible models that are not considered and that could facilitate the use of DL techniques to identify defects in PVs in real environments.

Another area of research explored is related to image capture. Since commercial sensors have high value and are not integrated with embedded systems and light sources for luminescence inspections, this research developed a camera for multispectral image acquisition (ultraviolet to infrared) focusing on solar plant monitoring. This camera must be lightweight and cost-effective. In addition to camera development, image processing and pattern recognition techniques were studied. Thus, this research aims to assist in the management of solar plant monitoring, focusing on predicting failures. Continuous monitoring can increase the efficiency of the monitored solar plant.

1.4 Contributions

This work contributes to five areas explored in PV monitoring studies. The first area concerns embedded sensors for image collection. Several studies use commercially available sensors, but these have high value in terms of the sensor and the platform required. Regarding the UVF technique, this research aims to fill the gap by developing a camera with multiple sensors and an edge device integrated with the light sources required in these techniques. In this way, the developed tool will be unique for PV excitation and image collection.

To conduct the UVF inspection with the developed camera, a light source is needed to illuminate the PV panel and excite the panel to fluorescence. To do this, a light concentrator was constructed to concentrate light at a long distance, allowing the UVF inspection by the developed camera, which is the second contribution of the work.

Since this work collects several images from different sensors, the third contribution concerns the need for real data. This work has built several sets of images for other researchers to use in their research, and some of these data sets are publicly available.

As some of the works found in the literature use AI to solve the problem of faults in PVs, this work has tested multiple CNNs to verify their performance in evaluating faults in PV panels, which is the fourth contribution of the work.

The fifth contribution area concerns computational algorithms for extracting information from images collected by the developed embedded system. This research developed low-cost sensors embedded in electronics with high computational power so that computational algorithms can be applied to these images to extract information from the collected images. These algorithms must be efficient to execute on the embedded electronics and provide fast and accurate responses.

1.5 Document structure

This document is organized as follows: chapter 2 reviews the state of the art that use as a basis for the development of the referred work; chapter 3 presents the methodology applied in each stage of the work; chapter 4 presents results obtained from the inspection of solar panels with the proposed solution; chapter 5 draws some conclusions obtained from the analysis of the results; and finally chapter 6 presents future work.

2 STATE OF ART

With the presented problem, it is necessary to review the methodologies and tools utilized and presented in the literature to solve these problems. This chapter is organized into four subsections, where section 2.1 refers to the faults that can occur in PV panels. Section 2.2 presents the methods that can be employed to inspect PV modules. Section 2.3 presents computational algorithms that can be used to process the data collected during an inspection. Finally, section 2.4 presents a review of edge devices and their uses.

2.1 Faults and Defects in Photovoltaic Panels

According to the International Energy Agency (IEA) document in a review about faults in PV panels, a PV panel fault could be a defect that degrades the power generation and can not be reversed in a regular operation or can cause a security fault condition. In this definition, environmental events are not considered faults (KÖNTGES *et al.*, 2014).

However, for example, dirty deposit and partial shadowing in PV modules can be considered as a means of stress on the PV that can cause a failure in the future (ABDULMAWJOOD; REFAAT; MORSI, 2018; FERRARA; PHILIPP, 2012) which completes the IEA definition.

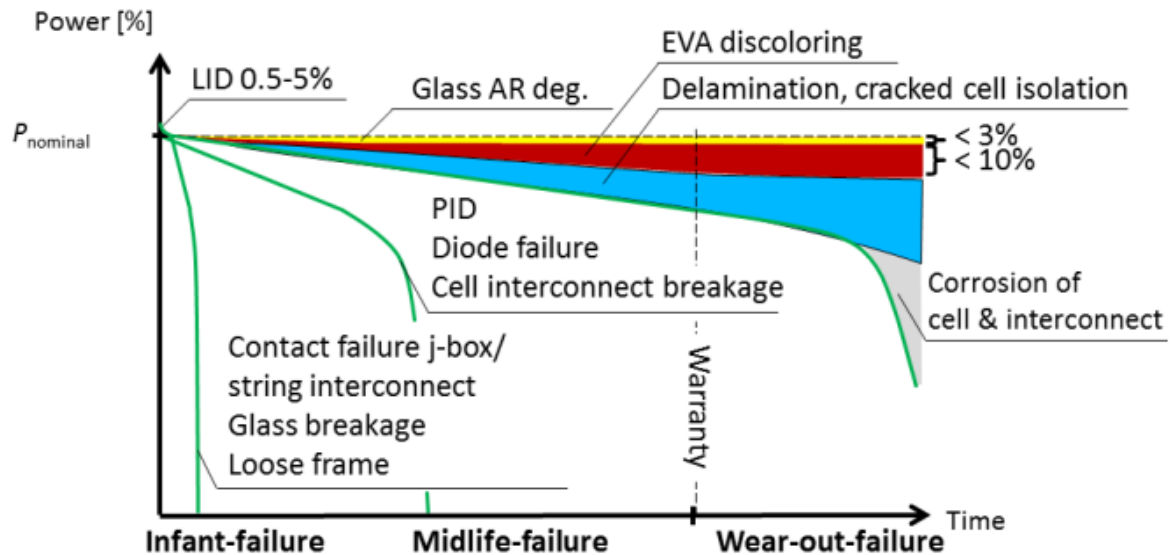
This complement is because, for example, partial shading causes non-uniform heating in the PV, which will result in more severe defects in the medium to long term. Furthermore, any event that reduces the generation power can be considered a failure (ABDULMAWJOOD; REFAAT; MORSI, 2018).

An example is Firth, Lomas and Rees (2010) work that evaluates annual losses due to PV failures. In that work, one of the plants was analyzed for two years. In the first year of installation, the system had 6.6% losses, and in the second year, 3.6%. Shading was the second cause of failure, generating the most yearly production losses. Failures in isolated components or breakage were the first cause of failures (FIRTH; LOMAS; REES, 2010).

For this reason, in the present work intends to conduct a general inspection of the solar plant, and any event that reduces the power generation and requires intervention to restore maximum power or may cause future losses will be considered a failure.

Among the failures in the solar plant, these are classified as infant-failure, midlife-failures, and wear-out-failures of the PV (KÖNTGES *et al.*, 2014). For better visualization, Figure 1 shows some of these failures that can occur according to the life of the PV.

Figure 1 - Three failure scenarios that can occur for wafer-type crystalline PV. In the figure, LID stands for light-induced degradation, PID stands for potential induced degradation, EVA stands for ethylene vinyl acetate, and j-box stands for junction box.



Source: Köntges *et al.*, (2014, p. 4).

Failures that occur at the beginning of PV operation (infant failures) have most impact over the manufacturer and the plant installer, as they are responsible for these failures. LID failure is a PV power adjustment shortly after its installation, which causes a divergence between the estimated power and the actual power generated. Other failures may be related to poorly made PV line connections, poorly fixed panels, diode failures, broken glass during installation or transportation, and broken internal cell connections (KÖNTGES *et al.*, 2014).

Midlife-failures typically occurs in PV cells, junction box and connection cables, problems in PV glass and lamination of internal electrical circuits (KÖNTGES *et al.*, 2014).

Finally, end-of-life failures (wear-out-failure) occur when a PV suffers irreversible damage, has operation safety problems, or its generation power drops by 70% to 80% of its initial value (KÖNTGES *et al.*, 2014).

Some other examples of failures that may occur are discoloration, delamination, yellowing of the cell, hot spots, snail trails, burn marks, cracks, broken

glass, and oxidation, among others (FERRARA; PHILIPP, 2012; HØIAAS *et al.*, 2022; KÖNTGES *et al.*, 2014).

By defining three levels of failures that can occur over the lifetime of the PV, we have a basis for the number of defects and failures that a solar plant is subject to.

Some failures originate according to the operating environment of the solar plant. For example, failures related to dirt accumulation result from the environment having winds that carry dust particles that settle on the panel (FERRARA; PHILIPP, 2012). Shading failure is related to poorly planned installations or shrub growth (ABDULMAWJOOD; REFAAT; MORSI, 2018).

Several defects are related to the PV operating temperature. These temperature anomalies can be related to the current and voltage the PV generates, leading to severe failures (TSANAKAS, John A.; HA; BUERHOP, 2016). An example would be a hot spot failure, which, if not resolved quickly, can permanently damage a PV (GALLARDO-SAAVEDRA; HERNÁNDEZ-CALLEJO; DUQUE-PEREZ, 2018).

That said, one tool alone may not be enough to identify such a range of defects. To this end, several solar plant inspection techniques can be applied, each with its specialty and pros and cons.

2.2 Methods Used for Photovoltaic Panel Inspection

Inspecting large solar plants can be costly and time-consuming. In addition, inspections can have a significant cost in the operation and maintenance (O&M) of the plant (GALLARDO-SAAVEDRA; HERNÁNDEZ-CALLEJO; DUQUE-PEREZ, 2018) and any tool that helps to reduce and redirect teams to perform more precise maintenance, makes it possible to reduce this cost.

Several methods in the literature can be used to identify specific problems according to their origin. These can be divided into inspections that collect images that allow visualization of the PV structure or electrical data (KOESTER *et al.*, 2022). Thus, subsection 2.2.1 will explore inspections using electrical parameters, and subsection 2.2.2 will present the PV inspection by images.

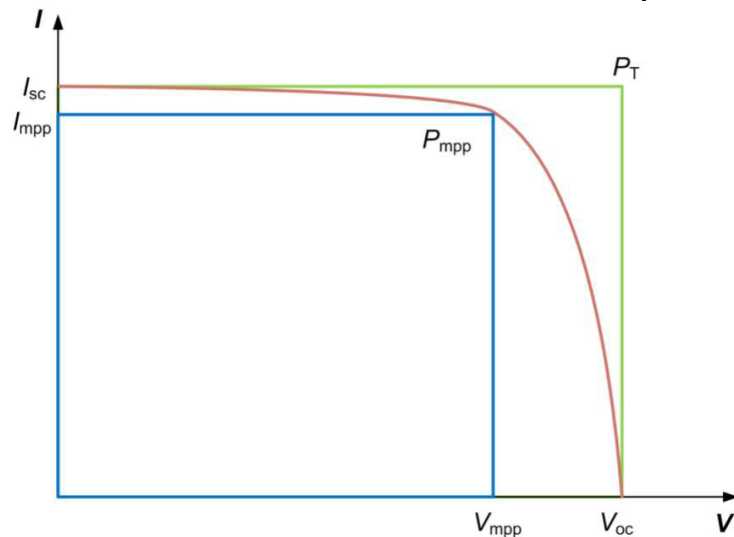
2.2.1 Inspection by Electrical Parameters

The leading information PV power generation companies observe is the voltage and current the solar plant generates. This analysis usually involves an entire

line of PVs (ABDULMAWJOOD; REFAAT; MORSI, 2018) or individually, which is rarer in field environments or carried out in specific cases.

Current and voltage analysis, known as the I-V curve, is used to verify the relationship between current and voltage generated by the PV to check for possible failures. Since this is an analysis of a curve, it is necessary to construct a graph between current and voltage. Figure 2 shows an example of this curve with its main parameters being I_{sc} , the short-circuit current V_{oc} the open-circuit voltage, P_{mpp} the maximum power point where the current and voltage corresponding to the maximum point are represented by I_{mpp} and V_{mpp} , and P_T which is the virtual power point (ABDULMAWJOOD; REFAAT; MORSI, 2018; KÖNTGES *et al.*, 2014).

Figure 2 - Schematic of an I-V curve of an illuminated module in perfect working order.

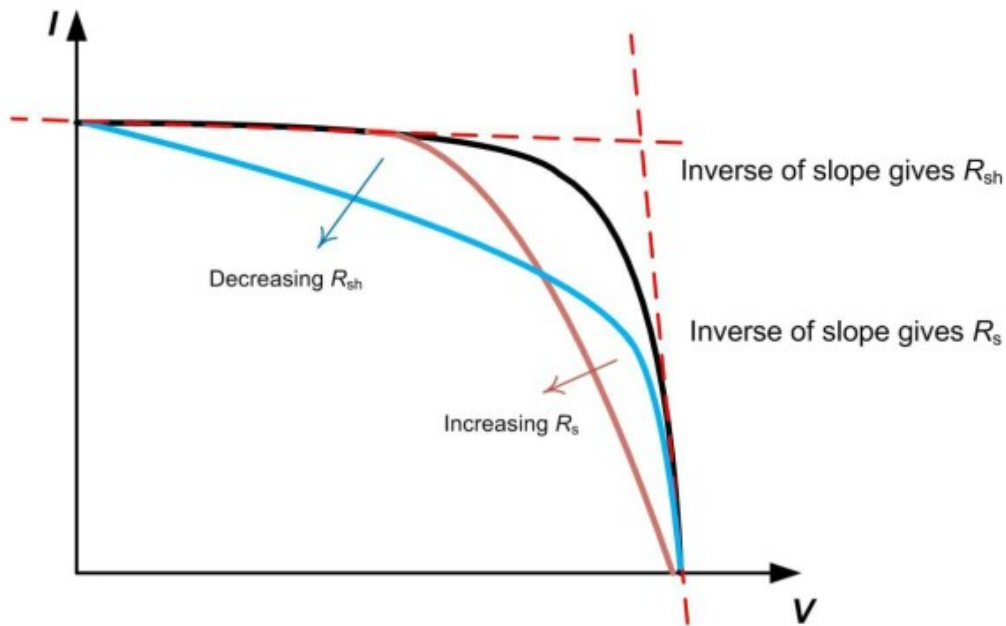


Source: Köntges *et al.*, (2014, p. 27).

This relationship between voltage and current values allows faults to be identified in a PV module or set. This curve can be calculated in the laboratory and field environments (KOESTER *et al.*, 2022; KÖNTGES *et al.*, 2014). This relationship changes according to possible faults that are occurring in the PV.

To better understand the changes the curve may undergo depending on the defect, it is necessary to define the solar cell's parallel resistance (R_{sh}) and the series resistance (R_s). These resistances help visualize the intersection of the straight lines drawn on the current and voltage curve (KÖNTGES *et al.*, 2014). For better visualization, Figure 3 shows a schematic of the influence of these resistances on the I-V curve.

Figure 3 - Schematic of the I-V curve of an illuminated module and the influence of series and parallel resistances on the I-V curve.



Source: Köntges *et al.*, (2014, p. 28).

Series resistance is a concentrated factor, where this concentrated series resistance means that all series resistances of a PV influence this value. It will have an increased value if the series resistance value of the module increases, which may cause problems in individual cells. Parallel resistance cannot be detected in a single cell, as the other cells block this detection. Parallel resistance influences the short-circuit and open-circuit current mainly when a hot spot effect occurs in the module (KÖNTGES *et al.*, 2014).

Even though this method is widely applied, its main problem is that it does not allow to accurately identify where a fault is occurring (ABDULMAWJOOD; REFAAT; MORSI, 2018; TSANAKAS, John A.; HA; BUERHOP, 2016). Because of this, other techniques must be used in conjunction with the voltage and current technique to verify more accurately where a fault occurs.

2.2.2 Inspection by Images

Due to the shortcomings of electrical parameter inspection, an efficient solution for inspecting large solar plants is using images that allow viewing of the PV structure (KOESTER *et al.*, 2022). When capturing PV images, only visible spectrum images (human eye) may not be sufficient due to the characteristics of the PV. Thus, in addition

to visible spectrum images, sensors can capture infrared spectrum images (TSANAKAS, John A.; HA; BUERHOP, 2016).

In conjunction with image acquisition, the PV can also be excited to emit light of specific wavelengths, thus allowing the capture of images with important information from a PV (ABDULMAWJOOD; REFAAT; MORSI, 2018; KOESTER *et al.*, 2022; KÖNTGES *et al.*, 2014).

Therefore, in the following subsections, the methods for inspecting solar plants through images will be detailed, whereas in subsection 2.2.2.1, the visual spectrum inspection will be detailed. In subsection 2.2.2.2, the infrared thermographic inspection will be explored. These first two methods do not require the PV panel to be excited to conduct the inspection. In this way, in section 2.2.2.3, the Ultraviolet Fluorescence Inspection will be detailed, a method where an excitation of the PV panel is necessary.

2.2.2.1 Visual Spectrum Inspection

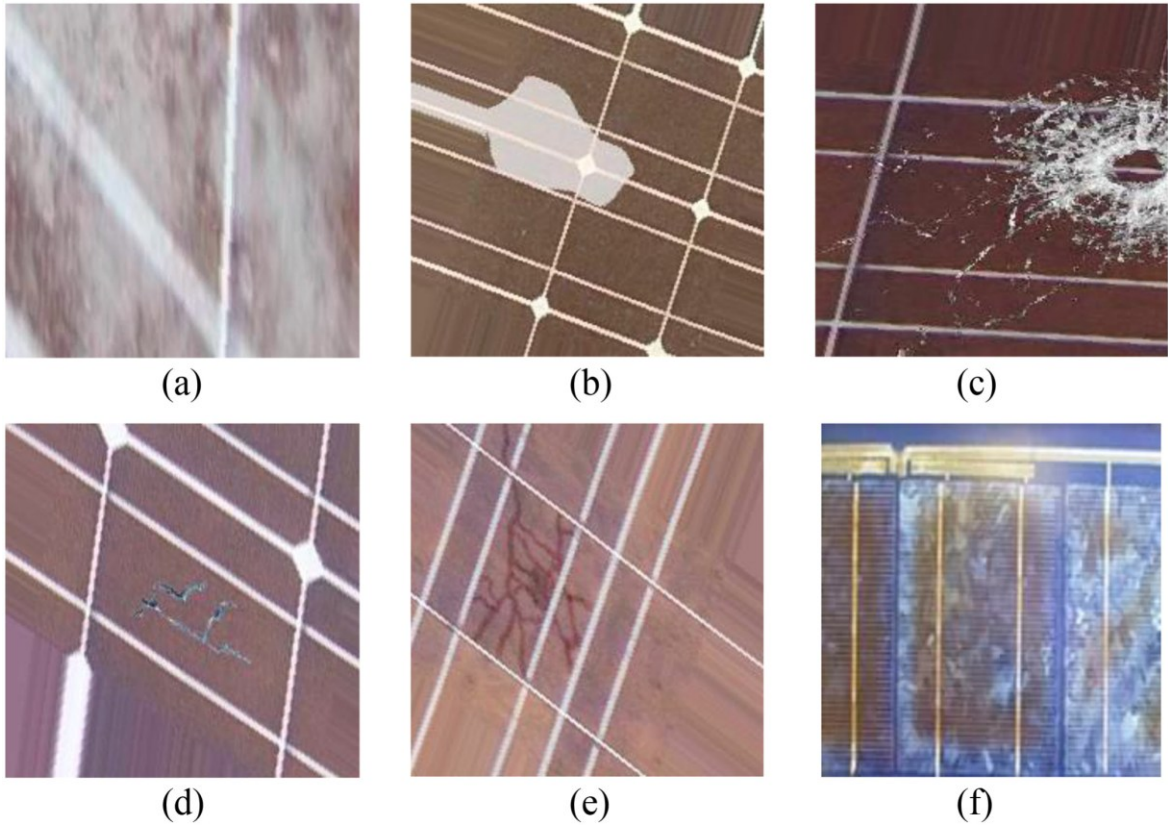
Inspection in the visible spectrum, which human eyes can carry out, is the first and most classic inspection carried out (ABDULMAWJOOD; REFAAT; MORSI, 2018; KOESTER *et al.*, 2022; KÖNTGES *et al.*, 2014). This inspection involves a specialized professional searching for defects visible to the naked eye through the solar plant.

This type of inspection can identify defects and failures such as discoloration, dirt accumulation, shading, obstruction by bushes, and cracks, among others (KÖNTGES *et al.*, 2014). For better exemplification, Figure 4 and Figure 5 show some defects and failures found in solar plants in the visible spectrum.

Even though this technique is simple, it becomes dangerous and time-consuming in large solar or rooftop plants. Therefore, techniques that benefit from inspection through the visible spectrum can facilitate and optimize this type of inspection. One such technique is using photographic cameras on the ground or attached to a Unnamed Aerial Vehicle (UAV). The same defects or faults the human eye finds can be identified with photographic cameras. In addition, this collection allows for the generation of a history of inspections performed.

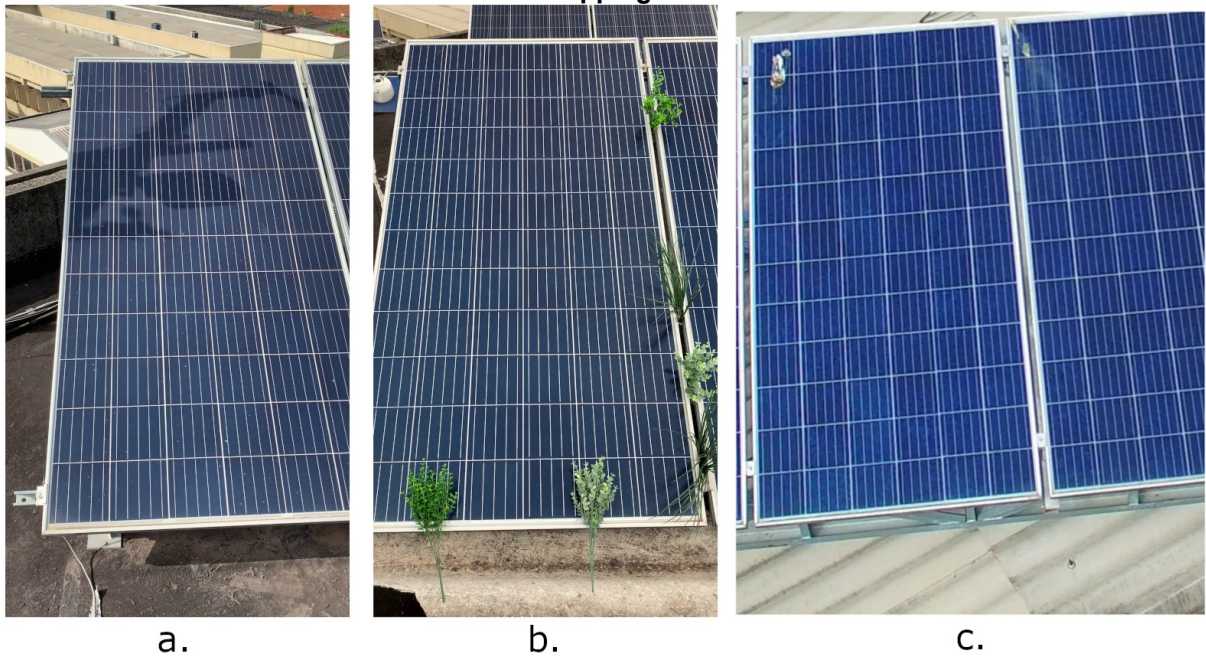
Nevertheless, using RGB cameras to capture photographs of visible spectrum faults that can occur, more than the capture of these photographs could be required. As a significant volume of images is captured, computational algorithms are needed to process these images (BERGHOUT *et al.*, 2021; STARZYŃSKI; ZAWADZKI; HARAŃCZYK, 2022).

Figure 4 - Different forms of defects and visible failures in PV, being, (a) dirt shading, (b) encapsulation delamination, (c) broken glass, (d) corrosion, (e) snail trail and (f) yellowing.



Source: LI, Xiaoxia et al., (2020a, p. 570).

Figure 5 - Faults that can be found in PV, being a. shading, b. obstruction by bushes and c. bird droppings.



Source: Own authorship (2024)

Another detail is that more than the visual spectrum image is needed to identify all the problems that can be identified in a PV module. With this, other portions of the spectrum can be used, as is the case of the infrared spectrum, which allows tracing a thermal profile of the PV panel to identify some faults.

2.2.2.2 Infrared Thermograph Inspection

Infrared thermography (IRT) is a PV inspection technique that allows for identifying multiple defects with a single tool (BUERHOP *et al.*, 2022). This tool allows for correlating faults found in the visible spectrum and the I-V curve (TSANAKAS, John A.; HA; BUERHOP, 2016).

Thermography inspection uses an infrared spectrum camera (7 μm to 14 μm) to identify anomalies in the PV through temperature. This inspection identifies hot spots in the PV, showing a non-uniformity in the plate temperature, which may indicate a defect or failure (JAHN *et al.*, 2018).

Table 1 presents the relationship between failure, thermographic image, and I-V curve for a better explanation. With this comparison, problems in the PV can be identified in a non-intrusive way. In the thermographic image the red color indicates the fault occurring in that PV panel.

Table 1 - Some faults identified through IRT and their relationship with the I-V curve
(continue)

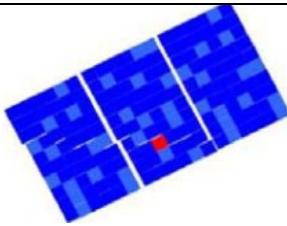
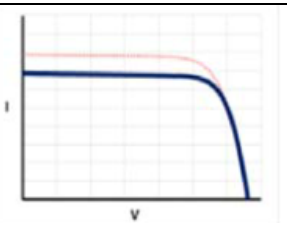
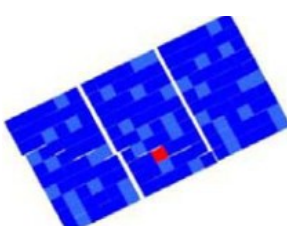
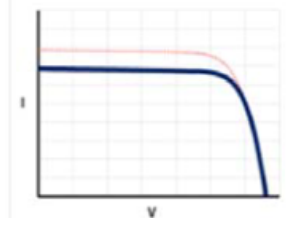
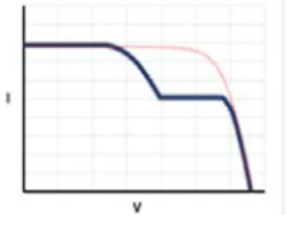
Fault Type	IRT Pattern	I-V Pattern
Optical degradation		
Broken cells, micro cracks, snail trails		 

Table 2 - Some faults identified through IRT and their relationship with the I-V curve
(continue)

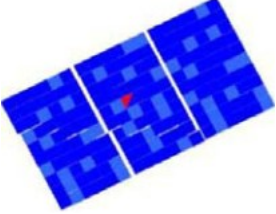
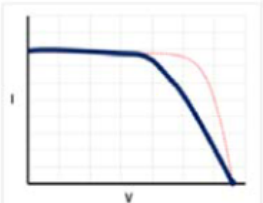
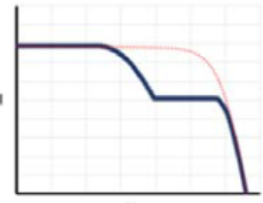
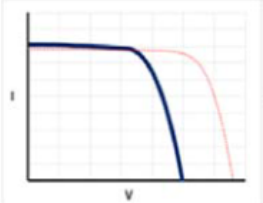
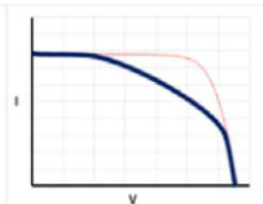
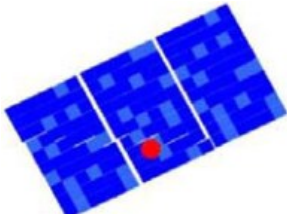
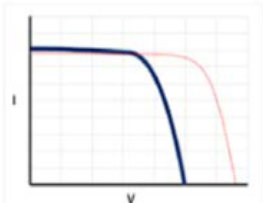
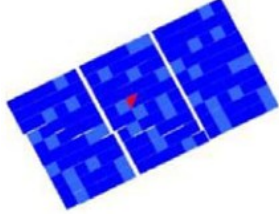
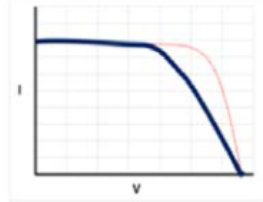
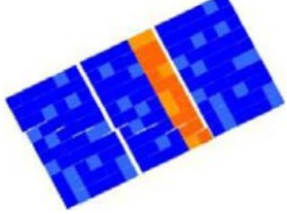
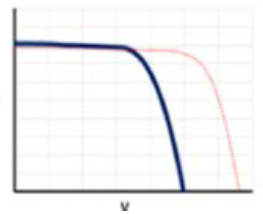
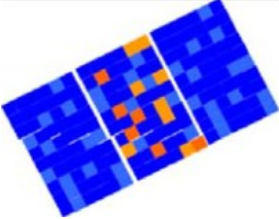
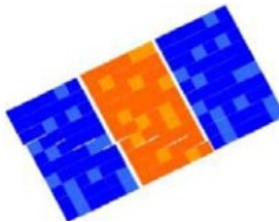
Fault Type	IRT Pattern	I-V Pattern
Broken cell – lack of material in the cell		 
Potential Induced Degradation (PID)		 
Short-circuited cell; shading		
Broken interconnector; Failed soldering		
Internal short circuit; Substring with open and defective bypass diode		

Table 3 - Some faults identified through IRT and their relationship with the I-V curve

Fault Type	IRT Pattern	I-V Pattern
All bypass diodes short-circuited; Wrong connection		N/A
Module disconnected		N/A

Source: Adapted from TSANAKAS; HA; BUERHOP, (2016, p. 707)

This technique can identify a wide range of defects and failures by analyzing this correlation table. However, since it is a technique that uses images if collected manually, it may be inefficient. Thus, UAVs can speed up this task and bring faster results (GALLARDO-SAAVEDRA; HERNÁNDEZ-CALLEJO; DUQUE-PEREZ, 2018).

The Figure 6 to Figure 8 present some examples of real faults that can occur because of partial shading. The Figure 6 showed a problem that grown grass can cause in the PV module, where the PV cell with the partial shadow is hotter than the hole panel. In order to avoid this type of problem, the grass must be pruned regularly. Considering the Figure 7 and Figure 8, it is possible to verify that the partial shadows are caused by inadequate installation planning, where wires cross the PV modules in the Figure 7. In the Figure 8, it is observed that one module causes the shadow in the other module, whereas in both cases, this partial shading causes multiple hotspots in the PV modules.

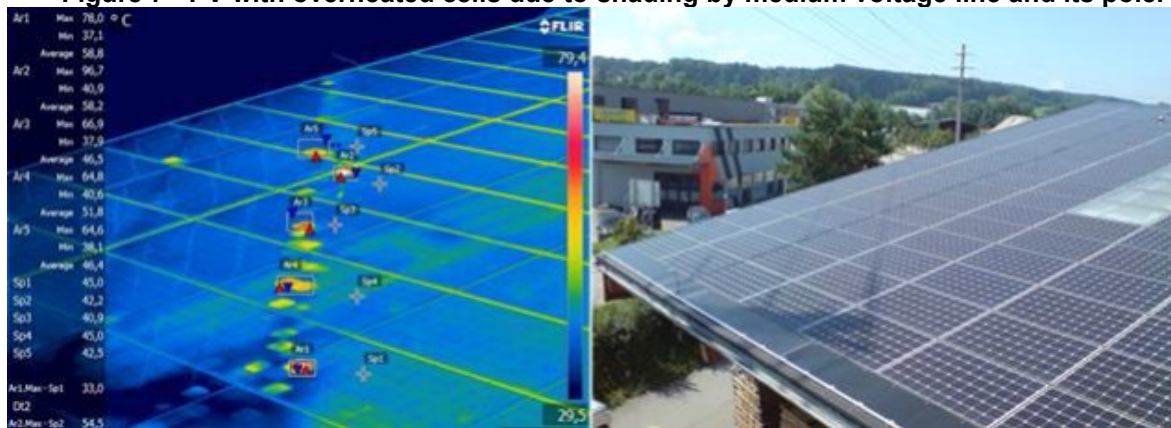
Another factor that must be considered when using UAVs is the resolution of the camera that will be used. For example, Figure 9 shows a capture of a thermographic camera with a resolution of 80×60 pixels compared to an RGB camera. This resolution must be sufficient to identify defects and cover the PV area to optimize the flight performed (GALLARDO-SAAVEDRA; HERNÁNDEZ-CALLEJO; DUQUE-PEREZ, 2018).

Figure 6 - PV with overheated cells due to shading by shrubs.



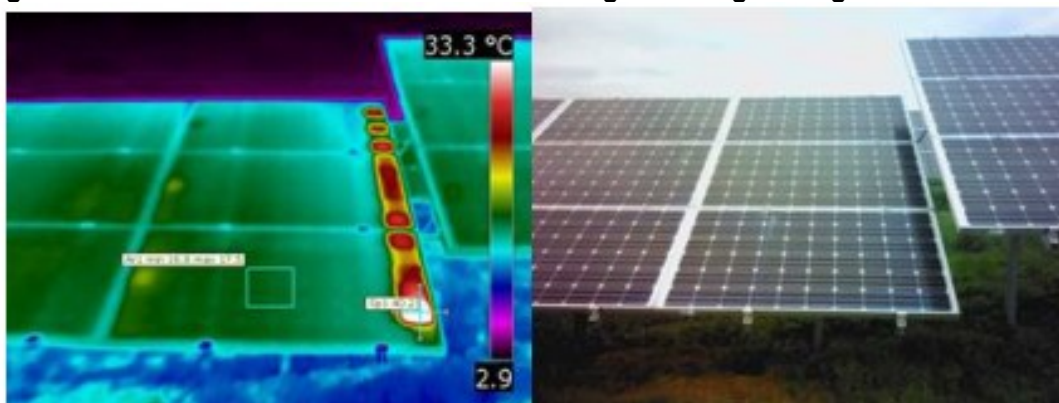
Source: JAHN et al., (2018, p. 39)

Figure 7 - PV with overheated cells due to shading by medium voltage line and its pole.



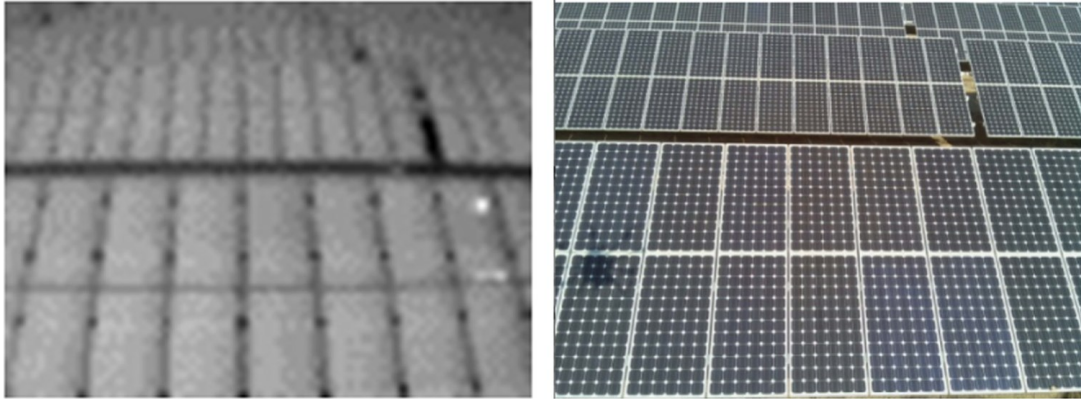
Source: JAHN et al., (2018, p. 39)

Figure 8 - PV with overheated cells due to shading from neighboring PVs.



Source: JAHN et al., (2018, p. 40)

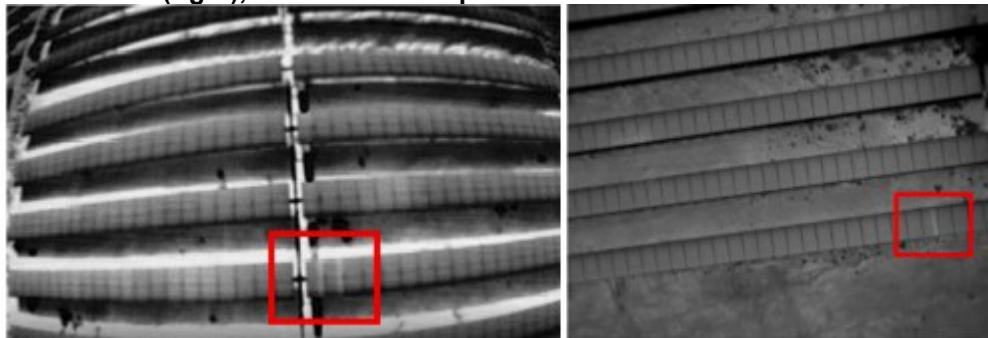
Figure 9 - IRT image (left image) captured from a 10 MW plant located in Spain with 80×60 pixel resolution sensor compared to an RGB image (right).



Source: GALLARDO-SAAVEDRA; HERNÁNDEZ-CALLEJO; DUQUE-PEREZ, (2018, p. 568)

An example of this analysis is the work developed by Kirsten Vidal de Oliveira, Aghaei e Rütther (2020), in which an extensive analysis was carried out comparing a UAV that had its RGB camera removed to install a low-cost thermal camera with a resolution of 640×480 pixels and a fisheye aspect (system 1) with a commercial UAV with a thermal camera with a resolution of 640×512 pixels and 12 Mpixel RGB attached (system 2). Figure 10 shows an example of a thermographic image from each system, The r. Regarding values, system 1 costs US\$6,000 and system 2 US\$15,000.

Figure 10 - Comparison of a disconnected subarray image between system 1 (left) and system 2 (right), where the red square shows the identified fault.



Source: KIRSTEN VIDAL DE OLIVEIRA; AGHAEI; RÜTHER, (2020, p. 717)

In this analysis, the two UAV systems were compared in terms of inspection time and flight height. For the 31.2 MW plant, system 1 flew at a height of 20 meters, requiring seven days and two people for the inspection. With system 2, the flight was carried out at a height of 30 meters, taking four days to be completed with two people. For these inspections, the information processing was carried out after the flight (post-processing) (KIRSTEN VIDAL DE OLIVEIRA; AGHAEI; RÜTHER, 2020).

Kirsten also performed real-time analysis with system 1 for a 36.7 MW plant, which took nine days and four people to complete. In this approach, when an error was

found, a pause was made on the fault found for immediate analysis, proving less efficient than post-flight analysis (KIRSTEN VIDAL DE OLIVEIRA; AGHAEI; RÜTHER, 2020).

However, this is a significant challenge since the higher the resolution, the more expensive the sensors are (over R\$80,000), which can make using this tool unfeasible. In the work developed by Kirsten, the difference in cost between the systems is ~60%. Even though System 2 is faster and more accurate, as System 1 is modified, it can be seen that the development of UAVs with thermal cameras can be optimized and their cost reduced.

Furthermore, even with this tool, the volume of images collected will be significant, and their manual analysis by a specialized professional can be time-consuming. Therefore, computational algorithms can optimize information collection from the captured images, significantly improving the results obtained by this technique (TSANAKAS, John A.; HA; BUERHOP, 2016).

However, sometimes, the inspection with thermography could not be sufficient to identify all the defects that can occur in the PV module. This way, some methods can excite the PV panel to inspect the PV cell structure in search of problems with the structure of the PV cell. One example of this type of inspection is the ultraviolet fluorescence inspection.

2.2.2.3 Ultraviolet Fluorescence Inspection

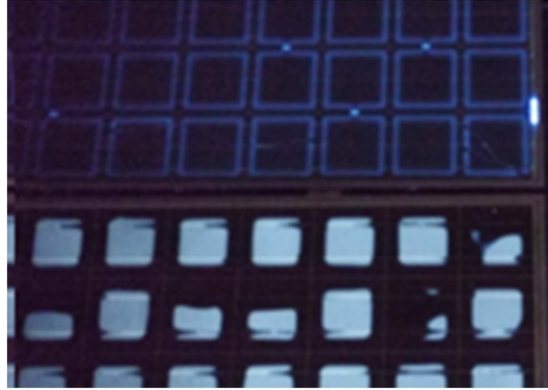
In the UVF inspection, a UV light source with a wavelength between 350 and 380 nm is required. When emitting this UV light on the PV, it will emit light with a wavelength between 400 nm and 700 nm (KONTGES *et al.*, 2020). By default, this inspection is performed at night to have better PV fluorescence contrast and to avoid needing a high-power light source (GILLELAND; HOBBS; RICHARDSON, 2019).

This UVF inspection is not possible on newly installed modules. For this light emission to occur with a sufficient fluorescence signal, the PV must have been exposed to a UV light source (in this case, the sun) with a dose of 80 kWh/m², which is equivalent to approximately 1.5 years of exposure in Germany (KÖNTGES *et al.*, 2014).

Another detail is the type of pattern that will form in a healthy cell after the emission of the UV light source. This pattern depends on the encapsulation material.

Two patterns can be identified, one being the square pattern and the other a ring pattern. Figure 11 shows an example of each of these patterns.

Figure 11 - Top image with ring pattern with sun exposure for one year, and bottom figure with square pattern with exposure for 4 years.



Source: KONTGES et al., (2020, p. 620)

The UV light source directly influences the contrast of the fluorescence image that will be captured. For example, Figure 12 shows three UVF samples collected with two light sources and two narrow-band filters. The Xenon light source is a professional camera flash with the Xenon tube changed to one that emits UV light. The LED source emits light at 365 nm with 3 W of power. In this image, the ZWB1 filter peaks at 361 nm with an output of 0.1% at 400 nm and 9.1% at 700 nm. The ZWB2 filter peaks at 372 nm, with 35 at 400 nm and 0.4% at 700 nm (GILLELAND; HOBBS; RICHARDSON, 2019).

Figure 12 - Same cell with three different types of UV illumination. Xenon flash with ZWB1 filter on the left, xenon flash with ZWB2 filter in the middle and 365 nm LED flashlight with ZWB2 filter in the right.



Source: GILLELAND; HOBBS; RICHARDSON, (2019, p. 2580)

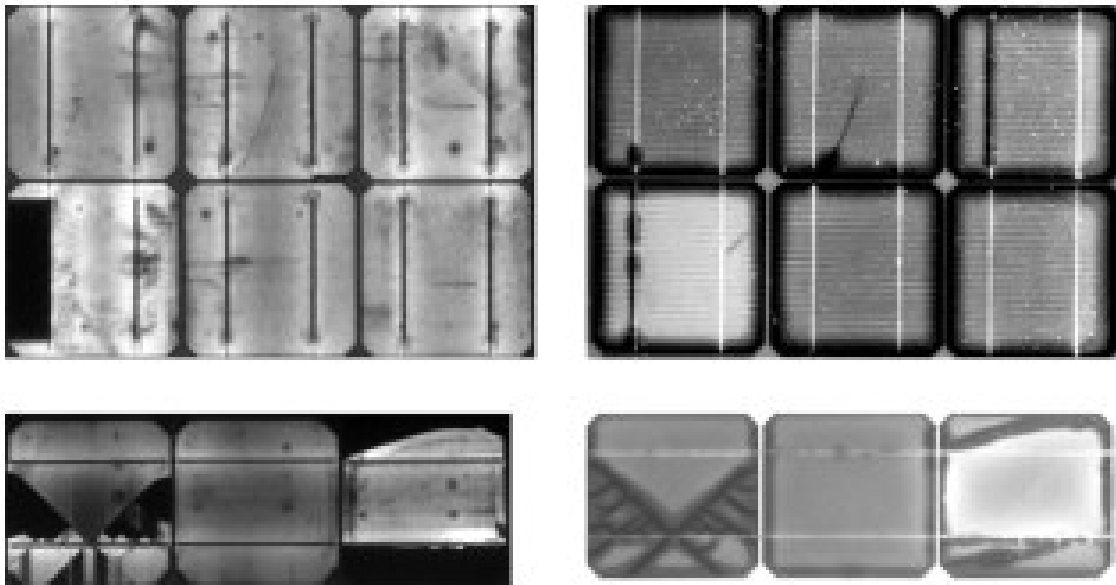
In this comparison between the different types of light and filters used, the image with 365 nm LED has the best contrast. Even so, due to the power of the light source, Gilleland used the Xenon light source with a ZWB1 filter because this filter

better rejects 400 nm and this is important to the UV light not interfere in the fluorescence analysis.

This analysis of PV by UVF aims mainly to identify broken cells, even making it possible to verify whether the crack found is recent or not. Since UVF is usually used to find structural faults in PV cells, it is generally compared to electroluminescence (EL) images with the same objective. However, obtaining an EL image is more complex than a UVF image because it requires a current source connected to the PV module and a specific camera to capture images in the 1150 nm wavelength (JAHN *et al.*, 2018).

Figure 13 shows the same set of cells photographed with EL and UVF images. This image contains healthy cells and cells with cracks, one of the most common defects found with the UVF method. This comparison makes it possible to verify that the UVF image is an excellent starting point for identifying defects in PV cells. Therefore, if necessary, after applying UVF, an EL image can be captured on a PV that has had problems identified with the UVF technique. Thus, performing an EL inspection on the entire solar plant is unnecessary.

Figure 13 - Left EL images of cell with inactive parts. Right UVF images of the same module.

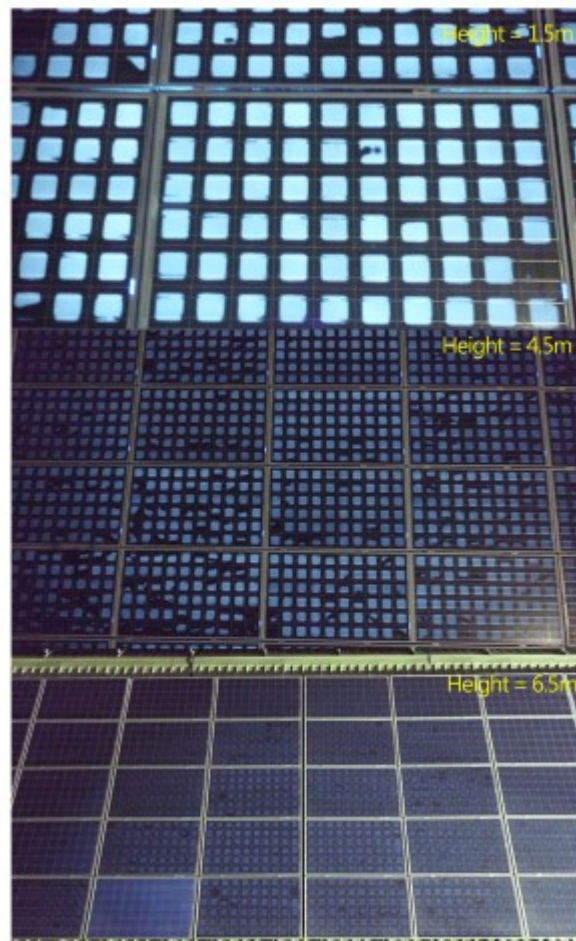


Source: KONTGES *et al.*, (2020, p. 628)

In the literature, it is possible to find several works that benefit from UVF to identify defects in PV and relate them to other inspection techniques, such as EL and IRT (GILLELAND; HOBBS; RICHARDSON, 2019; KONTGES *et al.*, 2020).

The work done by KONTGES et al., (2020) provides a detailed review of the use of the UVF technique. In this review, the authors detail how the inspection should be carried out and what patterns can be formed in the UVF image according to a photovoltaic cell's operation or damage. One of the inspections shown by the authors uses a UAV. In this inspection, a light source with three 20 W LEDs was used, but it is not detailed at which wavelength. For this to be possible, the authors emphasize that a commercial and low-cost drone must be used; the pilot must have little experience, a stable aircraft for night photography, and a low-noise camera and support for carrying a UV lamp. Meeting these requirements, the authors carried out tests at different flight heights, where the height of 4.5 m proved to be the most efficient, allowing the inspection of 720 modules per hour. This difference in details according to the flight height can be seen in Figure 14.

Figure 14 - UVF images captured at various height levels.



Source: KONTGES et al., (2020, p. 631)

In addition to UAV inspection, ground-based inspections can also be performed. The authors Gilleand, Hobbs and Richardson (2019) show the assembly of

a device that the operator can carry for ~1000 modules per hour. This device weighs 4 kg and costs US\$3500. This proposed methodology used a xenon lamp with a filter to pass the UV band and reject the visible light band. Even with this lamp being used, the authors demonstrate that a 365 nm LED light source allows the acquisition of images with better contrast. In addition to developing the acquisition tool, these authors use AI algorithms to detect cracks in PV cells, obtaining an accuracy of 91.7%. The developed algorithms, including some captured images, were made available to the scientific community.

However, as said previously, only the capture of images is not desired because of the volume of images generated in each inspection. Considering this, computational algorithms can automatically classify the captured images to make the inspection process more robust and precise.

2.3 Use of Computational Algorithms in the Photovoltaic Panel Inspection

The methods presented for PV inspection typically generate a large volume of data. For this reason, human analysis can be complex, time-consuming, and subject to failure (HØIAAS *et al.*, 2022).

To improve the inspection techniques presented, computational algorithms can be used. These algorithms improve the collected data, extract points of interest, and classify according to the information found (GAVIRIA *et al.*, 2022; LI, B. *et al.*, 2021).

Here, we will discuss techniques involving image processing since this is the focus of the work. It is worth noting that computational algorithms are also used in voltage and current analysis.

2.3.1 Traditional Image Processing Methods

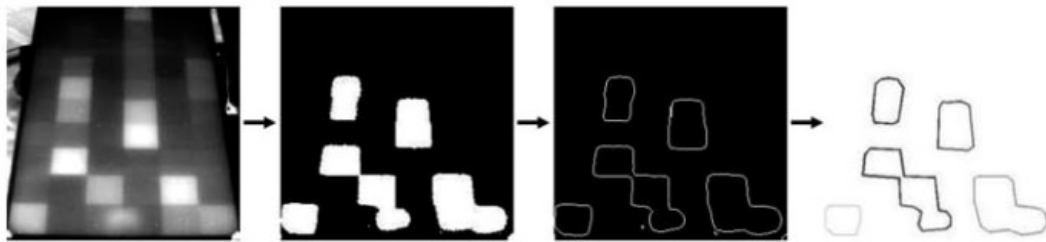
The area of digital image processing (DIP) is widely used to extract information from images. These DIP techniques improve the image by removing noise, enhancing colors, and extracting points of interest, among other processes that can be performed on any image (ARCHANA; JEEVARAJ, 2024).

For example, the authors Patel, Mclauchlan and Mehrubeoglu (2020) used traditional image processing techniques to identify damaged PVs in visible spectrum images. Even though the results were positive, this type of technique may have its

performance impaired by reflections, shadows, and other details that could be more interesting and cause classification errors. Even though this technique is interesting, it may need help in identifying PV panel defects when used alone. Since these techniques are not advanced, they are subject to classification errors or suffer from lighting differences (PATEL; MCLAUCHLAN; MEHRUBEOGLU, 2020).

Another example of work using traditional DIP techniques is presented by Tsanakas et al., (2015), who use the Canny filter to detect hot spots in thermographic images. The Canny filter is used to find edges in images. Figure 15 shows a processing result using the Canny filter, where the first image (the left image) shows the original image, the second image shows the pixel segmentation, the third image the result from the Canny filter and finally in the last image inversion to only shows the contours of hot PV cells. Even though the result is positive, the author mentions that this technique indicates false positives because it is susceptible to slight variations in the image's gray level (TSANAKAS, J.A. *et al.*, 2015).

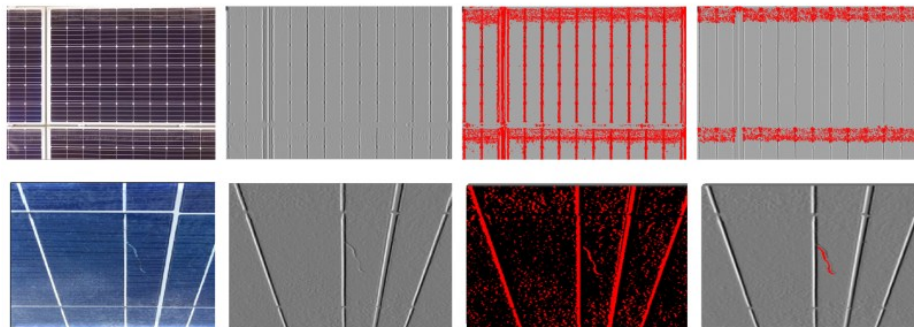
Figure 15 - Result of Canny edge detector and edge map.



Source: Adapted from TSANAKAS, J.A. *et al.*, (2015, p. 386)

Also using edge detection, Li, et al., (2017) used DIP to process images captured by UAVs. The authors mention that the technique allows the inspection of large solar plants quickly and accurately. Figure 16 shows an example of faults identified by Li.

Figure 16 - Image processing to identify different types of defects using edge detection.



Source: Adapted from LI, Xiaoxia et al., (2017a, p. 1243)

One algorithm that can be used in UVF inspection to enhance the image because of the night capture is the contrast-limited adaptive histogram equalization (CLAHE). This algorithm makes a limited equalization of the image's histogram to adjust the pixel intensity distribution and was used for medical images. However, it can be used as a general enhancement of the method to make the contrast of the image more visual (ARCHANA; JEEVARAJ, 2024; PIZER *et al.*, 1987).

Nevertheless, processing the whole image of PV panels is not desired. With this, a region of interest (ROI) must be defined and contain only the PV panels (PATEL; MCLAUCHLAN; MEHRUBEOGLU, 2020). In order to achieve this, segmentation algorithms can be applied in the image to segment only the ROI.

There are multiple methods of image segmentation. For example, methods with edge detection of the images can be used to segment the ROI. Another method is region division, where thresholding algorithms segment the image based on an input threshold (ARCHANA; JEEVARAJ, 2024).

However, more than these algorithms are required to understand more complex images, and because of this, more advanced algorithms are needed. Considering this, more advanced algorithms can be applied to have a more robust response, which is the case with artificial intelligence algorithms.

2.3.2 Artificial Intelligence Algorithms

In order to complement DIP techniques, the use of AI can help in better feature extraction and be more accurate in classifying previously defined defects. There are several techniques in this area, with the DL technique with CNN being widely used in recent works using images (SARKER, 2021).

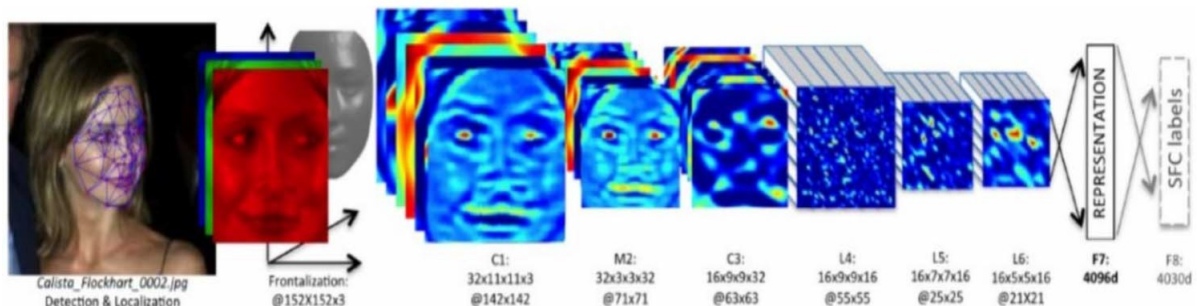
When we talk about AI, we initially think of Artificial Neural Networks (ANN), an AI algorithm that imitates the human brain's neurons (WEI *et al.*, 1998). This algorithm is well-known and used to solve various PV problems (LI, B. *et al.*, 2021).

However, ANN can only solve a few complex problems (ALBAWI; MOHAMMED; AL-ZAWI, 2017). Thus, more advanced techniques were developed to solve more significant problems using AI. One of these techniques is DL, which is explored in the following subsection.

2.3.2.1 Deep Learning

DL refers to a neural network with multiple layers. CNN is among the most popular DNNs (ALBAWI; MOHAMMED; AL-ZAWI, 2017). These consist of several layers of convolutions of the images to extract features from them. Each convolution filters the image to extract features from the submitted image (ALBAWI; MOHAMMED; AL-ZAWI, 2017). For better visualization, Figure 17 shows the result of several convolution layers. These features are the information that will be inserted into the neural network so that the image can be classified.

Figure 17 - Visualization of deep neural network convolution layers.



Source: ALBAWI; MOHAMMED; AL-ZAWI, (2017)

Thus, to build a CNN model, it must have several layers of convolutions to extract as much helpful information as possible. These convolutions also cannot be exaggerated or have a large size, as this can negatively impact the network. At the end of the CNN is a layer known as fully connected. This layer is responsible for classifying the image and contains the neurons with the weights that decide whether an image is of class X or Y, where this layer resembles a traditional ANN (ALBAWI; MOHAMMED; AL-ZAWI, 2017).

For further clarification, Figure 19 represents three CNN structures used in PV problems. In these three structures, it can be seen that each one has a set of convolutions with different filters (their sizes), number of layers, and layer structure.

One way to evaluate the performance of CNN is the use of the accuracy metric. To make que evaluation of the CNN by this metric, the confusion matrix is used to define if the trained CNN model is performing correctly, where this matrix compares the predictions made by the CNN model and the actual predictions that is expected. As an example, consider the Figure 18 as a confusion matrix of a binary classification. In this binary confusion matrix, it can be seen that the diagonal of the matrix is constituted of true positive (TP) and true negative (TN) results. The TP means that the

model predicted correctly the positive class of and the TN that the model predicted correctly the negative class. If the matrix only has values on the diagonal, the model makes all the predictions correctly. Otherwise, if the matrix has values in the false negative (FN) and false positive (FP) region, the model is not performing perfectly. These miss classifications occur when the evaluated instance is classified as FN instead of TP or the evaluated instance is classified as FP instead of TN. All the classifications outside the diagonal are not desired (ENCORD, 2023).

Figure 18 - Example of confusion matrix for a binary classification,
Predicted

Actual	Predicted	
	Positive	Negative
Positive	TP	FN
Negative	FP	TN

Source: Own authorship (2024)

Now if the explanation of the confusion matrix, to understand what the TP, FN, FP and TN are, it can be used the Equation 1 to calculate the accuracy of a CNN model (ENCORD, 2023):

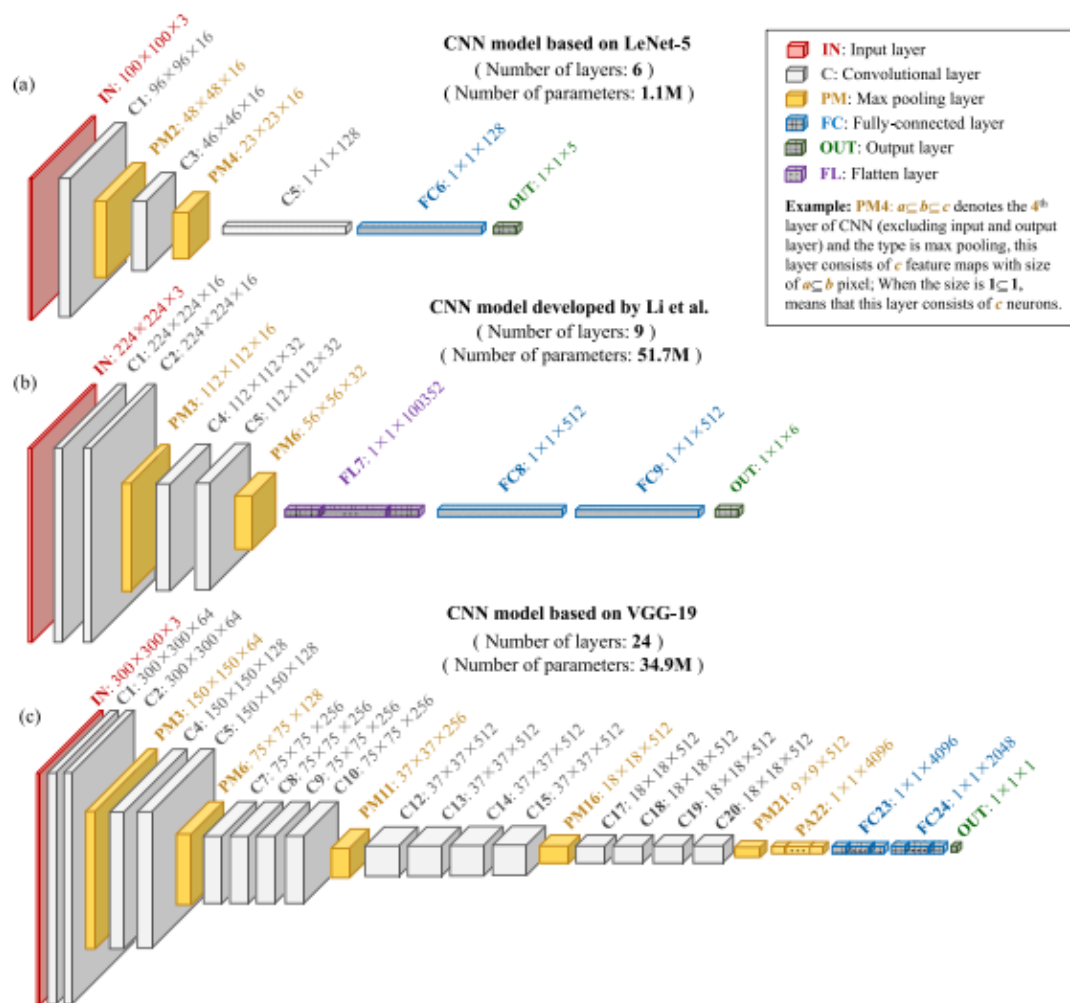
$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

The accuracy metric is commonly used to give the first look at the performance of the model for the problem in question. The values of accuracy are given in percentage, are 100% is the maximum value.

In the literature, it is possible to find several works that use DNN to solve problems with PV images. Regarding the determination of panels covered by dirt, Wang et al. (2022) propose a system with wireless communication to decide when to clean a panel in real time. For this, images are used, and dust accumulation is analyzed based on size per unit area. This information is used in conjunction with environmental and electrical data. The collection of information, including images, is carried out every three minutes, and this is the dataset used, but without details of its size. For classification, the authors tested several types of CNN model Resnet, where Resnet34 offered the best result, with an accuracy of 85.12%. Regarding the use of DNN, the review of articles presented by Li et al. (2021) shows a range of works using DL techniques to identify defects in solar panels. This review mentions two works regarding using DNN with visible spectrum images. One of them considers images of panel cells, using an unbalanced dataset with 21,445 images, proposing a CNN with

101.2M parameters to classify six types of defects and cells without defects, reaching an average accuracy of 94.3% (CHEN *et al.*, 2020). The other work cited proposed a CNN with 51.7M parameters to identify faults in photovoltaic modules, using a balanced dataset with 8,400 images that, according to the example given in the article, are of defective parts of the panel, considering five types of faults and panels without faults. These authors perform an in-depth analysis of the proposed CNN, the influence of dataset size and accuracy, and compare their model with VGG16 pre-trained with ImageNet data. In this comparison, VGG16 presented an average accuracy of 73.88%, while the proposed CNN presented 97.9% (LI, Xiaoxia *et al.*, 2019). Neither work mentions testing the models running on an embedded system under real test conditions.

Figure 19 - Examples of CNN architectures used to address PV classification problems.



Source: LI, B. et al., (2021, p. 11)

The work of Rico Espinosa, Bressan and Giraldo (2020) proposes the development of a CNN to identify flaws in panels from RGB images, considering the

following classes: cracks, shadow, dirt, and no flaws. In addition to classification, these authors performed semantic segmentation using CNN to extract only the solar panels from the image. The authors performed a binary classification test (with/without flaws) with the four classes to test the developed CNN. In the binary test, the average accuracy value of this network was 71.53%, and the average F1 was 73%. In classifying the four classes, the authors report that up to 70% accuracy is obtained.

Cao et al., (2021) propose a network specifically addressing the level of dirt on a panel. This proposed model presented an accuracy of 82.4% compared to a Resnet50, which presented an accuracy of 80.1%. The images presented in the article show a cell with dirt deposits and not the entire panel. Since the proposed network is simple, the authors state that it can be embedded but that new optimizations will be made.

To automatically identify bird droppings, researchers Moradi Sizkouhi et al., (2022) propose an autonomous aerial system with an embedded system for image processing. Feature extraction is used by modified VGG-16 to generate image maps and masks. With this system, it was possible to make predictions with an accuracy of 93.33%, but exclusively for detecting bird droppings in PV.

Naveen Venkatesh and Sugumaran (2021) use the VGG16 network pre-trained with ImageNet database data to identify lamination, burn marks, discoloration, broken glass, and snail trails in aerial images. In this work, the authors used data augmentation to improve the training of the classification layer and obtained 95.40% accuracy in validation.

Li et al., (2020a) present a solution with algorithms for detecting six visible defects: dirt shading, lamination shading, broken glass, connection corrosion, snail trail, and yellowing. The proposed algorithm is divided into three stages: the first identifies anomalous regions, the second uses DNN to extract features, and the third uses a Support Vector Machine (SVM) to classify the defects found. For classification, these images are sent to a high-performance computer, which makes massive and remote use of the proposal difficult. The solution presented an average accuracy among the defect classes of 98%. The authors compared it with other methodologies that presented inferior results, such as the pre-trained VGG-16, which provided an average accuracy of 64.84%. Not many details of the dataset are provided; only in the cross-validation stage is it reported that 126 images were used.

For dust detection in PV modules, Mohammed and Baalawi (2024) employed an algorithm to emphasize the dirty location. A CNN based on the EfficientNet model was developed to make the classification. These authors used multiple public datasets that can be found on the web. This methodology achieved up to 98% accuracy in detecting dirt in PV modules.

Also, with inspection in the visual spectrum, Kaur et al., (2024) used the VGG16 model to identify five types of faults in PV panels and one class of clean PV, where these faults are bird-drop, dusty, electrical-damage, physical-damage, and snow-covered. The training process used 885 images from an augmented Kaggle dataset. With this setup, an accuracy of 86% was obtained.

To classify six types of soiling in PV panels, Chaki et al. (2024) proposed a CNN to make this classification. It was used 34460 images for the training process, where for the training it was used a Mac Air M1 where an accuracy of 96.61% was reached for the classification of the six classes. With this computer, it was necessary 146 ms to infer an image.

It works not only with CNN in the visual spectrum but also with this type of algorithm found for the infrared spectrum. For example, the work done by Wang et al., (2024) proposes a high-resolution image dataset with IRT images with 5579 images. This dataset was tested in several CNN algorithms, and the accuracy ranges between 83% and 93.32%, where the Coat model obtained the best accuracy. In order to train and evaluate the networks, an Nvidia RTX 4080 with 16 GB was used.

Also, using CNN and IRT images, Manno et al., (2021) proposed four CNN models and tested multiple preprocessing techniques to enhance the IRT image. It collected 4000 images between UAV and ground images. The proposed CNN achieved 100% accuracy in the collected dataset.

Huerta Herraiz, Pliego Marugán and García Márquez, (2020) proposed a CNN for the segmentation and classification of IRT images from solar trackers to identify these images' hot spots. The authors used UAV images, achieving an accuracy of 99.02% with the CNN proposed. In this work, the authors used the GPS position of the UAV to estimate the geolocation of the hot spot.

As can be seen, multiple works use images directly or segmentation algorithms to classify ROI. The development of these segmentation algorithms can be complex. Another way to only consider the ROI in the image is the object detection technique. Taking this in consideration, one algorithm that has stood out for the object detection

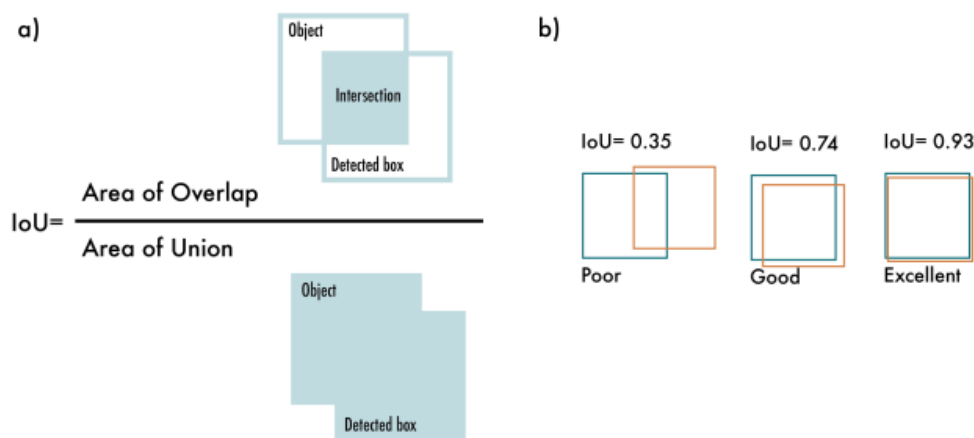
and classification of images was the You Only Look Once known as YOLO (REDMON *et al.*, 2015) .

The YOLO algorithm is a neural network that looks at an image only once and, using bounding boxes and class probabilities, makes regions in the image (REDMON *et al.*, 2015), as seen in the Figure 22. The YOLO is a single network, so it can be optimized to make detection and classification very fast (REDMON *et al.*, 2015)—the idea of how the YOLO works can be seen in the Figure 23. The figure shows that the input image is resized to be inputted in the CNN. After that, the results are thresholded by the model confidence to say if the detection object is from the class X or Y, for example, and because of the characteristics of the YOLO, the detection and prediction is speedy, with up to 150 frames per second (FPS) in the detection (REDMON *et al.*, 2015).

Several YOLO versions are available. In this comparison presented in Figure 24, we can see that from multiple YOLO versions, the YOLOv5 is the smallest and fastest and can achieve good mean average precision (mAP).

As can be seen, the YOLO is not evaluated by the accuracy metric. To calculate the mAP metric, some terms need to be clarified. First, as the YOLO predict bounding boxes to make que object detection, it is used the Intersection over Union (IoU) metric. The IoU is used to evaluate if the predicted bounding box is close to the ground truth box. For better understanding, consider the Figure 20 (SHAH, 2022; TERVEN; CÓRDOVA-ESPARZA; ROMERO-GONZÁLEZ, 2023).

Figure 20 - IoU example, where a) indicated how the IoU is calculated and b) shows some examples of IoU values



Source: (TERVEN; CÓRDOVA-ESPARZA; ROMERO-GONZÁLEZ, 2023)

As can be seen in the Figure 20, the IoU value is calculated by the Area of Overlap with the object and the detected bounding box by the area of union by the

object area and detected box area. The closer the value of the IoU is from 1, the best was the prediction of the objected location (SHAH, 2022; TERVEN; CORDOVA-ESPARZA; ROMERO-GONZÁLEZ, 2023).

However, to calculate the mAP it still needs two more metrics that are extracted from the confusion matrix, the same presented in the Figure 18. These two metrics are the precision and the recall, defined by equations 2 and 3 (ENCORD, 2023).

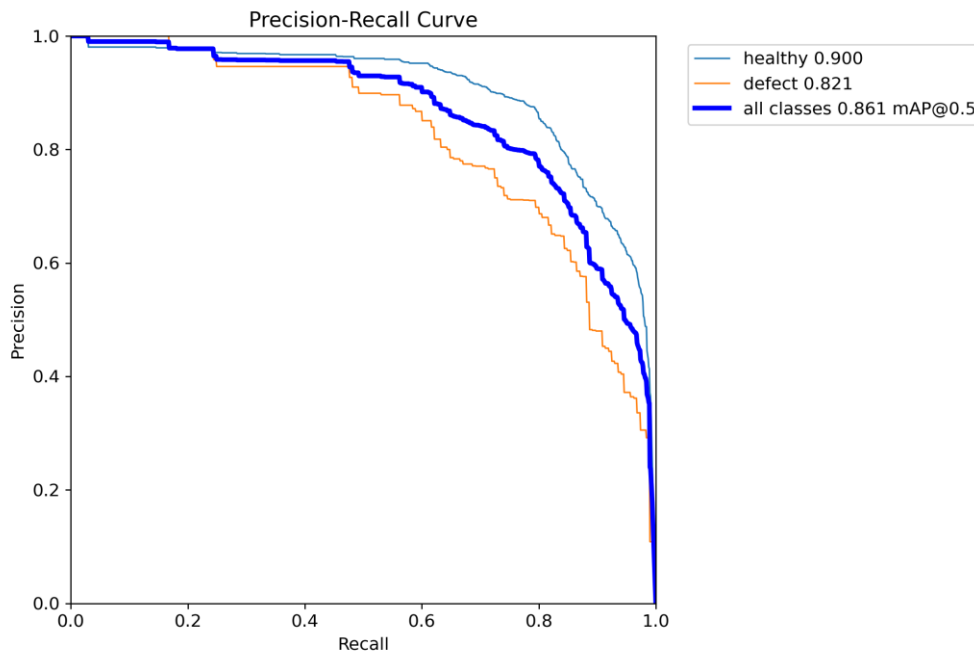
$$Precision = \frac{TP}{TP+FP} \quad (2)$$

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

The precision metric is used to verify if the model can find TP over all the predictions made by the model. This metric is important when the FP values are important. The recall metric is used to verify if the model can identify all the relevant instances (ENCORD, 2023)

With the precision and recall metrics, it can be made the precision-recall curve to verify if the model is performing correctly. As an example of precision-recall curve consider the Figure 21. This precision-recall curve shows the capability of the model to make positive predictions and the ability to detect real positives. The more top right the curve is, the better the model is performing (SHAH, 2022).

Figure 21 - Precision-recall curve from a YOLO trained model.



Source: Own authorship (2024)

Another step needed to calculate the mAP is to calculate the area under the precision-recall curve, and with this area, it is defined as the Average Precision (AP)

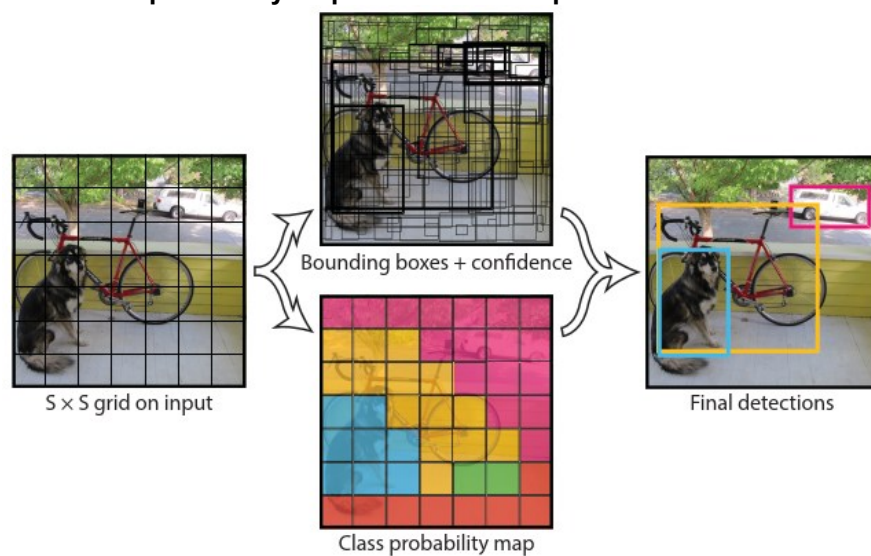
(SHAH, 2022)(LEARNOPENCV, 2022). With the value of AP, the value of mAP can be calculated by Equation 4. Inspecting the Equation 4 the mAP is calculated with the sum of the AP of each class “ k ” where “ n ” is the number of classes in the trained model (SHAH, 2022).

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k \quad (4)$$

Considering that the YOLOv5 is an excellent version of YOLO to make precise and fast detection and prediction in the case of PV panel fault detection and classification, let us look into the architecture of this version of the YOLO.

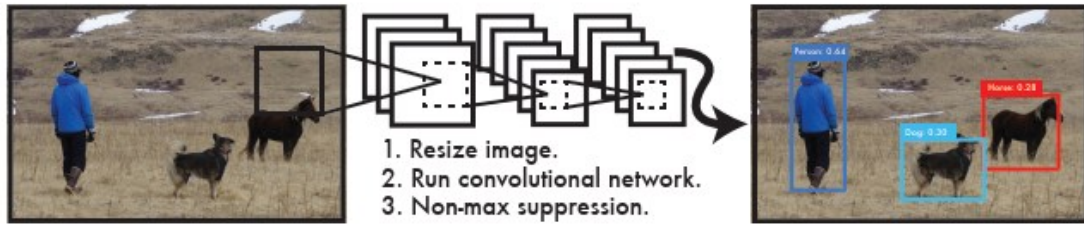
The YOLOv5 model has an architecture with a backbone, a neck, and a head, which can be seen in Figure 25. The backbone, the main body of the network, is based on a CSPDarknet53 with the objective of feature extraction from the input image. The neck incorporates structures such as Spatial Pyramid Pooling Fast (SPPF) and Path Aggregation Network (CSP-PAN) that aim to speed up the computation of the network. For the head, the YOLOv5 uses the YOLOv3 head, which is responsible for making the prediction provided by the backbone and neck (PYTORCH, 2024; TERVEN; CORDOVA-ESPARZA; ROMERO-GONZÁLEZ, 2023; ULTRALYTICS, 2024a). As the structure presented in the Figure 25 of the YOLOv5, it can be concluded that this structure is complex. However, this algorithm is ready to use by the libraries provided by the Ultralytics.

Figure 22 - Operation of the YOLO algorithm where the image is divided into a grid and then boundary boxes and probability maps are created to perform detection and classification.



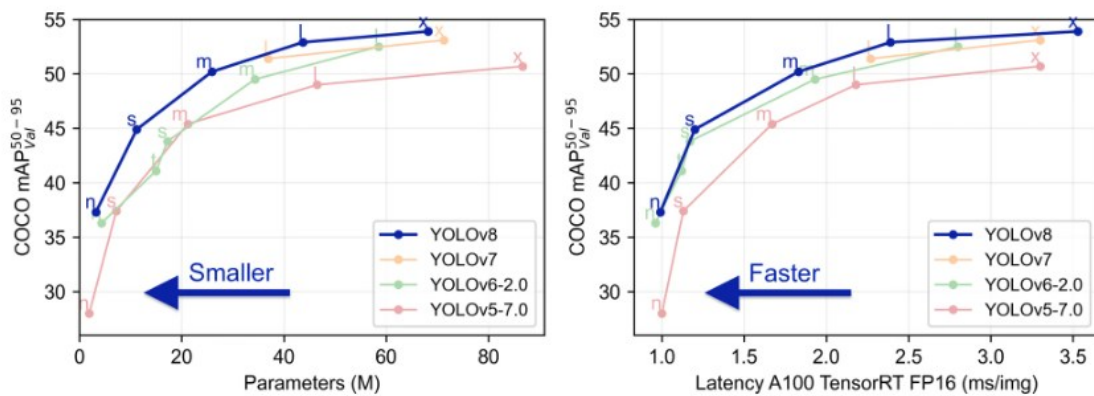
Source: REDMON et al., (2015, p. 2)

Figure 23 - YOLO workflow.



Source: REDMON et al., (2015, p. 1)

Figure 24 - Some YOLOs version, their mAP and latency



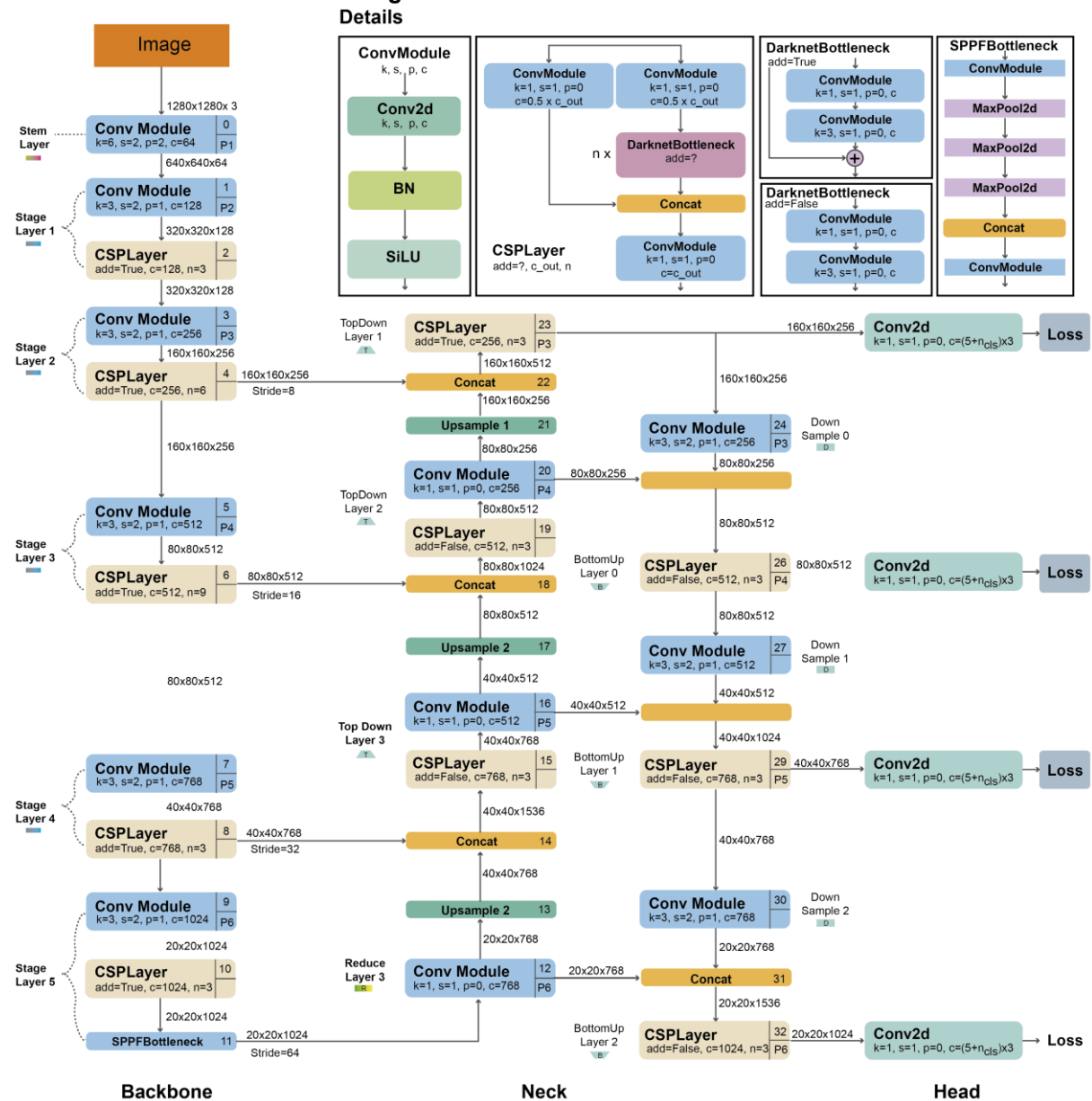
Source: (ULTRALYTICS, 2024b)

Several works use YOLO to solve problems with PV panels. For example, using the YOLO-World algorithm, Bassil et al., (2024) detected in the images with this specific YOLO to extract the ROI to make the classification of the image with other CNN. In this work, they make a binary classification of images between clean and dirty panels. They used 2121 images from Kaggle with data augmentation. This dataset and the approach with YOLO object detection were tested in multiple CNNs models, such as EfficientNetB0, EfficientNetB4, EfficientNetB7, ResNet50, VGG16, VGG19, MobileNetV2 and InceptionNetV3. From all these models, the best accuracy was obtained by the EfficientNetB7 with 89.8%.

Using the merge between the visual and infrared spectrum, Barrett et al., (2024) used the YOLOv8 to first detect the panel and then find damage in the detected panel. To do this, the YOLOv8s were used to detect the panel, achieving an mAP of 87%. With the detected panel, it was submitted to a YOLOv8m to identify and classify if the panel was damaged, achieving an mAP of 76%. To merge the images, the orthomosaic of the power plant was constructed, where a UAV with an IR camera with 640x512 pixels of resolution and an RGB camera with 12Mpix of resolution were used.

Using the YOLOv3, Di Tommaso et al., (2022) has used the YOLO for the detection of panels and classification in the visual and infrared spectrum. An Nvidia Tesla K80 GPU and the TL technique with the COCO dataset were used for the training process. As the images are from a UAV, an algorithm was used to automatically identify the borders of the PV panels in the infrared images and rotate them to increase the detection by the YOLO. With this, a mAP of 98% was obtained for panel detection, an mAP of 88.3% for hot spot detection, and an mAP of 70 for detecting six faults in the visual spectrum. With this setup, the system needed 0.98s to infer an image.

Figure 25 - YOLOv5 architecture.



Source: TERNEN; CORDOVA-ESPARZA; ROMERO-GONZÁLEZ, (2023, p. 1696)

For detecting six types of faults identified by IRT images, Zhang et al., (2022) used a YOLOv5. For the training, 902 UAV images were used, and with this dataset, an mAP of 80.88% was achieved.

The works cited above built their DNNs and compared them with pre-trained models. In some works, it is possible to notice that the network was based on a known model. This technique is applied because developing a new DNN is expensive and may need to be optimized, requiring great computational power. Therefore, to solve this problem, the Knowledge Transfer technique, known as TL, can be applied.

2.3.2.2 Transfer Learning

This approach uses prior knowledge acquired by a CNN during its training in a task (in this case, the ability to extract interesting features from images) to be applied in new situations (PAN; YANG, 2010), presenting relevant results in the context proposed here, as demonstrated in (DING *et al.*, 2018; GUTOSKI *et al.*, 2021). This way, there is no need to build and train a new network from scratch, making the process much faster.

There are two approaches to retraining a previously trained network. The first consists of simply removing the classification layer, initializing it with random weights, and retraining it for the new class of problems. For illustrative purposes, as shown in Figure 19, this process consists of replacing the Fully Connected and Softmax layers with new layers. The second approach consists of defrosting convolution layers and retraining them with images of the new problem to be treated, making the model more accurate but using more computational power. This process is fine-tuning (FT) because the convolution layers are defrosted (retrained) (SHIN *et al.*, 2016).

Some studies in the literature use this technique to solve PV classification problems. Using TL and defect classification from visible spectrum images of photovoltaic panels, the work developed by Ding et al. (2018) used this technique to classify eight classes of defects in solar panels. It is worth noting that the images presented by Ding are of defective parts of a PV panel and not of the panel as a whole. The authors of the work (DING *et al.*, 2018) used the GoogleNet network, with most of the frozen layers used as feature extractors and retrained the fully connected layer. In addition, traditional data augmentation techniques and Deep Convolutional Generative Adversarial Networks (DCGAN) were also used to generate fake images of defective photovoltaic modules. With the tests performed, this work presented an accuracy of

approximately 98% in identifying defects, showing the potential of this technique to diagnose defects automatically (DING *et al.*, 2018), but with the limitation of the significant use of artificial images.

For IRT, Korkmaz and Acikgoz, (2022) use TL to identify faults and classify 11 types of anomalies in thermal images. These authors used an AlexNet network trained with images from the ImageNet dataset as a basis for their analysis. The methodology used by these authors consisted of transferring the knowledge from AlexNet and adding some new convolution layers. An average accuracy of 97.32% was achieved for fault identification, and for the classification of the 11 types of anomalies, an accuracy of 93.51% (KORKMAZ; ACIKGOZ, 2022).

The literature contains works with TL and the infrared spectrum, as in the case of the work done by Tang *et al.*, (2024). In this work, the authors used TL in CNN models to reduce the complexity of CNN and make it more precise and faster. They used a VGG16 model reduced with TL with convolutional layers reduced by multi-scale feature extraction. With this technique, an increase of 0.9% in accuracy, 0.98% in precision, and 6.89% in F1 score metric was obtained. To make all tests, a 20000 aerial image dataset provided by Raptor Images Inc was used, where this dataset has eleven types of defects and one normal class. The hardware used was a GPU Nvidia RTX 3070. They achieved an accuracy of 80.42%.

Also in the infrared inspection, Akram *et al.*, (2020) proposed a CNN for binary classification of IRT images. Initially, the CNN was trained from scratch with an accuracy of 98.67%. After this, the CNN was trained with EL and FT with IRT images, achieving 99.23% accuracy. This CNN developed with TL needed low computational resources, where it only used a CPU and needed only 13 ms on average to infer an image.

2.4 Edge Device

One challenging task when using the DNN algorithms is the computational resources needed. Most of the works found in the literature use powerful computers with Graphical Processor Unit (GPU) with large computing capabilities to make the inference of images (GOROSPE *et al.*, 2021). Another approach that some work has used is cloud computing, where the data is collected by an Internet of Things (IoT) device and uploaded to the cloud to be processed (BOURECHAK *et al.*, 2023). This

solution is attractive but has drawbacks, such as response latency, high bandwidth to transmit the data, and the necessity of an internet connection (SU *et al.*, 2022).

One solution to this problem is Edge Computing (EC), which is used as an edge device that collects and processes all the data at the edge (BOURECHAK *et al.*, 2023; GOROSPE *et al.*, 2021; SU *et al.*, 2022). With this solution, a connection to the internet could not be needed because all the processing is made inside the edge device.

The use of edge devices to detect and classify PV modules can be found in the literature. For example, the work done by LI, *et al.*, (2020b) uses an edge device to process images captured by a UAV to classify seven types of faults that can occur in the visual spectrum in PV modules. The edge device has a Tegra K1 Quad-Core 4-Plus-1 ARM Nvidia Kepler-based GeForce GPU. The proposed method by the authors allows the detection and classification in 53 ms and a mean average precision of 98.4%.

There are found in the literature works that use edge devices with the infrared spectrum, as is the case of the work presented by Mellit, (2022). The authors use a Raspberry Pi 4 with TensorFlow Lite with Deep Convolutional Neural Network (DCNN) to classify faults in thermograph images from PV modules. They use two neural networks, one to make a binary classification to identify if the PV module has a fault and another to classify the four types of faults. In this work, they used a FLIR T540 with a 464 x 348 pixels resolution. With this hardware and the DCNN they developed, they achieved 99% accuracy in fault detection and 95.55% in fault classification.

Using the Nvidia Jetson Nano as the edge device and infrared images, the work done by Le, Le and Vu, (2023) presents the use of CNN in the edge device to make real-time classification of images in a UAV. This work does not give details of the camera used; it only uses the Nvidia Jetson Nano as the processing unit to classify twelve faults identified in the infrared spectrum. With this setup, they can infer each image in only 1.04 ms with an accuracy of 85.35% with the Jetson Nano.

As seen from the presented works found in the literature, edge devices with AI are well employed. Using this technology to inspect PV modules can help the O&M staff make fast and precise inspections, preventing maintenance.

3 MATERIAL AND METHODS

Two methodologies were applied to identify and classify PV panel faults based on the presented problem. The first methodology applied consists of directly classifying the captured image using a CNN with TL only to faults in the visual spectrum. The second one uses the YOLO algorithm to identify and classify images of faults in the visual spectrum, IRT, and UVF. In order to achieve the proposed solution, specific steps must be followed.

The first step concerns the edge device. As this work proposed using an edge device to capture, process, and classify the images of PV panels, the development of this device will be explained in subsection 3.1, from the prototype to the latest one. The edge device's development involves cameras (RGB and infrared), a voltage regulator, and a wireless connection.

UV lights are necessary to inspect using the UVF method, the second step after developing the edge device. As the edge device has an RGB camera that can capture the fluorescence of the PV panel, this step is done. UV lights alone can not achieve good fluorescence results with low weight and energy consumption. In order to achieve this result, a light concentrator was developed, which will be explained in section 3.2.

As this research involves the use of images to identify faults in PV panels and classify them, multiple datasets of images from the visual spectrum, IRT, and UVF were constructed. The construction of these datasets was explained in subsection 3.3.

In order to detect and classify the images from the PV panels from multiple spectrums, AI algorithms were chosen. As mentioned, two methodologies were applied to this step and will be explored in the 3.4 subsection.

Finally, with all the hardware and algorithms trained to identify and classify faults in PV panels, software was developed, allowing the user to control and visualize the inspection done by the constructed camera. This software will be explained in the 3.5 subsection.

3.1 Edge Device components

The edge device used in this work has a GPU to process the images and can make quick inferences with the AI algorithms. This way, the Nvidia Jetson Nano 4 GB was selected as the edge device to connect the cameras and process the acquired

images. This edge device has a low power consumption of between 5-10 W, a Quad-core ARM® Cortex®-A57 MPCore processor, a GPU NVIDIA Maxwell™ architecture with 128 NVIDIA CUDA® cores, 4 GB 64-bit LPDDR4, and a processing capability of 472 GFLOPs (NVIDIA, 2024a)(NVIDIA, 2024a). The edge device can be seen in Photograph 1.

Photograph 1 - Edge device Nvidia Jetson Nano developer kit.

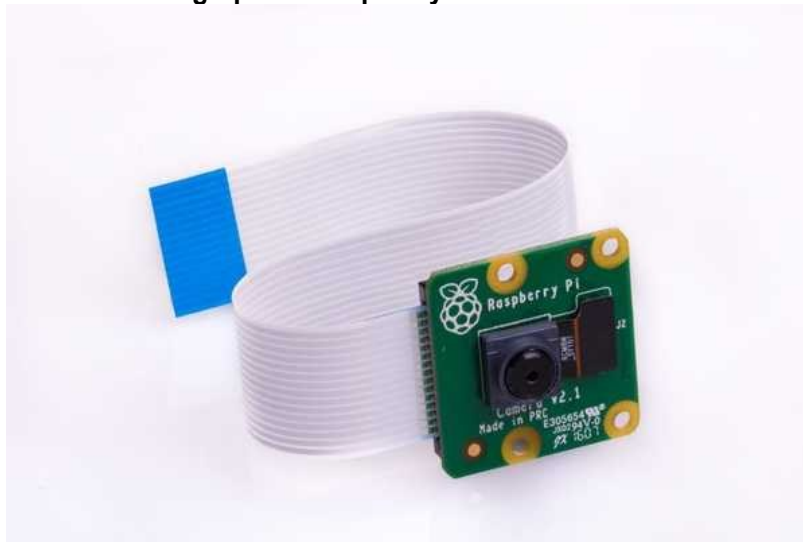


Source: (NVIDIA, 2024a)

The first prototype with the Jetson Nano used a Raspberry Pi camera V2 with 8 MPix and was equipped with the Sony IMX219 sensor and fixed focus that can be seen in Photograph 2. The Jetson Nano was powered and connected to a laptop with a USB cable, limiting the consumption to 5 W and, thus, less processing capability. This first prototype can be seen in Photograph 3 with the acrylic involucre. This prototype was used for the first methodology applied with the direct image capture and the use of CNN to classify this image, as will be explored in subsection 3.4.

With the same prototype, the first test was made with the UVF inspection, as seen in Photograph 4. The imaging sensor does not show good results with this test, and the image quality is poor, as seen in Photograph 5 where the image has salt and pepper noise which is not desired.

Photograph 2 - Raspberry Pi Camera Module 2



Source: (RASPBERRY PI, 2024)

Photograph 3 - First prototype version with the Jetson Nano, Raspberry Pi Camera Module 2 and the acrylic involucre.



Source: Own authorship (2024)

Photograph 4 - First prototype used for UVF inspection.



Source: Own authorship (2024)

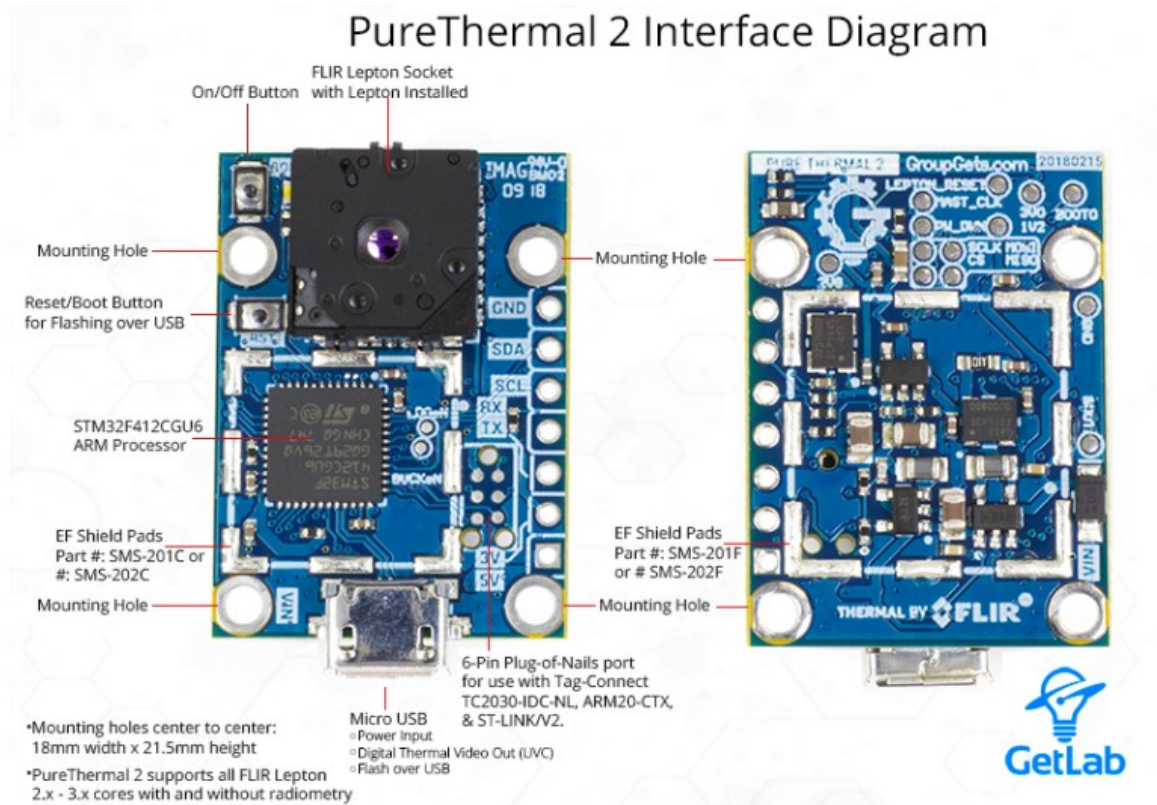
Photograph 5 - Poor image quality provided by the Raspberry Pi Camera module 2 in the UVF inspection.



Source: Own authorship (2024)

As the works needed an infrared camera to capture the IRT images, the FLIR Lepton 3.5 with the development board GroupGets PureThermal 2 allows the FLIR camera's connection to the Jetson with a USB cable. The FLIR Lepton and the development board are presented in Photograph 6. The FLIR Lepton 3.5 has a radiometric sensor with 160 x 120 pixels (GROUPGETS, 2024), allowing the capture of hotspots at a reasonable distance from the PV panel. As the constructed camera intends to make initial inspections, this infrared camera works perfectly with low cost, about 300 USD. Larger infrared sensors have high costs, with more than 2.000 USD.

Photograph 6 - FLIR Lepton 3.5 with the development board GroupGets PureThermal 2.



Source: (GROUPGETS, 2024)

Some problems occurred during the inspection when the Jetson was connected to the USB cable. The first problem was related to a low voltage problem, as the system needed more current to process all the images and transmit these images to the laptop. Because of this, a voltage drop occurred during operation, and the Jetson shut down as a device protection mode. Considering this, the second prototype was evaluated to be wireless and battery-powered.

The second prototype used a step-down DC-DC voltage regulator, the LM2596, connected to the Jetson's 2A jack, allowing up to 10 W and unlocking all Jetson's potential. Two lithium batteries (18650) with 3.7 V were used as a power source. With the power source problem solved, the Jetson with the batteries could be used for up to two hours. The Jetson Nano comes without a Wi-Fi card but comes with a PCI Express x1 port, allowing the installation of the Wi-Fi card. So, in the second prototype, the Intel 8265NGW was installed, allowing a hotspot for any mobile device to connect to the Jetson. The final upgrade in the second prototype was the RGB

camera. The Raspberry Pi V2 camera was changed to an Arducam IMX519 with autofocus and 16 Mpix resolution. This camera allows the capture of clearer images from the visual spectrum, mainly in the case of UVF inspection. This prototype can be seen in Photograph 7.

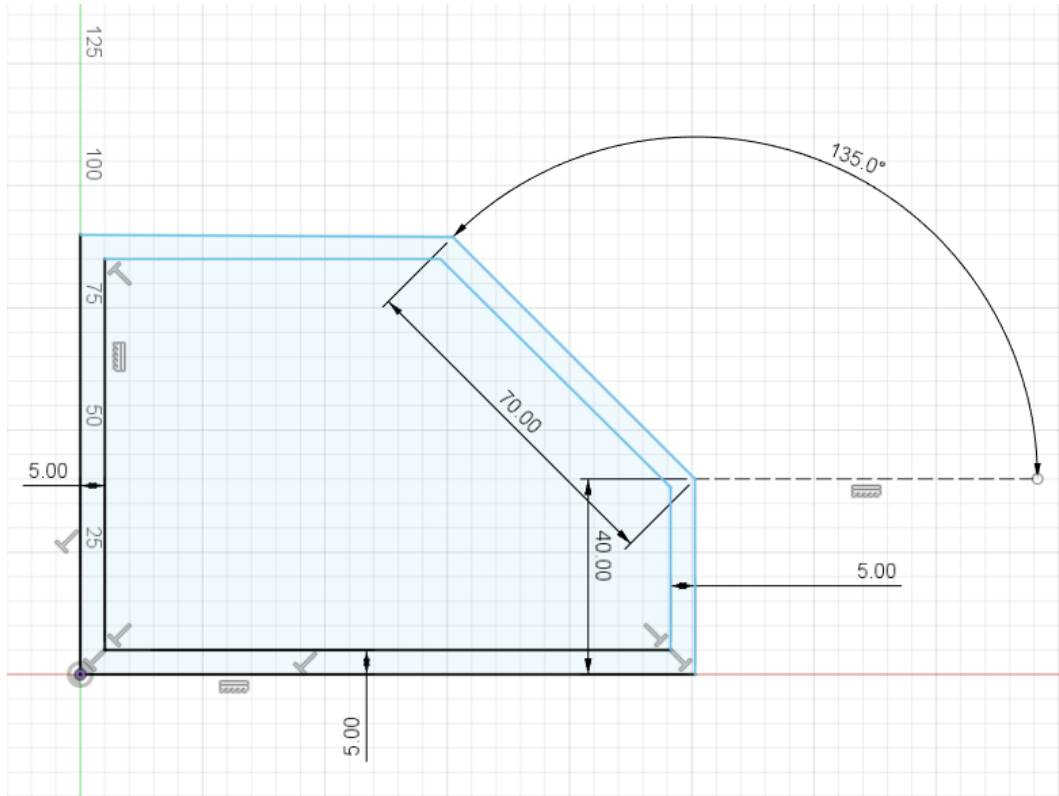
Photograph 7 - Second prototype of the developed camera, with the new imaging sensor, IR camera and wireless connection.



Source: Own authorship (2024)

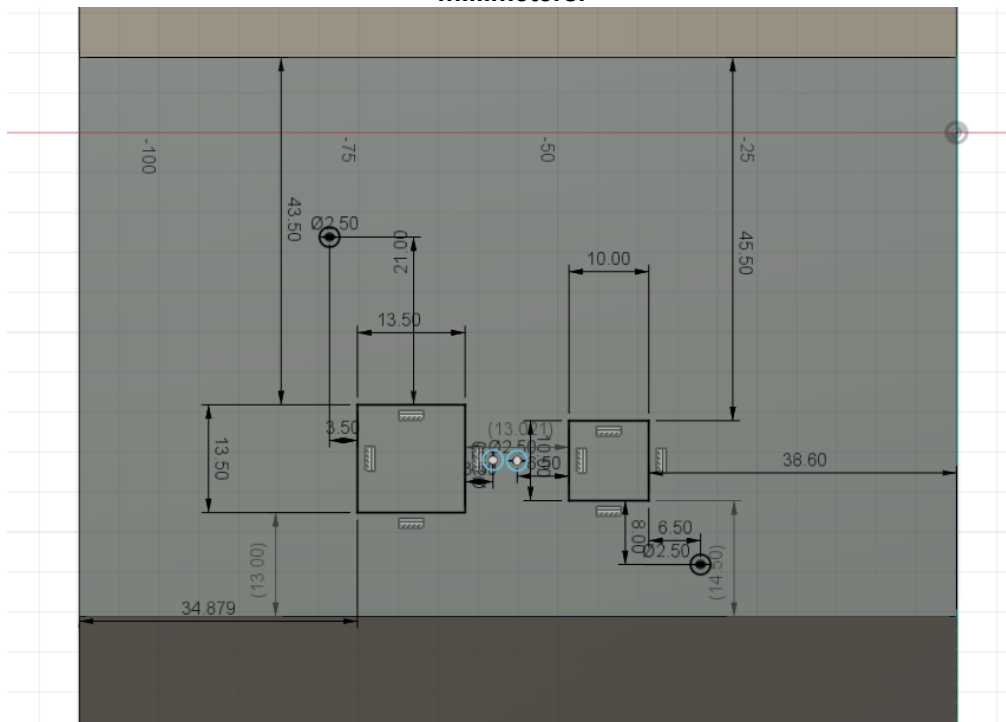
The final prototype concerns the camera's involucre, as it was changed from acrylic to 3D-printed using the Acrylonitrile Butadiene Styrene (ABS) for the printing. The model to be printed is presented in Figure 26 to Figure 28, and the mounted prototype is presented in Photograph 8 and Photograph 9. This final involucre has a 45° position of the camera to allow the person that will inspect not to position the camera with a 90° with the PV panel. With an angle in the involucre, the system can be used in a 180° position and coupled in a UAV to make inspections.

Figure 26 - Side outline for the 3D model to couple all the components of the camera. Measurements in millimeters.



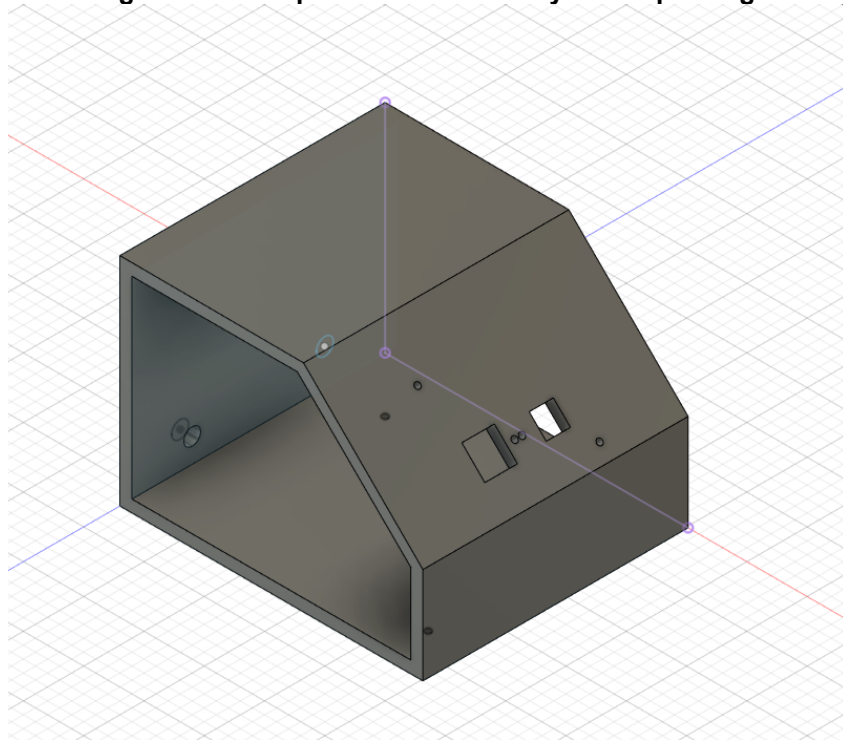
Source: Own authorship (2024)

Figure 27 - Front outline for the 3D model to couple the imaging sensors. Measurements in millimeters.



Source: Own authorship (2024)

Figure 28 - Complete 3D model ready for 3D printing.



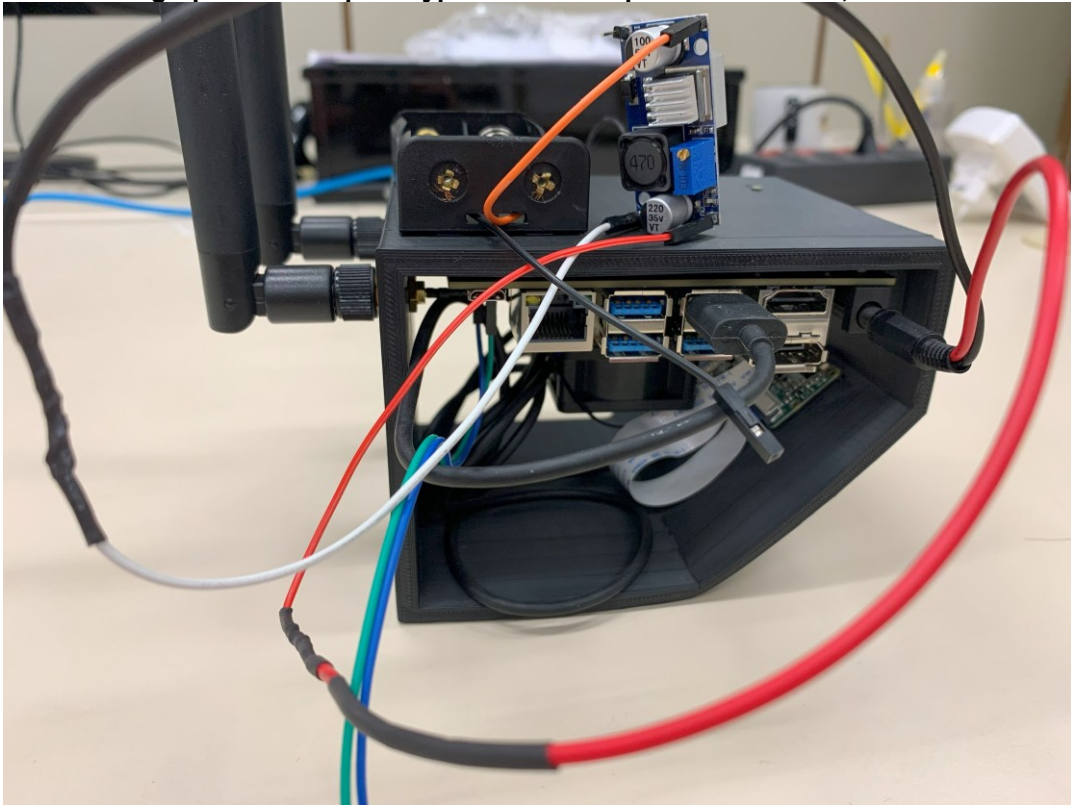
Source: Own authorship (2024)

Photograph 8 - Third prototype with the 3D printed involucre, front vision.



Source: Own authorship (2024)

Photograph 9 - Third prototype with the 3D printed involucre, side vision.



Source: Own authorship (2024)

3.2 UV Light concentrator

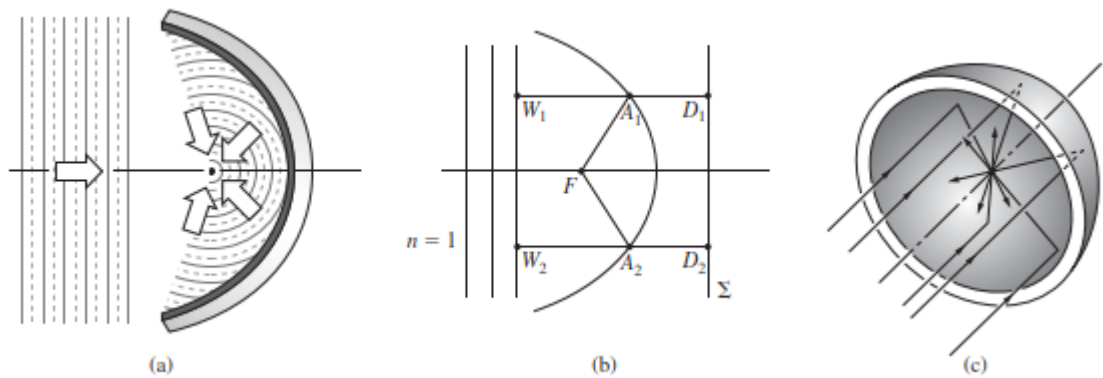
In order to conduct the UVF inspection, UV lights are needed beyond the RGB camera to excite the PV panel to fluorescence in the visual spectrum and inspect the PV cell. Considering this and the comparison with different types of lights presented in subsection 2.2.2.4, an LED with 365 nm was chosen. The 3 W LED part number JH-3535V12G45 from Ledguhon, powered by 3.6 V and 700 mA and with 365-370 nm, was the choice with a 120° aperture angle. The LED was soldered in an aluminum plate called CREE to dissipate the heat from the LED. The LED, the plate, and the soldered plate are presented in the Photograph 10.

As this LED has a wide aperture angle, executed tests showed that the fluorescence at a reasonable distance, about 1.5 m (KONTGES *et al.*, 2020), does not present a good result. This way, a parabolic reflector, in other words, a mirror, was used, as the LED positioned in the middle of the parabolic has the light concentrated in the infinite, as can be seen in the Figure 29. With this, the light will be concentrated, allowing better fluorescence for the PV panel.

The ThinkerCad software was used to construct this parabolic reflector. The 3D model of the parabolic can be seen in the Figure 30 to Figure 34. The parabolic

reflector is a complex form that behaves the LED precisely, avoiding power loss in the coupling. With this, as seen in the Figure 30, the 3D model has multiple volumes to make it precise. The first volume is the parabolic, where to have this parabolic with 3 mm of thickness, two parabolic were designed, the external with a radio of 25mm (Figure 31) and the internal with a radio of 22 mm (Figure 30). After that, the parabolic base was made with a cylindric with 10 mm of radio and 1 mm of height to glue this base in the heatsink (Figure 32). Inside the parabolic, it needed the square to position the LED. This square is 5x5x5mm and can be seen in Figure 33. All these volumes are coupled to form a unique volume, resulting in the parabolic seen in Figure 34.

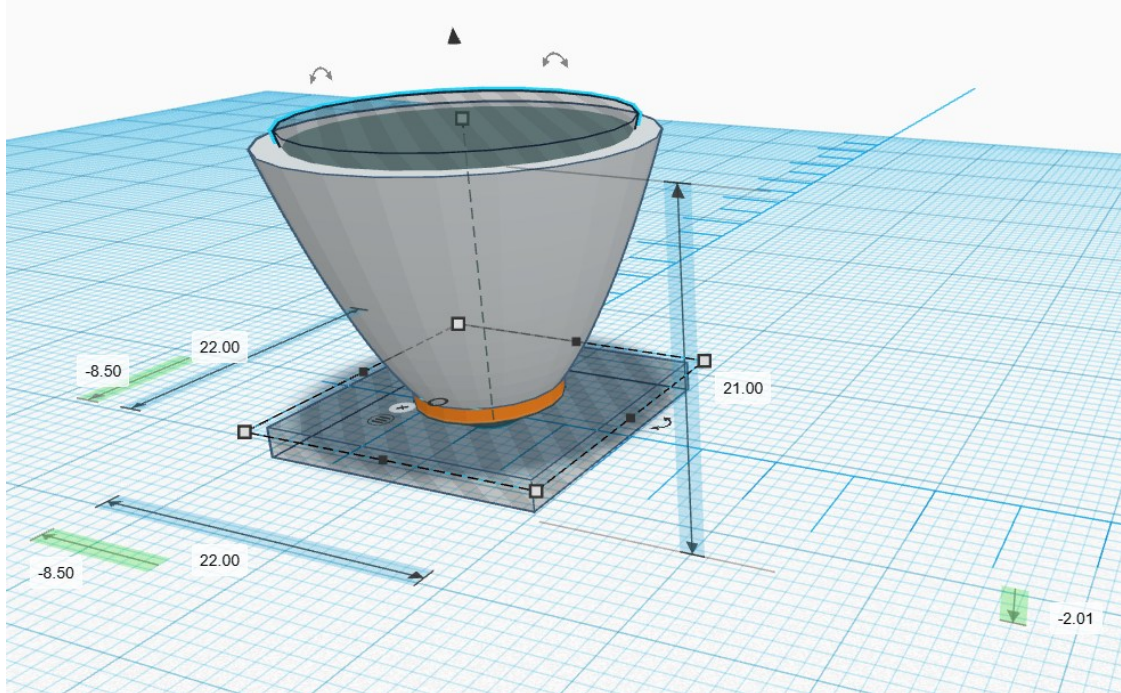
Figure 29 - Parabolic mirror.



Source: EUGENE, (2017, p. 192)

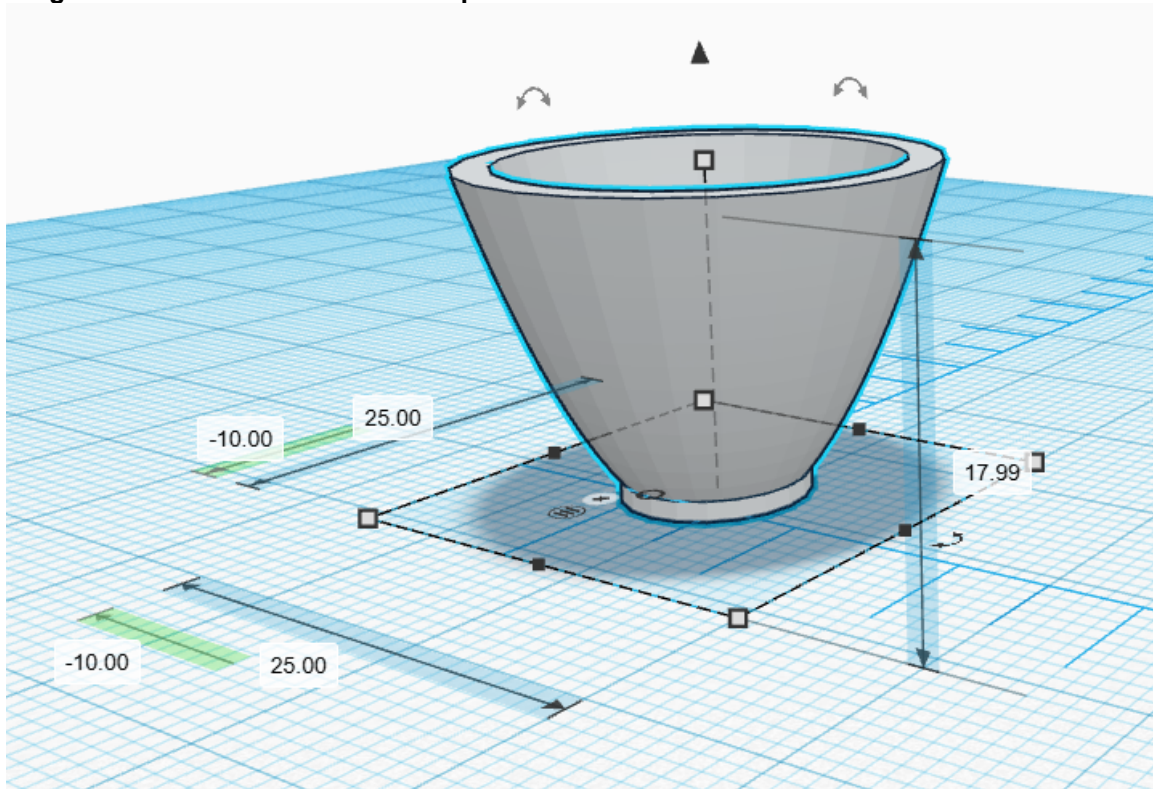
The 3D model was 3D-printed with ABS to couple the LED with the parabolic. However, only the 3D-printed parabolic in white color is not sufficient to concentrate the light. It needs to be a mirror or close to a mirror. With this, three steps were made to transform this 3D-printed parabolic into a mirror. The first step was to polish the parabolic to make it a smooth surface. After that, the parabolic was painted in bright black. This step is required for the chroma color to make the mirror effect. The final step was to paint the parabolic in a chroma color, making it look like a mirror. Finally, after the UV LED is soldered, the parabolic concentrator is attached to the heatsink epoxy glue. These steps can be seen in the Photograph 10.

Figure 30 - Internal volume of the parabolic concentrator. Measurements in millimeters.



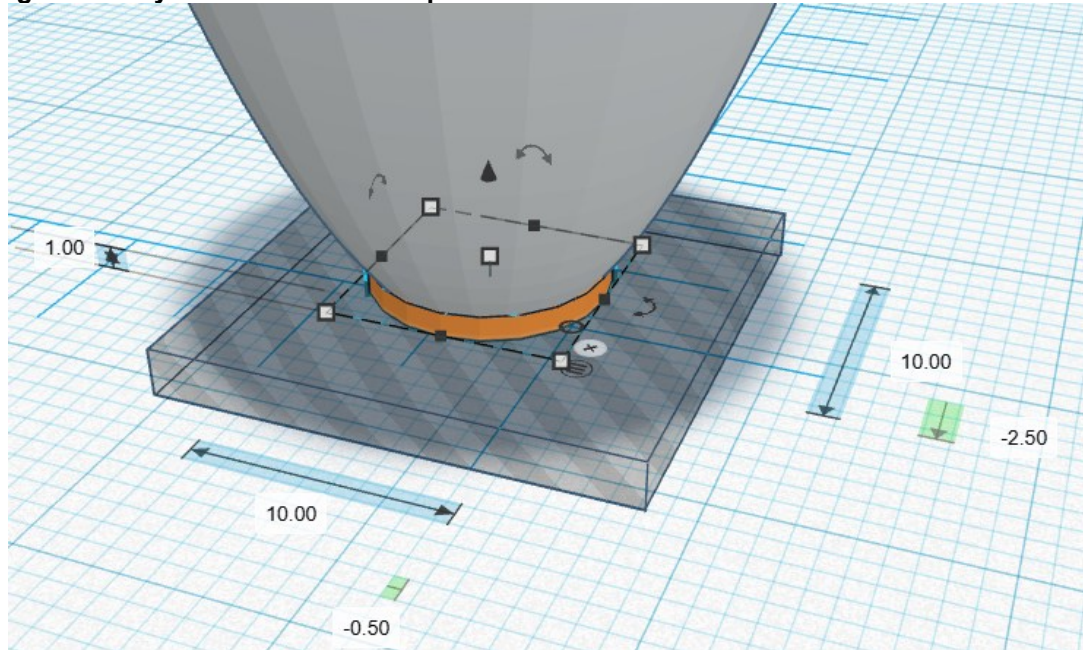
Source: Own authorship (2024)

Figure 31 - External volume of the parabolic concentrator. Measurements in millimeters.



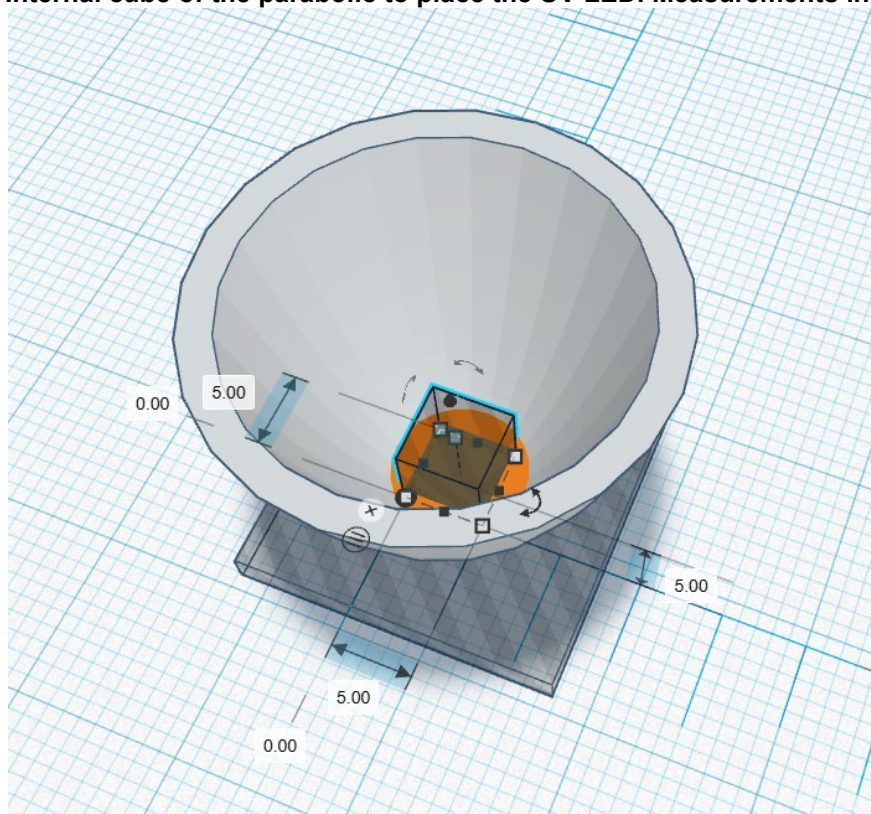
Source: Own authorship (2024)

Figure 32 - Cylindrical base of the parabolic concentrator. Measurements in millimeters.



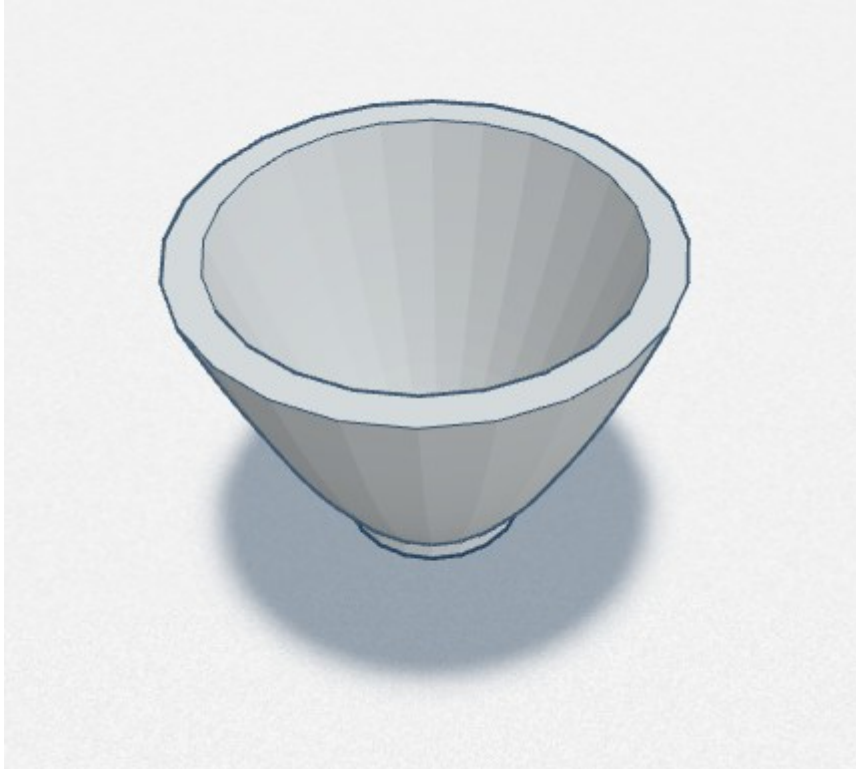
Source: Own authorship (2024)

Figure 33 - Internal cube of the parabolic to place the UV LED. Measurements in millimeters.



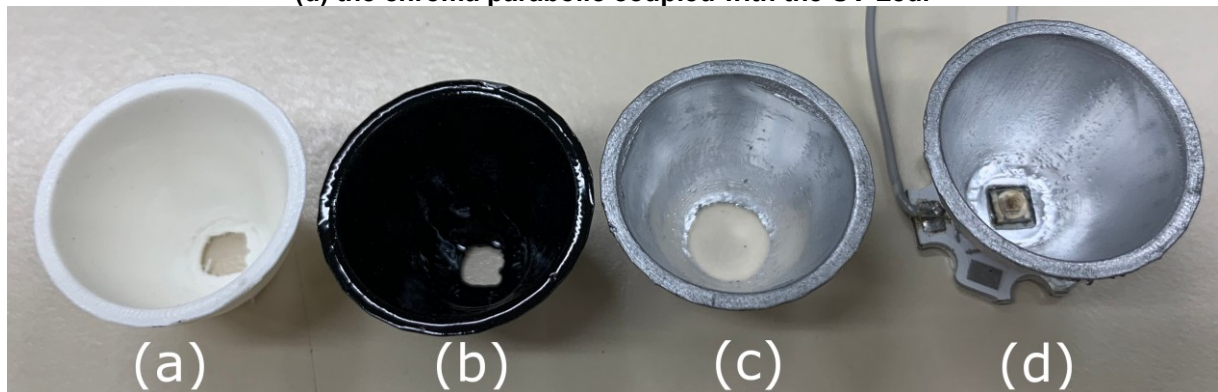
Source: Own authorship (2024)

Figure 34 - Finished 3D model of the parabolic concentrator. Measurements in millimeters.



Source: Own authorship (2024)

Photograph 10 - Parabolic reflector construction, where (a) is the 3D printed parabolic polished; (b) the parabolic painted in bright black; (c) parabolic painted with chroma color; and (d) the chroma parabolic coupled with the UV Led.

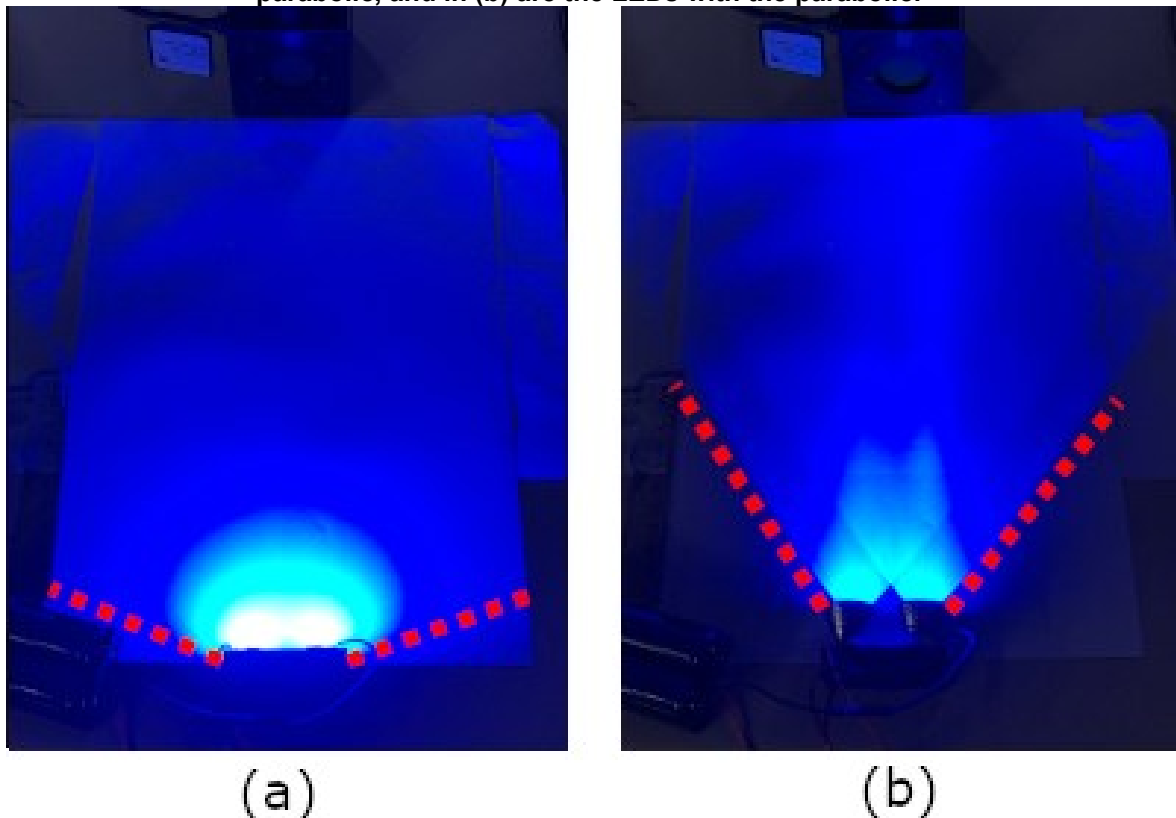


Source: Own authorship (2024)

To verify if the parabolic concentrator is performing the desired role, a test was conducted with a power meter. This test consisted of positioning two LEDs with and without the concentrator at 35 cm from the power meter, configured to measure a 365 nm light source, as seen in the Photograph 11. The power meter used was the Newport

843-R, with an average time of 1 second. The LEDs without the concentrator showed a power transmittance of only 1 mW, and the LEDs with the concentrator had 92 mW power, and the red dotted lines can see the concentration at the infinite in Photograph 11. This considerable difference proves that the concentrator is a game changer in the UVF inspection. Each concentrator weighs only 10 g, allowing long inspections by an operator or a UAV.

Photograph 11 - Experiment with the parabolic reflector, wherein (a) are the LEDs without the parabolic, and in (b) are the LEDs with the parabolic.



Source: Own authorship (2024)

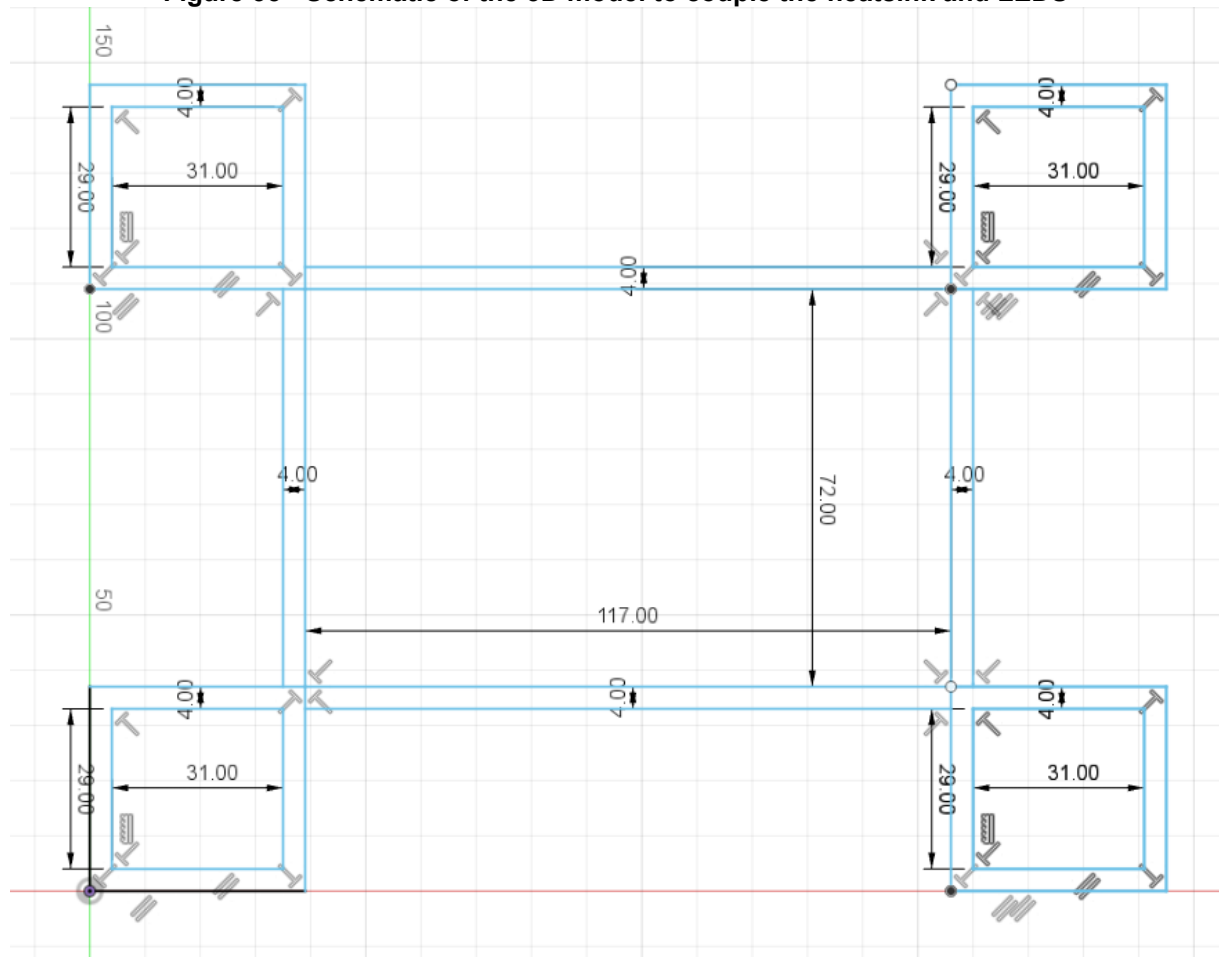
Considering the number of LEDs and how they are powered, three prototypes were constructed. The first prototype, seen in the Photograph 4, used two LEDs connected in series, powered directly by two 18650 batteries and a heatsink with two coolers to avoid temperature burnout. This system proved to be not desired, as when the batteries are fully charged, they have up to 4.2V, which causes the LED to burn.

To avoid the LED being burned because of over-voltage, a resistor was installed in series with the LEDs, allowing a good luminance when the battery is fully charged. However, a slight decrease in the battery voltage causes a low LED

luminance. In order to address this issue with the low luminance, the system was enhanced by incorporating two additional LEDs, bringing the total to four, as demonstrated in the prototype shown in Photograph 7.

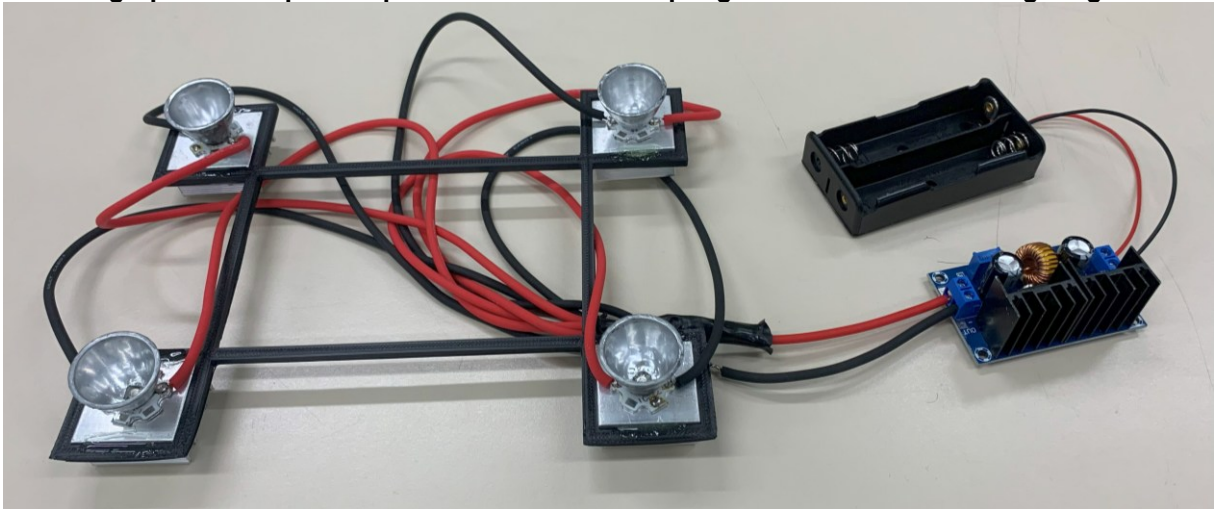
Nevertheless, this system needed to be more efficient. With this, a completely new system was made to be coupled with the last camera prototype. So, a 3D model was constructed to couple the four LEDs where each one has its heatsink. A DC-DC step-down voltage regulator (xl4016) powered by two 18650 3.7 V lithium batteries and the voltage regulator configured to power the LEDs with 3.6 V were used to power the LEDs. The LEDs were connected to the voltage regulator in parallel. The schematic of the 3D model is presented in the Figure 35, and the mounted system is in the Photograph 12 and Photograph 13. This final system proved more robust, avoiding LED burnout and providing better illumination of the PV panel with LED distribution.

Figure 35 - Schematic of the 3D model to couple the heatsink and LEDs



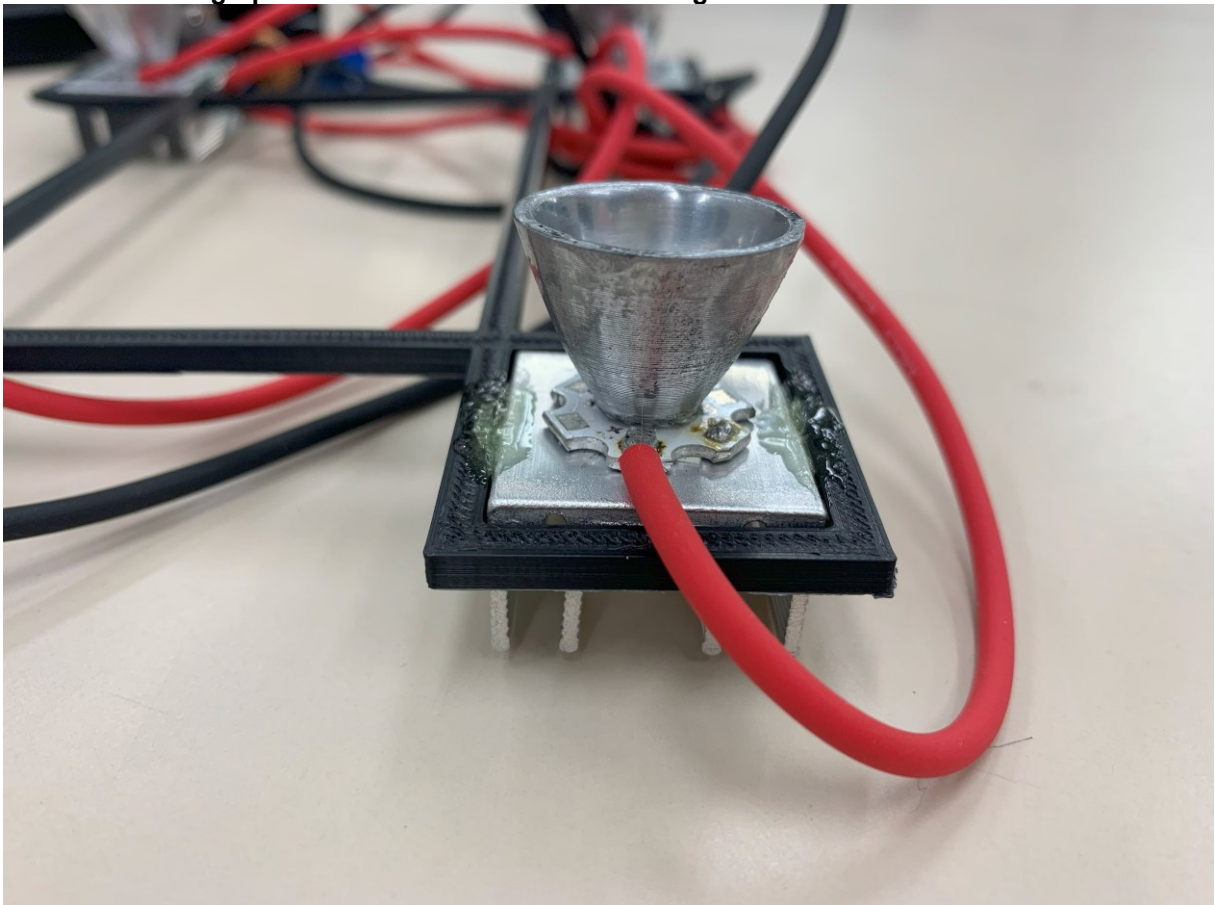
Source: Own authorship (2024)

Photograph 12 - 3D printed piece for UV LEDs coupling with tall LEDs ad voltage regulator.



Source: Own authorship (2024)

Photograph 13 - Detail in one UV LED with light concentrator and heatsink.



Source: Own authorship (2024)

3.3 Dataset

Due to the difficulty of finding datasets with many images with common defects in PVs, creating multiple datasets with some defects that can be identified and are frequently mentioned in the literature was necessary. By using multiple image sensors, each collection with these sensors will generate a dataset. The images will be collected according to each part of the spectrum to be monitored.

Two approaches to image acquisition can be performed: video or photography. If the image is captured using video, once the capture is complete, its frames will be extracted to be treated as static images.

Since some images contain several uninteresting PVs and objects, it will be necessary to apply computational algorithms to extract the points of interest from the captured image. The sliding window technique was initially applied to the visual spectrum dataset to extract the regions of interest containing only one PV. This technique was used only in the first methodology, as in the second, software was used to annotate where the PV panel is and for which class it is the annotated panel.

Once the image capture and pre-processing are complete, they must be separated into appropriate classes according to the type of defect or failure. Separations are also necessary for AI training.

Each dataset will contain a set of identified defects or faults. Each defect must be separated into classes manually and by the human eye. For example, some classes in the visible spectrum are PV without defects, dirty and shaded. Therefore, it will be necessary to separate the acquired images into each class for this dataset. This separation is necessary so that the AI can learn what each of the defects that it wants to classify is.

However, the abovementioned methodology was applied only to the visual spectrum in the first classification methodology of directly captured images. The second methodology used software to select the region of interest. This software is named CVAT, where it is possible to annotate the images with the desired class, e.g., in the IRT images, annotate the PV panel with and without a hotspot. This annotation is necessary for the YOLO algorithm, where for the training process, the boundary box to the algorithm must know how to detect the ROI to make further classification.

One task that needs to be done in each dataset is to separate them into the training and validation datasets. For the first methodology, the dataset was distributed

between training, validation, and testing. In this methodology, this division will be carried out in the proportion of 90% of the images for training and 10% for testing. Of the 90% of training, 80% constitutes the training dataset, and 20% is the validation dataset. Once the datasets have been created, training the AI is next. For the second methodology, only the training and validation datasets were used, and the proportion is diverse between the datasets and will be explored in the correspondence subsection.

In the following subsections, every dataset will be explained. The visual spectrum dataset will be explored in subsection 3.3.1, the IRT dataset in 3.3.2, and the UVF dataset in 3.3.3 subsection.

3.3.1 Visual Spectrum Dataset

In order to create this dataset, two smartphones with 12 Mpix cameras and a UAV DJI Phantom 3 Professional with 12 Mpix cameras were used to capture the visual spectrum images. The capture was made in video format of 1920x1080 pixels by the smartphones and 3840x2160 pixels by the UAV.

For this public dataset, the images were collected at solar power plants installed at the Universidade Tecnológica Federal do Paraná (UTFPR) - Curitiba Campus and at the Instituto Federal do Paraná (IFPR) - Jacarezinho Campus, Brazil. These collections were performed on different days, prioritizing days with few clouds.

In obtaining the dataset, priority was given to capturing images containing some of the primary defects that can impact the efficiency of electricity generation by solar panels. Among these defects, those that can be most easily replicated were chosen, such as obstruction of the solar panel by bushes, dirty panels, and shading. In addition to the defects, a class with clean panels was also included, which is the reference for a panel without defects. Figure 36 shows a sample of each class in this dataset. These classes will be detailed below.

Figure 36.1 shows images of PVs with shadows, whether from trees, cables, poles, or other objects. Some of the images collected represent real shadow situations. Others were created by inserting objects that caused shadows on the panels.

Figure 36.2 contains images of overlapping tree branches and bushes over solar panels, which partially obstruct the panels. It may or may not generate shadows, indicating the need to prune the vegetation where the panels are installed. Since it was impossible to find any actual situation in the environments used to capture the images,

this class was collected by positioning natural and artificial bushes over the panels to simulate such a situation.

Figure 36.3 shows a class where the accumulation of dust, sand, soil, or bird droppings on the plates interferes with energy generation. In the same way as the previous categories, this collection was made with real and simulated cases.

Images were collected of plates that did not present any of the irregularities of the previous classes, that is, with the ideal situation for total energy generation, as observed in the visible spectrum. A small sample of this class can be seen in Figure 36.4.

Figure 36 - Sample images from each class of the visible spectrum.



Source: Own authorship (2024)

In comparison, the visible spectrum image datasets mentioned in the Introduction have only one type of defect. The dataset presented in (MEHTA et al.,

2017) has a large volume of images, but only of one PV and with variants of one type of defect, sand accumulation. In (OZTURK; HANGUN; EYECIOGLU, 2021), the dataset presents images only of snow accumulation.

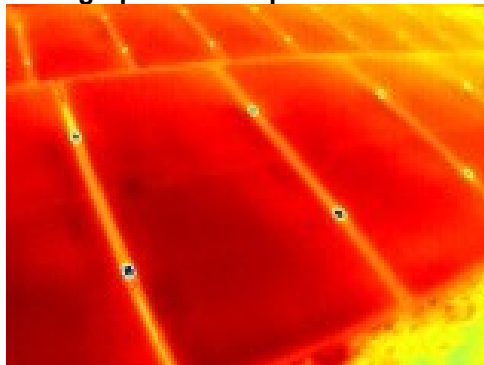
After capturing the images, choosing the best ones, and separating them into defined classes, 36,000 images were selected to compose the dataset. The separation defined in the general methodology was applied to these images, resulting in datasets with 25,920, 6,480, and 3,600 images. Once the dataset was built, the AI models were trained and tested in a real environment.

The same dataset was used for the YOLO network training, but the images captured by the UAV were not used. This choice was made because the first tests with YOLO and the camera were coupled with the camera in a pole so the inspector could hold the camera in your hand and conduct the inspection, a vision angle different from the UAV. In total, 10.263 images were selected, where 8215 was used for training and 2048 for validation.

3.3.2 IRT Dataset

The IRT dataset consisted of 1614 images, where 1286 was used for the training dataset and 328 for the training validation. An example of an image of this dataset is presented in the Photograph 14. This dataset contains IRT images of healthy PV panels and hotspots. A binary classification was chosen because the developed inspection tool intended to do an initial inspection. As the IRT images were used with the YOLO algorithm, each image was manually annotated using the CVAT software.

Photograph 14 - Sample of IRT dataset.



Source: Own authorship (2024)

3.3.3 UVF Dataset

The UVF dataset contains 3488 images, where 2751 were used for the training dataset and 737 for the validation dataset. The Photograph 15 shows an example of an image of this dataset. These images were used with the YOLO algorithm. Annotating each image with the CVAT software was necessary. As seen in the example image, it was chosen to make a binary classification between healthy and defective PV cells in the same way as the IRT images.

Photograph 15 - UVF dataset sample.



Source: Own authorship (2024)

3.4 AI Training

This work does not intend to create a new neural network but utilizes available models, as mentioned in the literature. Two methodologies were applied. The first one consists of utilizing pre-trained neural network models and uses the technique of TL to train these networks. This method aims to speed up the training process of CNN models and allows the testing of several models to find the one that best suits the problem presented. This methodology will be explained better in subsection 3.4.1.

The second methodology uses a different and specific neural network, the YOLO. This network makes the object detection in the image together with its classification, which is more desirable than only classifying the whole input image as

is done in the first methodology. This process of training the YOLO will be explored in subsection 3.4.2.

Tests were made to verify the performance of both methodologies in the Jetson Nano. With this, to optimize the inference time of the neural network, the DNN model was optimized to the Nvidia TensorRT, which is an Application Programming Interface (API) that extracts the full performance of Nvidia GPU with parallel processors with CUDA. With this optimization, the model's performance could be up to 36 times faster (NVIDIA, 2024b).

3.4.1 CNN Training

The TL technique was employed in this methodology. This method can make training faster, allowing multiple tests with different CNN models. This way, the best model for a specific problem could be found.

For the training step, 17 network models were initially chosen to be trained, tested, and compared. The classification metrics were obtained with CNN from multiple levels of complexity, where all the models were pre-trained with the ImageNet dataset (DENG *et al.*, 2009) with 1000 classes of objects. The choice of models used in this work was based on works found in the literature, network size, input image size, and availability in the TensorFlow/Keras (KERAS, 2023) selected development environment. This model diversity was intentional to verify how each would deal with the problem in question.

In order to perform the training, each set of images (training, validation, and testing) will be loaded with a batch size of 32 images. To verify the efficiency of these models, only a 2D Global Average Pooling, dropout of 0.2, and a dense layer, the size of the number of classes that the dataset to be trained has, will be added to the final part of the network. For better visualization, in Figure 23, this operation replaces the blue layers. In other words, FT was not initially performed. Each chosen network was trained for 20 epochs, with a learning rate of 0.001, loss function as categorical cross-entropy, and accuracy as a metric for evaluating the model.

After this initial stage, the three networks that delivered the best results were subjected to new training with FT. The choice to apply FT to the three best networks is to verify their performance with unfrozen convolutional layers. To do this, tests will be carried out to determine how many upper layers need to be unfrozen in order to avoid

the effect of overfitting. In this fine-tuning process, the networks will be trained again using the same parameters as in the previous stage.

Even though the dataset for the visual spectrum created is vast, the Data Augmentation (DA) technique will be applied to all training sessions to obtain greater model diversification and better learning robustness, aiming at using the model in real-world situations. Several DA tests will be performed. Initially, the following DA techniques were used: horizontal and vertical mirroring, rotation with a proportion of 20% with filling using the nearest neighbor algorithm, and increase/decrease of the width and height of the image with a proportion of 50%. All DA operations were performed randomly. Other DA techniques may be included, such as selecting those that present the best results and do not stray from the dataset.

Each DNN model is already pre-trained with an input image size. Thus, for training, the images will be resized according to the requirements of each model. All stages of the training process, including validation and testing, will use computers with Nvidia GPUs.

Since CNN is intended to be executed on embedded hardware, it will be verified whether the network that delivered the best result requires little computational power. Optimizations will be verified if it does, or a smaller network with results close to the best network will be chosen.

After the training and validation process, the best network will be optimized with the Nvidia TensorRT and tested in the Nvidia Jetson Nano edge device to verify the performance of this network.

3.4.2 YOLO Training

The YOLO training was more straightforward than the CNN training, with the choice of the size of the model and version. The YOLO v5 was chosen for this work because it is the smallest and fattest one from a range of YOLOs, as seen in Figure 24. These characteristics are essential to make the YOLO run on the edge of the device without any problems. For this work, the smallest one, the nano, was selected. This choice is also related to the edge because, as three YOLOs will be loaded, their size is crucial to avoid problems with processing time and RAM usage.

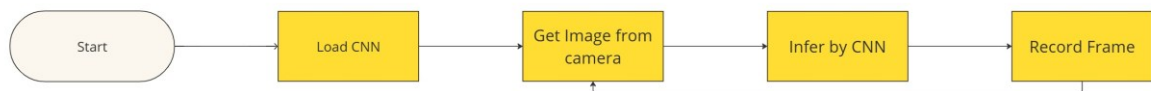
After each YOLO's training and validation process for each image spectrum, the Nvidia TensorRT was used to optimize the model. This optimization was not trivial, as the simple conversion of the model for the Jetson Nano for the TensorRT model did

not work for the Jetson Nano. In order to solve this problem, the mailrocketsystems/JetsonYolov5 repository from GitHub was used, converting the YOLO v5 Nano model into a TensorRT model.

3.5 Software to control the camera

As this work employed two methodologies, two pieces of software were developed. For the first software, it was more straightforward, as presented in the Figure 37. The first part of the software loads the trained network and initializes the camera. After that, it runs in an infinite loop, capturing real-time images, pre-processing them, making their classification, and storing the images.

Figure 37 - Flowchart for the first methodology.



Source: Own authorship (2024)

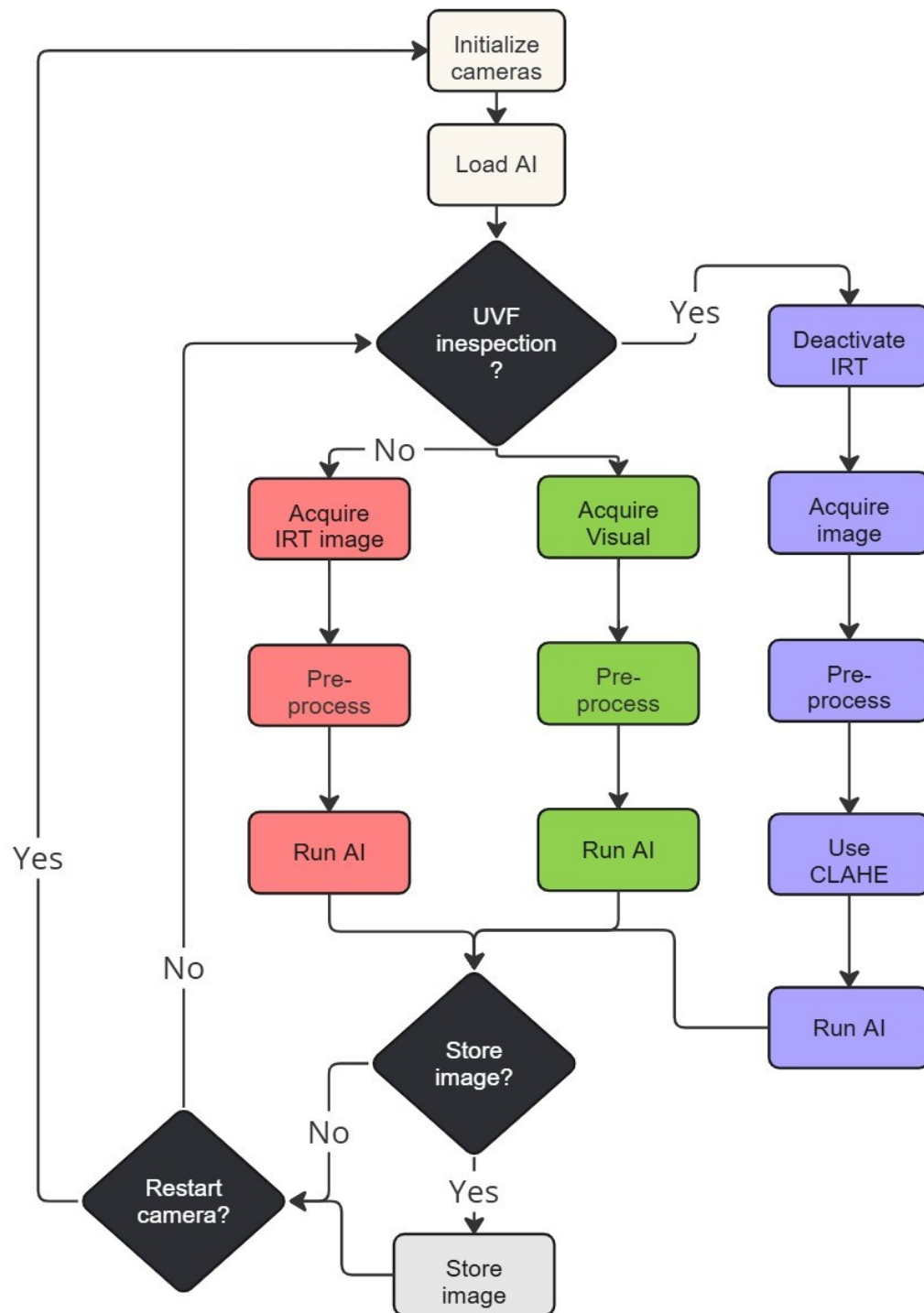
For the second methodology, the software evolved to a more complex structure, where this structure can be seen in the workflow presented in the Figure 38. This workflow was essential to make the system work perfectly, as it has two imaging sensors and three YOLOs. To start the software, an initialization routine of the cameras is called when Jetson is powered. After this camera initialization, the three neural networks are loaded to be read for the detection and classification of the images. These two processes are done only once due to their time-consuming nature. With the loaded system, it is verified if the UVF inspection has been selected. Since IRT images are not needed to make the UVF inspection, when the UVF inspection is chosen, the system deactivates the infrared camera.

With the UVF inspection selected, the first step is to capture a visual spectrum image, pre-process this image to be used in the AI network, and finally apply the CLAHE algorithm. After this, the AI algorithm identifies the PV cells from the CLAHE-processed image and classifies these identified cells to determine if these cells are healthy or defective. If the user selects the option to store the image, in the next step, the system will store this image; otherwise, the image is not stored, only shown in the software to the user.

On the other hand, if the UVF inspection is not selected, a parallel process begins to acquire visual and IRT images. The steps are the same as the UVF inspection: acquire an image, pre-process, and run AI, except for the CLAHE algorithm. This continuous process only halts when the Jetson is powered off. Each interaction verifies if the user requested a restart of the camera. This restart was necessary to solve issues such as autofocus or digital gain problems with the RGB camera. In the case of a restart, the process starts all over again. If no restart is requested, the system verifies again if it is a UVF inspection and takes the flow of the software according to the selected option.

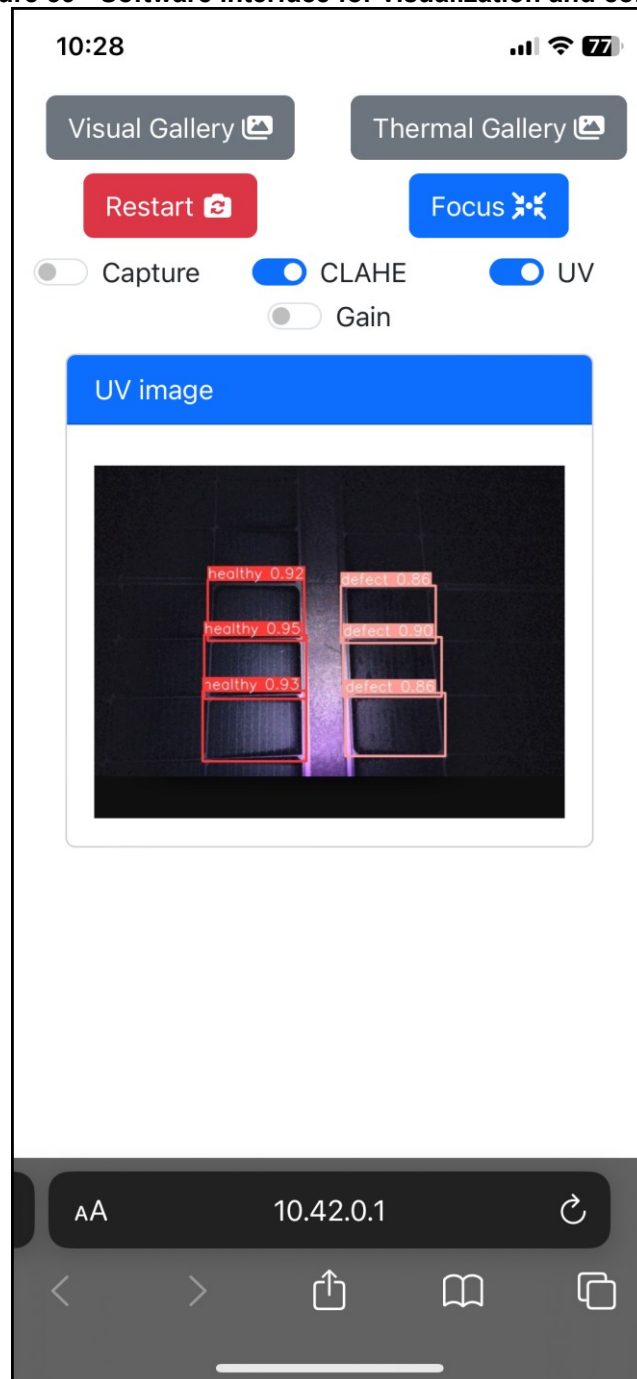
In order to make it easy to control and visualize the inspection in real time, the camera software was developed as a web-based application accessible by any device. The Figure 39 shows the graphical user interface (GUI) developed for better illustration. This GUI includes several options for the user. At the top of the software are two buttons to access the image galleries: one for the visual spectrum images, which includes the UVF images, and the other for the IRT images (button Thermal Gallery). The red button "Restart" can restart the camera software if needed. The "Focus" button requests an autofocus process in the RGB camera. The blue slides are options that, when selected or not, the system will execute that option or not. The "Capture" option is used to store or not the captured images. The "CLAHE" option is selected if wanted, and the CLAHE algorithm must be executed. The "UV" option is used if the user wants to do a UVF inspection, but when this option is selected, the IRT image will not be displayed, as shown in the figure. Finally, the "Gain" option is used to make the RGB camera use the entire gain available; otherwise, if not selected, only half of the digital gain is used. This option was developed because, in the UVF inspection, the entire gain causes salt and pepper noise, but in the visual spectrum inspection, the entire gain is desired.

Figure 38 - Flowchart for the second methodology.



Source: Own authorship (2024)

Figure 39 - Software interface for visualization and control.



Source: Own authorship (2024)

4 RESULTS AND DISCUSSION

This section presents and discusses the results of the two proposed methodologies. In section 4.1, the results of the first methodology are presented. Section 4.2 presents the results of the second methodology, which uses the YOLO network. Finally, section 4.3 discusses the general considerations about the two methodologies.

4.1 Results with CNN directly for visual spectrum

After collecting the dataset of visual spectrum images, the 17 network models were tested. These 17 models are selected in a way to cover the models used in the literature and models that are not used and can have a great potential in classification to the problem in question. Table 4 shows the training, validation, and testing results, with the respective accuracy values, the class where the most significant error occurred, and the total and trainable parameters of the network. In addition to the ordering from best to worst test results in the table, these values were highlighted to identify the best results in each stage (*italics and underlined*). Regarding the input image size, most networks used 224×224 pixel images. The exceptions were the InceptionResNetV2, InceptionV3, and Xception networks pre-trained with 299×299 pixel images.

When observing the training results, the MobileNetV3Large, DenseNet201, and EfficientNetB0 networks presented the best results. However, in the training validation, the EfficientNetB0 network is replaced by MobileNet. This result shows the importance of the validation dataset because, without it, this network could be considered one of the best when, in reality, it is not. The validation during the training allows the model to correct the training error with a dataset not knew in the training step, resulting in a better training. If this error not correct itself the training is suffering of overfitting.

For each network, the learning curves were analyzed. This analysis is performed by collecting each epoch's training and validation accuracy. Thus, for better visualization, Figure 40 and Figure 41 show the training and validation accuracy curves of the three networks that stood out. Not all networks were plotted because their visualization is compromised due to the number of networks trained.

When analyzing the training curves, it was found that only the MobileNet network showed signs of overfitting; that is, the network was saturated with the acquired knowledge, and this phenomenon was noticed from the tenth training epoch. However, when analyzing the validation data, only the MobileNetV3Large network showed constant learning without signs of overfitting. These results show a tendency for the MobileNetV3Large network to perform better than the other networks for the problem in question.

Table 4 - Efficiency of the models chosen in the training, validation and testing stages and parameter information for each model. The data are ordered from highest to lowest test accuracy value.

Network	Accuracy			Major Error Class	Parameters	Trainable Parameters
	Training	Validation	Test			
MobileNetV3Large	<u>96.02</u>	<u>97.92</u>	<u>97.72</u>	clear	3.000.196	3.844
DenseNet201	<u>95.52</u>	<u>95.66</u>	<u>96.00</u>	shadow	18.329.668	7.684
MobileNet	94.43	<u>94.92</u>	<u>95.47</u>	dirty	2.263.108	5.124
ResNet151V2	93.97	94.34	94.78	dirty	58.339.844	8.196
VGG19	91.39	94.12	94.72	dirty	20.026.436	2.052
MobileNetV2	93.87	94.04	94.47	clear	3.000.196	3.844
ResNet50V2	94.24	94.46	94.33	clear	23.572.996	8.196
EfficientNetB0	<u>95.25</u>	93.33	94.17	clear	64.107.931	10.244
Xception	93.26	94.34	93.97	shadow	20.869.676	8.196
EfficientNetV2L	89.43	92.87	93.00	clear	21,810,980	8,196
EfficientNetV2B0	94.83	92.45	92.53	clear	117.751.972	5.124
MobileNetV3Small	90.93	92.59	92.33	clear	941.428	2.308
InceptionV3	91.98	91	91.67	clear	2.263.108	5.124
VGG16	91.20	91.22	91.61	clear	14.716.740	2.052
DenseNet121	93.61	90.48	91.56	clear	7.041.604	4.100
EfficientNetB7	92.94	90.8	91.03	clear	5.924.436	5.124
InceptionResnetV2	83.61	79.20	78.36	clear	3.232.964	4.100

Source: Own authorship (2024)

The networks were then subjected to a test base to verify their behavior with data not used in training. In the test results, the top 3 from the validation stage were maintained with a difference of more than 1.5% in accuracy between the first and second networks models.

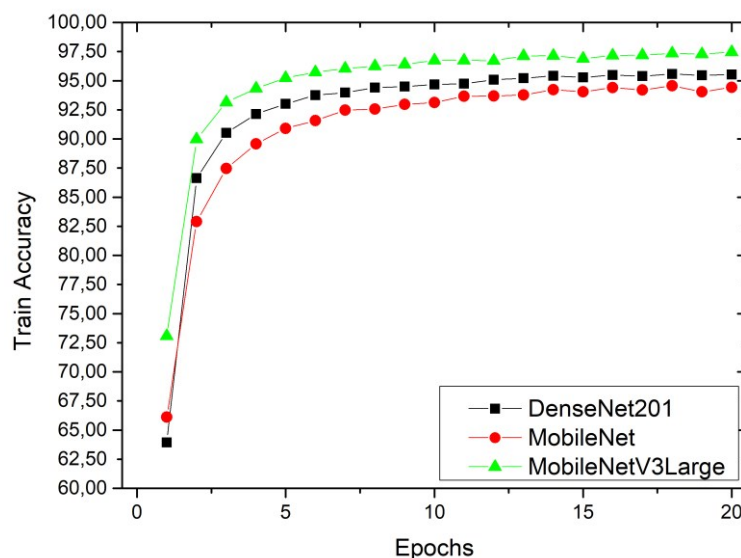
In conjunction with Table 4, the prediction confusion matrix was generated with the test data for each network. The confusion matrix made it possible to verify the

models' false positive/negative rates. Thus, it was possible to identify which class had the lowest accuracy for that model. This information is in the "Major Error Class" column of Table 4. Figure 42 to Figure 44 show the confusion matrix of the MobileNetV3Large, DenseNet201, and MobileNet networks for better exemplification. For the test stage, there were 3600 images, with each class having 900 images, and this matrix should have the number closest to 900 on its diagonal, where the further away this number is, the lower the accuracy in that class.

In general, the class that presented the most significant error was the clean class, as seen in Table 4. This confusion between classes can occur because, if visually analyzed by a human, in many images, it can easily be confused what would be a panel without faults with a faulty one.

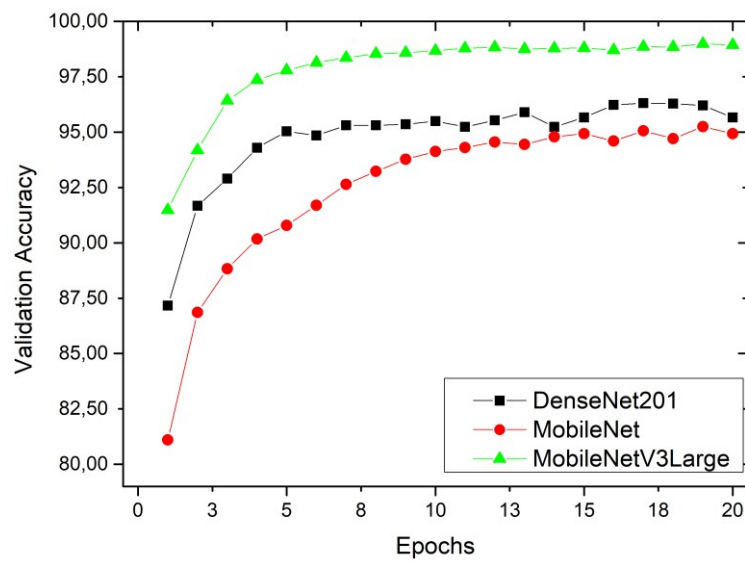
The definition of this threshold where a PV panel is clear or dirty is complex, and there are works in the literature that deal with specific methodologies to perform this definition (CHAKI *et al.*, 2024; MEHTA *et al.*, 2017; TRIBAK; ZAZ, 2019; ZHANG, Wenjie *et al.*, 2021). To better visualize this error, Figure 45 presents an example of erroneous classification performed by MobileNetV3Large without FT, where all the images presented should have been classified as clean.

Figure 40 - Learning curve of the accuracy value of the training stage for the top 3 networks without FT.



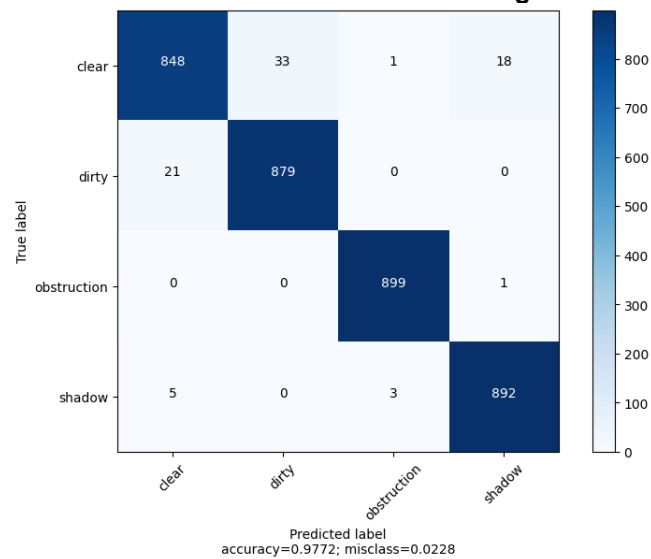
Source: Own authorship (2024)

Figure 41 - Accuracy curve of the validation result of the training stage of the top 3 networks without FT.



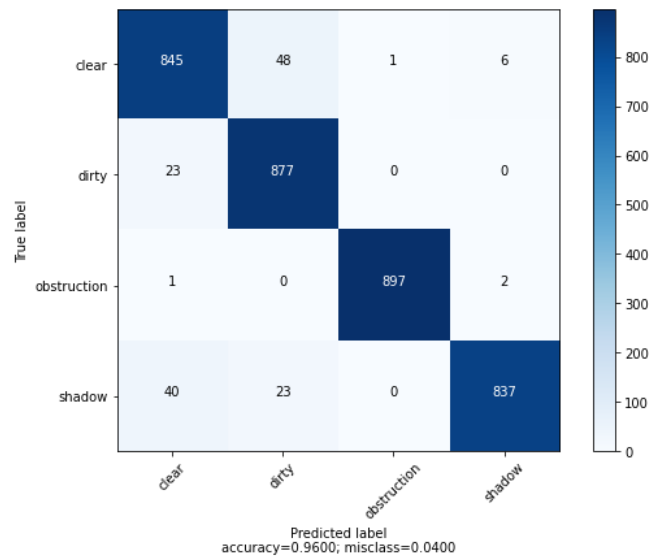
Source: Own authorship (2024)

Figure 42 - Confusion matrix of the MobileNetV3Large network before FT.



Source: Own authorship (2024)

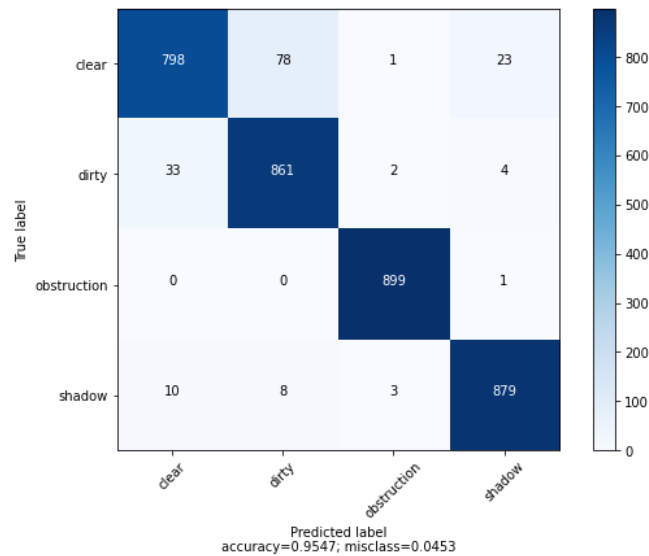
Figure 43 - Confusion matrix of DenseNet201 network before FT



Source: Own authorship (2024)

The superior result of the MobileNet networks was expected since the article that constitutes MobileNet shows that the network is capable of matching larger networks such as VGG16 (HOWARD, Andrew G. et al., 2017), in addition to the article on MobileNetV3 showing remarkable evolution (HOWARD, Andrew, et al., 2019). These results show that this network, even smaller than the others, can deliver excellent results (accuracy > 95%) for the problem addressed in this work.

Figure 44 - Confusion matrix of MobileNet network before FT



Source: Own authorship (2024)

Figure 45 - Examples of images misclassified by MobileNetV3Large before fine tuning. All of these images should have been classified as clean, but they were classified as obstruction (1), shadow (2), and dirty (3).



Source: Own authorship (2024)

This fact of smaller networks can also be observed in the result of the MobileNetV3Small network. This network is the smallest used in this work. Its results are similar to those of larger networks and indicate great potential in MobileNet-type networks for applications that require fast responses and low computational power.

The networks that used a larger input image performed similarly to those that used the 224×224 pixels input image. Since the size of the input image is a critical factor in using less computational resources, this result helps to show that larger images did not provide superior results.

FT was applied to the three best networks after completing this TL stage without defrosting the upper layers. Table 5 shows how many parameters were trained in each network and their performance in each training stage.

Table 5 - Efficiency of models in the training, validation and testing stages in FT.

Network	Accuracy			Error class	Trained parameters
	Training	Validation	Test		
MobileNetV3Large	99,38	99,48	99,64	dirty	801.204
DenseNet201	99,44	99,40	99,58	dirty	2.887.748
MobileNet	97,83	97,44	97,56	dirty	1.065.988

Source: Own authorship (2024)

The difference between MobileNetV3Large and DenseNet201 was narrower than without FT. However, observing the training data in each epoch, the MobileNetV3Large network showed more constant learning. Figure 46 and Figure 47 compare the accuracy curves in each stage of the training and validation of these networks. This result shows that for the problem in question, the MobileNetV3Large network stood out in all aspects. In addition to the numerical results, it was verified that the images presented in Figure 45 were correctly classified by MobileNetV3 after FT. Another point that needs to be highlighted is the fact that the MobileNet showed an unstable result, which is not desired, and because of this, it can be concluded that the evolution of the MobileNet corrected this instability problem.

The same analysis used without FT was used to analyze the results presented by the networks after the FT process, that is, to verify the confusion matrix of each network. Thus, Figure 48 to Figure 50 present the confusion matrices for the three networks in which FT was applied. This analysis shows that the predominant error class changed from clean to dirty, proving the complexity of distinguishing these two classes. However, all images in Figure 45 were classified correctly by MobileNetV3Large. From the confusion matrices, it can also be seen that the margin of error between MobileNetV3Large and DenseNet201 is narrow. Compared with MobileNet, the dirty class has a more significant difference in accuracy.

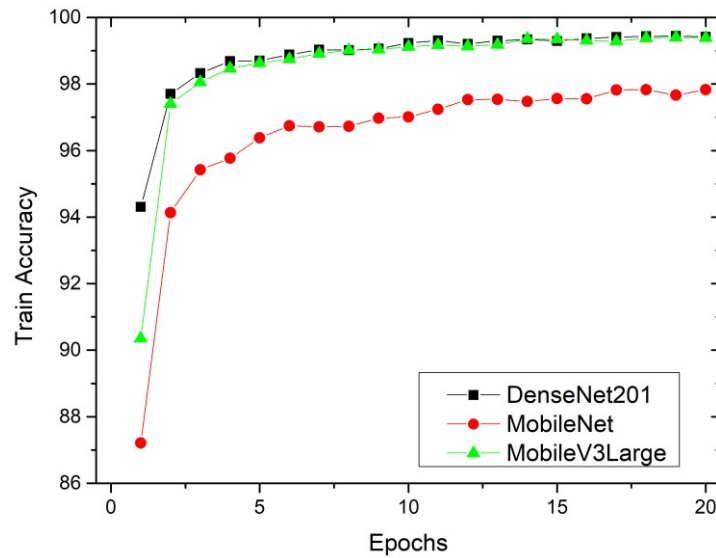
Even though DenseNet201 had a result close to that of MobileNetV3Large, it is worth remembering that the DenseNet201 network had almost three times more parameters trained, which requires much more computational resources to use this network.

Therefore, larger networks with many parameters require high computational power to perform training. This necessity also affects the inference time when the model is used for real applications, where computers with low computational power may take a long time to process an image or may not be able to load the network model due to its size and the RAM limitations of edge devices.

The results show that the TL technique can be a helpful tool to address the problem presented. Furthermore, the comparison made between several networks, observing the accuracy and size of the network, helps in the decision-making of which network to use. Interestingly, smaller networks performed equal or better results than larger networks for the problem presented. This result may instigate new research and applications with smaller networks since, as shown, the literature presents articles

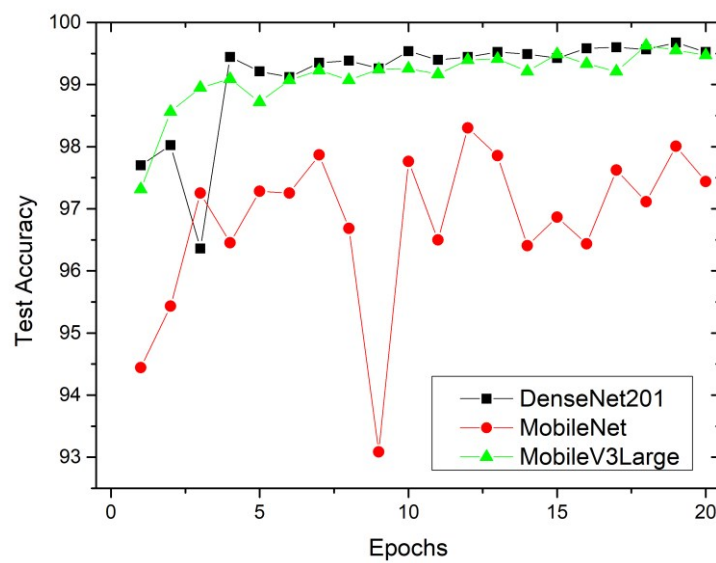
based on large networks, and their results can be optimized if based on more efficient networks.

Figure 46 - Learning curve of the accuracy value of the training stage for the top 3 networks with FT.



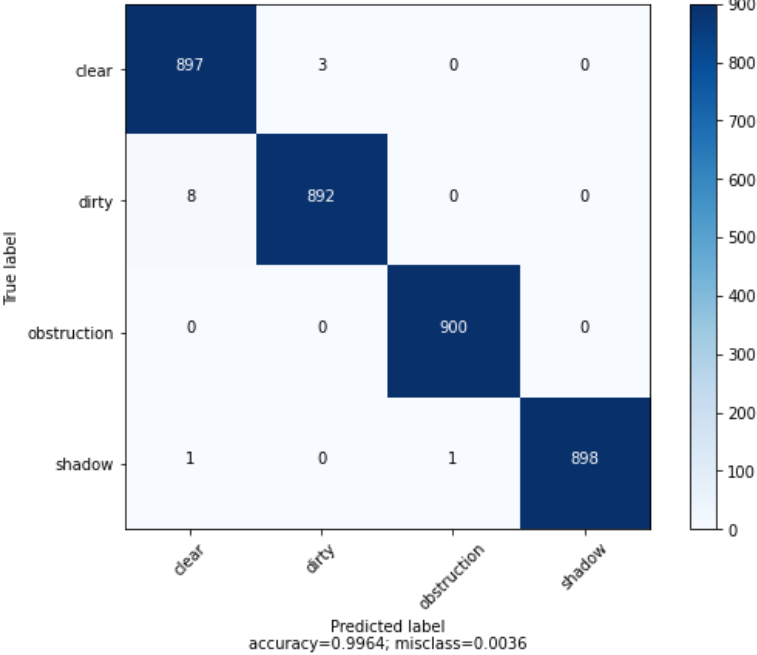
Source: Own authorship (2024)

Figure 47 - Accuracy curve of the validation result of the training stage of the top 3 networks with FT.



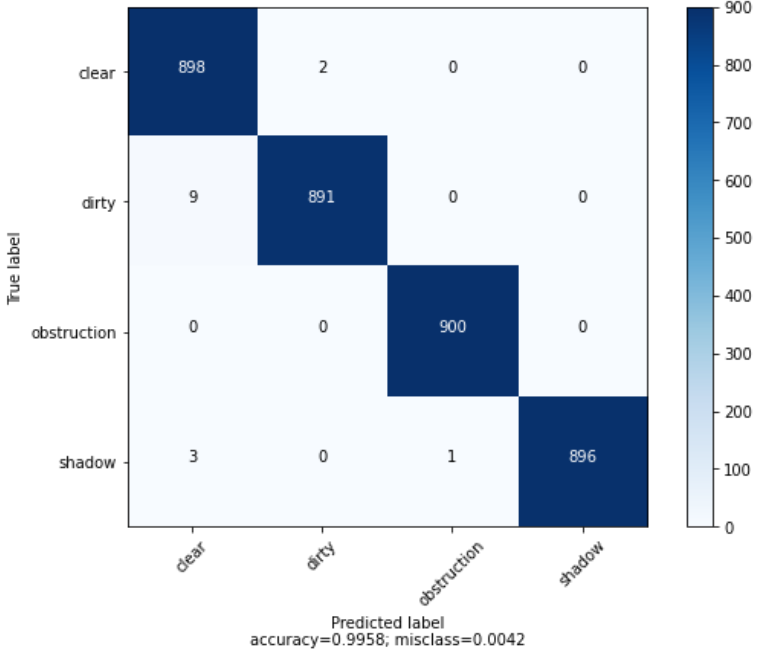
Source: Own authorship (2024)

Figure 48 - Confusion matrix of MobileNetV3Large network after FT

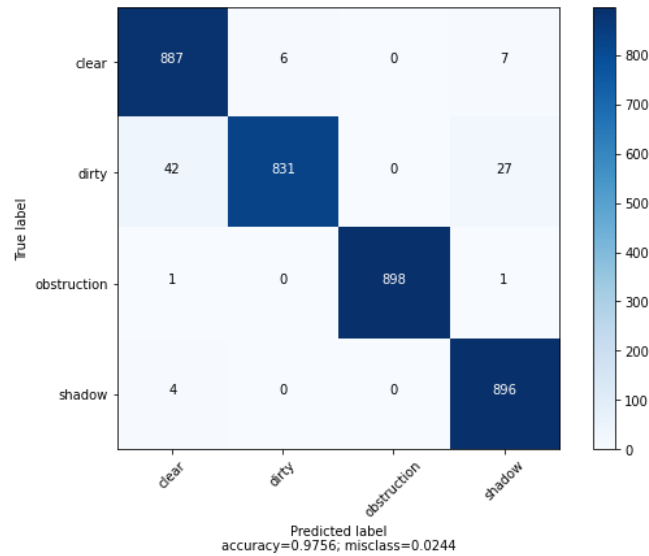


Source: Own authorship (2024)

Figure 49 - Confusion matrix of DenseNet201 network after FT



Source: Own authorship (2024)

Figure 50 - Confusion matrix of MobileNet network after FT

Source: Own authorship (2024)

4.1.1 Results with edge device and CNN directly

Once the training and testing stages were completed, MobileNetV3Large proved the most efficient. It was, therefore, the network chosen for testing in a real environment using the Nvidia Jetson Nano.

Initially, testing was performed directly with Tensorflow, with the images being pre-processed by OpenCV. In this methodology, the system needed 300ms to infer an image in 10W mode and 600ms in 5W mode. As this result was much lower than expected from the literature for MobileNetV3Large, the optimization with Nvidia TensorRT, as mentioned in the methodology, was applied.

With this optimization, in 10W mode, the system performs image inference in 50ms and the 5W mode in 90ms, showing that this optimization is essential.

With the positive result in 5W mode, the embedded system was tested in the field. This test consisted of simulating the three types of defects and the panel without defects to verify how the system would behave.

For better visualization, this real test was recorded and is available in GitHub repository¹. From this video, it can be seen that the system was able to correctly identify the predicted classes, in addition to showing fluidity in the identification due to the hardware and optimization performed.

¹ <https://github.com/abiffe/paper-pv-dnn>

4.1.2 Comparison with Related Works

The present work was superior when comparing the results obtained with those of the proposed networks mentioned in section 2.3.2. This positive result proves that the development and training of a CNN is not a simple task.

The results obtained were superior or similar in the direct comparison of results referred to in section 2.3.2 that used the same networks employed in this work.

Specifically, when comparing the results of the work developed by (LI, Xiaoxia *et al.*, 2020b), which presents classification tests on edge devices and comparisons with other networks in addition to the one proposed by these authors, the present work showed superior and promising results.

The significant difference between this work and the works under comparison is the extensive presentation of results with already known and pre-trained networks. This extensive comparison showed that smaller networks that are usually discarded in the works could potentially solve PV analysis problems. In addition, this work uses a commercially available edge tool (Nvidia Jetson Nano). It makes all the developed code available, facilitating its replication by researchers and solar power plant companies.

Regarding the dataset collected, organized, and made available to the community, it is essential to emphasize that because each work has different image datasets, the comparison between the methods cannot be made directly. Therefore, the public dataset made available in this work allows a later comparison between other methods, thus facilitating the development of more efficient solutions to address the problem presented. In addition, the provision of this dataset aims to inspire other research groups to make their data available and contribute to the information presented here.

4.2 Results using YOLO

As the results with the YOLO network are split into three networks, this section is divided into three subsections, where subsection 4.2.1 discusses the results obtained in the visual spectrum. Subsubsection 4.2.2 presents the results obtained from the IRT images. Subsection 4.2.3 presents the results of the UVF inspection. Finally, subsection 4.2.4 presents the results with the three YOLOs running in the edge device.

4.2.1 Visual Spectrum Inspection

For the visual spectrum inspection that uses the RGB camera from the edge device and daylight for inspection, for the four classes chosen to be inspected in this portion of the spectrum, the YOLO v5 Nano achieved a Mean Average Precision (mAP) with confidence of 0.5 (known as mAP@0.5) of 99.7%. The obtained result was the highest precision among all the trained YOLOs for this work. As the faults presented in this portion of the spectrum are widely spaced, the classification is relatively straightforward for a robust algorithm. Nevertheless, the classification of dirty panels remains challenging. This task is crucial and needs to be done precisely to avoid unnecessary cleaning and prevent hot spots that this dirt accumulation can cause. Figure 51 presents the detection and classification of a dirty PV panel to show how the algorithm detects faults in the visual spectrum.

Figure 51 - Classification by the YOLO for visual spectrum identifying a dirty PV.

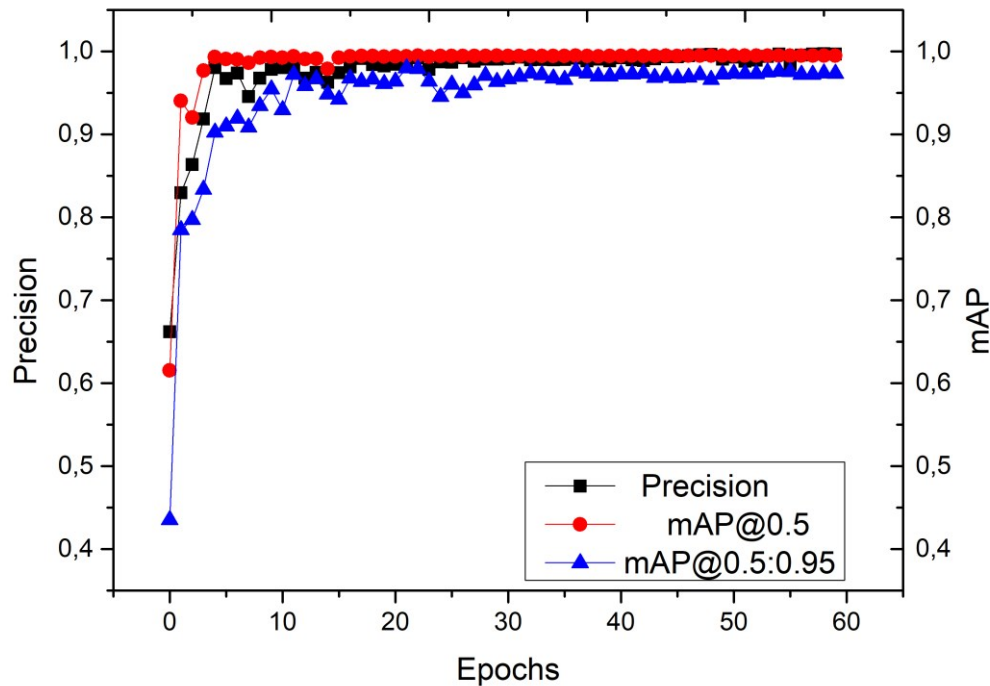


Source: Own authorship (2024)

Now, looking at the process of training the YOLO v5 Nano, the Figure 52 presents the mAP@0.5 compared with the mAP@0.5:0.95 for the 60 training epochs. The mAP@0.5:0.95 is the same mAP analysis but considering the detection

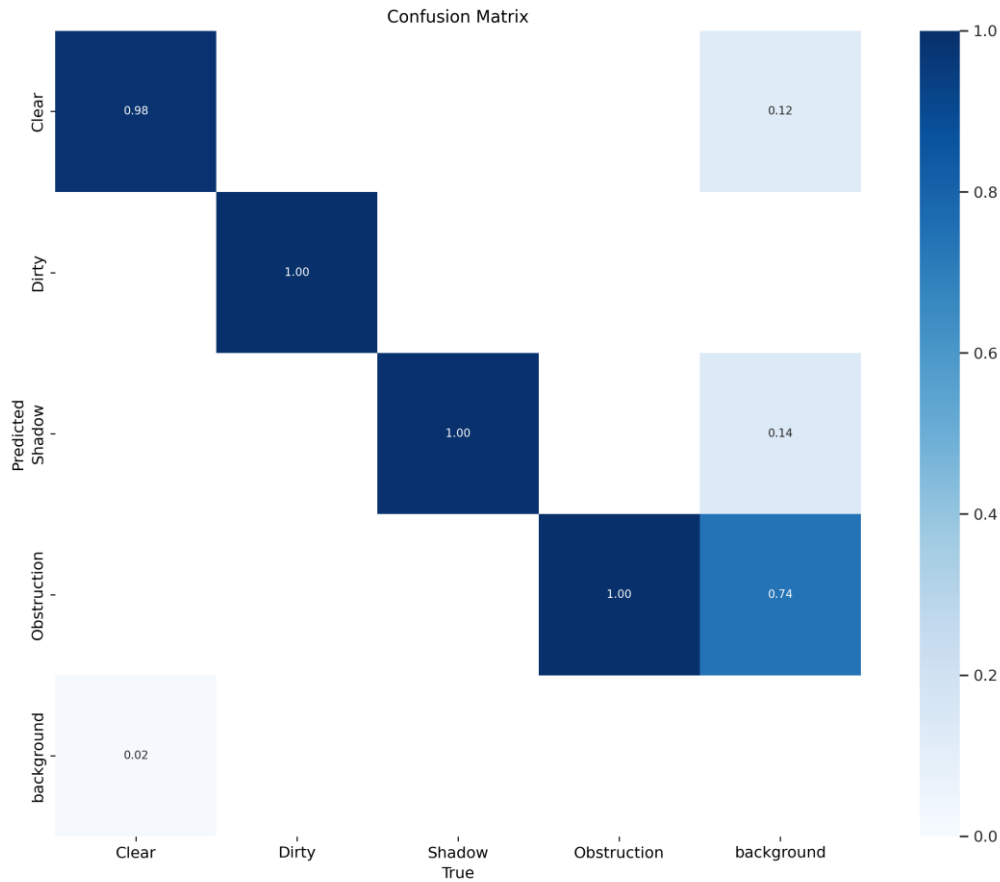
confidence between 0.5 to 0.95. The analysis of the presented graph shows that the precision growth is correct, without huge drops, and after the initial epochs, there is stabilized learning.

Figure 52 - Metrics for the YOLO in the visual spectrum.



Source: Own authorship (2024)

Another tool that helps identify if the model is performing as desired is the CM. Considering this, the Figure 53 shows the CM for the YOLO used in the detection and classification of the images from the visual spectrum. This CM shows that the model performed an excellent classification, where the only class with less than 100% precision was the clear class. This result can be explained by looking at the background class. This class means that the image has correctly identified the object and the background of the image. For the clear class, 2% of the images had problems with this background, with the 2% needed to achieve 100% precision. This result was expected, as the threshold between a clear PV panel and a dirty one is complex.

Figure 53 - Confusion matrix for the YOLO trained to the visual spectrum inspection.

Source: Own authorship (2024)

About this problem with the soiled PV panels, this theme is critical and extensively researched. This soiling effect, particle deposition on the PV panel, occurs in any region with high atmospheric suspended particles. This issue can result in 3-5% annual energy production losses, and cleaning can result in economic costs (CHRISTIAN SCHILL, 2022). With tools like those presented in this work, the O&M can regularly inspect the power plant and make precise decisions on where to clean the PV panels.

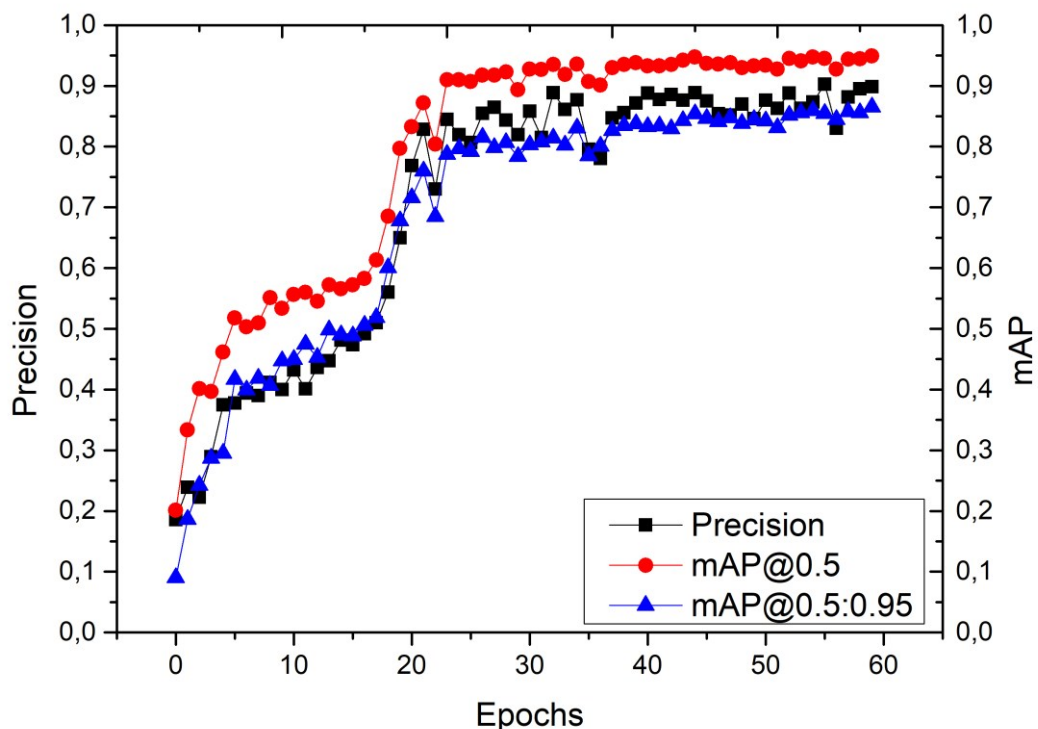
Concerning the partial shading effect that the YOLO trained to the visual spectrum can detect, the total output reduction because of this phenomenon can be up to 75%, where, depending on the irradiance level of the PV system, the power loss ranges from 10% to 70% (AL-SMADI; MAHMOUD, 2018). The partial shading effect can occur from poor installation planning, wires crossing the PV modules, or vegetation growth. When the issue regards the installation, a thorough analysis by the engineering team is required because of its complexity. Regarding the problem caused by vegetation growth, this problem can be mitigated concurrently with cleaning dirty PV

modules. The presented camera system can identify both issues, and the O&M team can address them in a single inspection, minimizing the downtime to solve those issues with the optimized planning that the camera allows with the preventive inspection.

4.2.2 IRT Inspection

The YOLO v5 Nano presented a $mAP@0.5$ of 94% for this inspection. For better analysis, the Figure 54 presents the training curve for the 60 epochs comparing the $mAP@0.5$ with $mAP@0.5:0.95$. By the analysis of this curve, it can be seen that the precision did not increase by more than 60% until the 20 epoch, and after the 25 epoch, the precision increased very slightly. In order to confirm the value of precision obtained in the best epoch, the confusion matrix is presented in the Figure 55, where the precision for the hot spot class was 92% and for the normal class 94%. The background class shows that the YOLO identified correctly the classes, with only 2% of misclassifications.

Figure 54 - Metrics for the YOLO in the infrared spectrum.

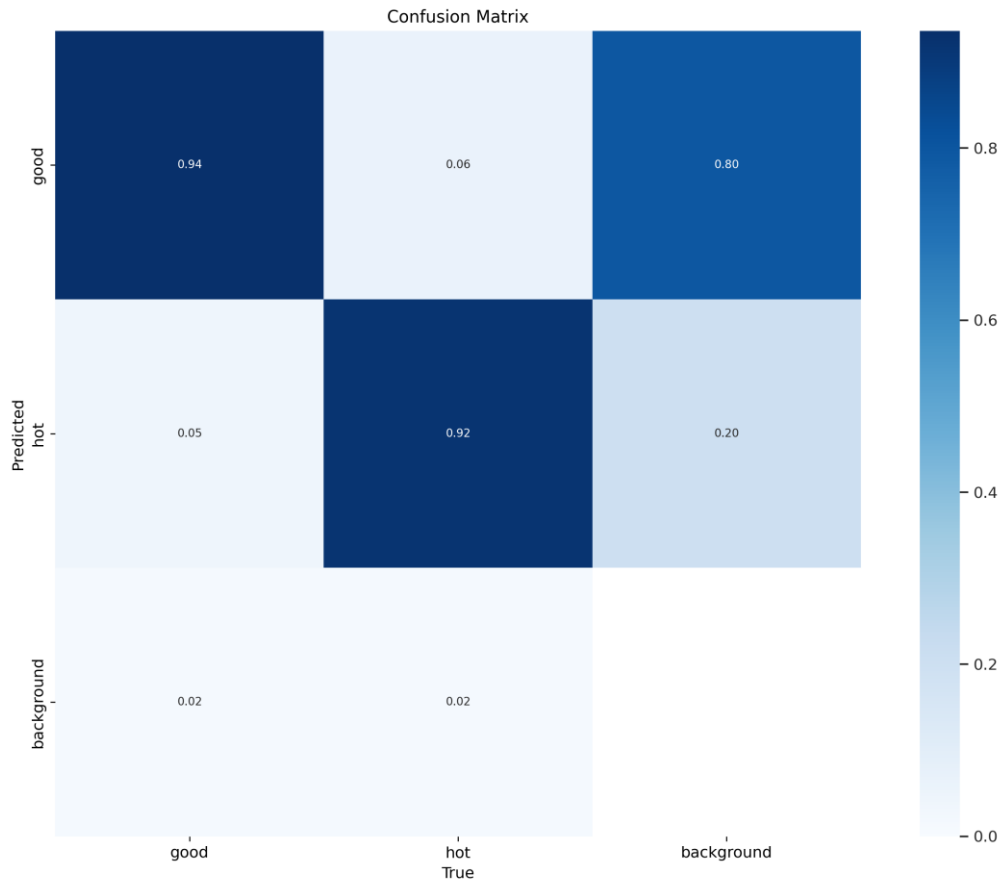


Source: Own authorship (2024)

Considering the results obtained, the trained YOLO for the IRT images is stable, with a good balance of performance between the two classes and minor

misclassifications. Despite using a low-resolution infrared camera, the model can identify minor hot spots effectively.

Figure 55 - Confusion matrix for the YOLO trained to the infrared spectrum inspection.



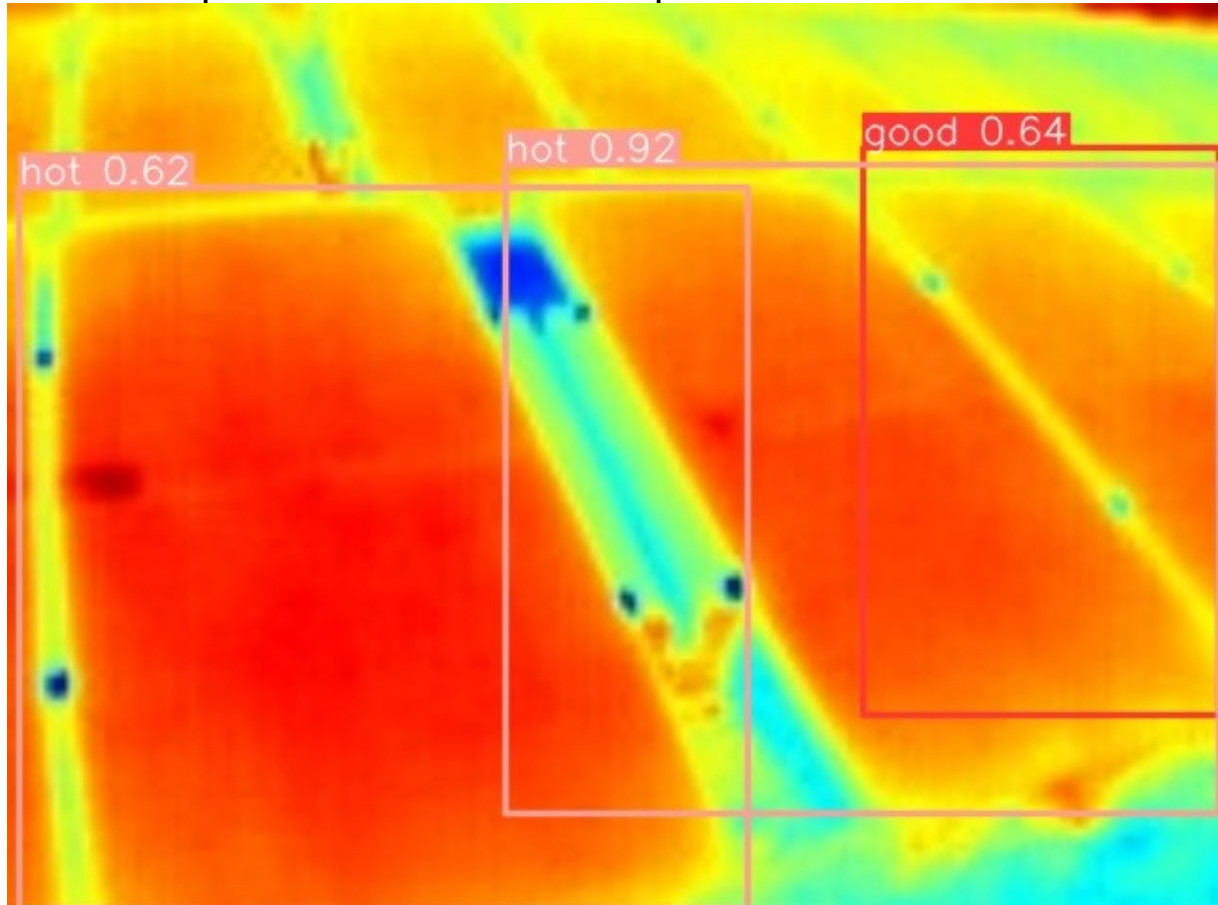
Source: Own authorship (2024)

The trained YOLO for IRT images was executed to classify images in a dataset collected in Milagro, Spain, to identify hot spots in the solar plant. Following this classification, power production was analyzed to determine if the hot spots indicated actual issues. Most identified issues corresponded to real production issues, demonstrating that the proposed system can detect genuine faults. By analyzing the power production, some of the inspected solar trackers presented a power loss of up to 6% when numerous hot spots were present. Identifying power losses in this inspected solar plant is straightforward because each solar tracker has a dedicated inverter.

Another inspection was conducted at the power plant in the UPNA in Spain. As this installation is relatively new, only a few hotspots were localized. The most occurring problem in this solar plant was at the diode junction, necessitating further investigation to determine the impact on power loss. As an example of this problem,

the Figure 56 presents the classification of a hot spot when a diode problem is occurring. In case of confirmation of this problem, the power loss could be at least 2% per PV panel (MERIBOUT *et al.*, 2023). From the 438 inspected panels, only one exhibited a cell hot spot, while 51 showed hotspots at the diode, a significant number of hotspots for a new plant, warranting thorough investigation.

Figure 56 - Example of YOLO classification of hotspot PV (hot) and normal (good). The diode problem can be seen in the darkest point in the middle of the PV.



Source: Own authorship (2024)

There can be many hotspot sources, so their analysis is quite complex. The losses that can affect the PV panel by hot spot depend on the number of hotspots identified, with performance ratios varying from -0.83% to -15.47% (DHIMISH; MATHER; HOLMES, 2018). As the hot spot causes significant heating of the PV module, this problem can be hazardous, where the temperature difference between a normal cell and a hot spot cell can exceed 50°C. This temperature difference was observed in the power plant at Milagro, Spain. In some extreme cases, the high-temperature difference could lead to highly undesirable fire ignition.

Typically, once per year, the power plant company conducts hot spot inspections. This inspection is not done regularly because of the challenges of performing this task without automation. Often, the company must have the specialized persons or equipment required to make this inspection. Because of these conditions, hiring specialized firms to conduct hot spot inspections is necessary. With this scenario, the presented solution has significant potential to assist O&M staff in conducting regular IRT inspections of power plants more efficiently and accurately.

4.2.3 UVF Inspection

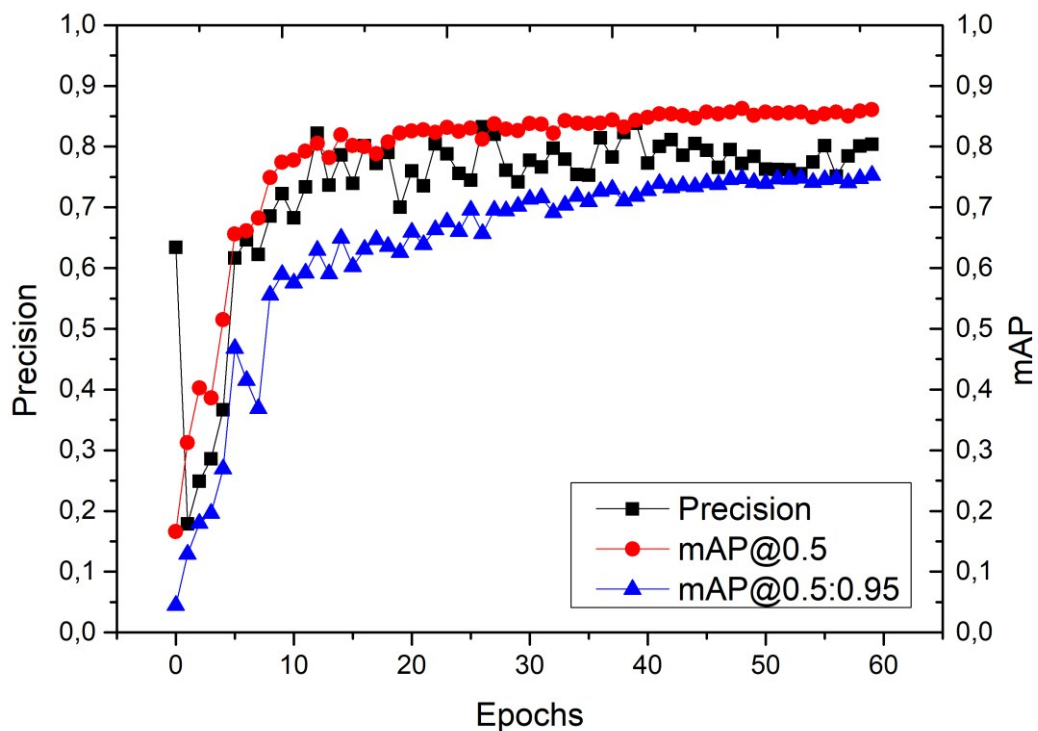
In the UVF inspection, the trained YOLO presented a $mAP@0.5$ of 86%. For better analysis, the Figure 57 shows the training curve over the 60 epochs comparing the $mAP@0.5$ and $mAP@0.5:0.95$. By analyzing the curves, it is noted that the precision grew correctly, without huge drops and constantly. Investigating these results more, the Figure 58 presents the CM for this trained model. By the CM, the precision for the healthy class is 88%, and for the defect class is 74%. With this analysis of the CM, it can be seen that the model did not classify correctly, where in 24% of the cases, the defect was classified as healthy and in 2% of cases as a background. For the healthy class, 6% was classified as a defect, and 6% was classified as a background. The result shows that the system has difficulty distinguishing between healthy and defective cells. This result was expected, as the modules at UPNA showed a low fluorescence, which is only six months old - the minimum age for a UVF inspection. Without the CLAHE algorithm, the results could have been worse. For better visualization of the impact of the CLAHE algorithm, the Figure 59 shows the comparison with and without CLAHE in a UVF inspection. As shown, when comparing Figure 59(a) with Figure 59(b), in (a), it is not possible to see the early corrosion, whereas in image (b), this corrosion is visible.

With this positive result, the YOLO model successfully identified healthy and defective cells from UVF images, which can be seen in the Figure 60. Of the 438 inspected panels at the UPNA power plant, 107 panels exhibited at least one cell defect, where the most common fault was the busbar corrosion. The executed inspection in this brand-new power plant showed results that need to be accompanied in the following year, like in the next one or two years after the PV module gets more solar irradiance and better fluorescence, to verify if the identified problems persist. According to the literature, this corrosion problem can lead to circuit discoloration,

resulting in a 1% annual loss in production (KOESTER *et al.*, 2022), which is significant. The UVF inspection is primordial to detect early issues in the PV cell structure and to claim for warranty if needed. The presented solution, which is UV lights coupled with parabolic reflectors to concentrate the light at long distances, enabled UVF image capture at a reasonable distance of 1.5 meters from the inspected PV module.

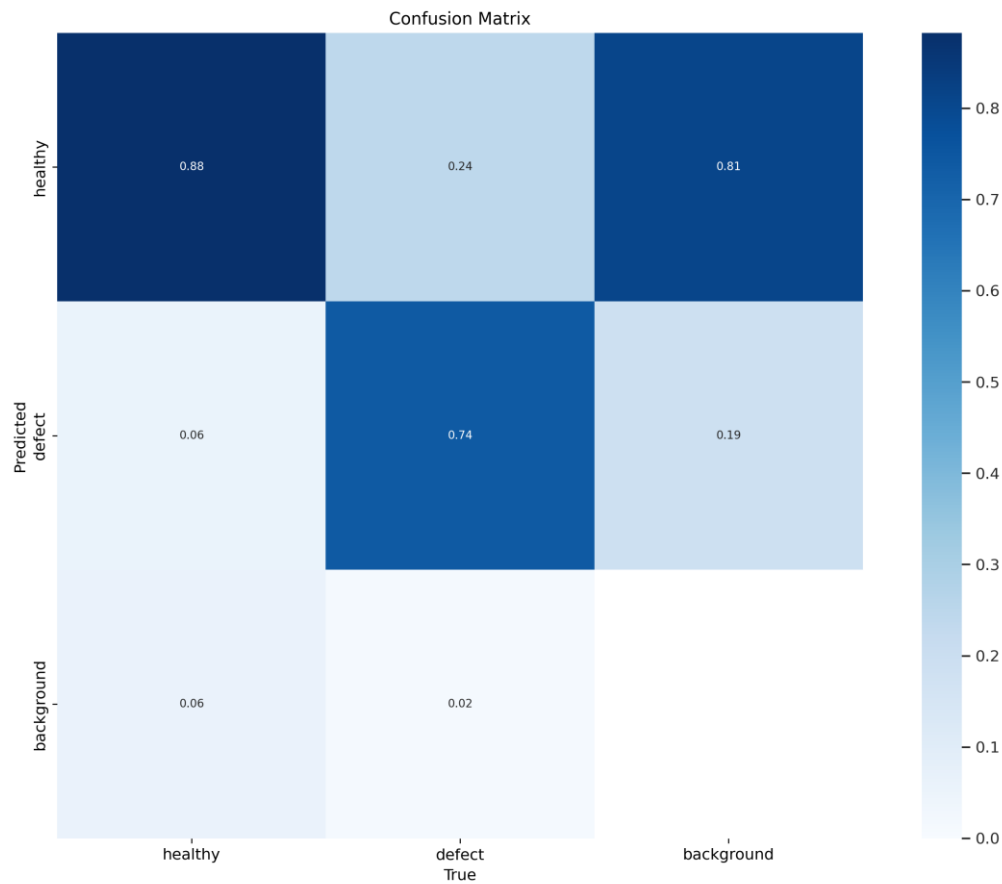
Many issues that the UVF inspection can identify, some of them could lead to more power loss or may have a correlation with other inspections. For example, the encapsulation yellowing that the UVF inspection can identify can lead to a 10% loss over the PV module lifespan (MORLIER *et al.*, 2018). Another example is when a hot spot is detected in the IRT inspection, where the UVF inspection can be applied to investigate whether the hot spot is due to a microcrack in the PV cell.

Figure 57 - Metrics for the UVF YOLO.



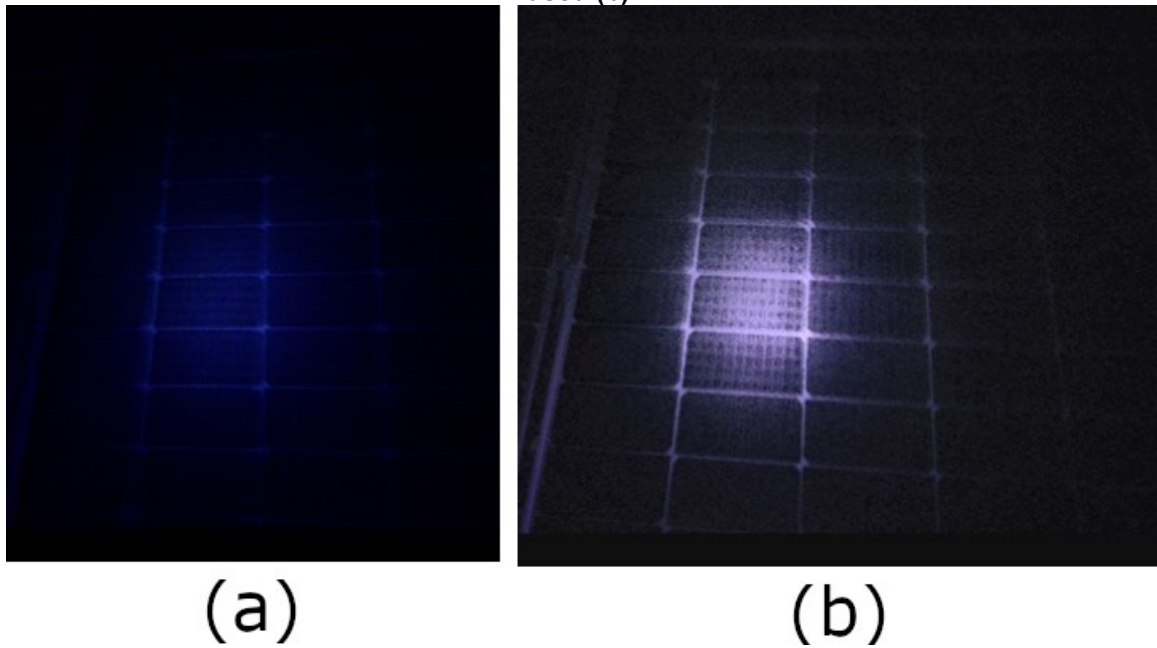
Source: Own authorship (2024)

Figure 58 - Confusion matrix for the YOLO trained to the UVF inspection.



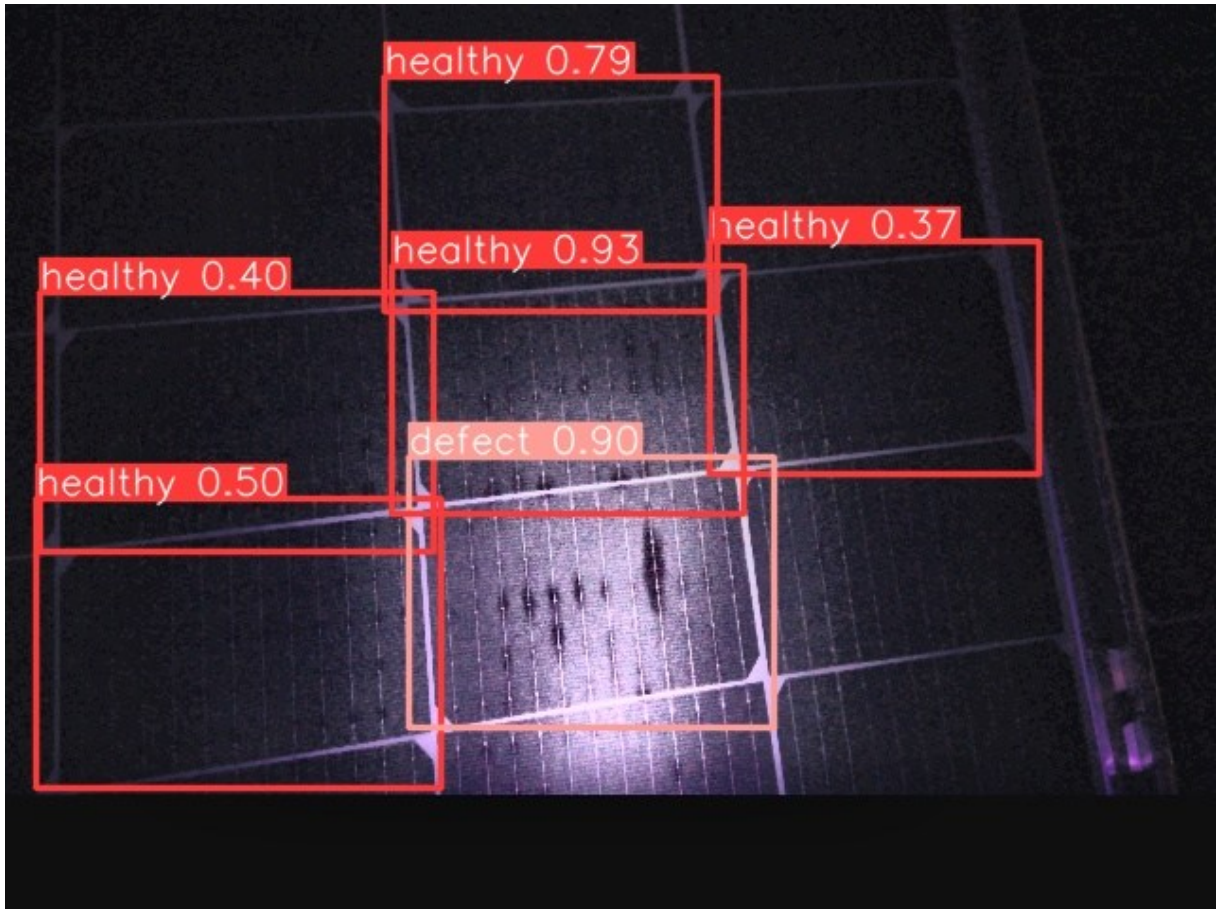
Source: Own authorship (2024)

Figure 59 - Difference between the original image (a) and the image with the CLAHE algorithm used (b).



Source: Own authorship (2024)

Figure 60 - Cell UVF classification by YOLO. A small corrosion is found in the cell and detected as a defect.



Source: Own authorship (2024)

4.2.4 YOLO in the Edge Device

After all the YOLOs were trained and validated, these models were tested in the edge device to verify their performance. Two tests were made, where the first did not use any optimization, and the second used the TensorRT optimization. All the tests were executed with Jetson's full performance with a maximum power of 10W.

The first test without the optimization consists of all three networks being loaded and using the OpenCV library to make the inference, where the YOLO model was converted to the ONNX format to use the OpenCV's DNN module. With this, to infer each image, it needed about 900 ms, which is very slow. Compared with the first methodology, it is slower if compared to the same test without the optimization. This result was expected, as the YOLO model is more complex and needs more computational resources. Nevertheless, it is a good result as the edge device could load three YOLO networks and make the inference without any problems.

In order to make the inference faster, the same method of the first methodology was used: TensorRT optimization. The three YOLOs were converted to a TensorRT-compatible model, and the test was made after the conversion. The three YOLOs are loaded, and the inference is made to verify the time needed to make this inference. The inference time varies between 40 to 50 ms. This result is outstanding as the same inference time was obtained for the first methodology. However, here, we have a network that detects and classifies the image, and this is perfect for making real-time inspections. With this excellent result, the complete system proved viable, showing that the composition of cameras, light concentrators, and edge devices proves to be a good tool for fast and precise PV panel inspections.

4.3 General considerations

Two methodologies are presented in this work. One is simple, considered an initial stage that proved fast and precise only for the visual spectrum algorithm but lacks a segmentation or object detection algorithm. However, this method was essential to verify the capability of the edge device chosen to compound the camera. This first method was essential for constructing the visual spectrum dataset, as this dataset was used as a basis for making the other two datasets.

The second methodology is more complex and complete, being an all-in-one system capable of inspecting visual spectrum, infrared, and UVF faults. The presented solution can help companies to make regular inspections, allowing preventive decision-making. As this second method used a complete algorithm to detect and classify faults in the multiple spectra inspected, it showed promising results, even with the smallest network model available. These outcomes indicate that YOLO v5 can be a helpful tool for inspecting PV panels, offering precise detection and classification.

For better comparison, Table 6 and Table 7 was constructed to compare the present work with the related works in the literature. In the observation these tables, it can be concluded that the present work has results near that found in the literature. Besides that, the present work has the advantage of using embedded device, as in the table only three works use embedded devices to make real time classification of faults in PV panels.

Table 6 - Comparison with related works.

					(continue)
Work	Model	Spectra	Metric	Embedded	Inference time (ms)
First methodology	MobileNetV3Large	Visual	Accuracy (99.64%)	Yes	~50
Second methodology	YOLO v5 Nano	Visual, IRT, UVF	mAP(86-99%)	Yes	~50
(WANG, Xiao <i>et al.</i> , 2022)	ResNet34	Visual	Accuracy (85.12%)	No	-
(CHEN <i>et al.</i> , 2020)	Proposed CNN	Visual	Accuracy (94.3 %)	No	-
(LI, Xiaoxia <i>et al.</i> , 2019)	Proposed CNN	Visual	Accuracy (97.9%)	No	-
(RICO ESPINOSA; BRESSAN; GIRALDO, 2020)	Proposed CNN	Visual	Accuracy (70%)	No	-
(CAO <i>et al.</i> , 2021)	Proposed CNN	Visual	Accuracy (82.4%)	No	-
(MORADI SIZKOUHI <i>et al.</i> , 2022)	Modified VGG16	Visual	Accuracy (93.33%)	No	-
(NAVEEN VENKATESH; SUGUMARAN, 2021)	TL in VGG16	Visual	Accuracy (95.40%)	No	-
(LI, Xiaoxia <i>et al.</i> , 2020a)	DNN + SVM	Visual	Accuracy (98%)	No	-
(MOHAMMED; BA ALAWI, 2024)	Based EffcientNetB7	Visual	Accuracy (98%)	No	-
(KAUR <i>et al.</i> , 2024)	VGG16	Visual	Accuracy (86%)	No	-
(CHAKI <i>et al.</i> , 2024)	Proposed CNN	Visual	Accuracy (96.61%)	No	146

Table 7 - Comparison with related works.

Work	Model	Spectra	Metric	Embedded	Inference time (ms)
(WANG, Bo <i>et al.</i> , 2024)	CNN Coat	IRT	Accuracy (93.32%)	No	-
(MANNO <i>et al.</i> , 2021)	Proposed CNN	IRT	Accuracy (100%)	No	-
(HUERTA HERRAIZ; PLIEGO MARUGÁN; GARCÍA MÁRQUEZ, 2020)	Proposed CNN	IRT	Accuracy (99.02%)	No	-
(BASSIL <i>et al.</i> , 2024)	YOLO + EffcientNetB7	Visual	Accuracy (89.8%)	No	-
(BARRETT <i>et al.</i> , 2024)	YOLOv8	IRT + Visual	mAP (76%)	No	-
(DI TOMMASO <i>et al.</i> , 2022)	YOLOv3	IRT	mAP (88.3%)	No	-
(KORKMAZ; ACIKGOZ, 2022)	TL AlexNet	IRT	Accuracy (93.51%)	No	-
(TANG <i>et al.</i> , 2024)	TL VGG16	IRT	Accuracy (80.42%)	No	-
(AKRAM <i>et al.</i> , 2020)	Proposed CNN	IRT	Accuracy (99.23%)	No	13
(LI, Xiaoxia <i>et al.</i> , 2020b)	Proposed CNN	Visual	Accuracy (98.4%)	Yes	53
(MELLIT, 2022)	Proposed CNN	IRT	Accuracy (99%)	Yes	-
(LE; LE; HA THI VU, 2023)	Proposed CNN	IRT	Accuracy (85.35%)	Yes	1.04
(GILLELAND; HOBBS; RICHARDSON, 2019)	(Proposed AI) OpenUVF	UVF	Accuracy (91.7%)	No	-

Source: Own authorship (2024)

Using AI to identify and classify faults in PV panels allows O&M staff to conduct fast and precise inspections in large solar plants. These are collected, and the

engineering team can use classified images to conduct a deep analysis and make precise decisions, such as when to clean the PV's modules, pruning brushes, or even invoice warranties. These actions can lead to cost savings in the maintenance of the power plant and, in the long term, enhance the operational efficiency and lifespan of this regularly inspected power plant.

Regarding limitations in the current form of the presented camera, the AI trained should account for all potential issues that can be detected during in-field inspections. This problem is reflected in the generalization of the trained AI, where for some cases, in a new power plant that will be inspected, the system could not make correct classification. As a solution to this limitation, in future work, a tool for capturing new images with new faults could be implemented to retrain the AI to consider this new issue identified. If executed correctly and continuously, this process will improve the AI system's performance.

Another problem that could occur when a plant is being inspected with the current form of the presented solution is when more than one fault is present in a PV panel. For example, a PV panel is dirty and has partial shadow at the same time. In this case, the system will return that the fault is classified as dirty or as shadow. To solve this problem, the system must be trained to consider multiple problems at the same time.

Another consideration that needs to be highlighted is the infrared camera used in this work. While suitable for preliminary inspections, its small sensor may produce blurred images in some cases, which is undesirable. For example, a camera with a large sensor should be used if a small hot spot is detected and the operator is uncertain about the issue. The camera used in this work was selected for its lightweight and low cost, approximately USD 300, making it the most expensive component of the developed hardware. Nonetheless, the infrared camera used is comparable in resolution to those used in commercial UAVs, demonstrating that a significant investment is optional for initial inspections.

Despite these drawbacks, the proposed solution has its merits as an innovative tool for in-field inspection. The embedded AI assists inspectors in quickly and accurately identifying faults, thereby enhancing safety in the solar plant and preventing product losses due to these faults.

5 CONCLUSIONS

Inspecting PV panels is time-consuming, what motivates development of tools to make the process faster and more precise. The presented study introduced an all-in-one solution with multiple cameras, light concentrators, and an edge device to conduct the initial inspection of PV modules. This solution can identify visual spectrum faults, thermal (hot spot) issues in daylight inspections, and UVF inspections at night to verify the PV cell structure.

In the construction of the camera, two methodologies are tested and validated to classify faults in PV panels, where the first methodology only complains about the visual spectrum, and the complete solution, the second method, allows the inspections of the three solutions for PV inspections.

The first method proved that the TL method allows the training of several neural network models so that models usually are not considered in the literature showed better results for the presented problem. With all these tests, the MobileNetV3Large proved to be the best results in the classification of images from the visual spectrum, where, with the FT applied, the accuracy obtained was 99.64% with an inference time approximately of 50 ms when the model is optimized to the Nvidia TensorRT. This first method was essential to prove that the edge device chosen for this work can respond quickly to the problem in question.

Beyond the first method proving the chosen system can classify faults in the visual spectrum, it was primordial to construct the public dataset of images for this portion of the inspected spectrum. Constructing a public dataset allows other researchers to use this dataset and have a comparable base, where the same images used in multiple works make their comparison easier. The experience in constructing this dataset allowed for better construction of the IRT and UVF datasets.

In the second methodology, the system could identify problems in the visual and infrared spectrum and excite the PV panel with UV light to make the UVF inspection. With this, it was possible to identify four types of faults in the visual spectrum, if the panel has hot spots or is normal with the IRT images, and if the PV cells are healthy or normal in the UVF inspection. The trained YOLOs in this methodology presented high precision with a mAP@0.5 of 99.7% for the visual spectrum images, 94.9% for the IRT images, and 86% for the UVF images, which is close to those values found in the literature, near 90%.

In-field validation was made to prove that the system can identify and classify real scenario problems. This test was made in a power plant with 438 PV modules, where 51 modules presented hotspots and 107 modules presented signs of corrosion in the UVF inspection. This positive result shows that the developed camera can provide a precise response in the initial inspection of the power plant.

The developed camera is lightweight at approximately 700g and cost-effective, with all the hardware used at around \$500, making it an excellent tool for solar plant inspections.

The presented all-in-one solution with AI algorithms has a high-throughput inspection capability, where all the loaded neural networks can provide real-time inspections, with inference times up to 40 ms per image. As this is a complete tool for PV inspection, the need for multiple tools and multiple specialists to make each inspection is mitigated. Therefore, the O&M staff can conduct regular inspections with better planning of scheduled tasks to make precise actions only when necessary.

The solution presented enables precise identification of faults in power plants, which is desired by the O&M team to perform precise maintenance at fault locations. For example, in the case of panels soiled by overgrown grass, workers can be directed precisely to the fault location, optimizing maintenance time.

As this work collects images for the panel's inspections, it was shown that a large volume of data is generated during each inspection. Because of this large volume, DL algorithms were essential to process the images returning if the inspected panel had some fault. These algorithms, along with the edge device and the optimizations made, allowed real-time inspections of solar plants. The camera is lightweight and capable of real-time inspections, so the O&M staff can use this information to plan maintenance better.

The developed camera is unique, with the RGB and IRT cameras and the UV lights to make three inspections. This camera will allow better inspection of PV panels, where, with the sensors and algorithms employed, the comparison of detected faults can be made with a unique tool, not requiring multiple inspections of the same power plant with different sensors, data collection, and powerful computers to process the collected data. This use of an edge device to process the images is essential, as most of the works found in the literature do not present real-time detection and classification, which is different from the presented solution.

The complete solution presented in this work, hardware and software, has potential to affect the inspection of solar power plants positively. The contributions of the work were directed to fill the gaps found in the literature, allowing better data management from the inspected PV modules. With this better management of the faults that occurred in the solar plant, the efficiency of the power plant can be improved, and if necessary, warranty claims can be made in case of some types of faults. All the information obtained can be compared with the real production of the power plant, causing the O&M team to make scheduled stops to maintain production at maximum capacity, thus allowing the return on investment in the solar plant to ensue as soon as possible.

6 FUTURE WORKS

For future works, some themes should be explored. The first theme is about the YOLOs trained, where, for complete inspection, a tool to retrain the YOLO with new images must be developed. This tool will make the system more robust, learn new problems, and allow for a better inspection.

The second theme is about the camera itself. As the camera is lightweight and wireless, this camera can be coupled to a UAV. Considering this, future work could pair this camera to a UAV to verify if the hardware constructed can make aerial inspections with the same quality as the hand inspection. This aerial inspection will allow inspections of large solar plants, rooftop solar plants, and even aquatic solar plants. Another point that can be improved in the developed camera is the addition of a SWIR camera to make photoluminescence and electroluminescence inspections. With this camera and near-infrared LEDs (~800 nm), the system will be complete, allowing the inspection of faults that can only be detected in the SWIR spectrum.

The third theme is about software. The developed software could be improved to have a base station to group all the data for later inspection, with a web interface where the user can view by GPS coordinate where some faults occur. With this, the O&M staff can verify some regions that need more attention than others with precision.

An improvement that can be made in terms of software is integrating the detection and classification of faults with electrical and meteorological data. This integration of information could help the O&M staff verify if the identified fault is reflected in a drop in energy production.

For a better understatement of the identified fault, natural language processing (NLP) could be used to describe the identified problem in the PV panel. This improvement can make the inspection analysis more precise and faster, where when a PV panel is inspected, a brief description of the PV panel will be given to the person inspecting the solar plant.

Finally, the edge device can be upgraded to a more recent one with more processing capability, allowing image detection and classification with more than three cameras.

PAPERS RESULTING FROM THIS WORK

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