Solar Panels Recognition Based on Machine Learning

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***Abstract*—Renewable energies, sustainable practices and carbon neutrality have become important goals for countries. Solar panels are a good alternative to produce energy. Monitoring, maintenance and fault detection processes represent aspects of vital importance when making concrete decisions that affects a certain percentage of the solar farms. In this paper we present a system capable of detecting solar panels location through machine learning.**

The main goal is to aid solar panels farm managers to locate solar panels in real time in a real area by using a machine learning model. With the use of a camera and a drone, we will be able to fly over the solar farm and identify the panels. The YOLO (You Only Look Once) object detection model is used, training and testing the neural network with a data-set of 280 images. The neural network was capable of recognize the panels in different images and videos in which we put it to the test but getting a good precision at the end.

***Index Terms*—machine learning, solar panels, drone, solar farms**

I. INTRODUCTION

Renewable Energies has become a really important part of our lives. The world we are living in is turning into one where renewable energies are well seemed to avoid pollution and make the planet a better place to live in. The use of solar panels is a good option to avoid polluting and reduce the CO_2 emissions.

In this paper we propose a system capable of detecting solar panels through machine learning. With the use of a drone, we will be able to fly over the area where the solar panels are located and identify them. The main purpose of this research it is to recognize solar panels in video or images as a first step for our future work.

This paper is organized as follows: section II analyzes related works, Section III describes the system proposed, Section IV shows the experiments and results and, finally, Section V presents the conclusions.

II. RELATED WORK

Computer Vision (CV) applied to objects have become in an important technological challenge. There are some frameworks in this field and there are a lot developers who need a faster and accurate system to detect objects. Is important to be noted that there is more than one field where the computer vision is very useful.

Most of the time this technology is implemented or used in real time because is more useful, but also, AI branches take advantage of it and become part of the CV system developed. When a CV system is being developed the main challenge is to determine what Neuronal Network to use.

Some research have incorporated Convolutional Neuronal Networks (CNNs) to improve the efficiency efficacy and effectiveness of Facial recognition because of the aforementioned but because the CNN's were more precise than algorithms like Principal Component Analysis, Elastic Bunch Graph Matching and Linear Discrimination Analysis [1].

The Neuronal Networks are also used to evaluate the caloric load existing in a food plate [2] and in many other health areas, the CNN's were also used to determine the amount of polyps in the images and videos obtained from colonoscopy exams [3]. On the other hand, the Probabilistic CNNs were used to explore better ways to improve the estimation of the human body posture [4].

CNNs are also used for bio-metrical security systems that need to verify the fingerprint [5]. Nowadays there are different CNNs that some researchers put in contrast to determine which one is the best for an specific task like Palvanov and Cho [6] did in his research were they compared between Residual CNN's (ResNet) and capsul network (CaspNet) to see which of them was better at recognizing and analyzing in real time the handwriting, concluding that CaspNet required less time to be trained and save the model. Other research like Chen and Tao [7] used regression to detect objects in real time. Most of these systems not only are interested in object detection but also in pattern learning, Zhu, Vial, Lu, Tian and Cao [8] designed a tool that learns and detects actions in videos.

Some developers take beyond the vision by computer and not only implement it for the detection and recognition of objects, but they also add functions such as classification, tracking objects and even characteristics of these like Liu, Zhao and Cong [9] who made a system that determine the similitude of the attributes between the objects. Rivas, Chamoso, Gonzlez and Corchado [10] used CNN and a drone to detect cattle. Siewert et al. [11] analyzed the use of sensors around an operating area of uncontrolled airspace. On the roads, the use of computer vision has taken center stage and has been implemented for vehicle detection, tracking and

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trajectory [12] [13], and determine the distance and texture of pedestrians [14].

It is also implemented in the industry to learn machine characteristics and its mechanical parts [15] as well as in in the manufacturing industry [16]. You Only Look Once (YOLO), is a real time object detector that uses only one CNN. There are 4 well known versions of of YOLO: YOLO, YOLO-9000, YOLO.V2 and YOLO.V3.

Du [17] mentioned in his paper that YOLOV2 provide better balance and precision than YOLO.

Mugahed et al. [18] implemented YOLO for the detecting and classifying breast cancer. Hamed and Avaznia [19] made a joint version of Fast R-CNN with YOLO to detect objects in images captured by automatic driving vehicles, they concluded that their approach is slower than YOLO but faster than Fast R-CNN.

The rapid regression design introduced in YOLO can be combined with Deep CNN for detection and simultaneous semantic segmentation in roads [20]. Hsu, Ambikapathi, Chung and Su [21] designed a vehicle license plate detector in the road with YOLO and YOLOv2.

Hsieh, Lin, and Hsu [22] used YOLO and Fast R-CNN to count the objects present in a parking lot using a drone.

YOLO has been tested with collections of images tracked on the web [23], and has been subject to changes in its source code considering that YOLO contains many classes for the classification of objects and has failures in the positioning and bad approach of training, as well as deficiencies in the detection of small objects, therefore solutions have been sought that optimize together the speed, accuracy and consumption of energy in the recognition systems, one option is to make use of Tiny YOLO, a version of just 28MB that is much faster and lighter [24], researchers like Li, Chen and ChaoYang [25] used Tiny YOLO In Fault Tolerance (FT) processors and determined that their performance is equivalent to the current best performance of the processor, other research also designed frameworks using YOLO as a base [26].

Other models for object detection like Tensorflow and Caffe 1.0, have been test to compare their performance with YOLO [27]. TensorFlow is an open source library from Google, that thanks to Keras CNN parameters can be edited, trained and tested.

III. System Proposed

We proposed a system capable of detecting solar panels location through machine learning. Fig. 1 shows an overview of the approach. Drone will be used to catch video in real time while it is flying on the solar panels system. The video captured by the drone is showed in the tablet in real time. The idea is difference the panel with the fault of the other panels using a machine learning model. Also, the system in the tablet will send the signal to the drone for that a red dot (laser light) be shown on the panel with the fault. The red dot shown on the panel is very important to obtain the actual position within the panel system. In this paper we addressed the development of a machine learning model to solar panels recognition.

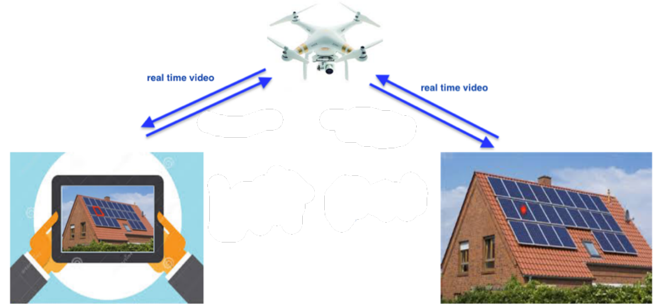

Fig. 1. Overview of the Solar Panel Recognition System.

A. Machine Learning Model

Darknet is a CNN evaluate it on the PASCAL VOC detection data-set. The network architecture is inspired by the GoogLeNet model for image classification. This network has 24 convolutional layers followed by 2 fully connected layers. Darknet is different from GoogLeNet because instead of the inception modules, Darknet implements 1×1 reduction layers followed by 3×3 convolutional layers as it is shown in fig. 2

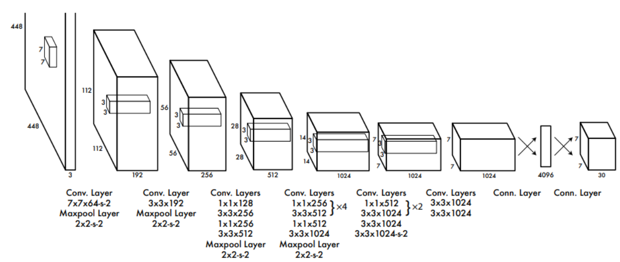

Fig. 2. Darknet CNN Architecture. Taken from [28]

For the system proposed, we use "Darknet" as our CNN since it is capable of running YOLOV3, which, due to its speed and efficiency was the most suitable object recognition framework based on our researching.

As there was not a pre-trained data-set we had to create or own. To start building it, we began to label all 280 pictures used to get an accurate precision. The software used to label the images is called BBox-Tool, developed in python. The user just has to select the file were pictures are and load them into the program, the second step is to label each picture.

The main purpose it is to save a file per picture where the software stores the coordinates, in this case of each panel in the picture. Once all pictures are being loaded and labeled, a ".txt" file is generated and stored in a file called "Labels" and because YOLO can not be trained with this files the user has to use another software to convert it into a file that YOLO is able to use. What it basically does is to take each of the ".txt" files and convert what it contains into the right format. The file still being a ".txt", what changes are the coordinates that

Fig. 3. Solar farm at Technológico de Costa Rica, San Carlos.

have been changed so that YOLO is now capable to read and will store it in a file that the user can choose.

Once the pictures and the files are ready it is time to train YOLO, the process is simple, however the time that it might take will depend on the hardware available.

IV. Experiments and Results

A. Capturing Images at Solar Farm

The images were captured with a phantom 4 drone in the solar farm located at Instituto Technológico de Costa Rica, Campus San Carlos. Fig.3 shows this solar farm. There are 72 solar panels. The images were captured from different angles and heights.

Each image has 4000x3000 resolution.

B. Training the Machine Learning Model

As there was no previously trained data-set to recognize Solar Panels we decided to train our own. We called it Data-Set For Solar Panels (DSFSP).

To train the machine learning model, we used 280 images.

Each image has 4000x3000 resolution however to train the DSFSP we downgrade the quality of them to FullHD (1920x1080) with the help of a tool developed in python. Before training the machine learning model we had to label each image to determine the position of the object in the picture. To complete the labeling task, we used BBox-Tool. Once all the pictures were labeled, we started to train the machine learning model using different amounts of pictures per training to compare between them till get the final results. It is important to clarify that we only use one class for the data-set, in this case the class we use is solar panel.

Each class needs an average amount of 2000 iterations to train the machine learning model. The first data-set was made-up with 100 pictures and stopped after 1000 iterations getting unsatisfied results. In the second attempt we increase the quantity of pictures from 100 to 150, and just like in the other model we trained, we stopped after 1000 iterations. So as it is shown in the Fig. 4 and Fig. 5 the number of pictures determines the accuracy of the detection however the number of iteration its important to get a low loss average and a better interception over union (IOU).

the third try we added 50 more images to get a total of 200 pictures in the set. Differently from the two first ones we stopped it at 2000 iterations. Fig. 6 shows the number solar panels recognized.

For the final data-set we increased it by adding 80 pictures and stopped after more than 5000 iteration in Fig. 7. At the end is noticeable that between more images and iterations per training then better results are obtained.

Fig. 4. Machine learning model trained with 100 pictures.

Fig. 5. Machine learning model trained with 150 pictures.

V. Conclusions and Future Work

We implement a system capable of detecting solar panels using machine learning. The systems runs in real time and can classify individually each solar panel successfully. Analyzing the purposes of related systems who implemented computer vision as a solution, we determined that the one who satisfied our needs was YOLO and because of this we undertook the creation of our database DSFSP, to store the data for tests.

With 280 images to train and after more than 5000 YOLO obtained accurate results. This project collaborates with the country with the carbon neutrality and sustainability, The Solar Panel Recognition System is just the beginning for future works where we want to implement a more complex system

Fig. 6. Machine learning model trained with 200 pictures.

Fig. 7. Machine learning model trained with 280 pictures.

capable of detecting abnormalities over the Solar Panel to prevent loss of energy.

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