Strawberry Disease Detection in Precision Agriculture

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Abstract: Crop disease detection in precision agriculture has an important impact on farming, improving production, and reducing economic losses. This is why some efforts have been done in this direction. This paper compares 4 object detection algorithms based on deep learning to detect diseases in strawberry crops. Here, we present a step towards detecting the most common diseases to prevent economical losses. The main purpose is to detect mainly three diseases of the strawberry crops, i.e. Botrytis cinerea, Leaf scorch, and Powdery mildew, to take further actions if the crops are unhealthy. We have chosen these three diseases because these are frequent and unpredictable issues, and the risk of infection is high. For this, we trained four algorithms, two based on Single Shot MultiBox Detector and two based on EfficientDet algorithm. We focus the analysis on the two best results based on the mean average precision. We have used Google colab for training, then a Core i5 host computer and an Nvidia Jetson nano were used for testing. We have achieved a detection network with a mean average precision of 81% in the best case, in detecting the three proposed classes. While using an NVIDIA Jetson nano, the accuracy increases up to 86% due to the dedicated GPU that processes Convolutional Neural Networks(CNN).

1 INTRODUCTION

Precision agriculture has recently gained much attention due to the increasing needs of the population around the world. There are several applications, such as (Torky and Hassanein, 2020),(Srivastava et al., 2019), and (Priya and Ramesh, 2020), where technologies as Blockchain or Internet of things are brought into the agricultural field. For example, in ((Klerkx et al., 2019) and (Lezoche et al., 2020)), current applications that involve computer vision are addressed. Moreover, machine learning is used in applications as classification (e.g. (Ümit Atila et al., 2021),(Mathew et al., 2020), (Chouhan et al., 2020)) and disease detection (e.g. (Gomez Selvaraj et al., 2020), (Mojjada et al., 2020), (Chen et al., 2020)).

Several machine learning techniques for object detection have also been developed. For example, a method based on deep convolution neural networks, released in 2014 is the Region-based Convolutional Network (R-CNN) (Girshick et al., 2013). Since then, there have been improvements to this technique, e.g. Fast R-CNN (Girshick, 2015), and Faster R-CNN. (Ren et al., 2015). Other detection networks, such as YOLO (YouOnlyLookOnce) (Redmon and Farhadi, 2017) and EfficientDet (Tan et al., 2020) can also be used for object detection. For further information on this topic, the reader is encouraged to review (Wu et al., 2020).

Precision agriculture is a highly growing technology that aims to bring technology into farming process. Crops suffer from various diseases that need to be controlled, to prevent other problems that at their time led to money looses. There are defined ways in agriculture to control or prevent diseases, e.g. applying different products, pruning, and so on. In fields like fruit farming, to make decisions regarding diseases prevention, e.g. fungicide application in a preventive way, information about the crops is required, including data from the leaves and the fruit. This information can be obtained from RGB images. Therefore, in this paper, we address the problem of object detection using artificial intelligence, as a method to detect diseases in strawberry crops. We compare 4 object detection algorithms, analyzing the ones that achieve the highest mean average precision (mAP). The analysis allows to choose the one that performs the task more accurately, regarding the mAP criterion.

In the literature, there are different solutions to the problem of crops disease detection in precision agriculture, with different targets. For example, regarding machine learning techniques for classification, in

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(Mathew et al., 2020), authors propose a methodology for the classification of three important foliar diseases in the banana crop, using texture features as elliptical local binary pattern. This method has a great accuracy in classifying the diseases. However, it does not give information about the location of the disease. Moreover, in (Park et al., 2017), the authors propose a deep learning mechanism to diagnose and predict diseases in strawberry's leaf and fruit. In this case, the image has to be taken close to the fruit, and then it has to be processed in a different engine. Regarding leaf diseases classification, in (Chouhan et al., 2020) a computer vision methodology to automate the disease diagnosis of Jatropha Curcas (Huang et al., 2020) is proposed with high classification accuracy. In this case, the authors have identified that increasing the segmentation performance and using a Deep neural network for the classification task would yield to better results, due to the difference between the use of artificial intelligence algorithms there is no room for comparison, because the authors use AI to classify whereas in this article, it is to detect.

There are other solutions to the scope problem that do not use artificial intelligence, but they use digital image processing. For example, in (Sheikh et al., 2019) the authors implemented an image processing algorithm and deep learning methods on images of crops with diseases, to help the farmers to cultivate and reducing the diseases. The algorithm has a great accuracy, but it does not provide the location of the disease in the plant. Moreover, the work is only focused in detecting problems in the leaves. Regarding only image processing, for instance in (Prakash et al., 2017), the authors propose a framework that includes image preprocessing, Segmentation using clustering feature extraction by statistical Gray-Level Co-Occurrence Matrix (GLCM) & Classification of diseases using Suport Vector Machines(SVM). This algorithm could be implemented in different plant species with few changes.

Object detection can be applied to solve other tasks such as position tracking, which is useful in many fields such as autonomous driving. For example, this problem can be solved with deep learning algorithms, training a detection Network such as YOLO and analyzing the changes in the generated detection. In (Ciaparrone et al., 2020), the authors provide a survey on Deep Learning Models that solve the task of Multiple Object Tracking on single-camera videos, comparing several models and demonstrating that Deep Learning algorithms are as effective solving this task as solutions such as LiDar and depth images.

In this paper, we show a comparison of 4 algorithms to detect strawberry diseases, i.e. powdery mildew, botrytis cinerea, leaf scorch, immature strawberry, and healthy strawberries. At the end, we determine the best detection algorithm based on the best mAP. For this, we trained two deep learning based object detection algorithms in a custom dataset. Fig.1 illustrates the implemented strategy. First, we create a custom dataset for the required classes using some data sources. Then, we have an image processing stage where we normalize the images, for this we use the OpenCV library. We generate an inference graph that can be used in other computers with lower specifications than the host computer. This was done employing the Tensorflow 2.0, an object detection API, as deep learning framework. The model was trained in Google colab with Intel(R) Xeon(R) CPU @ 2.20GHz and 16GB NVIDIA Tesla T4 GPU. However, the trained models were tested in an Intel Core i5-7200 with 2 GB NVIDIA Geforce MX940 GPU.

We aim to detect 3 common diseases and two growing states in the strawberry crops, with the idea of taking corrective actions using the CERES agricultural robot. We address the strategy to detect the diseases and the growing states, while the decision making algorithm is not part of this paper.

In section 2 we present the complete strategy for object detection, showing how we trained the object detection algorithms and the image processing as well. Section 2.1 presents how and why we selected the proposed classes. We analyze the results in section 3, and we give some conclusions and recommendations in section 4.

2 METHODS

In this section, we describe the strategy used to detect strawberry diseases. To do this, we trained the EfficientDet detection network model with efficientNet, (Tan et al., 2020), Single Shot MultiBox Detector(SSD) with Resnet 50 (Liu et al., 2015), SSD with mobilenet V2. Every detection network uses different methods to solve the detection process, EfficientDet, works with EfficientNet (Tan and Le, 2019) as the backbone network, BiFPN as the feature network, and shared class/box prediction network. SSD works with Resnet 50 (He et al., 2015) as backbone. It is a feed-forward convolutional network that produces a fixed-size collectionThe more accurate the model is the of bounding boxes and scores for the presence of object class instances in those boxes, followed by a non-maximum suppression step to produce the final detections.

For the purpose of our work, we trained every detection network with a custom dataset created with

PlantDoc dataset (Singh et al., 2019), Strawberry dataset (Pérez-Borrero et al., 2020) and a custom dataset created from Google images. The former dataset contains 450 images. The hole dataset has a complex background with a remarkable light change.

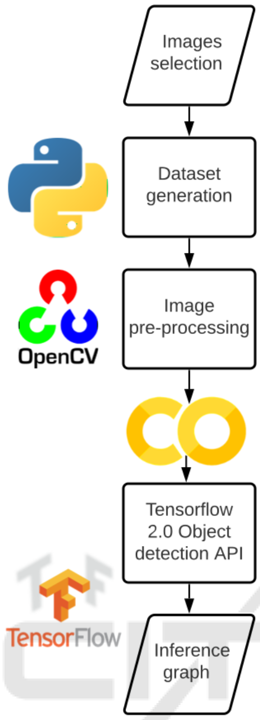

Figure 1: Implemented strategy and project pipeline.

2.1 Data Acquisition

In this paper we aim to detect some of the most common strawberry diseases, as well as immature and healthy strawberries. The selected diseases in this project were:

- **Powdery Mildew:** This is a fungal disease which affects a wide range of field crops, trees, shrubs, vines, flowers, vegetables, fruits, grasses, and weeds. The most common symptom in the infected plants is the presence of white powdery spots on leaves and stems. The lower leaves are the most affected part, but the disease can appear in any part of the plant. Additionally, powdery mildew, causes powdery growth on the surface of young shoots, leaves, flowers, and fruits. Powdery mildew is caused by many variants of fungal species in the genera Erysiphe, Microsphaera, Phyllactinia, Podosphaera, Sphaerotheca, and Uncinula(Carisse and Fall, 2021).
- **Botrytis Cinerea:** It is a fungal pathogen that causes grey mould mainly in the fruits. This pathogen affects the fruits in the field, storage, transport and market. The presence of grey mould is the most common reason for fruit rejection by growers, shippers and consumers, leading to significant economic losses (Petrasch et al., 2019).
- **Leaf Scorch:** It is caused by a fungal infection which affects the foliage of strawberry plantings. The fungal species responsible are called Diplocarpon earliana. Strawberries with leaf scorch may first show signs of issue with the development of small purplish blemishes that occur on the topside of leaves. If the disease is allowed to advance, the spots will grow larger and darker. In the worst cases, those spots may even cover entire portions of the crop, including plant leaves and cause them to completely dry and fall from the plant.
- **Inmature Strawberry:** this includes fruit light in mass, stunted or distinctly rubbery in texture. In the case of the strawberry, it is also caracterized by a green color.
- **Healthy Strawberry:** Fruit in great conditions.

For further information of the diseases and the strawberry's growing, the reader is referred to (Hancock et al., 2008) and (Vanti et al., 2021).

The proposed dataset consists of 450 images splitted in a training set with 300 positive images. The test set has 100 positive images and the validation test set consists of 50 images. For each class, there is an amount of 90 images distributed in 60 images for the training set, 10 images for the validation set and 20 images for the test set. However, the number of annotations per class is:

- **Powdery Mildew:** 188 annotations.
- **Botrytis Cinerea:** 179 annotations.
- **Leaf Scorch:** 174 annotations.
- **Inmature Strawberry:** 193 annotations.
- **Strawberry:** 186 annotations.

2.2 Object Detection

Object detection algorithms have many applications such as autonomous driving. For example, companies like Tesla, Apple, Toyota, Nissan, etc., use them to avoid collisions during a course (Wang et al., 2020). In this paper, we compare 4 object detection algorithms and we define which one fits better with our requirements to be implemented in the CERES agricultural robot (Santiago. et al., 2020), based on the mAP. For this, we detect the 5 classes mentioned before. The proposed architecture is shown in Fig. 2. The

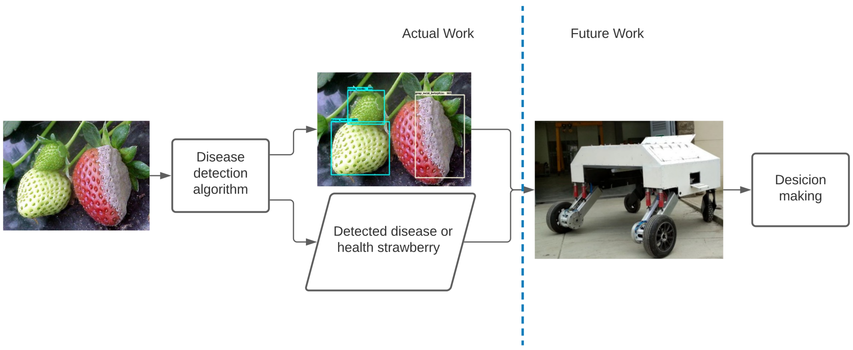

Figure 2: Proposed architecture for the research.

process consists of an image acquisition step; then, the detection algorithm returns the bounding boxes with the detection, and the detected class. In this section, we show the training process for each detection network and the image pre-processing stage, Fig. 1 illustrates the flowchart of the strategy proposed in this paper.

2.3 Models Training

The first stage of the training process includes image prepossessing and normalization, as shown in Fig. 1. This is done in OpenCV, where we apply transformations such as random horizontal flip, crop and re-scale, to get more images for the process. Then, the re-sizing process for our images varies depending of the detection algorithm, e.g for EfficientDet, the image input shape is 512x512 pixels. After that, we normalize the images between 0-1, and finally, we change the image format to RGB, because OpenCV works with BGR image format. In this way, we have data ready to train the object detection models.

The training process is shown in Fig. 3. We tested two object detection deep learning based algorithms with different backbone CNN. The training process consists of five steps. First, the generation of the record files, which is done by running some python scripts after labeling every single image in the dataset. This is done because the data are in 'xml' format, but it is needed in 'recod' data format. The second step is to select the backbone Convolutional Neural Network (CNN) for the detection algorithm. In table 1 we show the CNN for each iteration. The fourth step includes the setting of the training options, which are also shown in Table 1. Those hyperparameters were chosen to avoiding overfitting of the obtained results. Finally, a label map for the classes to start training the algorithms is required.

Additionally, the batch size of each training process is limited by the hardware capacity. Our host computer reduced the batch size of 1, while in Google colab we were able to use a batch between 8 to 16, due the Testa T4 GPUs provided.

3 RESULTS AND ANALYSIS

In this section we present and explain the results of training the two algorithms, i.e. EfficientDet-D0 and SSD-Resnet50. These two algorithms give us the best practical results based on the mean average precision (mAP).

Testing was carried out with the test set, which contains 100 images. However, the hyperparameters change in each training iteration. In table 1 we show the number of training iterations done for each algorithm. Every model iteration was tested in a 50 images validation set. During the experimentation process, we used a 60% threshold during the detection task.

The tests consisted on the detection process of an image test set. The results of the detector, the scores,

Table 1: Training parameters for each detection algorithm.

Train iterations	Algorithm	Backbone CNN	Iterations	Input shape	Batch size
5	EfficientDet-d0	EfficientNet	20000	512x512	16
4	SSD	Resnet 50	15000	640x640	8
2	EfficientDet-d3	EfficientNet	10000	768x768	8
2	SSD	Mobilenet	10000	320x320	16

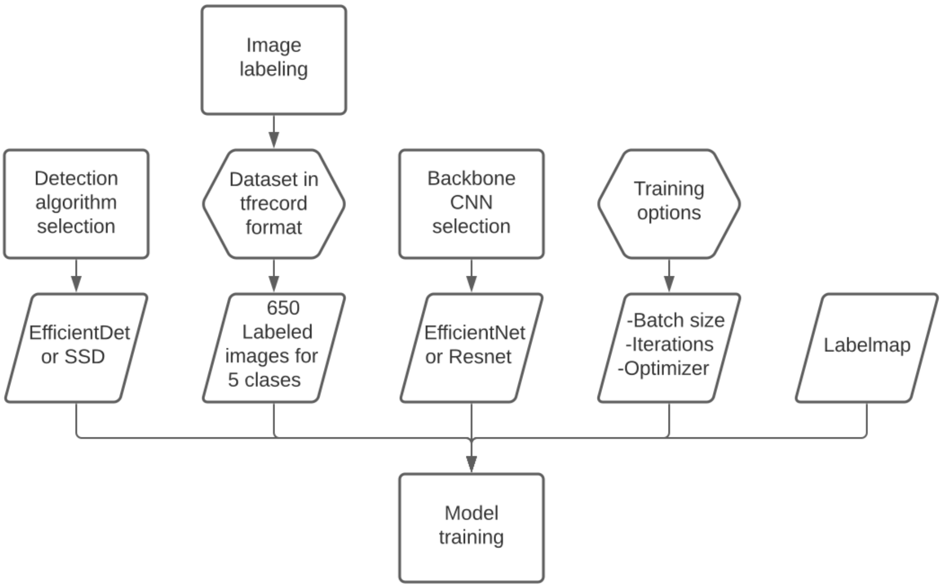

Figure 3: Training process for the detection algorithms.

and the bounding boxes per image are compared with the ground truth proposed for the test set. The ground truth is a table that contains the information about the location of the image on the computer where the test is carried out, and the bboxes of each image. The trained models were tested in a NVIDIA JETSON Nano ARM® Cortex® -A57 MPCore with Maxwell 128 GPU Uand in an Intel Core i5-7200 with 2 GB NVIDIA Geforce MX940 GPU.

The average precision is defined as the average of the precision scores after each true positive. The mAP compares the ground-truth bounding box with the detected box. The more accurate the model, the higher the mAP value. In Table 2, the Average precision results per class are shown as well as the mAP of each detection network.

3.1 EfficientDet-D0

The training process with the dataset proposed in section 2.1 lasted 175 minutes, using Intel(R) Xeon(R) CPU @ 2.20GHz and 16GB NVIDIA Tesla T4 GPU provided by Google Colab. In Fig. 4 the training loss by the epochs is shown. The final training iteration process consisted of 15000 iterations with 16 Batch size. According to the amount of data used to train

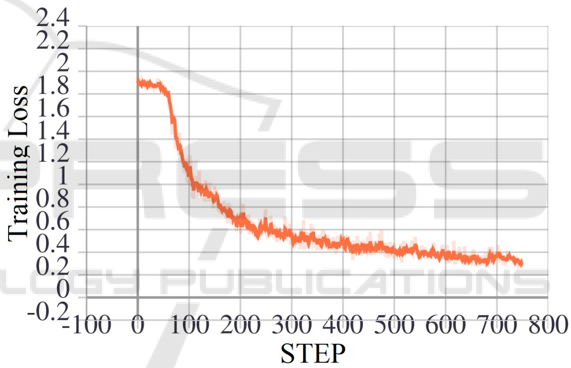

Figure 4: Training loss graph for EfficientDet - EfficientNet D0.

the detector, we achieved a mAP of 81% in the Core i5 Computer, and 86% with a minimum error of 0.034 in the NVIDIA Jetson Nano which reflects the action of the cuBlas and cuDNN libraries which increases the detection accuracy in 5% on the Jetson with respect to the Core i5 computer. The inference time is about 300 *ms*. This was the best result obtained during the trials. The training iterations are shown in table 1.

Table 2: Detection rates.

	Strawberry	Inmature Straw	Powdery Mildew	Botrytis	Leaft Scoarch	MAP
EfficientDet-D0	92	88	76	89	86	86,2
EfficientDet-D3	95	92	64	72	80	80,6
SSD-Resnet50	90	85	78	81	80	82,8
SSD-Mobilenet	76	78	68	80	74	75,2

3.2 SSD-Resnet50

The training process with the dataset proposed in section 2.1 lasted 200 minutes, using Intel(R) Xeon(R) CPU @ 2.20GHz and 16GB NVIDIA Tesla T4 GPU provided by Google Colab. In Fig. 4 the training loss by the epochs is shown. The final training iteration process consisted on 20000 iterations with 8 Batch size.

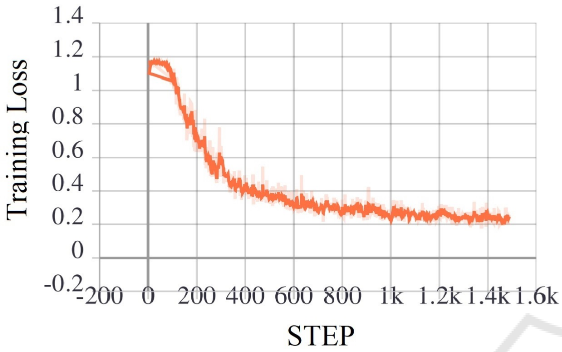

Figure 5: Training loss graph for SSD - resnet 50.

According to the amount of data used to train the detector, we achieved a mAP of 77% in the Core i5 Computer, and 83% with a minimum error of 0.034 in the NVIDIA Jetson Nano , which evidences that the cuBlas and cuDNN libraries increase the detection accuracy in 6% on the Jetson with respect to the Core i5 computer. The inference time is about 215 *ms*.

In Fig. 6 we show a set of output images of the best model, that in our case, for the proposed task was EfficientDet-D0.

4 CONCLUDING REMARKS

In this paper, we chose a strategy to detect diseases in strawberry crops. To do this, we compared 4 object detection algorithms based on deep learning, and we presented the best two algorithms regarding their mean average precision (mAP). With the chosen strategy we detect three diseases of the strawberry crops, and two growing states, i.e. immature strawberry and healthy strawberry.

For this work we used Google colab. Then a Core i5 host computer and a Nvidia Jetson nano were used for testing. We have achieved a detection network with a mAP of 81% in detecting the three proposed diseases (classes). While using a NVIDIA Jet-

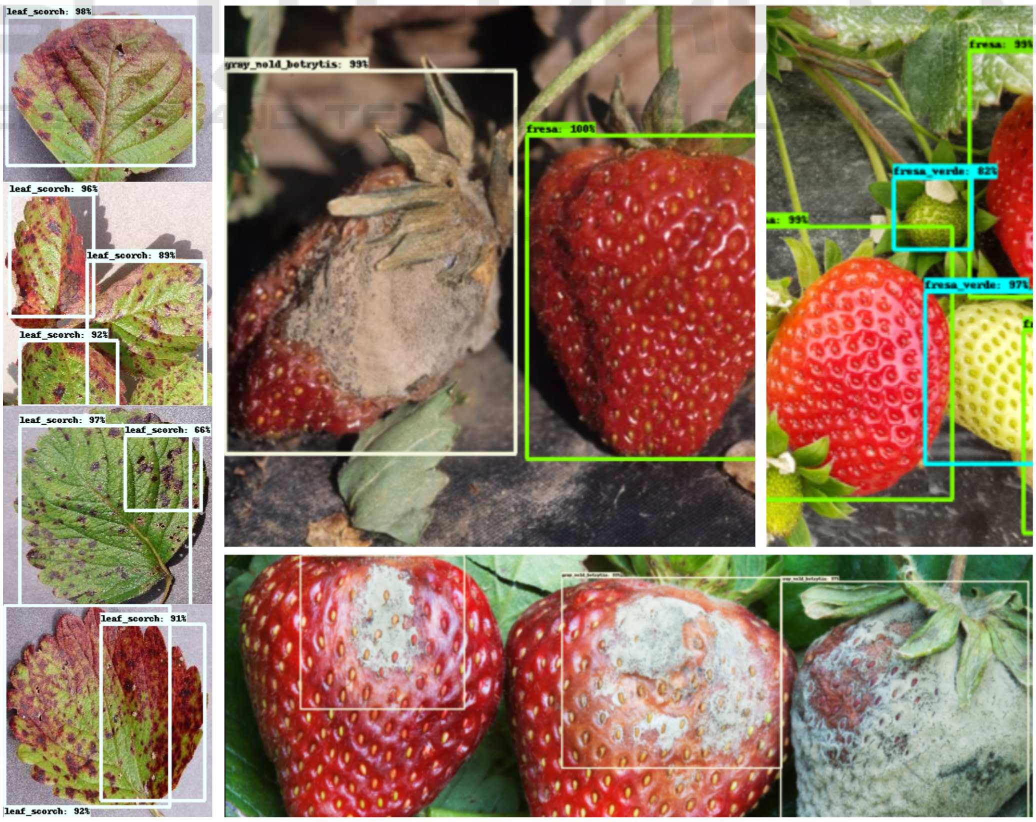

Figure 6: Results of detecting the proposed classes.

son nano, the accuracy increases up to 86% due to the dedicated GPU that process Convolutional Neural Networks(CNN).

The use of better detection datasets would increase the obtained mAP, mainly in the detection of powdery mildew disease, where the average precision was of 75% in the EfficientDet-D0 best train iteration. Moreover, an optimization step regarding the Nvidia Jetson nano with TensorRT would decrease the inference time. We will address this in our future work for the implementation of the algorithm in the CERES agro-robot (Santiago. et al., 2020).

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