DrBerry: Detection of Diseases in Blueberry Bush Leaves

Cristopher Morales, Edgar Cavero and Willy Ugarte[a]

Department of Computer Science, Universidad Peruana de Ciencias Aplicadas, Lima, Peru

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Abstract: The following research presents a mobile application that can recognize the following plages usually found on blueberry leaves: oidium, heliothis and alternaria. These diseases affects the growth of the bush an thus reduce its yield. Additionally, an open dataset will be available for future investigations. Yolov5, a convolutional neural network, is used for the development of the model, data collection was performed in the Fundo San Roberto, Huaral-Peru, and data augmentation techniques were used to increment the amount of workable data. Thanks to this the following results were obtained: accuracy of 84% and recall of 91%. We predict that the model could be improved to recognize other plages given the right amount of data.

1 INTRODUCTION

Our main goal is the detection of diseases in the leaves of the blueberry bush, with the scientific name *Vaccinium corymbosum*.

This research topic was chosen because the blueberry is currently the main agricultural export product of Peru, which gives it great economic importance and motivates the care of crops from diseases that can damage it.

For the development, the creation of a dataset of images of blueberry leaves was proposed, since there was no public use dataset for this plant at least on our research. After the dataset was created, a YoloV5-based model was trained in order to detect three different diseases (Oidium, Alternaria, Heliotis) [1] commonly present in blueberry leaves during the budding stage.

Finally, with the trained model, a mobile application will be created for Android devices which can be used locally without the need to use the internet, since many crops are not within the reach of mobile networks.

For as long as man has been able to grow crops, they have always been affected by the forces of nature, be they weather problems or pests. Nowadays, we have been able to learn to predict the weather quite accurately thanks to various scientific devices, however, pests are still a problem to be tamed. Generally, in Peru, technological advances are usually applied years after they are developed and are often limited to private property.

The last 5 years have seen major changes in the ranking of products exported abroad within the agricultural sector, with a new export leader that has managed to impose itself on more traditional products such as grapes, avocado and coffee.

This product is the blueberry and, at the time of writing[2], it has become the main agricultural product exported from Peru.

This explosion in the export of the fruit is reflected in a great source of income for Peru, so it is necessary not to miss the opportunity to research technological products that can contribute to reduce maintenance costs and production losses.

The problem arises from the high demand for blueberry production because, to the best of our knowledge, there is very little work on the identification of blueberry leaf diseases, with the exception of the private sector.

If a person with limited contacts or resources wants to conduct a research, it will be difficult to do since they must obtain data, travel to blueberry or-

[a] https://orcid.org/0000-0002-7510-618X

[1] "Integrated Management of Pests and Diseases of Cranberry Crops" (in spanish) - Bayer CropScience - https://cdn.blueberriesconsulting.com/2016/12/manejo-integrado-enfermedades-arandano.pdf

[2] "The blueberry is positioned as the main national agro-export product in the last twelve months" - National Ministry of Commerce and Turism of Peru - https://www.gob.pe/institucion/mincetur/noticias/672598-el-arandano-se-posiciona-como-el-principal-producto-de-agroexportacion-nacional-en-los-ultimos-doce-meses

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chards and collect their own necessary information, all assuming they are allowed access to the crops since, to the best of our knowledge, there are not public datasets available to use for training. It is for these reasons that in a public way it is far from being solved.

Previous studies have been carried out for different types of agricultural products such as (Yu et al., 2023) soybeans, (Luaibi et al., 2021) citrus, (Gunisetti et al., 2022) maize and (Amin et al., 2022) corn, in which the use of both computer vision and convolutional neural networks have been used to detect various diseases.

However, these products have different pests from which they are affected. In addition, although similar research has been done in Peru, according to our search we did not find a public use data-set for our blueberry species to be treated in order.

The main components of our solution consist of an image recognition application using YoloV5 that is capable of being used on a mobile device without the need for an Internet connection to make use of the model.

In addition to the application, a dataset of blueberry bush leaf images will be created and made freely available for future research. The limitations of our work are temporal, since it was carried out in a specific year, and technological, since the application must run on mobile devices.

Our main contributions are as follows:

- We are developing a model in Yolov5, which allows us to infer from an image diseases in the leaves of the blueberry bush.
- We have constructed a dataset based on 3 diseases of blueberry bush leaves.
- We have performed an experimental analysis with the data collected.

This paper is distributed in the following sections: First, we have summarized important papers about the use of Yolov5 within the agricultural sector in Section III, then we will explain some important concepts and theorems about Yolov5 in Section IV. After that we will explore in detail the experiments we carried out during the development of the project in Section V and finally, we show our main conclusions.

2 RELATED WORKS

It has become very popular in recent years the use of computer vision and deep learning to find solutions to all kinds of problems, among these we find the area of disease detection in plants. We have found different works that helped us understand the use of Yolo while also inspiring us to try our own approach, from these we can highlight the articles on modifications on the base architecture of Yolo and the approach of development in mobile devices.

In (Mathew and Mahesh, 2022) the authors propose a method for the detection of diseases in the pepper plant leaves that can be used in mobile phones. For its implementation they decide to use Yolov5, following all the basics suggested when working with Yolo, like getting the data-set, labeling in a manual way and training the model. Before the training they had to make different experiments to get the most appropiate kind of model since Yolo have different models variants like nano, small and medium, these being the ones suggested if the end goal is to deploy the model on a cellphone. Like them, we have decided to opt for the same model variants for our implementation since we also plan on use our model on mobile devices. Thanks to them we have a better knowledge about the use different versions models of Yolo and will follow the suggested steps when working with it.

In (Liu et al., 2022) the authors propose a modified architecture of the Yolov4 model, adding a triple attention mechanism and the focal loss function, as well as using the K-means method to group the data and specifying a new anchor box. The first change was crucial since some pest in tomato are to small to notice and by adding these modules they will have three parallel branches to capture the data and get more focus on the feature channels. Contrary to them, since the data we recollected was taken at short distance and most of the diseases evaluated occupies enough pixels of the images, we opt to use the base Yolov5 model without changing its layers.

In (Chen et al., 2022) the authors propose to add new modules to the Yolov5 model, they replaced the module C3 for an Involution-Bottleneck module. After that, they add the SE module to the last layer of the backbone network, and finally they replace the loss function by Efficient Intersection over Union in order to minimize the discrepancy and accelerate the convergence of the model. The first change was useful since they want to reduce the number of operations through the learning process and get more focus on long-distance information of the spatial range while reducing the number of network parameters. By replacing the loss function they seeked to reduce the discrepancies and accelerate the model convergence, obtaining an average accuracy of 70 %, 5% higher than traditional Yolo. We, on the other hand, are using the base model of Yolov5 because most of our images are in a short-distance, getting us a benefit on model convergence since we have less instances to infer on images. As a result, our results are similar with an

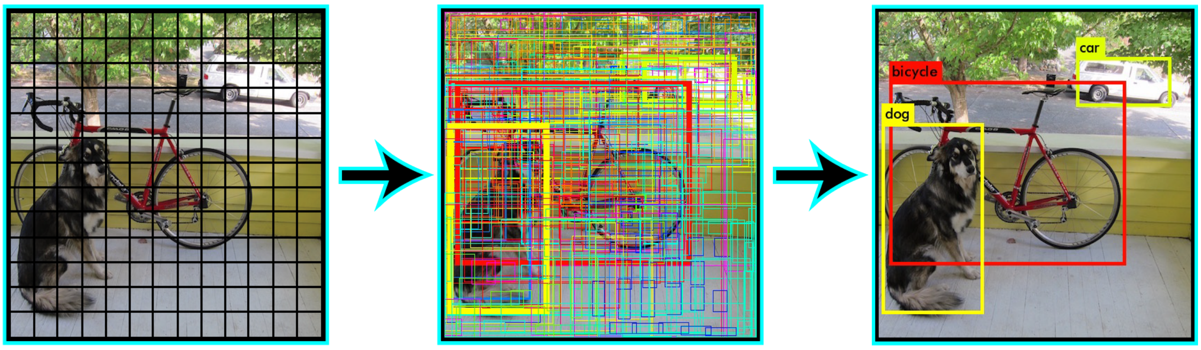


Figure 1: Residual Boxes Generated in Image, from (Redmon et al., 2016).

average accuracy of 86% to our images.

In (Dai et al., 2022) the authors propose the development of an hybrid model of Yolov5, they seek for a model that can help them reduce time and computational costs, for that reason they develop DA-ActNN Yolov5, where Activation Compressed Training(ActNN) is used to compress the modules and parameters of Yolo, this is done without affecting the model structure and the final model performance an, as a final result, they got that the time consumption time doesn't exceed 30 minutes and the model runs more efficiently in a 0.65% compared with Yolo. Instead, as one of our main contributions is the creation of our open dataset, we decided to use the base Yolov5 structure in order to avoid missing our deadlines.

In (Delgado and Obeso, 2019) the authors made a research in order to prove the effectiveness that a machine learning solution would have on the identification of plages and diseases that affects blueberry bushes in Trujillo, Peru. Their investigation concluded that a computer vision-solution will improve the chances of recognizing plagues in the berry bush leaves. However, the research didn't include a database to work with, something that could have helped in the development of such machine learning solution. As part of our contributions we provide an open dataset for future models and, since the investigation was done on both the same type of crop and on similar climate conditions, we can rest asure knowing that our Yolov5 model will help in recognizing the plagues of the berry bush leaves.

3 LEAF DISEASE IN BLUEBERRIES BY INFERENCE WITH Yolov5

3.1 Preliminary Concepts

In this section, we present the main concepts used in the development of our work.

We seek to perform detection (inference) of blueberry bush leaf diseases, using computer vision and convolutional neural networks, where these methods help us to extract the necessary information from the images of the leaves.

Definition 1 (Residual Boxes (Redmon et al., 2016))**.** *This is when an image is divided into grids of fixed dimensions, say n*n. Where each cells is trying to detect object inside them.*

Example 1 (Residual Boxes)**.** *We can see the residual boxes generated in the Figure 1.*

Definition 2 (Bounding Box Regression (Redmon et al., 2016))**.** *This marks an outline that highlights an object in an image. Where their attributes are Height, width, class and box center.*

Example 2. *We can see on the second step of the Figure 1 how some areas are highlight in yellow.*

Definition 3 (Intersection Over Union (IoU) (Redmon et al., 2016))**.** *This describes how the boxes are overlap. Where if IoU is equal to 1 is meaning that the predicted bounding box is the same that the real box. This mechaninsm help us to eliminated bounding boxes that are not equal to the real box.*

Example 3. *We can see on the third step of the Figure 1 how the image get more clear after deleting some bounding boxes to get one with the most probability score.*

Definition 4 (YOLO Arquitecture (Redmon et al., 2016))**.** *It is a sequence of 3 components:*

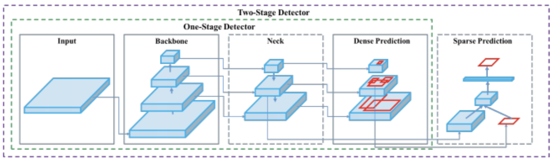


Figure 2: Object Detector Arquitecture, from (Bochkovskiy et al., 2020).

- *Backbone: This refers to a type of neural network called a convolutional neural network, which is designed to gather and combine visual characteristics from images at various levels of detail.*
- *Neck: This refers to the use of a sequence of layers in a neural network to blend and merge visual features extracted from images, in order to propagate them through the network and make a prediction based on them.*
- *Head: This refers that uses the features from neck and uses them to make predictions, including the location of object and their corresponding classes.*

Example 4. *We can see on the Figure 2, how the architecture is represented and follow different steps until get the prediction.*

3.2 Method

In this section, the main contributions proposed will be explain and detailed.

3.2.1 Blueberry Bush Leaf Diseases Dataset

Our first contribution is the creation of a dataset that was used to train the Yolov5 model, which contains 4 classes: three of diseases and one of healthy leaves.

There is a total of 439 images containing 1 single disease and 105 images with 2 or more diseases.

The picture were taken at the Fundo San Roberto, located at the Sayan district, Huaura Province, in the Lima region.

The climate was sunny the picture were taken during midday, the cameras used were a Huawei Y7 2019 cellphone, a Samsung A30 and a Sony CyberShot DSC-W630.

- Image Pre-Processing: After the collection of the images, they received a manual filter where those that contained very blurry or distorted images were discarded in order to guarantee the quality of the images. Later, different data augmentation techniques were used in the images in order to increase the number of total images; For this, we used the image data generator, from the Keras library in Python, in order to reduce a possible overfitting problem and increase the diversity of our data, as shown in Figure 3. We have also made a reshape to the images to reduce the number of pixels in order to reduce computational costs when training the model. Then, we apply a combination of data augmentation techniques such as: rotation transform, to rotate the image to horizontal an vertical flip with a parameter of 0.6; brightness transformation, where 0.0 means minimum brightness and 1.0 means maximum brightness; channel shift transformation, where a channel shift range of 60 is applied; finally the fill mode reflect is used to fill in the proximity pixels.

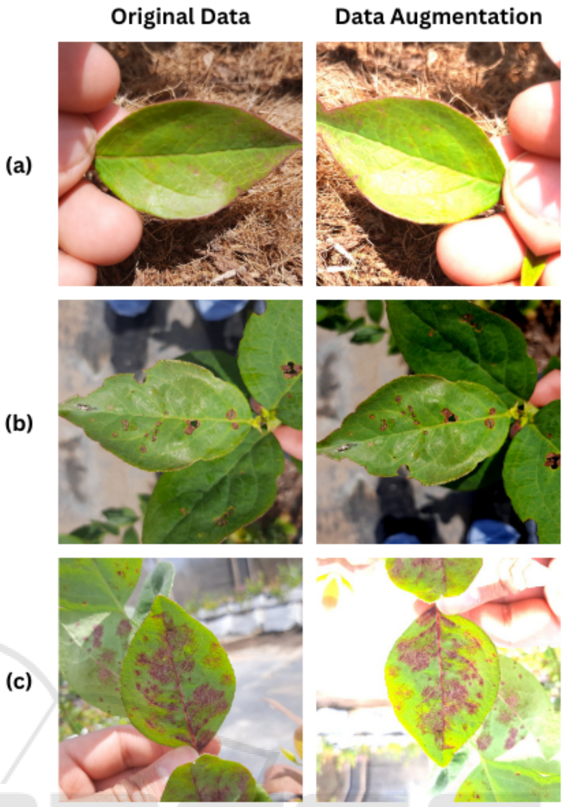
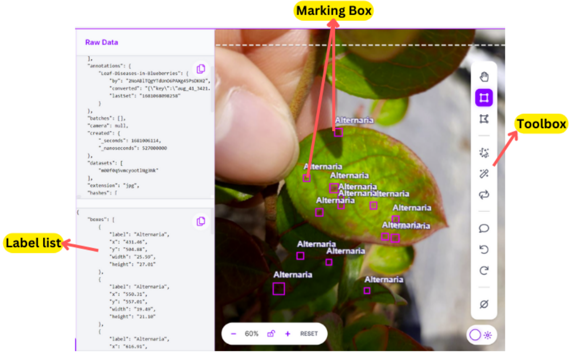


Figure 3: Examples of Diseases Alternaria (a) ,Heliothis (b), Oidium (c).

- Labeling Images Using Roboflow: Continuing the pre-processing, we have used the Roboflow tool and its online manual labeling tool as shown in Figure 4, which gives us a compressed file containing our data and labels in folders organized and ready to use in Yolo.

3.2.2 Architecture

Our second contribution for this investigation is the use of computer vision and convolutional neural networks in our plague detection model using the Yolov5 framework.



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      "height": "21.10"
    },
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      "label": "Alternaria",
      "x": "616.91",
```

Figure 4: Roboflow Label Tools berry leaves an example.

In Figure 5 we can observe the workflow, it all starts by taking a picture of a blueberry bush leaf.

- Take a photo: We take a picture of the leaf that we want to analyze with our program, it will be saved on our image gallery.
- Upload Image: From the app we search for the picture that we took and select it, its format can be in JPEG or PNG.
- Scaling Image: Once the image is loaded it will be scaled to 1024x1024 px.
- Residual Boxes: Our detection model divides the image into an array of square cells in a N*N format, where each cell in the array is given the task of locate and predict the classes inside the area it covers with its respective probability and confidence values.
- Bounding Box Regression: This step consists of determining the bounding boxes that corresponds to the rectangles that highlight all the objects in the image, it is possible to have as many bounding boxes as there are objects in the given image. Yolo will determine the bounding boxes using a unique regression model which follows the following format, where Y represents the final vector of each bounding box.

$$Y = [pc, bx, by, bh, bw, c1, c2] \tag{1}$$

  - pc: represent the probability value of the grid containing an object.
  - bx,by : represents the x and y coordinate values of the center of the bounding box.
  - bh,bw : represents the height and width values of the bounding box
  - c1,c2 : represents the classes found in the images, we can have as many classes as the case requires. In our case there are 4.
- Intersection Over Union: Within our images, multiple candidate grid boxes may appear for the prediction, although not all of them are relevant. That is the objective of the IOU, where the less relevant grid boxes are discarded to keep the relevant ones.

4 EXPERIMENTS

In this section we will talk about the experiments carried out, as well as everything necessary to replicate them, and the results obtained from the experiments will also be discussed.

4.1 Experimental Protocol

In this subsection we will detail the development environment configurations in which the experiments were carried out, as well as the hardware and software used.

Finally, the step-by-step will be detailed to carry out your own training.

A computer has been used as the development platform, the operating system was Ubuntu 22.04.2 and the Pytorch framework and Yolov5 environment were created in Anaconda.

The program was coded in Python 3.10.6 and the cuda version was 12.1. For the hardware, an AMD Ryzen 7 5700x CPU processor, NVIDIA Geforce RTX 3070 GPU and 32 GB of RAM at 3200 Mhz have been used.

The specific configurations are found in the Table 1.

4.1.1 Training a Custom Yolov5 Model

- Setting up the Yolo enviroment: We must clone the Yolov5 repository from Github (Jocher, 2020). Yolov5 runs on Torch, where it can easily be run on Google Colab or Kaggle. Cloning creates a file named Yolov5 on the machine, where it will contain Yolo's specific directory structure.
- Setting up data and directory structure: In order to label and manage the structure of the files quickly and easily, the Roboflow tool has been used where, after uploading and labeling our images, we can download a zip file which will contain the files necessary for our training.
- Training the model: Training the model is done by running the train.py file from the notebook. Parameters such as number of epochs, batch size, image size, among others, can be established. Once executed, a folder will be generated which will contain the weights of the trained model. To carry out the detection of diseases we must use the detect.py file. After training, the best.pt file

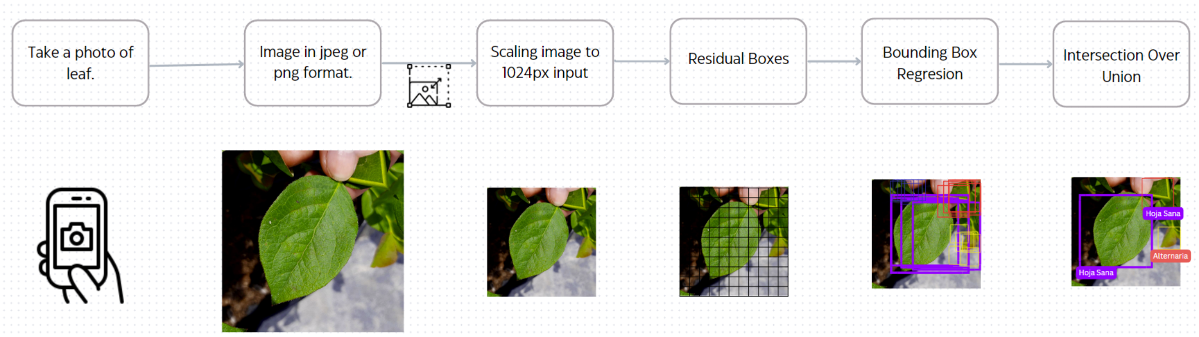


Figure 5: Framework Flow.

Table 1: Development environment setting.

Parameter	Configuration
Operating system	Ubuntu 22.04.2
Deep learning framework	PyTorch 1.21.1
Programming language	Python 3.10.6
GPU accelerated environment	CUDA 12.1
GPU	Geforce RTX 3070 8gb
CPU	AMD Ryzen 7 5700x @3.4 Ghz

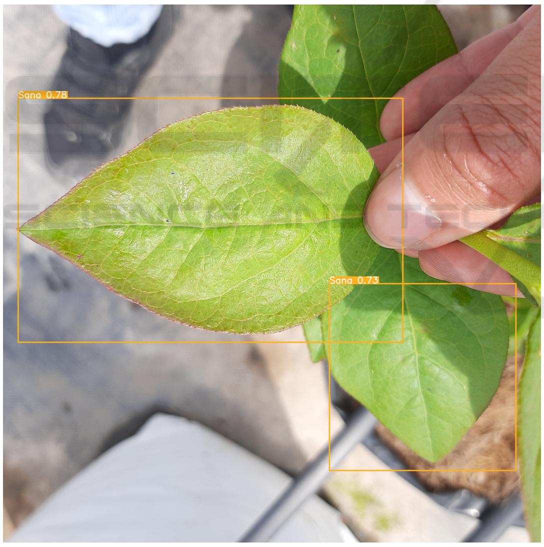


Figure 6: Healthy leaf detected.

located in runs/train/exper/weights/best.pt is obtained. The Figure 6 is an example of the images that are generated after the training has finished.

4.2 Results

In this subsection, we will talk about the experiments carried out and the results obtained in each one of them will be detailed.

4.2.1 Model Evaluation Metrics

To achieve the tests or evaluations of the model for the detection of Alternaria, Heliothis, Oidium and healthy leaves, an exhaustive analysis has been carried out on the performance of the model, and other methods have also been discussed, such as the following indicators: Precision (P), Recall (R), F1-Score (F1), Accuracy (A) and Average Precision (AP).

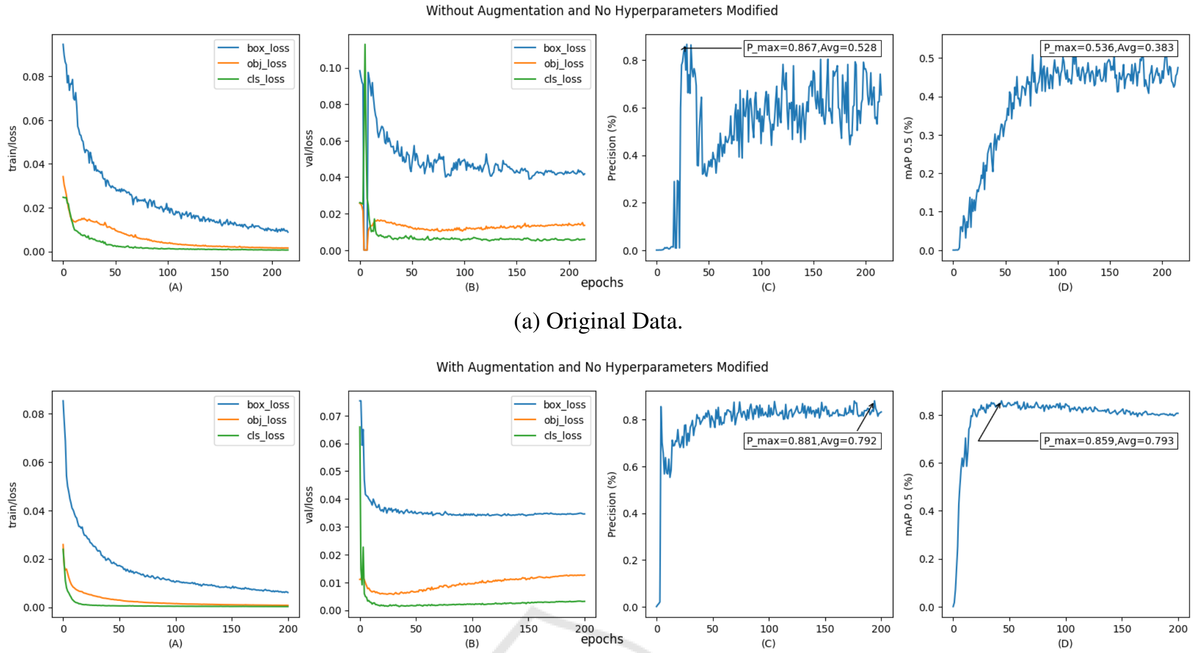
4.2.2 Analysis of Data Augmentation Results

Initially, we want to check if applying data augmentation techniques to our blueberry leaf dataset is beneficial for training our Yolov5s model.

This test evaluates the model using the mAP, precision and loss value metrics, in Figure 7a and Figure 7b, which show the train values, validation loss as well as the precision and mAP50 values at each epoch and, when comparing both versions, a better recognition percentage is observed in the DrBerry model when using data augmentation techniques to the dataset.

The validation and training loss values decrease over time, as well as showing some points of convergence, as well as giving us an emphasis on a possible overfitting since the train/loss values decrease and val/loss increase as shown in Figure 7a and Figure 7b.

The curves represented in Figure 7a and Figure 7b show us a great difference when using data augmentation methods, obtaining better results in both accuracy and mAP from the start of the training.



(a) Original Data.

(b) Augmented Data.

Figure 7: Train Loss (a), Validation Loss (b), Accuracy rate (c), mAP50 rate (d).

It can also be seen that the accuracy value ranges remained high until the end of the training.

As shown in Table 2, tests were performed with three groups of data augmentation techniques applied to the DrBerry dataset and trained with the Yolov5s model.

The results were compiled to evaluate the performance of each combination in order to find the most favorable one.

All the trainings were carried out with a batch size of 8, with 300 epochs, in some cases the intervention of the early stopping mechanism was recorded, and with all the default learning rates that can be found in the route ./yolov5/data/ hyps/hyp.no-augmentation.yaml.

Number 2 presents the use of 3 data augmentation techniques with which a value of 81.8% accuracy was obtained while Number 3 presents the use of 4 data augmentation techniques where we obtain an 86.4% accuracy, a 4.6% improvement compared to the previous one.

On the other hand, Number 4, with 5 data augmentation techniques, presents a value of 79.5% accuracy and, although the latter shows a worse performance, it shows us that modifying this value is not recommended for the type of images we are working with.

The augmentation of data has helped us to obtain significant improvements when using Yolov5s model compared to when we did not use it.

4.2.3 Analysis of Data Augmentation and Modified Hyperparameters

In order to validate the performance of the hypeparameters in conjunction with the data augmentation techniques applied, the following Figure 8 is shown where the legends of data_original, data_v1,data_v2 and data_v3 refer to to the techniques used in Table 2.

The results of the experiments show us considerable improvements between the use of improved hyperparameters against the results that do not use them, where the results obtained in Hyp-Low Augmented managed to reach values of 88%, 94% and 94% in accuracy, recall and mAP50 respectively.

These are significant values since we were able to increase 5%, 24% and 14% compared to the data without increased hyperparameters.

Likewise, we highlight the MOSAIC hyperparameter, which helps us to have more variability in our images Figure 9, which helps us to reduce overfitting as shown in Figure 10.

This can be seen in tables (C) and (D), where in the first case these values are not converging but rather they are increasing over time, contrary to the second case where the values decrease over time until they converge.

Table 2: Results obtained from training Yolov5s with different data augmentation methods.

Rotation Range	Horizontal Flip	Vertical Flip	Brightness	Channel Shift	Diseases	Precision%	Recall%	mAP50%
					Alternaria	62.4	**81.6**	**77.8**
					Heliothis	66.8	36.5	58.0
					Oidium	**83.7**	34.3	44.9
					Healthy	63.2	25.6	33.0
					All	69.0	44.5	53.4
✓	✓	✓			Alternaria	67.5	63.3	54.4
					Heliothis	84.4	57.4	78.7
					Oidium	**88.4**	76.5	90.2
					Healthy	86.7	**86.1**	**94.0**
					All	81.8	70.8	79.3
✓	✓	✓	✓		Alternaria	84.8	68.5	76.7
					Heliothis	88.4	61.0	79.3
					Oidium	**89.4**	82.1	**92.8**
					Healthy	82.9	**82.7**	89.8
					All	86.4	73.6	84.7
✓	✓	✓	✓	✓	Alternaria	82.1	**88.8**	**88.9**
					Heliothis	**89.0**	71.7	80.1
					Oidium	81.6	76.5	81.8
					Healthy	65.3	65.4	64.8
					All	79.5	75.6	78.9

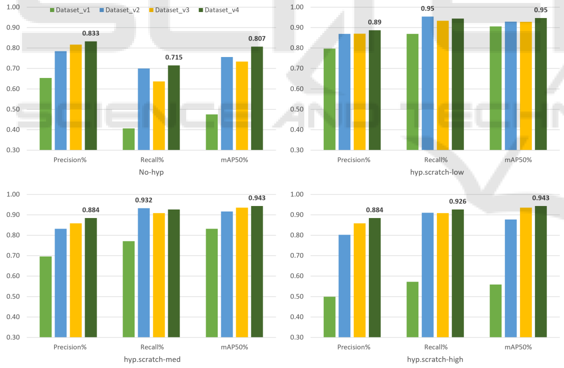


Figure 8: Training for Yolov5s with various kinds of data augmentation techniques and types of hyperparameters.

4.2.4 Analysis of Yolov5s and Yolov5m Using Data Augmentation and Modified Hyperparameters

Table 3 shows the comparison of the results obtained after carrying out different experiments, in this case Number 3 of Table 2 has been used as data for our evaluations, where we obtain similar results between precision, recall and mAP50, highlighting the increase of 5%, 0.1% and 2% respectively in the M version of the Yolov5 model.

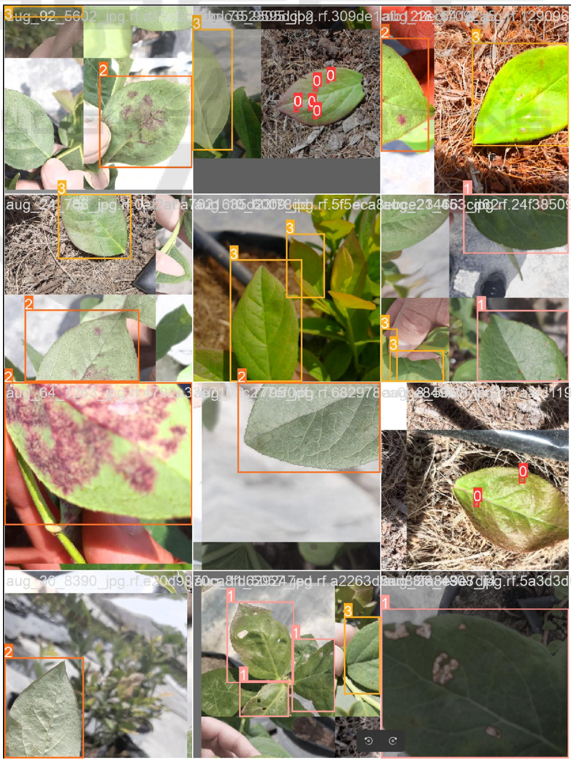


Figure 9: Result applying the MOSAIC hyperparameter.

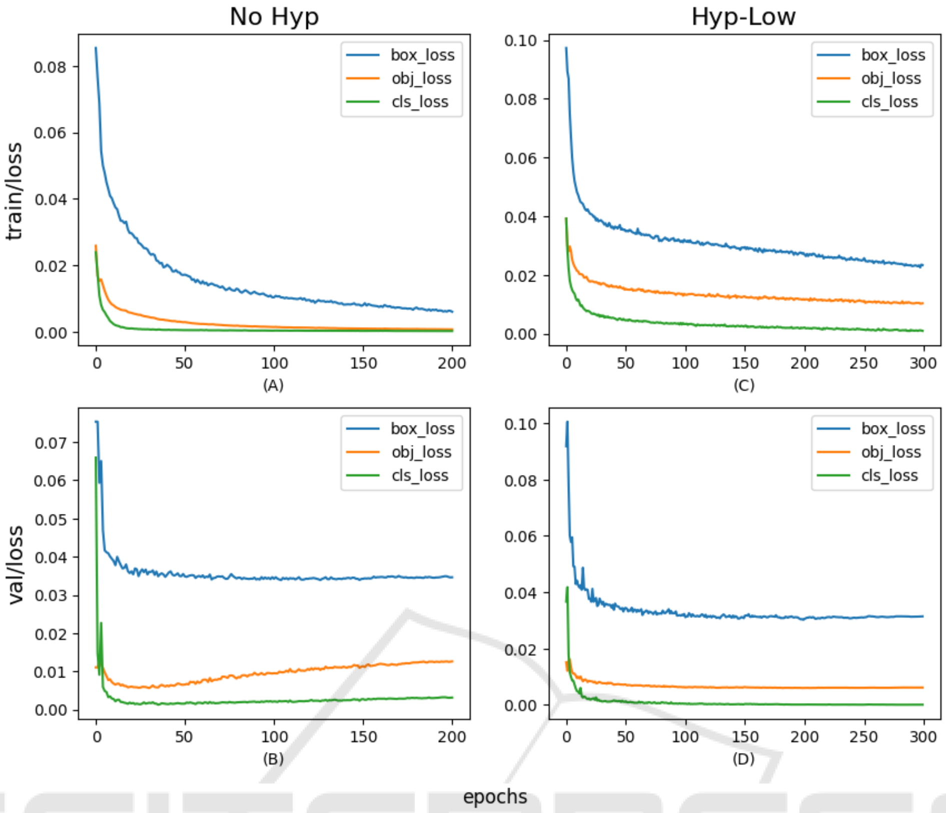


Figure 10: Yolov5 S No Hyp vs Hyp Low.

Table 3: Results obtained from training with Yolov5s and Yolov5m utilizando Hyp Low in Testing Images.

Model	Weigth	Diseases	Precision %	Recall %	mAP50 %
Yolov5s	14.11Mb	Alternaria	81.4	90.4	90.9
		Heliothis	86.9	88.4	92.2
		Oidium	97.9	98.7	99.4
		Healthy	87.5	92.8	94
		All	88.4	92.6	94.1
Yolov5m	40.61Mb	Alternaria	87.4	87.9	90.6
		Heliothis	96.4	92.7	98.0
		Oidium	98.8	98.7	99.2
		Healthy	89.3	91.6	96.7
		All	**93.0**	**92.7**	**96.1**

5 CONCLUSIONS AND PERSPECTIVES

In this work we managed to create a Yolov5 model capable of identifying three different types of plagues that afflicts the blueberry bush's leaves, reaching a 94.1% and 96.1% mAP50 as shown in the Table 3.

We also point out that our model presents a high Recall percentage, value that we consider important in the identification of diseases in the plant's earlier stages, since a misidentification may result in the plant being considered healthy, when that is not the case, left unchecked and potentially damaging its growth.

We also want to point out the importance of the dataset and the data-augmentation techniques we applied, being able to collect data is not an easy task when the source is not easily available and it can result in a suboptimal dataset, thus, by applying data augmentation we managed to improve our results as it has been previously discussed, and other works try different approaches for similar problems (Rodríguez et al., 2021; Leon-Urbano and Ugarte, 2020; Lozano-Mejía et al., 2020).

For future works we have thought about taking two possible routes: i) Making an recomentadion software that, using our current model, gives the user useful information about the disease detected, what potential harm it could have on the blueberry bush if left unchecked and posible solutions.

It would be an offline solution since some plantations lacks the internet connectivity. ii) Improve our model making it able to detect more diseases, by the time of this writing new versions of Yolo have been developed and it would be interesting to see what benefits they can bring to our proyect.

We could also explore different data augmentation techniques to further improve our dataset for future trainings.

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