Weed Identification Technique in Basil Crops using Computer Vision

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Abstract: - The promotion of organic and ecological production seeks the sustainable and competitive growth of organic crops in countries like Peru. In this context, agro-exportation is characterized by-products such as fruit and vegetables where they need to comply with organic certification regulations to enter products into countries like the US, where it is necessary to certify that weed control is carried out using biodegradable materials, flames, heat, media electric or manual weeding, this being a problem for some productive organizations. The problem is related to the need to differentiate between the crop and the weed as described above, by having image recognition technology tools with Deep Learning. Therefore, the objective of this article is to demonstrate how an artificial intelligence model based on computer vision can contribute to the identification of weeds in basil plots. An iterative and incremental development methodology is used to build the system. In addition, this is complemented by a Cross Industry Standard Process for Data Mining methodology for the evaluation of computer vision models using tools such as YOLO and Python language for weed identification in basil crops. As a result of the work, various Artificial Intelligence algorithms based on neural networks have been identified considering the use of the YOLO tool, where the trained models have shown an efficiency of 69.70%, with 3 hours of training, observing that, if used longer training time, the neural network will get better results.

Key-Words: - Crops, farm, agricultural, basil, machine learning, Classification algorithms, yolo, Weed

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1 Introduction

In Peru, in 2008, a proposal for the promotion of organic and ecological production is presented, which seeks the sustainable and competitive growth of organic crops in Peru, [1], [2]. During 2019, agricultural exports have been characterized by products such as fruit and vegetables, with the United States, Germany, the Netherlands, and Spain as main clients. These markets need to comply with organic certification regulations to enter the US, it is necessary to be accredited under the USDA Organic Standards 7 CFR 205, [3]. Its Operational Standard for Pests and Weeds indicates that the problem of weed control must be carried out with coverage of biodegradable materials, mowing, flames, heat, electrical means, or manual weeding.

The problem from the nutritional point of view, vegetables are affected by their nutritional properties such as: the minimal presence of lipids, high iron, and calcium content, which make a product in great demand for local and foreign consumption, [1]. These products are affected by weeds due to competition for water, light, nutrients, CO_2, and space. This is why it is important to recognize the weeds of the crop, as it helps to increase the yield per hectare to solve this problem.

The problem related to the presence of weeds in crops can be solved from the technological field using solutions such as performing a mechanical removal of the weeds, using a robot that can move in the crop, [4], but that will generate stress that affects the flavor and nutrients in basil. Another type of solution is related to the use of a multispectral imaging system, which increases certain nutritional properties of the plant. That is why before carrying out any weed control task, it is necessary to differentiate between the crop and the weed whose most used technique is image processing. This causes the staff to be replaced by robots in the near future using Deep Learning image recognition techniques in blueberries during the rooting stage, for efficient use of resources, [4], [5], [6].

One of the solutions to improve cultivation processes is related to identifying diseases in plant leaves through image processing, using artificial intelligence and machine learning computational tools, [7]. One of the technologies called to contribute with a solution is Edge Computing, [8], which allows for reducing latency and improving computing power closer to the client together with cloud computing.

In the case of this research, the area of study is basil fields with weed presence problems in rural areas and limited access to cable internet. Based on what was previously described, the problem has been identified and this paper poses the following research question: How is it possible to identify weeds to contribute to the care of basil crops in rural areas?

Therefore, this research shows the evaluation of the object identification model to detect weeds in a basil plot, for which the following specific objectives will be met: Select an object identification algorithm for the classification of weeds in a basil plot; Implement the weed identification algorithm in a basil plot; Evaluate the effectiveness of the identification algorithm. As a first step, the use of a research methodology is proposed through literature review techniques to evaluate the most appropriate technologies. Subsequently, a methodology based on CRISP (Cross Industry Standard Process for Data Mining) is selected to implement computer vision algorithms. In addition, a development methodology is used, which integrates computer vision techniques, based on an iterative and incremental.

The present investigation contributes value in the aspect of the identification of weeds in crops to allow the production of the greatest amount of product per hectare. In addition, the efficiency of the artificial intelligence tool to differentiate weeds from basil crops is described, which can then be applied to a mechatronic device or to identify areas with many weeds.

The development of this paper is written as follows. Section 2 shows the most relevant papers. The most important concepts about the technologies used are shown in section 3. Subsequently, section 4 describes the proposed system and section 5 mentions the results. The conclusions are then described in section 6.

2 Related Works

This section describes the existing research related to the use of identification and classification algorithms through deep learning techniques through image processing in crop fields and the importance of the development of a country.

In, [9], the author describes how globalization has driven development in many third-world countries. It is mentioned that there is a growing demand for vegetables and fruits since 1986, having a great leap since 2000, thanks to agro-export agriculture. This is why many companies, related to this area, manage better resources to optimize production, among which we have: technical irrigation, and access to water projects, in products (Quinua, Grapes, Asparagus, Avocados, etc). The results of the study indicate that the export sectors use valid development strategies for low incomes.

The use of image processing techniques can be used to detect crops with small products, at different stages of their growth, where the difficulty lies in their size and color change during their growth, [10]. These investigations describe the use of tools such as Yolo, which uses convolutional processes to extract semantic details based on the DSE-V (Vertical Dimensions) and DSE-H (Horizontal) modules, [11], [12]. The results in [10], show an effectiveness of 85% in the detection of the crop, in a natural environment. In addition, YOLO version 3 was used, which has the Binary Cross Entropy (BCE) function, allowing to efficiently estimate the loss of classification and loss of confidence using mean square error (MSE).

In other research, the Yolo V5 tool is used to identify weeds in crops, [13], in real-time. The objective of this article is to carry out an early detection to avoid damage to the crops. For this, a convolutional neural network is developed with the software YOLO_CBAM (Convolutional Block Attention Module) that allows improving the extraction, correcting, suppressing, and extracting irrelevant features, improving the performance of the network. A Jetson AGX was used for the training and deployment of the solution, verifying a performance improvement from 0.90 to 0.92.

Automation in agriculture is an emerging topic and integrates methods of artificial intelligence, [14], or the use of drones, [15]. This makes it possible to contribute to protecting crops from aspects such as: climate change, population growth, and food security. This paper describes weeding, irrigation, and fumigation processes, thanks to sensor information and the use of robots. In addition, for the wedding application, precision techniques with Artificial Intelligence and Computer Vision are used.

Other research describes how the use of Internet of Things technologies in agriculture enables early detection of rice diseases, [16]. This paper comments that farmers lose between 15% and 20% of their profits due to bacterial, viral, or fungal diseases that attack rice. In addition, this paper seeks to identify the "brown spot" disease using convolutional neural networks and real-time image recognition. For the training and tests with images of the rice paddy, software technologies such as Keras and Tensorflow are used, [17], [18].

3 Weed Image Processing

3.1 Tools for Algorithm Generation

Some of the most used tools for the development of artificial intelligence include Python, C++, R, Java, Prolog, and Matlab. In the case of Python, this is a programming language, with great development for different platforms. Among its advantages we have Treatment of a large volume of data, ideal for Big Data, Simple and easy to learn, and Dynamic Variables, [19], [20]. The most used libraries and frameworks for the creation of artificial intelligence algorithms have:

- OpenCV. It is an open-source library, specialized in computer vision applications. It has algorithms developed for image processing, [21].
- Matplotlib. Allows you to create static and interactive visualizations. Transform data in lists to graphs, has an API that gives the appearance of Matlab, projections, and image mapping, [22].
- PIL. An open-source Python image library that has features for image processing. It allows various image formats for processing.

3.2 Framework for Digital Image Processing (DIP)

The YOLO (You Only Look Once) algorithm is used as a powerful tool for object detection in applications such as autonomous driving, and image and video processing, among others, [23]. This algorithm is based on neural network techniques that allow the detection of objects by dividing the image into a grid of cells of NxN dimensions. During training, you learn to recognize patterns and relevant features of objects in images to generalize and detect objects in never-before-seen images.

In each cell, bounding boxes indicating the presence of objects are generated, and a confidence score is calculated for each detection (Fig. 1). These boxes provide estimates of the location of detected objects relative to the cell boundaries within the grid. These estimates are based on the width (W) and height (H) of the detected objects (Fig. 2) while the boxes are associated with a confidence score, which indicates the certainty that an object is present in that box. The advantage of this procedure is that it allows the detection of objects in a single pass over the entire image, instead of using sliding windows or multi-stage detection methods. This makes YOLO faster and more efficient compared to other approaches.

3.3 Weed Identification

The weed interferes in the various stages of the agricultural process, which compete for water, light, and nutrients, producing chemical compounds that alter the development of other plants, [24]. These are agents that allow the proliferation of other pathogenic elements and have a negative impact on the main crop.

Fig. 1: NxN grid

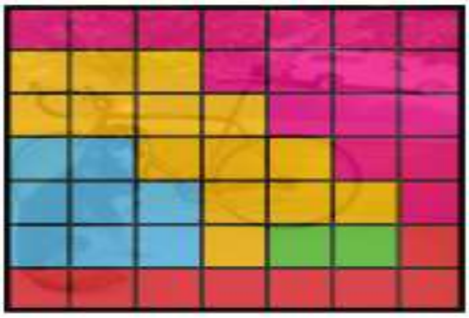

Fig. 2: Class probability map

To eliminate them, the following techniques can be used:

- Mechanics. Soil preparation before planting is considered, considering its geographical, physical, and biological characteristics that could efficiently impact its control.
- Herbicides. Chemicals used to control weeds are called herbicides. It is necessary to identify the weed, to select the appropriate herbicide, through a selective application process.
- Thermal. It consists of applying fire which is effective and economical. The young weeds die at a temperature of approximately 50°C and in some cases, it will be necessary to increase this temperature.
- Technological. Among some of the technologies that are applied as a proactive method is the use

of lasers, which eliminate unwanted plants. Another alternative is the application of radiation, X-rays, gamma, etc.

4 Proposed Solution

This project is focused on detecting weeds in basil crops, using object detection algorithms, and integrating artificial intelligence techniques and the YOLO software package. In Fig. 3, we show a flowchart of our project, with the following stages:

- Image acquisition. The camera of a Motorola G9 cell phone is used, which is taken in the open field, with natural lighting, for a total of 72 photos. Priority is given to using natural lighting during image capture to recreate the real conditions in which basil crops are found, which contributes to obtaining more accurate and applicable results in real weed detection situations.
- Preparation of DataSet. It is necessary to rename the images, reduce the resolution of the images to 1200 x 1600 pixels, manually label the weeds in the images, and separate the images into 3 folders: “Train”, “test” and “valid”. The hand tagging process involves visually highlighting areas where weeds are found using bounding boxes.
- Training. Yolo V4 is used, through the Google Colab interface, to train the neural network with the images. During training, the neural network learns to recognize and detect weeds in the images, adjusting its internal parameters and weights.
- Validation. Yolo makes it easy to identify weeds by displaying fuchsia boxes, with a Weed class mark.

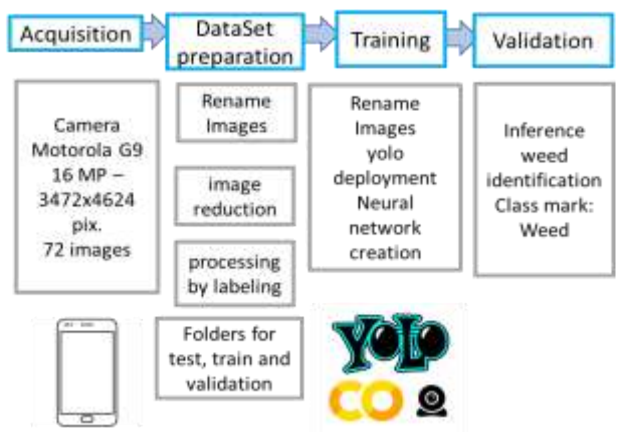

Fig. 3: Project flow chart

4.1 Selection of Object Detection Algorithm

For the selection process of the object detection algorithm, a systematic review of the literature is carried out, finding scientific papers with real applications. For this, a methodology based on [25], was carried out to select documents in the Scopus, Google Scholar, and ScienceDirect databases with a search period of 5 years ago in English. Based on the search for scientific papers, the most important techniques to identify objects and process images, focused on agriculture, were selected. Algorithms based on Viola-Jones, 1-stage YOLO, and 2-stage convolutional neural networks were identified.

In the case of the Viola-Jones technique, it is used to extract features from objects using cascade classifiers. These classifiers are combined to form a strong classifier that can detect specific objects. On the other hand, YOLO is based on applying convolutional neural networks by dividing the image into a grid and bounding boxes for object classification. In the inference stage, the neural network processes the image and predicts the classes of the detected objects. Both approaches require a training stage using labeled data sets to apply the inference stage.

4.2 Implementation of the Object Identification Algorithm

To implement the algorithm, it is necessary to carry out training, validation, and deployment processes using previously prepared images (Fig. 4). The following steps are performed:

- The training and validation procedure begins with the preparation of the images, considering different types of weeds and they are used in the training and validation stage.
- Subsequently, the images are divided into training and validation sets, which allow us to evaluate and adjust the performance of the model during training.
- The Google Colab platform is used, and the YOLO software packages are installed to implement the ranking algorithm.
- Then the configuration of training parameters such as the number of iterations, the batch size, and the learning rate are performed to evaluate the behavioral results of the model.
- During training, the model learns to recognize and classify weeds in the basil images by performing multiple iterations to gradually improve model performance in the Validation.
- Finally, the deployment of the model is carried out, marking the areas of undergrowth in the resulting images with the "weed" class mark.

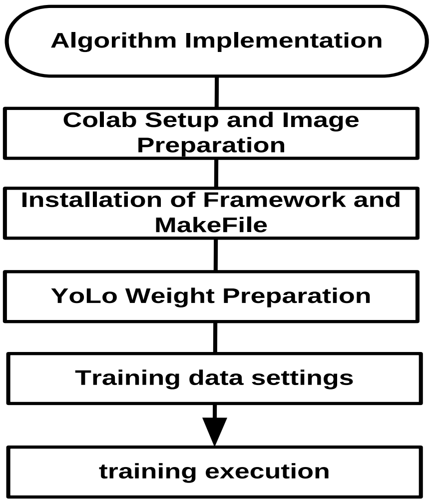

Fig. 4: Implementation process

5 Results

5.1 Object Detection Algorithm Selection

In the field of object detection, there are different approaches and algorithms used. These include two-stage algorithms such as Region-based Convolutional Neural Networks (R-CNN) and their variants such as Fast R-CNN, Faster R-CNN, and R-FCN (Region-Based Fully Convolutional Networks).

Therefore, these algorithms have proven to be effective in accurate object detection in a variety of applications. However, in this research, we chose to use YOLO (You Only Look Once), which is a single-stage approach that uses a 24-layer convolutional neural network based on GoogleNet.

The choice of YOLO V4 was based on its ability to run on different operating systems, such as Linux and Windows, and its ability to work with both static and real-time images. By using YOLO V4, accurate object identification was achieved in the context of this project.

5.2 Dataset Preparation

As a result of the image acquisition, a resolution of 3472 x 4624 pixels and an average size of 6MB were considered. Subsequently, they were transformed to a resolution of 1200 x 1600 pixels and a size of 700Kb on average (Fig. 5).

Fig. 5: Weed and Basil Photos Uploaded

The collected images were renamed by a script that will allow renaming each photo as: weed_0, weed_1, and so on. To facilitate the training of the neural network, these renamed files were stored in the “imagenesMaleza_rename” folder. Then the Labeling of these images was carried out, to manually create and locate the name of the class: "Weed".

Weeds were manually selected over the 72 renamed images, using a rectbox that will serve us for training (Fig. 6). The file created by each image was a text file with a “.txt” extension, where the location coordinates of each manually recognized weed are stored (Fig. 7). Once the labeling is finished, we will proceed to divide the dataset into 3 subfolders: Train (80%), Validation (15%) and Test (5%). This was done with another script called “Split Files” (Fig. 8).

Fig. 6: Rectbox creation and weed class

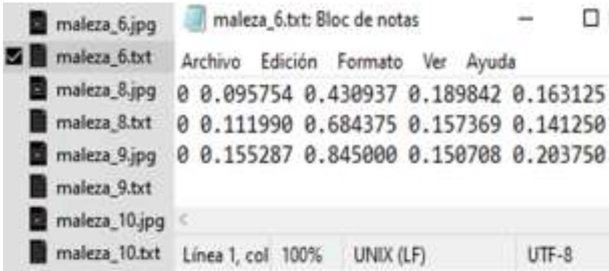

Fig. 7: Files with the location coordinates of the weed

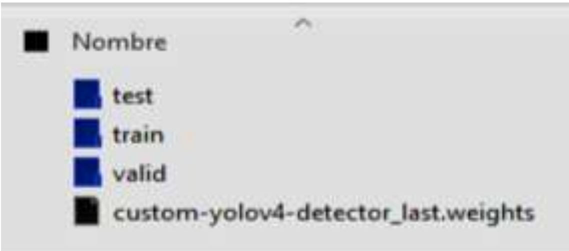

Fig. 8: Training, testing, and validation folders

Analyzing the results described above, it was considered that the data preparation and labeling steps were crucial to ensure the quality and accuracy of neural network training in weed recognition in basil crops. As a discussion of the results, it can be stated that the successful implementation of these processes contributed to obtaining an effectively labeled and organized data set for the training and evaluation of the weed detection algorithm. This, in turn, laid the foundation for the results obtained in terms of the ability to identify weeds using computer vision.

5.3 Deployment of the Object Identification Algorithm

To deploy the algorithm, the following steps are performed in Google Colab:

- The Darknet Framework is installed to create a virtual workspace.
- Create a MakeFile file, which will give instructions to the Make function, to perform all tasks.
- Download the weights of the algorithm that YOLO has by default.
- Custom data configuration for the use of folders, train, validate, and test in our workspace.
- YOLO settings for image processing, saturation, exposure angle, rotation, etc. for the training process.
- Execution of the configuration script
- Training process.
- It will proceed from inference, using the images from the test folder.

To carry out the prediction process, the new weights obtained are used, through the "darknet" command, to which a series of options will be passed as parameters to display the results (Fig. 9). Concluded the previous process, the images with the class mark are shown, identifying the weeds. Fig. 10 shows an example image with the identification. Once the identifications are made, the percentage of correct answers is determined, considering different training times (Fig. 11).

From the results shown, his analysis shows that with different training times, the classification results in images have significant improvements. We attach a series of images with the weed identifier boxes, of the results shown above. Fig. 12 shows the classification results with one hour of training, while Fig. 13 shows the results with three hours of training. Finally, it was verified that the model performs a correct detection of weeds with the test images, as shown in Fig. 14.

Fig. 9: Prediction process


Fig. 10: Weed identification

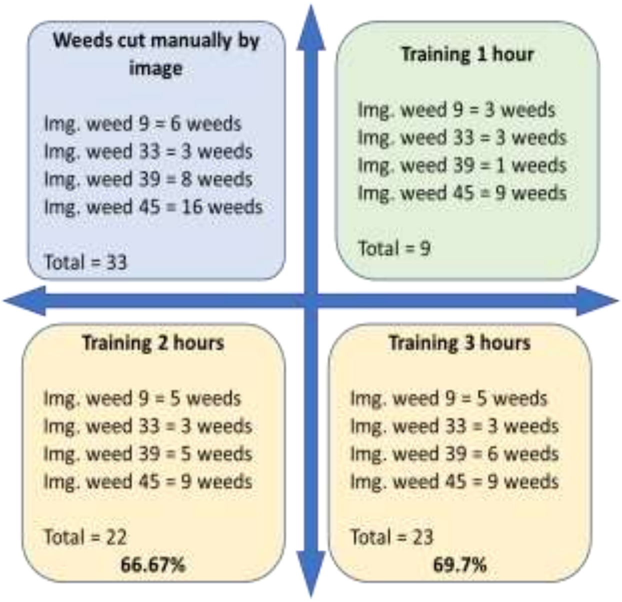

Fig. 11: Summary of success vs training time

Fig. 12: Identification with 1 hour of training

Fig. 13: Identification with 3 hours of training

Fig. 14: Identification with an improved dataset

6 Conclusions

Various Artificial Intelligence algorithms based on neural networks have been identified considering the use of the YOLO tool. This tool is useful due to its speed of processing, easy implementation, and because it allows training automation by adjusting parameters depending on the type of analysis of interest. In addition, collaborative development was carried out using the Python language and the Google Colab tool, accessing the GPU available online to optimize the training processes.

During the evaluation of the algorithm, an efficiency of 69.70% has been obtained, with 03 hours of training, observing that if a longer training time is used for the neural network, better results will be obtained. On the other hand, it should be considered to use a larger number of photos for training, to increase the efficiency of the algorithm.

Also, as recommendations for future work, we can indicate that if the resolution is reduced, the processing time will decrease using Yolo v4. On the other hand, the use of the GPU using Google Colab sometimes limits access to the Web resource for some hours. An alternative that was not used was to use a paid Colab account or use a computer with the software installed and a GPU. Like other online alternatives, the use of Amazon Elastic Computer Cloud as an alternative to Google Colab can be compared in the future.

In other words, a greater number of photos with labels of different types of weeds could be used to identify the type of weed. In addition, other algorithms such as EfficientDet or RetinaNet could be compared, which, like YOLO, are one-stage.

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