ISSN 1870-4069

Intelligent Hybrid Decision Making System Focused on Recommendations for the Treatment of Heterogeneous Seasonal Citrus Fields

Antonio Romero[1], Eddy Sánchez-DelaCruz[1], Alberto Ochoa[2]

[1] Instituto Tecnológico Superior de Misantla,
Veracruz, Mexico

[2] Universidad Autónoma de Ciudad Juárez,
Mexico

romeroa_cv123@hotmail.com, esanchezd@misantla.tecnm.mx,
alberto.ochoa@uacj.mx

Abstract. The implementation of an intelligent drone that replaces one of the main tasks of farmers, direct visual inspection, in order to reduce future damage to citrus production generated by bird pests, where the use of a convolutional neural network will serve to extract characteristics and generate a classification model capable of distinguishing between healthy foliage of a tree and that which is not, Consequently, it presents some kind of pest produced by the birds taking into account the coloration of the leaves, as well as, to extract the coloration of the leaves that present diseases, with the purpose of optimizing and improving the activities immersed in the cultivation of the citrus fruits. In addition, to reduce the damage of pests of birds, which will significantly increase productivity in the agricultural sector annually, therefore, through the implementation of unmanned aerial vehicles, provide visual recognition to reduce the indirect effects generated by the type of pests and thus optimize the activities and techniques of citrus cultivation, carrying out the incorporation of the image repository for decision making created.

Keywords: Smart drone, citrus cultivation, bird pests, convolutional neural network.

1 Introduction

One of the main problems that farmers have to face is pests in their crops that generate great losses and threaten food security, as well as economic problems for the farmer due to losses. Currently, the technique used to detect bird attacks on crops is a traditional method of control in the fields, direct visual inspection, which consists of personally supervising the planting, that is, the farmer has to go to the area of interest in order to watch and monitor the crops, this method is slow and is not applicable to large areas of land (Bokolonga et al., 2016). However, there are other methods that experience efficiency, but at a higher cost, therefore, the detection of attacks on crops is suitable for viewing from the altitude with the help of an application that allows easy use and detection of the damaged crop.

On the other hand, drone technology provides a solution to the conflicts or difficulties that currently exist for a farmer because they allow for a more extensive and complete expansion of inspections, thus helping to work in the agricultural sector, in addition, manual work is reduced with the implementation of this collaboration, since it benefits them in the field activities due to the fact that the unmanned aerial vehicle becomes the eyes of the citrus grower in order to make this task easier, since with the help of the cameras it captures images showing if the crop has pests and showing the state of the plantation and improving the crop control techniques (Vatalaro et al., 2016).

On the other hand, there are a variety of artificial intelligence techniques that can be implemented and that can help improve the agricultural sector, so we worked with a Neuronal Convolutional Network, which was trained with images of citrus crops to achieve greater accuracy in pest detection and that after this, this classification model was intended for a mobile application for greater control and also to allow better management (De Rango et al., 2019).

In contrast, once the detection of the disease caused by bird pests has been made, this analysis serves as a repository for a new classification, which is stored directly in the cloud. The different diseases that this pest causes to citrus plantations were analyzed and recognized by expert growers in the area of Misantla, obtaining a coincidence of recognition that exceeds 98% of identification in which the coloring of the foliage is taken into account, as well as the citrus fruit.

1.1 Object Classifier and Object Detector

Firstly, it is important to know how to differentiate between an object classifier and an object detector. An image classifier is an algorithm that is dedicated to classifying images within a specific category. For example, a group of images of a crop with pests were assigned and this only mentions that the predominant object in the photo is the particular damage, while an object detector is an algorithm that is responsible for identifying various elements within the image and thus classifying them, for example, they receive an image containing a citrus crop and identify that there is a pest, bird, tree, etc. within the image (Gonzalez, 2007).

1.2 Artificial Neural Network

Artificial Neural Networks are part of Artificial Intelligence, they are also networks trained through the inputs obtained from external or internal scenarios in the system and these inputs are multiplied by randomly assigned weights, a neural network is an integration of various learning systems, that is why they have the ability to learn through previous training, the ANNs are programming objects that mimic the functioning of biological neurons (Rivas-Asanza et al., 2018).

On the other hand, NNAs have many advantages such as adaptive learning in which you learn to perform tasks from a set of data being that in the process of learning these data are represented as inputs and weights, In addition, self-organization as you can create your own organization or representation of information received, the neural networks self-organize their information they receive during the learning of the

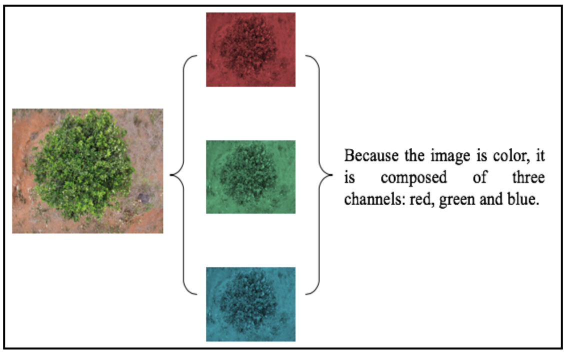

Fig. 1. RGB example.

operation using the mathematical methods Adeline, Madeline and Perceptron among others. Additionally, tolerance to partial failures knowing that the partial destruction of the network damages its operation but does not destroy it completely. This is due to the redundancy of the information contained, that is, this leads to the information not being lost since it works like the human body. Similarly, their operation is in real time, as they can be carried out by computers or special hardware devices to take advantage of the capacity of the NNAs (Matich, 2001).

Convolutional Neural Network

CNNs are similar to ordinary neural networks such as the multi-layer perceptron, they are composed of neurons that have weights and biases that they can learn. Each neuron receives some input, performs a scalar product and then applies a trigger function. What distinguishes CNNs is that they explicitly assume that the inputs are images, which allows us to encode certain properties in the architecture; favoring efficiency gains and reducing the amount of parameters in the network. CNNs even solved the problem that ordinary neural networks do not scale well for high definition images. CNNs work by consecutively modeling small pieces of information, and then mixing the information in the deeper layers of the network, so they are able to model complex variations and behaviors giving fairly accurate predictions (Briega, 2016).

The CNN is a type of Artificial Neural Network with supervised learning that processes its layers imitating the visual cortex of the human eye to identify different characteristics in the inputs that ultimately make it able to identify objects and "see". For this, CNN contains several specialized hidden layers with a hierarchy: this means that the first layers can detect lines, curves and specialize until they reach deeper layers that recognize complex shapes such as a face or the silhouette of an animal (Na8, 2018).

Pixels and Neurons

To start, the network takes the pixels in the image as input. Here you have an image with 4000×3000 pixels high and wide, that's equivalent to 12000000 neurons. And that's in case you only have 1 color (grayscale). If you had a color image, you would need 3 RGB channels (network, green, blue) and then you would use 4000x3000x3 = 36000000 neurons as input.

Fig. 2. Persian Lemon tree.

Before feeding the grid, it is convenient to normalize the values as input. The colors of the pixels have values ranging from 0 to 255, a transformation of each pixel will be carried out: "value/255" and there will always be a value between 0 and 1. This range, due to the operation of convolutional networks, makes it possible to identify the characteristics for each vector incorrectly. To correct this, it is convenient to previously normalize the image, in a process known as zero mean and unit variance normalization. To summarize, it refers to a 3-dimensional matrix where each dimension represents a layer of color, and each of these layers has values ranging from 0 to 255, and represent the intensity of that color, where the computer to display takes a value and draws a pixel of the resulting color of the mixture.

2 Choice of the Crop to be Analized

Below, you will find statistical information on agricultural production in Misantla, Ver. on an annual basis in the products it generates, the information offered is on area sown, area harvested and the value of production, for seasonal crops in the area (SEDARPA, 2017).

The study includes crops with better production in the municipality, which are ordered in a descending manner, that is, from more to less production, which will help define the crop to be covered by the project.

It is possible to identify in the previous graph, four different types of products, which are: the lemon, the orange and the tangerine, being these first two elements those that produce more the region of Misantla, which gives to understand that as much the orange and the lemon are two of the fruits that but are cultivated, for that reason, they are taken like reference to be compared with the other products, in where the planted surface takes part, the production in weights, which is taken to determine the type of culture that will be to which the intelligent drone is implemented.

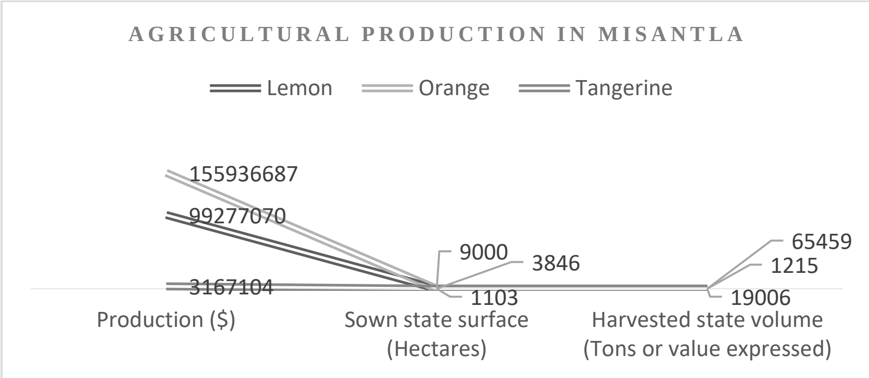

Fig. 3. Agriculture production.

Based on the data provided by the Secretariat of Agricultural, Rural and Fishing Development (SEDARPA) and taking as reference the analysis of the graph, it is concluded that the crop to work on the project and which will be implemented the use of drone, will be the citrus, since it presents a greater production in the city of Misantla, as well as a larger area of cultivation than the other fruits. On the other hand, it is proposed that in this type of citrus fruit is also affected by bird pests.

2.1 Process to be Automated

According to citrus growers in the Misantla area, Ver., the greening of citrus fruits can cause the shoots and foliage to die, giving them a scarce and untidy appearance, as well as not growing as much as they should or blooming at the wrong time of year, for example in summer or autumn instead of spring. Citrus greening, also known as Huanglongbing, is a bacterial infection transmitted by an insect called the Asian citrus psyllid (Mead, 2020).

In summary, the damage caused by HLB is as follows:

- Economic death of the plant.
- Severe fruit and leaf drop.
- Decrease in fruit weight.
- Decrease in the sugar level.
- Increase of the acidity level.
- Decrease in size and percentage of juice
- A young plant does not produce fruits.

The symptoms can be found throughout the year, however, are easier to see from September to March because in this season the color of the leaves changes and the pest becomes visible, the disease affects all parts of the tree's crown: leaves, twigs and fruits, as the disease progresses, it will cause the whole tree to decrease. In addition, leaf symptoms include mottled spots, yellow veins, clogged veins or green islands, yellow veins, clogged veins or green islands are not diagnostic alone, on the other hand mottled spotting is the best diagnostic symptom of green leaf. And spotting is a random pattern

Fig. 4. Leaf symptoms.

Fig. 5. Greening and nutrient deficiency problems.

of yellowing that occurs on leaves that is not the same on the right and left sides of the leaf (Florida, 2018).

A simple procedure to determine if the symptoms are the same in both halves of a leaf is the following, draw two circles in opposite halves of the leaf in order to appreciate if the pattern is the same in both circles as in the following figure. The figure above shows two types of problems, on the left side a green problem and on the right-side problems with nutrient deficiency with a line as suggested above.

In addition, the pest problem does not only affect the appearance of the leaf. The external appearance of the fruit can also be affected, whether it is deformed or looks small and green. Taste problems, a variation of salty and bitter. And the internal appearance may have aborted seeds, a yellow spot under the calyx button and/or a curved central core.

Finally, the identification of the problems that include all the tree, beginning to present/display yellow buds, death in its branches, delays in the growth, present/display flowering out of season and a remarkable general reduction of the tree.

2.2 Materials and Methods

Table 2 describes the characteristics of the laptop, as well as the drone and the system requirements of the two devices mentioned.

The following process was determined from the literature review that was done taking into account work related to digital image processing for the detection and analysis of images in precision agriculture, where the stress that plants present is taken into account to analyze the images.

First, the dataset was built up from images obtained by the DJI Mavic Mini drone. Once the dataset was built, a pre-processing of images was applied to filter and delimit regions of interest, followed by the application of segmentation to the images to identify the regions affected by the pests, in order to extract the characteristics and, here, a label was made to obtain the most relevant characteristics and identify them. Finally, to

Fig. 6. Fruit problems.

Fig. 7. Foliage problems.

achieve the classification, the crops with pest in order to later determine the damage they present.

2.3 Acquisition of the images

Were carried out 8 flights with a DJI mavic mini, the images taken by the drone are stored in jpeg format with a size of 5,438,160 bytes and dimensions of 4000 × 3000 pixels each, have a focal length of 4.49, are sectioned by folders according to the type of citrus, including 2 main, the Persian lemon and late orange valencia and a sub-folder within each type of citrus which refer to whether the crop has or not pest.

2.4 Development

The development of the application is the process of classifying images or recognizing them. In this process, an image is shown to the device's camera sensor and it will tell you which class the image belongs to. By means of image classification and training a deep learning model of convolutional neural network and the help of a google online tool, the model is exported to the TensorFlow lite version that is compatible with the Android device in order to implement it in the application.

To perform the training of the model the platform to perform the image classifier is teachable machine from google. At the end of the training, you can export the model of your choice. The model was exported to the Lite version of TensorFlow. Google's

Table 1. Material specifications.

Personal computer	
Model	MacBook Pro (13-inch, Early 2011)
System	macOS High Sierra
Type of System	64 bits
Procesador	2.3 GHz Intel Core i5
Graphics card	Intel HD Graphics 3000 512 MB
RAM	8 GB 1600 MHz DDR3
Hard disk drive	240GB SSD
Drone	
Model	DJI Mavic Mini
Take-off weight	Folded: 140 × 82 × 57 mm (length × width × height) Unfolded: 160 × 202 × 55 mm (length × width × height) Unfolded (with propellers): 245 × 290 × 55 mm (length × width × height)
Camera	
Sensor	1 / 2.3" CMOS Effective Pixels: 12PM/2.3" CMOS
ISO range	Video: 100 - 3200 (automatic) 100 - 3200 (manual) Photo: 100 - 1600 (automatic) 100 - 3200 (manual)
Photo size	4:3: 4000×3000 16:9: 4000×2250
Video resolution	FHD: 1920×1080 25/30/50/60 p 2.7K: 2720×1530 25/30 p
Maximum bit rate	40 Mbps
Photo formats	JPEG

Teachable Machine was used, which is an Artificial Intelligence platform that allows the user to train independently to a neural network, while the system can react to known images with sounds or GIF animations. At least 30 frames are required for the Teachable Machine to learn movement recognition. To start the training, the user must hold down the "train" button for a few seconds and make a certain gesture or show something to the computer (Ulasovich, 2016).

The tool allows you to immerse yourself in the definition of the model, algorithm and data processing as well as, focus only on the deployment of the model that is generated, the tool works in the browser, with a webcam or with files that are hosted locally or in Google Drive, and in a few minutes you can quickly understand how a model "learns" through a simple classification demonstration.

To start training the classification model, first different categories or classes were created to carry out the training and have it learn. Four classes were created as shown in figure 3, which are two types of citrus fruits with their respective healthy and pest variables. With the classes or labels defined, from the local storage the samples of each class are uploaded to the platform so that the training can begin. More than 200 images were uploaded with 4000 × 3000 resolution per class.

After having the classes ready, it is already possible to train the classification model. The model takes only a few minutes to train. Not only is the speed of training excellent, but you are given valuable dynamic metrics such as accuracy, training loss and dataset test with the observed class accuracy.

Fig. 8. Persian lemon harvest.

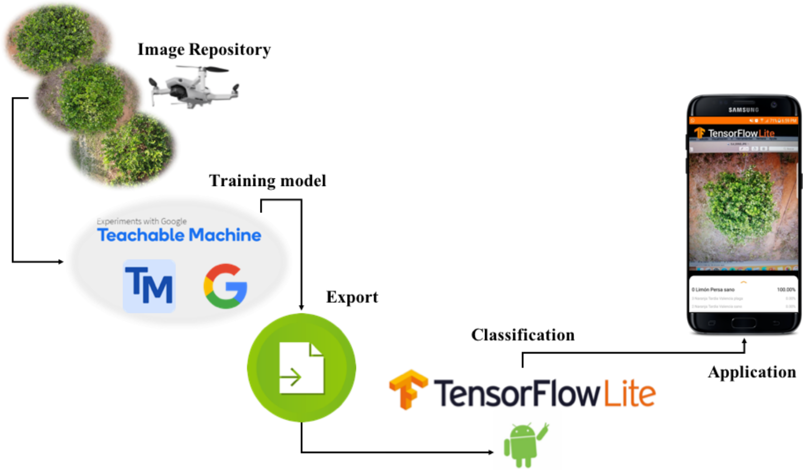

Fig. 9. General description.

The network "input" block comes first. Here, the digital media enters the system (in figure 3 on the top left). Then there is the "learning" block (top, middle), where the model learns and interprets the input. The "output" block (top right), is where the interpretation of the model does something like recognizing the inputs and categorizing the results, so it is important to prepare and load the data set in the teachable machine platform with the Google site as well as define the number of classes, for the case of the project were defined 4 classes. The image classification model was trained there and finally, it was exported.

During the training, you can change the number of hyper-parameters as:

- Number of periods,
- Lot size,
- Learning rate.

Then, it was necessary to export the model in TensorFlow lite format for implementation in Android devices. The ".tflite" files must be placed in the assets

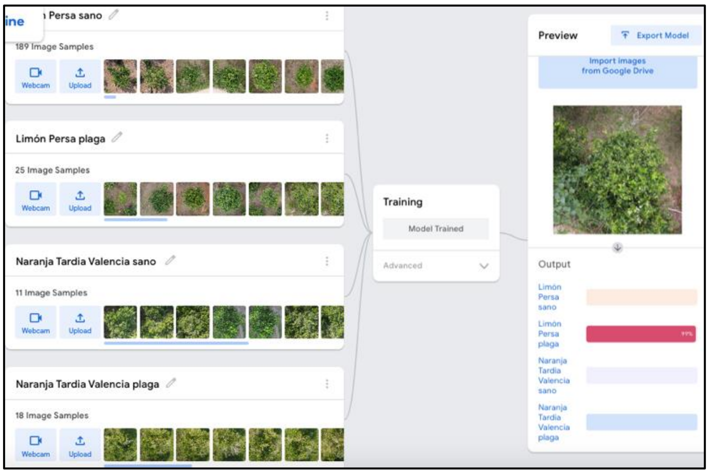

Fig. 10. Training the model.

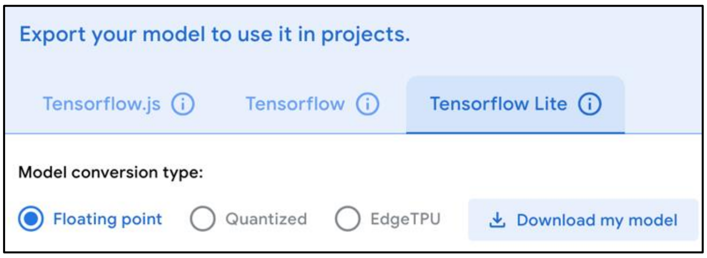

Fig. 11. Exporting the model.

folder of the Android project directory and renamed in the java file that is reading it. In addition, you can download the tflite quantified and FLOAT file format.

2.5 Results

The identification of the type of culture has been obtained by means of the model as well as the classification of the images by means of the convolutional neural network as shown in figure 13. Summarizing: it is possible to say that the important elements that were used to create the CNN were the input layer, this is the pixels of the image, providing height, width and depth working with 3 for Red, Green, Blue.

The Convolution Layer then performs the process of the output of neurons that are connected in "local regions" of input (ie nearby pixels), calculating the product scale between their weights (pixel value) and a small region to which they are connected in the input volume. On the other hand, the Relu layer will apply the activation function on the elements of the matrix and the sampling or subsampling will be in charge of making a reduction in the height and width dimensions, but the depth is maintained, finally the traditional layer of feedforward neuron network that will connect with the last layer of subsampling and will end with the amount of neurons that we want to classify.

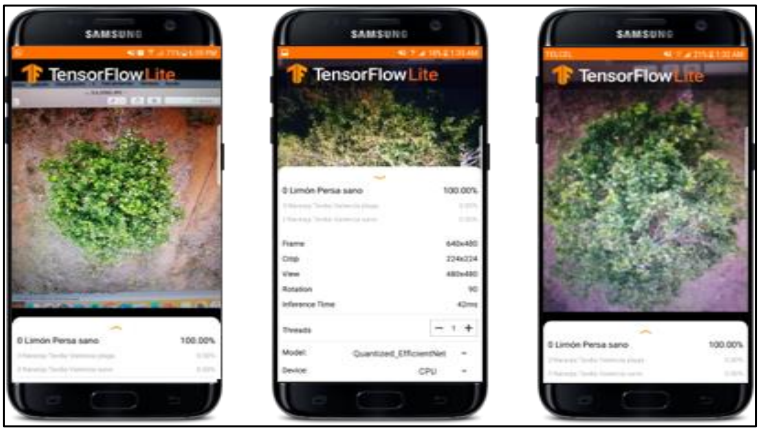

Fig. 12. Image processing.

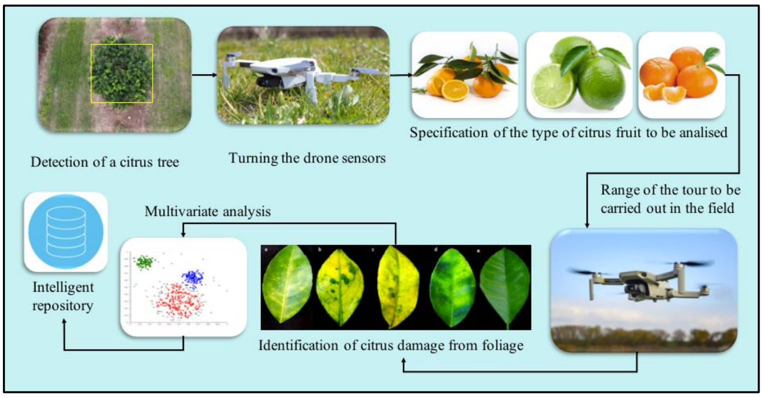

Fig. 13. System layout.

Due to the incorporation of the images and the training of the model it was possible to obtain an identification of the type of culture of 98%, while for the classification of healthy culture and culture with plague the precision in minor, obtaining 88% since at the moment the set of data is unbalanced and this affects the accuracy of the model.

Previously in the figure 10, the operation of the system is appreciated in a general way, starting from the top left, the detection of the type of citrus tree, the sensors of the drone are activated, later it makes the specification of the type of fruit to be analyzed within a range determined by the user, later, it carries out the identification of the damage of the foliage from taking characteristics of color, as following step a multivariate analysis with the purpose of determining the contribution of the factors.

3 Conclusions and Future Research

The original approach of the project has been the study in the fields of deep learning as well as convolutional neural networks. The different methods and techniques used during the development of systems for image recognition have been explored. During the development several of the original decisions were alternated such as taking into account the recognition of objects within the image. It has been possible to verify the importance of the performance of a neural network since it is not only based on the architecture of the network but the data set available alters the final result, so a balanced data set with a large amount of samples is critical.

The main complications presented are divided into two more relevant ones, image processing and the model. The constructed data set has largely overwhelmed the final accuracy of the application, requiring a much larger data increase than what has been done currently. However, despite providing non-optimal results in some cases, it offers a clear insight into the importance of the available data, as well as the functioning of the neural networks in terms of image perception and how they are treated.

The task of predicting what an image symbolizes is called image classification. An image classification model is trained to recognize various kinds of images. An example of this is the model that has been worked with previously which was trained to recognize images of citrus crops. Thus, when a new image is provided as input to the model, it will generate the probabilities that the image represents each of the crop types it was trained with. In addition, during training, an image classification model receives images and their associated labels, where each label is the name of a different concept, or class, that the model will learn to recognize with enough training data often hundreds or thousands of images per label, an image classification model can learn to predict whether the new images belong to one of the classes in which it has trained to what this prediction process is called inference.

To perform the inference, an image is passed as input to a model. Then, the model will generate a series of probabilities between 0 and 1. Each number in the output corresponds to a label in the training data. By associating the output with the labels with which the model was trained, it was possible to see that the model predicted a high probability that the image represents a pest crop.

The accuracy of the model measured in terms of the frequency with which the model correctly classified an image, which generates a set accuracy of 98%, the performance in terms of the amount of time it takes a model to run inference, which it does in real time since the less time, the faster the model. Also, the disk size varies with its performance and accuracy. The size can be important for mobile development where it can affect the download sizes of the application or when working with hardware where the available storage can be limited, this is the case of the 3.4 Mb model used.

References

1. Bokolonga, E., Hauhana, M., Rollings, N., Aitchison, D., Assaf, M. H., Das, S. R., Biswas, S. N., Groza, V., Petriu, E.M.: A compact multispectral image capture unit for deployment on drones. Conference Record - IEEE Instrumentation and Measurement Technology Conference, pp. 2–7 (2016). doi.org/10.1109/I2MTC.2016.7520445.
2. Briega, R.E.L.: Redes neuronales convolucionales con TensorFlow (2016) https://relopezbriega.github.io/blog/2016/08/02/redes-neuronales-convolucionales-con-tensorflow/.
3. De Rango, F., Potrino, G., Tropea, M., Santamaria, A. F., Palmieri, N.: Simulation, Modeling and Technologies for Drones Coordination Techniques in Precision Agriculture. In Advances in Intelligent Systems and Computing, 873, Springer International Publishing

(2019) doi: 10.1007/978-3-030-01470-4_5.
4. Florida, U.: UF/IFAS Citrus Extension: Plant Pathology (2018) https://crec.ifas.ufl.edu/extension/greening/symptoms.shtml.
5. Gonzalez, T.F.: Handbook of approximation algorithms and metaheuristics. Handbook of Approximation Algorithms and Metaheuristics, pp. 1–1432. (2007) doi: 10.1201/9781420010749.
6. Matich, D.J.: Cátedra: Informática Aplicada a la Ingeniería de Procesos-Orientación I Redes Neuronales: Conceptos Básicos y Aplicaciones (2001)
7. Mead, F.W.: Oficinas Regionales sag-senasa enverdecimiento de los cítricos (Huanglongbing) (2020)
8. Machinelearning: Convolutional Neural Networks: La Teoría explicada en Español | Aprende Machine Learning (2018) https://www.aprendemachinelearning.com/como-funcionan-las-convolutional-neural-networks-vision-por-ordenador/.
9. Pentón Saucedo, Á., del Castillo Serpa, A.: Aplicación de la tabla ortogonal en el diseño de los casos de prueba de software. Avanzada Científica, 15(2), pp. 1–12 (2012)
10. Rivas-Asanza, W., Mazon-Olivo, B., Mejía-Peñafiel, E.: Capítulo 1: Generalidades de las redes neuronales artificiales. Redes Neuronales Artificiales Aplicadas Al Reconocimiento de Patrones, pp. 11–35 (2018) http://repositorio.utmachala.edu.ec/handle/48000/12499.
11. SEDARPA: Veracruz Estadísticas Agrícolas (SEDARPA) (2017) http://www.veracruz.gob.mx/agropecuario/estadisticas-agricolas/.
12. Ulasovich, K.: Teachable Machine, la inteligencia artificial de Google, te responde con un GIF | N+1: artículos científicos, noticias de ciencia, cosmos, gadgets, tecnología (2016) https://nmas1.org/news/2017/10/09/inteligencia-artificial.
13. Vatalaro, F., Mazzenga, F., Giuliano, R.: The Sub-Band Vectoring Technique for Multi-Operator Environments. IEEE Access, 4, pp. 3310–3321 (2016) doi: 10.1109/ACCESS.2016.2580198.