

Weed Detection in *Capsicum Annuum* L. Crops Using Photogrammetry and Deep Learning Algorithms

Detección de malas hierbas en cultivos de *Capsicum Annuum* L. mediante fotogrametría y algoritmos de aprendizaje profundo

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Abstract: *Cuscuta spp.* is a parasitic plant that causes losses estimated at 50 % of the yield of a wide variety of agricultural crops, including vegetables, forages, and trees. In the search for alternatives to solve this problem, small farmers are exploring the application of new technologies to food production. This paper presents a remote-sensing *Cuscuta spp.* classification model based on aerial images collected by UAVs to generate orthophotos showing infested areas. The proposed model segments the characteristic yellowish color of the stem of *Cuscuta spp.* in the HSV color space to train a deep Convolutional Neural Network (CNN). The experiments included RGB images of a Chili bell pepper (*Capsicum annuum Linnaeus*) crop with *Cuscuta spp.*. In addition, we performed model 5-fold cross-validation with different datasets by using images collected during three consecutive weeks to identify the growth of the weed-affected area. According to the metrics used, ResNet architecture proved to be the best model for classifying *Cuscuta spp.* and non-*Cuscuta*. The proposed method allows smallholders to detect and locate the weed in the early stages of growth to facilitate removal and mitigation efforts.

Keywords: aerial photography, field crops, pattern recognition, ResNet architecture, unmanned aerial vehicles, pests.

Resumen: la *Cuscuta spp.* es una planta parásita que causa pérdidas estimadas en el 50 % del rendimiento de una amplia variedad de cultivos agrícolas, incluidos verduras, forrajes y árboles. En la búsqueda de alternativas para resolver este problema, los pequeños agricultores están explorando la aplicación de nuevas tecnologías en la producción de alimentos. Este trabajo presenta un modelo de clasificación de *Cuscuta spp.* con teledetección mediante imágenes aéreas recolectadas por UAV con las que se generan ortofotos donde se señalan las zonas infestadas. El modelo propuesto segmenta el color amarillento característico del tallo de *Cuscuta spp.* en el espacio de color HSV para llevar a cabo el proceso de entrenamiento de una Red Neuronal Convolutiva (CNN) profunda. En los experimentos se incluyeron imágenes RGB de un cultivo de pimiento picante (*Capsicum annuum Linnaeus*) con presencia de *Cuscuta spp.*. Además, realizamos la validación cruzada de 5 iteraciones del modelo con diferentes conjuntos de datos al emplear imágenes recolectadas durante tres semanas consecutivas para identificar el crecimiento de la zona afectada por la maleza. La arquitectura ResNet, de acuerdo con las métricas empleadas, resultó ser el mejor modelo para clasificar *Cuscuta spp.* y no *Cuscuta*. El método propuesto permite a los pequeños productores identificar y localizar la maleza en las primeras fases de crecimiento para facilitar las labores de eliminación y mitigación.

Palabras clave: fotografía aérea, cultivos de campo, reconocimiento de patrones, arquitectura ResNet, vehículos aéreos no tripulados, plagas.



Introduction

Chili bell pepper (*Capsicum annuum* Linnaeus) production has a high value in world markets as nutritious food, a source of natural colorants, and cosmetic and pharmaceutical products. Mexico is the leading exporter of green chili and the second-largest producer worldwide. In 2020 alone, 159,980 hectares were planted, producing 2,800,000 tons of dry and green chili with an approximate commercial value of 1,700 million dollars (SIAP, 2021). However, small farmers' difficulties put their crops and livelihoods at risk. Changing agroecosystem factors directly influence crop growth and can negatively affect plant health by making plants more susceptible to diseases, pests, and weeds (Bajwa et al., 2020). The proliferation of weeds threatens the health of chili crops and represents a factor related to the reduction of yield, the increase in production costs, and the decrease in income of small farmers (Blanco-Valdes et al., 2018).

Cuscuta spp. is a weed with yellow or orange thread-like stems attached to the host plant by numerous sucking haustoria (Ahmadi et al., 2019). It is a native species of Asia, Africa, and Europe (Iqbal et al., 2014) that infests a wide range of crops, including vegetables, forage crops, ornamentals, fruit, and woody plants (Aly & Dubey, 2014). Also, it spreads through cracks in stems from which to extract water and nitrogenous compounds, and affects photosynthesis (Le et al., 2015). This weed can cause losses of 50 % to 75 % of crop yield (Aly & Dubey, 2014); in the case of *Capsicum Frutescens*, losses were estimated between 60 % and 65 % (Mishra, 2009). In traditional *Capsicum annuum* Linnaeus production systems, *Cuscuta* spp. weeds infection is identified by the farmer through direct observation at stages when the expansion is visible to the human eye and, in most cases, when it has invaded large areas. The impacts of infestation are reflected in the development and production of the crop, so it is necessary to design novel alternatives for early identification and strengthen the crop management of small farmers.

Unmanned aerial vehicles (UAVs) are a disruptive technology in the agricultural sector that is useful for strengthening risk control strategies by collecting crop data to support prevention, monitoring, control, and management tasks in food production systems. In addition, drones can correctly be applied to vegetable crops for weed detection, morphological and geometrical feature extraction, crop health and pest scouting, water management, yield, biomass, ripening estimation, and aerial spraying (Canicatti & Vallone, 2024). This advance allows early diagnosis, identification, differentiation, and detection of variable symptoms of crops (Ali et al., 2023). Thus, family farmers can reduce their risk of crop loss.

Low-cost aerial platforms have been used to collect RGB (Red, Green, and Blue), multispectral, and thermal imagery of crops for the purpose of plant species identification (Oldeland et al., 2017; Pandey & Jain, 2022;), phenological stage-based monitoring (Burkart et al., 2018), water stress (Martínez et al., 2017; Zhang et al., 2021), plant health (Qiao et al., 2022), nutrient (Krienke et al., 2017), and pathogen identification (Ishengoma et al., 2021; Tetila et al., 2020; West et al., 2017). Moreover, multispectral imagery collected by UAVs over *Capsicum annuum* crops has been used to monitor plant health (Sosa-Herrera et al., 2019) and thermal imaging to determine plant water stress (Coulombe et al., 2018). It is also used to process images of *Capsicum* crops and diagnose health conditions based on Normalized Difference Vegetation Index (NDVI) values (Puteh et al., 2021) and machine learning methods.

Recently, deep learning techniques have identified visual symptoms of Tobacco Mosaic Virus (TMV) and Pepper Huasteco Yellow Vein Virus (PHYVV) (Yee-Rendon et al., 2021). The above approaches require multispectral cameras, as RGB images require more processing to extract features than multispectral images. However, advances in image recognition and analysis are based on RGB images. For this reason, we propose to apply a low-cost UAV to collect RGB images of the *Capsicum annuum* L. crop and classify them with a deep Convolutional Neural Network (CNN) to identify areas infested with *Cuscuta spp.* The proposal uses transfer learning for the DenseNet, ResNet, VGG16, and Xception models; these models are considered among the most popular pre-trained CNN architectures used in the literature (Khan et al., 2020).

Materials and Methods

The experiment was conducted from July to October 2021, starting in week 17 and concluding in week 32 of the growth and flowering of the chili bell pepper (*Capsicum annuum* L.). The experimental field was a rectangular area with 1.4 hectares located in the Mezquital Valley in the state of Hidalgo, Mexico (20°08'18.2" N 99°16'28.2" W), as shown in Figure 1. The analysis was carried out in a field with chili bell pepper plants during the spring production cycle. It began with transplanting plantlets with a similar density throughout the plot and distributed in equidistant double rows. Small farmers use the flood irrigation system periodically to provide water for the excellent development of plants and use traditional field practices to support the production process.

Flight Mission of Image Acquisition

This study employed a low-cost DJI Mavic Pro quadcopter (DJI Innovations, Shenzhen, China) equipped with a CMOS-type camera capable of 12-megapixel photography, a 78.8-degree field of view (FOV) lens, 28 mm focal length, f/2.2 aperture, less than 1.5 % distortion, and 1.6' focal range. The drone was equipped with an intelligent 3S LiPo battery with 3830 mAh for an autonomy of 20 minutes. In addition, a Micro SDHC class 10 memory with a capacity of 32 GB was used to store the captured images.

The DJI It is equipped with a GPS that provides accurate positioning data with real-time correction stored in the images' Mavic Pro drone is an UAV with applications in various areas, including the agricultural sector metadata when the camera is shooting with high accuracy. In the case of the ground station, a 2.4 GHz remote control with a range of 7 km was used.

Flight plans were made using Pix4D Capture software, with a ground control station (GCS) connected to a remote control in which the flight pattern was based on way-point mode. The study flight plans were conducted at 30 meters altitude with winds less than ten m/s using the same camera parameter settings; the trajectory was plotted over the crop field and under similar lighting conditions when flights were conducted around 13:00 hours. All parameters met the requirements and limitations of operating a UAV in Mexican and international airspace.

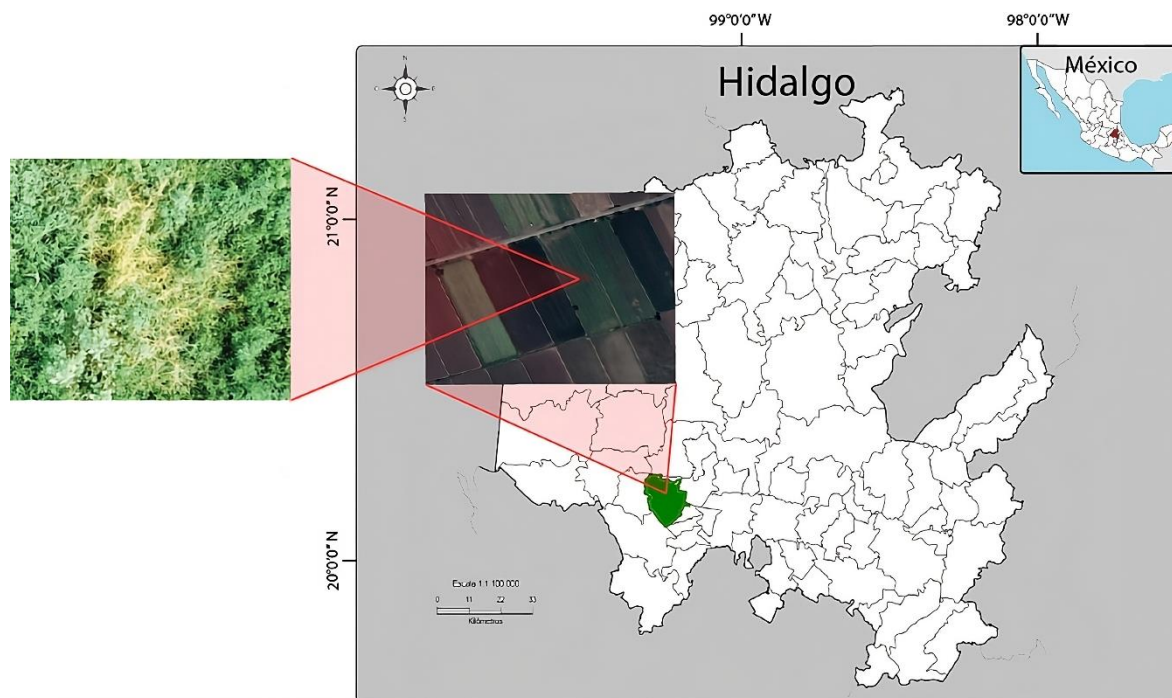


Figure 1. Experimental Field Location: (a) Geographical and (b) Crop Area
Source: Own elaboration

Three data sets were collected from the *Capsicum annuum* L. field between weeks 17 and 32 of crop development (August 8, 2021; August 29, 2021, and September 11, 2021), and the data set contained 750 images (Cornejo-Velazquez & Clavel-Maqueda, 2024). Figure 2 presents three orthophotos that show the crop in different developed crop stages and the location of some areas with different color tones.

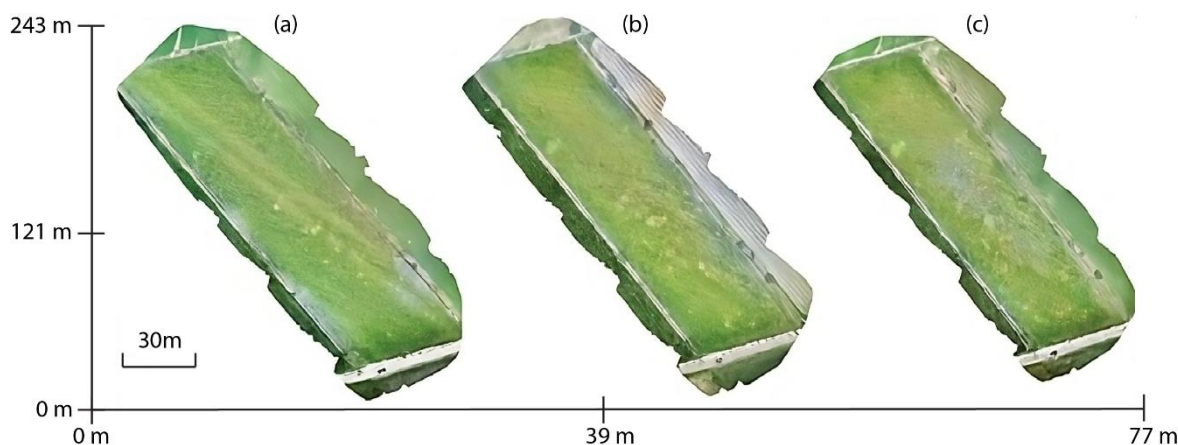


Figure 2. Orthophotos: (a) August 8, 2021, (b) August 29, 2021, and (c) September 11, 2021.
Source: Own elaboration

Image Segmentation in HSV Color Space

Color image segmentation means dividing an image into regions or objects of interest based on their characteristic colors. The color spaces indicate how the color is defined, which allows analyzing and taking advantage of the information represented in the image. In general, the HSV color space is the most widely used for color segmentation because colors are distinguished by their hue, intensity value, and saturation. Hue represents the dominant color as we perceive it, which is associated with the dominant wavelength in a mixture of light waves that are defined between 0 to 360. In addition, intensity value represents the perceived illumination that some object reflects more or less light. In contrast, saturation refers to the amount of white light mixed with the dominant color to differentiate an intense color from a pale one. The hexane model attempts to transform the dimensions of the RGB color cube into a set of measurements that model to distinguish hue better. Smith (1978) presented transformation algorithms for forward and backward conversions between the RGB and HSV models. The forward conversion from RGB to HSV is given by Equations 1 to 6.

$$V = \max(R, G, B) \quad (1)$$

$$X = \min(R, G, B) \quad (2)$$

$$S = \frac{V - X}{V} \quad (3)$$

$$R = \frac{V - R}{V - X}; G = \frac{V - G}{V - X}; B = \frac{V - B}{V - X} \quad (4)$$

$$\text{if } R = V \text{ then } H = (\text{if } G = X \text{ then } 5 + B \text{ else } 1 - 6); \quad (5)$$

$$\text{if } G = V \text{ then } H = (\text{if } B = X \text{ then } 1 + R \text{ else } 3 - B) \\ \text{else } H = (\text{if } R = X \text{ then } 1 + R \text{ else } 5 - R);$$

$$H = \frac{H}{6} \quad (6)$$

Currently, there are a wide variety of libraries to process color; for example, the OpenCV libraries (OCV, 2023) normalize between 0 to 180 for ease of use, as shown in Figure 3. The segmentation of RGB images requires going from RGB to HSI, segmenting the tone from the characteristic intervals to identify the areas of interest later in the original RGB image.

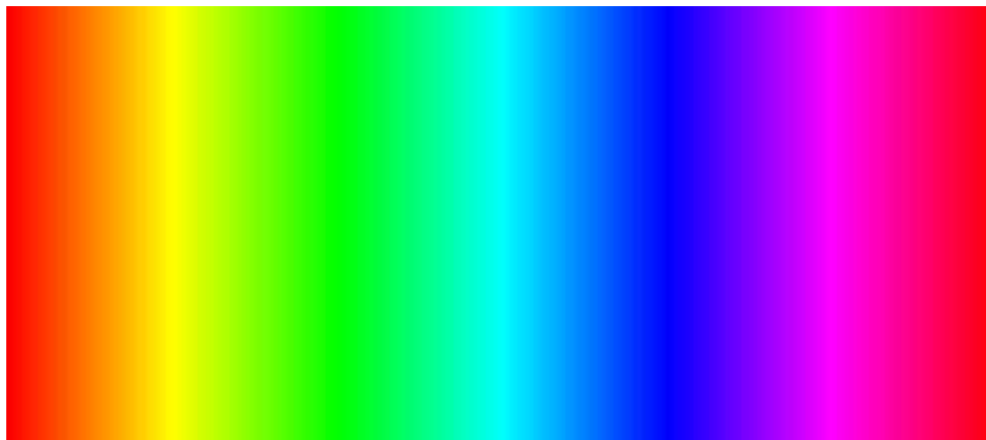


Figure 3. Representation of the Hue Channel with the OpenCV Libraries

Source: OCV (2023)

Convolutional Neural Networks

Image recognition is one of the most studied areas of computer vision due to its application in various sectors to recognize or interpret an image. CNNs play an important role because they achieve superior performance in certain areas, such as computer vision techniques to analyze images by automatically extracting useful information. The main task of CNNs is to extract features from the images based on layered or hierarchical learning; that is, the algorithm learns by levels.

The architecture of CNNs is analogous to the connectivity pattern of neurons in the human brain and was inspired by the organization of the visual cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the receptive field, which overlaps to cover the entire visible area. A CNN can successfully capture features in an image by applying convolution filters. The goal of the convolution operation is to extract high-level features, such as edges, from the input image. CNNs need not be limited to a single convolutional layer. Conventionally, the first convolution layer captures low-level features such as borders, color, and gradient orientation, among other features. While adding layers, the architecture also accommodates high-level features, providing the network with a complete understanding of the image in the dataset.

CNNs are adapted to improve the image data set due to reducing the number of parameters involved. It is easier to process without losing features; this is important for designing architectures that are good at learning features and scalable to massive data sets. Several effective CNN architectures facilitate the development of new applications in object detection, image classification, and segmentation tasks, such as DenseNet (Huang et al., 2017), Inception (Szegedy et al., 2016), ResNet (Xie et al., 2017), VGG16 (Simonyan & Zisserman, 2014), and Xception (Chollet, 2017). In general, four criteria (Equations 7 to 10) are used to measure the performance of advanced applications.

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \quad (7)$$

$$Recall = \frac{TP}{TP + FN} \quad (8)$$

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

$$F1\ Score = \frac{1 \cdot Precision \cdot Recall}{Precision + Recall} \quad (10)$$

Where:

TP = Number of true positives

FP = Number of false positives

TN = Number of true negatives

FN = Number of false negatives

The mentioned metrics can determine the architecture that performs better when designing computer vision applications.

Proposed Method

The proposal seeks to give the farmer a general overview of the pest to facilitate decision-making in reasonable response times. We delimit the area of interest by HSV color space segmentation and classify the remaining area with the CNN. The model is divided into six stages:

1. Acquire images by UAV.
2. Segment the set of images based on the characteristic tone of *Cuscuta spp.*
3. Identify infected regions with the CNN.
4. Highlight the infected areas in red in the entire set of images acquired by the UAV.
5. Generate the orthophoto with the set of images with the areas highlighted in red.
6. Calculate the percentage of infestation.

The diagram in Figure 4 shows the main steps of the proposed method. In the following sections, we briefly describe the most relevant details for the proposal stages.

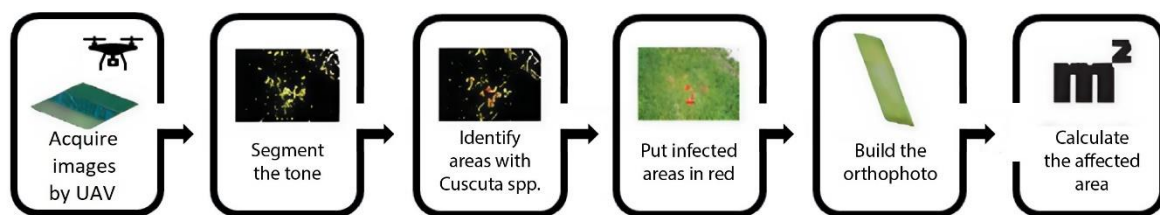


Figure 4. Flowchart of the Proposed Method

Source: Own elaboration

The proposed method is based on our research group's previous work that uses image segmentation with U-Net Xception-Style (Gutiérrez-Lazcano et al., 2022). However, in this research, we used image segmentation in HSV color space and different CNN architectures to validate their efficiency. It has been designed to provide small farmers with visual and quantitative elements to carry out more detailed evaluation tasks on the field and decide on the strategy to eliminate or mitigate the infestation.

***Cuscuta spp.* Segmentation in HSV Color Space**

In segmentation, the RGB image is first converted to the HSV color space so that all pixels in the image are represented using Hue, Saturation, and Intensity Values. It is easy to segment an object of interest from the intervals in which its characteristic color is found. In this study, the distinctive yellow pixels of *Cuscuta spp.* were identified in a range between 20 and 35 degrees, as shown in Figure 5. The algorithm uses Python and the OpenCV libraries to go from RGB to HSV.

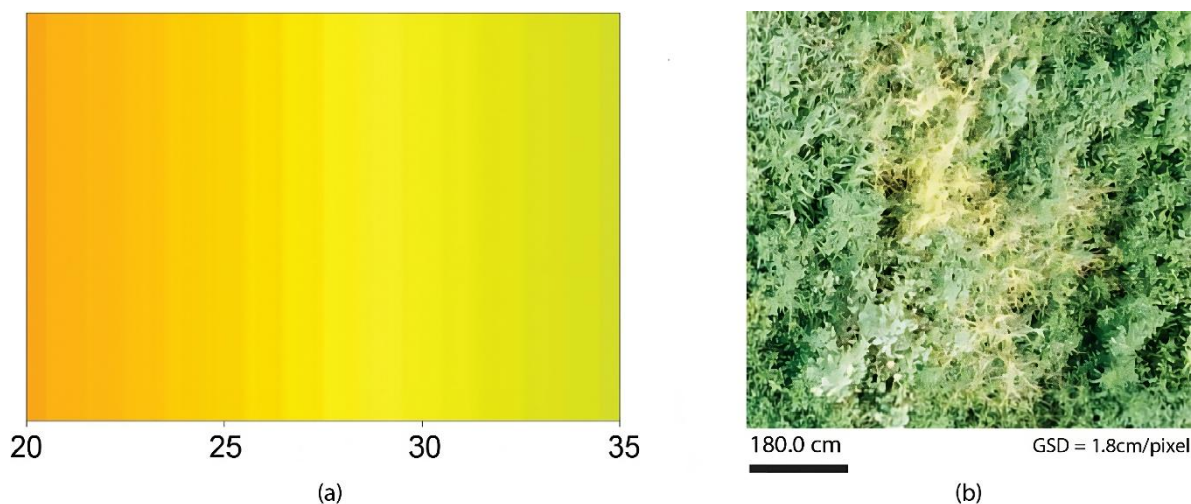


Figure 5. Tone Intervals: (a) Hue Channel and (b) Characteristic Yellow in a Crop

Source: Own elaboration

Cuscuta spp. hue ranges may also be present in other growing regions, confounding classification. Figure 6 shows the segmentation between 20 and 35 degrees of an image captured by the UAV, where *Cuscuta spp.* stands out. It is important to highlight that the method used processes the images collected under open sky conditions and with solar illumination and is able to identify infested areas. However, it also indicates some non-plague-related areas. Currently, it is easy to resolve the confusion by using deep learning to identify regions of interest, as described in the next section.

Deep Convolutional Neural Network Training and Classification

The process of image classification for detecting *Cuscuta spp.* started with collecting image data from segmentation. The collected data set was pre-processed and labeled before moving on to the classification task. The training data set comprised 48,172 images with *Cuscuta spp.* and 48,217 images with a Hue similar to *Cuscuta spp.* Model validation used a collection of 2,267 infested crop images and 2,259 non-*Cuscuta* images. Some of the training and validation images are shown in Figure 7.

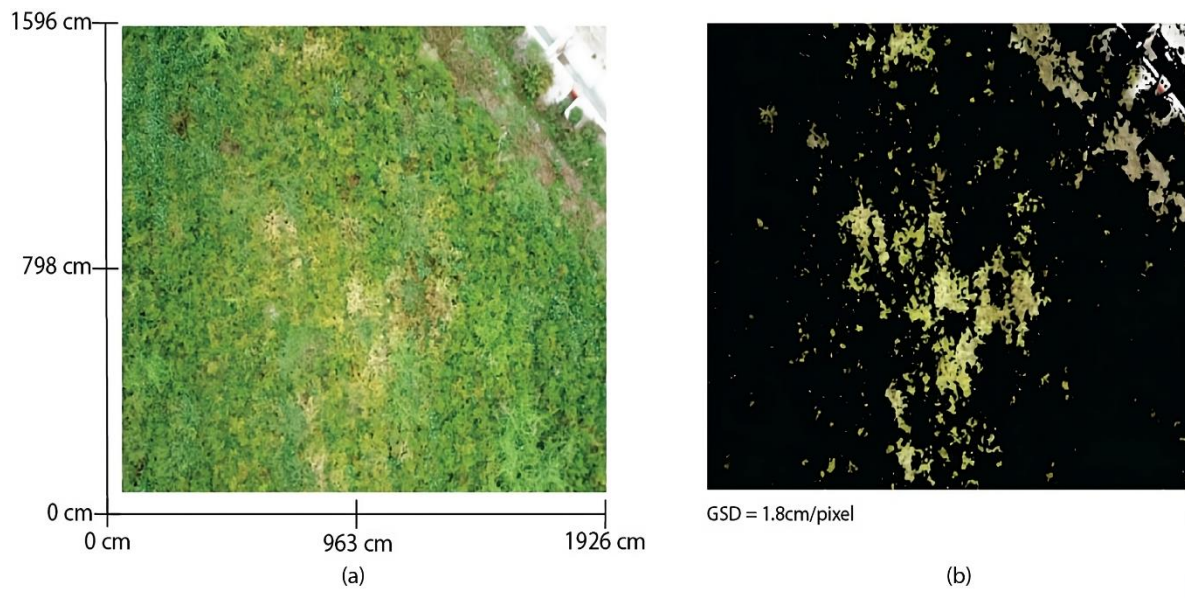


Figure 6. Comparative: (a) UAV Image and (b) Image Segmentation in HSV

Source: Own elaboration

Deep Convolutional Neural Network Training and Classification

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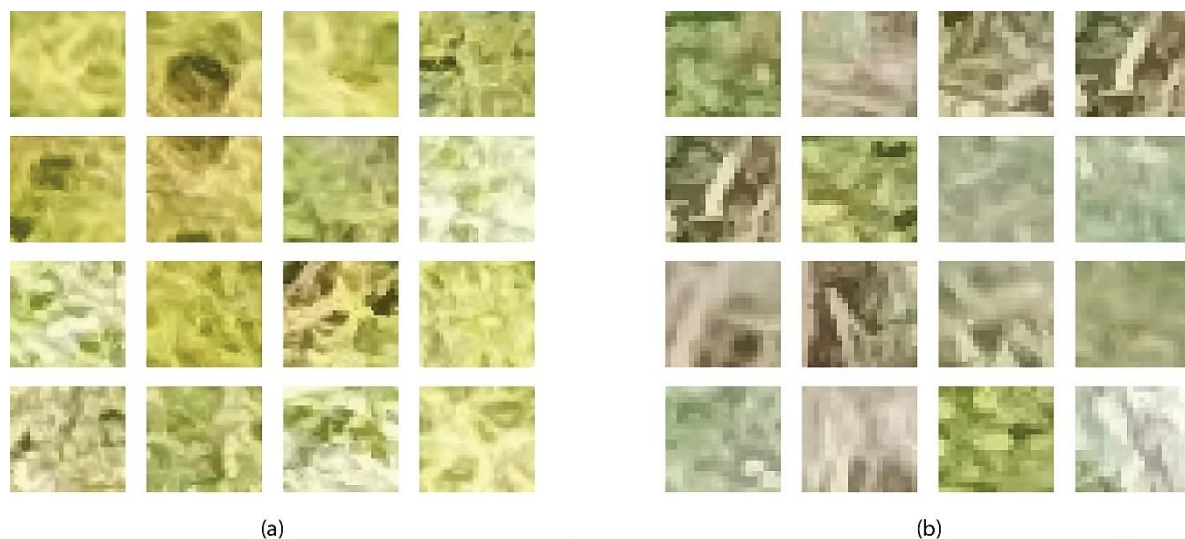


Figure 7. Images Size 24×24 px with (a) Infested Crop and (b) Non-*Cuscuta*

Source: Own elaboration

The proposal handled the architecture of DenseNet (Huang et al., 2017), InceptionV3 (Szegedy et al., 2016), MobileNet (Howard et al., 2017), ResNet (Xie et al., 2017), VGG16 (Simonyan y Zisserman, 2014), and Xception (Chollet, 2017) models to identify the weed. In addition, we used the pre-trained weights from the ImageNet dataset as a starting point to improve the overall patterns found in the dataset. CNN architectures were trained on a computer with Intel Core i7-9700 running at 3.0 GHz, 32 GB of RAM, and an NVidia GeForce GTX 1660 SUPER GPU with 6 GB of Video RAM. The tools used in this experiment are based on Keras (Chollet, 2015), TensorFlow (Team, 2015), Scikit-learn (Cournapeau, 2007), and OpenCV (ODM, 2023).

Once the models were trained, they were validated to select the best-performing architecture. We computed the fitting scores (Accuracy, Precision, Recall, and F1 Score) on a separate testing dataset using a 5-fold cross-validation strategy to robustly evaluate the proposed model's performance. In this method, we divided the dataset into five subsets and, in each iteration, used one subset as the testing dataset while the remaining subsets trained the model. Table 1 reports the averaged performance scores derived from the testing datasets across all folds. By evaluating the model on data not used during training, we provide a more reliable assessment of its ability to generalize to new, unseen samples, thus avoiding overly optimistic results that can occur when evaluating the entire training dataset.

Table 1. Metrics of Different CNN Architectures for *Cuscuta spp.* Classification

Model	Accuracy	Precision	Recall	F1 Score
DenseNet	96.02 %	93.78 %	98.19 %	95.93 %
Inception	95.29 %	92.80 %	97.67 %	95.1 8 %
MobileNet	96.11 %	95.98 %	96.24 %	96.11%
ResNet	97.41 %	97.61%	97.23 %	97.42 %
VGG16	95.89 %	96.51 %	95.33 %	95.92 %
Xception	95.71 %	93.03 %	98.32 %	95.60 %

Source: Own elaboration

Each segmented section was classified from the trained models to discard the areas that do not contain the pest. Figure 8 shows the classification of the samples highlighted in red. Note that it is not confused with the segmented regions free of *Cuscuta spp.*

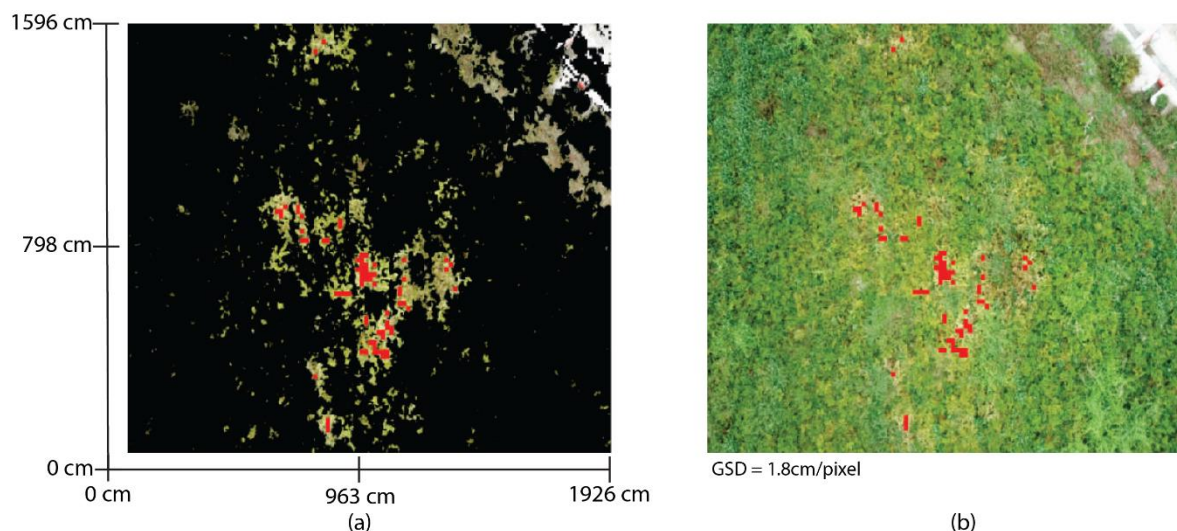


Figure 8. *Cuscuta* spp. Identification: (a) Segmented Area and (b) UAV Image
Source: Own elaboration

Results and Discussion

Using a UAV to collect aerial images of the studied crop has been efficient, which strengthens the opportunities to use this technology in smallholder food production systems. These were in accord with the application area for crop and weed detection described by Canicatti and Vallone (2024).

Due to the nature of *Cuscuta* spp., color segmentation in HSV images allows discrimination between the crop and the weed, reducing the search space in the image analyzed. This is an advantage in automatic weed classification based on RGB and CNN images because they do not process the entire image, only the segmented parts.

The results suggest that CNN-based classification models and HSV segmentation can effectively identify *Cuscuta* spp. when trained on UAV images. Also, the validation indicates that all models performed satisfactorily, with overall accuracy ranging from 96.0 % to 97.4 %. In addition, no excessive or inadequate fit was observed in the models. Table 1 shows in bold the best values of the evolution metrics of the models, where the ResNet architecture stands out for Accuracy, Precision, and F1 Score and Xception for Recall. The highest accuracy achieved among all the models is ResNet, with 97.41 %. Therefore, the proposed system identifies the ResNet model as the best model to identify the pest.

The high classification rate allows for accurate identification of the *Cuscuta* spp. areas from the sequence of images acquired by the UAV, making it easy to generate orthophotos with the *Cuscuta* spp. areas throughout the crop. We used WebODM (ODM) for drone image processing and orthophoto generation. Also, it provides information related to the surface area. In our study case, the crop area given by 243 m × 77 m (verified with the farmer) corresponds to 0.0025 m² per pixel in the orthophoto. Figure 9 shows the results of the three study cases where the infected

areas are highlighted in red. In addition, we determine the percentage of crop affectation as the infestation area, as shown in Table 2.

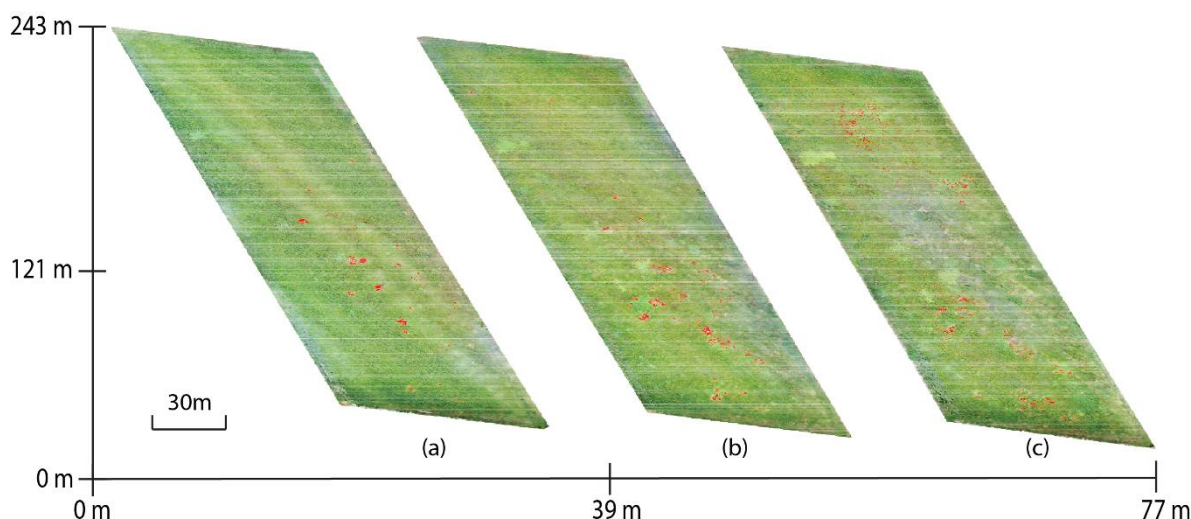


Figure 9. *Cuscuta spp.* Identification: (a) August 8, (b) August 29, and (c) September 11

Source: Own elaboration

Table 2. Estimated Infestation Area of the Study Cases

Date	Infected pixels	Cuscuta %	Cuscuta m ²
08/08/2021	17,069	0.29	42.7
08/29/2021	25,383	0.43	63.5
09/11/2021	37,714	0.67	94.3

Source: Own elaboration

All percentages affected by the pest are calculated from orthophotos. Consequently, there is a great need to compare the proposal's details and clarify the vision between expectations and reality for early detection of *Cuscuta spp.* However, because host plant tissue is invaded through a weed-induced fissure in the host plant stem, quarantining and burning the infested area is recommended (Winston et al., 2014). For this reason, it prevents the exact quantification of the results presented. However, we consider that the high accuracy rates of the proposed classification model allow us to give results that are close to reality.

In agreement with Sanz et al. (2015), it was important for our work and will be relevant for future replications to consider the requirements and guidelines of international and national legislation to reduce the risks of flying UAVs over crop fields.

The results presented are limited by the configuration of the flight plans conducted that allowed the construction of the data sets analyzed. Further experiments are needed to extend the application of the proposed method to other crops or weeds.

Conclusions

Smallholder farming operations are exploring the benefits of employing agricultural robotics to improve their production operations. Autonomous drones with cameras installed can acquire aerial photography of crops and use it to locate invasive weeds such as *Cuscuta spp.* The study presents a model to detect and classify *Cuscuta spp.* from UAV images. The proposal demonstrates that models based on CNN effectively detect the presence of weed, which allows for identifying the best architectures in the training and validation data sets. The results show that the ResNet architecture performs better to classify *Cuscuta spp.* and non-*Cuscuta*.

On the other hand, the proposed methodology generates orthophotos to have a general view of the entire crop and the progress of the pest, which allows labeling the specific coordinates of where the highest concentration of invasive weeds is. This finding is promising, given the challenging conditions of smallholder farming systems. In addition, we conclude that the proposal presented lays the foundations for detecting dodder early and facilitating its removal. In future work, we plan to design a technological package that can be transferred to small producers so that they can directly use this technology to monitor and maintain their crops.

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Authors' Contributions

Conceptualization, ADR, CCB and ECV; methodology, ADR and CCB; software, ADR and CCB; data collection, ECV and MCM; validation, ADR, CCB and ECV; formal analysis, ADR and CCB.; investigation, ADR, CCB, ECV and MCM; resources, CCB; data curation, ADR; writing—original draft preparation, ADR, CCB and ECV; writing—review and editing, ADR, CCB, ECV and MCM; visualization, ADR, CCB and ECV; supervision, CCB, ECV and MCM; project administration, MCM; All authors have read and agreed to the published version of the manuscript.

Ethical Implications

This article has no ethical implications for its preparation.

Conflict of Interest

The authors declare no conflicts of interest in this study.

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References

- Ahmadi, K., Omid, H., Amini Dehaghi, M., & Naghdi Badi, H. (2019). A Review on the Botanical, Phytochemical and Pharmacological Characteristics of *Kelussia odoratissima* Mozaff. *Journal of Medicinal Plants*, 18(72), 30-45. <https://doi.org/10.29252/jmp.4.72.S12.30>
- Ali, Z. A., Yang, C., Israr, A., & Zhu, Q. (2023). A Comprehensive Review of Scab Disease Detection on Rosaceae Family Fruits via UAV Imagery. *Drones*, 7(2), 97. <https://doi.org/10.3390/drones7020097>
- Aly, R., & Dubey, N. (2014). Weed Management for Parasitic Weeds. In B. Chauhan & G. Mahajan (Eds.), *Recent Advances in Weed Management*. Springer. https://doi.org/10.1007/978-1-4939-1019-9_14
- Bajwa, A. A., Farooq, M., Al-Sadi, A. M., Nawaz, A., Jabran, K., & Siddique, K. H. (2020). Impact of climate change on biology and management of wheat pests. *Crop Protection*, 137, 105304. <https://doi.org/10.1016/j.cropro.2020.105304>
- Blanco-Valdes, Y., Leyva-Galán, Á., & Castro-Lizazo, I. (2018). Determination of the critical period of weeds competition in pepper crop (*Capsicum annum*, L.). *Cultivos Tropicales*, 39(3), 18-24. <https://ediciones.inca.edu.cu/index.php/ediciones/article/download/1461/pdf/7291>
- Burkart, A., Hecht, V. L., Kraska, T., & Rascher, U. (2018). Phenological analysis of unmanned aerial vehicle-based time series of barley imagery with high temporal resolution. *Precision Agriculture*, 19, 134-146. <https://doi.org/10.1007/s11119-017-9504-y>
- Canicatti, M., & Vallone, M. (2024). Drones in Vegetable Crops: A Systematic Literature Review. *Smart Agricultural Technology*, 100396. <https://doi.org/10.1016/j.atech.2024.100396>
- Chollet, F. (2015). Keras: Deep Learning for humans. <https://keras.io>
- Chollet, F. (2017). Xception: Deep learning with depth wise separable convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1251-1258). IEEE. <https://doi.org/10.1109/CVPR.2017.195>
- Cornejo-Velazquez, E., & Clavel-Maqueda, M. (2024). *Set of images of chile crop areas collected with flight plans* [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.11123207>
- Coulombe, J., Brown, P., White, S., Xu, C., & Koech, R. (2018, August). Detection of crop water status using UAV mounted sensor. In *XXX International Horticultural Congress IHC2018: VII Conference on Landscape and Urban Horticulture, IV Conference*, 1279, 271-278.
- Courneau, D. (2007). *Scikit Learn: Machine Learning in Python*. <https://scikit-learn.org/stable/>
- Gutiérrez-Lazcano, L., Camacho-Bello, C. J., Cornejo-Velazquez, E., Arroyo-Núñez, J. H., & Clavel-Maqueda, M. (2022). *Cuscuta spp.* Segmentation Based on Unmanned Aerial

- Vehicles (UAVs) and Orthomosaics Using a U-Net Xception-Style Model. *Remote Sensing*, 14(17), 4315. <https://doi.org/10.3390/rs14174315>
- Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv*. <https://doi.org/10.48550/arXiv.1704.04861>
- Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4700-4708). IEEE. <https://doi.org/10.1109/CVPR.2017.243>
- Iqbal, M., Hussain, M., Abid, A., Ali, M., Nawaz, R., Waqar, M., Ashgar, M., & Iqbal, Z. (2014). A review: Cuscuta (*Cuscuta planiflora*) major weed threat in Punjab–Pakistan. *International Journal of Advanced Research in Biological Sciences*, 4, 42-46. <https://ijarbs.com/pdfcopy/july2014/ijarbs6.pdf>
- Ishengoma, F. S., Rai, I. A., & Said, R. N. (2021). Identification of maize leaves infected by fall armyworms using UAV-based imagery and convolutional neural networks. *Computers and Electronics in Agriculture*, 184, 106124. <https://doi.org/10.1016/j.compag.2021.106124>
- Khan, A., Sohail, A., Zahoor, U., & Qureshi, A. S. (2020). A survey of the recent architectures of deep convolutional neural networks. *Artificial intelligence review*, 53, 5455-5516. <https://doi.org/10.1007/s10462-020-09825-6>
- Krienke, B., Ferguson, R. B., Schlemmer, M., Holland, K., Marx, D., & Eskridge, K. (2017). Using an unmanned aerial vehicle to evaluate nitrogen variability and height effect with an active crop canopy sensor. *Precision Agriculture*, 18, 900-915. <https://doi.org/10.1007/s11119-017-9534-5>
- Le, Q. V., Tennakoon, K. U., Metali, F., Lim, L. B., & Bolin, J. F. (2015). Impact of *Cuscuta australis* infection on the photosynthesis of the invasive host, *Mikania micrantha*, under drought condition. *Weed Biology and Management*, 15(4), 138-146. <https://doi.org/10.1111/wbm.12077>
- Martínez, J., Egea, G., Agüera, J., & Pérez-Ruiz, M. (2017). A cost-effective canopy temperature measurement system for precision agriculture: A case study on sugar beet. *Precision Agriculture*, 18, 95-110. <https://doi.org/10.1007/s11119-016-9470-9>
- Mishra, J. S. (2009). Biology and management of *Cuscuta* species. *Indian Journal of Weed Science*, 41(1 & 2), 1-11. https://www.isws.org.in/IJWSn/File/2009_41_Issue-1&2_1-11.pdf
- OCV. (2023). *OpenCV – Open Computer Vision Library*. <https://opencv.org>
- ODM. (2023). *WebODM - OpenDroneMap*. <https://www.opendronemap.org/webodm/>
- Oldeland, J., Große-Stoltenberg, A., Naftal, L., & Strohbach, B. J. (2017). The potential of UAV derived image features for discriminating savannah tree species. In *The Roles of Remote Sensing in Nature Conservation: A Practical Guide and Case Studies* (pp. 183-201). Springer. https://doi.org/10.1007/978-3-319-64332-8_10
- Pandey, A., & Jain, K. (2022). An intelligent system for crop identification and classification from UAV images using conjugated dense convolutional neural network. *Computers and Electronics in Agriculture*, 192, 106543. <https://doi.org/10.1016/j.compag.2021.106543>
- Puteh, S., Rodzali, N. F. M., Abdul Majeed, A. P. P., Khairuddin, I. M., Ibrahim, Z. Z., & Razman, M. A. M. (2021). Classification of *Capsicum frutescens* health condition through features extraction from NDVI values using image processing. In *RiTA 2020: Proceedings of the 8th International Conference on Robot Intelligence Technology and Applications*. Springer Singapore. https://doi.org/10.1007/978-981-16-4803-8_41
- Qiao, L., Tang, W., Gao, D., Zhao, R., An, L., Li, M., Sun, H., & Song, D. (2022). UAV-based chlorophyll content estimation by evaluating vegetation index responses under different

- crop coverages. *Computers and Electronics in Agriculture*, 196, 106775. <https://doi.org/10.1016/j.compag.2022.106775>
- Sanz, D., Valente, J., del Cerro, J., Colorado, J., & Barrientos, A. (2015). Safe operation of mini UAVs: a review of regulation and best practices. *Advanced Robotics*, 29(19), 1221–1233. <https://doi.org/10.1080/01691864.2015.1051111>
- SIAP. (2021). *Panorama agroalimentario*. Secretaría de Agricultura de México.
- Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv*. <https://doi.org/10.48550/arXiv.1409.1556>
- Smith, A. R. (1978). Color gamut transform pairs. *ACM Siggraph Computer Graphics*, 12(3), 12-19. <https://doi.org/10.1145/965139.807361>
- Sosa-Herrera, J. A., Vallejo-Pérez, M. R., Álvarez-Jarquín, N., Cid-García, N. M., & López-Araujo, D. J. (2019). Geographic object-based analysis of airborne multispectral images for health assessment of *Capsicum annuum* L. crops. *Sensors*, 19(21), 4817. <https://doi.org/10.3390/s19214817>
- Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2818-2826). IEEE. <https://doi.org/10.1109/CVPR.2016.308>
- Team, G. B. (2015). *TensorFlow*. <https://www.tensorflow.org/>
- Tetila, E. C., Machado, B. B., Astolfi, G., de Souza Belete, N. A., Amorim, W. P., Roel, A. R., & Pistori, H. (2020). Detection and classification of soybean pests using deep learning with UAV images. *Computers and Electronics in Agriculture*, 179, 105836. <https://doi.org/10.1016/j.compag.2020.105836>
- West, J. S., Canning, G. G., Perryman, S. A., & King, K. (2017). Novel technologies for the detection of *Fusarium* head blight disease and airborne inoculum. *Tropical Plant Pathology*, 42, 203-209. <https://doi.org/10.1007/s40858-017-0138-4>
- Winston, R. L., Schwarzländer, M., Hinz, H. L., Day, M. D., Cock, M. J., & Julien, M. H. (2014). *Biological control of weeds: a world catalogue of agents and their target weeds* (5th ed). USDA Forest Service, Forest Health Technology Enterprise Team. http://www.ibiocontrol.org/catalog/JulienCatalogueFHTEET_2014_04.pdf
- Xie, S., Girshick, R., Dollár, P., Tu, Z., & He, K. (2017). Aggregated residual transformations for deep neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1492-1500). IEEE. <https://doi.org/10.1109/CVPR.2017.634>
- Yee-Rendon, A., Torres-Pacheco, I., Trujillo-Lopez, A. S., Romero-Bringas, K. P., & Millan-Almaraz, J. R. (2021). Analysis of New RGB Vegetation Indices for PHYVV and TMV Identification in Jalapeño Pepper (*Capsicum annuum*) leaves using CNNs-based model. *Plants*, 10(10), 1977. <https://doi.org/10.3390/plants10101977>
- Zhang, L., Han, W., Niu, Y., Chavez, J. L., Shao, G., & Zhang, H. (2021). Evaluating the sensitivity of water stressed maize chlorophyll and structure based on UAV derived vegetation indices. *Computers and Electronics in Agriculture*, 185, 106174. <https://doi.org/10.1016/j.compag.2021.106174>