SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 11, No. 4, (2025), pp. 1811-1820
Open Access. Online & Print

DOI: 10.5281/zenodo. 18678058

CROP CLASSIFICATION AND UNWANTED PLANT DETECTION USING ARTIFICIAL INTELLIGENCE IN AERIAL IMAGERY FOR PRECISION AGRICULTURE

Diego Alfonso Peláez Carrillo[1*], Diego José Barrera Oliveros[2], Cristian Camilo Meza Peláez[3], Oscar Eduardo Gualdron Guerrero[4]

[1-4]*Department of Mechanical, Mechatronic and Industrial Engineering, Department of Electrical, Electronic, Systems and Telecommunications Engineering, School of Engineering and Architecture, Universidad de Pamplona, Norte de Santander, Colombia.*
[1]*diego.pelaez@unipamplona.edu.co*, [2]*diego.barrera@unipamplona.edu.co*,
[3]*oscar.gualdron@unipamplona.edu.co*, *4meza.cristian@unipamplona.edu.co*

Received: 11/11/2025
Accepted: 18/12/2025

Corresponding Author: Diego Alfonso Peláez Carrillo
diego.pelaez@unipamplona.edu.co)

ABSTRACT

In light of the paramount importance of precision agriculture, this research proposes an algorithm leveraging artificial intelligence that can classify various crop types and identifying the presence of weeds within the designated study areas. The present algorithm was developed in Python and incorporates convolutional neural network (CNN) models that were specifically designed to segment regions with carrot and potato crops. Segmentation is achieved through the implementation of a U-shaped neural model, which utilizes data acquired from aerial imagery. This information undergoes a process of analysis and selection, with the objective of subsequent integration into the network. Furthermore, a classification model is employed that emphasizes the differentiation between the two crop types. In conclusion, the CNN response is regarded as a novel estimate, which, in this instance, is directed towards the identification of areas that are afflicted with weeds. The final process is associated with a recently developed semantic segmentation model that is also U-shaped. This model has been adapted to identify weeds in the designated fields.

KEYWORDS: Crop, Artificial Intelligence, Weeds, Neural Network, Deep Learning.

1. INTRODUCTION

Precision agriculture currently plays an important role in sustaining populations and supplying food. The enhancement of agricultural methodologies and the augmentation of productivity represent pivotal elements in the pursuit of sustainable development within communities. In this regard, the utilization of state-of-the-art technologies, including machine learning, deep learning, and image processing, constitutes a valuable strategy for crop optimization and efficient agricultural land management.

In the contemporary era, the advent of artificial intelligence (AI) engendered a paradigm shift in the realm of application design, enabling the development of applications for a myriad of purposes. The present study proposes the development of an algorithm based on convolutional neural networks (CNN) that can differentiate between two distinct categories of crops: potato crops and carrot crops. The classification aims to characterize the area according to the crops in order to subsequently determine the existence of weeds (plants that can cause unfavorable changes in the vegetation under study) that may affect the yield and health of these crops.

The use of aerial images of crops in the RGB spectrum provides a detailed and comprehensive view of agricultural areas, facilitating the characterization and subsequent identification of crops and weed areas.

The employment of neural networks in the processing of these images facilitates the extraction of specific patterns and characteristics, thereby enabling the classification of crops of interest and the identification of regions invaded by weeds.

AI is an area of current technology that is concerned with the development of intelligent machines, which are designed to emulate reasoning, learn, and act independently (Iberdrola, n.d.). The objective of this field is to facilitate the execution of tasks by machines in a manner analogous to that of human performance, guided by logical reasoning (Boden, 2022).

AI-based systems possess the capacity to process voluminous amounts of data. In a similar vein, AI employs a multitude of techniques to address a diverse array of tasks (Rouhiainen, 2018). As Russell (2020) points out, this technology has been used in a wide range of applications, including machine learning, robotics, pattern recognition, and computer vision.

Conversely, photography finds application in a myriad of disciplines, including cartography, urban planning, environmental monitoring, geological studies, agricultural research, advertising, and tourism. These types of images can be captured from a variety of platforms, including airplanes, helicopters, drones, and hot air balloons. In the domain of agricultural research, the utilization of aerial photographs has emerged as a valuable tool for investigating a range of agricultural concerns. These concerns include, but are not limited to, the efficiency of crops, the health of plants, and the distribution of pests. This initiative has been demonstrated to assist farmers in enhancing their agricultural practices and augmenting their productivity (D, 2020; Musso, 2020).

Precision agriculture constitutes a set of technologies that utilize data to enhance sustainability and efficiency in the agricultural sector. These technologies have the capacity to collect data on soil, climate, and crops. The subsequent utilization of this data enables informed decision-making processes concerning planting, fertilization, irrigation, and harvesting (Alvarado Zabala & Moreno Marín, 2019). For instance, agricultural producers have the capacity to utilize precision agriculture to promptly detect and address issues affecting their crops, thereby minimizing yield loss (Alvarado Zabala & Moreno Marín, 2019).

The utilization of artificial intelligence (AI) has emerged as a pivotal instrument in addressing the challenges impeding the advancement of crop development. Through the implementation of sophisticated algorithms and machine learning systems, agricultural professionals are able to anticipate and address challenges associated with pests, diseases, and weeds.

The capacity to process voluminous agricultural data in real time facilitates the early identification of potential threats and the more efficient implementation of preventive measures. In this regard, the integration of AI within agricultural production systems has been shown to enhance efficiency, while concurrently contributing to the enhancement of safety and sustainability. This is achieved by mitigating risks and reducing the adverse environmental impact on crops (Torres, 2018). Among the natural risks that hinder crop development are weeds, which act as hosts to pests or microbes that cause different diseases in crops. This is since many insects live in weeds (University of Costa Rica, 2018). The employment of technologies such as drones and artificial intelligence has the potential to mitigate these risks.

1.1. Weed Management in Agriculture

Preventive weed management is a strategy employed to avoid adverse scenarios pertaining to the crop under scrutiny. In the context of this research, it facilitates the analysis of crops through the utilization of aerial photography. Achieving this preventive management necessitates the consideration of the characteristics of the plant to be controlled and the natural conditions, as well as the following actions

- Identify crops and varieties: Classify plant types according to leaf size, since those with large leaves and considerable height compete with those with small leaves (INTAGRI, 2017).
- Reduce the weed seed bank: Controlling weeds before they generate more seeds helps improve crop production (INTAGRI, 2017).
- Intercropping: this involves planting different crops in a staggered pattern so that they quickly cover the soil surface, creating a barrier to light and preventing weeds from developing (INTAGRI, 2017).
- Cover crops: these compete directly with weeds for light, water, and nutrients (INTAGRI, 2017).

1.2. Unmanned Aerial Vehicle

UAV is an acronym for "unmanned aerial vehicle," which refers to an aircraft without a human operator on board. The aircraft's operation is characterized by two distinct modes: autonomous flight and remote-control operation. The transition between these modes is facilitated by remote control systems that enable the operator to direct the aircraft in accordance with the desired trajectory. This phenomenon is believed to be sustained by aerodynamic forces, and the possibility of recovery is uncertain (Ferreras, 2017), as posited by Garijo, Verdejo, Lopez Perez, and Perez Estrada (2009), and subsequently corroborated by Austin and Brewster (2023).

The autonomy that these types of vehicles can have is also linked to the type of control used, which could be intelligent. Similarly, the images that can be captured by these devices require processing, just as the automatic driving of the vehicle requires thinking about the implementation of AI-based strategies.

1.3. Machine Learning (ML), Deep learning (DL)

The term "machine learning" is defined as a branch of artificial intelligence that enables computers or machines to acquire knowledge without being directly programmed. Machine learning does not require human intervention by a programmer to instruct the machine on the steps to achieve a task and perform it automatically (Torres, J., 2020; Anand, Rudra, & Sudeep, 2021).

In a similar vein, deep learning (DL) facilitates the development of diverse models comprising multiple processing layers within various hierarchical layers. These models are employed to ascertain and comprehend representations, as well as data characteristics, at increasingly intricate levels of complexity. They enable the execution of a succession of linear and non-linear transformations, resulting in data that closely resembles the anticipated output (Torres, J., 2020).

1.4. Artificial Neural Networks

ANNs are based on the biological neural networks found in the human brain. They are made up of certain elements that behave similarly to real biological neurons in their most common functions. Each part is organized in the same way as the human brain (Bueno, 2019).

A considerable body of research has been dedicated to assessing the viability of implementing AI-based control techniques. **Examples include** The utilization of unmanned aerial systems and deep learning for agricultural mapping in Dubai (Larabia & Al, 2021) and the development of an intelligent system for crop identification and classification from UAV images using a dense convolutional neural network (Pandey & Jain, 2021) are two notable examples.

The primary research in these studies focuses on the recognition and mapping of cultivated areas using aerial images and neural networks. With regard to the recognition of marijuana: As demonstrated in the works of Syamasudha Veeragandham (2022), Baruffaldi (2022), and Jiménez López, Camargo, and Garcia Ramirez (2020), convolutional layers in pre-trained models have been found to be effective for the classification of common weeds in peanut and corn crops, weed recognition using adversarial neural networks, and the development of intelligent systems for weed management in pineapple cultivation using precision agriculture concepts. These works illustrate the diverse range of methods available for identifying weeds and invasive agents.

2. METHODOLOGY

To implement the proposed research idea, the methodological structure shown in Figure 1 was used.

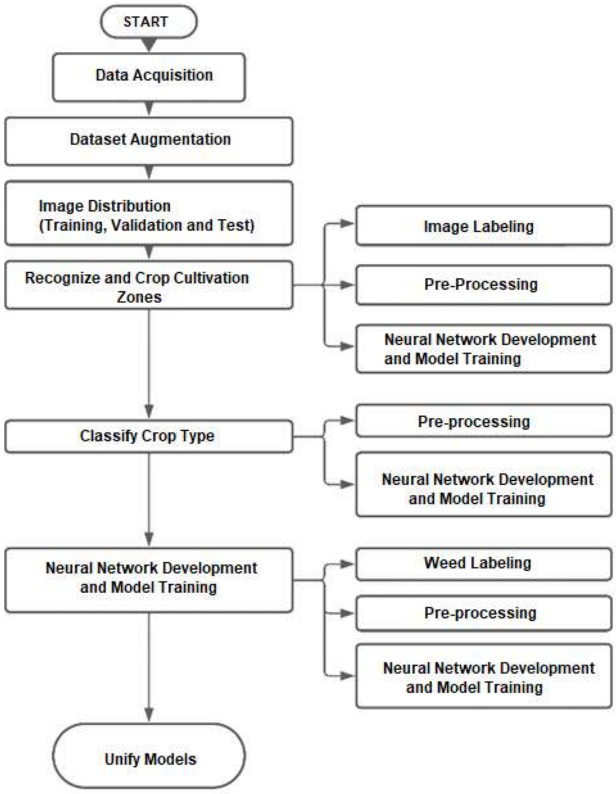


Figure 1: Research Development Process.
Own Elaboration.

2.1. Data Acquisition

In order to obtain aerial images in RGB color channels of potato and carrot crops, a DJ Mavic Pro 2 drone was used, given that it has good resolution, allowing for HD 4K images. The process carried out with the drone can be seen in Figure 2.

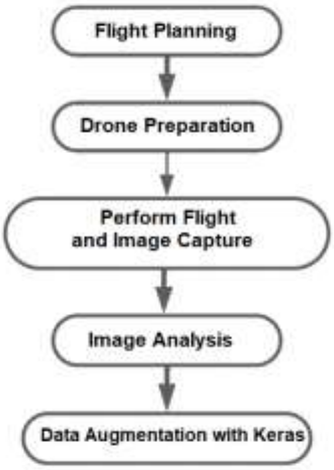


Figure 2: Steps for Acquiring Data.
Own Elaboration.

The initial phase of the study involved the identification of the areas to be photographed. The potato and carrot crops located on the outskirts of Pamplona, Norte de Santander, were selected for this purpose.

Subsequently, the drone was flown at an altitude of 30 meters, effectively covering a substantial area without compromising image quality. Subsequent to the formulation of the flight plan, it was imperative to ensure the drone's readiness by assessing the battery charge, confirming the secure fastening of the propellers, and verifying the drone's operational condition.

The drone flight successfully captured a total of 364 images. The selection of these images was predicated on their capacity to impart pertinent information. Following the selection process, 297 photographs remained. As illustrated in Figure 3, the left image provides minimal information, while the right image is pertinent to the process.

Figure 3: Image Selection.
Own Elaboration.

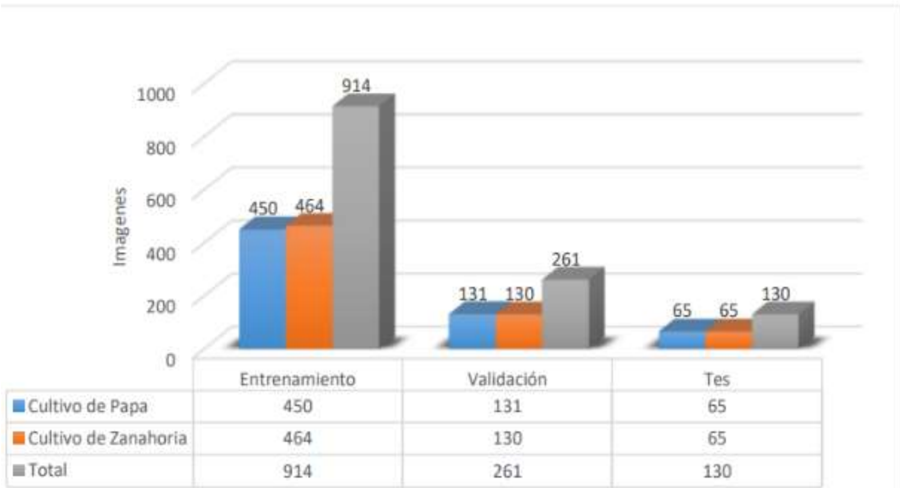
2.2. Increase in the Dataset

To improve the performance of the neural network, data augmentation was performed using Keras. This consists of creating new images from existing images by applying various transformations, such as rotation, displacement, horizontal flipping, and 5% zoom, which allows the neural network to perform better.

2.3. Distribution of Images

Following the augmentation of the dataset, a total of 1,306 images were obtained, which were subsequently grouped as follows: the images were divided into three parts, with 914 images (70%) allocated for training, 261 images (20%) designated for validation, and 130 images (10%) assigned for testing, as illustrated in Figure 4.

It is important to note that, in each of the three phases (training, validation, and testing), both potato and carrot crops are considered.



	Entrenamiento	Validación	Tes
Cultivo de Papa	450	131	65
Cultivo de Zanahoria	464	130	65
Total	914	261	130

Figure 4: Dataset Description.
Own Elaboration.

2.4. Identify and Clear Areas for Cultivation

In order to achieve a more precise classification of crops and identification of areas affected by weeds, it was decided that the areas cultivated with potatoes and carrots would be extracted using object segmentation. This method utilizes the superimposition of a color layer on the image to identify a specific object.

This estimation facilitates the generation of a cutout exclusively encompassing the designated area of interest. In this instance, the Python tool "Labelme" was utilized for the segmentation process. This tool facilitates the creation of polygonal labels within the images, thereby generating a mask that subsequently enables more efficient management of information during the training process.

A deep learning model with an U-shaped architecture was implemented, as illustrated in Figure 5. The input data initially undergoes a comprehension or contraction stage comprising 11 3x3 convolution layers, with a rectified linear unit (ReLU) activation function, 4 2x2 max pool layers, and 5 dropout layers. The initial stage of this process involves the application of a 64-filter, which is followed by a doubling of its value as it traverses each layer. This process continues until the most compressed point is reached, at which point a 1024-filter is employed. In the subsequent section, the expansion consists of eight convolutional layers with a size of 3x3, a rectified linear unit (ReLU) activation function, four up-convolutions with a size of 2x2, five dropout layers, and finally a convolutional layer with a size of 1x1. Each stage of the process is connected by four layers: copy, crop, and two additional layers. The implementation of dropout layers is an effective strategy to mitigate the risks of overfitting and underfitting in machine learning models.

The total number of layers in the model was 40. The model was executed on Google Colab, which is equipped with 12 GB of RAM and a 15 GB GPU.

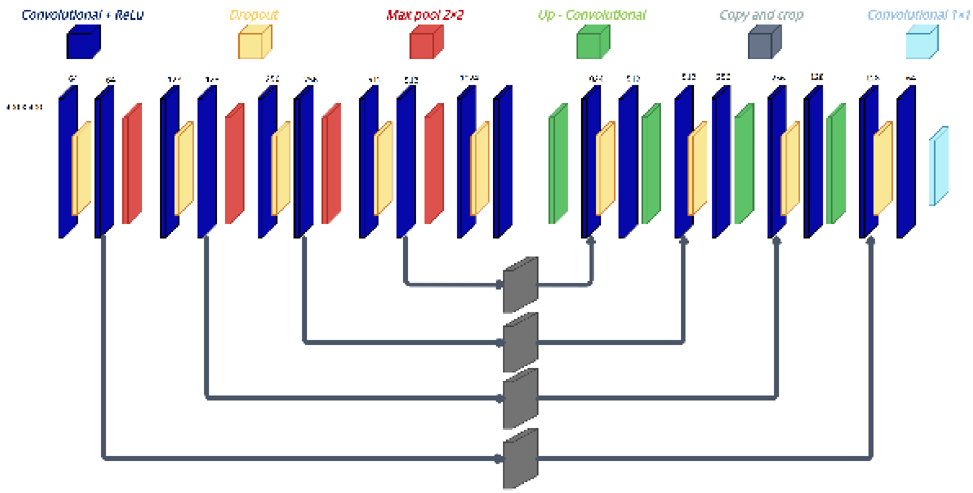


Figure 5: U-Shaped Architecture Model Implemented.
Own Elaboration.

2.5. Classification of Crop Type

Following the segmentation of the crop area, the subsequent step involves the classification of potatoes and carrots. To this end, a basic convolutional neural network is designed, enabling the classification between the two classes.

The images are resized to 650 x 650 for the training phase, and a label is assigned to indicate the type of crop. This process is then repeated to train and optimize the network.

Two distinct classification models were subjected to evaluation. The initial model employed a VGG16 architecture, while the subsequent model utilized simpler architecture. The selection of the most appropriate model was guided by the consideration of several performance metrics, including precision, recall, and the F1-score, as outlined in Tables 1 and 2.

The following formulas are required to calculate these metrics (Equation 1, Equation 2, Equation 3, Equation 4).

TP =True Positive
FP=False Positive
FN=False Negative
TN=True Negative

$$Accuracy = \frac{TP}{(TP+FP)} \text{ ------(1)}$$

$$Recall = \frac{TP}{(TP+FN)} \text{ -----------(2)}$$

$$Accuracy = \frac{(TP+TN)}{(TP+FN+TN+FP)} \text{ ---(3)}$$

$$F1 - Score = \frac{(Accuracy\ x\ Recall)}{(Accuracy + Recall)} \text{ ----(4)}$$

Table 1: VGG16 Model Metric Results.
Own Elaboration.

	Accuracy	Recall	F1- Score
Carrot	0.851	0.891	0.870
Potato	0.883	0.841	0.862
accuracy			0.866

Table 2: Basic Proprietary Model Metrics Results.
Own Elaboration.

	Accuracy	Recall	F1- Score
Carrot	0.954	0.985	0.969
Potato	0.984	0.952	0.968
accuracy			0.866

With these values, the confusion matrix was obtained for each of the models, as shown in Figure 6 and Figure 7.

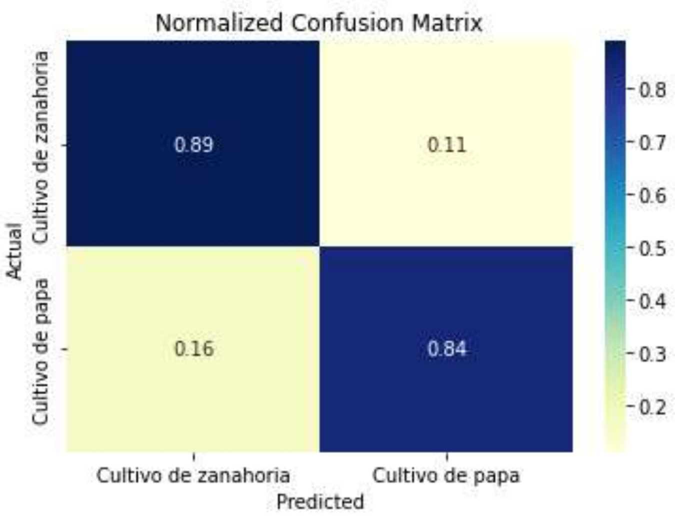


Figure 6: VGG16 Confusion Matrix.
Own Elaboration.

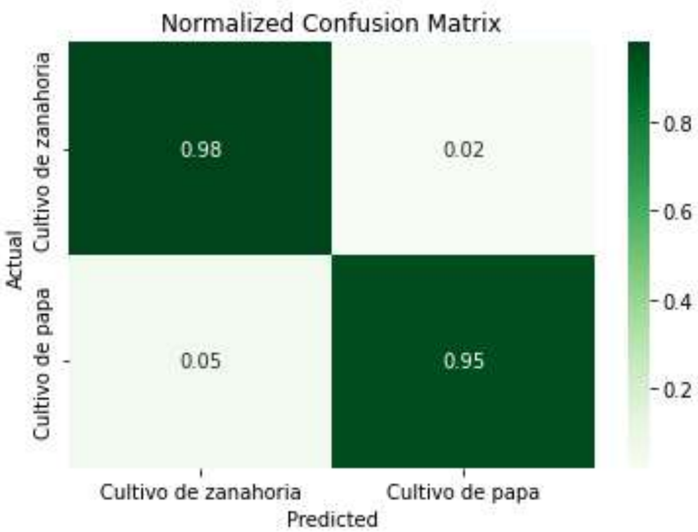


Figure 7: Confusion Matrix, Own Model.
Own Elaboration.

For the development of the project, simple architecture was applied due to its previously proven results, consisting of different layers such as 3 Conv2D + ReLu activation function, 3 Maxpooling, 1 Dense + ReLu activation function, 3 Dropout, and 1 Flatten, as shown in Figure 8.

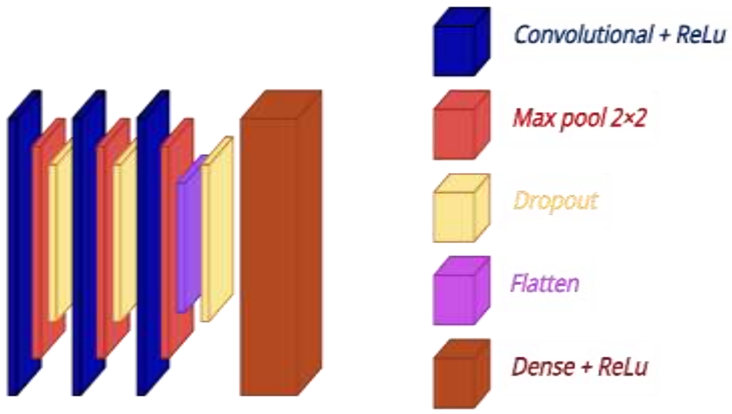


Figure 8: Basic Classification Model.
Own Elaboration.

2.6. *Identify Areas of Weeds*

Following the completion of the initial steps, which entailed the harvesting and classification of the crops, the team proceeded to the final phase of the process: the identification of areas that necessitated weed removal. To achieve this objective, we have reimplemented semantic segmentation and the U-shaped model architecture, which facilitates the identification of weeds. This necessitated the process of image labeling, entailing the selection of areas exhibiting weeds for the purpose of training.

2.7. *Unify Models*

Once the different models have been developed, they are unified to consolidate a single model capable of selecting areas according to the crop under study, classifying them according to the type of agricultural production, and identifying weeds. The procedure is shown in Figure 9.

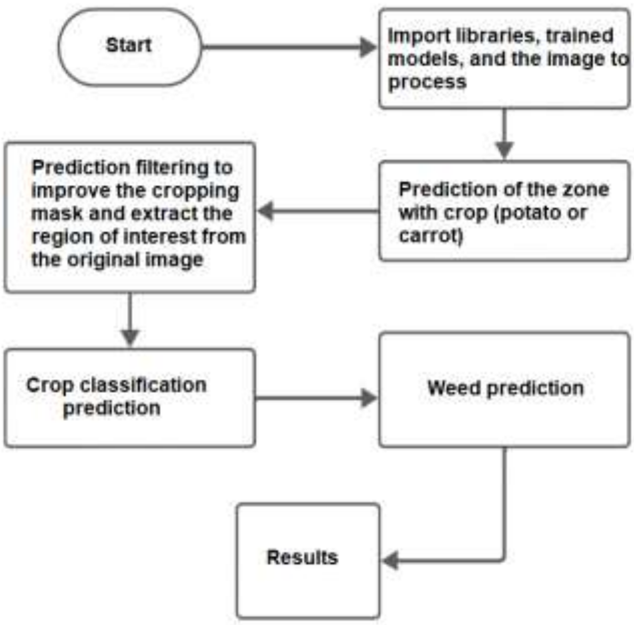


Figure 9: Final Algorithm Procedure.
Own Elaboration.

3. RESULTS

First, the results of recognizing and cutting out the cultivated areas will be presented. Then, the classification of the classes will be examined. Next, weed recognition will be discussed. Finally, the complete operation will be analyzed.

3.1. Neural Network Training and Prediction to Recognize and Crop the Cultivation Area

During the training of the model, network efficiency exhibited variability across the 40 epochs. However, efficiency levels surpassed 90% by the conclusion of the training, thereby signifying the efficacy of the U model in accurately recognizing and segmenting cultivated areas. Subsequently, loss was analyzed with respect to the epochs, which facilitated the determination of whether overfitting or underfitting existed. In this instance, standard behavioral patterns were noted.

Subsequent to the implementation of the model, the cultivated areas can be segmented, and subsequently, a mask can be generated for the purpose of cropping the area. Given the model's lack of absolute precision, the implementation of filtering techniques is essential for enhancing the mask and mitigating information loss.

3.2. Crop Classification

As mentioned above, a simple structure was used for the crop classification, which provided good results, distinguishing between the two types of classes, potato and carrot. Finally, the confusion matrix is analyzed in Figure 7, Recall, F1-Score, Accuracy, and Precision in Table 2, where we show the efficiency of the model with 96.8% accuracy for the classification.

3.3. Neural Network Training for Identifying Weed Areas

Next, from the training of the model for weeds, we observed how the efficiency of the network varied over the 45 epochs, where an efficiency of over 97% was obtained, confirming once again that our model does not contain overfitting or underfitting.

The weed prediction results provided by our model include a segmentation of the area of interest. To achieve this result, the image was initially divided into four quadrants, thereby facilitating a more accurate prediction while minimizing information loss. This is of particular importance given the tendency of weeds to be easily confused with crops. After the processing stage, the image undergoes a process of reconstruction.

3.4. Overall Results

As a result of the research, an algorithm capable of recognizing crop areas has been developed. The area of interest is cropped, then classified, and finally the areas with the highest number of weeds are recognized, along with identification of the type of crop (potato or carrot).

4. CONCLUSION

Convolutional neural networks have been employed to develop an algorithm capable of performing semantic segmentation in aerial images of crops. The advent of unmanned aerial vehicles (UAVs) has profoundly impacted various sectors, including agriculture. The ease with which aerial images can be acquired from such devices, coupled with the seamless integration of data augmentation techniques using TensorFlow and Keras, has led to the development of innovative processes aimed at enhancing various industry verticals. A notable example is the field of product production, where the timely removal of weeds has become a pivotal aspect of agricultural practices, underscoring the potential of UAVs to transform traditional farming methodologies.

The models implemented allow for the identification and delineation of crop areas with an efficiency that exceeds 90%. This segmentation capability facilitates crop classification, and thanks to the use of convolutional networks, which are specially designed for image processing, we achieved an efficiency of over 96% for the classification of crops such as potatoes and carrots. Subsequently, the generated cutout can be utilized to identify areas within the crop that contain weeds through semantic segmentation, a process that can be accomplished by employing a U-shaped neural network model. The efficacy of this model has been demonstrated, even when operating with a limited number of images. It has been shown to achieve 93% efficiency, thus providing a valuable tool for farmers and agronomy experts.

The efficacy of the proposed algorithm was determined to be over 93% effective during the validation process. The effectiveness of this approach is derived from its capacity for classification and its potential for segmentation. This project is characterized by a cascading approach, wherein the efficiency of the system is determined by the most efficient of the implemented models. In this instance, the semantic segmentation of crops has been identified as the optimal approach, exhibiting an effectiveness of 93%. The implementation of this algorithm has been demonstrated to be of significant benefit in the identification of areas with weeds, which is a substantial advantage in the effort to combat pests and diseases that affect crops. Furthermore, it has been shown to enhance the sustainability of the agricultural process.

REFERENCES

Alvarado Zabala, P. J., & Moreno Marín, A. F. (2019). *Agricultura urbana de precisión*. Uniandes.

Anand, N., Rudra, R., & Sudeep, T. (2021). *Machine learning in signal processing*. CRC Press.

Austin, J., & Brewster, S. (agosto de 2023). *Wirecutter*. Obtenido de https://www.nytimes.com/wirecutter/reviews/best-drones/

Baruffaldi, J. M. (2022). *Redes neuronales adversarias para el reconocimiento de malezas*. EST, Concurso de Trabajos Estudiantiles.

Boden, M. (2022). *Inteligencia artificial*. Turner.

Bueno, F. (2019). *Redes neuronales: Entrenamiento y comportamiento*. Madrid: Universidad Complutense Madrid.

D, J. (2020). *bptfotografia* (becasparatodos). Obtenido de https://bptfotografia.com/que-es-fotografia-aerea/

Ferreras, A. D. (2017). *Modelado, control y percepción en sistemas aéreos autónomos*. Sevilla, España: Escuela Superior de Ingenieros Universidad de Sevilla.

Garijo Verdejo, D., Lopez Perez, J. I., & Perez Estrada, I. (2009). *Control de un vehículo aéreo no tripulado*. Universidad Complutense de Madrid.

INTAGRI. (2017). *Manejo de malezas en la agricultura orgánica*. Artículos Técnicos de INTAGRI(16), 5.

Jiménez López, A., Camargo, D. A., & Garcia Ramirez, D. Y. (2020). *Sistema inteligente para el manejo de malezas en el cultivo de piña con conceptos de agricultura de precisión*. *Ciencia y Agricultura, 17*.

Larabia, A., & Al, K. (2021). *Uso de sistemas aéreos no tripulados y aprendizaje profundo para el mapeo agrícola en Dubai*. Heliyón.

Musso, C. (agosto de 2020). *Blog del Fotógrafo SL* (Blog del Fotógrafo SL). Obtenido de https://www.blogdelfotografo.com/fotografias-aereas/

Pandey, A., & Jain, K. (2021). *An intelligent system for crop identification and classification from UAV*. Elsevier Ltd.

Rouhiainen, L. (2018). *Inteligencia artificial*. Alienta Editorial.

Russell, S. (2020). *En Artificial Intelligence: A Modern Approach*. Pearson.

(s.f.). Obtenido de *Iberdrola*: https://www.iberdrola.com/innovacion/que-es-inteligencia-artificial

Syamasudha Veeragandham, S. (2022). *Efectividad de capas convolucionales en modelos pre-entrenados*. Elsevier.

Torres, J. (2018). *Deep learning: Introducción práctica con Keras*. Barcelona: WATCH THIS SPACE.

Torres, J. (2020). *Python deep learning: Introducción práctica con Keras y TensorFlow 2*. Alpha Editorial.

Universidad de Costa Rica. (2018). *Relación de las malezas con la presencia de plagas y enfermedades*. Obtenido de http://www.buenaspracticasagricolas.ucr.ac.cr/index.php/manejo-de-coberturas/relacion-de-las-malezas-con-la-presencia-de-plagas-y-enfermedades