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CONVOLUTIONAL NEURAL NETWORK FOR DETECTION OF NATIVE ORCHID TYPES IN HONDURAS

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***Abstract*-- The detection and classification of objects in flower farm environments have been a necessary support that should be considered, not only because it facilitated the categorization of flowers but also because it reduced the required time, as it no longer needed to be carried out by an expert. The use of convolutional neural networks has been on the rise in all sectors, whether in the automotive industry, livestock, aviation, among others. This is due to their characteristics that leverage artificial intelligence training to achieve precise and efficient detection and classification of objects, but all these methods had a high cost and could not be manipulated by just anyone. The implementation of this resource, working hand in hand with the YOLOv8 algorithm, represented a significant advancement in the field of flower type detection and classification. Keywords: classification, flower farms, convolutional neural network, YOLO, Python, RoboFlow, artificial intelligence.**

I. INTRODUCTION

The present thesis constitutes a comprehensive research study that focuses on the detection of native orchid types in Honduras using a convolutional neural network. Throughout this work, advancements in the field of computer vision and artificial intelligence will be explored, with a special emphasis on the use of deep learning algorithms for the identification and classification of endemic orchid species within Honduran territory.

The research is conducted in the context of the growing concern for biodiversity conservation and the preservation of plant species at risk of extinction. Orchids, due to their beauty and uniqueness, hold a special place in this concern, and Honduras, with its diverse range of microclimates and ecosystems, harbors a wide diversity of these species, some of which are in critical danger of disappearing.

The utilization of a convolutional neural network as the primary tool in this research offers an innovative approach to orchid detection and classification, as it allows for efficient processing of high-resolution images, which was previously a laborious and challenging task. This will enable botanists, scientists, and nature enthusiasts to identify different orchid species more accurately in their natural habitat.

The main objective of this thesis is to develop a system for the accurate, efficient, and accessible detection and classification of native Honduran orchids. The practical application of this research could have a significant impact on the conservation of these species by facilitating their monitoring and tracking in the field. Furthermore, it is expected that this work will contribute to scientific knowledge and promote public awareness of the importance of preserving Honduras' biological richness.

Throughout this document, the methods used in the construction and training of the convolutional neural network will be explored in detail, the obtained results will be analyzed, and the implications of this research within the context of Honduras' biodiversity and ecology will be discussed. The study's limitations will also be presented, and areas for future research will be proposed.

This thesis represents a significant effort at the intersection of artificial intelligence and botany, with the goal of contributing to the knowledge and preservation of native Honduran orchids, thereby enriching the country's natural and cultural heritage.

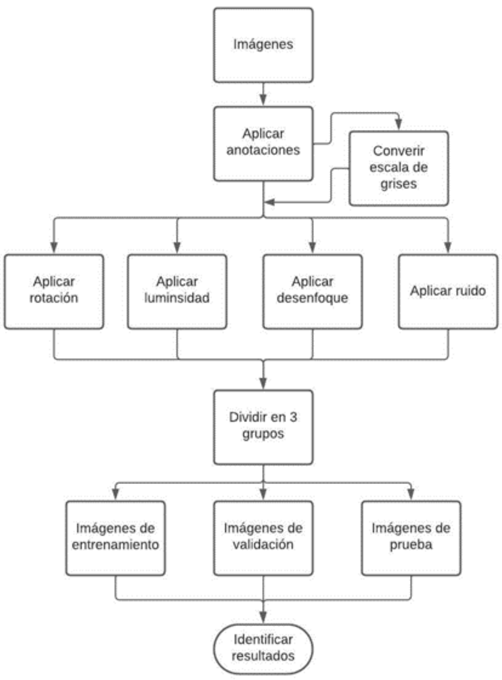


Fig. 1. Flowchart of steps to be followed in network training.

II. RELATED WORK

Worldwide, approximately 369,000 species of flowering plants have been documented. However, most people face challenges when trying to differentiate among the various varieties of flowers[1]. Within the field of computer vision, agriculture has been extensively explored to automate various activities, such as calculating the harvest by counting fruits, assessing a plant's ability to absorb sunlight, determining its water needs, detecting excesses or deficiencies of nutrients in the plant, evaluating its foliage, and identifying stress in the plant through stem and branch measurements [2]. Knowing the types of flowers, we are observing is of utmost importance, not only out of curiosity but also in agriculture, as many of these flowers are harvested for sale.

Understanding different flower species is crucial for preserving and managing biological diversity. Additionally, flowers play a vital role in the food chain and serve as essential habitat for nearly all pollinating insects[3]. In 2019, Büsra Rumeysa Mete and Tolga Ensari presented a methodology for flower classification using both deep learning algorithms and machine learning algorithms, such as SVM, Random Forest, KNN, and Multilayer Perceptron (MLP)[4]. Apart from viewing flowers solely as a means of making money in a business context, their benefit to the ecosystem must also be considered.

Within the category of flowers, orchids constitute one of the largest families. In addition to using leaves, stems, and roots, in general, the flower can also be used as a criterion for identifying orchid species[5]. Deep learning algorithms are being employed to perform complex tasks such as the identification of relevant attributes, image segmentation, and semantic classification, and recently, these strategies have had a significant impact on the categorization of flower varieties[6]. The orchid is an important flower in our country, not only because it grows in Central America but also because it is our national flower.

The Convolutional Neural Network (CNN) was introduced in 1989 by LeCun and colleagues as an approach to flower classification based on conventional neural networks, primarily focusing on a combination of flower-specific image feature extraction processes to improve classification accuracy[4]. The evolution of digital image processing technology today can be harnessed to simplify the task of identifying objects in an image by people[7]. The ease we have in identifying objects or types of objects using neural networks is of paramount importance, not only for its simplicity but also for its accuracy.

III. FLOWERS VARIETY

Depending on the variety, flowers may appear similar among different types, as is the case with gerberas; in some variants, only the color and the shape of the flower's center vary, while the petals have a similar appearance [2]. The image preprocessing stage plays a crucial role in extracting valuable information from the images, as this process implements a procedure to ensure that images taken under normal circumstances are appropriately treated and processed [7]. Due to this, images need to undergo preprocessing steps to enhance saturation and use grayscale to train the network more efficiently, always considering that the quality of the images taken will not always be 100% flawless.

Daily, we encounter a wide variety of flower species in our homes, parks, road edges, fields, and on our rooftops, but we are completely unaware of what types of flowers they are or where they came from, and we often lack information about their names [8]. In recent times, thanks to advancements in computer vision technology, there has been significant progress in flower classification in this field. This is especially relevant because various types of flowers share similarities in terms of shapes, colors, and petals [2]. The high degree of similarity among types of flowers, not only within the same species but also across different species, is what creates confusion when trying to accurately determine the species of each one and their differences from others.

A. *MACHINE LEARNING*

Within the field of computer vision, image classification has emerged as a significant research topic in recent years and has made considerable progress. Thanks to the development of electronic and mobile technology, people have easy access to various images, such as flowers or pets [9]. Flowers play a significant role in people's lives as they can appear at all stages of human life, and individuals have a desire to become familiar with the different types of flowers they encounter even in their daily routine [10]. Human curiosity drives us to conduct research, and using technology as a means facilitates our work and manipulation in everyday environments.

Machine learning is a methodology of artificial intelligence used to acquire knowledge of patterns contained in datasets [11]. CNN is a hierarchical deep neural network consisting of convolutional layers, subsampling layers, and fully connected neural layers [9]. CNNs have the capability to automatically extract hierarchical features for the purpose of image classification or segmentation [3]. Most research relies on CNNs for their practicality and high utility in object detection and classification.

If the entire image is considered for feature extraction in terms of shape and texture, the resulting descriptor will not be the same as the descriptor previously calculated in the database [12]. The creation of digital images generates image data for further processing and analysis. The system transforms the digital image and sends it to a computer for processing and storage through various procedures, such as image capture, image digitization, noise removal, and attribute identification [13]. Therefore, it is important to obtain various images from different angles, saturations, grayscale scales, and translucency to better train recognition when exposed to various types of image noise.

Images are examined using different shape, color, and texture attributes. The use of color in plant retrieval is more challenging compared to most Content-Based Image Retrieval (CBIR) applications, as many flowers share similar hues with their main color [12]. In relation to this, the use of shape data and petal counting presents challenges related to the perspective from which the images were taken [2]. Depending on the research, most concluded that the analysis is difficult depending on how the photograph was taken.

Due to the significant advancement of Convolutional Neural Networks (CNNs) in various areas, we apply transfer learning from a CNN-based model to automatically distinguish between different types of flowers. Transfer learning approaches enhance our network's performance on a reduced dataset [3]. Focusing on the detection of local flowers requires considering various factors. The classification and detection of flowers represent a considerable challenge due to the wide variety of floral species that exhibit very similar shapes, sizes, colors, and even patterns [4]. Due to the high efficiency achieved using CNNs, it is the primary choice in studies focused on flower type detection.

B. *Orchid Categorization*

Orchids can be categorized based on their genes, shape, color, seeds, and sometimes roots and their environment [14]. This is because orchids have a distinctive feature in their flower known as the labellum, which sets them apart not only from other flowers but also from other orchid varieties [5]. We can say that the orchid is a special flower not only due to its beauty but also because of its rarity and unique characteristics.

Despite this, some orchids exhibit similar colors and appearances, even if they belong to different species. Both floriculturists and other individuals can occasionally make mistakes due to this similarity in the appearance of orchid species. This similarity makes it challenging for botanists to group all orchid findings accurately, which is known as orchid family classification [14]. We examined the impact of the CBIR system on orchid species, considering the presence or absence of the labellum in the flower. We conducted a feature performance analysis to determine which feature significantly influences the system's performance. Furthermore, we evaluated the system's performance in both the validation and testing phases [12]. To understand the world of orchids through intelligent detection, the CBIR system assists us in a similar manner as the CNN described in [3].

C. *Important Aspects in Image Processing*

One of the fundamental aspects of digital image processing is the calculation of features from the dataset to be analyzed. Subsequently, the results obtained from feature extraction calculations can be used in combination with a classifier for identification. There are various classifier options available [9]. The computer's performance is then verified on the remaining 30 percent of the data collection. The selection of the percentage of data chosen for training and testing is done arbitrarily [11]. It is essential to determine which calculations will be performed or what aspects will be analyzed in the images to differentiate between each flower.

The parameters of the convolutional layer consist of a set of learnable filters called kernels. Each filter has a small receptive field used for the convolution operation on the input feature map. The feature map is one channel of the input, such as the red channel in the first layer. A dot product is performed between the filter and the input channel to generate a corresponding two-dimensional activation feature map for that filter (Hu et al., 2020). Digital images play a crucial role in this context. Digital imaging is a representation of an image through spatial and temporal sampling [7]. Given the difficulty of real-time video or live camera analysis, using digital images simplifies the process when dealing with CNN.

The deep learning model utilizes several nonlinear layers to extract discriminative and robust features for accurate classification. Deep learning methods have recently flourished in various research areas, including image processing, voice recognition, natural language processing, and remote sensing [15]. Like other fields in computer vision, image classification performance has been significantly enhanced through the application of deep learning methods, especially Convolutional Neural Networks (CNN) [19]. When it comes to digital image analysis, there are many aspects to consider. Taking the specific field of this research into account, which focuses on orchid types, it is necessary to understand what kind of information the images obtained from the field or cultivation will provide.

In various applications, only a fixed, trained model is required to perform inferences or predict the most likely class for test targets. On the other hand, the most time-consuming part, the training of the deep CNN model, can be performed offline using high-performance computing machines [20]. By using findings from research on task-oriented model separation from pre-trained CNN models, we can create heterogeneous submodels tailored to each mobile device [21]. Convolutional Neural Networks (CNN) are becoming the predominant standard in image recognition [22]. CNNs have been instrumental in object detection and classification due to their high efficiency.

Fuzzy clustering avoids forcing an object to belong exclusively to one of the classes at the boundary between two categories. Instead, it assigns a membership degree within a range of 0 to 1 to indicate partial affiliation [14]. The image preprocessing stage plays a crucial role in extracting valuable information from images, as this process ensures that images used under normal conditions can be processed properly [7]. Since the extracted feature is of first order, an initial process is required, typically done in grayscale image processing to simplify the image.

This is a manual approach to tracing a contour based on a series of manually selected points on the visually identified boundary, creating a path that minimizes the sum of local costs. Its speed is due to the use of dynamic programming principles [18]. The color of the flower plays a significant role in image classification, as it provides additional information in terms of segmentation and recognition [13]. Color properties of flower images are used in the HSV color space. Individual features of the HSV color space (hue, saturation, and value) have been evaluated. Pixel features are obtained by considering the variation in visual perception of pixel hue, saturation, and intensity values [17]. The clarity of the images regarding pixels must also be considered, as more pixels provide more information in the image.

D. *Convolutional Neural Networks on Mobile Devices*

Given the limited computational resources, mobile devices can hardly meet the requirement of real-time inference processing based on modern Convolutional Neural Network (CNN) architectures, as inference time plays a crucial role in user experience. It is essential to propose effective acceleration methods for mobile devices [23]. When performing convolution operations, it is essential to ensure that the overall image features are not lost and that the network depth meets the requirements for abstract feature extraction [24]. During research and fieldwork, a computer is not always available, and it is not the most portable option. Hence, studies have been conducted to show that even with the processing limitations of mobile devices, CNN can be used through cloud computing.

These high-performance models have considerable space and calculation complexity due to millions of parameters and mathematical operations. These requirements make the implementation of deep learning models on mobile devices with limited resources challenging. To address this situation, only a small number of studies have proposed knowledge distillation-based approaches and patch-based models to obtain compact CNN models designed for mobile eye recognition [25]. Intelligent applications for mobile devices are widely prevalent today. These applications continue to collect new and sensitive data from various users, while they are expected to constantly adjust the embedded machine learning model as these recent data are collected [21]. The use of mobile devices has become indispensable nowadays, and hence, it is expected to efficiently use CNN.

Specifically, a conscious partition of the network is performed for CNN computation between the mobile device and the cloud to minimize latency. During the inference process, typically, three stages are developed, including local inference of the surface layers on the mobile device, wireless transmission, and data transmission optimization [23]. CNN-based approaches often employ constant-sized image fragments, which restrict the shapes of inputs to the subsequent steps [15]. However, using CNN on mobile devices is not always the best option for processing since they need to be connected to the cloud, requiring a stable internet connection.

To achieve intelligence on devices, there are two common approaches in terms of where computation is performed: (I) a cloud-based solution that uploads data to the cloud and then receives results; (II) local computation, processed through a local computation engine [20]. The process begins by training a machine learning model using a dataset and running the corresponding algorithm. Then, a test is performed to evaluate the algorithm's accuracy. Next, the results are examined, and confusion matrices are generated. Finally, a system performance analysis is conducted [11]. The most challenging and time-consuming part is training the network by selecting images, which must be done image by image consecutively.

To reduce inference time without compromising recognition accuracy, cloud capacity has been used to support the execution of Convolutional Neural Networks (CNN) on mobile devices [23]. There are three significant vulnerabilities in the cloud-based solution, which encompass latency, privacy, and energy consumption. In the cloud-based solution, data needs to be transmitted to or from the cloud, depending on the network environment, which could lead to data leaks during data transfer. Moreover, inference conducted in the cloud consumes over twice the energy compared to local mobile device processing [20]. Two solutions were concluded regarding the use of CNN on mobile devices: utilizing the device's internal resources, which does not require it to be high-end for quality processing, or using the cloud, which requires a stable and interference-free internet connection throughout communication for image processing. Both solutions have their advantages and difficulties, and these must be considered when working in the field.

In recent times, deep learning has gained widespread acceptance in various application contexts, ranging from image recognition to text translation [26]. Each mobile device has the capability to mix feature-extracting layers and individual or multiple context-sensitive layers, selected based on their processing capacity and local heterogeneous tasks [21]. CNN, short for Convolutional Neural Networks, is a category within neural networks that has at least one convolutional layer. This layer combines two mathematical functions to generate a third. Its primary application is in image classification [27]. Creating a mathematical model is also necessary to consider variables and decisions when training the network.

To implement a deep Convolutional Neural Network on a mobile device, it is necessary to reduce the model size to avoid heavy storage usage in the system. Also, it is necessary to reduce the computational complexity due to limited computing capability on mobile devices [20]. In 2016, Yuanyuan Liu and colleagues explored a method for classifying 79 flower categories using a CNN. However, they achieved an accuracy of 76.54% with their model, while a simple CNN achieved an accuracy of 70.12%. Furthermore, when applying their model to the Oxford 102 Flowers dataset, accuracy increased to 84.02% [4]. The importance of keeping our research in the cloud is that we can combine our samples with samples from other research to achieve a higher rate of accuracy.

An additional challenge is the availability of numerous encyclopedias and manuals that allow the identification of the genus and species of local and regional floras. However, there is no unified system for classifying all plants worldwide. Although some systems have been created for plant data recognition and management, the lack of a single methodology persists [16]. Many image processing applications use the Fuzzy C-Means (FCM) method for segmentation processes, such as breast cancer detection, pest analysis, and other preliminary stages in image processing [14]. Throughout the research, various image detection methods have been studied, and all of them aid. However, focusing on a single method requires a detailed study of the variables.

E. Applied Techniques and Instruments

The techniques we will be addressing in the research are computer vision and artificial intelligence. The main tool to be used is the RoboFlow platform. RoboFlow is a computer vision platform that, if we have internet access, we will have access to. This platform allows us to leverage the YOLO algorithm, which will be used for the detection and classification of objects.

The choice of the YOLO algorithm is because it has the capability to perform object detection and classification, providing us with the efficiency we seek for the classification of types of orchids.

IV. Methodologic

The focus of this research centers on the automation of object classification processes through the training of a convolutional neural network (CNN). Due to the main characteristics of the research, a mixed approach is concluded, taking quantitative features as a starting point. As a neural network working with artificial intelligence, it operates on mathematical principles to perform specific analyses. Based on these principles, we conduct statistics to compare the results obtained in percentage form. The samples, obtained independently, form the database where we are identifying specific characteristics outlined in the form of hypotheses to control the expected data, encompassing the qualitative features of the research.

A. *Techniques and instruments applied.*

The techniques we will be addressing in the research are computer vision and artificial intelligence. The main tool to be used is the RoboFlow platform. RoboFlow is a computer vision platform that, if we have internet access, provides us with the ability to leverage the YOLO algorithm, which will be used for object detection and classification.

The choice of the YOLO algorithm is because it has the capability to perform object detection and classification, providing the efficiency we seek for the classification of orchid types.

The main materials for the development of the project scope consist primarily of a computer with internet access, as the database operates on an online server. Additionally, a camera with a connection to a microcontroller capable of executing Python commands is required. The microcontroller can be external, for example, a Raspberry Pi, or it can be the one included in mobile phones through pre-prepared software for its operation. Furthermore, #22-gauge cables are needed to make the relevant connections.

B. *Study Methodology*

The following section addresses the steps to develop the intelligent system for the detection and classification of orchids. The methodology employed was the incremental model, in which seven increments were proposed, each with its respective analysis and corrections to achieve a higher percentage in the defined study metrics. The use of this specific model is crucial in CNN training because, with each increment, artificial intelligence learns from each annotation, evolving to obtain better metric percentages. The following image depicts the diagram proposed by Harlan Mills of the incremental model with its specific characteristics in each increment.

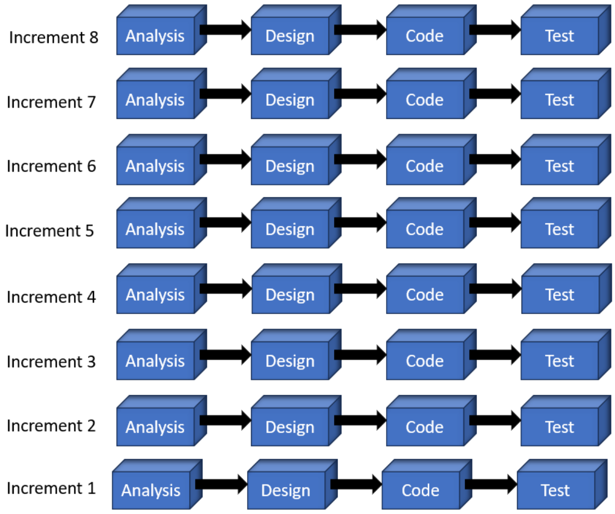


Fig. 2. First Increment.

On the first increment, was developed Phalaenopsis detection, the second increment, was developed Spathoglottis detection, the third increment, was developed Miltonia detection, on the fourth increment, was developed Phalaenopis + Spathoglottis + Miltonia, on the fifth increment, was developed Phalaenopis + Spathoglottis + Miltonia + Labellum + new images, the sixth increment, was developed Phalaenopis + Spathoglottis + Miltonia, the seventh increment, was developed Phalaenopis + Spathoglottis + Miltonia with YOLOv8, on the eighth increment, was developed Phalaenopis + Spathoglottis + Miltonia + new images with YOLOv8.

1) *Image Sample Preparation*

The preliminary preparation of sample images is of utmost importance in the development of the research, as the entire process begins with the analysis of these images. The collection of images is obtained independently in .jpg format, and they are captured in HD quality. Primarily, the obtained images encompass three specific regions of the country, starting mainly in San Pedro Sula due to its being the current residential area. It continues with Siguatepeque, which represents the central region of the country, considering its high concentration of nurseries due to its humid climate. As the third zone, Ocotepeque represents the western region of the country.

2) *Image processing*

The processing of images is a crucial stage in the development of the research. To carry out this task, the RoboFlow tool was utilized with the YOLO algorithm. The following are the steps to perform this processing:

Image uploading.
Image tagging.
Image processing.

The way annotations were carried out on the RoboFlow platform is depicted in Figure 10, where the labeling of the Miltonia species is shown. This method was used to label the other orchid species.

Fig. 10. Eighth Increment.

Link dataset: https://app.roboflow.com/fase11-wtxk0/fase-1.6/11

3) *Evaluation metrics*

In this section, the evaluation metrics used and provided by the RoboFlow platform are specified, presented in charts for easy comprehension. The metrics include the mean Average Precision (mAP), Box Loss, Class Loss, Object Loss, Precision, and the percentage of correctly identified annotations (Recall).

Mean Average Precision (mAP): This metric is used to measure the performance of computer vision and is calculated by jointly evaluating Recall and Precision. When assessing the quality of model detections, we typically compare them to ground truth and categorize them into four groups. A case where the model correctly detects an object is called True Positive (TP). When an object is found that is not actually in the image, it is a False Positive (FP). On the other hand, when an object in the ground truth is not detected, it is a False Negative (FN). The last group is formed by True Negatives (TN), but in the case of object detection, it is not considered. It can be interpreted as all correctly undetected objects: the background (MAY 6 & Read, 2020). The four groups form the confusion matrix, illustrated below:

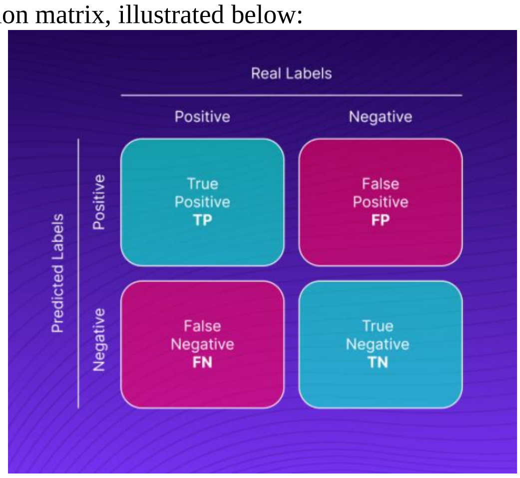


Fig. 11. Confusion matrix.

From the confusion matrix, we can conclude two equations:

Precision= TP/(TP+FP), Precision is a measure of how often your model makes a prediction, and how often it is correct.

Recall= TP/(TP+FN), Recall is a measure of how often your model has correctly predicted when it should have.

Box Loss: This metric evaluates how accurate the bounding box of the annotation is and its location.

Class Loss: This metric assesses the model's accuracy in assigning the correct class annotations in detections.

Object Loss: This metric evaluates the model's accuracy in detecting objects in the image.

All these metrics are of great importance when evaluating the results obtained from each training version. The following images provide an example of the evaluation of these metrics:

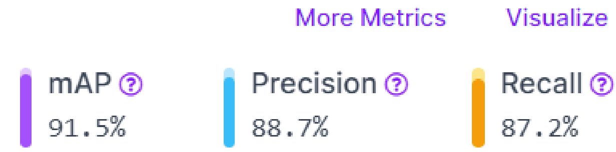


Fig. 12. Evaluation metrics.

The metrics that encompass Box Loss, Class Loss, and Object Loss are presented in graphs that depict the starting percentage and how it evolves throughout the training until reaching the percentage when the training has concluded, as shown in the following image:

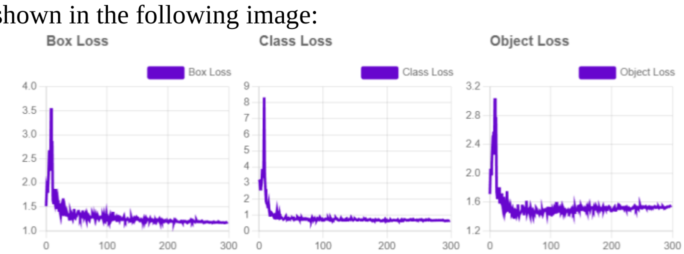


Fig. 13. Graphs of the metrics

V. Results

In this section, the results obtained from the RoboFlow platform are presented and analyzed from the first increment to the seventh increment. It illustrates how characteristics were modified throughout these increments to achieve improved outcomes.

A. *Results Obtained*

The research, using the incremental methodology, was conducted in eight significant increments, which were adjusted to achieve the highest mAP metric percentage. Considering that the percentage would always surpass ninety percent, taking into account the labeling method, which features to label, types of augmentation to use, image format, among other adjustments made, we reached the final increment, achieving a 93.7% in the mAP metric, which was satisfactory for the research as it met the initial requirements of obtaining a percentage greater than ninety percent and using a minimum of 2,000 images.

1) *First Increment*

In the first increment, the focus was on one of the three categories of orchids, specifically the Phalaenopsis. The percentages obtained in the specific metrics were mAP: 90.8%, Precision: 90.1%, and Recall: 83.0%, which were satisfactory, especially the mAP percentage, which is the average precision, being higher than 90%.

Fig. 14. First increment percentage.

As an initial method, since it is the first increment, only one of the categories was chosen to maximize precision and reduce potential issues in the network for categorization. This approach was used for the first three increments, each focusing on a different category. Once each category was individually categorized, the network could be trained with all categories together, thereby increasing the percentage in the metrics from the initial increment. The following graphs depict the metrics for the first increment, focusing on only one category.

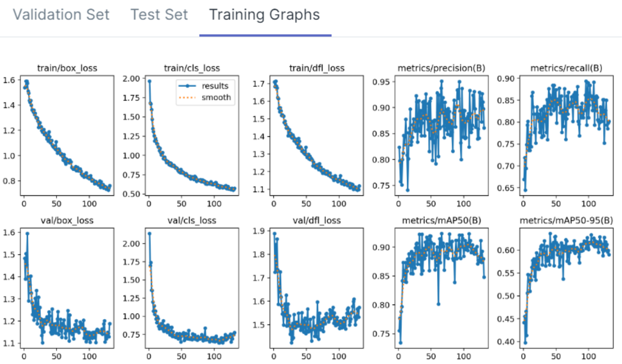


Fig. 15. Graph of results for the first increment.

Analyzing the graphs, positive trends are observed in the Box Loss, Class Loss, and Object Loss graphs, which show a descending trend approaching zero.

2) Last Increment

In the last increment, the decision was made to carry out the training with the YOLOv8 algorithm in Python due to the satisfactory percentages obtained in the previous increment. By using YOLOv8, better results were expected. This option was not chosen in earlier increments because it was anticipated to achieve highly satisfactory percentages on the RoboFlow platform before transitioning to YOLOv8. As the final increment, the goal was to specifically increase the percentage of the Precision metric. This involved continuing training with the YOLOv8 algorithm in Python and adding new images from all three categories. Unexpectedly, the mAP metric dropped to 93.7%, which was not a drastic change but was unexpected when compared to the anticipated increase in the Precision metric, which reached 93.4%. In the case of Recall, there was a slight increase to 88.5%. Analyzing the final graphs of the Box Loss, Object Loss, and Class Loss metrics compared to the fourth increment, which was the first with all three categories together, the expected trend of smoothing the descent towards zero was achieved without as much percentage jump, as detailed in the following illustration.

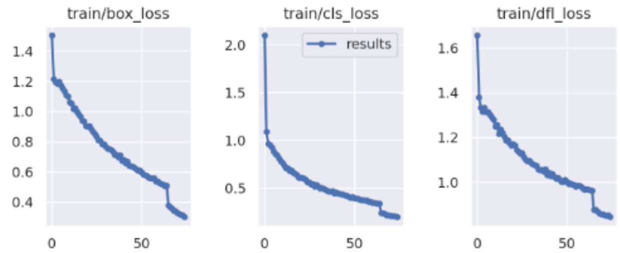
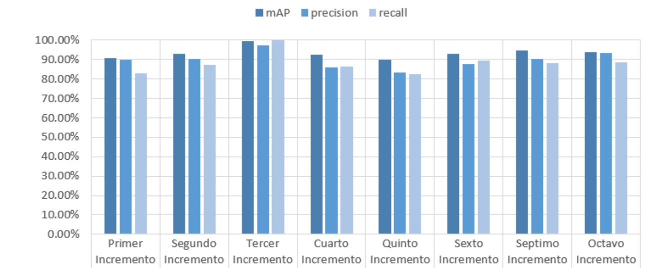


Fig. 16. Graph of results for the last increment.

B. *Comparison of Results*

Throughout the course of the research, corrections and changes were made based on the results obtained, following the incremental model process. A satisfactory percentage was achieved in the eighth increment, now applying the YOLOv8 algorithm. The following illustration compares the percentages of each increment throughout the research.



	Primer Incremento	Segundo Incremento	Tercer Incremento	Cuarto Incremento	Quinto Incremento	Sexto Incremento	Septimo Incremento	Octavo Incremento
mAP	90.80%	93.00%	99.50%	92.70%	90.00%	92.90%	94.60%	93.70%
precision	90.10%	90.40%	97.40%	85.90%	83.40%	87.80%	90.30%	93.40%
recall	83.00%	87.40%	100.00%	86.50%	82.50%	89.60%	88.10%	88.50%

Fig. 17. Comparison of results obtained.

VI. Conclusions

This research represents an advancement in the detection and classification of objects through the training of artificial intelligence accompanied by a neural network, as these are not firmly established in the field of flowers. Throughout the course of the research, a convolutional neural network was successfully designed, implemented, and trained with the aim of detecting and classifying three types of native orchids in Honduras. Using the RoboFlow tool and the YOLOv8 algorithm, categories of Phalaenopsis, Spathoglottis, and Miltonia were successfully detected, which are three of the most well-known orchid variants prevalent in our territory.

A dataset of 2189 images was created on the RoboFlow platform, containing images of the three types of orchids under study. The images were collected from three different zones in the country, including the northern zone with San Pedro Sula, the central zone with Siguatepeque, and the western zone with Ocotepeque, to cover a large part of the national territory and conduct a more comprehensive investigation.

With the use of the YOLOv8 algorithm in Python, the percentages obtained in the metrics established by the RoboFlow platform were improved, achieving satisfactory results that conclude the successful training of the convolutional neural network for specific detection and classification, based on the analysis of sample images.

The percentage obtained in the last increment was very satisfactory with respect to the initial objectives. A detection accuracy average of 93.7% was achieved for each image using the YOLOv8 algorithm in Python. This was an improvement over the previous results obtained without the use of YOLOv8 on the RoboFlow platform, which had an average detection accuracy of 92.9% for each image. With this percentage, it was concluded that the convolutional neural network had a more than acceptable accuracy for the detection and classification of orchids.

VII. Recommendations

It is necessary to highlight certain recommendations for those considering using the research as a basis or simply for information gathering.

Data Augmentation:

Increase the orchid categories; the research focused on only three different categories due to the workload involved in training an extensive network. By increasing the number of categories, the network can detect, it can become more robust, considering the vast number of orchid variants makes this a viable option.

Add more images of these categories to achieve an increase in accuracy. Although accuracy depends not only on the quantity of images but also on how labeling is done and factors such as brightness, exposure, image quality, and even image size are considered. However, by adding more images while taking all these factors into account, there is a possibility of increasing accuracy.

Expand the sampling collection zones to cover not only three zones in the country but also reach lesser-known areas to analyze a greater variety of flower variants.

Applicability:

The original applicability studied is to use the software on mobile devices or microcontroller components designed for this purpose. Due to the way the training was conducted to achieve accurate detection, one must be close to the flower. By improving the camera quality for analysis and proposing a different analysis approach, not only focusing on the main feature of the lip, but it may also be possible to achieve detection from a greater distance and not necessarily with the flower at a specific frontal angle.

References

[1] Akiyama, T., Kobayashi, Y., Sasaki, Y., Sasaki, K., Kawaguchi, T., & Kishigami, J. (2019). Mobile Leaf Identification System using CNN applied to plants in Hokkaido. 2019 IEEE 8th Global Conference on Consumer Electronics (GCCE), 324-325. https://doi.org/10.1109/GCCE46687.2019.9015298

[2] Alipour, N., Tarkhaneh, O., Awrangjeb, M., & Tian, H. (2021). Flower Image Classification Using Deep Convolutional Neural Network. 2021 7th International Conference on Web Research (ICWR), 1-4. https://doi.org/10.1109/ICWR51868.2021.9443129

[3] Almadan, A., & Rattani, A. (2021). Compact CNN Models for On-device Ocular-based User Recognition in Mobile Devices. 2021 IEEE Symposium Series on Computational Intelligence (SSCI), 1-7. https://doi.org/10.1109/SSCI50451.2021.9660033

[4] Apriyanti, D. H., Arymurthy, A. M., & Handoko, L. T. (2013). Identification of orchid species using content-based flower image retrieval. 2013 International Conference on Computer, Control, Informatics and Its Applications (IC3INA), 53-57. https://doi.org/10.1109/IC3INA.2013.6819148

[5] Chen, C.-F., Lee, G. G., Sritapan, V., & Lin, C.-Y. (2016). Deep Convolutional Neural Network on iOS Mobile Devices. 2016 IEEE International Workshop on Signal Processing Systems (SiPS), 130-135. https://doi.org/10.1109/SiPS.2016.31

[6] Cho, S.-Y. (2012). Content-based structural recognition for flower image classification. 2012 7th IEEE Conference on Industrial Electronics and Applications (ICIEA), 541-546. https://doi.org/10.1109/ICIEA.2012.6360787

[7] Cho, S.-Y., & Lim, P.-T. (2006). A novel Virus Infection Clustering for Flower Images Identification. 18th International Conference on Pattern Recognition (ICPR'06), 2, 1038-1041. https://doi.org/10.1109/ICPR.2006.144

[8] Dai, X., Spasić, I., Meyer, B., Chapman, S., & Andres, F. (2019). Machine Learning on Mobile: An On-device Inference App for Skin Cancer Detection. 2019 Fourth International Conference on Fog and Mobile Edge Computing (FMEC), 301-305. https://doi.org/10.1109/FMEC.2019.8795362

[9] Deepika, K., Ruth, I., Keerthana, S., Sathya Bama, B., Avvailakshmi, S., & Vidhya, A. (2012). Robust plant recognition using Graph cut based flower segmentation and PHOG based feature extraction. 2012 International Conference on Machine Vision and Image Processing (MVIP), 44-47. https://doi.org/10.1109/MVIP.2012.6428757

[10] Do, T.-B., Nguyen, H.-H., Nguyen, T.-T.-N., Vu, H., Tran, T.-T.-H., & Le, T.-L. (2017). Plant identification using score-based fusion of multi-organ images. 2017 9th International Conference on Knowledge and Systems Engineering (KSE), 191-196. https://doi.org/10.1109/KSE.2017.8119457

[11] Gai, Y., Fan, W., Xu, X., & Zhang, Y. (2011). Flower species identification and coverage estimation based on hyperspectral remote sensing data. 2011 IEEE International Geoscience and Remote Sensing Symposium, 1243-1246. https://doi.org/10.1109/IGARSS.2011.6049424

[12] He, A., & Tian, X. (2016). Multi-organ plant identification with multi-column deep convolutional neural networks. 2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 002020-002025. https://doi.org/10.1109/SMC.2016.7844537

[13] He, X., & Chen, Y. (2019). Optimized Input for CNN-Based Hyperspectral Image Classification Using Spatial Transformer Network. IEEE Geoscience and Remote Sensing Letters, 16(12), 1884-1888. https://doi.org/10.1109/LGRS.2019.2911322

[14] Hu, F., Yao, F., & Pu, C. (2020). Learning Salient Features for Flower Classification Using Convolutional Neural Network. 2020 IEEE International Conference on Artificial Intelligence and Information Systems (ICAIIS), 476-479. https://doi.org/10.1109/ICAIIS49377.2020.9194931

[15] Islam, S., Ahmed Foysal, Md. F., & Jahan, N. (2020). A Computer Vision Approach to Classify Local Flower using Convolutional Neural Network. 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), 1200-1204. https://doi.org/10.1109/ICICCS48265.2020.9121143

[16] Jain, V., & Yadav, A. (2021). Analysis of Performance of Machine Learning Algorithms in Detection of Flowers. 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), 706-709. https://doi.org/10.1109/ICICV50876.2021.9388599

[17] Koolwal, D., Jain, P. K., & Agarwal, A. (2016). Computer Vision Based Overlapped Flowers Detection. Proceedings of the International Conference on Advances in Information Communication Technology & Computing, 1-4. https://doi.org/10.1145/2979779.2979857

[18] Kumar, V. (2023). Implementation of wireless hardware system for used in agriculture irrigation process. AIP Conference Proceedings, 2721(1), 070035. https://doi.org/10.1063/5.0154078

[19] Liu, X., Wang, H., Jing, H., Shao, A., & Wang, L. (2020). Research on Intelligent Identification of Rock Types Based on Faster R-CNN Method. IEEE Access, 8, 21804-21812. https://doi.org/10.1109/ACCESS.2020.2968515

[20] Nithin, M. S., Shaik, A., Balasundaram, A., Surya Deveswar Reddy, K. U., Ram kakarla, L. S., & Selvakumar, A. (2022). Transfer Learning Based Effective Approach for Classification of Flowers. 2022 1st International Conference on Computational Science and Technology (ICCST), 316-320. https://doi.org/10.1109/ICCST55948.2022.10040338

[21] Pawar, S., Raj, W., Bibikar, S., Patil, B., Kumari, S., & Patil, A. (2022). Identification of Flowers using Machine Learning. 2022 International

Conference on Innovations in Science and Technology for Sustainable Development (ICISTSD), 42-47. https://doi.org/10.1109/ICISTSD55159.2022.10010418

[22] Pei, Y., Huang, Y., Zou, Q., Zhang, X., & Wang, S. (2021). Effects of Image Degradation and Degradation Removal to CNN-Based Image Classification. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(4), 1239-1253. https://doi.org/10.1109/TPAMI.2019.2950923

[23] Pramadi, F. P., Atika Sari, C., Rachmawanto, E. H., & Rosal Ignatius Moses Setiadi, D. (2020). Flowers Identification using First-order Feature Extraction and Multi-SVM Classifier. 2020 International Seminar on Application for Technology of Information and Communication (iSemantic), 22-27. https://doi.org/10.1109/iSemantic50169.2020.9234260

[24] Qin, Z., & Jiang, H. (2020). Towards Context-aware Distributed Learning for CNN in Mobile Applications. 2020 IEEE/ACM Symposium on Edge Computing (SEC), 320-320. https://doi.org/10.1109/SEC50012.2020.00045

[25] Rezaei, S., Kroencke, B., & Liu, X. (2020). Large-Scale Mobile App Identification Using Deep Learning. IEEE Access, 8, 348-362. https://doi.org/10.1109/ACCESS.2019.2962018

[26] Sabri, N., Ibrahim, Z., & Rosman, N. N. (2016). K-means vs. Fuzzy C-means for segmentation of orchid flowers. 2016 7th IEEE Control and System Graduate Research Colloquium (ICSGRC), 82-86. https://doi.org/10.1109/ICSGRC.2016.7813306

[27] Saitoh, T., Aoki, K., & Kaneko, T. (2004). Automatic recognition of blooming flowers. Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004., 1, 27-30 Vol.1. https://doi.org/10.1109/ICPR.2004.1333997