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# Decorative Wreaths Assessment Using a Deep Learning Approach

## Evaluación de Coronas Decorativas utilizando un Enfoque de Deep Learning

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***Abstract*—** The floriculture industry is an increasing sector in Baja California, that exports most of its production. Products like decorative wreaths depend mainly on human inspection, which has often been prone to human errors and challenges in meeting the quality criteria. Implementing advanced technologies and automated inspection methods in floriculture, aiming to eradicate human errors, seems to contribute to minimizing defective products and ensuring compliance with quality standards and export regulations. In this paper, we assess the YOLO implementation, a deep learning approach, in the defect identification process. Results show that accuracy ranges from 48.4% to 81.3% and MaP from 53.2% to 87.6% using ten epochs. This paper provides valuable evidence for future studies and implementations regarding deep learning approaches used to evaluate the visual characteristics in the floriculture industry.

***Keywords*—**Floriculture, YOLO, deep learning. Accuracy, Precision, Recall, MaP.

***Resumen*—**La industria de la floricultura es un sector en crecimiento en Baja California, que exporta la mayor parte de su producción. Los productos como las coronas decorativas dependen principalmente de la inspección humana, que a menudo ha sido propensa a errores humanos y desafíos para cumplir con los criterios de calidad. La implementación de tecnologías y métodos de inspección automatizados en la floricultura para reducir los errores humanos, parece contribuir a minimizar los productos defectuosos y garantizar el cumplimiento de los estándares de calidad y las normas de exportación. En este artículo, evaluamos la implementación de YOLO, un enfoque de aprendizaje profundo, en el proceso de identificación de defectos. Los resultados muestran que la precisión varía del 48.4 % al 81.3 % y el MaP del 53.2 % al 87.6% utilizando diez épocas. Este documento proporciona evidencia valiosa para futuros estudios e implementaciones con respecto a los enfoques de aprendizaje profundo utilizados para evaluar las características visuales en la industria de la floricultura.

***Palabras Claves*—**Floricultura, YOLO, aprendizaje profundo, exactitud, precisión, Recall, MaP.

## I. INTRODUCTION

Mexican floriculture is a tradition and an important activity that generates over 250,000 direct jobs and nearly one million indirect jobs. Additionally, 60 % of its production is carried out by female hands. Twenty percent of the national flower production is destined for export. Mexico has embarked on its path to the global flower market, which is valued at around 44 billion US dollars annually [1].

Floriculture is a discipline that involves the industrial cultivation of various types of flowers and ornamental plants. Over the years, this activity has become one of the most profitable within the agricultural sector, as it generates significant economic benefits due to the demand in both domestic and international markets [2].

It is worth noting that floriculture products are not exclusively cut flowers but rather a range of related products, including live plants, bulbs, onions, tubers, tuberous roots, shoots, and rhizomes, as well as cuttings and grafts, flowers and buds (cut for bouquets or decorations, fresh, dried, bleached, dyed, impregnated, or prepared in other ways), foliage, leaves, branches, and other plant parts without flowers or buds, as well as herbs, mosses, and lichens, for fresh bouquets or decorations. To simplify the harmonized international trade system, this category is expressed as live plants and floriculture products [3].

Traditionally, plant disease detection has heavily relied on human inspection, where experts visually examine plants for signs of disease. However, this manual approach can be time-consuming, subjective, and limited by the expertise of the individual inspector. Recently, a growing interest has been in utilizing deep learning techniques for automated plant disease detection.

Countries like India rely heavily on agriculture, which is crucial for its economy, as it employs 70% of the population [4]. However, when plants become diseased, their yield is significantly reduced. Unfortunately, the detection of plant diseases is often delayed, leading to decreased yield and even plant mortality. Manual detection of diseases by experts over vast acres of land requires a large number of specialists, resulting in higher production costs. Typically, plant diseases manifest in various parts such as leaves, stems, flowers, and fruits. Detecting diseases on the leaves is comparatively easier than on other parts like stems, flowers, or fruits, as symptoms usually appear first on the leaves. The effectiveness of a classifier depends on the feature extraction algorithm used. Hence, it is crucial to develop an automated tool for leaf detection that can identify the specific type of disease; recent advancements in deep learning algorithms have significantly improved the accuracy of plant disease classification [4].

While human inspection still plays a role in certain cases, the integration of deep learning algorithms offers several advantages. It provides a faster and more objective approach to detect and diagnose plant diseases, potentially saving time and resources. However, it is important to note that the combination of human expertise and deep learning algorithms can lead to even more robust and accurate disease detection systems. Ongoing research in this area aims to optimize the integration of human inspection and deep learning to further enhance plant disease management practices.

## II. RELATED WORK

In most cases, quality inspection involves a human operator inspecting the product to determine its compliance. However, the accuracy and reliability of inspection often prove unsatisfactory [5]. Literature shows that the accuracy of correctly rejecting precision-manufactured parts by human operators is close to 85%, while the industry average is close to 80% [6]. Similarly, operator errors accounted for 23% of inaccuracies in quality control in the oil and gas industry [7].

Non-destructive testing (NDT) methods in low-capacity, high-consequence production operations, such as the assembly and disassembly of nuclear weapons, heavily rely on human visual inspection. Upon receiving them from the manufacturer, cables, critical components, tools, and equipment used in these operations undergo some level of visual inspection before each use to verify their quality and functionality. Additionally, NDT methods such as radiography, magnetic particles, and liquid penetrant testing rely on human-performed visual inspection [8].

An important type of quality inspection in manufacturing is visual inspection. Operators visually assess the product's condition at different stages and decide whether it can proceed to the next process [5]. The literature also mentions the advantages of implementing visual inspection, including reducing labor costs, eliminating human error during subjective judgment, and creating real-time visualized product data for documentation, traceability, and labeling [9].

Some evidence suggests that deep learning techniques surpass human inspection of grapevines [10]. There is such a large gap in performance between humans, the baseline system, and deep learning that an in-depth statistical analysis is not needed. It is obvious that there is a significant difference. Human recognition does not meet the minimum expectations for a production-level system (two sigma levels of performance) and supports the adage that it is hard to recognize grapevine yellow (as a defect) from sight [10].

These findings shed light on the limitations of relying solely on human inspection for quality control purposes. The results indicate that human operators, despite their expertise, can introduce errors and inconsistencies into the inspection process, potentially compromising the overall quality of the products. As such, the development and implementation of automated inspection systems, such as computer vision and artificial intelligence algorithms, hold promise for enhancing inspection accuracy and reducing human-induced errors. By leveraging these technologies, manufacturers can improve quality control practices and ensure the delivery of products that meet or exceed established standards.

In recent years, the development of AI techniques has been increased. Regarding inspection purposes, Table 1 shows two studies presenting the main architectures used including ResNet101, ResNet50, VGG19, VGG16, AlexNet, SSD, Faster-RCNN, YOLOv4, YOLOv5, and Apple-Net. These studies centered on the classification of various characteristics including color, volume or density, shape, texture, color, and shape. The objects of investigation encompassed a diverse range of agricultural products, such as apples and cornweeds. In the context of this scholarly article, it is essential to explicate the precise definitions of the metrics. "Acc" represents accuracy, "P" signifies precision, "mAP" denotes mean average precision, and "R" stands for recall.

**Table 1**. Examples of deep learning architectures used in agroindustry.

| **Autor** | **Dataset** | **Feature** | **CNN** | **Acc (%)** | **P (%)** | **mAP (%)** | **R (%)** |
|---|---|---|---|---|---|---|---|
| Veeragandham et al [11] | Corn weed | Shape | ResNet101 | 98.33 | 98.35 | NR | 98.33 |
| | | | ResNet50 | 99.16 | 99.17 | NR | 99.16 |
| | | | VGG19 | 94.5 | 94.6 | NR | 94.5 |
| | | | VGG16 | 96.83 | 96.93 | NR | 96.83 |
| | | | AlexNet | 99 | 99.01 | NR | 99 |
| Zhu [12] | Apples leaf | Color and shape | SSD | NR | 86.2 | 86.5 | 88.7 |
| | | | Faster-RCNN | NR | 82.1 | 81.2 | 84.9 |
| | | | YOLOv4 | NR | 84.5 | 90.3 | 86.7 |
| | | | YOLOv5 | NR | 87.6 | 89.8 | 90.3 |
| | | | Apple-Net | NR | 93.1 | 95.9 | 94.4 |

## III. PROBLEM STATEMENT

Although human inspection remains relevant in specific scenarios, the incorporation of deep learning algorithms brings forth numerous benefits. By providing a faster and more objective method for detecting and diagnosing bad-quality products, the integration of deep learning algorithms has the potential to save time and resources. It is worth emphasizing that combining human expertise with deep learning algorithms can result in even more reliable and precise disease detection systems. Current research endeavors in this field are focused on optimizing the fusion of human inspection and deep learning to further enhance plant disease management practices.

Automated visual inspection using deep learning is widely used in recent years. In the field of agriculture, deep learning can be deployed to reduce effective manpower, best time utilization, and supreme classification with improved accuracy. In agriculture, DL can be imported into many applications like soil identification, disease classification, fruit grading and many more [7].

The primary objective of this study is to identify previous studies focusing on the comparison between human inspection and deep learning techniques in the realm of plant inspections. The aim is to identify and analyze a range of methodologies and their respective accuracy rates employed in the field. By doing so, the study seeks to shed light on the effectiveness and potential advantages of utilizing deep learning algorithms as compared to traditional human inspection methods. Through an examination of existing literature, this research endeavors to provide valuable insights and recommendations for enhancing the accuracy and efficiency of plant inspections in various floricultural contexts. Additionally, it delves into the adverse consequences associated with inadequate inspections. These consequences can include subpar product quality, financial losses due to rejected or returned shipments, non-compliance with export regulations (such as the exclusion of plants with seeds when exporting to the United States), and diminished customer satisfaction.

## IV. METHODOLOGY

### A. *Tools*

The tools employed in this project encompassed a highly capable computing system featuring an AMD Ryzen 5 4600H Radeon Graphics processor, running at a clock speed of 3.00 GHz, supplemented with a substantial 32 GB RAM. The operating system utilized was the 64-bit version of Windows. Additionally, a NVIDIA GeForce GTX1660 Ti graphics card was incorporated to enhance computational performance. To facilitate image capture, a Logitech C920 PRO HD WEBCAM was utilized, capable of capturing images at a resolution of 1920x1080 pixels.

It is worth emphasizing that the selection of these tools was made with careful consideration to ensure optimal performance and efficiency throughout the project. The utilization of a robust computing system, equipped with advanced components, aimed to leverage the capabilities of YOLOv8 effectively. The Logitech C920 PRO HD WEBCAM, renowned for its high-resolution imaging capabilities, was chosen to capture detailed images, thereby enhancing the accuracy and quality of the object detection process.

### *B. Dataset*

For the dataset, a total of 851 images were collected, specifically focusing on defective flower wreaths with the following defects: low foliage volume, missing material in sections, high foliage volume, correct piece, and brown wreath color. These images were captured on different days and at various times throughout the day to introduce variability and ensure the model's robustness when presented with diverse environmental conditions.

The deliberate inclusion of such variations in the dataset, encompassing different lighting conditions and temporal factors, introduced noise to the images. This intentional introduction of noise aimed to enhance the model's ability to adapt to real-world scenarios and improve its performance by training it on a more comprehensive and representative dataset.


**Fig. 1.** Example of the dataset created by our own source for the wreaths.

It is important to note that the incorporation of a diverse range of defects and the deliberate introduction of noise in the dataset were undertaken to bolster the model's capability to accurately detect and classify defective flower wreaths in a realistic setting. These considerations aimed to ensure the model's generalizability and effectiveness when applied to real-world scenarios beyond the controlled environment of the training dataset.

### *C. Metrics*

The performance metrics employed in this study encompassed precision, recall, and mean average precision (mAP). These metrics were utilized to assess and evaluate the effectiveness and accuracy of the object detection models.

*Accuracy*

The accuracy indicates the rate of correctly classified images out of all the images in a test set for a particular growth stage class, which shows the overall effectiveness of the classifier [13] see equation (1).

$$Accuracy = \frac{\sum correctly\ classified\ images}{\sum images} \quad (1)$$

Similarly, accuracy is also represented as the equation (2).

$$Accuracy = \frac{\sum_{i=1}^{k} \frac{TP_i+TN_i}{TP_i+TN_i+FP_i+FN_i}}{k} \quad (2)$$

Where k represents total class labels. TP, TN, FP, and FN are the numbers of the true positives, true negatives, false positives, and false negatives predictions for the considered class, respectively [14].

Another variant to estimate the accuracy is shown in the equation (3)

$$ACC = \frac{TP+TN}{P+N} \quad (3)$$

TN is the number of true negatives and TP is the number of true positives, N is the number of negative samples and P is the number of positive samples [10].

Finally, the accuracy formula shown in equation 4, represents the average percentage of images classified correctly in multi-class classification; which it is more important for a balanced dataset [11].

$$Accuracy = \frac{TN+TP}{TN+TP+FP+FN} \quad (4)$$

Regarding accuracy, this is considered the ratio of correctly labeled images to the total number of samples [15], showing the level of a model to predict the class of a prelabeled image [16], thus being the overall effectiveness of the classifier [17].

*Precision*

The precision represents the proportion of true positive images among all images predicted to be positive [13], and can be estimated such as in the equation (5).

$$Precision\ (GS) = \frac{\sum images\ with\ GS\ classified\ as\ GS}{\sum images\ classified\ as\ GS} \quad (5)$$

The equation (6) is also used by several studies to estimate the precision [10], [11], [15], [18], [19].

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

Where TP (true positive) indicates the number of correctly detected objects, FP (false positive) indicates the number of falsely detected objects [18]. Similarly, precision is also known as positive predictive value (PPV) using the same equation as in (6) [10].

Complementary definitions of precision include the average percentage of the actual positives and total positives [11], the probability given a positive label, how many of them are actually positive [15], or the performance of a model to predict the positive class [16]. Finally, precision is also considered the class agreement of the data labels with the positive labels defined by the classifier [17].

*Recall*

The recall represents the proportion of images predicted to be positive among the images that are true positive [13]. An utilized formula to estimate the recall is given in the equation (7).

$$Recall = \frac{TP}{TP+FN} \qquad (7)$$

Where TP (true positive) indicates the number of correctly detected objects; FP (false positive) indicates the number of falsely detected objects, and FN (false negative) indicates the number of missed objects [18].

Recall shows the average percentage of predicted positives and total actual positives, and it is highly recommended for the false negatives than the false positives [11]. Recall or Sensitivity is the accuracy of positively predicted instances describing how many were labeled correctly [15]. In addition, recall shows the degree of the model predicts the positive class when the actual class is positive [16].

Mean Average Precision ($mAP$)

The $mAP$ is defined as the average of the AP values for all categories [18]. The $mAP$, also known as the mean average precision, is commonly used to measure a model performance [19]. The formula of $mAP$ is shown in equation 8.

$$mAP = \frac{\sum_{i=1}^{K} P(i)\Delta R}{N} \qquad (8)$$

where $k$ indicates the number of samples in the test set, $P(i)$ is the size of the precision when i samples are recognized, ΔR(i) is the change of the recall rate when the detected samples change from i to i+1, and N is the number of categories in the multi-class detection task [20].

*D. Experimental strategy*

A partitioning scheme was employed for the training process, allocating 70% of the images for training and reserving the remaining 30% for validation purposes. During this stage, two architectures were explored, namely YOLOv5, and YOLOv8, to determine the most effective and accurate model for the given task.

Both YOLOv5 and YOLOv8 architectures were evaluated. These state-of-the-art object detection models are renowned for their exceptional accuracy and efficiency. These models excel at detecting objects in real-time scenarios by leveraging anchor-based detection and a carefully designed network structure.

The selection and evaluation of multiple architectures aimed to identify the most suitable model that could effectively handle the complexities of the dataset and deliver accurate and reliable object detection results. Extensive experimentation and analysis were conducted to determine the optimal architecture that would yield the highest performance on the given task.

It should be emphasized that the choice of these architectures was motivated by their track record of success in object detection tasks and their ability to handle a wide range of object classes effectively. By exploring multiple architectures, the training process aimed to identify the model with the best trade-off between accuracy, speed, and resource efficiency for the specific application.

## V. FIGURES AND TABLES

The detection performance of YOLOv8 is demonstrated in Figure 2, showcasing its ability to accurately detect classes such as brown color, void regions, and objects with low volume.

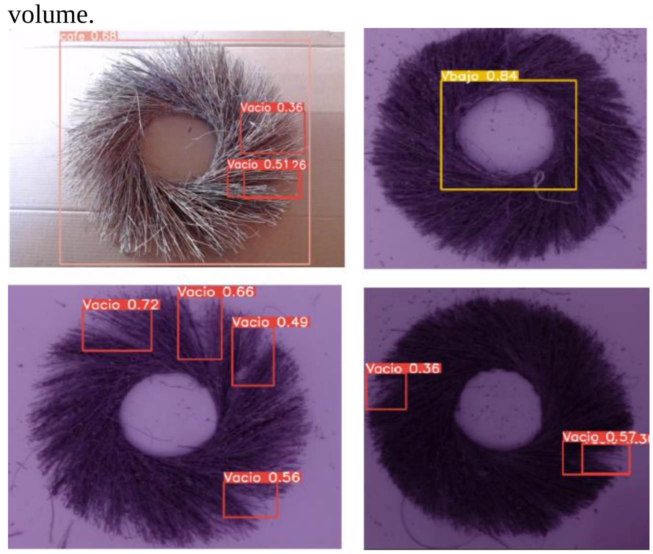


**Fig. 2.** Example of class detection using YOLOv8 with 10 epochs.

The detection performance of YOLOv5 is showcased in Figure 3, illustrating its ability to accurately identify classes such as green color and void regions, while exhibiting no detection of the low volume class.

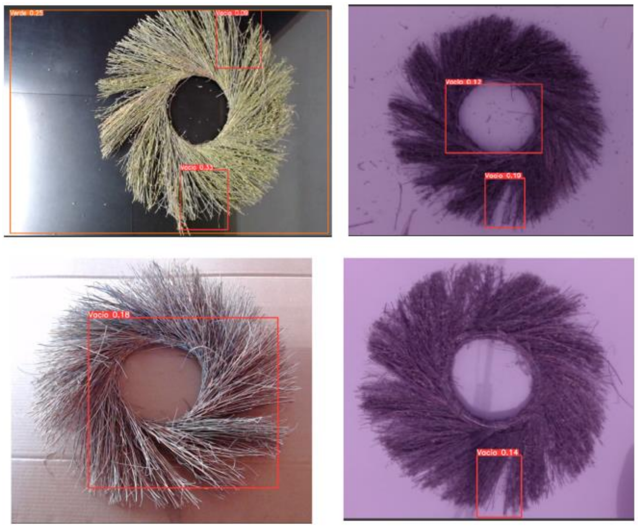

**Fig. 3.** Example of class detection using YOLOv5 with 10 epochs.

## VI. RESULTS

A comparative analysis of two employed architectures, namely YOLOv5 and YOLOv8, is depicted in Table 2. The precision results obtained were 48.4%, and 81.3% respectively. The YOLO models were trained to detect six distinct classes, enabling the identification of errors.

**Table 2.** Example of class detection using YOLOv5 with 10 epochs.

| Architecture | Dataset | Epochs | Precision | Recall | Map | Time (h) |
|---|---|---|---|---|---|---|
| YOLOv8 | 851 | 10 | 81.3 | 78.3 | 87.6 | 1 |
| YOLOv5 | 851 | 10 | 48.4 | 84.2 | 53.2 | 0.23 |

## VII. DISCUSSION

The obtained results indicate notable differences in performance between YOLOv8 and YOLOv5 architectures in terms of precision, recall, and mAP. When considering the precision metric, YOLOv8 achieved a significantly higher value of 81.3%, while YOLOv5 demonstrated a lower precision of 48.4%. This suggests that YOLOv8 exhibited better accuracy in correctly identifying and classifying the target objects compared to YOLOv5.

Regarding recall, YOLOv5 achieved a higher value of 84.2%, indicating its ability to effectively detect a larger proportion of the actual positive instances in the dataset. In contrast, YOLOv8 demonstrated a lower recall rate of 78.3%, implying that it may have missed some of the positive instances during the detection process.

The mAP (mean average precision) metric provides an overall assessment of the detection performance. YOLOv8 achieved a higher mAP value of 87.6%, indicating its ability to achieve a balance between precision and recall. On the other hand, YOLOv5 exhibited a lower mAP of 53.2%, suggesting a comparatively lower overall detection performance.

In terms of training time, YOLOv8 required 1 hour to complete the training process, while YOLOv5 demonstrated a significantly shorter training time of 0.23 hours. This implies that YOLOv5 offers faster training speed, which may be advantageous in scenarios where time efficiency is crucial.

Overall, the results suggest that YOLOv8 outperformed YOLOv5 in terms of precision and mAP, while YOLOv5 showed higher recall. The choice between these architectures should consider the specific requirements of the application, such as the trade-off between accuracy and detection speed. Further analysis and evaluation are recommended to validate and refine these findings.

## VIII.CONCLUSION

In conclusion, based on the comparison of the two architectures (YOLOv5 and YOLOv8) presented in Table 2, it can be observed that they exhibit varying levels of precision. YOLOv5 achieved a precision rate of 48.4%, while YOLOv8 achieved a higher precision rate of 81.3%. These architectures were trained to detect six different classes for error identification. These findings suggest that the choice of architecture depends on the specific requirements and objectives of the inspection task, considering the trade-off between precision and the number of classes to be detected. Further experimentation and evaluation are necessary to determine the most suitable architecture for a particular application in the context of visual inspection. It is important to note that for this type of inspection, training time is not a critical concern as it is typically conducted once for the given dataset. Finally, further research in this area is crucial to explore the potential of automated inspection systems and their integration into industrial settings for enhanced quality assurance.

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