Web Application of Convolutional Neural Networks with YOLOv8 for Early Detection of Diseases in Strawberry Crops

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Abstract--- In this research, we address a critical problem for strawberry growers in Lima: the management of phytosanitary diseases. Traditionally, these farmers relied on time-consuming, imprecise, and error-prone visual observation methods, resulting in annual production losses of 49.44%. We developed a comprehensive technological system based on convolutional neural networks (CNNs) using the YOLOv8 architecture, specifically designed to identify diseases such as powdery mildew, anthracnose, and gray mold, representing a significant shift toward precision agriculture methodologies. Our research was applied, with a quasi-experimental design and a quantitative approach. We worked with 474 high-resolution images of strawberry crops from 38 producers in Manchay Alto, Pachacamac district. Statistical analysis using SPSS version 27 with the Wilcoxon signed-rank test revealed statistically significant results ($p = 0.000$), achieving a very good technical accuracy of 96.74% (mAP@50) and remarkable system effectiveness, with 84.4% of cases reaching a high level. The system demonstrated superior performance compared to traditional inspection methods, facilitating timely disease detection and accurate diagnoses. Agronomic validation by local experts confirmed 91-94% accuracy for four locally present diseases, while identifying systematic false positives for three diseases not present under Lima's specific microclimatic conditions, revealing a critical gap between international training datasets and local disease prevalence that has significant implications for agricultural AI deployment in diverse agroclimatic regions.

Keywords--- convolutional neural networks, YOLOv8, strawberry crops, disease detection, computer vision, precision agriculture, domain adaptation

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1 Introduction

Here in Peru, and particularly in the fields around Lima, convolutional neural networks are completely changing the way we identify and manage crop diseases. These technologies offer solutions that significantly surpass traditional inspection methods. They allow for the identification of plant pathologies with an accuracy of nearly 94% [1], far exceeding manual inspections, which are characterized by subjectivity and human error [2].

The presence of pathogens significantly reduces the productive efficiency of strawberry crops. According to data provided by MIDAGRI [3], plantations with healthy plant material achieve yields of 40 tons per hectare, while those with infections barely produce half that amount. This problem not only affects harvested volumes but also their market value in the Peruvian context. Losses due to botrytis or rot can reach between 30% and 40% of national production [4].

Strawberry growers in Lima face multiple challenges in disease management. Traditional observational methods are not only time-consuming and resource-intensive, but also result in late and inaccurate diagnoses. In our experience, initial symptoms are frequently mistaken for other problems such as pest damage or nutritional deficiencies. This inefficient approach has contributed to alarming annual losses of 49.44% in strawberry production in Lima [5], jeopardizing both the growers' livelihoods and regional food security.

In this research, we propose implementing an innovative web system based on adaptive artificial intelligence architecture, specifically designed for the accurate and early detection of pathologies in strawberry crops through computerized image analysis. YOLOv8, as a cutting-edge computer vision technology, offers unique processing capabilities in agricultural environments characterized by variable conditions [6], allowing the dynamic evaluation of indicators such as lighting and leaf density.

The novelty of our approach lies in three key contributions: (1) the first deployment of YOLOv8 for strawberry disease detection in Peru's specific agroclimatic conditions, addressing a gap in the literature where YOLO-based systems have not been validated for Peruvian agriculture; (2) a comprehensive agronomic validation framework that bridges the gap between international training datasets and local disease prevalence, revealing that only 4 of 7 trained disease classes are relevant to Lima's microclimate; and (3) a complete web-based system validated through a quasi-experimental pre-test/post-test design with 38 real strawberry producers, demonstrating statistically significant improvements ($Z = -18.869$, $p < 0.001$) over traditional inspection methods. Unlike previous studies that focus exclusively on model performance metrics under laboratory conditions, our work evaluates the full deployment pipeline from training to field validation with end users.

2 Related works

2.1. Deep Learning for Plant Disease Detection

Efficient disease management in agricultural crops has been a critical factor in ensuring productivity, especially in regions with varying environmental challenges. Hussain et al. [7] investigated the use of deep learning methods to identify Chenopodium album in potato fields in Atlantic Canada, demonstrating that CNNs can process high-resolution images to classify invasive species with high accuracy, achieving 88% accuracy and 97% precision.

Automated visual inspection of crops has emerged as a key tool for meeting trade standards, optimizing the quality of agricultural products. Narciso Horna and Manzano Ramos [8] developed a CNN-based system to evaluate blueberries according to export criteria in Peru, highlighting its ability to identify quality characteristics in real time with 96.67% accuracy in quality classification.

The systematic analysis of crop diseases has consolidated the role of CNNs as an innovative methodology in agriculture. Iparraguirre-Villanueva and colleagues [9] conducted a comprehensive review on the detection of pathologies in rice at the national agricultural level, demonstrating that these networks offer a robust approach for image-based diagnosis, reporting average accuracies between 94% and 96% in different studies analyzed.

Shelar et al. [20] proposed a CNN-based model for identifying pathologies in diverse crops in India, highlighting its adaptability to different agricultural environments and achieving an accuracy of 95.6%. Similarly, Ning et al. [21] designed a convolutional network for detecting pathologies in rice from China, prioritizing precision, speed, and a lightweight design that facilitates implementation on portable devices, achieving 95% accuracy with a processing time of 18.2 ms per image.

2.2 YOLO Architectures Applied to Agriculture

The YOLO (You Only Look Once) family of architectures has gained significant traction in agricultural applications due to its real-time detection capabilities. Terven et al. [19] provided a comprehensive review of YOLO architectures from YOLOv1 to YOLOv8 and YOLO-NAS, documenting the evolution of these models and their increasing suitability for domain-specific applications including agriculture. Their analysis highlighted that YOLOv8 introduced the anchor-free decoupled head and the C2f module, which improved gradient flow and feature representation.

Fernandez Fernandez and Pinglo Cabezas [22] analyzed the use of CNNs for identifying diseases in rice crops, concluding that effectiveness depends on integration with specific contextual data, identifying precision ranges between 97% and 99% depending on dataset conditions. Furthermore, Radocaj et al. [14] presented a comprehensive review of transfer learning approaches in precision agriculture, demonstrating that pre-trained models can be effectively adapted to specific agricultural tasks with limited local data, which informed our methodology of using YOLOv8s pre-trained weights with domain-specific fine-tuning.

2.3 CNN Applications in the Peruvian and Latin American Context

In the Peruvian context, Lozada-Portilla et al. [23] implemented a CNN-based system to detect late blight caused by Phytophthora infestans in potato crops, achieving an accuracy of 90%, sensitivity of 83%, and specificity of 100%. This work demonstrated the viability of customizing CNNs for specific pathogens in Peruvian agricultural conditions. In Ecuador, Analuisa-Aroca et al. [24] employed the ResNet-50 architecture to identify weevils in maize, achieving 93% accuracy and 92% precision in detecting infestations, highlighting the need for specific datasets for local conditions.

Despite these advances, a significant gap exists in the literature regarding the application of YOLO-based architectures specifically for strawberry disease detection in Peru. Most existing studies focus on laboratory settings without field validation, and none address the critical issue of domain adaptation when international datasets are deployed in local agroclimatic conditions. Our work addresses this gap by providing both technical model evaluation and practical field validation with local expert agronomists.

3 Strawberry disease characteristics

3.1 Angular leafspot

According to Ellis et al. [15], Angular Leaf Spot, caused by the bacterium Xanthomonas fragariae, is characterized by water-soaked spots on the leaves with angular edges. As the infection progresses, the spots enlarge and turn brown. This disease weakens plants by reducing their photosynthetic capacity. In severe cases, it can decrease crop yield.

3.2 Anthracnose fruit rot

Ellis et al. [15] describe fruit anthracnose, caused by Colletotrichum acutatum, as a disease that primarily affects strawberry fruit. Symptoms include necrotic spots on the fruit that expand over time, causing decay. Disease development is favored by high humidity and warm temperatures.

3.3 Blossom blight

According to Ellis et al. [15], Blossom Blight, caused by Botrytis cinerea, affects strawberry flowers, causing rapid decay. Symptoms include wilting of the flowers, which turn brown and disintegrate. The infection progresses rapidly under conditions of high humidity and cool temperatures, affecting crop quality.

3.4 Gray mold

Ellis et al. [15] indicate that Gray Mold, also caused by Botrytis cinerea, affects both fruits and flowers. On fruits, it manifests as rapidly expanding gray spots, leading to decay. The disease develops in cool, damp conditions. It can be spread by airborne spores.

3.5 Leaf spot

According to Ellis et al. [15], Leaf Spot, caused by fungi such as Mycosphaerella fragariae, is characterized by brown to black spots that appear on the leaves. These spots affect the plant's photosynthetic capacity, weakening it and reducing fruit production.

3.6 Powdery mildew

Ellis et al. [15] indicate that powdery mildew on fruits and leaves, caused by Sphaerotheca macularis, appears as a whitish coating on fruits and leaves. This disease develops under conditions of high humidity and moderate temperatures, affecting commercial quality and reducing photosynthetic capacity.

4 Methodology

4.1 Research design

Our work adopted an applied research approach with a quasi-experimental design and quantitative methodology. According to Fomunyam [10], applied research is characterized by using scientific knowledge to solve specific problems. The quasi-experimental design is appropriate when random assignments cannot be made for ethical or practical reasons [11].

4.2 Population and Sample

The study population consisted of 474 images of strawberry crops from plantations belonging to 38 producers in Manchay Alto, Pachacamac district, Lima. We used a census sample, working with the entire available population. This decision is based on Otzen and Manterola [12], who indicate the importance of establishing specific criteria that define the characteristics of the elements that make up the study population.

It is important to clarify that the 474 images constitute the complete census of the study area and were used for field validation, not for model training. The YOLOv8 model was trained using a separate dataset of 988 images from the Roboflow platform (see Section V). The 474 field images represent approximately 12.5 images per producer, covering the full variability of real agricultural conditions in Manchay Alto. As a census study encompassing the totality of available strawberry producers in the zone, no sampling technique was required. Furthermore, with n = 474 observations, the Wilcoxon signed-rank test achieved extremely high statistical power (Z = -18.869), providing robust evidence for hypothesis testing.

4.3 Data collection instrument

The technique used was structured observation using an observation sheet specifically designed to evaluate the CNN system in identifying diseases in strawberry crops. This sheet consisted of 15 items organized into three dimensions: Model Accuracy (5 items), Model Performance (5 items), and Effectiveness (5 items). Each item used a graded scale from 1 to 5, with specific descriptions for each level to facilitate objective pre-test and post-test evaluation.

4.4 Experimental design: pre-test and post-test methodology

The quasi-experimental design followed a pre-test/post-test single-group structure. In the pre-test phase, each of the 474 images was evaluated using traditional visual inspection methods by agricultural technicians and producers, who completed the observation sheet based on their conventional diagnostic approach. The same 474 images were then processed through the CNN-YOLOv8 web system, and the observation sheet was completed again during the post-test phase based on the system's detection results. This design allows direct comparison of disease detection performance before and after CNN system implementation on the same sample of images.

The observation instrument was validated by a panel of three experts, and reliability was assessed using Cronbach's Alpha coefficient, yielding values of 0.886 (pre-test, good internal consistency) and 0.937 (post-test, excellent consistency). The Kolmogorov-Smirnov test was applied to assess normality (pre-test: D = 0.181, p = 0.000; post-test: D = 0.279, p = 0.000), confirming non-normal distributions. Consequently, the non-parametric Wilcoxon signed-rank test for related samples was selected for hypothesis testing, as it is appropriate when data do not meet the normality assumption required by parametric tests such as Student's t-test [11].

5 Dataset and preprocessing

For training the YOLOv8 model, we used the public dataset "Strawberry Disease Detection Dataset" available on the Roboflow platform [13], which originally contains 988 images and 2,275 labeled instances across seven disease categories: Blossom Blight (83 images, 117 instances), Angular Leafspot (186 images, 232 instances), Leaf Spot (230 images, 808 instances), Fruit Powdery Mildew (55 images, 134 instances), Leaf Powdery Mildew (213 images, 698 instances), Gray Mold (176 images, 215 instances), and Fruit Anthracnose (45 images, 71 instances).

We implemented data augmentation techniques to increase the robustness of the model and improve generalization, including image rotation (degrees=10.0), translation (translate=0.1), scaling (scale=0.5), shear distortion (shear=2.0), horizontal and vertical flipping (fliplr=0.5, flipud=0.5), mosaic techniques (mosaic=1.0) and mixup (mixup=0.15), as well as HSV variations (hsv_h=0.015, hsv_s=0.7, hsv_v=0.4). After preprocessing and augmentation, the effective dataset comprised 12,906 images, distributed into 8,238 for training (63.83%), 4,119 for validation (31.92%), and 549 for testing (4.25%).

5.1 Domain adaptation strategy

A key challenge in this research was the domain gap between the training data (Roboflow dataset with images from international sources) and the local validation data (474 images captured in Manchay Alto, Lima). Lima's strawberry-growing conditions present specific characteristics: an arid desert climate with low rainfall, sandy soils that cause dust accumulation on leaves, and microclimatic conditions that differ substantially from the regions where the training images were collected.

To mitigate this domain gap, we implemented three complementary strategies: (1) Transfer learning from YOLOv8s pre-trained weights on the COCO dataset, which provides robust general feature extraction capabilities that transfer well across visual domains [14]; (2) Aggressive data augmentation (rotation, translation, HSV variations, mosaic, and mixup) to increase the model's robustness to variations in lighting, scale, and image quality; and (3) A post-hoc agronomic validation layer by local agricultural experts familiar with Lima's specific conditions, which served as a critical domain adaptation verification mechanism. During field image collection, additional challenges arose from sandy soil conditions causing dust accumulation on leaves, which was addressed through prior leaf cleaning and selection of representative photographs.

6 System Architecture

The strawberry crop disease detection system was structured in a modular, three-layer architecture: presentation (HTML5/CSS3/JavaScript), business logic (Python/Flask), and persistence (SQLAlchemy). The core of the system is the YOLOv8 model, which offers real-time detection with a latency of 18.2ms per image.

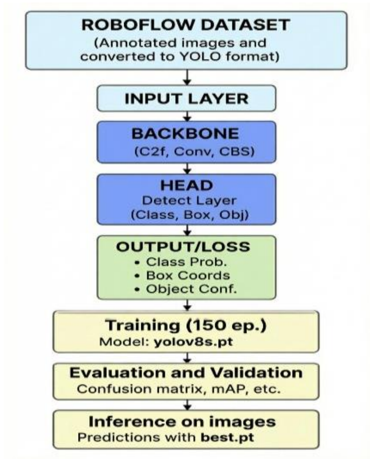

Fig. 1. YOLOv8 architecture used for strawberry disease detection showing the complete pipeline from dataset input to inference output.

We selected YOLOv8 for three main reasons: real-time detection with high accuracy, computational efficiency for limited devices, and an optimized architecture for detecting early symptoms in leaves and fruit. The implemented transfer learning methodology follows contemporary approaches that have demonstrated superior effectiveness in agricultural applications compared to training from scratch [14].

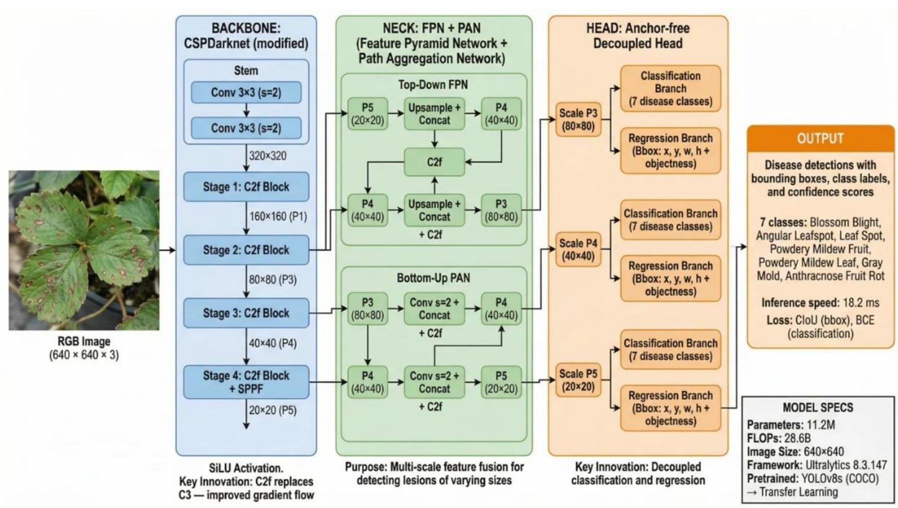

Fig. 2. Internal architecture of the YOLOv8s model used in this study, comprising CSPDarknet backbone with C2f modules, FPN+PAN neck for multi-scale feature fusion, and anchor-free decoupled detection head processing seven strawberry disease classes across three scales (P3, P4, P5).

6.1 Comparative Analysis of YOLO Versions

To justify the selection of YOLOv8 as the core architecture for our disease detection system, we conducted a comparative analysis against other prominent versions of the YOLO family, based on official benchmarks and peer-reviewed literature. Table I summarizes the key characteristics and performance metrics of four representative YOLO versions evaluated on the MS COCO val2017 dataset.

Table 1: Comparative Analysis of YOLO Versions on the MS COCO Dataset

Model	mAP@50-95	Params(M)	Speed(ms)	Detection	Innovation
YOLOv5s	37.40%	7.2	1.1	Anchor-based	CSPDarknet
YOLOv7	51.40%	36.9	-	Anchor-based	E-ELAN
YOLOv8s	44.90%	11.2	1.2	Anchor-free	C2f+Dec.Head
YOLOv9c	53.00%	25.3	-	Anchor-free	PGI+GELAN

Although YOLOv7 [17] and YOLOv9 [18] achieve higher mAP scores, they require significantly more parameters (36.9M and 25.3M respectively), which impacts deployment feasibility on resource-constrained environments. YOLOv8 [6] introduces an anchor-free decoupled head and the C2f module that replaces C3 from YOLOv5, improving gradient flow and feature representation [19]. With 11.2M parameters and a +4 to +9 mAP improvement over YOLOv5 for comparable inference times [19], YOLOv8s provided the optimal balance between accuracy, efficiency, and deployment simplicity for our web-based agricultural application.

7 Training Process

The YOLOv8 model was trained over 150 full epochs, implementing data augmentation and optimization techniques to improve model generalization. We used the pre-trained YOLOv8s (small) model as a starting point, applying transfer learning to adapt prior knowledge to the specific detection of strawberry diseases.

Table 2. Training Configuration and Reproducibility Details

Parameter	Value
Base model	YOLOv8s (yolov8s.pt)
Framework	Ultralytics 8.3.147
Epochs	150
Image size	640 x 640 pixels
Batch size	16 (GPU) / 8 (CPU)
Optimizer	AdamW
Initial / Final LR	0.001 / 0.01
GPU	NVIDIA GeForce RTX 3050 (4GB)
Dataset split	Train/Valid/Test = 8238 / 4119 / 549 (63.83% / 31.92% / 4.25%)
Total training time	Approximately 9 hours (32,323 seconds)
Data augmentation	rot=10, trans=0.1, scale=0.5, shear=2.0, fliplr=0.5, flipud=0.5, mosaic=1.0, mixup=0.15
Dataset source	Roboflow [13]

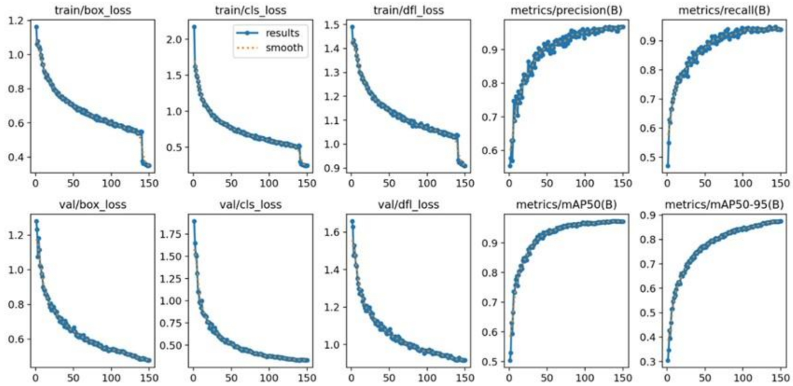

Fig. 3. Training evolution curves showing loss and metrics progression over 150 epochs, demonstrating model convergence and optimal performance achievement**.**

8 Results and Discussion

The final evaluation of the validation set yielded very good results that significantly exceeded the established objectives. The overall metrics achieved were: mAP@50 of 0.9674 (96.74%), mAP@50-95 of 0.8862 (88.62%), Accuracy (P) of 0.9667 (96.67%), Recall (R) of 0.9392 (93.92%), F1-Score of 0.9527 (95.27%), and an inference speed of 18.2 ms per image.

8.1 Model Performance by Disease Class

Table 3 shows the detailed model performance for each specific strawberry disease, demonstrating very good results in all pathology categories.

Table 3. Model Performance by Disease Class

Disease	Precision	Recall	AP@50	AP@50-95
Blossom Blight	100%	98.9%	99.50%	90.5%
Angular Leafspot	98.1%	97.8%	99.30%	95.0%
Leaf Spot	97.3%	97.2%	98.47%	95.7%
Powdery Mildew Fruit	96.8%	91.5%	96.66%	88.5%
Powdery Mildew Leaf	94.4%	94.0%	96.13%	91.8%
Gray Mold	95.1%	90.7%	94.08%	79.7%
Anthracnose Fruit Rot	94.9%	87.3%	93.04%	79.2%

8.2 Agronomic Validation Results

A critical factor for the practical application of our CNN system was the agronomic validation performed by local experts familiar with Lima's specific microclimatic conditions. Table IV presents comprehensive validation results comparing CNN detections with expert confirmations across all disease categories.

Table 4. Agronomic Validation Results by Disease Type in Lima Conditions

Disease	CNN Det.	Expert	Specif.	Status
Leaf Spot	156	142	91.0%	Confirmed for Lima
Angular Leafspot	89	81	91.0%	Confirmed for Lima
Blossom Blight	67	63	94.0%	Confirmed for Lima
Gray Mold	34	32	94.1%	Confirmed for Lima
Powdery Mildew Leaf	78	0	0%	Not present locally
Powdery Mildew Fruit	45	0	0%	Not present locally
Anthracnose Fruit	23	0	0%	Not present locally

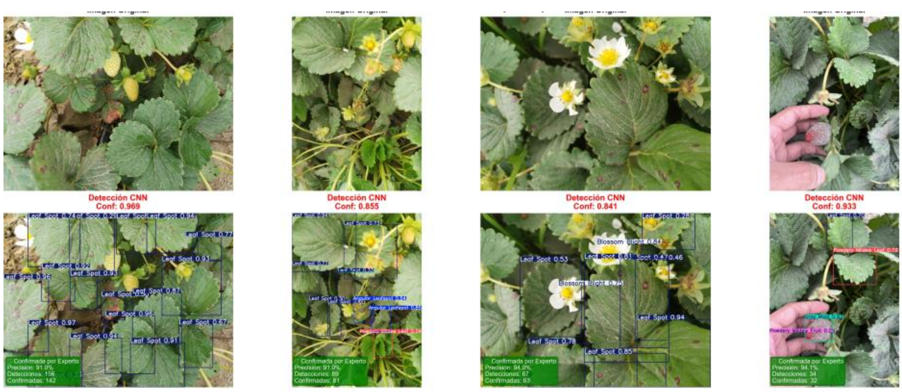

Fig. 4. Agronomic validation comparison showing original images and CNN-YOLO detections for four diseases confirmed by expert validation in Lima conditions**.**

8.3 Analysis of False Positives for Non-Present Diseases

Agronomic validation revealed that three diseases (Powdery Mildew Leaf, Powdery Mildew Fruit, and Anthracnose Fruit Rot) generated a combined total of 146 systematic false positive detections (78 + 45 + 23), representing 29.7% of all CNN detections (146 out of 492 total detections). These false positives are attributed to three main factors:

First, the environmental conditions required for these diseases do not exist in Lima. Powdery mildew (Sphaerotheca macularis) requires sustained high relative humidity (>60%) and moderate temperatures (15-25°C), conditions that are intermittent rather than sustained in Lima's arid climate. Anthracnose (Colletotrichum acutatum) thrives under frequent rainfall and extreme humidity, whereas Lima receives minimal annual precipitation (<10mm). Second, visual similarity between disease symptoms and other conditions: the CNN model confused symptoms of hydric stress, mechanical damage, and dust accumulation on leaves (common in Lima's sandy soils) with powdery mildew symptoms. Third, the domain gap between the training dataset (international conditions) and local conditions meant the model learned visual patterns associated with these diseases from environments where they naturally occur, but these patterns overlap with non-pathological conditions in Lima.

To mitigate these false positives in practical deployment, we propose two strategies: (1) implementing a post-processing filter based on local microclimatic conditions that suppresses detections for diseases confirmed as absent by agronomic experts, and (2) fine-tuning the model with a reduced class set containing only the four locally confirmed diseases. These findings underscore the critical importance of agronomic validation when deploying AI systems trained on international datasets in specific local conditions.

8.4 Reliability Analysis

Table 5. Reliability Analysis Using Cronbach's Alpha Coefficient

Evaluation	Cronbach's Alpha	Interpretation
Pre-test	0.886	Good internal consistency
Post-test	0.937	Excellent consistency

8.5 Detection Frequency Analysis

Table 6 . Pre-test Detection Frequency Distribution

Detection Level	Frequency	Percentage	Cumulative %
Low Level	133	28.1%	28.1%
Medium Level	341	71.9%	100.0%
High Level	0	0.0%	100.0%
Total	**474**	**100.0%**	

Table 7. Post-test Detection Frequency Distribution

Detection Level	Frequency	Percentage	Cumulative %
Low Level	0	0.0%	0.0%
Medium Level	74	15.6%	15.6%
High Level	400	84.4%	100.0%
Total	**474**	**100.0%**	

8.6 Performance Evaluation Scale

Table 8 . Performance Evaluation Scale for CNN System

Level	Score Range	Percentage	Interpretation
Low	15-35 points	20%-47%	Deficient
Medium	36-55 points	48%-73%	Regular
High	56-75 points	74%-100%	Satisfactory

8.7 Statistical Hypothesis Testing

Table 9. Wilcoxon Signed-Rank Test Results for Hypothesis Validation

Hypothesis	Z-value	Significance	Result
General Hypothesis	-18.869	0.000	Accepted
Precision (H1)	-18.498	0.000	Accepted
Performance (H2)	-18.958	0.000	Accepted
Effectiveness (H3)	-18.742	0.000	Accepted

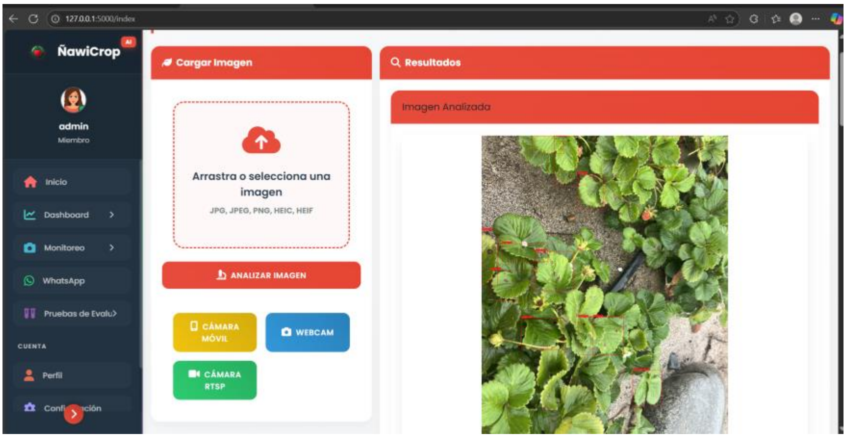

Fig. 5. Image detection result interface (Source: Own elaboration of the website).

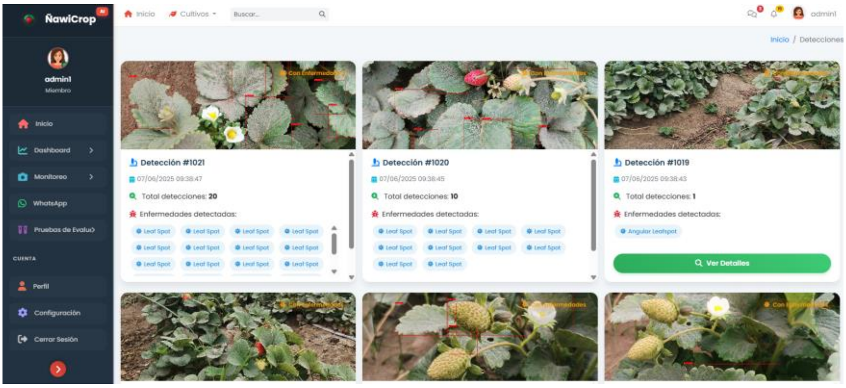

Fig. 6. Image results module interface**.**

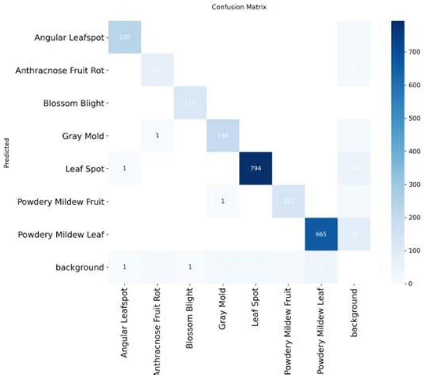

Fig. 7. Confusion matrix showing model classification performance across different disease classes with high accuracy on diagonal elements.

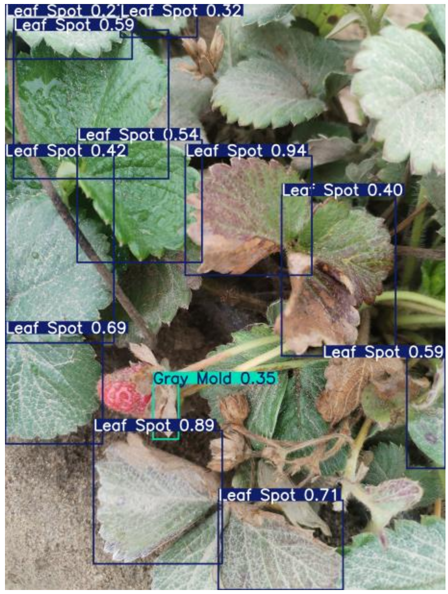

Fig. 8. Real-time detection system outputs showing identified diseases with bounding boxes and confidence scores for field application validation.

Fig. 9. Training batch examples showing diverse disease symptoms and data augmentation effects applied during model training phase.

The results confirm that the overall objective of developing a CNN system for the timely detection of strawberry diseases was successfully achieved, validating the proposed general hypothesis. Compared to Shoaib et al. [1], who reported 94% accuracy under laboratory conditions, our study not only technically surpassed this benchmark (96.74%) but also demonstrated practical viability by increasing the accuracy from 0% to 84.4% at a high level, evidencing the superiority of the CNN system over traditional visual inspection methods.

The system demonstrated very good performance in identifying specific strawberry diseases, with Blossom Blight achieving the highest accuracy (100%) and Angular Spot showing remarkable consistency (98.1% accuracy, 97.8% recall). Statistical validation using Wilcoxon tests confirmed significant improvements in all dimensions: accuracy (Z =

-18.498, p = 0.000), throughput (Z = -18.958, p = 0.000), and effectiveness (Z = -18.742, p = 0.000).

Agronomic validation revealed critical insights into the local prevalence of diseases, showing high specificity for four diseases actually present in the crops of the Lima study area, achieving concordance levels exceeding 90% with expert criteria for locally relevant pathologies. However, systematic false positives were identified for three diseases not present under Lima's specific microclimatic conditions, validating the need for local adaptation of models trained with international datasets.

This finding has significant implications for the agricultural AI community. While the model achieved excellent technical metrics on the Roboflow validation set (96.74% mAP@50), the agronomic field validation revealed that 29.7% of detections corresponded to diseases that are climatically impossible in Lima. This gap between technical performance and practical applicability underscores a critical challenge: international datasets, while valuable for model training, may not capture the agroclimatic specificity required for local deployment. Our results align with findings by Fernandez Fernandez and Pinglo Cabezas [22], who emphasized that CNN effectiveness depends on integration with specific contextual data.

Compared to similar YOLO-based studies in agriculture, our approach is distinguished by the inclusion of end-user validation with real producers [20], [21]. While Ning et al. [21] achieved comparable processing times (18.2 ms), their evaluation was limited to technical metrics without field deployment. Our pre-test/post-test design with 38 real producers provides ecological validity that purely technical evaluations lack, demonstrating that the CNN system not only performs well in controlled conditions but effectively transforms disease management practices in real agricultural settings.

9 Conclusions

A CNN-based system was successfully developed, enabling the timely and accurate detection of diseases in strawberry crops in Lima, Peru. The system achieved technical model metrics of 96.74% (mAP@50) and system effectiveness, with 84.4% of cases reaching a high level of detection, and a processing speed of 18.2 milliseconds per image. The implemented system transformed traditional phytosanitary diagnostic methods, increasing the percentage of high-level detection from 0% to 84.4%, demonstrating its effectiveness as a technological tool for optimizing agricultural productivity and reducing economic losses in the strawberry sector.

The developed CNN system facilitated achieving very good accuracy, with technical metrics of the trained model of 96.67% accuracy and 93.92% recall, allowing the correct identification of seven main diseases that affect these crops with reliability superior to traditional visual inspection methods, providing farmers with instant and objective diagnoses for informed decision-making.

Critically, agronomic validation revealed that only four diseases (Leaf Spot, Angular Leaf Spot, Blossom Blight, and Gray Mold) are actually present under the strawberry growing conditions of Lima, achieving 91-94% specificity for these locally relevant pathologies. Three diseases (Leaf Powdery Mildew, Fruit Powdery Mildew, and Fruit Anthracnose) generated systematic false positives because they are not present under the specific environmental conditions of Lima, highlighting the essential need for regional adaptation of international datasets in agricultural AI applications and the critical importance of validation by local experts in precision agriculture systems.

9.1 Future Work

Future research directions include integrating multispectral imaging for early disease detection, developing lightweight models for edge computing deployment, implementing temporal analysis to track disease progression, extending the model to other high-value crops in Peru, integrating it with IoT sensors for comprehensive monitoring, developing mobile applications for field use, collaborating with agricultural extension services, and developing training programs for farmers. Additionally, expanding the local dataset to include more diverse conditions specific to Lima will improve the model's adaptation to regional variations.

A priority for future work is the retraining of the model using only the four disease classes confirmed as present in Lima (Leaf Spot, Angular Leafspot, Blossom Blight, and Gray Mold), which is expected to eliminate false positives while maintaining or improving detection accuracy for locally relevant pathologies. Additionally, building a larger local image dataset through continued collaboration with Manchay Alto producers will enable more robust domain adaptation and improve generalization to other strawberry-growing regions in Peru.

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