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Research Article

Keywords: Disease detection, Computer vision, Convolutional Neural Networks, Peach

Posted Date: November 12th, 2025

DOI: https://doi.org/10.21203/rs.3.rs-7895853/v1

Additional Declarations: No competing interests reported.

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Abstract

This study introduces a robust early disease detection system for peach crops, leveraging computer vision and artificial intelligence to address significant economic losses caused by Brown Rot (Monilinia spp.) and Leaf Curl (Taphrina deformans). The methodology comprises a structured approach, starting with the collection of a high-quality dataset of 640 images captured under real-world field conditions. These images, representing healthy and diseased fruits and leaves, underwent a rigorous preprocessing pipeline that included background removal, color space conversion, resizing, and contour detection to optimize them for model training. A Convolutional Neural Network (CNN) was developed and validated using k-fold cross-validation, achieving an outstanding accuracy of 90.28% for fruit disease detection and 96.43% for leaf disease detection during the validation phase. The model's final performance, evaluated with a confusion matrix, demonstrated a remarkable 100% precision for Brown Rot in fruits and 96.4% precision for Leaf Curl in leaves. These results confirm the system's reliability and its potential for practical application in precision agriculture. The project culminates in a functional web application, showcasing the viability of deploying deep learning solutions as accessible tools for farmers to facilitate timely and proactive crop management.

Keywords: Disease detection, Computer vision, Convolutional Neural Networks, Peach,

1 Introduction

Agriculture is a fundamental pillar of the global economy, providing essential food and raw materials for human survival and development. However, the presence of pests and diseases in crops poses a constant threat, causing significant production losses and severely affecting farmers' livelihoods[1]. Peach cultivation (Prunus persica), which originated in China and is widely grown in temperate climates, faces considerable challenges from diseases like Leaf Curl (Taphrina deformans) and Brown Rot (Monilinia spp)[2], [3]. These diseases can cause severe damage to leaves, branches, and fruits, drastically reducing crop yield and quality.

In Colombia, peach cultivation is of great economic importance, particularly in the department of Boyacá, where 37.79% of the national production is concentrated . In 2022, this department had 813.69 hectares planted with a production of 11,830.05 tons [4] . Nevertheless, the presence of diseases such as Leaf Curl and Brown Rot has led to significant economic losses, impacting not only production but also fruit quality, which directly affects farmers' income [5]. These diseases, caused by fungi that thrive under specific humidity and temperature conditions, represent a significant challenge for their control and prevention [6][7].

Leaf Curl (Taphrina deformans) is one of the most prevalent diseases in Boyacá's peach crops, affecting approximately 30% of the plantations[8]. This disease manifests in leaves, branches, and fruits, causing deformities and reducing the plant's photosynthetic capacity, which directly impacts its growth and productivity [9]. On the other hand, Brown Rot (Monilinia spp) initially attacks the flowers, later spreading to the fruits and causing their decomposition [10]. If not managed properly, this disease can lead to direct and indirect losses exceeding 80% of production[11].

Given this problem, there is a need to develop technological tools for the early detection of these diseases, facilitating timely decision-making to mitigate their negative effects. In this context, artificial intelligence (AI) and computer vision have emerged as promising technologies for identifying and classifying crop diseases, offering efficient and scalable solutions[12], [13]. These technologies enable the automated analysis of plant images, identifying patterns and features associated with specific diseases, which reduces reliance on manual visual inspection and improves diagnostic accuracy[14], [15].

This work proposes the design of a computer vision and AI-based system for the early detection of Leaf Curl and Brown Rot in peach crops located in Cómbita, Boyacá. The system integrates advanced image processing techniques and convolutional neural networks (CNNs) to analyze images of leaves and fruits, providing farmers with an accessible and efficient tool to monitor the health of their crops [16], [17].

The project is divided into several stages. First, images of peach leaves and fruits, both healthy and affected by the mentioned diseases, are collected to build a robust and representative database. Subsequently, image processing techniques such as background removal, RGB color space adjustment, and resizing are applied to optimize the images and highlight relevant features for analysis [18], [19]. Once the images are processed, an AI model based on convolutional neural networks is developed and trained using the structured database, with model parameters adjusted to maximize accuracy in disease identification [20], [21].

The trained model is integrated into a web application developed using a Low Code development platform, ensuring a user-friendly and efficient experience. The application allows farmers to upload images of their crops from their mobile devices, which are then processed by the AI model to generate a prediction about the state of the leaves and fruits, indicating whether they are healthy or show signs of Leaf Curl or Brown Rot [22], [23].

The results obtained during the application's testing were highly satisfactory, achieving 94.6% accuracy and 96.4% precision in disease detection in leaves, and 91.6% accuracy and 100% precision in disease detection in fruits [24], [25]. These results demonstrate the effectiveness of the proposed system as a reliable tool for the early detection of diseases in peach crops, enabling farmers to take preventive and corrective measures promptly, thus reducing the risk of economic losses and improving production sustainability [24], [25].

This project represents a significant step forward in the use of technology for agriculture, combining computer vision and artificial intelligence to develop a practical and effective solution for the early detection of diseases in peach crops. Furthermore, the project aligns with the Software Engineering and Logical Tools Automation research line of the Telecommunications Engineering program, contributing to the development of technological tools that benefit farmers and promote sustainable food production [26], [27].

In summary, this work addresses a critical problem in Colombian agriculture by proposing an innovative solution based on emerging technologies. The implementation of this system will not only benefit farmers in Cómbita, Boyacá, but also has the potential to be scaled to other regions and crops, contributing to food security and the economic development of the country [28], [29].

2 Literature Review

The automatic detection of plant diseases using computer vision and artificial intelligence has experienced exponential growth in recent years, transforming traditional agricultural practices [30]. This technological revolution is based on the ability of deep learning algorithms to identify complex visual patterns in digital images, overcoming the limitations of conventional manual inspection methods[31]. Convolutional neural networks (CNNs) have emerged as the dominant architecture in this field, demonstrating exceptional capabilities for the classification, detection, and segmentation of pathological symptoms in plant tissues.

The development of automated phytosanitary diagnostic systems addresses the growing need to optimize global agricultural production, where losses due to diseases account for between 20-40% of the total crop yield [32]. The implementation of computer vision technologies offers significant advantages, including early diagnosis, reduced operational costs, minimized pesticide use, and real-time processing capabilities [33].

2.0.1 Disease Detection in Leaves

Early identification of foliar diseases is a critical application of computer vision. Studies have demonstrated the high effectiveness of CNNs for disease classification across a variety of crops. For instance, in a study on cucumber leaf disease recognition, a pretrained CNN was employed for deep feature extraction, optimized with a Whale Optimization Algorithm (WOA), and classified using an ES-KNN, achieving an accuracy of 96.5% [34]. Similarly, for the classification of fungal diseases in mango leaves, a Multilayer Convolutional Neural Network (MCNN) was proposed, which demonstrated accurate classification upon validation on two datasets [34],[35]. For crop disease recognition, an automated system based on PLS regression achieved an average accuracy of 90.1%, and specifically for tomato disease, reached 87.11% [35].

Symptom detection in leaves is a task that can benefit from methodologies beyond simple classification. In the case of onion downy mildew, a deep learning system used class activation mapping (CAM) to localize disease symptoms, achieving a mean average precision (mAP) ranging from 74.1 to 87.2 [36]. For disease detection in potato leaves, advanced segmentation models have been explored, such as one using an Enhanced Radial Basis Function Neural Network (ERBFNN), which achieved high segmentation accuracy of 98.92% [37]. A similar study on biotic stress detection in coffee leaves, using a ResNet50 architecture, achieved a classification accuracy of 95.24% and an 86.51% severity estimation [38]. Beyond disease detection, semantic segmentation of leaves has significantly improved with architectures like D-SegNet, which uses dense blocks to capture detailed and contextual features, delivering accurate segmentation in plant leaves [39].

Other studies have addressed challenges of generalization and data imbalance. Samin et al. proposed CapPlant, a capsule network-based framework for plant disease classification, which achieved an overall test accuracy of 93.01% [40]. This architecture offers a robust alternative to traditional CNNs. In the context of imbalanced data, a study on cassava disease detection demonstrated an accuracy improvement of more than 5% by employing techniques such as focal loss and minority class resampling using SMOTE [41].

Computer vision is also essential for weed detection and classification. An approach combining maximum likelihood classification with convolutional neural networks proved effective in identifying weeds in canola fields, highlighting the capability of these techniques to differentiate between crop plants and unwanted vegetation [42].

2.0.2 Disease Detection in fruits

Computer vision has also been successfully applied to disease detection, ripeness estimation, and fruit counting. To detect ripeness in dates, an "Intelligent Harvesting Decision System" (IHDS) was proposed that employs computer vision and deep learning techniques [43]. This system achieved 99.4% accuracy in detecting seven ripeness stages. A similar study on the same crop reached a precision of 99. 058% and an F1 score of 99.34% [38].

Beyond classification, researchers have explored fruit detection and yield estimation. Apple detection in orchards has been addressed successfully by various methods. An approach combined convolutional neural networks with watershed segmentation and the circular Hough transform, achieving an r2 = 0.826 in the estimation of the fruit count [44]. Another work focused on the detection of apple flowers using deep convolutional neural networks, which is a critical step for the estimation of early yield [45].

A more recent study introduced the use of transformer-based networks for maturity segmentation in tomatoes, demonstrating that these architectures can outperform CNNs in tasks requiring large-scale contextual understanding [46].

2.0.3 Application of Neural Networks and Deep Learning

The literature review confirms that Convolutional Neural Networks (CNNs) are the predominant architecture in this field. Pretrained models such as VGG19, ResNet50, and EfficientNetB7 have been widely adopted through transfer learning, consistently achieving accuracies above 95% in most cases Deep learning networks [2].

The current trend is moving toward hybrid and ensemble approaches to enhance robustness and accuracy. For example, a deep CNN ensemble model (DECNN) achieved 98.33% accuracy in diagnosing nutrient deficiencies in rice, demonstrating that combining multiple models can mitigate individual errors [47].

In pest detection, the fusion of multi-scale information has been proposed as a key strategy to improve accuracy, addressing the challenge posed by variable pest sizes in images [48]. Furthermore, deep residual learning architectures have been employed to identify pests in complex field environments, showcasing the robustness of these designs against real-world challenges [49].

2.0.4 Gaps in the Literature and Justification for the Present Study

Despite advancements, several limitations in the existing literature justify the present study. Most research focuses on either disease detection or fruit ripeness separately, without integrating both for combined monitoring of leaves and fruits within a single species. Although some studies, such as that by Esgario et al. [38], address classification and severity in coffee leaves, there is no documented approach for the integrated detection of foliar and fruit diseases in peach.

Moreover, while the reviewed studies demonstrate high accuracy, they often rely on datasets containing a limited number of images captured in controlled environments, which do not always translate into comparable performance under real field conditions. Barth et al. [50] showed that thousands of synthetic images are required to optimize performance when the empirical dataset is very small. This finding underscores the challenge of the scarcity of high-quality labeled data, a significant barrier to the application of AI in agriculture.

Finally, and critically, most of the work has been conducted in geographic and climatic contexts different from the Colombian setting. There are no known studies validating these technologies under the specific conditions of Cómbita, Boyacá, where factors such as climate, topography, and peach varieties may influence the visual manifestation of diseases such as Peach Leaf Curl (caused by Taphrina deformans) and Brown Rot (Monilinia spp.). The present study addresses these gaps by proposing an integrated computer vision and artificial intelligence system for the early and simultaneous detection of these diseases in peach leaves and fruits, in order to validate its efficacy under the region's specific agroclimatic conditions.

The following table provides a comprehensive overview of the most relevant studies identified in our literature review. Table 1 synthesizes key information from each article, including the specific crop or object of study, the primary methodology employed, and the reported accuracy or results. This structured summary helps to contextualize our research by highlighting the state of the art in computer vision for agriculture and identifying the existing gaps in the literature that our study aims to address.

3 Materials and Methods

The development of an early detection system for Leaf Curl (Taphrina deformans) and Brown Rot (Monilinia spp) in peach crops was based on a structured methodology encompassing several phases, from data acquisition and preprocessing to model validation and deployment in a practical environment. This approach was designed to ensure the solution's robustness and applicability in real-world field conditions, combining rigorous computer vision and deep learning techniques to address the inherent variability of agricultural settings. Indeed, the methodology integrates quantitative and qualitative approaches to ensure that the solution is both effective and practical, using computer vision techniques to train a detection algorithm from crop images. Consequently, the integration of these methodological approaches aims to provide a tool that is not only technically robust but also aligned with the daily challenges faced by farmers. See Fig. 1.

Table 1 Summary of studies on crop disease recognition and plant analysis using deep learning.

Reference	Study Objective	Crop / Object	Main Methodology	Results / Accuracy	Key Contributions / Limitations
[34]	Recognition of leaf diseases	Cucumber	Pre-trained CNN + WOA + ES-KNN	96.50%	Demonstrates the effectiveness of optimization with evolutionary algorithms.
[40]	Classification of plant diseases	General (Plants)	Capsule Networks (CapPlant)	93.01%	Proposes a robust alternative to traditional CNNs.
[35]	Classification of crop diseases	Tomato	DNN feature fusion + PLS regression	Avg. 90.1% (87.11% tomato)	Shows the use of statistical methods with deep learning.
[38]	Classification and severity of biotic stress	Coffee leaves	ResNet50	95.24% (classif.), 86.51% (severity)	Shows an integrated detection approach (classification and severity).
[36]	Detection of downy mildew symptoms	Onion	Deep Learning Networks + CAM	mAP 74.1%–87.2%	Offers interpretability through class activation maps (CAM).
[37]	Detection of diseases	Potato leaves	ERBFNN (segmentation model)	98.92% segmentation accuracy	Focuses on precise segmentation of affected areas.
[43]	Detection of maturity and weight	Dates	Computer vision + DL	99.4%	Demonstrates the application for harvest decision-making.
[2]	Identification of cultivars	Olive	VGG19, ResNet50, EfficientNetB7	98%	Highlights the successful use of transfer learning.
[47]	Diagnosis of nutrient deficiencies	Rice	Deep CNN ensemble model	98.33%	Shows improved robustness with ensemble models.
[41]	Detection of diseases	Cassava	Transfer learning + imbalance handling	Accuracy improvement ¿5%	Solves the problem of data scarcity and imbalancend.

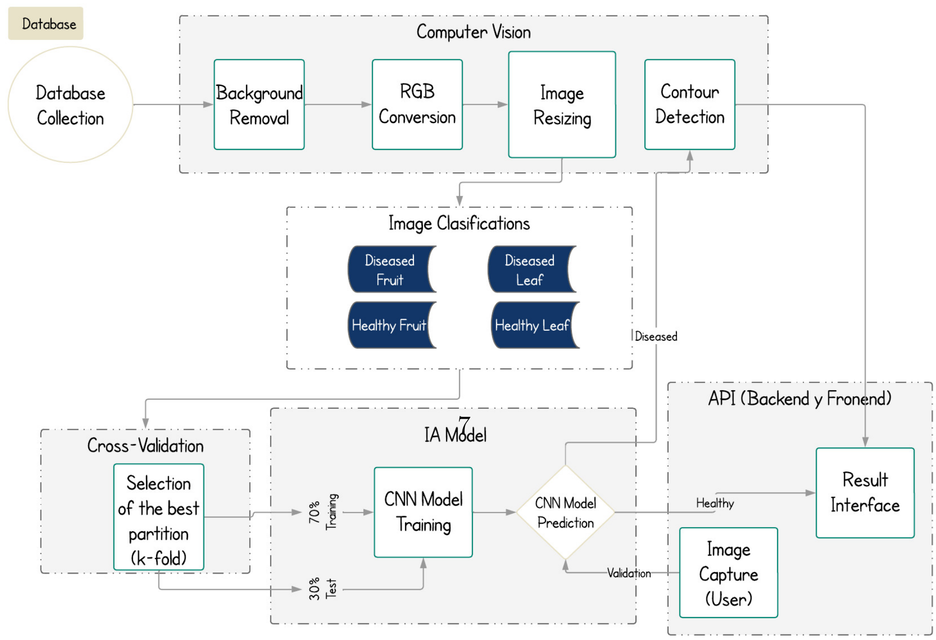

Fig. 1 Block diagram of the methodology used for the project.

3.1 Dataset Description

The dataset for this study was built from 640 high-quality images captured in a 3-hectare peach orchard in Cómbita, Boyacá. Unlike other datasets that use images from controlled environments, the acquisition was performed under real field conditions. This ensures the representativeness of the natural variability of the environment, including variations in lighting, background, and disease manifestations.

To specifically address the diseases affecting each part of the plant, the set was divided into two main groups: leaves and fruits. The database was structured into four classes for classification: healthy fruits, healthy leaves, fruits with Brown Rot (Monilinia spp), and leaves with Leaf Curl (Taphrina deformans). The initial distribution of the dataset was 141 healthy fruits, 219 diseased fruits, 120 healthy leaves, and 160 diseased leaves.

The collected images include visual examples of the four classes, both healthy and disease-affected, as illustrated in Fig. 2, which shows a peach with Brown Rot, a healthy peach, a leaf with signs of Leaf Curl, and a healthy leaf.

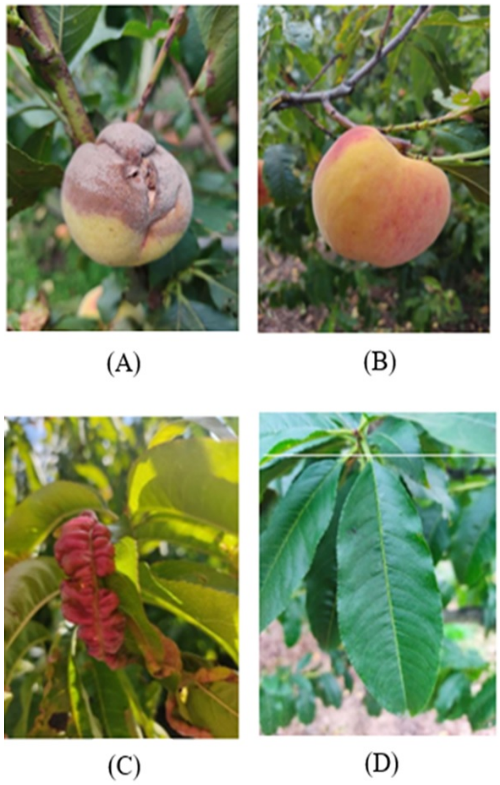

Fig. 2 (a) A fruit with Brown Rot (Monilinia spp), showing brown spots and tissue degradation. In contrast, (b) presents a healthy fruit for comparison. (c) A leaf with signs of Leaf Curl (Taphrina deformans), characterized by deformations and reddish discoloration. (d) A healthy leaf, which serves as a reference for the classification model.

3.2 Dataset Preprocessing

The dataset underwent a rigorous preprocessing, a critical stage for optimizing images before model training. This process aimed to mitigate the noise inherent in capturing images in field environments while standardizing the data to ensure consistency and the model's ability to learn relevant features. To this end, several computer vision techniques were applied.

Background Removal: This was implemented using segmentation algorithms to isolate leaves and fruits, eliminating distracting background elements like branches or soil. This technique was fundamental to focusing the model's analysis exclusively on the regions of interest, which improved disease detection accuracy. The segmentation process for fruits and leaves is illustrated in Fig. 3.

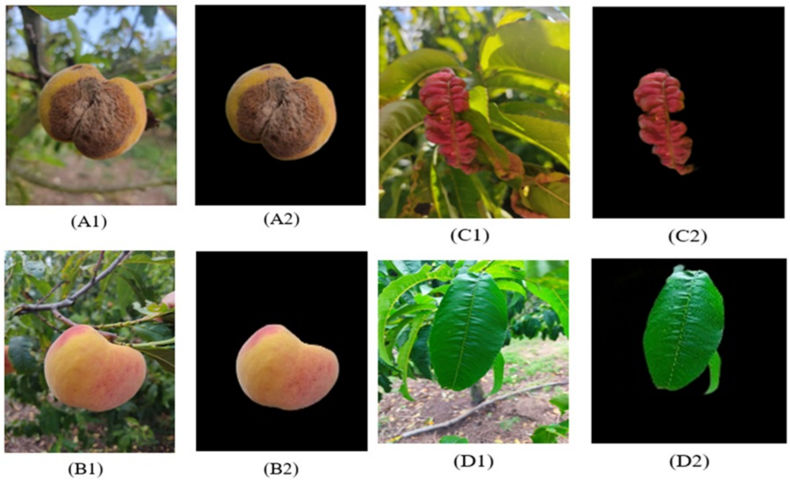

Fig. 3 (a1) and (b1) show diseased and healthy fruits, respectively. (a2) and (b2) demonstrate background removal on the fruits by segmenting the object of interest. (c1) and (d1) show a diseased leaf and a healthy leaf, respectively. (c2) and (d2) demonstrate background removal on the leaves, segmenting the object of interest.

Color Space Conversion: The images, typically captured in BGR (Blue, Green, Red) format, were converted to the RGB (Red, Green, Blue) color space. This conversion is essential to ensure compatibility and correct visual and computational interpretation, and was carried out using Python's PIL library. Fig. 4 shows the result of this conversion on the leaf and fruit images.

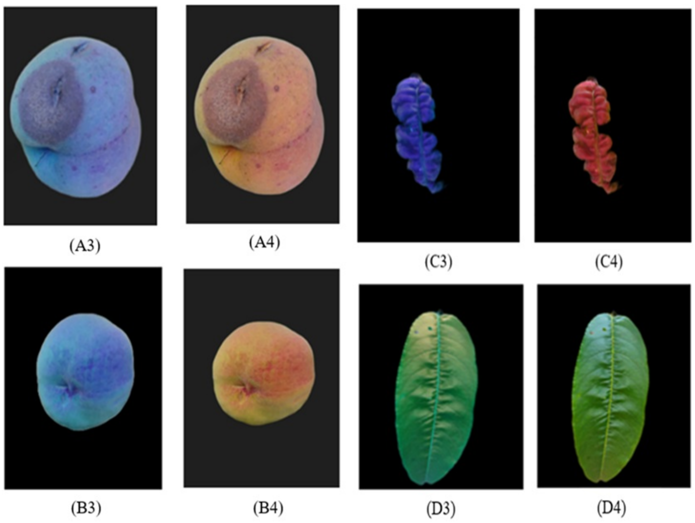

Fig. 4 (a3) and (b3) show a diseased and a healthy fruit in BGR format, respectively. (a4) and (b4) are the versions converted to RGB. (c3) and (d3) show diseased and healthy leaves in BGR format. (c4) and (d4) correspond to the images in RGB.

Resizing: To standardize the input data and optimize computational load, all images were resized to a uniform resolution of 150 x 150 pixels. Maintaining the same input proportion and size is crucial for the model to process data consistently, as shown in Fig. 5.

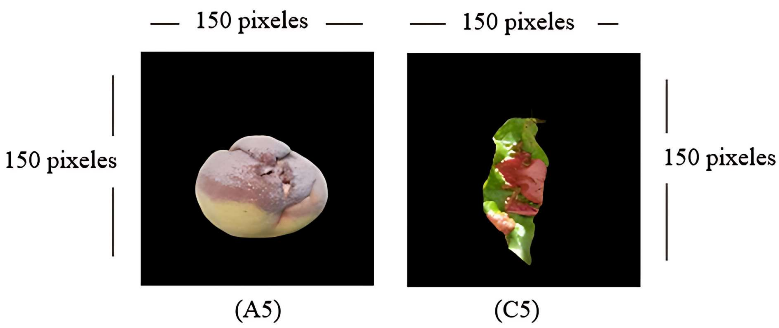

Fig. 5 (a5) A fruit with Brown Rot that has been resized to 150 x 150 pixels. (c5) A leaf with Leaf Curl, resized to the same dimensions.

Contour Detection: A contour detection technique was applied to highlight the shapes and boundaries of the areas affected by the diseases. This visualization improved the model's ability to identify specific pathological patterns in the images, facilitating the analysis of the regions of interest. Fig. 6 presents an example of contour application on a peach fruit and a leaf.

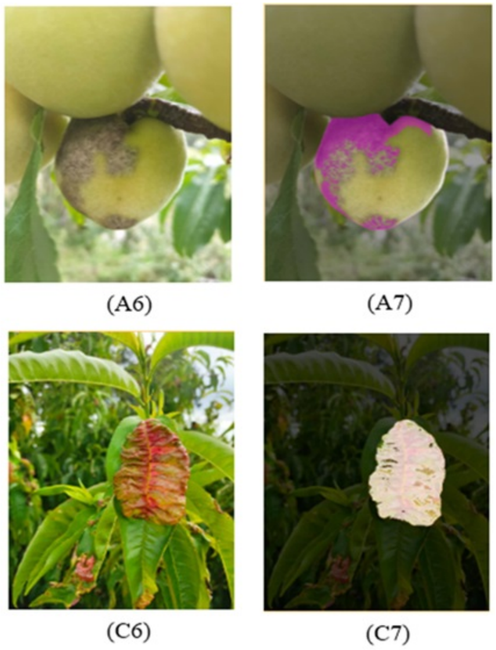

Fig. 6 (a6) A fruit with Brown Rot in its original state. (a7) A visualization of the same fruit with the contour overlaid on the affected area to highlight the pathology. (c6) A leaf with Leaf Curl in its original state. (c7) A visualization of the same leaf with contour detection identifying the area of the pathology.

The implementation of these preprocessing techniques ensured the quality and uniformity of the dataset, laying a solid foundation for the subsequent stages of the project.

3.3 Database Structuring for Model Training

For training the AI model, a database was structured to include four classes: healthy fruits, healthy leaves, fruits with Brown Rot (Monilinia spp), and leaves with Leaf Curl (Taphrina deformans). This process is crucial for the correct training of the algorithm, which is why 640 images were collected, pre-resized to 150 x 150 pixels, and subjected to background removal. Subsequently, the images were organized into separate folders, one for leaves and another for fruits. The number of images in each of the classes can be seen in Table 2.

3.4 Cross-Validation

Cross-validation was a fundamental stage in evaluating the proposed model's robustness and mitigating the risk of overfitting. This technique is essential to ensure that the

Table 2 Initial Database Structure

Initial Database Image Distribution			
Type	**Healthy**	**Diseased Pathology**	**Quantity**
Fruit	x		141
Leaf	x		120
Fruit		Brown Rot (Monilinia Spp)	219
Leaf		Leaf Curl (Taphrina deformans)	160
Total			640

model doesn't just memorize training data but also demonstrates an effective generalization capacity on new data. This is particularly relevant in agricultural applications due to the high variability in crop conditions. The methodology is based on partitioning the dataset into subsets, known as folds, to subject the model to a series of rigorous evaluations and obtain a more reliable estimate of its performance.

In the case of the fruit dataset, which consists of 360 images, these were randomly divided into 5 folds, each with 72 images. The validation process determined that fold number 4 had the highest validation percentage, at 90.28%. Consequently, these images were reserved for the testing phase, while the remaining were used for training.

Similarly, for the leaf dataset, which comprised 280 images, the division into 5 folds resulted in 56 images per fold. The system identified fold number 2 as having the highest validation, reaching 96.43%. As with the fruits, these images were reserved for the testing phase, and the rest were allocated for model training. The distribution of images reserved for testing can be seen in more detail in Table 3 for the fruit and leaf models.

Table 3 Number of test images for the fruit model and the leaf model.

Classes	**Quantity**
Diseased Fruit	41
Healthy Fruit	31
Diseased Leaf	29
Healthy Leaf	27
Total	128

3.5 Model Implementation

At this stage, artificial intelligence techniques were implemented to develop an accurate and effective predictive model for detecting Brown Rot and Leaf Curl diseases in peach crops. The model was built using Convolutional Neural Networks (CNNs), an architecture particularly effective for image analysis due to its capacity to capture spatial features and local patterns.

The neural network architecture consists of three convolutional layers with a ReLU (Rectified Linear Units) activation function. The first layer had 16 neurons, the second

32, and the third 64. This configuration allows the model to learn from a large number of image features without significantly increasing the computational load.

Table 4 Cross-validation images used for model training.

Model Training Images	
Classes	**Quantity**
Diseased Fruit	178
Healthy Fruit	110
Diseased Leaf	131
Healthy Leaf	93
Total	512

Model training was performed using the data resulting from cross-validation. For the fruit model, 288 images (178 diseased, 110 healthy) were used over 10 epochs, achieving a validation accuracy of 88.63%. For the leaves, the model was trained with 224 images (131 diseased, 93 healthy) over 10 epochs, reaching a validation accuracy of 90.9%. See Table 4. These results demonstrate the model's high capacity to classify images with a significant level of accuracy.

Table 5 Resultados del modelo de detección de enfermedades.

Método	**Precision**	**Accuracy**	**Sensibility**	**Specificity**
Brown Rot Detection (Fruit)	1.000000	0.916666	0.853658	1.000000
Leaf Curl Detection (Leaf)	0.964285	0.946428	0.931034	0.962962

3.6 Confusion Matrix

The confusion matrix was used to assess the quality of the classification model, serving as a fundamental tool in the evaluation of machine learning-based models. This matrix allows for the breakdown and visualization of the model's performance in terms of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).

From the confusion matrix data, it was possible to calculate key metrics such as precision, sensitivity (recall), specificity, and F1-score. The analysis of these values allowed for the identification of the model's strengths and the areas that required adjustment. This feedback was crucial for fine-tuning parameters such as the learning rate or the number of layers, which ensured the model achieved optimal levels of performance, accuracy, and robustness.

3.7 Web Application

The trained AI model was integrated into a web application to offer a practical and accessible tool for farmers. The front-end of the application was developed with a Low Code web development platform selected for its efficiency in building user interfaces. This choice facilitated a seamless integration with the back-end, which was implemented in a Jupyter Notebook environment.

The process for using the web application was designed to be simple and is divided into the following steps, ensuring a friendly and efficient user experience:

1. Application Execution: The process begins with the execution of the web application, whose interface guides the user through each necessary step to perform disease detection.
2. Image Upload: The user can easily upload an image of a peach leaf or fruit. This image can be taken directly from a mobile device and uploaded using the upload button.
3. Image Submission: Once the image is uploaded, the user can submit it for analysis. This process is fast and direct, designed to minimize the time and effort required.
4. Processing and Analysis with Jupyter: The submitted image is processed by the code hosted in the Jupyter environment. This code is responsible for the following preprocessing and analysis tasks:

   Image Preprocessing: Includes operations such as color space conversion, removal of irrelevant backgrounds, and image resizing to ensure it is in the correct format for analysis.

   AI Analysis: Using the CNN model, the image is analyzed to detect features of Brown Rot or Leaf Curl.

   Prediction: The AI model generates a prediction based on the features detected in the image.
5. Result Visualization in Anvil: The analysis results, including the processed image and the diagnosis, are returned to the Anvil interface. This information is presented clearly and understandably, allowing the farmer to see the state of the initially uploaded fruit or leaf.
6. Diagnosis: The provided diagnosis indicates whether the image shows signs of Brown Rot or Leaf Curl, which is crucial information that helps the farmer make timely decisions about crop management.

4 Results

The primary objective of this project was to implement a system that integrates artificial intelligence and computer vision technologies for the early identification of diseases in peach crops. The results presented below offer a detailed analysis of the findings obtained during the implementation and evaluation of the proposed system.

To achieve this objective, several development and testing stages were carried out. The results obtained in the crucial stages of the project are detailed below.

First, high-quality images of peach fruits and leaves, both healthy and affected by Brown Rot (Monilinia spp) and Leaf Curl (Taphrina deformans), were collected. These images were organized into an initial database, as shown in Fig. 7, which contains images of both fruits and leaves in healthy and diseased states.

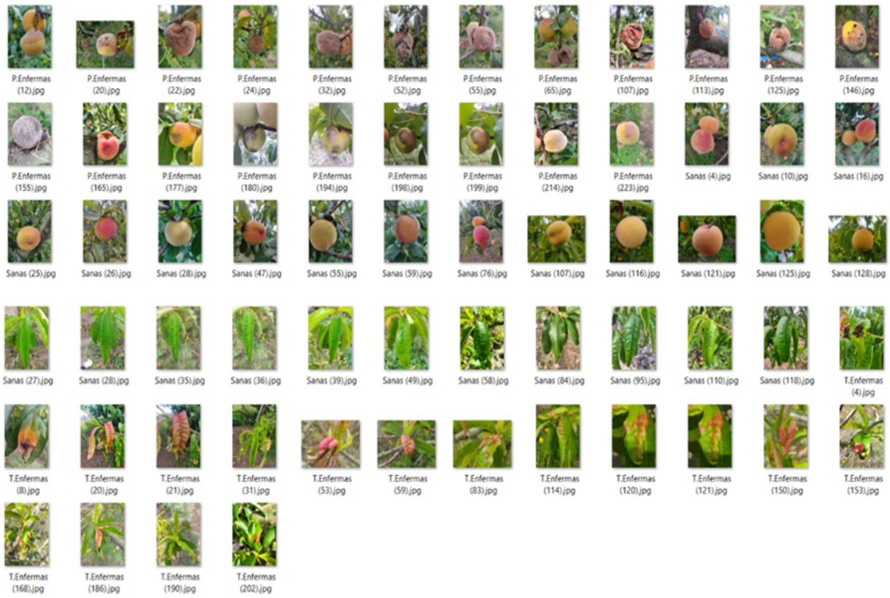

Fig. 7 Background removal on the dataset for fruits and leaves, both healthy and diseased.

Subsequently, computer vision techniques were applied to prepare the images for training the AI model, as seen in Fig. 8. Preprocessing techniques, such as background removal, allowed for obtaining the regions of interest in the images.

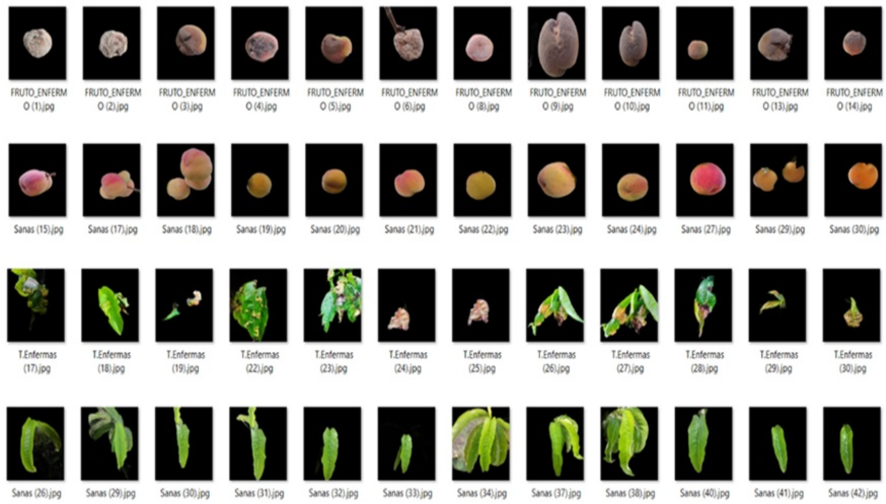

Fig. 8 Background removal on the dataset of fruits and leaves, both healthy and diseased.

Next, the artificial intelligence model was developed and implemented to analyze the images and detect signs of the mentioned diseases. In this stage, different techniques were applied to evaluate the model's performance in terms of precision and accuracy. Consequently, the best set of images for training and testing was determined using the cross-validation technique. In Figures 9 and 10, the result of applying this technique for both fruits and leaves can be verified.

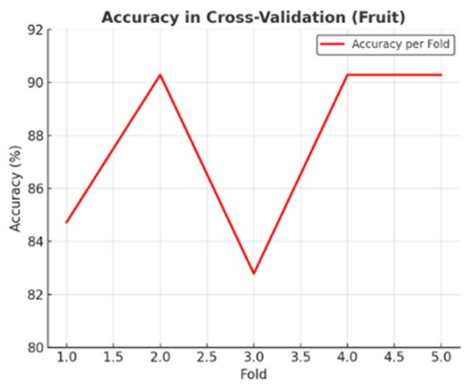

Fig. 9 Results of the cross-validation applied to the fruit, achieving an accuracy of 90.28%.

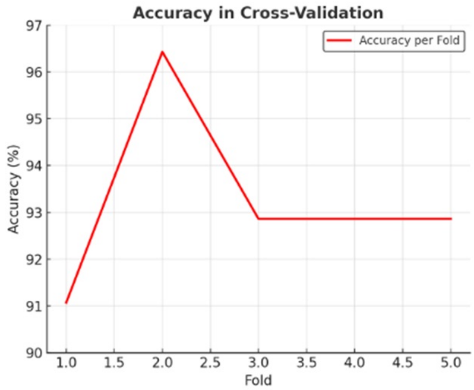

Fig. 10 Results of the cross-validation applied to the leaf, achieving an accuracy of 96.43%.

For fruits, the cross-validation model achieved an accuracy of 90.28%. In the case of leaves, the accuracy was 96.43%. The system indicated that the best images for testing the fruit model were those from fold 4, and for the leaf model, those from fold 2.

The AI models were trained with the images selected through cross-validation. Figure 11 shows the training process for the fruit model, while Figure 12 details the process for the leaves.

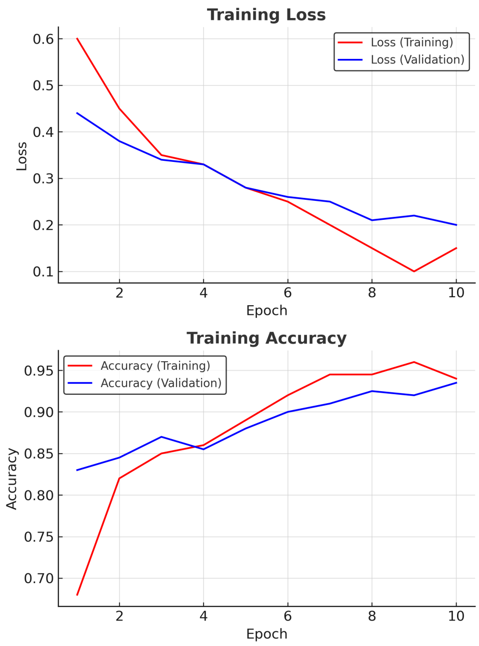

Fig. 11 Training accuracy and loss for the fruit model.

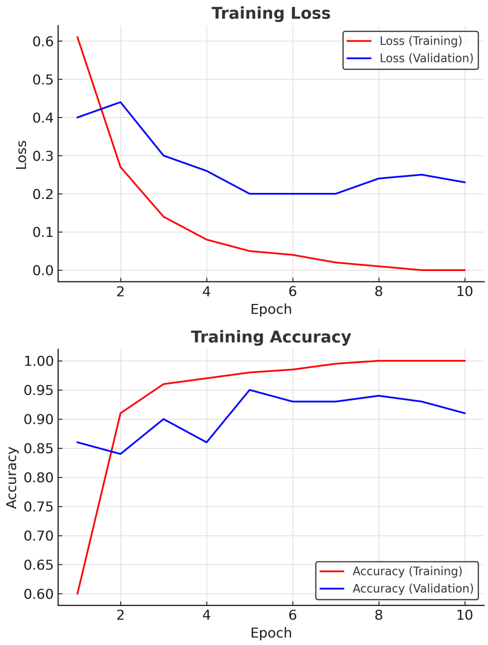

Fig. 12 Training accuracy and loss for the leaf model.

Finally, the AI models were tested with the test images designated in the cross-validation stage to evaluate their accuracy and precision using the confusion matrix. The evaluation of the trained fruit model, using 72 test images, yielded an accuracy of 91.6% and a precision of 100%, as shown in Table 4 and Figure 13. Meanwhile, the evaluation of the leaf model, with 56 test images, obtained an accuracy of 94.6% and a precision of 96.4%, with the results detailed in Table 5 and Figure 14.

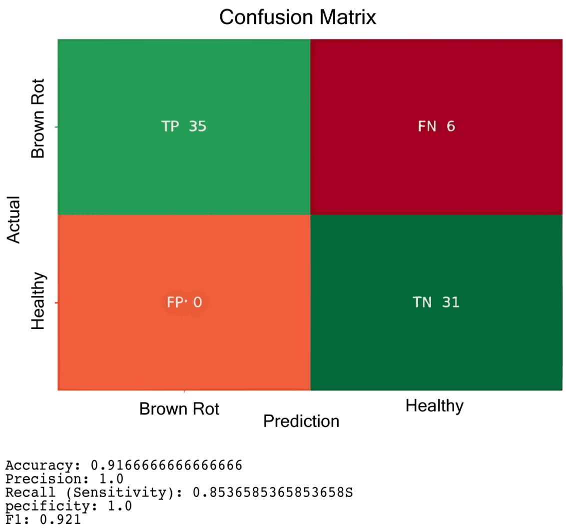

Fig. 13 Results of the confusion matrix from the evaluation of the AI fruit model.

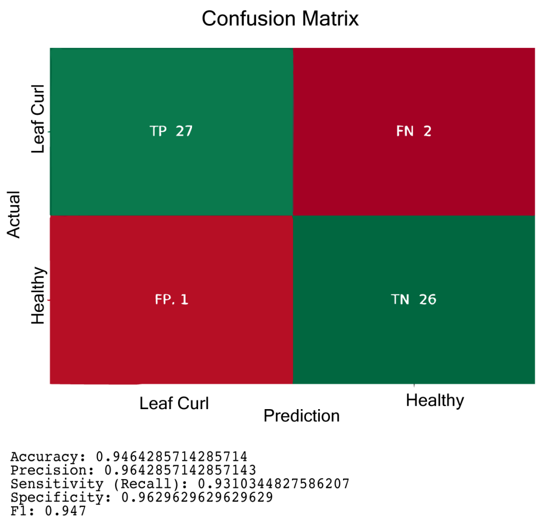

Fig. 14 Results of the confusion matrix for the evaluation of the AI leaf model.

Regarding the system's integration, adjustments were made to the connection between the back-end and the front-end to achieve optimal image sending and receiving times, adapted to the user's bandwidth. Figures 15 and 16 show the web application interface in operation, illustrating the prediction results for a peach fruit and leaf, respectively

Fig. 15 The web application interface, showing the result for the state of the peach fruit.

Fig. 16 The web application interface, displaying the result for the state of the peach leaf.

5 Conclusions

The implementation of an early disease detection system for peach crops using computer vision and artificial intelligence represents a significant step forward for precision agriculture. This study successfully validated a robust methodology, extending from image capture under real-world field conditions to the deployment of a precise and efficient classification model. A key aspect of this research was the rigorous validation of the model. The results obtained, with 100% precision for identifying Brown Rot in fruits and 96.4% for detecting Leaf Curl in leaves, confirm the system's high capacity to classify pathologies with an accuracy level exceeding 90%. These performance metrics, supported by detailed analysis via confusion matrices, reaffirm the model's reliability for application in agricultural environments. Furthermore, the project highlights the feasibility of integrating deep learning solutions into accessible tools for farmers. The lessons learned during the development of the web application demonstrate that AI technologies can be effectively deployed to offer real-time diagnoses, thereby facilitating timely and proactive decision-making for crop management. Despite these promising results, this work opens new avenues for future research. Expanding the dataset is crucial to improving the model's generalization and its adaptability to a wider variety of environmental conditions and disease manifestations. Future research could explore the integration of advanced techniques to mitigate variations in lighting and pest proliferation, as well as the optimization of the model's architecture for deployment on edge devices.

6 Declarations

- **Funding:** This research was funded by the Universidad Nacional Abierta y a Distancia (UNAD) under the Research Call No. 12.
- **Conflict of interest / Competing interests:**The authors declare that they have no conflict of interest or competing interests.
- **Ethics approval and consent to participate**Not applicable.
- **Consent for publication:**Not applicable.
- **Data availability:**The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.
- **Materials availability:** Not applicable.
- **Code availability:** The source code developed for this study is available upon reasonable request from the corresponding author.
- **Author contribution:** All authors contributed to the conception, design, implementation, and writing of the manuscript. All authors read and approved the final version of the article.

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