

Precision Agriculture: Application of AI Technology for the Early Detection of Diseases in Plants

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Abstract

Precision agriculture has emerged as an innovative solution to meet the current challenges in agricultural production. The implementation of artificial intelligence (AI) technologies has allowed the development of advanced systems for the early detection of plant diseases, contributing to the improvement of productivity and sustainability. This study looks at the use of AI Technology, such as machine learning and computer vision, to identify early signs of disease in crops. The results of various experimental applications are presented, highlighting their effectiveness compared to traditional methods. The findings suggest that integrating AI into precision agriculture can optimize crop management and reduce pesticide use, benefiting both the farmer and the environment.

Keywords:

Precision agriculture, artificial intelligence, disease detection, computer vision, agricultural sustainability.

Introduction

Agriculture faces increasingly complex challenges due to global population growth, the effects of climate change, and the need to ensure long-term food security. It is estimated that by 2050 it will be necessary to increase food production by **70%** to meet global demand (FAO, 2021). However, factors such as the spread of disease in crops, inefficient use of resources, and environmental degradation limit farmers' ability to achieve this goal (Gebbers & Adamchuk, 2022).

In this context, precision agriculture has established itself as an innovative approach that allows agricultural practices to be optimised through the use of advanced technologies.

The integration of artificial intelligence (AI) has revolutionized this area, offering tools such as computer vision, machine learning, and the analysis of large volumes of data, which allow crops to be monitored in an automated way and detect anomalies more accurately (Li et al., 2021).

Early detection of diseases is a critical issue in agricultural production. Diseases such as mildew, rust, and fusarium wilt can devastate entire crops if not identified and treated early. According to Picon, Alvarez, and Carrasco (2022), economic losses from crop diseases amount to more than **20%** of annual global production, which puts the stability of food supply chains at risk. Traditionally, the identification of plant diseases has been done through manual visual inspections, a process that is costly, inefficient, and subject to human error (Zhang, He, & Tang, 2022).

The addition of AI Technology offers an efficient and accurate alternative to address this challenge. Tools based on artificial intelligence, such as machine learning algorithms and convolutional neural networks (CNNs), make it possible to analyze high-resolution images captured by drones, sensors, or cameras, and detect specific patterns associated with diseases in early stages (Mohanty, Hughes, & Salathé, 2020). These advances not only contribute to the reduction of production losses, but also promote more sustainable practices, by minimizing

the indiscriminate use of pesticides and other agricultural inputs (Lu & Reyna, 2021). Likewise, the use of these technologies facilitates informed decision-making, resulting in more efficient management of resources and an increase in the profitability of producers (Li et al., 2021). According to recent studies, the use of artificial intelligence in precision agriculture has managed to increase crop yields by **15-20%**, simultaneously reducing operating costs and environmental impact (Gebbers & Adamchuk, 2022).

The present article aims to analyze the application of AI Technology in the early detection of plant diseases, evaluating its efficacy and benefits compared to traditional methods. The available technological tools, their implementation in case studies and the positive impact they generate on both agricultural productivity and environmental sustainability will be explored.

Theoretical Framework

Precision agriculture is an approach based on advanced technologies to crop management that allows the use of agricultural inputs to be optimized and production maximized. This concept has gained relevance in recent years thanks to the incorporation of tools such as artificial intelligence (AI), big data, remote sensing, and robotics (Gebbers & Adamchuk, 2022). In particular, AI has transformed the detection of diseases in plants, by offering fast, accurate and sustainable solutions.

1. Artificial Intelligence in Precision Agriculture

Artificial intelligence encompasses technologies such as **machine learning and convolutional neural networks (CNNs)**, which allow processing large amounts of data and recognizing complex patterns in crop images (Li et al., 2021). These technologies have been successfully applied in the detection and classification of diseases, overcoming the limitations of traditional methods (Mohanty, Hughes, & Salathé, 2020).

Table 1. Comparison between traditional methods and AI-based methods

Feature	Traditional Methods	AI-based methods
Precision	60-75%	90-95%
Diagnostic speed	Lenta (manual)	Fast (automated)
Costs	High (labor)	Moderate (once implemented)
Scalability	Limited	Loud
Use of inputs (pesticides)	Inefficient	Localized and efficient

Source: Mohanty, Hughes, and Salathé (2020); Zhang, He and Tang (2022).

Computer vision, an essential component of AI, makes it possible to identify visual symptoms of diseases such as leaf spots, color changes, and structural deformations, by analyzing high-resolution images captured by drones, cameras, or satellites (Lu & Reyna, 2021). This data is processed with **Machine Learning** algorithms, trained to distinguish between healthy and diseased crops with a high level of accuracy.

2. Technological Tools in Disease Detection

AI-based technologies include various tools that work together for the detection and monitoring of diseases:

- **Drones and remote sensors:** They allow the acquisition of large-scale aerial images in real time, facilitating the detection of symptoms not perceptible to the naked eye (Picon et al., 2022).
- **Convolutional neural networks (CNNs):** These networks are capable of classifying images with high accuracy, identifying specific patterns associated with different diseases (Zhang et al., 2022).
- **Internet of Things (IoT):** Connected devices collect information about humidity, temperature, and other environmental conditions that favor the spread of disease (Gebbers & Adamchuk, 2022).

Table 2. Top diseases detected with AI Technology

Cultivation	Illness	Technology Used	Fountain
Tomato	Mildew	Convolutional neural networks	Mohanty et al. (2020)
Corn	Corn rust	Computer vision	Zhang et al. (2022)
Wheat	Fusariosis	Machine learning	Lu & Reyna (2021)
Grape	Powdery mildew	Drones and Image Analysis	Li et al. (2021)

These tools not only improve detection accuracy, but also allow farmers to act proactively to prevent the spread of disease and minimize economic losses.

3. Benefits of AI in Precision Agriculture

The implementation of AI Technology in agriculture has multiple benefits:

- **Reduction of pesticide use:** By detecting diseases in early stages, it is possible to apply localized treatments, reducing the use of chemical products by **30%** (Picon et al., 2022).
- **Increased productivity:** An increase in crop yield of up to **20%** has been demonstrated thanks to early intervention (Gebbers & Adamchuk, 2022).
- **Environmental sustainability:** By optimizing the use of inputs, environmental impact is minimized and more sustainable agriculture is promoted (Li et al., 2021).

Table 3. Impact of AI on agricultural productivity

Indicator	Traditional Value	Value with AI
Crop yield	60-70%	80-90%
Use of pesticides	Inefficient	Located (-30%)
Diagnostic times	1-2 weeks	Real-time
Loss due to illness	Up to 20%	Less than 5%

Source: Li, Zhao and Wang (2021); Gebbers and Adamchuk (2022).

4. Limitations and Challenges

Despite its benefits, the use of AI in the detection of agricultural diseases faces challenges such as:

1. **Initial implementation costs:** Adopting technologies such as drones and sensors can be costly for smallholder farmers (Zhang et al., 2022).
2. **Lack of training:** Specialized training is required to interpret the data generated (Picon et al., 2022).
3. **Technological dependence:** Internet connectivity and digital infrastructure are limited in some rural regions (Lu & Reyna, 2021).

Methodology

The study was developed using a quantitative and experimental approach, in order to evaluate the effectiveness of **artificial intelligence (AI)** in the early detection of diseases in tomato and corn crops. The methodology was designed in four main phases: **data collection, image processing, AI model training, and outcome evaluation.**

1. Data Collection

To obtain images of the crops, drones equipped with high-resolution cameras and multispectral sensors were used. The drones flew over plots of 10 hectares for 12 weeks in three periods of crop growth: germination, vegetative development and flowering.

Instruments used:

- **DJI Phantom 4 Pro drones** with **20 MP** cameras and automated flight capability.
- **Micasense RedEdge-MX multispectral sensors**, which capture images in **RGB**, near- infrared (NIR), and redband spectra, useful for identifying changes in chlorophyll (Zhang et al., 2022).

- **GPS and GIS applications** to georeference plots and organize the data obtained (Li et al., 2021).

2. Image Processing

The collected images were processed using specialized software in visual analysis and **Machine Learning** algorithms. The workflow included the following stages:

1. Data pre-processing:

- Noise removal in images.
- Lighting and contrast correction.
- Image segmentation to isolate leaves, stems, and fruits.

2. Spectral analysis:

Vegetation indices such as NDVI (Normalized Difference Vegetation Index) were used to assess changes in plant health:

$$(NIR - RED)$$

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

Low NDVI values indicated early signs of stress in plants (Lu & Reyna, 2021).

3. Algorithm training:

Convolutional neural networks (CNNs) were implemented trained with a labeled dataset of images of healthy and diseased plants. The selected architecture was **VGG16** and **ResNet-50**, widely used in computer vision (Mohanty et al., 2020).

Table 1. Tools and algorithms used in image processing

Tool	Function	Reference
Drone DJI Phantom 4 Pro	Aerial Image Capture	Zhang et al. (2022)
Micasense RedEdge-MX	Multispectral sensors	Li et al. (2021)
Python (TensorFlow, Keras)	AI Model Training	Lu & Reyna (2021)
NDVI	Plant stress assessment	Mohanty et al. (2020)

3. AI Model Training

Two models of **Convolutional Neural Networks (CNNs)** were trained, applying supervised learning techniques. The steps included:

- **Training and validation dataset:** 500 labeled images of healthy and diseased plants (250 tomato and 250 corn) were used.
- **Model Configuration:**
 - CNN architecture: **ResNet-50 and VGG16**.
 - Parameters: Learning rate **0.001**, 50 epochs, and batch size of 32 images.
 - Optimization: Adam algorithm (Picon et al., 2022).

4. Evaluation and Validation of Results

To measure the effectiveness of the trained models, common performance metrics in computer vision were calculated:

- **Accuracy:**

Proportion of correct predictions with respect to the total.

- **False positive (FP) and false negative (FN) rate:**

Incorrect identification of healthy or diseased plants.

- **Processing Time:**

Evaluation of the time required to process images and issue a diagnosis.

Table 2. Performance metrics of trained models

Model	Accuracy (%)	False Positives (%)	False Negatives (%)	Processing Time(s)
ResNet-50	94.2	3.5	2.3	12.5
VGG16	92.5	4.2	3.3	15.2

Source: Results of the experimental study.

5. Experimental Procedure

1. Plots of tomato and corn crops were selected on two agricultural farms.
2. Drone flights were scheduled once a week, for 12 consecutive weeks.
3. The collected images were processed in **Python** using the TensorFlow and OpenCV libraries.
4. The diagnoses obtained using AI were compared with diagnoses made manually by **expert agronomists** to validate the accuracy of the models.

6. Data Analysis

The analysis was performed using **descriptive statistics** and **mean comparison** tests to assess the difference between manual and AI-based methods. The **SPSS 26** software was used to perform Student's t-tests and determine statistical significance.

Results

The application of artificial intelligence (AI) in the early detection of diseases in tomato and corn crops showed positive and consistent results in terms of **accuracy, efficiency and cost reduction**. The data collected during the 12 weeks of monitoring allowed to compare the performance of the models trained with traditional manual methods, highlighting the advantages of systems based on **convolutional neural networks (CNNs)**.

1. Accuracy in Disease Detection

The **ResNet-50** and **VGG16** models showed high levels of accuracy in identifying diseases such as **downy mildew** in tomatoes and **rust** in maize. Significant differences were observed in the effectiveness of the models compared to manual methods performed by agricultural experts.

Table 1. Accuracy Comparison Between Manual Methods and AI

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
Handbook (Experts)	76.8	72.5	80.3
ResNet-50 (AI)	G4.2	G2.8	G5.5
VGG16 (AI)	92.5	91.3	93.8

Source: Experimental data (2024); Mohanty, Hughes, & Salathé (2020).

The accuracy of AI models was on average **20% higher than** manual methods, confirming AI's ability to detect early symptoms of diseases that might go unnoticed by the naked eye (Zhang, He, & Tang, 2022).

2. Reduced Time to Diagnosis

The time required to analyze images and issue diagnoses using the trained models was significantly shorter compared to manual diagnosis.

Table 2. Diagnostic Time Comparison Between Methods

Method	Average Time (per 1 ha plot)
Handbook (Experts)	2-3 hours
ResNet-50 (AI)	12.5 seconds
VGG16 (AI)	15.2 seconds

Source: Results of the experimental study.

AI models processed and analyzed images in **real time**, reducing diagnosis time by **98%**, allowing immediate intervention in case of disease detection (Li, Zhao, & Wang, 2021).

3. Identification of Specific Diseases

During the study, neural networks successfully identified the most common diseases in the monitored crops. The performance was validated by comparing the results with manual diagnoses of agricultural experts.

Table 3. Diseases detected and accuracy by culture

Cultivation	Illness	Accuracy (%)	False Positives (%)	False Negatives (%)
Tomato	Mildew	93.7	3.2	3.1
Corn	Corn rust	94.5	2.8	2.7
Tomato	Fusariosis	91.2	4.1	4.7

Source: Results of the experimental study.

False positive and false negative values remained low in all cases, highlighting the ability of the ResNet-50 and VGG16 models to differentiate diseases with high accuracy (Lu & Reyna, 2021).

4. Impact on Input Use and Operating Costs

Early detection using AI allowed localized treatments to be applied, significantly reducing pesticide use and operating costs.

Table 4. Economic impact of using AI

Indicator	No AI	With AI	Reduction (%)
Pesticide use (litres/ha)	12.5	8.5	32%
Input costs (\$/ha)	150.00	102.00	31.6%
Crop yield (ton/ha)	6.5	7.8	20% increase

Source: Experimental results (2024); Picón, Álvarez, & Carrasco (2022).

An average reduction of **32%** in pesticide use was observed due to accuracy in disease detection and timely intervention. In addition, crop yields increased by **20%** thanks to the application of specific treatments and in early stages (Picon et al., 2022).

5. Statistical Analysis

To validate the results, statistical tests were performed to compare means between manual and AI-based methods:

- **Student's t-test:** A significant difference ($p < 0.05$) was found between the accuracies obtained by manual methods and AI models.
- **NDVI correlation and disease symptoms:** NDVI analysis showed a significant correlation ($r = 0.89$) with the presence of diseases detected by AI (Zhang et al., 2022).

Conclusion of the Results

The results obtained demonstrated that artificial intelligence, specifically the **ResNet-50** and **VGG16** models, offers significant advantages in the early detection of diseases in agricultural crops. Key findings include:

1. High accuracy in disease identification (over 90%).
2. Reduction of diagnostic time by **98%**.
3. Savings in pesticide use and operating costs by **30%**.
4. Increased crop yields by **20%**.

The implementation of AI in precision agriculture represents an effective and sustainable solution to meet today's agricultural challenges.

Conclusions

The implementation of **artificial intelligence (AI)** in precision agriculture, focused on the early detection of diseases in crops, has proven to be an effective and transformative tool for agricultural production. Throughout the study, significant improvements in **accuracy, efficiency, and sustainability were evidenced**, supporting the incorporation of these technologies in diverse agricultural environments.

First, the results obtained with the **ResNet-50** and **VGG16** models reveal an **accuracy of more than 90%** in the identification of diseases such as mildew, fusarium wilt and corn rust, which represents an improvement of more than **20%** compared to traditional manual methods. This ability to detect early symptoms, even at stages imperceptible to the human eye, allows farmers to intervene in a timely manner, preventing the spread of disease and reducing economic losses (Zhang, He, & Tang, 2022).

In terms of **time efficiency**, automated AI diagnostics reduced processing times to **seconds**, compared to the hours required for manual inspections. This not only optimizes time management in agricultural work, but also allows the supervision of large crop areas with greater frequency (Lu & Reyna, 2021). The continuous and real-time monitoring capacity offered by these technologies is key to the adoption of **proactive** strategies in disease management (Picon, Alvarez, & Carrasco, 2022).

Another relevant finding of the study is the **reduction in the use of inputs**, particularly pesticides, which decreased by **30%** thanks to localized and specific detection of the affected areas. This approach allows treatments to be applied only where necessary, reducing the environmental impact associated with the excessive use of agrochemicals (Li, Zhao, & Wang, 2021). Thus, AI contributes to a more **sustainable** agriculture, aligned with the Sustainable Development Goals (SDGs), such as responsible production and environmental protection (FAO, 2021).

The economic impact was also significant, with a **31%** reduction in operating costs due to the efficient use of inputs and the reduction of manual work. In addition, crop yields increased by **20%**, demonstrating the long-term profitability of adopting these technologies in agriculture (Gebbers & Adamchuk, 2022).

However, despite its benefits, **significant challenges** remain for the large-scale implementation of AI in agriculture. These include:

1. The **high upfront costs** of acquiring drones, sensors and specialized software, which can be prohibitive for small producers.
2. The **technological and training gap**, especially in rural regions where technological infrastructure is limited (Picon et al., 2022).
3. The need for **high-quality data** and robust storage and processing systems, which are essential for the proper functioning of AI models (Li et al., 2021).

However, with the continued development of technology and the progressive reduction of costs, it is expected that these barriers can be overcome in the coming years, allowing **artificial intelligence** to be accessible to a greater number of agricultural producers.

In conclusion, AI applied to precision agriculture not only optimizes crop management by providing fast and accurate diagnostics, but also contributes to the sustainability and

profitability of the agricultural sector. Early detection of diseases represents a crucial advance in **global food security**, by ensuring increased food production with a reduced environmental impact. The integration of AI, together with supportive policies and training programs, can transform today's agriculture, consolidating it as an efficient, technological and sustainable practice to meet the challenges of the 21st century.

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