Detecting mealybug, iron spot and nutrient deficiency by using the physical characteristics of coffee using artificial intelligence

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**Abstract** The cultivation of coffee in Colombia is essential for the economy and local communities. However, diseases and pests that affect coffee seedlings represent a persistent challenge for production and farmers. Detecting these threats early and accurately is crucial to protecting plant health and ensuring crop quality. In this context, it is proposed to develop an application driven by artificial intelligence that allows detecting and analyzing diseases in coffee leaves.

The goal of this project is to design and create an app that transforms the way farmers address diseases in their coffee crops. Through the integration of artificial intelligence algorithms and neural networks, it seeks to provide farmers with an effective tool that accurately identifies various stages of diseases in coffee seedlings. In addition, the project seeks to detect the presence of the cochineal, a pest that can wreak havoc if not dealt with quickly.

**Resumen** El cultivo de café en Colombia es esencial para la economía y las comunidades locales. Sin embargo, las enfermedades y plagas que afectan los plantones de café representan un desafío persistente para la producción y los agricultores. Detectar estas amenazas de manera temprana y precisa es crucial para proteger la salud de las plantas y garantizar la calidad de los cultivos. En este contexto, se propone desarrollar una aplicación impulsada por inteligencia artificial que permita detectar y analizar enfermedades en las hojas de café.

El objetivo de este proyecto es diseñar y crear una aplicación que transforme la forma en que los agricultores abordan las enfermedades en sus cultivos de café. A través de la integración de algoritmos de inteligencia artificial y redes neuronales, se busca brindar a los agricultores una herramienta efectiva que identifique con precisión diversas etapas de enfermedades en plántulas de café. Además, el proyecto busca detectar la presencia de la cochinilla, una plaga que puede causar estragos si no se trata rápidamente.

**Keywords:**  Artificial intelligence, coffee, coffee diseases, seedbeds, models.

**Palabras clave:** Inteligencia artificial, café, enfermedades del café, almácigos, modelos

Introduction

Colombia distinguishes itself as one of the main exporters of the most appreciated coffee worldwide. Between 2021 and 2022, the country exported around 13.1 million kilograms of parchment coffee [1]. This crop is not only vital to the national economy, but also to the communities that depend on it. However, pests and diseases that affect coffee plants are a continuous challenge that reduces production and, consequently, the income of coffee farmers. Despite technological and scientific advances, current tools to detect and combat these threats are not effective enough in the face of the rapid evolution of these challenges.

This is where artificial intelligence (AI) offers a promising solution. By applying advanced algorithms and neural networks, it is possible to develop an effective tool that allows for the early and accurate detection of diseases and pests in coffee leaves. This would be a significant change in the way farmers face these challenges and could improve both crop quality and farmers' incomes.

This project aims to create an AI-powered application that addresses this gap in problem detection and analysis in coffee crops. By integrating innovative technologies and a centralized database, it seeks to provide farmers with an accessible and reliable tool to confront threats to their crops. Ultimately, this initiative seeks to strengthen coffee production in Colombia and ensure the sustainability of farmers in an ever-changing agricultural environment.

# Problems associated with coffee diseases in Colombia

Diseases in coffee seedlings, such as stem disease, iron spot, nematodes and moths, pose serious threats that can reduce both coffee production and quality in Colombia [2]. These diseases directly affect plant health, causing tissue damage and limiting plants' ability to grow and develop healthily.

Despite the existence of application development models that seek to address these problems, they are not yet implemented, with the exception of those developed by CENICAFÉ [3], a company affiliated with the National Federation of Coffee Growers that focuses its efforts on the research of this crop. This entity uses images to analyze and quantify the area affected by various diseases. However, the current tool has obvious limitations. By way of example, although it offers accurate and objective measurements of the severity of the disease in contrast to traditional methods of subjective assessment, its application is currently restricted to the diagnosis of iron stain. This circumstance constitutes a notable restriction, as it does not have the ability to detect or analyze other common diseases that affect coffee seedlings.

In addition, these applications often present obstacles in terms of accessibility, due to the lack of technical knowledge and technological resources among farmers. This restricts their usefulness for those farmers facing a wider diversity of diseases in their seedlings, limiting their ability to effectively prevent and treat these problems.

The lack of adoption of adequate technological tools to manage diseases in coffee seedlings has direct repercussions on the livelihood of farmers in Colombia. The inability to effectively identify and prevent diseases can lead to loss of income for both farmers and their families, as crop production and quality are compromised.

In order to address this problem, the following questions are posed that will be addressed and resolved throughout the development of this article:

How to analyze diseases in coffee seedlings according to the technical and functional requirements of the application to be developed?

How to design an application that detects and monitors diseases in coffee seedlings at an early age using AI systems?

How to develop the application for early disease monitoring in coffee seedlings, applying AI systems and following the best development practices?

How to evaluate the application by testing accuracy, performance and implementation in coffee seedlings?

How to implement the application of early detection of diseases in coffee seedlings and provide farmers with timely solutions and alerts?

How to deploy the app to ensure its continued use in the farming operation and allow farmers to access historical data and useful alerts?

# Review of Models Applied to the Detection of Diseases in Coffee Plantations

The following article, entitled "COMPUTER VISION: APPLYING FILTERS AND SEGMENTATION IN COFFEE LEAF IMAGES", discusses the preprocessing of digital images of coffee leaves. This process involves the preparation of the images through the application of filters aimed at eliminating the noise present in the images under study. To achieve this, noise removal is carried out using smoothing filters (Medium, Gaussian) and enhancing filters (Sobel, Laplacian, Gaussian Laplacian and High Boost). In addition, the article highlights the image-based segmentation approach of grayscale coffee leaves, obtaining optimal results by using the RG channels without the B component to eliminate the edges generated by the shadows in the image. To detect edges, the methods of Sobel and Canny are applied [4].

The methodology used is developed as follows:

* Dataset: Photographs are collected under appropriate lighting conditions to avoid reflections and shadows in the images. During this process, the coffee leaves were arranged on backgrounds of various colours (black, Gray, white).
* Instruments for obtaining the dataset: A standard digital camera is used to capture the images. The resulting images contain three colour components: RGB (Red, Green, Blue).
* Application of filters: Filtering techniques are applied to reduce noise through the use of Gaussian, Medium, Sobel, Laplacian and High Boost filters. This aims to obtain more accurate information from the sheets under study. Likewise, the segmentation strategy based on grayscale coffee leaf images is highlighted, with the approach of using only the RG channels, excluding component B, to eliminate the edges caused by shadows in the image.

**Metrics**: The authors state that one of the best combinations is Gaussian Laplacian, due to the lower sensitivity of the median filter to the texture of coffee leaves and the sensitivity of Gaussian Laplacian to contours, detecting in most of the analysed cases up to approximately 95% accuracy in the detection of the coffee leaf. indicating that it is a very effective method. [5]

In another article entitled "A DEEP LEARNING APPROACH COMBINING INSTANCE AND SEMANTIC SEGMENTATION TO IDENTIFY DISEASES AND PESTS OF COFFEE LEAVES FROM IN-FIELD IMAGES", the relevance of identifying and treating pests and diseases with the aim of preventing these crucial problems affecting farmers is highlighted. In addition, it is noted that conventional approaches to computer vision recognition are insufficient to address these complex issues, which has led to the emergence of innovative methods in recent years.

Deep learning is underlined as a significant trend in this field. Its application focuses on detecting and recognizing biotic stresses in images taken in the field using mobile devices. These images can present challenges due to factors such as lighting, noise, and complicated backgrounds.

In the aforementioned study, the authors have developed an integrated framework that employs a combination of different convolutional neural networks (CNNs) to improve the detection and recognition of lesions in coffee trees.

This approach breaks down into three key stages:

* Instance Segmentation: Uses the Mask R-CNN network, achieving an accuracy of 73.90% and a completeness of 71.90%.
* Semantic Segmentation: It uses the UNet and PSPNet networks, with an average intersection over the junction of 94.25% and 93.54%, respectively.
* Classification: Implements a ResNet to discern and classify the various features present in the image.

**Metrics:** It takes accuracy and completeness as a reference, obtaining 73.90% in the first and 71.90% in the second. The results obtained are encouraging and represent a significant advance in the automatic detection of diseases and pests in coffee crops. The proven effectiveness of these tests suggests that this approach could be transferred to an integrated mobile platform, providing a valuable real-world tool for farmers and other professionals in the field of agriculture. [6]

In their article titled "USING IMAGE PROCESSING TO DETERMINE THE SEVERITY OF IRON SPOT IN COFFEE LEAVES," Cenicafé presents the use of image processing techniques to assess the severity of iron spot disease in coffee leaves. The authors have developed a program using Matlab that allows images to be analyzed and the area affected by the disease to be measured. This enables a more accurate and faster measurement of leaf area and disease severity, offering reliable results for further investigations.

As for the specifics:

* Instruments for the dataset: Images were captured with an OLYMPUSâ CAMEDIA DIGITAL C-3040 ZOOM camera. Set the disc to "A/S/M" mode for still images and manual mode. Macro mode has been selected in the control panel to focus on foreground objects.
* Program: Matlab version 5.3 was used.
* Methodology for obtaining the dataset: The object was photographed at a distance of 20 to 80 cm, avoiding the use of flash due to the shadows that affected the quality of the photos. The images were saved at a resolution of 640 x 480 on a white background and in diffused light.
* Program Details: A simple thresholding was applied to the saturation plane of the leaf image. To detect the necrotic zone, a statistical classifier was used that selected the minimum Mahalanobis distance for four classes, with a threshold of 0.

**Metrics:** The metric used in the article is the percentage of severity of Iron Spot disease in coffee leaves. This percentage is calculated as the ratio of the area of necrosis to the healthy area of the leaf, multiplied by 100. [3]

The following article, "COFFEE RUST DETECTION WITH UAV-BASED VEGETATION INDICES AND DECISION TREE MACHINE LEARNING MODELS," focuses on research to detect coffee rust severity (CLR) by using imagery captured by unmanned aerial vehicles (UAVs) and machine learning (ML) algorithms. Through vegetation indices and decision tree models, the methodology allows to classify CLR infestation into various stages. The Logistic Model Tree (LMT) method stands out as the most effective, with F measurements of 0.915 and 0.875 for the early and advanced stages of the disease.

The methodology used in this project covers the following aspects:

* Problem Identification: The relevance of accurate and early detection of Hemileia vastatrix disease (CLR) for effective management in coffee crops is addressed.
* UAV Use: Unmanned aerial vehicles with a Sequoia camera are used to image with a spatial resolution of 10.6 cm in four spectral bands.
* Vegetation Index Extraction: 63 vegetation indices are extracted from the images, representing different aspects of plant growth and health.
* CLR Infestation Classification: The infestation is classified into four classes, based on the severity of the rust on the plants.
* Decision Tree Modeling: Several decision tree-based algorithms, including LMT, J48, REP Tree, Random Tree, and Random Forest, are evaluated using a 10-folder cross-validation approach.
* Model Evaluation: The results are analyzed to determine the most accurate model in predicting infestation classes.
* Practical Application: The proposed framework is presented as a tool for detecting CLR in unsampled plants, contributing to precision agriculture practices.

**Metrics:**  The Logistic Model Tree (LMT) method stands out as the most effective in accurately predicting infestation classes, with F-measurements of:

* For early stages of CLR (2 to 5% rust): 0.915
* For later stages of CLR (20 to 40% rust): 0.875

These results highlight the effectiveness of the proposed framework in the modelling of rust in coffee plantations, and its potential application in precision agriculture. [7]

In another article, "DEVELOPMENT OF A DIAGNOSTIC SUPPORT METHOD USING COMPUTER VISION TECHNIQUES TO IDENTIFY NUTRITIONAL PHOSPHORUS DEFICIENCY IN LEAVES OF COFFEE PLANTS (COFFEA ARABICA L.) OF THE CASTILLO VARIETY IN THE PHENOLOGICAL PHASE OF FORMATION AND FRUIT FILLING", the authors focused on the automated diagnosis of nutritional phosphorus deficiency in coffee plants, specifically in the municipality of Acevedo. The research was divided into four phases: design of the imaging device, creation of a dataset with images of healthy and phosphorus-deficient leaves, development of an algorithm to identify the deficiency, and validation of the method.

The methodology involved the following steps:

* Design and Construction of the Image Capture Equipment: A device was created to isolate the background and standardize the working distance. A blue background was chosen to maximize pixel separation.
* Construction of a Data Set: Images of phosphorus deficient and non-phosphorus deficient coffee leaves were collected in the municipality of Acevedo, creating a representative dataset.
* Algorithm Development:
  1. Image Preprocessing: Preparation of images for analysis.
  2. Image Segmentation using Super Pixels: Separation of areas of interest.
  3. Feature Extraction: Color and texture identification.
  4. Feature Reduction: Use of techniques such as extra tree classifier, LDA and PCA.
  5. Classification: Evaluation of four types of classifiers, choosing the decision tree classifier as the most effective.
  6. Graphical Interface: A graphical interface was created using QtPy5 and Python.
* Validation of the Proposed Method: Validation under field conditions to verify the efficacy of the algorithm in the detection of nutritional phosphorus deficiency in coffee leaves.

**Metric:**

* F-score for the Identification of Phosphorus Nutritional Deficiency: 0.994, demonstrating a high ability to distinguish between healthy and phosphorus deficient leaves.
* Comparison with Controlled Conditions: The proposed method showed a 6% lower performance than an algorithm trained under controlled conditions.

In conclusion, the research presented a viable methodology for the diagnosis of nutritional deficiencies in coffee plants under real conditions, despite the fact that areas for improvement were identified in future studies. [8]

The article titled "DISEASE DETECTION IN THE AGRICULTURAL SECTOR USING ARTIFICIAL INTELLIGENCE" addresses various investigations on the detection of diseases in agricultural crops using artificial intelligence techniques. The proposed approaches seek to acquire characteristics of plant leaves and fruits, using classifying or clustering algorithms to identify signs of disease. Although the accuracy of the results varies, overall, promising results are obtained. The main conclusion is that these algorithms can be a valuable tool for the early detection of plant diseases, benefiting farmers by enabling timely diagnoses and reducing economic losses.

The methodology used comprises four stages:

* Data Acquisition: Images of disease-affected leaves were captured using digital cameras.
* Pre-processing: Techniques such as scaling, denoising, and histogram equalization were applied to improve image quality.
* Feature Extraction: Relevant features were identified in the images, such as texture and color.
* Classification: A classification algorithm was used to determine the disease present in the plants.

**Metrics:** The results obtained varied depending on the crop and the algorithm used. For example, in passion fruit cultivation, the SVM algorithm achieved an accuracy of 56%. For wheat cultivation, the accuracy was 70%. In the case of coffee farming, the fuzzy logic algorithm reached an accuracy of 85%. Other examples include an accuracy of 82% for pomegranate cultivation using SVM and an accuracy of 86.54% for crops such as banana, bean, lemon, and rose using a combined algorithm approach.

In summary, it was concluded that algorithms such as SVM, fuzzy logic and artificial neural networks were effective in the classification of diseases in plants, demonstrating encouraging results in various crops. However, the accuracy varied depending on the crop and the algorithm used. [9]

In the article "SYSTEM OF INSPECTION AND CLASSIFICATION OF LEAVES OF MEDICINAL PLANTS BY MEANS OF ARTIFICIAL VISION", the authors present the idea of developing a software capable of identifying varieties of medicinal plants according to their colors and determining their suitability for the production of oil or tincture.

The methodology is as follows:

* Data Collection: It begins with the collection of images, considering the state of the leaves that will be studied in the project. Aspects such as backlight lighting, where the camera is positioned in the direction of the light, are considered.
* In-Depth Research and Component Selection: A thorough investigation of the concepts to be used is carried out and low-cost components that offer adequate performance are selected. It uses an embedded system, Raspberry Pi 3, among others.
* Application of Convolutional Neural Systems: Convolutional neural systems with a layer of 32 filters and a 3x3 core are used. A multi-layered neural network that processes images based on HSV color theory is also used.
* Image Segmentation and Dataset Construction: Image segmentation is performed using the Kmeans algorithm, which is unsupervised classification. The dataset consists of a total of 977 images per class, with the purpose of forming a convolutional neural network using the Keras library.

**Metrics:** The results demonstrate 98% accuracy in sorting plants. This indicates that the neural system is functioning properly, exceeding the threshold of 85% accuracy with the use of CNN. Other results include 61.66% accuracy with Kmeans and 48.33% with MLP.

In summary, the paper presents a methodology that uses computer vision to inspect and classify leaves of medicinal plants. The approach ranges from data collection to the application of convolutional neural systems and segmentation algorithms. The results obtained highlight the high precision achieved in the classification of plants by means of the neuronal system, evidencing its effectiveness in this context. [10]

In the article entitled "DEVELOPMENT OF A REAL-TIME STATE RECOGNITION SYSTEM FOR COFFEE CROPS USING ARTIFICIAL NEURAL NETWORKS", a technique that combines image processing and machine learning through neural networks to identify the state of coffee plantations in real time, making use of the concept of deep learning, is presented. This approach allows computational models to learn data representations with multiple levels of abstraction. The methodology used is as follows:

* Design of the Convolutional Neural Network: The creation of a convolutional neural network with eight layers, divided into four convolutional layers and four fully connected layers, is proposed.
* Segmentation: Six neurons are established that generate segmented images after passing through the convolutional layers. These images are classified into categories such as healthy, affected by red mite, oxidation at different levels, among others.
* Parameters: Filters with different depths are used in the lattice, with a total of 16, 32, 64, 128, 256, and 512 filters, respectively, for the convolutional layers.
* Programming and Training: The neural network is compiled and optimized using the Adam optimizer. The model is then trained with the help of Google Colab.

**Metrics:** During training, metrics such as loss, accuracy, and mean square error are employed. The results show an accuracy of 98.72% on the training dataset and an accuracy of 70.16% on the validation dataset.

In summary, the article addresses the development of a system that uses convolutional neural networks to recognize the state of coffee plantations in real time. The methodology encompasses everything from the creation of the neural network to the segmentation and parameters used in the process. The results highlight the high precision achieved in the classification of different plant states, demonstrating the effectiveness of the proposed approach. [11]

# Methodology

It is proposed to develop an innovative application that detects the problems of cochineal, iron stain and nutrient deficiency associated with coffee. The development of such a tool requires a methodical and adaptable approach to ensure its effectiveness and accuracy. In this context, the Scrum methodology, known for its iterativity and responsiveness, will be used to carry out this project. Here's how Scrum will be implemented in the application development.

Six main phases will be implemented for the development of the application.

**Phase 1.** Analyse the technical and functional requirements of the application to be developed according to the diseases in coffee seedlings.

To comply with this initial phase, work will be carried out in small phases of defined time, in order to comply with the Scrum methodology. During its development, it is necessary for each Sprint to present advances regarding the requirements, in order to obtain feedback and an adjustment to these requirements.

**Phase 2.** Design an application that detects and monitors diseases in coffee seedlings at an early age using AI systems.

Given the focus on user experience and the need for effective adoption by farmers, the User-Centered Design (UCD) methodology has been selected. This methodology prioritizes a deep understanding of the user's needs and behaviors, ensuring an implementation that is practical and useful in a real agricultural environment.

**Phase 3**. Develop the application for the early monitoring of diseases in coffee seedlings, applying AI systems and following the best development practices.

For the next phase, the coding, the code writing policies, the security with which the application will work, the version in which the application will start, and the development environment will be taken into account.

**Phase 4**. Evaluation of the application through tests of accuracy, performance and implementation in coffee seedlings.

The integration testing methodology is presented as the most suitable option to evaluate the prototype of the application. This choice is justified by the need to ensure that all parts of the system interact correctly and fulfill their functions in an integrated manner. Given the complexity of the software and the diversity of functions it offers, integration testing will make it possible to identify possible flaws in the interaction between the different components

Problems that these tests seek to solve:

* Identification of Interactions that cause Problems: This type of test allows you to discover problems in communication and coordination between modules or services.
* Joint Functionality Validation: Ensures that individual system functions work together as expected.
* Early Detection of Defects: By evaluating integration at an early stage, it makes it easier to correct problems before they become major obstacles.
* Global Quality Assurance: Contributes to the quality of the system as a whole, providing confidence in the robustness of the application.

**Phase 5.** Implement the application of early detection of diseases in coffee seedlings with a comprehensive approach to security that includes infrastructure, access, authentication, encryption, and incident management, among others.

For the implementation of the application, the configuration of the IPv6 server, the ports and their security, access and security management, monitoring and registration, and the continuous updates that are a fundamental part of the implementation of the application will be taken into account.

**Phase 6**. Deploy the application in coffee seedlings, configuring it and verifying its operation to facilitate the detection and management of diseases.

In this final phase, it is important to have the application and the user manual as well as to do so. In order to detail every important aspect of the app's functionality.

# Results and discussion

**Phase 1. Analyze the technical and functional requirements of the application to be developed according to the diseases in coffee seedlings.**

In this first phase, the functional and non-functional requirements necessary for the creation of the application dedicated to the early detection of diseases in coffee seedlings have been successfully completed. The main goal of this app is to provide farmers with an effective tool to identify and address three key diseases: Iron Spot, Nutrient Deficiency and Moth (Cochineal Arinoza). The key achievements and results of this phase are summarized below:

Functional and Non-Functional Requirements:

* A detailed list of functional and non-functional requirements that the app must meet has been developed, including detecting and classifying diseases, tracking disease progress, and generating alerts.

The requirements for the development of the application were based on the IEEE iso 830 protocol of 1998.

**Phase 2. Design an application that detects and monitors diseases in coffee seedlings at an early age using AI systems.**

In Phase 2, an app has been designed that uses artificial intelligence (AI) to detect and monitor diseases in coffee seedlings at an early stage. Key accomplishments include designing the application architecture, initiating AI model training, UI design, generating alerts, and initial testing. This design lays the groundwork for the implementation of the application, and the next phase focuses on development.

**Phase 3. Develop the application for the early monitoring of diseases in coffee seedlings, applying AI systems and following the best development practices.**

In phase 3, the application code is created, taking into account the functional and non-functional requirements of the first phase, in addition, it is structured based on the MVC architectural model using the mockups of the previous phase.

In this phase, the programming languages that will be used in the development of the application, the database that will store the user's data, the code writing policies and the version in which the application will be released are selected.

**Phase 4. Evaluation of the application through tests of accuracy, performance and implementation in coffee seedlings.**

It was determined that the best tests for the application are unit, integration, acceptance, performance, and security testing.

* Unit testing focuses on verifying the behavior of individual units of code.
* Continuous integration testing helps detect issues early in the development process, enabling faster and more reliable delivery.
* User acceptance testing (UAT) is essential in Scrum as it ensures that the functionality delivered meets the end-user's expectations. By including UAT as an early priority, you ensure that each iteration meets user requirements and aligns with customer expectations.
* Performance testing is critical to ensure that the application is efficient and can handle expected workloads. Including performance testing iteratively allows you to identify and address performance issues over time, rather than discovering them at later stages of development.

1. Security is a critical consideration in any application, and performing security testing on an ongoing basis helps identify and fix vulnerabilities as software is developed. This contributes to building a more secure application from the start. For this reason, the following tests will be performed:

* Unit test format.
* Continuous Integration Testing.
* User Acceptance Testing (UAT).
* Iterative Performance Testing.
* Continuous Security Testing.
* Test cases.
* Audit.

**Phase 5. Implement the application of early detection of diseases in coffee seedlings with a comprehensive approach to security that includes infrastructure, access, authentication, encryption, and incident management, among others.**

In Phase 5, a detailed emphasis has been placed on connection security, focusing on the implementation of IPv6 protocols and data protection through encryption. In addition, key security aspects such as secure infrastructure, authentication and access control, continuous monitoring, and regulatory compliance have been highlighted.

**Phase 6. Deploy the application in coffee seedlings, configuring it and verifying its operation to facilitate the detection and management of diseases.**

In phase 6, reference is made to the user manual which will have the following scheme:

**CoffeeControl App User Manual**

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