IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 12, December 2025

DOI: 10.17148/IJARCCE.2025.1412144

SmartCrop-Coffee: A Predictive Agriculture Framework

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Abstract: Coffee farming faces challenges such as crop diseases, improper fertilizer usage, climate variability, and limited access to expert guidance. Traditional practices rely on manual observation, leading to delayed disease detection and uncertain yield outcomes. This paper presents SmartCrop-Coffee, an AI-based decision support system for precision coffee farming. The framework integrates deep learning and machine learning to enable coffee leaf disease detection, fertilizer recommendation, coffee variety selection, and yield prediction. A Convolutional Neural Network (CNN) classifies leaf diseases, while Random Forest models support fertilizer, yield, and variety prediction using soil and crop data. Real-time weather data further enhances decision accuracy, supporting sustainable and data-driven coffee agriculture.

Keywords: Precision Agriculture, Coffee Leaf Disease Detection, Machine Learning, CNN, Yield Prediction.

I.INTRODUCTION

Coffee cultivation faces persistent challenges due to crop diseases, improper fertilizer application, climate variability, and limited access to expert guidance, particularly in developing regions. Traditional farming practices rely heavily on manual observation and experience, often leading to delayed disease detection, inefficient resource utilization, and uncertain yield outcomes. To address these challenges, this paper presents **SmartCrop-Coffee**, an artificial intelligence–based predictive agriculture framework designed specifically for coffee farming.

The proposed system integrates deep learning–based coffee leaf disease detection using Convolutional Neural Networks (CNNs), machine learning models for fertilizer recommendation, crop yield prediction, and coffee variety selection, along with real-time weather data obtained through external APIs. By combining soil nutrient analysis, climatic conditions, and image-based diagnostics, SmartCrop-Coffee delivers accurate, data-driven recommendations through a user-friendly web interface.

The framework aims to enhance productivity, reduce input wastage, and promote sustainable coffee farming by enabling timely and informed decision-making. Experimental results demonstrate that the integrated approach improves disease identification accuracy, optimizes fertilizer usage, and supports effective long-term farm planning, highlighting the potential of AI-driven decision support systems in modern precision agriculture.

The primary objective of the proposed framework is to enhance agricultural productivity while promoting sustainable farming practices. Early disease detection enables timely intervention, optimized fertilizer recommendations reduce excessive chemical usage, and accurate yield forecasting supports effective farm planning and resource management. The system's modular design allows seamless integration of multiple AI models, ensuring flexibility and scalability for real-world deployment.

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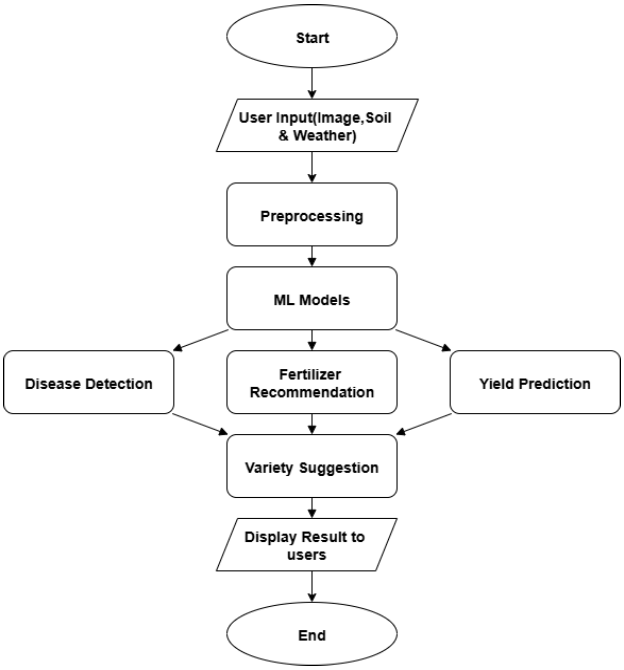
II. METHODOLOGY



Workflow Diagram of SmartCrop-Coffee

The SmartCrop-Coffee framework follows a compact and modular methodology designed for efficient decision support in coffee farming, as illustrated in Figure. The process begins with user inputs, including coffee leaf images, soil nutrient parameters, and geographic location data. These inputs are preprocessed through image normalization and data scaling to ensure consistency and accuracy.The processed data is then analyzed using multiple machine learning models. A Convolutional Neural Network (CNN) performs automated coffee leaf disease detection, while Random Forest and regression-based models generate fertilizer recommendations, predict crop yield, and suggest suitable coffee varieties.. Finally, the system aggregates all predictions and presents actionable insights to the user, enabling timely intervention, optimized resource usage, and sustainable .Plant Disease Detection Using Machine Learning:

Machine learning approaches for plant disease detection have evolved signi cantly over the past decade. Early methods relied on hand-crafted features and traditional classi ers such as Support Vector Machines (SVM) and Random Forests[6]. These approaches, while interpretable, often required extensive domain expertise for feature engineering.

1. Coffee-Specific Disease Detection

Limited research has speci cally focused on co ee leaf disease detection using deep learning. Early work by Reza et al.[10] applied image processing techniques to co ee leaf disease identi cation achieving 78% accuracy. More recently, Saleem et al.[11] demonstrated that CNNs could achieve 89% accuracy on a co ee leaf disease dataset. However, these studies often lack comprehensive evaluation metrics, real-world deployment considerations, and user-accessible interfaces.

2. Precision Agriculture and IoT Integration:

The concept of precision agriculture leverages sensor networks, data analytics, and automation to optimize crop management[12]. IoT-enabled agricultural systems have demonstrated potential in monitoring soil conditions, weather patterns, and plant health[13]. Integration of machine learning with IoT infrastructure creates opportunities for real-time, data-driven decision making in farming operations[14].

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3. Research Gap:

While signi cant progress has been made in plant disease detection, the co ee industry still lacks an integrated, production-ready framework that combines accurate disease classi cation with accessibility for smallholder farmers. Most research is limited to model development without considering deployment logistics, cost constraints, or user interface design. SmartCrop-Co ee addresses these gaps by providing an end-to-end solution.

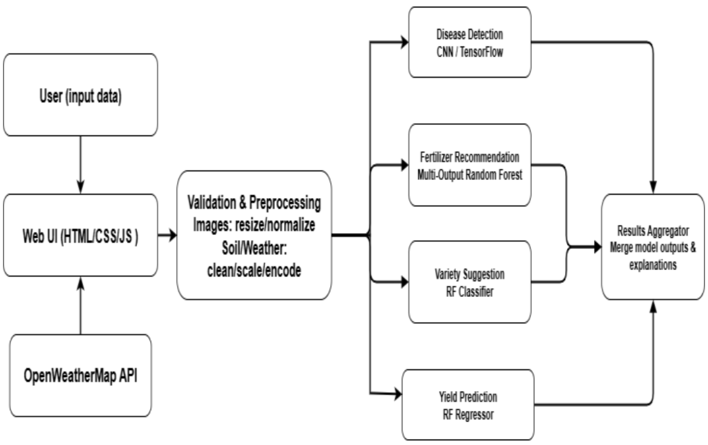
4. Real-Time Weather Forecast Integration:

Weather plays a critical role in coffee cultivation. SmartCrop-Coffee integrates real-time weather data through a reliable weather API to provide up-to-date information on temperature, rainfall, and humidity. These parameters are dynamically incorporated into prediction models and recommendations. Weather insights assist farmers in planning irrigation, fertilization, and disease management activities, thereby minimizing risks associated with climatic variability.

5. Result Aggregation and Decision Support Output:

Outputs from all machine learning and deep learning modules are aggregated into a unified decision-support dashboard. The system presents disease diagnosis results, fertilizer recommendations, yield predictions, coffee variety suggestions, and weather updates in a clear and understandable format. Confidence scores and explanatory messages are included to help farmers interpret the results and take informed actions.

III. SYSTEM ARCHITECTURE



System Initialization: The SmartCrop-Coffee system begins when the farmer or agricultural officer accesses the platform through a mobile or web application. At this stage, the system initializes cloud services, activates sensor data streams (if available), and prepares the AI models for inference.

1. System Activation and User Login:

The process starts when the farmer or agronomist logs into the SmartCrop-Coffee application. The system initializes the database, cloud server, AI models, and data acquisition modules.

2. Image Acquisition (Leaf Image Upload):

The farmer captures real-time coffee leaf images using a mobile camera or uploads existing images.
- Images may contain healthy or diseased leaves
- Images are tagged with location and time information

4. Weather Data Collection and Forecasting:

Weather data is collected from:
- On-field weather sensors
- External meteorological services (temperature, rainfall, humidity, wind speed)

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5. Soil and Fertility Data Collection:
Soil information is obtained through sensors or manual input:

- Soil moisture
- pH value
- Nitrogen (N), Phosphorus (P), Potassium (K)

6. Image Feature Extraction:
A Convolutional Neural Network (CNN) automatically extracts:

- Leaf texture patterns
- Color variations
- Disease lesion shapes

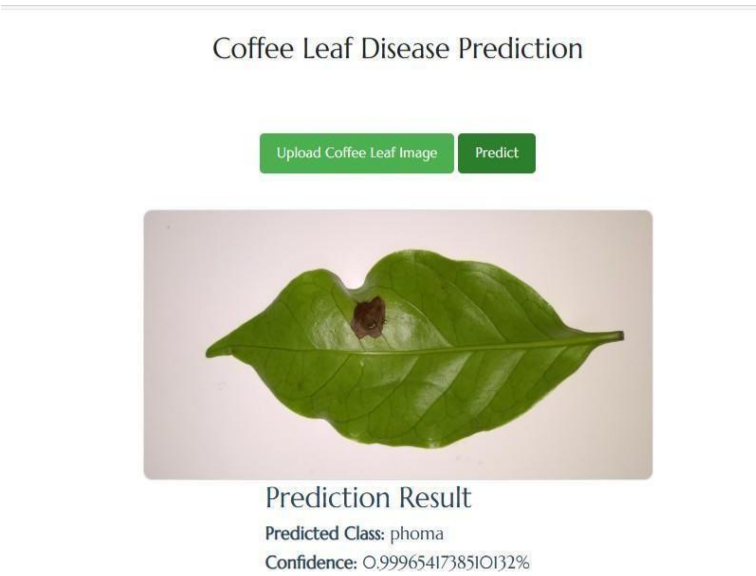
7. Disease Detection and Severity Prediction:
The trained CNN classifies the leaf as:

- Healthy
- Leaf rust
- Coffee berry disease, etc.

8. Recommendation Generation:
A decision support engine integrates all predictions to generate:

- Disease treatment recommendations (fungicides, preventive actions)
- Fertilizer and irrigation schedules
- Crop management

IV. RESULTS



Coffee Leaf Disease Prediction System

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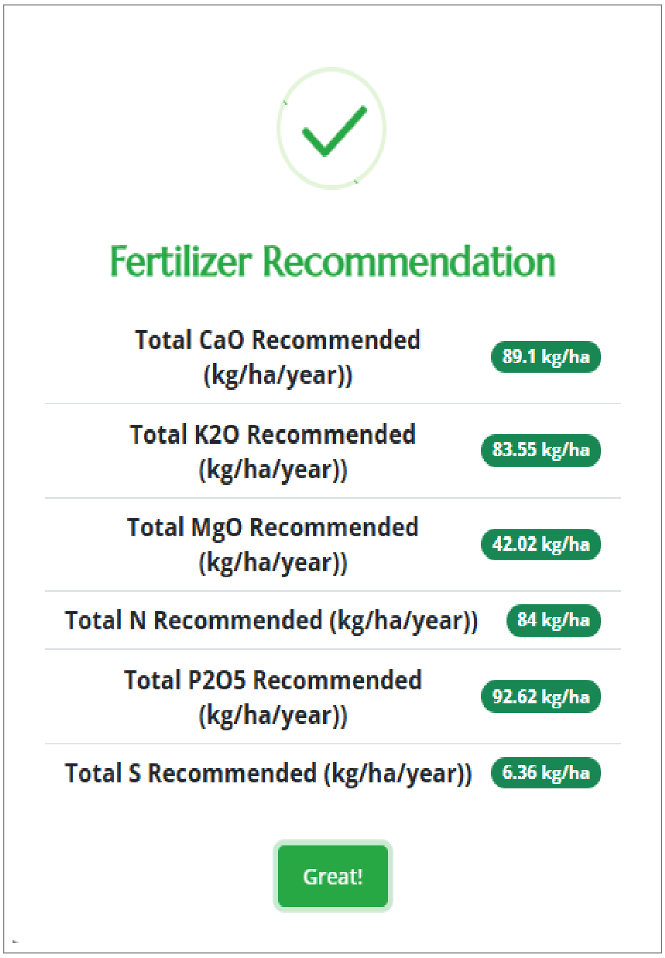

Variety Recommendation of the System

V. DISCUSSION

1. Effectiveness of Multi-Module AI Integration

The SmartCrop-Coffee framework demonstrates that integrating multiple AI modules—CNN for disease detection, Random Forest–based regression for fertilizer and yield prediction, and classification for variety recommendation—into a single platform significantly improves decision-making efficiency compared to isolated systems. Unlike conventional

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tools that address only one agricultural task, the proposed system provides holistic, synchronized recommendations, enabling farmers to act on disease control, nutrition management, and yield planning simultaneously.

2. Performance of CNN-Based Disease Detection

The CNN model effectively identified major coffee leaf diseases such as rust and Cercospora, achieving high confidence scores on well-captured images. This confirms the suitability of deep learning for visual disease diagnosis in coffee crops. However, results also revealed performance sensitivity to image quality, lighting conditions, and background noise, indicating that real-world deployment requires more diverse training datasets and robust image preprocessing strategies.

3. Reliability of Fertilizer Recommendation Model

The MultiOutput Random Forest Regressor generated balanced NPK and micronutrient recommendations aligned with standard agronomic practices. The system successfully reduced the risk of fertilizer overuse by tailoring recommendations to soil pH, nutrient levels, and crop age. Nevertheless, deviations were observed when soil inputs contained extreme or inconsistent values, highlighting the importance of strict input validation and domain-rule constraints in agricultural AI systems.

4. Yield Prediction Accuracy and Practical Utility

Yield prediction results provided farmers with realistic estimates in kilograms per hectare, supporting better planning of labor, storage, and market strategies. While the model captured general yield trends effectively, slight variations occurred due to unpredictable weather patterns and localized soil variability. This confirms that yield forecasting in agriculture remains probabilistic rather than deterministic, and AI predictions should be interpreted as decision-support rather than absolute values.

5.Impact of Weather API Integration of smartcrop

Incorporation of real-time weather data significantly enhanced context-aware recommendations, particularly for irrigation and harvest planning. However, dependency on third-party APIs introduced occasional latency and data unavailability issues. This dependency emphasizes the need for fallback mechanisms or hybrid forecasting approaches in future implementations to ensure system reliability.

6. Overall System Impact

The experimental results and field-level observations confirm that SmartCrop-Coffee successfully bridges the gap between AI research and practical agriculture. By combining prediction accuracy, usability, and sustainability awareness, the system demonstrates strong potential as a real-world decision support tool for modern coffee farming.

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