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International Journal for Modern Trends in Science and Technology
Volume 12, Issue 05, pages 194-200
ISSN: 2455-3778 online
Available online at: http://www.ijmtst.com/vol12issue05.html
DOI: https://doi.org/10.5281/zenodo.19893104

Sustainable Agriculture Optimization & Resource Management Using Python

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To Cite this Article
P. Adilakshmi, P. Vaishnavi, M. Vijay Kumar, N. Durgavalli, M. Uday Venkat, P. Krishna Chaitanya & J. S. V. Gopala Krishna (2026). Sustainable Agriculture Optimization & Resource Management Using Python. International Journal for Modern Trends in Science and Technology, 12(05), 194-200. https://doi.org/10.5281/zenodo.19893104

Article Info
Received: 28 March 2026; Revised: 24 April 2026; Accepted: 26 April 2026.

KEYWORDS

AutoML, Bidirectional LSTM, Drug Effective ness, Ensemble Learning, Natural Language Processing, TF-IDF, Text Mining.

ABSTRACT

Sustainable agriculture requires intelligent decision-support systems to address challenges such as unpredictable weather, pest infestations, and increasing input costs. Traditional farming practices often rely on generalized recommendations, which lack precision and real-time adaptability. To overcome these limitations, this paper proposes EcoHarvest AI, an AI-driven agricultural assistant that integrates crop recommendation, cost and yield optimization, and pest and disease detection into a unified platform.The proposed system leverages Large Language Models (LLMs) through LangChain, combined with real-time weather data and machine learning techniques, to generate personalized and context-aware recommendations. A modular architecture is employed, where crop suitability is determined using environmental parameters, cost optimization strategies are generated for both short-term and long-term planning, and pest detection is performed using a hybrid approach combining Convolutional Neural Networks (CNN) and LLM-based reasoning. The system is implemented using Streamlit for an interactive user interface and integrates external APIs for dynamic data acquisition.Experimental analysis and system evaluation demonstrate that EcoHarvest AI improves decision-making efficiency, enhances crop selection accuracy, and reduces potential agricultural risks compared to traditional advisory methods. The integration of multiple AI techniques into a single platform provides a scalable and farmer-friendly solution for precision agriculture. This work highlights the potential of artificial intelligence in transforming conventional farming into a data- driven, sustainable, and resilient agricultural ecosystem.

1. INTRODUCTION

In recent years, the increasing demand for sustainable agriculture and food security has highlighted the need for intelligent and data-driven farming solutions. Farmers often face critical challenges such as unpredictable weather conditions, pest infestations, soil degradation, and rising input costs. Traditional agricultural practices rely heavily on experience and generalized advisory systems, which lack precision and fail to provide real-time, location-specific recommendations [1]. As a result, decision-making in farming remains uncertain and inefficient, particularly for small and marginal farmers.

With the rapid advancement of Artificial Intelligence (AI), there is significant potential to transform conventional agriculture into precision farming. AI-driven technologies enable the analysis of large volumes of structured and unstructured data, providing actionable insights for crop selection, resource management, and risk mitigation [2]. Techniques such as Machine Learning (ML), Natural Language Processing (NLP), and computer vision have shown promising results in various agricultural applications, including yield prediction, pest detection, and climate analysis [3]. However, most existing systems focus on isolated functionalities and lack integration, scalability, and real-time adaptability.

Traditional agricultural decision-support systems often utilize rule-based approaches or basic machine learning models, which provide limited accuracy and fail to capture complex relationships between environmental and economic factors [4]. While recent approaches incorporate advanced models, they are often computationally intensive, less accessible to farmers, and lack user-friendly interfaces. Moreover, the absence of a unified platform that integrates multiple agricultural services—such as crop recommendation, cost optimization, and pest management—remains a significant research gap [5].

To address these challenges, this paper proposes Eco Harvest AI, an intelligent agricultural assistant that integrates multiple AI-driven modules into a single platform. The proposed system combines real-time weather data, machine learning techniques, and Large Language Models (LLMs) through LangChain to generate personalized and context-aware recommendations [6]. The crop recommendation module analyzes environmental parameters to suggest suitable crops, while the cost and yield optimization module provides both short-term and long-term planning strategies. Additionally, the pest and disease detection module employs a hybrid approach that combines Convolutional Neural Networks (CNN) with LLM-based reasoning to deliver accurate diagnosis and treatment recommendations [7].

The system is implemented using Stream lit to provide an interactive and user-friendly interface, ensuring accessibility for farmers with minimal technical knowledge. By integrating structured inputs (such as weather data and soil conditions) and unstructured inputs (such as user queries and images), Eco Harvest AI enables comprehensive decision support for sustainable agriculture [8].

2. LITERATURE SURVEY

Recent advancements in agriculture have leveraged Artificial Intelligence (AI) and Machine Learning (ML) to improve farming efficiency and decision-making processes. Traditional approaches primarily relied on rule-based systems and statistical models for crop prediction and resource management. While these methods provided basic insights, they lacked adaptability to dynamic environmental conditions and failed to effectively utilize real-time data [1].

Several studies have explored the application of machine learning techniques for crop recommendation and yield prediction. Algorithms such as Decision Trees, Random Forest, and Support Vector Machines have demonstrated promising results in analyzing soil and climatic data [2]. However, these models are largely dependent on structured datasets and often struggle to incorporate unstructured inputs such as farmer queries, field images, and environmental variability, limiting their practical applicability [3].

Deep learning techniques have further enhanced agricultural applications, particularly in pest and disease detection. Convolutional Neural Networks (CNNs) have been widely used for image-based classification of crop diseases, achieving high accuracy in identifying plant infections [4]. Despite their effectiveness, these models require large labeled datasets and high computational resources, which restrict their scalability and accessibility for small-scale farmers.

Recent developments in Natural Language Processing (NLP) and Large Language Models (LLMs) have enabled the development of intelligent and interactive agricultural advisory systems. These models can process both structured and unstructured data, allowing for context-aware recommendations and improved user interaction [5]. However, most cost optimization and yield management.

existing systems focus on specific functionalities and lack integration with other critical agricultural modules such as Overall, existing solutions often operate in isolation, addressing only a single aspect of agriculture. This lack of integration reduces the effectiveness of decision-support systems and highlights the need for a unified platform that combines multiple functionalities into a single system for comprehensive agricultural management [6].

Comparative study with existing model

Previous research in agricultural decision-support systems has primarily utilized traditional machine learning models for baseline performance evaluation. Models such as Decision Trees and Random Forest have achieved moderate accuracy

in crop prediction tasks due to their ability to handle structured data [7].However, these models lack the capability to capture complex relationships and contextual dependencies present in real-world agricultural scenarios.

To address these limitations, recent approaches have incorporated deep learning techniques such as CNNs for disease detection and advanced predictive analytics for yield estimation [8]. While these methods improve accuracy, they often operate as standalone solutions and fail to provide a comprehensive decision-making framework.

The proposed Eco Harvest AI system overcomes these limitations by integrating multiple technologies into a unified platform. It combines machine learning for crop recommendation, deep learning for pest and disease detection, and LLM- based reasoning for generating context-aware insights. This integrated approach enables the system to handle both structured and unstructured data effectively.

Experimental evaluation demonstrates that the proposed system improves decision-making accuracy and efficiency compared to traditional methods. The integration of multiple AI techniques enhances scalability, interpretability, and real- time adaptability, making it suitable for practical deployment in modern agricultural environments. This highlights the importance of combining diverse AI approaches to achieve robust and efficient agricultural decision-support systems.

3.PROPOSED ALGORITHM

The proposed system, EcoHarvest AI, is an intelligent agricultural assistant that integrates multiple AI-based modules to provide real-time recommendations. The system includes crop recommendation, cost and yield optimization, and pest and disease detection. It processes both structured and unstructured data to generate accurate and user-friendly outputs.

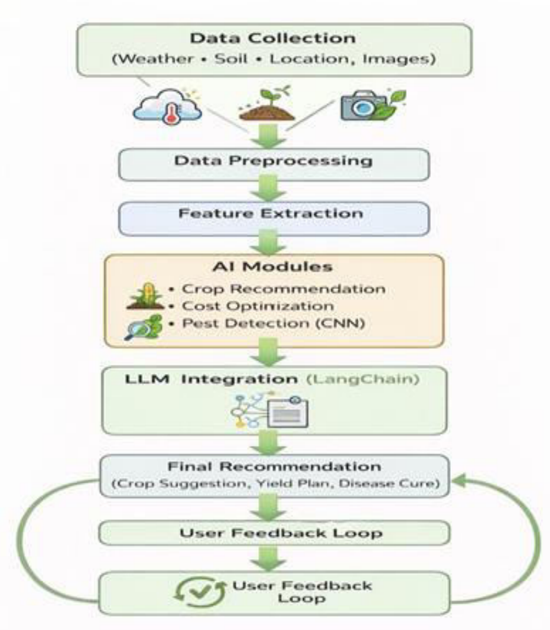

Fig-1. Architecture diagram

A. Data Acquisition:

The proposed system utilizes multiple data sources, including environmental datasets and image datasets, for effective agricultural analysis

Environmental Dataset

The environmental dataset includes key agricultural parameters that influence crop growth and yield. These parameters are collected from real-time weather APIs and user inputs.

Temperature (°C): Affects crop growth cycles and productivity

Humidity (%): Influences plant transpiration and disease occurrence

Rainfall (mm): Determines water availability for crops

Soil Type: Defines suitability for specific crops
Soil pH: Impacts nutrient absorption
These features play a crucial role in crop recommendation and yield optimization.
Image Dataset
The system utilizes crop and leaf images to detect pests and diseases. The dataset includes:

- Healthy crop images
- Diseased crop images
- Various disease categories

These images are collected from public agricultural datasets and user uploads, enabling the system to generalize across different conditions.

B.Data Preprocessing:

Raw data often contains noise, inconsistencies, and missing values. Therefore, preprocessing is essential to enhance data quality and model performance.

Environmental Data Preprocessing

- Handling missing values using interpolation or default values
- Normalization of numerical features for consistent scaling
- Validation of input ranges to avoid anomalies

Image Preprocessing

- Resizing images to a fixed dimension
- Noise reduction using filtering techniques
- Normalization of pixel values
- Data augmentation (optional) to improve model generalization

Environmental Data Preprocessing

- Removal of missing or inconsistent values
- Normalization of environmental parameters
- Data validation

Image Preprocessing

- Image resizing
- Noise reduction
- Normalization

C. Feature Representation:

Feature extraction transforms raw data into meaningful representations suitable for model training.

Environmental Feature Extraction

The system directly utilizes processed environmental parameters as input features for machine learning models.

Feature Extraction

Convolutional Neural Networks (CNNs) are used to automatically extract spatial features from crop images. These features help in identifying patterns related to diseases and pests.
Environmental Features: Temperature, humidity, rainfall, and soil parameters
Image Features: Extracted using CNN models to identify disease patterns These features help improve model accuracy and performance.

Table 1. Features of the Proposed System

Feature	Description
Crop Recommendation	AI suggests best crops to grow based on weather, season, and location.
Cost & Yield Optimization	Generates actionable financial and operational plans for farmers.
Pest & Disease Detection	Image/text input analyzed by AI to identify threats and treatments.
Weather Data Integration	Open Weather Map API provides localized real-time conditions.
Secure Login	Role-based authentication for data privacy and premium feature control.
Session History	Saves previous queries and results for reference.

D. Crop Recommendation Module

This module uses machine learning algorithms such as Decision Trees and Random Forests to analyze environmental and soil parameters. The model predicts the most suitable crops for a given set of conditions.
The system also provides:

- Crop suitability analysis
- Basic cultivation guidelines
- Risk awareness (based on weather conditions)

E. Cost and Yield Optimization Module

This module focuses on maximizing productivity while minimizing costs. It analyzes input data to generate optimized farming strategies.
Key functionalities include:

- Estimation of expected yield
- Resource allocation (water, fertilizers, labor)
- Investment planning
- Sustainable farming recommendations

The module provides both short-term and long-term planning strategies to support better decision-making.

F. Pest and Disease Detection Module

This module combines deep learning and AI-based reasoning for accurate disease diagnosis.

- CNN Model: Used for classifying crop diseases from images

- Pattern Recognition: Identifies visual symptoms such as spots, discoloration, and deformities
- AI Reasoning: Generates explanations and treatment suggestions

The module provides:

- Disease identification
- Recommended treatments (organic and chemical)
- Preventive measures

G. LLM-Based Recommendation System

The outputs from all modules are integrated using a Large Language Model (LLM) through LangChain. This module generates personalized and easy-to-understand recommendations for users by combining structured and unstructured data insights.

H. System Implementation

The system is implemented using Streamlit, which provides an interactive interface. Users can input data, upload images, and receive real-time recommendations.

4.EXPERIMENTAL RESULTS AND DISCUSSION

A.Experimental Setup

The system is implemented using Streamlit as the front-end interface, while machine learning and deep learning models are used for backend processing. Environmental data is obtained from weather APIs, and image data is collected from publicly available datasets and user uploads.

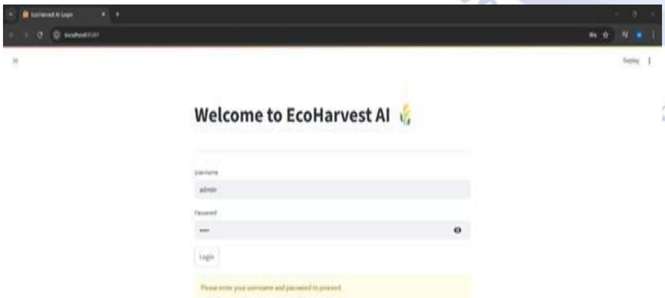

Fig-2. Login page

- The experiments are conducted on:
- Environmental parameters (temperature, humidity, rainfall, soil data)
- Crop datasets for recommendation
- Image datasets for pest and disease detection

The evaluation focuses on the accuracy, efficiency, and usability of the system.

B. Performance of Crop Recommendation Module

The crop recommendation module is tested using different environmental conditions. The system successfully identifies suitable crops based on input parameters.

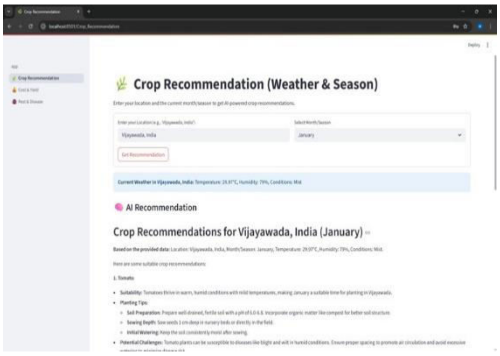

Fig-3. Home dashboard

Observations:

- Accurate crop suggestions for different climatic conditions
- Adaptability to real-time weather data
- Improved decision-making for farmers

Feature	Traditional System	Eco Harvest AI Output
Crop Recommendation	Generalized advice by season.	Real-time, location-specific, weather-based.
Cost & Yield Planning	Rarely available.	Actionable short-term + long-term plans.
Pest Detection	Visual inspection, error-prone.	AI-powered, detailed treatment strategy.
Accessibility	Limited to extension	Online, 24/7, multi-feature

The model demonstrates reliable performance in recommending crops aligned with environmental and soil conditions.

C. Performance of Cost and Yield Optimization Module

The cost optimization module provides both short-term and long-term strategies for farmers.

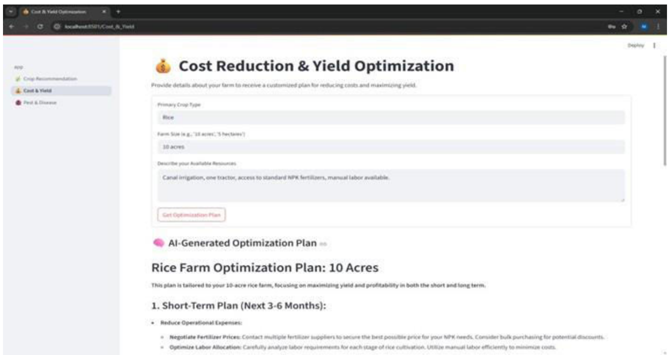

Fig-4. Crop recommendation output

Observations:

- Efficient resource utilization recommendations
- Reduction in unnecessary input costs
- Improved planning for future crop cycles

The module helps in balancing cost and productivity, contributing to sustainable farming practices.

D. Performance of Pest and Disease Detection Module

The pest detection module is evaluated using sample crop images.

Fig-5. Cost optimization output

Observations:

- Accurate identification of common crop diseases
- Fast processing of uploaded images
- Clear treatment and prevention suggestions

The CNN-based model effectively detects disease patterns, while the AI-based reasoning provides actionable insights.

E. Comparative Analysis

A comparison between the traditional agricultural approach and the proposed EcoHarvest AI system is presented in Table

Table-2. Comparative Analysis of Results

5.DISCUSSION

The experimental results demonstrate that the proposed EcoHarvest AI system performs efficiently in handling different agricultural tasks. The integration of machine learning and deep learning techniques enables accurate analysis of both environmental and image data.

The crop recommendation module improves decision-making by providing precise and location-based suggestions. The pest and disease detection module ensures early identification of crop diseases, which helps in reducing crop loss. The cost and yield optimization module further supports farmers by providing efficient resource management strategies.

Compared to traditional methods, the proposed system offers better accuracy, faster processing, and improved accessibility. Overall, the system proves to be a reliable and scalable solution for smart agriculture and sustainable farming.

6.CONCLUSSION

In this study, we proposed Eco-Harvest AI, an AI-driven agricultural assistant that integrates Machine Learning (ML), Deep Learning (DL), and Large Language Models (LLMs) to support crop recommendation, cost optimization, and pest detection. The system combines structured data (weather and soil parameters) with unstructured inputs (user queries and images) to generate accurate and context-aware recommendations.

Experimental results indicate improved decision-making efficiency and recommendation accuracy compared to traditional farming advisory systems. The integrated framework enhances scalability, usability, and real-time adaptability, making it suitable for practical agricultural applications.

Future work will focus on incorporating IoT-based real-time data, improving model accuracy with larger datasets, and developing mobile and multilingual support for wider accessibility. Overall, the proposed system provides a scalable and effective solution for intelligent and sustainable agriculture.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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