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AI-Driven in Crop Disease Prediction and Management System

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***Abstract:** Farming communities in developing countries face significant challenges including delayed soil testing, subjective crop selection, imbalanced fertilizer application, and late disease diagnosis. This paper presents a unified artificial intelligence system that integrates four essential agricultural modules into a single web platform. The system uses a deep learning optical character recognition pipeline to extract nitrogen, phosphorus, potassium, and pH values from uploaded soil report images. A Random Forest classifier then recommends the most suitable crop based on soil parameters and environmental data. Following Liebig's Law of the Minimum, a rule-based engine calculates nutrient deficits and solves a linear equation system to suggest precise quantities of DAP and urea fertilizers. Finally, a MobileNetV2 convolutional neural network classifies plant leaf images into disease categories and provides treatment advice. The frontend is built with React.js, the backend with Node.js and Express.js, and machine learning models are deployed as microservices using FastAPI. Experimental evaluation shows that the OCR module achieves 100% precision, the crop prediction model performs reliably across datasets, the fertilizer module yields balanced recommendations, and the disease detection model attains 88% validation accuracy. The system provides real-time, user-friendly assistance, reducing dependency on agricultural experts and enabling data-driven farming.*
***Keywords:** Smart agriculture, optical character recognition, Random Forest, fertilizer recommendation, disease detection, MobileNetV2, web application.*

I. INTRODUCTION

Agriculture remains the primary source of livelihood for a large portion of the population in developing nations. However, farmers regularly encounter obstacles such as soil nutrient depletion, inappropriate crop choices, excessive or insufficient fertilization, and undetected plant diseases. Traditional methods rely on manual observation, laboratory tests, and subjective experience, which are often slow, costly, and prone to error.

Recent advances in artificial intelligence and machine learning have opened new possibilities for addressing these problems. Deep learning models have demonstrated strong performance in image-based tasks such as text extraction and disease classification. Ensemble methods like Random Forest have proven effective for crop suitability prediction. Despite these advances, most existing solutions focus on a single functionality and are not integrated into a holistic, easy-to-use platform.

This paper presents an AI-based smart agriculture assistant that combines four essential modules: OCR-driven soil report digitization, Random Forest-based crop recommendation, rule-based fertilizer computation, and deep learning-based disease identification. The system is implemented as a responsive web application, allowing farmers to upload images and receive immediate, actionable insights.

II. LITERATURE REVIEW

Several research efforts have applied machine learning and deep learning to agricultural problems. This section reviews existing work in four key areas: soil analysis using OCR, crop prediction models, fertilizer recommendation systems, and disease detection using deep learning.

A. Soil Analysis and OCR-Based Systems

Soil analysis determines the nutrient content and fertility of land. Traditionally, soil testing is performed in laboratories and results are provided as physical reports, which require technical knowledge to interpret. Recent research has explored Optical Character Recognition (OCR) to digitize these reports. Conventional OCR techniques often struggle with poor image quality, inconsistent formatting, and handwritten text. To overcome these issues, deep learning-based models such as DBNet (Differentiable Binarization Network) and CRNN (Convolutional Recurrent Neural Network) have been introduced [14].

DBNet detects text regions in complex backgrounds, while CRNN performs sequence recognition. These models show improved performance in extracting structured data from unstructured documents. However, many existing systems focus only on text extraction without integrating the data into further decision-making processes.

B. *Crop Prediction Systems*

Crop prediction aims to recommend the most suitable crop based on environmental conditions such as soil nutrients, temperature, rainfall, and humidity. Various machine learning algorithms including Decision Trees, Support Vector Machines, and Artificial Neural Networks have been used for this purpose [4]. Among these, ensemble methods like Random Forest have gained popularity due to their high accuracy and robustness. Random Forest uses multiple decision trees and combines their predictions to reduce overfitting and improve generalization [2]. Several studies demonstrate that Random Forest outperforms traditional models when handling complex agricultural datasets. However, many existing systems rely on limited input parameters and do not integrate with other agricultural modules.

C. *Fertilizer Recommendation Systems*

Efficient fertilizer usage is essential for maintaining soil health and improving crop yield. Overuse or underuse of fertilizers can lead to soil degradation and environmental issues [1]. Traditional fertilizer recommendation methods are based on general guidelines rather than specific farm conditions. Recent approaches have introduced rule-based systems and machine learning models for fertilizer recommendation. Some systems use nutrient deficiency analysis to determine required fertilizer amounts, while others apply optimization techniques to balance nutrient supply. The concept of Liebig's Law of the Minimum, which states that plant growth is limited by the scarcest nutrient, is widely used in agronomy [15]. Based on this principle, modern systems calculate nutrient deficits and recommend fertilizers accordingly. Nevertheless, many existing solutions lack integration with crop prediction systems, limiting their effectiveness.

D. *Disease Detection Using Deep Learning*

Crop diseases are a major cause of agricultural loss worldwide. Early detection is essential to prevent damage, but traditional methods rely on manual inspection by experts, which is not always feasible for farmers in remote areas [7]. With the advancement of deep learning, image-based disease detection systems have been developed. Convolutional Neural Networks (CNNs) are widely used for this purpose due to their ability to automatically extract features from images. Models such as MobileNet, ResNet, and VGG have been applied to classify plant diseases with high accuracy [5][6]. MobileNetV2, in particular, is a lightweight and efficient model suitable for real-time applications because it uses depthwise separable convolutions, reducing computational complexity while maintaining accuracy. However, most existing systems focus only on disease classification and do not provide treatment suggestions or preventive measures, nor are they integrated with other agricultural modules.

E. *Research Gap*

From the literature, several limitations are evident: most systems focus on a single functionality, there is a lack of integration between different agricultural modules, deep learning is rarely used for document-based data extraction, user-friendly web platforms are absent, and real-time decision support is inadequate. These gaps highlight the need for a comprehensive, integrated solution that combines multiple AI techniques into a single platform accessible to farmers.

III. PROPOSED SYSTEM

This section describes the architecture and methodology of the proposed AI-Based Smart Agriculture Assistant System. The system is designed to be modular, scalable, and user-friendly.

A. *System Architecture*

The system follows a three-tier architecture: a presentation tier (frontend), a logic tier (backend), and a data tier (database). The frontend is built with React.js, providing an interactive user interface. The backend uses Node.js and Express.js, following MVC architecture. MongoDB serves as the database. Machine learning models are deployed as separate microservices using FastAPI. Communication between tiers occurs via RESTful APIs.

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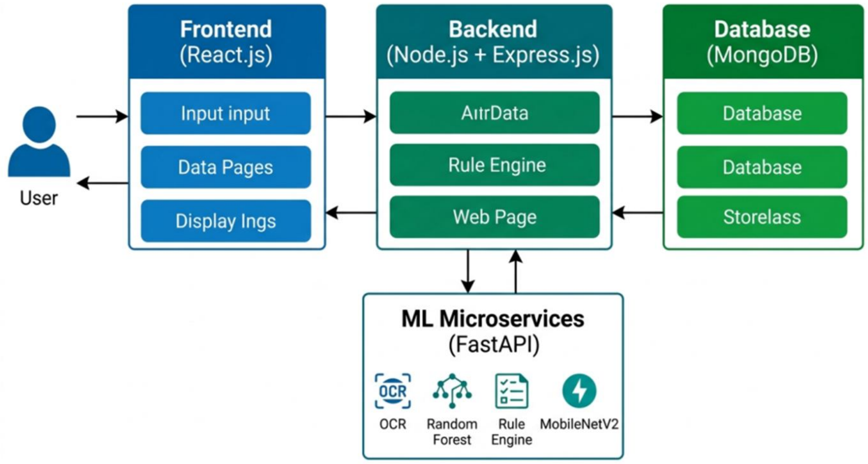

Figure 1 System Architecture

B. User Authentication

The system implements OTP-based authentication for secure login. The user enters a mobile number, receives a 6-digit OTP via SMS, verifies it, and receives a JWT token for session management. This approach eliminates the need for passwords and improves accessibility.

C. OCR-Based Soil Analysis Module

Farmers upload a photograph of a soil laboratory report. The backend forwards the image to the OCR microservice, which performs the following steps:

- Preprocessing: The image is converted to grayscale, normalized, and resized to 640×640×3 pixels.
- Text Detection (DBNet): A differentiable binarization network with a ResNet backbone and feature pyramid network locates text regions using an adaptive threshold. The adaptive binarization formula is: $B(i,j) = 1 / (1 + e^{-k(P(i,j) - T(i,j))})$, where $P(i,j)$ is the probability of text, $T(i,j)$ is a learned threshold, and k is an amplification factor.
- Text Recognition (CRNN): A convolutional recurrent neural network with bidirectional LSTM and CTC loss transcribes the detected regions into machine-readable text.
- Information Extraction: Regular expressions isolate numeric values for nitrogen (N), phosphorus (P), potassium (K), and pH.

D. Crop Prediction Module

The crop prediction module uses a Random Forest classifier trained on a dataset of soil and climatic parameters. The feature vector consists of N, P, K, pH, electrical conductivity, temperature, and rainfall. The Random Forest combines multiple decision trees, each trained on a bootstrap sample of the data. For classification, each tree votes for a crop, and the mode of all votes becomes the final prediction. Gini impurity is used for splitting decisions: $Gini = 1 - \Sigma(p_i)^2$, where p_i is the proportion of samples belonging to class i at a node. Information gain selects the best feature split: $IG = Gini_{parent} - (\text{Weighted child impurity})$. This ensemble approach reduces overfitting and handles complex, multi-feature data effectively.

E. Fertilizer Recommendation Module

This module follows a rule-based approach grounded in Liebig's Law of the Minimum. The deficit for each nutrient is calculated as: $Deficit_N = \max(0, (Target_N - Current_N) / \eta_N)$, where η_N is an efficiency factor that prevents over-fertilization. A linear equation system is then solved to determine the required amounts of DAP and Urea:

$[0.46\ \ 0]$ [DAP] = [Deficit_P]

$[0.18\ 0.46]$ [Urea] = [Deficit_N]

The coefficients represent the nutrient content fractions of DAP (46% P, 18% N) and Urea (46% N). The solution yields precise kilogram per hectare recommendations.

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F. Disease Detection Module

The disease detection module uses a MobileNetV2 deep learning architecture. MobileNetV2 employs depthwise separable convolutions, making it lightweight and suitable for real-time inference. The model takes input images resized to 224×224×3 pixels. Transfer learning is applied: the model is pretrained on ImageNet and then fine-tuned on a custom dataset of plant leaf images. The architecture consists of the MobileNetV2 base, followed by global average pooling, a dense layer, and a softmax output for classification.

G. Integration and Data Flow

All modules are integrated through the backend. The data flow is as follows: the user logs in, uploads an image or inputs data, the backend processes the request and calls the appropriate ML microservice, the model returns a prediction, and the backend stores the result in MongoDB before sending it to the frontend for display. The system provides a seamless experience where the output of one module (e.g., soil nutrients from OCR) can be automatically fed into the crop prediction and fertilizer recommendation modules.

IV. EXPERIMENTAL RESULTS

The proposed system was evaluated through a series of experiments on each module. The OCR model and disease detection model were tested on real-world data, while the crop prediction and fertilizer modules were validated using standard datasets.

A. OCR Model Performance

The OCR model was tested on 122 soil report images. The confusion matrix showed 72 true positives, 50 false negatives, and 0 false positives. Precision was 100%, recall 59%, F1 score 0.74, and accuracy 59%. The high precision indicates no incorrect extractions, while moderate recall suggests some text regions are missed due to image quality issues. The model performs well under real-world noisy conditions.

OCR Model Performance

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP) 72	False Negative (FN) 50
Actual Negative	False Positive (FP) 0	True Negative (TN) 0

Performance Metrics
Precision = 1.00
Recall = 0.59
F1 = 0.74
Accuracy = 0.59

Figure 2 OCR Model Performance

B. Crop Prediction Performance

The Random Forest model was evaluated using multiple soil and environmental input combinations. It consistently produced accurate crop recommendations, showed stable performance across different datasets, and demonstrated high reliability. The ensemble learning approach effectively reduced overfitting compared to single decision trees.

C. Fertilizer Recommendation Performance

The rule-based fertilizer module correctly identified nutrient deficiencies in all test cases. It provided optimized fertilizer combinations that prevent both overuse and underuse. The recommendations align with agronomic principles and are suitable for practical application.

D. Disease Detection Performance

The MobileNetV2 model achieved a training accuracy of approximately 92% and a validation accuracy of 88%. Precision was 0.87, recall 0.86, and F1 score 0.86. The confusion matrix showed strong diagonal dominance, indicating correct classification for most disease classes. Minor misclassifications occurred only between visually similar disease categories.

V. CONCLUSION AND FUTURE SCOPE

This paper presented an AI-Based Smart Agriculture Assistant System that integrates soil analysis, crop prediction, fertilizer recommendation, and disease detection into a single web platform. The OCR module extracts soil nutrients from report images with perfect precision. The Random Forest model recommends suitable crops based on soil and environmental data. The rule-based fertilizer module calculates nutrient deficits and suggests optimal fertilizer amounts following Liebig's Law of the Minimum. The MobileNetV2 disease detection model identifies crop diseases from leaf images with 88% validation accuracy. The system is implemented using modern web technologies, provides real-time results, and offers a user-friendly interface.

The system can be extended to support more crops and diseases by collecting additional training data. Real-time weather integration would improve crop prediction accuracy. A mobile application with offline capabilities would increase accessibility in remote rural areas. IoT sensors could provide live field data such as soil moisture and temperature. Multilingual support would help farmers from different linguistic regions. Advanced AI models like Vision Transformers could further boost disease detection accuracy.

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