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Smart Agriculture System for Crop Selection and Disease Detection Using AI

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Abstract— Agriculture plays a vital role in ensuring food security and supporting economic development. However, the sector is increasingly challenged by factors such as climate change, unpredictable weather patterns, soil degradation, and the rapid spread of crop diseases. These challenges often lead to reduced crop yield and financial losses for farmers. To overcome these limitations, the integration of advanced technologies like Artificial Intelligence (AI) and Machine Learning (ML) has become essential in modern agriculture. This paper presents a Smart Agriculture System designed for efficient crop selection and early disease detection using Al techniques. The proposed system utilizes various datasets, including soil properties, weather conditions, and environmental parameters, to recommend the most suitable crops for a given region. Machine learning algorithms are employed to analyze these factors and provide accurate predictions that support better agricultural planning.

Furthermore, the system incorporates image processing and deep learning models to identify plant diseases from leaf images at an early stage. Early detection helps in taking timely preventive measures, thereby reducing crop damage and improving overall productivity. The system is designed to be user-friendly and can assist farmers in making informed, data-driven decisions.In addition, the proposed approach promotes efficient utilization of resources such as water, fertilizers, and pesticides, minimizing waste and environmental impact. By reducing manual effort and improving accuracy, the system contributes to sustainable and smart farming practices. Overall, the integration of Al and ML technologies enhances agricultural efficiency, productivity, and long-term sustainability.

***Keywords*—**Smart Agriculture, Crop Selection, Disease Detection, Artificial Intelligence, Machine Learning, Deep Learning, Convolutional Neural Network (CNN),Image Processing, Soil Classification, Leaf Disease Prediction, Fertilizer Recommendation, Flask, TensorFlow, OpenCV, Python, Precision Agriculture, Decision Support System..

I. INTRODUCTION

Agriculture is a vital sector that supports human life and the economy, especially in countries like India. Traditional farming methods mainly depend on manual observation and farmers' experience, which can sometimes lead to low productivity, improper crop selection, and unexpected crop losses due to diseases and changing environmental conditions. To overcome these challenges, modern technologies like Artificial Intelligence (AI) are being integrated into agriculture to develop smart and efficient farming systems.In this project, advanced Machine Learning techniques such as Multi-Layer Perceptron (MLP) and Convolutional Neural Networks (CNN) are used to enhance agricultural decision- making. The MLP model is utilized for crop selection by analyzing various parameters such as soil nutrients (NPK values), temperature, humidity, rainfall, and pH levels.

Based on these inputs, the system predicts the most suitable crop that can yield better productivity under given conditions. On the other hand, the CNN model is applied for plant disease detection, where leaf images are processed and classified to identify diseases at an early stage with high accuracy.This smart agriculture system combines data analysis, predictive modeling, and image processing to provide real-time support to farmers. It not only helps in selecting the right crop but also assists in monitoring crop health and preventing major losses by early disease identification. Furthermore, it reduces the excessive use of fertilizers and pesticides, thereby promoting environmentally sustainable farming practices.By integrating MLP and CNN, this system transforms traditional agriculture into a modern, data-driven approach. It improves productivity, minimizes risks, and supports farmers in making informed decisions. Overall, the use of AI in agriculture plays a key role in increasing efficiency, ensuring food security, and advancing the future of smart farming.

A. Advantages of Smart Agriculture System

- **Early Disease Detection**:The CNN model detects crop diseases at an early stage by analyzing leaf images, which helps farmers take immediate action and prevent widespread crop damage**.**
- **Accurate Crop Recommendation:**By analyzing soil and weather data, the system recommends the most suitable crops for the current conditions, helping farmers make better planting decisions.
- **Yield Prediction :**The AI model predicts the expected yield in advance, allowing farmers to plan their harvest, storage, and sales more effectively.
- **Fertilizer and Pesticide Guidance:** The system provides precise fertilizer and pesticide recommendations based on detected diseases and environmental conditions, reducing unnecessary chemical usage and promoting eco-friendly farming.
- **Real-Time SMS Notifications:**Farmers receive instant alerts and suggestions through SMS, ensuring timely decisions even in areas with limited internet connectivity.
- **Reduced Crop Loss:**With timely disease detection and proper recommendations, the system significantly reduces crop loss and improves overall farm productivity**.**
- **Cost Effective:**By optimizing the use of fertilizers, pesticides, and other resources**,** the system helps farmers reduce unnecessary expenses and increase their profit margins.
- **User Friendly:** The system is designed to be simple and accessible, making it easy for farmers with limited technical knowledge to use it effectively.
- **Supports Sustainable Farming:**By minimizing the overuse of chemicals and promoting data-driven decisions, the system encourages environmentally sustainable agricultural.

II. LITERATURE REVIEW

In recent years, machine learning and deep learning techniques have gained significant attention in agricultural and environmental applications due to their ability to process complex, high-dimensional data and deliver accurate predictions. Many researchers have proposed various ML- based models to address challenges in soil remediation, crop disease detection, and climate prediction. However, each approach has its own strengths and limitations.

Palansooriya et al. (2022) proposed a machine learning framework titled "Prediction of Soil Heavy Metal Immobilization by Biochar Using Machine Learning." This study focuses on predicting heavy metal immobilization efficiency in biochar-amended soils using Random Forest, SVR, and Neural Network algorithms trained on 162 data points with 20 input variables. The study identified nitrogen content in biochar and biochar application rate as the two most significant features. A GUI web application was also developed for practical use. However, the model's generalizability is limited due to the small and heterogeneous dataset compiled from varied experimental conditions.

Nikitha et al. (2023) introduced a comparative study titled "Leaf Disease Detection and Classification," which evaluates SVM, KNN, and CNN models for detecting eight soybean leaf diseases. The CNN model achieved an accuracy of 96%, significantly outperforming SVM (76%) and KNN (64%) on the soybean leaf dataset. The study confirms CNN's superiority in automatic spatial feature extraction. However, the training-testing accuracy gap indicates overfitting due to limited dataset size, which may affect real-world performance. Harakannanavar et al. (2022) proposed a model titled "Plant Leaf Disease Detection Using Computer Vision and Machine

Learning Algorithms," combining DWT, PCA, GLCM feature descriptors with a CNN classifier for tomato leaf disease detection. The proposed DWT+PCA+GLCM+CNN model achieved an overall accuracy of 99.09% on 600 tomato leaf samples across six disease categories. While the multi-descriptor approach provides rich feature representation, the model was evaluated only on a single local dataset, limiting its applicability to other crop types or environments.

Pandian et al. (2022) developed a model titled "A Five Convolutional Layer Deep Convolutional Neural Network for Plant Leaf Disease Detection," using a Conv-5 DCNN trained on over 234,000 augmented images across 39 disease classes. Five augmentation techniques including GAN and Neural Style Transfer were employed. The proposed model achieved a classification accuracy of 98.41%, precision of 0.94, recall of 1.0, and F1-score of 0.97, outperforming all transfer learning and traditional ML techniques. However, the model was not tested under real-world field conditions with varying lighting and backgrounds.

Praveen et al. (2023) presented a study titled "A Novel Classification Approach for Grape Leaf Disease Detection Based on Different Attention Deep Learning Techniques," integrating SE, ECA, and CBAM attention mechanisms into Faster R-CNN, YOLO-X, and SSD models for grape disease detection. Experiments on the PlantVillage grape dataset showed that YOLO-X with combined attention mechanisms achieved the best mAP of 88.96% with the fewest parameters and strong real-time performance. However, the dataset contains only four disease categories, which limits the scope of the detection system for broader vineyard applications.

A survey (2023) titled "Machine Learning Methods in Weather and Climate Applications: A Survey" reviewed more than 20 ML methods applied to weather and climate prediction, identifying eight promising techniques for both short-term and medium-to-long-term forecasting. The survey covered models ranging from early ANN-based precipitation forecasting to advanced architectures such as 3D Neural Networks and GAN-based global precipitation models. The study found that while ML performs well in short-term weather prediction, medium-to-long-term climate forecasting remains challenging due to complex variables and data limitations, with significant relevance to agricultural planning and disaster management.

Tarek et al. (2022) evaluated multiple models in a study titled "Optimized Deep Learning Algorithms for Tomato Leaf Disease Detection with Hardware Deployment," comparing ResNet50, InceptionV3, AlexNet, MobileNetV1, MobileNetV2, and MobileNetV3 on the PlantVillage tomato dataset of 16,004 images across 10 disease classes. MobileNetV3 Large with Adagrad optimizer achieved the highest accuracy of 99.81%, while MobileNetV3 Small achieved 98.99% with a Raspberry Pi 4 latency of only 251 ms. The study successfully demonstrated IoT-based hardware deployment for real-time field use. However, the models were tested only on controlled lab images and have not yet been validated in open-field agricultural conditions.

A. Comparative Analysis and Research Gap

From the above literature, it is observed that most machine learning and deep learning based smart agriculture systems successfully address issues such as crop disease detection, soil analysis, and climate prediction. However, several common limitations still exist across these models.

Most systems focus only on single crop disease detection and do not provide an integrated platform combining both crop selection and disease detection. Additionally, existing models are evaluated only on controlled benchmark datasets and have not been validated under real-world field conditions. Few systems incorporate environmental parameters such as soil nutrients, temperature, and rainfall into crop recommendation. Scalability and hardware deployment remain major concerns in certain approaches.

B. Objective of the Proposed System

To overcome the limitations identified in existing systems, the proposed work aims to develop an intelligent, integrated, and user-friendly Smart Agriculture System for Crop Selection and Disease Detection using Artificial Intelligence. The system combines data-driven crop recommendation with deep learning-based disease detection to support farmers in making accurate and timely agricultural decisions.

By leveraging machine learning and deep learning techniques, the proposed system ensures accurate crop prediction, yield estimation, and real-time disease classification, while the added user-friendly interface enhances the overall accessibility of the system for farmers with limited technical knowledge. This combination helps in minimizing crop losses,

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optimizing resource utilization, and promoting sustainable agricultural practices.

III. METHODOLOGY

The proposed system follows a structured methodology to ensure accurate and reliable crop selection and disease detection using artificial intelligence and deep learning techniques. The workflow consists of multiple stages, including data collection, preprocessing, model training, prediction, and result display. The design of this system is inspired by existing machine learning and deep learning based smart agriculture frameworks [1]–[7].

1. Initially, the data collection process is carried out where the farmer provides input details such as soil nutrient values (Nitrogen, Phosphorus, Potassium), pH level, temperature, humidity, and rainfall. During this stage, the system also accepts leaf images captured using a camera or mobile device for disease detection purposes. The raw data collected from multiple sources may contain missing values, noise, and inconsistencies that can affect model performance. Therefore, the collected data undergoes thorough cleaning and validation before being used for training and prediction.

2. The collected input data is then subjected to the preprocessing phase, where numerical features such as soil parameters and weather conditions are normalized using min-max scaling to bring all values to a uniform range. For image data, techniques such as resizing to 256×256 pixels, histogram equalization, and data augmentation including rotation, flipping, and contrast adjustment are applied to increase dataset diversity and reduce overfitting during model training. The processed features are then prepared separately for the crop recommendation and disease detection modules.

3. During the crop recommendation phase, the processed soil and weather parameters are fed into a Multilayer Perceptron (MLP) model trained on agricultural datasets. The MLP model consists of multiple hidden layers with ReLU activation functions and a softmax output layer for multi-class crop classification. The model analyzes the input features and predicts the most suitable crop for cultivation along with an estimated yield value, enabling farmers to make informed planting decisions based on their local soil and climate conditions. The use of MLP-based multilayer learning enhances prediction accuracy as discussed in prior systems [1], [3].

4. During the disease detection phase, the uploaded leaf image is passed through a Convolutional Neural Network (CNN) model trained on crop leaf disease image datasets such as PlantVillage. The CNN architecture consists of multiple convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for final classification. The image is classified into the corresponding disease category and the system provides the detected disease name along with recommended treatment and pesticide measures to help farmers take immediate corrective action.

5. During the model evaluation phase, both the MLP and CNN models are evaluated using standard performance metrics including accuracy, precision, recall, and F1-score. Cross-validation techniques are applied to ensure the models generalize well on unseen data. The trained models are then saved and integrated into the system for real-time prediction.

6. Finally, the results are displayed through a user-friendly interface designed for farmers with limited technical knowledge. The interface provides crop recommendations, yield estimates, and disease detection outputs along with treatment suggestions in a simple and accessible format. The system is designed to be lightweight and deployable on low- cost hardware, making it practically suitable for use in rural agricultural environments.

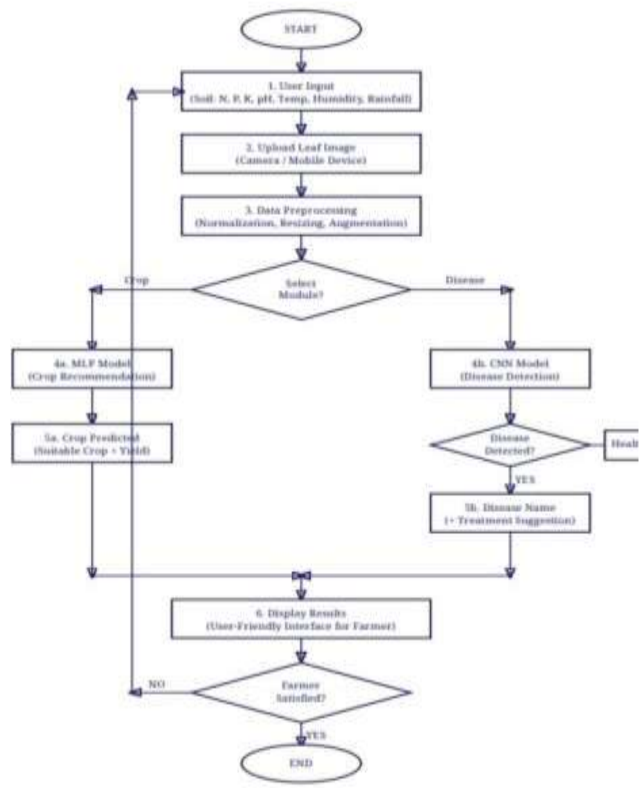

Fig. 1. Flowchart