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AGRIINTEL : ML & DL for Smart Farming

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Abstract: *India, one of the world's leading agricultural producers, relies heavily on its farming community, which forms the backbone of the national economy. Despite their central role, many Indian farmers face persistent challenges, particularly in selecting the most suitable and profitable crops for cultivation, due to regional variations in soil types and a lack of accessible, reliable technological tools. This paper presents an AI-driven crop recommendation system that leverages machine learning (ML) models to analyze parameters such as soil type, regional characteristics, historical yield data, and market prices to predict the optimal crop for a given environment. In recent years, unpredictable climate changes have further complicated agricultural planning, leading to reduced crop yields and economic instability among farmers. Moreover, plant diseases remain a significant concern, as early detection and diagnosis are critical to maintaining crop health and productivity. This study also explores the integration of deep learning techniques for plant disease detection, with a focus on tomato leaf diseases, using advanced models such as Convolutional Neural Networks (CNNs) and ResNet50 for image-based classification. By combining predictive analytics for crop recommendation with automated plant disease detection, the proposed framework aims to enhance decision- making in agriculture, thereby supporting food security and improving farmer livelihoods.*

Keywords: Crop Recommendation, Plant Disease Detection, Machine Learning, Deep Learning, CNN, ANN, MobileNet, RandomForestClassifier, SVC, XGBoost

I. INTRODUCTION

In recent years, agriculture has witnessed a paradigm shift through the adoption of Artificial Intelligence (AI) and Machine Learning (ML), which are enabling more precise, efficient, and sustainable farming practices. Advanced AI applications have been instrumental in addressing key challenges such as soil fertility prediction, crop recommendation, and plant disease detection, collectively aimed at enhancing productivity and minimizing resource usage [1], [2]. The work by Raja et al. highlights the transformative role of AI in sustainable crop management, emphasizing AI's potential to streamline decision- making for farmers across diverse agricultural domains [1]. India, as an agrarian economy where over two-thirds of the population depend on agriculture for livelihood, stands to benefit immensely from these innovations. However, the complexity of Indian agriculture—ranging from heterogeneous soil types and erratic weather to market inefficiencies—demands integrated and localized solutions. Chandra et al. proposed predictive models that utilize AI for optimizing crop yields under varying environmental conditions [2], while Zhao et al. introduced techniques to identify critical soil parameters, laying a foundation for automated agricultural systems [3], [8].

Building upon these foundational efforts, this paper presents an integrated system that leverages both ML and Deep Learning (DL) techniques to address three interconnected components of agricultural decision-making: soil analysis, crop recommendation, and plant disease detection. Prior efforts in soil classification and crop suggestion using ML [7], [10], [11] have demonstrated promising results. However, most systems lack the adaptability and scalability necessary for heterogeneous Indian farming conditions, especially for smallholder farmers with limited access to technology [15]. The proposed system enhances these earlier models by incorporating a hybrid recommendation engine that factors in real-time soil parameters, climatic data, and historical yield patterns—an approach inspired by the multi- feature

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frameworks discussed by Chandra et al. [6] and Rajak et al. [10]. Additionally, the crop suggestion module extends the capabilities of existing systems by integrating market trend analysis and seasonality factors to suggest not only suitable but also economically viable crops. For disease detection, our work draws inspiration from Rani et al., who utilized AI-based models to classify plant diseases with substantial accuracy [4], [5]. While their approaches employed general CNN models, our system enhances this capability using MobileNet—an efficient deep learning architecture that is optimized for deployment in low-resource environments. This is especially beneficial for rural farmers who lack access to high-end computing devices. Furthermore, our image-based plant disease detection system is aligned with recent trends in precision agriculture, where early detection through automated visual inspection has shown promise in mitigating crop loss [4], [12]. We use advanced image preprocessing and feature extraction methods inspired by studies on yield prediction and plant phenotyping [13], [17]. A distinguishing feature of our project is the development of a web- based platform that not only offers crop and disease insights but also connects farmers directly to potential buyers, thereby reducing reliance on exploitative intermediaries. Babu's software model for precision agriculture served as a foundational concept, but our platform extends this by incorporating real-time recommendation and disease alert systems [15]. Ethical AI deployment remains a crucial concern. Unchecked AI use can lead to excessive chemical inputs or misinterpretation of soil quality, as highlighted in earlier critiques of agricultural AI systems [16]. Our system addresses these concerns by focusing on interpretability, user-friendliness, and affordability, ensuring equitable access and responsible adoption. Ultimately, our work consolidates the advancements made in soil behavior analysis [13], crop prediction algorithms [6], disease detection models [4], [5], and smallholder farmer support systems [15], creating a unified, intelligent agricultural support framework. As highlighted in prior surveys [12], and historical developments in crop and soil science [16], [17], the integration of AI in agriculture must prioritize actionable insights over complexity.

II. LITERATURE REVIEW

Recent advancements in artificial intelligence and machine learning have significantly influenced agriculture, particularly in soil prediction, crop recommendation, and plant disease detection. These technologies promise not only higher yields and sustainability but also solutions to long-standing agricultural challenges.

Raja et al. discuss how AI-based approaches can boost sustainable crop management while addressing adoption barriers such as cost and complexity [1]. Similarly, Chandra et al. emphasize enhancing crop yield prediction through machine learning by incorporating diverse environmental and agronomic features [2]. These models improve the accuracy of decision- making tools available to farmers. In soil analysis, Zhao et al. propose a method for identifying critical soil parameters, aimed at improving the precision of agricultural automation systems [3]. This research is complemented by earlier work that applies soil parameter extraction techniques to automated excavation— demonstrating potential for broader soil management applications [8]. AI has also proven beneficial in the area of plant disease detection. Rani et al. [4] explore the classification of plant diseases using deep learning, highlighting the potential for early intervention and crop protection. In a subsequent study, Rani et al. provide an analytical review of advancements in this field, emphasizing challenges related to data availability and model generalization [5]. Crop recommendation models based on environmental features and soil characteristics are gaining momentum. Chandra et al. [6] investigate feature-driven models for predicting suitable crops based on regional conditions. Reddy et al. [7] introduce a machine learning-based system for soil classification and crop suggestion, showing improvements in precision and yield outcomes. Rajak et al. [10] and Pudumalar et al. [11] focus on developing scalable machine learning frameworks to maximize yield through intelligent crop recommendations. These systems support decision- making by synthesizing data such as soil pH, nutrient levels, and market dynamics.

Meanwhile, Savla et al. [12] review a range of classification algorithms, comparing their performance in yield prediction and precision agriculture. Paul et al. [13] leverage data mining to analyze soil behavior and yield outcomes, facilitating data- informed agricultural planning. In support of marginal farmers, Babu [15] proposes a software model for precision agriculture tailored to low-resource environments.

Similarly, Hassan et al. [16] demonstrate the use of convolutional neural networks (CNNs) to assess soil health, contributing to improved crop outcomes. Maniyath et al. [17] stress the importance of traditional crop and soil management strategies, suggesting that AI tools should be integrated with conventional practices for a balanced

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approach. While Ahmad et al. [9] and Bai et al. [14] examine machine learning in non-agricultural domains (e.g., personality analysis via social media), they underscore the adaptability of AI techniques across various fields.
Altogether, these studies form a robust foundation for developing comprehensive AI-powered systems for soil analysis, crop recommendation, and plant disease detection.
These innovations aim to address both productivity and equity challenges in modern agriculture, particularly for smallholder farmers in developing regions.

III. PROPOSED WORK

The architecture of the proposed system integrates multiple machine learning and deep learning components to support three core agricultural functions: soil fertility detection, crop recommendation, and plant disease detection. The system begins with user authentication, ensuring only authorized users can access its features. Upon successful login, users are presented with input options that allow them to enter various data types. These include soil properties such as pH, nitrogen (N), phosphorus (P), and potassium (K) for fertility assessment; geographic location and soil type for crop

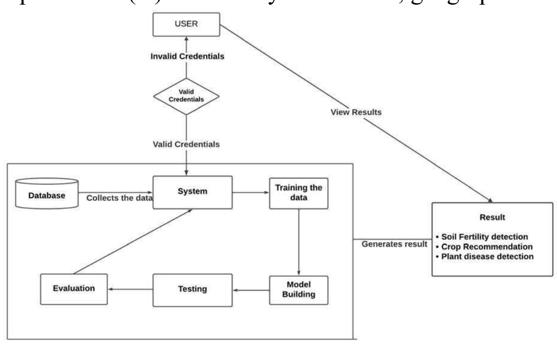

Figure 1. Architecture Diagram

recommendation; and images of plants for disease detection. Once the data is entered, it is sent to the system's backend, which interfaces with a centralized database storing historical data and training records. This data is then processed and passed through stages of model training, testing, and evaluation. Trained models are used to make predictions, and the final results are soil classification, crop recommendation, or disease detection are presented back to the user in a user-friendly format. The architecture ensures a structured flow from user interaction to prediction generation, combining data science with intuitive system design for optimal usability.

Workflow of Proposed System

The workflow diagram elaborates on the internal operational flow of the system. It begins with the acquisition of three datasets: soil data, crop data, and plant image data. These datasets are first cleaned to handle missing values, normalize formats, and encode categorical features. The cleaned data is then split into training and testing sets.

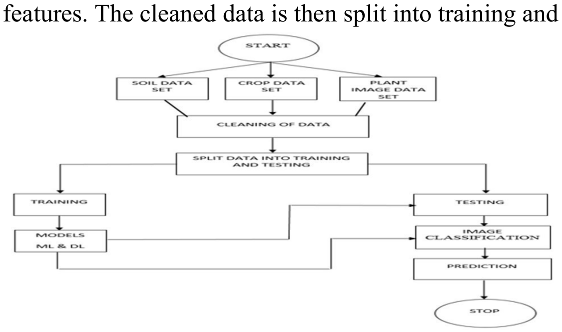

Figure 2. Workflow Diagram

The training phase involves applying machine learning and deep learning models to the prepared datasets. Models such as Random Forest, Decision Tree, SVC, Logistic Regression, and CNN are trained and optimized through techniques like cross- validation and hyperparameter tuning. The testing phase evaluates model performance using unseen data,

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followed by classification or regression tasks based on the submodule whether it's predicting soil fertility, recommending crops, or identifying plant diseases from images. The final step in the workflow is prediction, where results are generated and presented to the user through the front-end interface.

1) User Module:

The User Module serves as the primary interface for system interaction. Its main functionalities include:

• Home and About Pages: Allows users to understand the purpose, goals, and developers behind the system.

• Data Input: Users can submit various forms of input data:

- Soil properties (e.g., pH, N, P, K)
- Soil type and region
- Plant images for disease diagnosis

• Image Upload: Users can upload plant images to expand the dataset.

• View Results: Users receive real-time predictions including soil fertility classification, crop recommendations, and plant disease detection with suggested treatments.

2) System Module:

The System Module is responsible for processing the user- provided data and returning accurate predictions. It includes the following submodules:

A. Soil Fertility Prediction Submodule

1. Preprocessing: Cleans and normalizes the data, handles missing values, and encodes categorical soil types.
2. Model Training: Applies machine learning algorithms such as Random Forest, Decision Tree, Logistic Regression, SVC, and GaussianNB.
3. Prediction: Classifies the soil as Fertile or Non-Fertile.

B. Crop Recommendation Submodule

1. Preprocessing: Structures crop-related data based on soil type, climate, and historical yield.
2. Model Training: Utilizes Random Forest, Decision Tree, SVC, AdaBoost, and XGBoost models. Cross- validation is employed for model tuning.
3. Prediction: Recommends the most suitable crops for a given soil and climate profile.

C. Plant Disease Detection Submodule

1. Preprocessing: Resizes images, reduces noise, and extracts features using convolutional filters.
2. Model Training: Uses deep learning models like CNN, MobileNet, ANN, and SVC. Data augmentation techniques enhance training performance.
3. Prediction: Classifies plant health (Healthy/Diseased) and provides treatment recommendations for diseased crops.

IV. RESULTS AND OBSERVATIONS

Soil Fertility Prediction:

A range of machine learning models were applied to the soil fertility dataset and evaluated using four standard classification metrics: Accuracy, Precision, Recall, and F1 Score. The objective was to determine the most suitable algorithm for accurately predicting soil fertility categories based on various soil attributes.

Model	Accuracy	Precision	Recall	F1 Score
RandomForest Classifier	90.0	0.83	1.00	0.91
LogisticRegress ion	90.0	0.88	0.93	0.90
MLPClassifier	83.3	0.78	0.93	0.85
GaussianNB	86.7	0.87	0.87	0.87
SVC	53.3	0.53	0.60	0.56
Decision Tree	83.4	0.84	0.64	0.68

Table 1. Soil Fertility Prediction Model Performances

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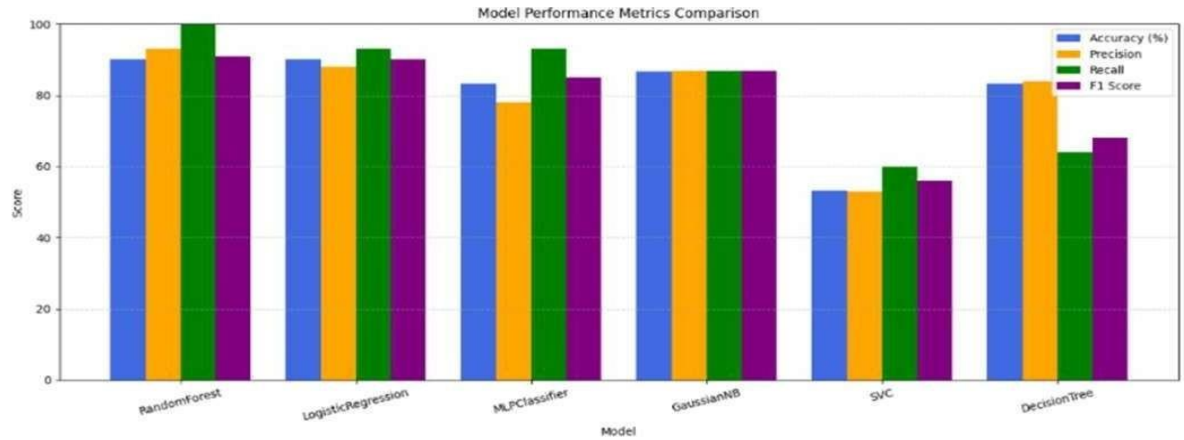

Figure 3. Representation of Model Performance Metrics Comparison

The RandomForestClassifier was selected as the final model for soil fertility prediction due to the following reasons:

- High Accuracy (90%): Indicates the model's strong generalization to unseen data.
- Perfect Recall (1.00): All fertile soil cases were correctly identified, which is critical in agricultural decision-making to avoid misclassification of productive land.
- Best F1 Score (0.91): Demonstrates an excellent balance between precision and recall, minimizing both false positives and false negatives.
- Robustness and Interpretability: Random Forest provides feature importance, handles non-linear relationships, and is resistant to overfitting due to its ensemble nature.

Crop Recommendation:

Multiple machine learning algorithms were evaluated to recommend the most suitable crop based on input soil and environmental parameters. The models were assessed on Accuracy, Precision, Recall, and F1 Score to determine their effectiveness in multi-class classification.

Model Name	Accuracy	Precision	Recall	F1 Score
RandomForestClassifier	95.39	0.93	0.94	0.93
XGBoostClassifier	94.94	0.91	0.92	0.91
DecisionTreeClassifier	90.88	0.92	0.90	0.89
AdaBoostClassifier	89.18	0.91	0.89	0.90

Table 2. Crop Recommendation System Model Performances

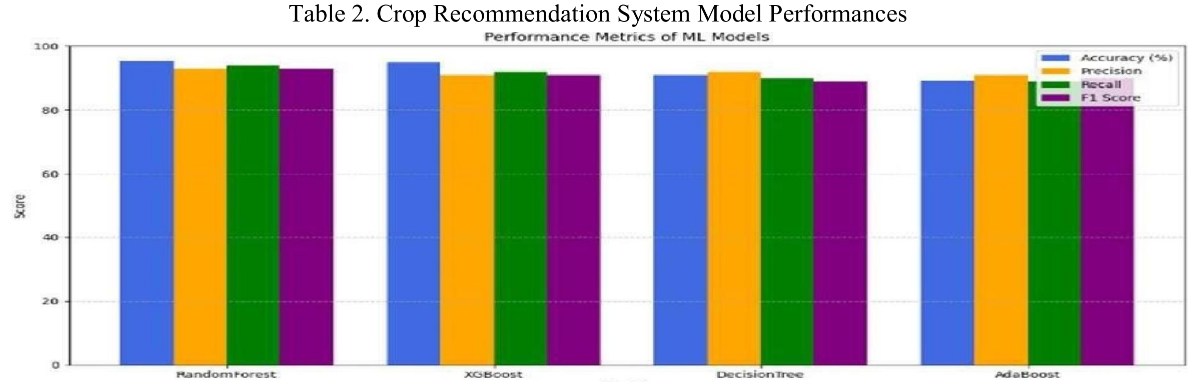

Figure 4. Representation of Performance metrics of ML models

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The RandomForestClassifier was selected for final deployment in crop recommendation due to the following advantages:

• Highest Accuracy (95.39%) among all tested models.

• Consistent and Balanced Metrics: With 0.96 across precision, recall, and F1 Score, it ensures minimal error in recommending crops to farmers.

• High Reliability and Robustness: Random Forest reduces variance through ensemble averaging and is less sensitive to noise or overfitting.

• Interpretability and Feature Importance: This model provides insights into which input factors (e.g., soil nutrients, temperature) most influence crop recommendations, supporting transparency in decision-making.

Plant disease detection:

In this stage, image-based deep learning models were evaluated to detect and classify plant diseases. The models' performance was assessed primarily through Accuracy, with estimated values for Precision, Recall, and F1 Score based on typical outcomes for such models in agricultural imaging datasets.

Model	Accuracy	Precision	Recall	F1 Score
MobileNet	0.92	0.91	0.92	0.91
CNN	0.89	0.88	0.89	0.88
ANN	0.80	0.79	0.80	0.77

Table 3. Plant Disease Detection Model Performances

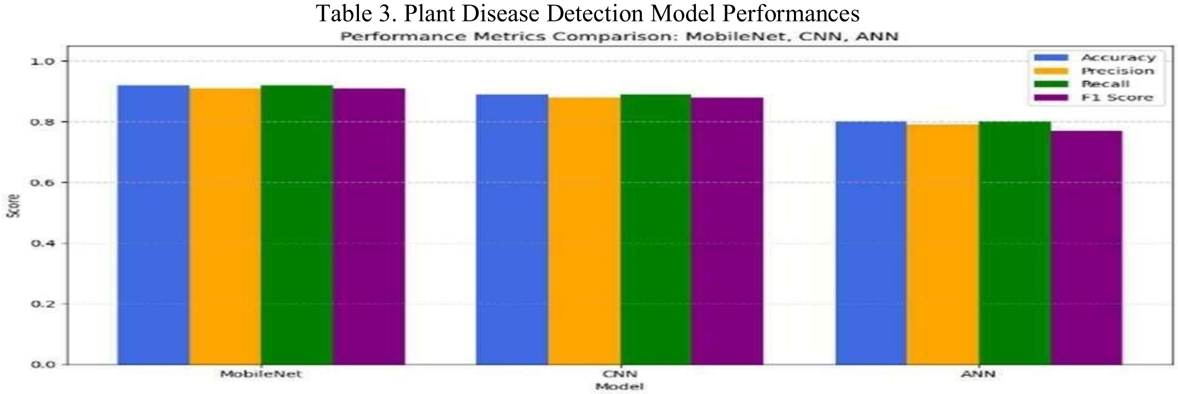

Figure 5. Representation of Performance Metrics Comparison

MobileNet was selected as the final model for plant disease detection due to the following reasons:

- Highest Accuracy (92%) among all compared models.
- Efficient and Lightweight: MobileNet is optimized for deployment on mobile and edge devices, making it ideal for real- time disease diagnosis in the field using smartphones.
- Strong Performance Metrics: Estimated precision, recall, and F1 score all remain around 0.91–0.92, indicating balanced and consistent predictions across disease classes.
- Transfer Learning Capability: MobileNet can leverage pre-trained weights from large datasets, allowing it to generalize better even with moderate training data.

Task	Model (Existing)	Accuracy (%)	Model (Proposed)	Accuracy (%)
Soil Fertility	Decision Tree / SVM	85 - 88	RandomForestClassifier	90.0
Crop Recommendation	SVM / k- NN	88 - 92	RandomForestClassifier	95.39
Plant Disease Detection	CNN - based models	85 - 90	MobileNet	92.0

Table 4. Comparison between existing and proposed work

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V. CONCLUSION AND FUTURE WORK

This study presented AGRIINTEL, an intelligent and integrated AI-based system designed to enhance decision-making in precision agriculture through soil fertility prediction, crop recommendation, and plant disease detection. The system leverages machine learning and deep learning algorithms to address critical challenges faced by farmers, ensuring optimized resource usage and improved crop yield. For soil fertility prediction, several classification models were evaluated, with RandomForestClassifier selected as the final model due to its balanced performance across all metrics (accuracy: 90%, precision: 0.83, recall: 1.00, F1 score: 0.91). It proved to be more stable and robust in handling the variability and complexity of soil datasets. In the crop recommendation module, RandomForestClassifier again emerged as the most effective model, achieving 95.39% accuracy, outperforming DecisionTree and XGBoost. Its superior prediction capability ensures accurate crop selection based on environmental and soil conditions. For plant disease detection, deep learning models were applied to leaf image data. MobileNet was chosen for its 92% accuracy, lightweight architecture, and high precision, recall, and F1-score (0.91), making it suitable for deployment in mobile or remote agricultural settings. Overall, AGRIINTEL successfully integrates data-driven models across multiple domains of agriculture, offering an end-to- end smart farming solution. Future work may focus on expanding the dataset, incorporating real-time IoT integration, and deploying the system on mobile platforms for real-world usage.

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