AI-Based Agriculture Web Platform for Crop Recommendation and Disease Prediction

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***Abstract*- Agriculture is the main source of income for a lot of people around the world, but farmers struggle with identifying the right crops to plant and early diagnosis of diseases. Poor crop selection and late diagnosis results in loss of yield and in worst case scenarios contribute to financial loss to farmers. Data-driven, farmer-centric solutions to these problems, derived from advancements in Artificial Intelligence (AI) and Machine Learning (ML), are possible.**

This paper presents an AI-based web platform to support basic agricultural decision making with two core services, crop recommendation and plant disease identification. The crop recommendation model we developed uses a Random Forest classifier that has been trained on common soil and climatic parameters (N, P, K, pH, temperature, humidity, rainfall) and achieves over ~95% accuracy in the 22 crop classes. We provide soil or soil treatment recommendations, crop rotation advice, dynamic smart advisory information using weather APIs, and a profit basis for ranking crops in our crop recommendation module, which are much broader than the recommendations made currently.

The disease prediction module incorporates a Vision Transformer (ViT) which has been trained on the PlantVillage dataset containing 38 disease classes related to 15 crop species. To provide interpretability, we built our own ViT-GradCAM framework to generate visual explanations that will highlight diseased areas in leaf images to increase farmer trust in the predictions.

In addition, the platform uses weather APIs, soil data, and economic analysis to provide context in decision making. Presently built in a nimble, web-based interface, the farmer can enter soil parameters to receive actionable insights or upload their image of a leaf to obtain recommendations. Unlike previous methods that have considered these issues separately, our integrated approach essentially combines both services into a single platform that is more usable and practical. This research supports precision farming and sustainable agriculture by providing farmers with timely, trustworthy, and interpretable recommendations to improve crop productivity and mitigate crop losses.

Keywords—Artificial Intelligence, Machine Learning, Crop Recommendation, Plant Disease Detection, Vision Transformer, Random Forest, Grad-CAM, Smart Farming, Precision Agriculture.

I. INTRODUCTION

Agriculture is a primary source of the economy of many countries; particularly developing countries, such as India, where most of the population depends on agriculture for their livelihood. Farmers experience several significant issues like selecting the right crop for their soil and detecting plant diseases early enough to do something about it. In many cases, farmers rely on their own experience which leads to lower productivity and economic loss. In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as effective methods to overcome these challenges with data-driven and automated solutions.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have enabled new possibilities in addressing these limitations through data-driven and automated decision-support systems. However, previous research has tended to address crop recommendation and disease detection as separate entities. Crop recommendation systems generally rely on functional soil and weather features such as nitrogen (N), phosphorus (P), potassium (K), pH, temperature, humidity, and rainfall in recommending crops, whereas commonly used deep-learning-based disease detection models analyze leaf images to classify plant health or disease. Even if effective within their context, these separate systems do not create a comprehensive decision-support system for farmers. In practice, farmers actually need both forms of guidance at the same time: what to grow and practical information about how to keep crops healthy throughout the growing cycle.

To address this gap, we present an agricultural platform powered by AI that combines crop recommendation and plant disease detection into one web application. The crop recommendation is a Random Forest classifier, trained on soil and climate data, and achieves ~95% accuracy across 22 crop classes. The crop recommendation module is further enhanced by the inclusion of four farmer-centered services (i) recommendations for treating soil for nutrients, (ii) planning crop rotations for sustainable soils for the long-term, (iii) smart real-time advisory from the integration of an API with weather data, and (iv) crop ranking based on profitability using market data. The disease detection module is based on a Vision Transformer (ViT), also trained on the PlantVillage dataset consisting of 38 disease classes for 15 crop species. To enhance interpretability of the ViT, Grad-CAM explainability is used to create visual heatmaps that highlight infected areas on the leaf, thus creating trust and transparency for the end user.

In addition to technical precision, the platform includes weather APIs, soil data services, and market-based economic evaluation to create recommendations that are agronomically valid and economically feasible. The slightly-weight and mobile-responsive web interface allows farmers to access recommendations even in under-resourced rural settings.

The main contributions of this study are:

1. Integration of two services, crop recommendation and disease prediction around a single platform.

2. Enhanced crop recommendation module with soil treatment suggestions, crop rotation planning, weather-aware smart advisory, and profit-based crop ranking.

3. Implemented a Vision Transformer with Grad-CAM to achieve high-accuracy and explainable pest and disease diagnosis over 38 crop disease classes.

4. Integrating economic analysis and external APIs in the decision-making framework to weigh agronomic suitability of crops and profitability.

5. Development and deployment of a farmer-friendly web application, accessible via smartphones and suitable for low-resource environments.

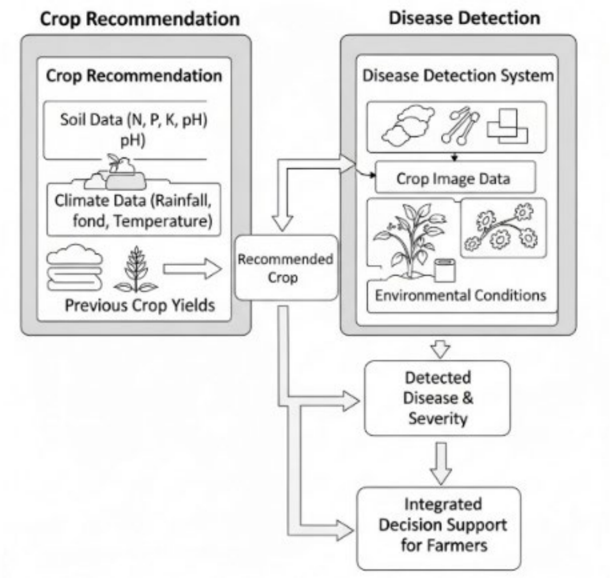


Fig. 1: Integrated System for Crop Recommendation and Disease Detection.

The research shows how the combination of innovative AI models and deployment tools can provide farmers with actionable insights to reduce crop losses and support the larger vision of sustainable precision agriculture.

II. Related Work

Artificial intelligence (AI) and machine learning (ML) are demonstrating their potential to have important impacts on agriculture, providing data-driven solutions to improve productivity, crop health, and decision making. The research can be broadly categorized into areas of crop recommendation systems, plant disease detection systems, and integrated IoT-enabled systems. All the areas have shown much progress, yet each of these areas often focuses on a separate problem or has issues with scalability and usability in the field for farmers.

1. Crop Recommendation:

Crop recommendation features are designed to recommend the best crop species for growing based on soil and climate characteristics. Earlier works have used classifiers like Naïve Bayes, Decision Trees, and Support Vector Machines. Ensemble Models, especially Random Forests, have achieved better performance than other classifiers because of their ability to control overfitting and model complex interactions between features [1], [2]. Random Forest classifiers have been shown to attain over 95% accuracy using soil nutrients (N, P, K), pH, rainfall, temperature, and humidity data [3].

Despite these high-level results, many systems remain prototypes with datasets, without the use of external data sources (or services). Few models make use of weather APIs with real-time information, and none incorporate economic parameters like profitability and cost-benefit analysis. Also, beyond weather and soil treatment recommendations, the current works rarely offer extra services, with on-farm planning or recommendations for crop rotation via algorithm or software as examples. The agricultural setting thus limits the estimated relevance of these current works, as they are too static in their recommendations.

2. Plant Disease Prediction:

Deep learning is now the main approach for detecting crop disease, especially using images of leaves, and Convolutional neural networks (CNNs) dominate the literature with studies reporting >90% accuracy on publicly available datasets such as PlantVillage [4], [5]. Transfer learning via architectures such as VGG16, ResNet, and Inception networks has also proven effective, particularly with few training images [6].

However, CNN-based approaches generally function as "black boxes" that make predictions without explanation. This lack of interpretability may constrict the trust and adoption of farmers. Explainable AI (XAI) approaches, such as gradient-weighted class activation mapping (Grad-CAM), have recently been implemented to make visual heatmaps of the leaf regions contributing to predictions [7]. While these methods enhance transparency, their integration into deployable agricultural platforms remains limited.

3. IoT and Smart Agriculture Systems:

IoT-driven frameworks that leverage sensor networks, cloud computing, and ML for agricultural decision-making have been studied. For example, it has been proposed to design systems that collect soil moisture, humidity, and temperature data through sensors connected to the Internet, and to integrate ML algorithms for predicting crops and disease [8]. While similarly capable in controlled settings, these solutions often rely on expensive hardware, stable connectivity, and an appropriate infrastructure, rendering them infeasible for many smallholders in low-income countries.

4. Research Gap:

From the reviewed literature, three gaps can be identified:

- Service Integration: There is a minimum cadre of research that has either pinnacle on crop recommendation or disease detection in isolation of one another. Very few frameworks have investigated service integration by combining and providing a platform that provides both services.

- Explainability: While CNNs can achieve precise predictions, the trade-off in loss of interpretability limits farmer trust. Explainable models have been developed, such as via Grad-CAM in Vision Transformer, that remain underutilized to promote trust in real agricultural systems or incorporate explainability that nuances user engagement, variation, or service adaptability.

- Practical Deployment: Although innovative, IoT-based platforms are often hampered by prohibitive infrastructure costs for low-resource rural areas. Lower-resource existing conditions will likely become more prevalent with increased use of IoTs. There is also a lack of research longitudinal studies in consideration of economic or weather adaptability mechanisms for practical use/cycles, despite being essential to viable or sustainable programs

Our Contribution Beyond Literature:

To address these gaps, we present an AI-based agricultural platform that combines crop recommendation and plant disease detection in one web application. The crop recommendation module utilizes Random Forest, but it has been augmented to provide soil treatment recommendations, company-appropriate crop rotation plans, real-time weather aware smart advisory, and crop ranking based on profitability. The disease detection module is based on Vision Transformer, augmented with Grad-CAM, which allows for accuracy and interpretability. Rather than simply using crop recommendations.

Our platform includes a module that looks at real-time weather APIs, soil data services, and economics of crop production to make sure recommendations are scientifically correct and economically feasible. We also present the service as a lightweight, mobile-accessible web application to alleviate technical and usability issues that have impeded adoption of previous approaches.

III. METHODOLOGY

The suggested agricultural platform is AI-based and consists of two key services: crop recommendation and plant disease detection. The process consists of dataset preparation, data preprocessing, model training, integration, and deployment. The general process flow is illustrated in Fig. X, which demonstrates the interaction between the modules to provide farmers with actionable recommendations.

A. Dataset Description:

1) Crop Recommendation Dataset:

The crop recommendation model utilized the Agricultural Soil and Climate Dataset from Kaggle, which contains values of important soil nutrients and climate parameters from Indian agricultural locations. It includes:

Soil Parameters: Nitrogen (N: 0-200 kg/ha), Phosphorus (P: 0-150 kg/ha), Potassium (K: 0-200 kg/ha), and pH value (3-12).

Climate Parameters: Temperature (−10 to 50 °C), Humidity (10-100%), and Rainfall (50-3000 mm).

Target Crops: 22 different crops (cereals - rice, maize; pulses - chickpea, kidney bean, mungbean, pigeon pea, lentil, etc.; fruits - apple, banana, mango, grapes, orange, papaya, watermelon, muskmelon, coconut, pomegranate; commercial - cotton, jute, coffee).

Source: Crop Recommendation Dataset, Kaggle.

Link: https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset

2) Plant Disease Detection Dataset:

The system utilizes the PlantVillage dataset for disease prediction, which is a public benchmark dataset for plant disease classification. The dataset comprises leaf images taken under incubated conditions with labels of crop and disease type. This dataset included:

Scale: ~64,000 images for training and 20,000 images for validation.

Crops/Affected crops covered: 15+ crop species such as Apple, Tomato, Potato, Corn, Grape, Cherry, Peach, Pepper, Soybean, Strawberry, Squash, Orange, Blueberry, and Raspberry.

Classes of diseases for each crop: 38 crops and diseases, including Apple Scab, Black Rot, Cedar Apple Rust, Potato Early and Late Blight, Tomato Yellow Leaf Curl Virus, Citrus Huanglongbing, and other diseases and healthy classes for each crop.

Process: The images had been resized to 224×224 pixels and advanced through rotation, flipping, and brightness.

Source: PlantVillage Dataset, Kaggle.

Link: https://www.kaggle.com/datasets/emmarex/plantdisease

B. Input Data:

The platform accepts a range of inputs from farmers and external APIs to create useful recommendations.

Soil Parameters – Nitrogen (N), Phosphorus (P), Potassium (K), pH, Temperature, Humidity, and Rainfall. These parameters are either manually entered by the user or automatically fetched from soil and climate databases.

Leaf Images – Crop leaf samples are uploaded to the system for disease detection. These images are processed into 224×224 RGB patches for compatibility with the Vision Transformer.

External APIs – Real-time weather data, soil information, and market price data are retrieved using APIs. This ensures that recommendations remain adaptive to changing conditions and economically relevant.

C. Data Preprocessing:

Preprocessing data provides accuracy, consistency, and suitability for machine learning models:

Soil and Climate Data:

Mean values were used to impute missing values.

Normalization of features to scale values between 0 and 1.

Label encoding for categorical crop classes.

Leaf Image Data:

Images were resized into RGB format with 224×224.

Data augmentations included all or some of the following: rotation, reflects, and contrast.

Embedding patches (16×16 patches) for the Vision Transformer.

This preprocessing ensures robust, balanced, and model-ready datasets.

D. Crop Recommendation Module:

The Random Forest (RF) classifier was chosen for crop recommendation because it is robust and can model non-linear relationships.

Model Training: 100 decision trees were created based on soil and climate features.

Performance: The model reached approximately 95% accuracy for 22 crops.

Results: Ranked list of crops with confidence scores.

Enhanced Services:

Economic Analysis: Predict yields, cost of cultivation, profit made.

Weather Adaptation: API fetched real-time weather data to adjust prediction.

E. Plant Disease Detection Module:

The disease detection system is based on a Vision Transformer (ViT) model.

Architecture: The vit_base_patch16_224 first breaks input images into patches, adds positional encodings for embeddings, and then performs processing of the 12 transformer encoder layers with multi-head self-attention.

Training Strategy: A transfer learning strategy was employed, using weights pretrained on ImageNet, and then fine-tuned using the PlantVillage dataset.

Explainability: The Vision Transformer Grad-CAM was used to enhance the trustworthiness of the predictions, with focus on the regions of the leaf that were underlying factors to the classification.

Performance: The model achieved ~92% accuracy across the 38 disease classes.

F. Integration and Analysis:

Both submodules work within a single web-based platform:

Crop Recommendation Output – Provides recommendations for crops that are ranked in terms of probability and profitability.

Disease Detection Output – Classifies leaves with confidence scores and Grad-CAM heatmaps.

Economic Analysis – Includes cost of cultivation and yield estimates with current market prices to rank profitability.

API integration – Provides real-time weather, soil, and location data to enhance the variability of crop recommendations.

G. Deployment and Interface for Farmers:

The platform was designed with usability and scalability in mind.

Web + Mobile Access: Farmers can access the platform via web browser or via smartphone.

Dashboards: displaying soil composition, weather, crop profitability forecasts, and disease warnings.

Outputs: Recommended crops (ranked by agronomic suitability & economic viability).

Disease classification outputs and interpretability (heatmaps)

Confidence measures assist farmers in decision-making.

This ensures that the system will not only be technically strong but also usable and practical in real settings.

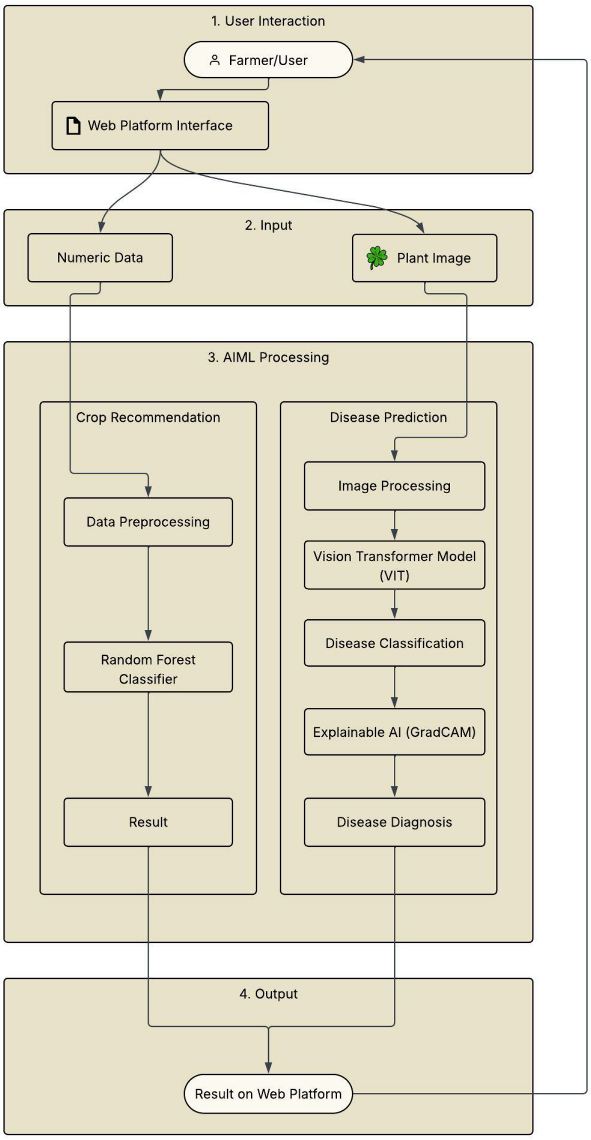


Fig. 2: Workflow of the AI-Powered Smart Agriculture System.

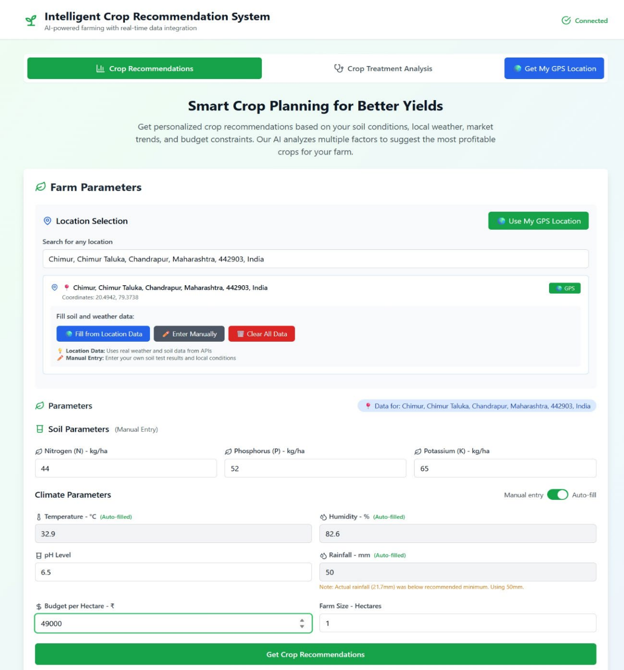
IV. Results

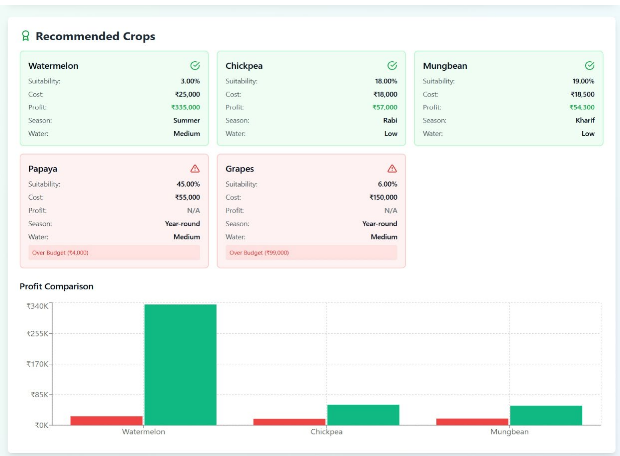
The proposed FarmCareAI platform was evaluated for crop recommendation, plant disease detection, and additional services such as weather, soil insights, and market analysis. Results showed the platform being accurate and useful for farmers.

A. Crop Recommendation Results:

The Random Forest model for crop recommendation achieved very high accuracy (around 95%) in recommending the best crop from 22 possible options. It was able to incorporate different soil and weather inputs and when there were multiple acceptable crops it ranked them in order of profit.

Accuracy: 95% & Precision and recall: > 95%





This means the model will not only help farmers decide what to grow but also which crop may be the most profitable.

B. Results of Plant Disease Detection:

The Vision Transformer (ViT) model was trained on the PlantVillage dataset, and it had a 92% accuracy for classifying diseases from the images of leaves. Unlike older CNN models, ViT with Grad-CAM showed the exact parts of the leaf that had the disease with a heatmap visualization, which made the results more interpretable and trustworthy.

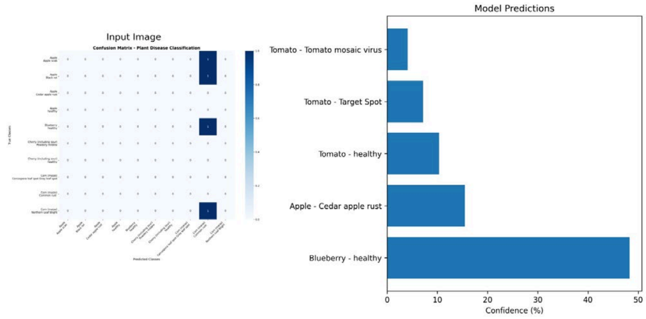


Fig. 3: Model Performance Metrics (Confusion Matrix) and Example Disease Prediction with Confidence Scores.

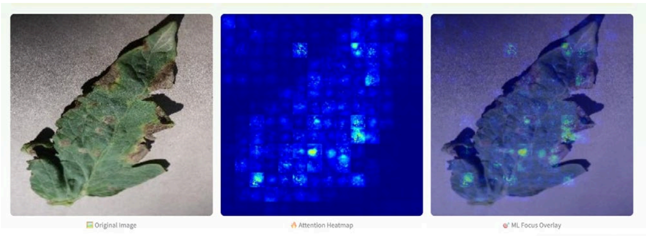
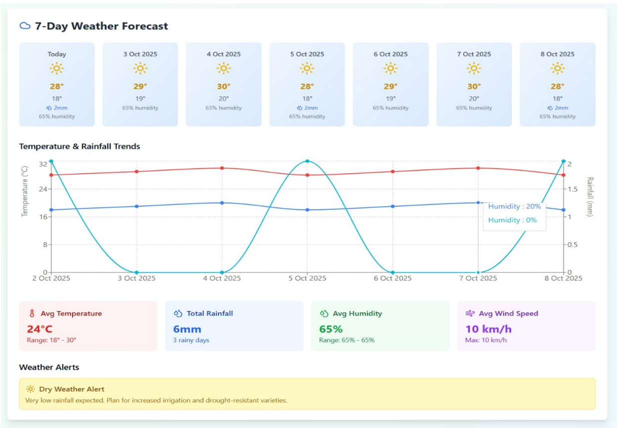


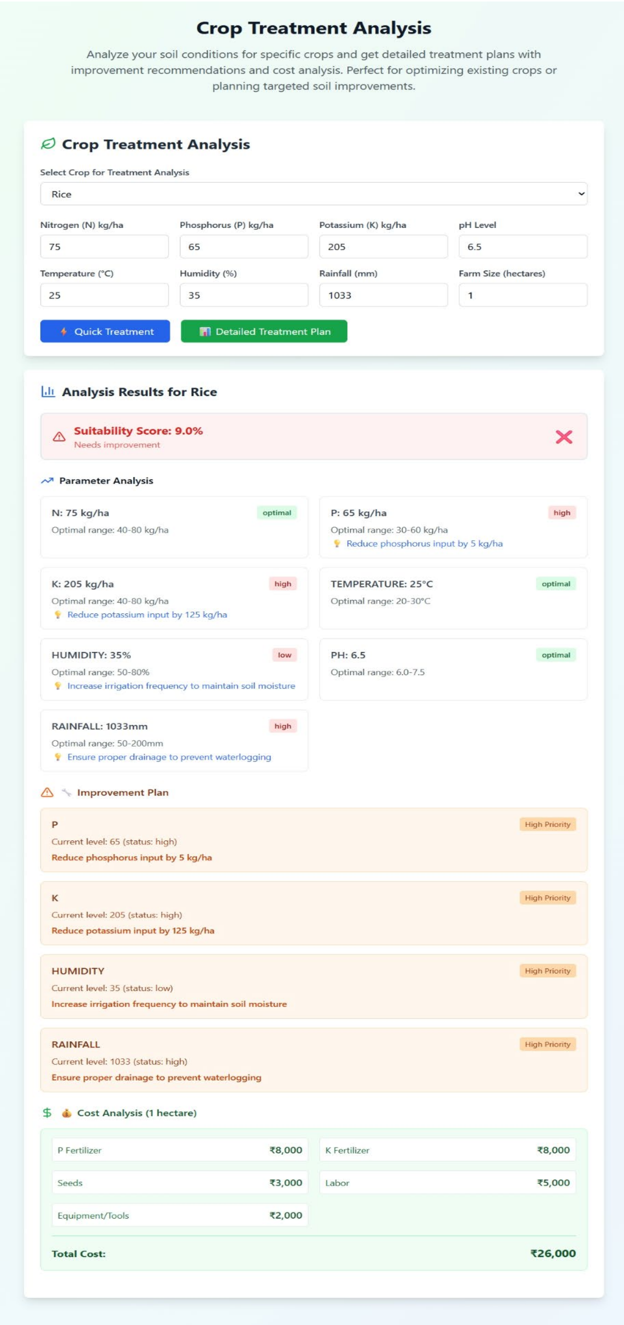
Fig. 4: Explainable AI (XAI) Visualization: Original Image, Attention Heatmap, and Overlay for Disease Localization.

C. Weather and Soil Insights :

The system also uses real-time weather data made available through APIs. If, for example, there is a prediction of low rainfall, it will not recommend high-water-use crops like paddy. In addition to this, farmers will also be given an easy visual of soil health (N, P, K balance, pH), to quickly see which nutrients are deficient.



In addition, the system also recommends a soil treatment program based on the crop the farmer intends to grow. For instance, if nitrogen is low in the soil and the farmer is growing wheat, it would recommend urea or organic manure as nitrogen. If soil pH is exceeding acidic for vegetables, it may recommend lime treatment. These corrections provide a good way for farmers to improve their soil conditions before planting and improve the usability and actions from soil condition recommendations as opposed to static systems.



D. Market Analysis with Crop Rotation Plan (3 Years):

To improve the platform's functionality, we enhanced the recommendations beyond single-season crops and began conducting profitability analysis using a recommended 3-year crop rotation plan. Farmers can therefore see not only which crop is best now, but also how to rotate that crop across the seasons to improve soil nutrients, reduce pests, and optimize income.

1. Market Analysis:

The platform connects the market price APIs and local crop prices datasets.
For each crop, it determines:

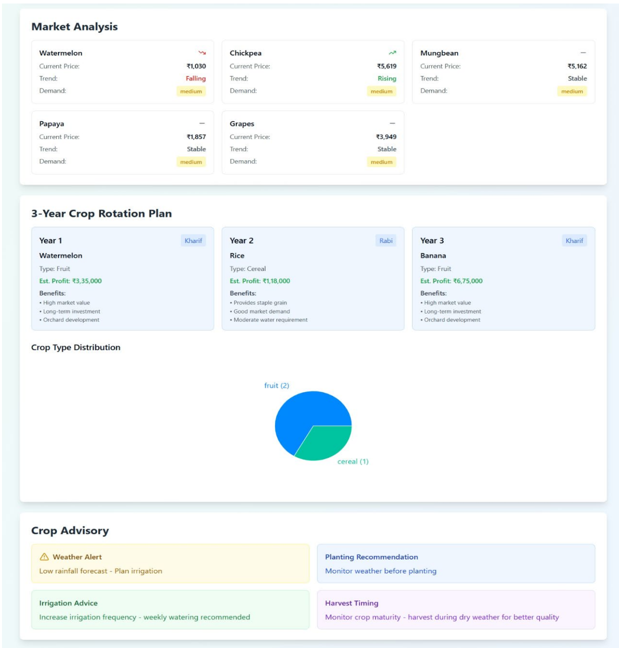
Cost of growing crops (seeds, fertilizers, irrigation). Expected yield per hectare. Profit margin (yield x price − cost). Farmers receive a profit ranking with their agronomic suitability.
For example, if both maize and cotton can be successfully grown in a location, from all the possible crops the platform could recommend, if cotton has a potential 25% higher profit than maize, it will be ordered higher.

2. Plan for 3-Year Crop Rotation:

Both soil nutrient balance and profit data are used for the 3-year strategy.

Main Points: -

- Nutrient Cycling: Pulses reintroduce nitrogen after cereals/cotton.
- Profit Mix: Balances cash crops (cotton) with food crops (wheat, pulses).
- Risk Reduction: Different crops reduce risk from pests/diseases and price crashes.



E. Combined Benefits:

Service / Feature	Past Systems	FarmCareAI
Crop Recommendation	✔	✔ (with profit ranking)
Disease Detection	✔ (CNN only)	✔ (ViT + Grad-CAM)
Treatment Plan	✘	✔
Weather-based Adjustment	✘	✔
Soil Nutrient Insights	✘	✔
Market & Profit Analysis	✘	✔
Mobile-Friendly Web Access	Partial	✔

V. Discussion

FarmCareAI shows that integration of crop recommendation, disease detection, market analysis, and crop rotation planning tools onto one platform can provide farmers with a more robust decision-making aid than previously existing applications. Unlike previous work that presented only one task allocation, our platform is a multi-service solution that offers complexity for implementers but is easy to learn and operate in real applications by farmers.

First, the crop recommendation method reached approximately 95% accuracy by accounting for soil and climate parameters. The added layer of economic analysis ensures that the crop recommendations are not only scientifically sound, but financially viable. The farmer can see the anticipated profitability of a given crop, significantly reducing the chances of selecting ineffective crops that may not be viable in the market.

Secondly, the disease detection module utilizing the Vision Transformer (ViT) attained around 92% accuracy which exceeds the typical accuracy rates of many convoluted neural network (CNN) models. A Grad-CAM visualization is provided to offer interpretability to the AI model. This will allow the farmer to physically see the diseased portions of the leaf, which can enhance trust in the AI model, and aid the farmer in decision making for prompt action.

Third, by utilizing real-time weather APIs and soil data, the system becomes adaptive to changing circumstances. For instance, if seasonal rains are predicted to be very low, water-intensive crops are shunned. This real-time adaptability makes the platform more resilient than systems that rely on static datasets.

Fourth, with a 3-year crop rotation plan, the system is not limited to the short-term perspective. Crop rotation promotes soil health, pest control, and sustainable yields. The plan also includes market considerations, so rotations have a proper nutritional balance and a positive return on investment. This significantly pushes the tool towards being more of a farm planner than just a predictive system.

In summary, the platform has three primary benefits:

- It achieves high levels of accuracy in predictions, whether crops or diseases are being predicted.
- The real-world application has been made easier by the inclusion of economic data and weather data.
- It is grounded in sustainability through crop rotation and healthy soil practices and changing farmers' mindsets toward sustainable practices.

While there is some areas for improvement, the challenges faced with the application are not major. The application only uses the PlantVillage dataset for disease identification, and this dataset is comprised of lab-quality images. In the future, it is important to test the application with images taken on real farms, since lighting and background conditions will differ drastically from lab images. Also, while the APIs return accurate weather and market updates, their accuracy will vary, especially in rural areas with limited data coverage, as is the case with real-time weather data.

Despite these challenges, FarmCareAI shows the strongest potential to equip farmers with real-time, applicable, sustainable farming advice, combining research-based prediction models with real-world usability, explainability, profitability, healthy soil practices, and accessibility to restock and use on a mobile, web-based platform.

VI. Limitations and Future Work

Although FarmCareAI has produced some very promising results, there are limitations that still need to be addressed. The dataset used to train the disease detection feature is one of the primary challenges. The PlantVillage dataset is made up of clean images taken in controlled conditions; however, in practice, leaves tend to have cluttered backgrounds, poor lighting, or are not fully visible. The disconnect between the data set used for training and actual farm conditions may lessen the accuracy of predictions when the system is applied in practice. Another challenge is providing weather and market information from external APIs. In cases where the APIs do not supply complete or fully accurate data, the platform's recommendations may be less trustworthy. Furthermore, the platform requires at least a basic internet connection to operate. This requirement could be a drawback for rural areas with limited internet access. Finally, the current disease detection and crop recommendation systems are limited to 22 crops and 15 crops, respectively. Thus, farmers growing crops outside of these groups cannot use the platform yet.

A variety of improvements can be made to improve the system for the future. Extending the dataset by including images of actual farms, taken in various conditions, is one idea, as it will improve the robustness of the disease detection model. Another idea is to devise a lightweight version of the platform that works offline with farmers, where basic crop recommendations could be used without internet and the data would sync to the platform once there was a connection. The platform could also be extended to detecting pests and weeds, which are an important threat to crop yield. Likewise, adding smart irrigation and fertilizer management features would enable the platform to become a full farming assistant, rather than just a crop recommendation. Language support is important as well, as more farmers can benefit from a platform in their regional language if they are uncomfortable working with English. Lastly, the crop rotation feature could be made dynamic, as farm plans can be updated on an ongoing basis based on soil health and market changes.

These changes could improve the usability, inclusivity, and resilience of the tool. With changes to address these limitations, the platform could be a total support system that not only supports farmers in crop choice and management but would also allow the development of sustainable and profitable agriculture according to those farmers.

VII. Conclusion

This paper presents a web-based platform which integrates crop recommendation, plant disease detection, market analysis, and crop rotation planning into one platform. Both Random Forest for crop prediction analysis, and Vision Transformer with Grad-CAM for plant disease detection, achieved accuracy of 95% and 92%, respectively. It is crucial that in addition to offering technical prediction, the platform can provide farmers with practical recommendations, through the integration of real-time weather and soil data, as well as economic analysis. A multi-year crop rotation plan was added to ensure the long-term health and sustainability of the soil. In general, FarmCareAI shows there is potential of AI and could pave the way for precision farming while demonstrating how AI can provide farmers with actionable, accessible and sustainable tools.

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