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An Integrated Machine Learning-Driven Multimodal Framework for Crop Health Diagnosis and Predictive Soil Health Optimization

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ABSTRACT: *Agriculture supports the livelihoods of millions of farmers in India; however, crop productivity is increasingly threatened by plant diseases, declining soil fertility, and unsustainable farming practices. Limited access to timely disease diagnosis and scientific soil assessment often compels farmers to rely on excessive use of fertilizers and pesticides, leading to soil degradation, environmental pollution, and increased cultivation costs. A critical issue is the imbalance of essential soil nutrients, particularly nitrogen (N), phosphorus (P), and potassium (K), which significantly influence crop growth, yield quality, and long-term soil sustainability. This study proposes an integrated machine learning-driven multimodal framework for crop health diagnosis and predictive soil resource optimization. The proposed system combines image-based crop analysis with data-driven soil modelling to detect plant diseases, estimate soil characteristics, and forecast nutrient requirements, including NPK levels. By integrating visual crop assessment with predictive soil analytics, the framework generates context-aware, data-driven recommendations tailored to specific crop and soil conditions. Furthermore, a lightweight intelligent recommendation module is incorporated to enhance user interaction and provide simplified, actionable guidance. The proposed framework supports informed decision-making in disease management and nutrient planning, thereby improving agricultural productivity while minimizing excessive input usage. Overall, the system offers a practical and scalable decision-support solution for sustainable and precision agriculture.*
Keywords: *Agricultural Decision Support Systems, Crop Health Diagnosis, Machine Learning, Nutrient Forecasting, NPK Analysis, Precision Agriculture, Smart farming, Soil Health Optimization*

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I. INTRODUCTION

Agriculture plays a vital role in sustaining the livelihoods of a large proportion of the global population, particularly in developing countries such as India, where it serves as a primary source of income and a key driver of food security. However, agricultural productivity continues to face significant challenges due to the increasing prevalence of crop diseases, declining soil fertility, and inefficient nutrient management practices. Limited access to timely diagnostic tools and scientific guidance often compels farmers to rely on traditional practices or to overuse chemical fertilizers and pesticides. Such practices accelerate soil degradation, increase environmental risks, and reduce long-term agricultural sustainability, ultimately affecting both crop yield and quality. Therefore, there is a growing need for intelligent, data-driven solutions to support early crop health assessment and efficient soil resource management [1].

Recent advancements in machine learning (ML), computer vision, and generative artificial intelligence (GenAI) have enabled the development of intelligent agricultural systems capable of analyzing crop images to detect diseases and extracting meaningful insights from soil and environmental data. These technologies facilitate automated disease detection and support data-driven soil analysis. By leveraging such techniques, modern systems can assist farmers in making informed decisions, thereby promoting precision agriculture and improving overall farm productivity [2].

Despite these advancements, most existing approaches address crop disease detection and soil analysis as separate tasks, thereby limiting their practical applicability. Image-based models typically focus on disease classification without incorporating underlying soil conditions, while soil analysis techniques often operate independently of crop health status. This lack of integration restricts the generation of comprehensive and context-aware recommendations. Additionally, many existing solutions do not adequately consider essential soil nutrients such as nitrogen (N), phosphorus (P), and potassium (K), which are critical for plant growth and yield optimization [3]. Challenges related to accessibility and usability in resource-constrained environments further hinder the widespread adoption of such systems.

To address these limitations, this study proposes an integrated machine learning-driven multimodal framework for crop health diagnosis and predictive soil resource optimization. The framework combines image-based crop analysis with data-driven soil modelling to enable the simultaneous assessment of plant health and soil conditions. Convolutional neural networks (CNNs) are employed for crop disease detection and visual estimation of soil moisture, while machine learning techniques, including Linear Regression and Random Forest, are utilized to predict soil properties and nutrient levels such as nitrogen (N), phosphorus (P), and potassium (K). The models are trained and evaluated using publicly available datasets, including crop, soil, and fertilizer datasets sourced from Kaggle. Furthermore, Generative AI is incorporated to deliver context-aware, interactive, and user-friendly recommendations to farmers [4].

By integrating these components, the proposed system generates actionable insights for disease management and nutrient planning. Unlike conventional approaches that operate in isolation, the system provides a unified and practical solution for precision agriculture. It aims to reduce excessive fertilizer usage, improve soil health, lower input costs, and promote sustainable farming practices. Ultimately, this research contributes to the development of an intelligent decision-support system that empowers farmers with timely, accurate, and comprehensive agricultural guidance [5]. The key novelty of this work lies in the integration of multimodal data sources with intelligent recommendation generation within a single unified framework.

1.1 Objectives of the study

- To develop an integrated machine learning-driven multimodal framework for crop health diagnosis and soil resource optimization.
- To enable accurate crop disease detection and soil moisture estimation using CNN-based image analysis.
- To predict soil properties and essential nutrient levels (N, P, and K) using machine learning models such as Linear Regression and Random Forest.
- To address excessive fertilizer usage and soil fertility degradation through data-driven nutrient management strategies.
- To incorporate Generative Artificial Intelligence (GenAI) for delivering context-aware, interactive, and user-friendly agricultural recommendations.
- To support informed decision-making by integrating crop health assessment with predictive soil analytics.
- To design a practical decision-support system that promotes precision agriculture, reduces input costs, and enhances sustainable farming practices.

These objectives collectively aim to bridge the gap between crop health assessment and soil resource management by providing an integrated and data-driven solution [6]. The proposed approach is expected to enhance decision-making efficiency and promote sustainable agricultural practices.

II. MATERIALS AND METHODS

This section describes the methodology adopted to design and develop an integrated machine learning-driven framework for crop health diagnosis and predictive soil resource optimization. The proposed approach combines multiple computational techniques to analyze both crop conditions and soil characteristics in a comprehensive manner. It follows a structured pipeline consisting of data collection, preprocessing, model development, and result generation to ensure accurate and reliable outcomes. The models are trained and evaluated using publicly available datasets, including crop images, soil data, and fertilizer data sourced from Kaggle. By integrating image-based analysis with data-driven prediction models, the methodology provides a unified and practical solution for informed decision-making in agriculture.

The proposed framework incorporates both deep learning and machine learning techniques to perform distinct tasks. Convolutional Neural Networks (CNNs) are utilized for crop disease detection from leaf images and for extracting visual features from soil images to support soil condition assessment. For soil health prediction, supervised models such as Linear Regression and Random Forest are employed to estimate key nutrient levels, including nitrogen (N), phosphorus (P), and potassium (K), using soil and environmental parameters. Linear Regression captures linear relationships between input features and continuous outputs, while Random Forest models complex patterns, non-linear patterns to improve prediction accuracy. The outputs from these models are further utilised to generate tailored, context-aware recommendations for crop management and nutrient optimization [7].

2.1 Dataset Description and Sources: The datasets used in this study are obtained from publicly available repositories on Kaggle and consist of two primary components: a crop dataset and a soil-fertilizer dataset. The crop dataset is sourced from the Kaggle repository titled "Crop Analysis and Prediction". It consists of approximately 2,200 samples with eight input features and one target variable. The dataset includes soil nutrient parameters such as nitrogen (N), phosphorus (P), and potassium (K), along with environmental attributes such as temperature, humidity, pH value, and rainfall. The target variable represents the crop type suitable for the given conditions. This dataset is utilized for crop prediction and analysis within the proposed framework.

Attribute	Description	Data Type	Role in Model
Nitrogen (N)	Ratio of nitrogen content in the soil	Numerical	Input Feature
Phosphorus (P)	Ratio of phosphorus content in the soil	Numerical	Input Feature
Potassium (K)	Ratio of potassium content in the soil	Numerical	Input Feature
Temperature	Average ambient temperature ( )	Numerical	Input Feature
Humidity	Relative humidity (%)	Numerical	Input Feature
pH Value	Soil acidity or alkalinity level (0-14 scale)	Numerical	Input Feature
Rainfall	Average rainfall (mm)	Numerical	Input Feature
Crop Label	Crop type suitable for the given conditions	Categorical	Target Variable

Table 1. Description of Crop Dataset Features

The soil-fertilizer dataset is obtained from the Kaggle repository titled "Fertilizer Recommendation System using Machine Learning". It contains approximately 1000 samples with multiple features, including soil type, crop type, and nutrient values such as nitrogen (N), phosphorus (P), and potassium (K), along with environmental and categorical attributes. This dataset is used for soil fertility assessment, nutrient level prediction, and fertilizer recommendation using machine learning models such as Linear Regression and Random Forest.

Category	Attributes Included	Descripton	Role in the Proposed System
Soil Nutrients	Nitrogen (N), Phosphorus (P), Potassium (K)	Essential macronutrients influencing crop growth and soil fertility	Nutrient Prediction and Fertilizer Planning
Environmental Factors	Temperature, Humidity, Rainfall	Climatic conditions affecting crop suitability and productivity	Crop recommendation and yield optimization
Soil Condition	pH Value	Indicates soil acidity/alkalinity affecting nutrient availability	Soil fertility assessment
Crop Information	Crop Type	Suitable crop based on the given soil and environmental conditions	Target for the recommendation system
Fertilizer Insight	Fertilizer Recommendation	Suggest optimal fertilizer based on nutrient deficiency and crop requirement	Decision support for fertilizer usage

Table 2. Description of Soil-Fertilizer and Crop Recommendation Dataset

Unlike the crop dataset presented in Table 1, this dataset is utilized to support soil fertility assessment and fertilizer recommendation within the proposed framework. It enables nutrient-level analysis and helps identify appropriate fertilizer inputs based on crop requirements. Furthermore, by analysing nutrient imbalances, the dataset contributes to identifying conditions that may increase crop vulnerability to diseases, thereby supporting a more comprehensive crop health management approach.

Together, these datasets support multiple tasks within the proposed framework, including crop prediction, soil fertility assessment, and fertilizer recommendation. The integration of these datasets enables the development of a comprehensive and data-driven system for agricultural decision support.

2.2 Data Preprocessing: Data preprocessing is performed to ensure the consistency, quality, and suitability of the datasets for model training and evaluation. Since the proposed framework utilizes structured datasets, preprocessing focuses on handling tabular data derived from crop and soil-fertilizer datasets.

Initially, data cleaning is conducted to handle missing values, remove duplicates, and eliminate inconsistencies. Numerical features such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH value, and rainfall are normalised or standardized to ensure uniform scaling across features. Categorical variables, including crop type and soil type, are encoded using appropriate techniques such as label encoding or one-hot encoding.

Additionally, outliers are identified and treated to enhance model performance. The processed data is then divided into training and testing sets to evaluate model effectiveness and generalization capability.

These preprocessing steps facilitate efficient learning and improve the accuracy and reliability of crop production, soil fertility assessment, and recommendation generation within the proposed framework.

2.3 System Architecture of the Proposed Framework: The proposed system introduces a machine learning-driven unified architecture that integrates the capabilities of CropGuard AI and SoilCare Agent to facilitate an intelligent and comprehensive agricultural diagnostic framework. The architecture is designed to process multimodal inputs, including crop leaf images, soil photographs, structured soil parameters (N, P, K, pH), and natural language queries. This integrated approach ensures a holistic understanding of crop conditions and soil health dynamics [8].

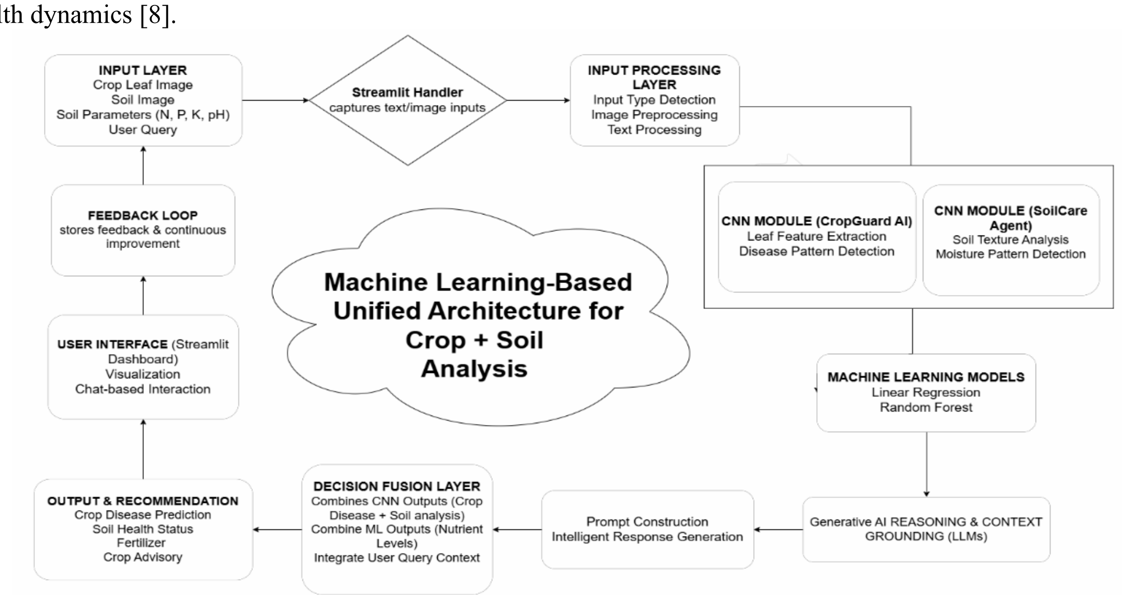

Figure 1. Unified Architecture integrating CropGuard AI and SoilCare Agent for multimodal agricultural analysis

Figure 1 illustrates the unified architecture of CropGuard AI and the SoilCare Agent for multimodal agricultural analysis. The workflow begins with user interaction through a Streamlit-based interface, where diverse inputs, including visual, numerical, and textual data, are captured and directed to the input processing layer. This layer performs automatic input type identification followed by modality-specific preprocessing. These operations include image resizing and normalization, text tokenization, and numerical feature scaling, ensuring consistency and data quality across the pipeline [9].

The processed data are subsequently evaluated through specialized computational modules:

- **Convolutional Neural Networks (CNNs):** These are utilized for deep visual feature extraction. The CropGuard AI module identifies disease patterns in crop leaves, while the SoilCare Agent analyzes soil images to extract morphological features such as texture and moisture-related characteristics [10].
- **Machine Learning Models:** In parallel, structured environmental data and soil parameters are analyzed using Linear Regression and Random Forest algorithms to estimate nutrient levels with improved accuracy.

The analytical outputs from these modules are integrated within a Decision Fusion Layer, which combines visual predictions, numerical estimations, and contextual inputs to generate diagnostic results. To enhance interpretability, a lightweight language-based reasoning component is incorporated to provide concise, context-aware explanations of the system's outputs.

Finally, the framework delivers actionable insights, including crop disease classification, soil health assessment, fertilizer recommendations, and crop advisory suggestions, through an interactive dashboard. A feedback mechanism is also incorporated to support continuous learning and iterative system refinement based on real-world usage.

2.4 Crop Disease Detection using CNN: The crop disease detection module leverages Convolutional Neural Networks (CNNs) to automate the identification of plant diseases from leaf images. CNNs are well-suited for this task as they effectively learn discriminative visual features, such as color variations, lesion patterns, and texture irregularities, associated with different diseases.

2.4.1 Methodology and Feature Extraction: Initially, raw input images undergo preprocessing steps, including resizing, pixel intensity normalization, and noise reduction, to ensure data consistency and enhance model performance. The CNN architecture follows a hierarchical feature extraction process:

- **Feature Extraction:** Multiple convolutional layers apply learnable filters to capture both low-level features (edges and textures) and high-level patterns (disease-specific regions) from input images.
- **Dimensionality Reduction:** Pooling layers are applied after convolution to reduce spatial dimensions and computational complexity.
- **Classification:** The extracted feature maps are flattened and passed through fully connected layers. A softmax activation function is used at the output layer to generate probability scores for each disease class.

To improve interpretability, the system provides concise explanatory outputs based on the predicted disease class.

Algorithm 1: CNN-Based Crop Disease Detection:
Input: Raw leaf image *I*
Output: Predicted disease class *D*
1. Acquire input image I and resize to fixed dimensions $H * W$
2. Normalize pixel intensities to the range [0,1] and perform preprocessing.
3. Apply the convolution operation:

4. Apply ReLU activation:

5. Perform max-pooling for dimensionality reduction.
6. Repeat convolution-activation-pooling for hierarchical feature extraction.
7. Flatten feature maps into a feature vector x.
8. Pass x through fully connected layers:

9. Compute class probabilities using Softmax:

10. Predict final class:

2.4.2 Implementation and Deployment: The CNN model is implemented using a Python-based deep learning framework such as TensorFlow or PyTorch. The architecture comprises multiple convolutional layers with ReLU activations, followed by max-pooling layers and a fully connected layer for classification.
The model is trained on labeled plant disease datasets using categorical cross-entropy as the loss function:

and optimized using the Adam optimizer to ensure stable convergence. The trained model is deployed within a Streamlit-based interface to enable real-time disease prediction and user-friendly interaction [11].

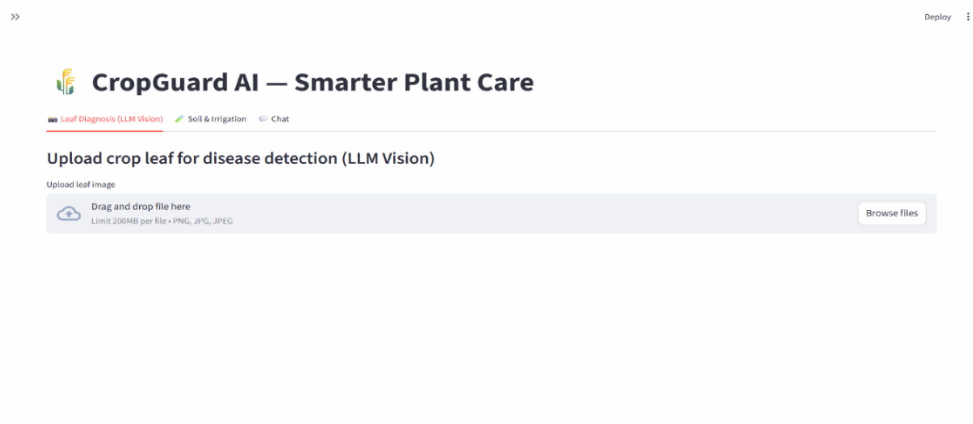

Figure 2. User interface for crop leaf image upload and disease diagnosis in CropGuard AI

2.5 Soil Image Analysis using CNN (SoilCare Agent): The SoilCare Agent employs a Convolutional Neural Network (CNN) architecture to perform non-invasive soil condition analysis. This module enables the automated classification of soil moisture into three distinct categories: Dry, Normal, and Wet. Using RGB soil images, the CNN learns hierarchical visual features that capture moisture-related surface characteristics [12].

The convolutional layers utilize learnable filters to extract spatial features, such as texture patterns, surface granularity, and color variations, which reflect changes in soil appearance under different moisture conditions. Pooling layers are incorporated to reduce feature dimensionality while preserving salient spatial hierarchies, thereby enhancing computational efficiency and reducing overfitting. The extracted feature maps are passed through fully connected layers to perform multi-class classification. The predicted outputs are further utilized as inputs for downstream soil health assessment modules [13].

Algorithm 2: CNN-Based Soil Moisture Classification:
Input: Raw Soil Image I
Output: Predicted class *S*
1. **Acquisition and Resizing:** Resize the input image to a fixed dimension (e.g., 224 * 224)
2. **Preprocessing**: Normalize pixel intensities such that $I \in [0,1]$ and apply Gaussian blurring.
3. Feature Extraction: Apply 3 * 3 convolutional filters followed by ReLU.
4. Spatial Downsampling: Perform 2 * 2 max-pooling.
5. Feature Learning: Repeat convolutional blocks for hierarchical feature extraction.
6. Flattening: Convert feature maps (3D) into a 1D feature vector *V*.
7. Dense Processing: Apply fully connected layers with Dropout regularization.
8. Probabilistic Classification: Generate class probabilities using the Softmax:

9. **Prediction**: $S \in \{Dry, Normal, Wet\}$

Figure 3. Illustrates the SoilCare interface and real-time prediction output.

The model is implemented using a Python-based deep learning framework, such as TensorFlow or PyTorch. It is trained on a labeled soil image dataset and integrated into the SoilCare Agent to support real-time inference and scalable soil monitoring applications.

Component	Crop Disease Detection	Soil Image Analysis	Purpose
Input Layer	RGB leaf images	RGB soil images	Provide visual input for analysis
Preprocessing	Resizing, normalization	Resizing, normalization, noise reduction	Ensure data consistency and improve performance
Feature Extraction	Conv2D layers (ReLU activation)	Conv2D layers (ReLU activation)	Learn visual patterns (soil texture/lesions)
Kernel Configuration	3 * 3 filters	3 * 3 filters	Capture local spatial patterns
Spatial Downsampling	MaxPooling Layers	MaxPooling Layers	Reduce dimensionality and computation cost
Feature Flattening	Flatten Layer	Flatten Layer	Convert feature maps to a feature vector
Classification	Dense layer + Softmax activation	Dense layer + Softmax activation	Predict disease class or moisture level
Output Storage	Disease class	Moisture class (Dry, Normal, Wet)	Final Prediction output

Table 3. Combined CNN Framework for Disease and Soil Analysis

2.6 Machine Learning-Based Crop and Fertilizer Recommendation: The SoilCare Agent employs a supervised machine learning framework to provide crop and fertilizer recommendations based on key soil fertility parameters. The system processes multidimensional input features, including Nitrogen (N), Phosphorus (P), Potassium (K), soil pH, and environmental factors such as temperature and rainfall, to determine suitable crops under varying agricultural conditions.

To improve prediction accuracy and generalization, the model is trained on a combination of historical soil datasets and augmented samples. This approach enables the system to capture complex relationships between soil nutrients and crop suitability. The model is designed to minimize prediction error while ensuring efficiency for real-time inference [14].

Model	Model Implementation	Algorithm	Purpose
Classification	RandomForest classifier(n_estimators=100)	Random Forest	Crop Classification
Forecasting	LinearRegression()	Linear Regression	Predict nutrient trends (N, P, K)
Model persistence	Joblib.dump() / joblib.load()	Joblib	Model storage and reuse
Data Processing	feature selection, CSV loading	Pandas, Numpy, Scikit-Learn	Data Preparation and Preprocessing

Table 4. Machine Learning Models for Crop and Fertilizer Recommendation

After training, the machine learning models are serialized and stored in .pkl format to support efficient real-time inference during deployment. As illustrated in Figure 4, users provide soil and environmental parameters through the interactive interface, and the system predicts the most suitable crop along with corresponding fertilizer recommendations. These outputs support balanced nutrient management, improve crop yield, and promote sustainable agricultural practices.

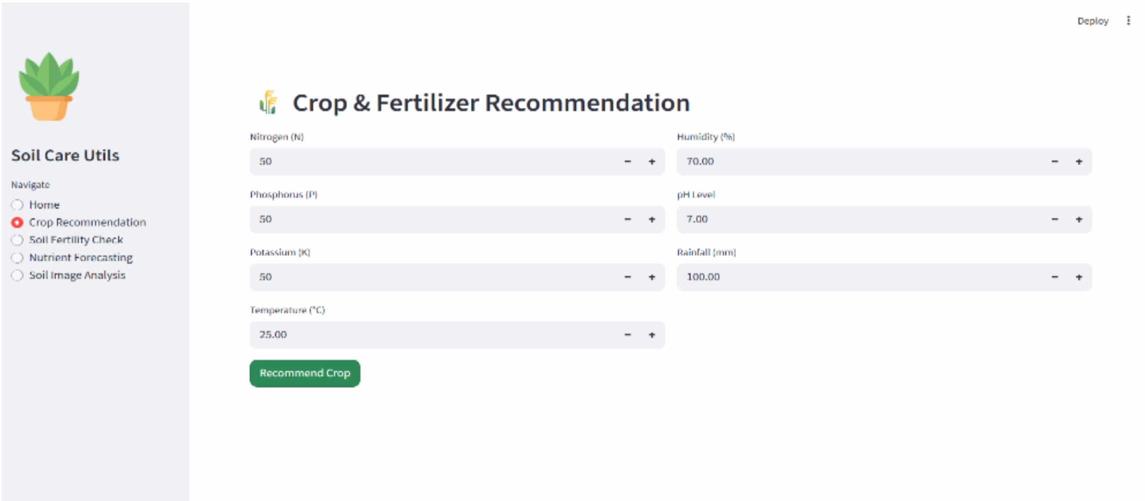

Figure 4. Illustrates the machine learning-based Crop and Fertilizer Recommendation Interface of the SoilCare Agent.

2.7 Soil Fertility Assessment and Decision Support Module: The Soil Fertility Assessment module provides a quantitative evaluation of soil health by analyzing essential macronutrients-Nitrogen (N), Phosphorus (P), and Potassium (K)-along with soil pH levels. To ensure accurate and user-friendly data entry, the module incorporates an interactive slider-based interface (Figure 5), enabling precise input of laboratory-verified or field-measured soil parameters [15].

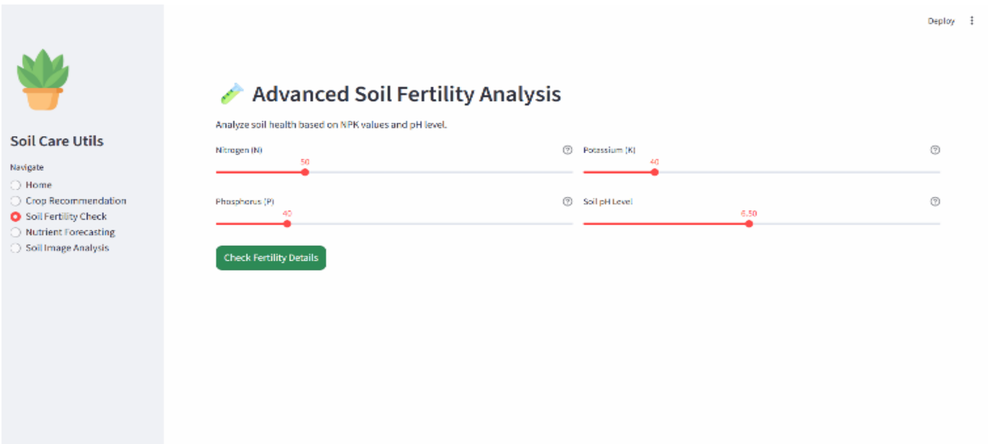

Figure 5. Advanced soil fertility analysis interface illustrating N-P-K and pH inputs, soil health classification, and nutrient status indicators.

2.7.1 Algorithmic Framework and Classification: The diagnostic engine operates using a rule-based inference mechanism calibrated against established agronomic threshold values. Each soil parameter is classified into one of three critical categories:

- **Optimal:** Nutrient levels meet crop physiological requirements without causing environmental impacts.
- **Deficient**: Nutrient levels fall below recommended thresholds and may affect crop growth.
- **Excess:** Nutrient concentrations exceed optimal limits, indicating potential toxicity or environmental risks such as leaching.

2.7.2 Actionable Recommendations and Crop Suitability: Based on the classification results, the module generates actionable recommendations to support decision-making. These include fertilizer application suggestions and pH rectification strategies, such as liming or acidification. In addition, the system performs crop suitability analysis by matching soil nutrient levels and pH conditions with crop requirements. The system recommends the Top-5 suitable crops based on this evaluation, supporting informed agricultural planning.

2.8 Nutrient Forecasting and Soil Health Prediction: The Nutrient Forecasting module enhances effective soil management by analyzing historical soil nutrient data to predict future nutrient trends. Using a regression-based time-series approach, the system estimates the temporal variation in key macronutrients, enabling the identification of potential nutrient depletion or stabilization patterns, as illustrated in Figure 6. Historical nutrient values are represented using continuous solid lines, while future projections are depicted using dashed lines to distinguish observed data from predicted trends. This visualization improves interpretability and allows users to easily analyze long-term nutrient behavior.
The forecasting outputs are tightly integrated with the soil fertility assessment and crop recommendation modules, ensuring consistency between current soil conditions and future nutrient planning. By combining predictive insights with actionable recommendations, the module supports informed fertilization strategies, promotes sustainable soil management, and helps prevent nutrient imbalances[16].

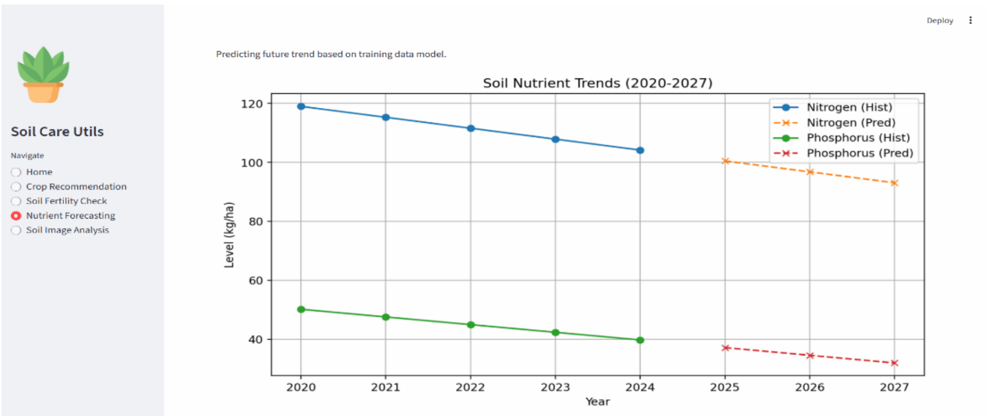

Figure 6. Time-series visualization of historical and predicted soil nutrient trends used for long-term soil health forecasting.

The proposed framework integrates multiple analytical modules, including CNN-based image analysis, machine learning-based recommendation models, rule-based soil fertility assessment, and time-series nutrient forecasting into a unified decision support system. Each component contributes complementary insights, enabling a comprehensive analysis of crop health, soil condition, and nutrient dynamics. This integration ensures that both current diagnostics and future predictions are considered when generating actionable recommendations, thereby enhancing decision-making accuracy and supporting sustainable solutions for real-world deployment. The effectiveness of the proposed framework is evaluated in the subsequent section through experimental results and performance analysis.

IV RESULTS AND EVALUATION

The results presented in this section demonstrate the effectiveness of the proposed integrated framework, which leverages machine learning and deep learning techniques for crop health diagnosis and soil health optimization. The evaluation follows the methodological workflow, systematically analyzing the performance of key components, including the CNN-based crop disease classification model, ML-based soil parameter prediction module, and the intelligent recommendation system. The findings highlight that integrating multimodal data, comprising crop images, soil attributes, and user inputs, enhances prediction accuracy, model reliability, and overall decision-making in precision agriculture.

4.1 Crop Disease Detection Results (CropGuard AI): The performance of the CropGuard AI module is evaluated based on its ability to detect and interpret crop diseases from leaf images in a real-time setting. Given the practical orientation of the system, the evaluation emphasizes functional correctness and visual interpretability rather than relying solely on quantitative metrics. The model was tested on diverse crop leaf images exhibiting both healthy and diseased conditions.

The CNN-based architecture effectively captures discriminative visual features such as color variations, lesion patterns, and texture irregularities. The system consistently produces predictions that align with observable disease characteristics, indicating its capability to generalize across different image conditions. Figure 7 illustrates the system interface, where a user uploads a crop image and receives immediate diagnostic feedback. The model successfully identifies viable infection patterns in the input image and provides corresponding outputs, demonstrating its applicability in real-world agricultural scenarios.

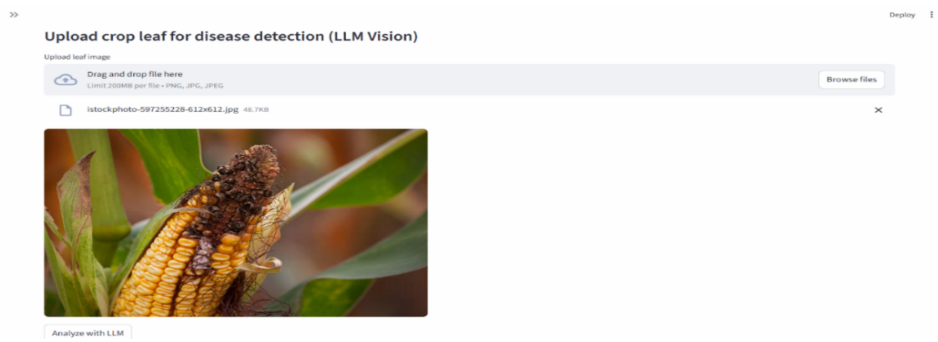

Figure 7. CropGuard AI interface showing real-time crop disease detection from an uploaded leaf image

In addition to prediction capability, the module offers a user-friendly interface that simplifies that simlifies interaction, enabling non-technical users to utilize the system efficiently. This highlights the practical relevance of CropGuard AI in supporting early-stage disease detection and reducing dependency on manual inspection.

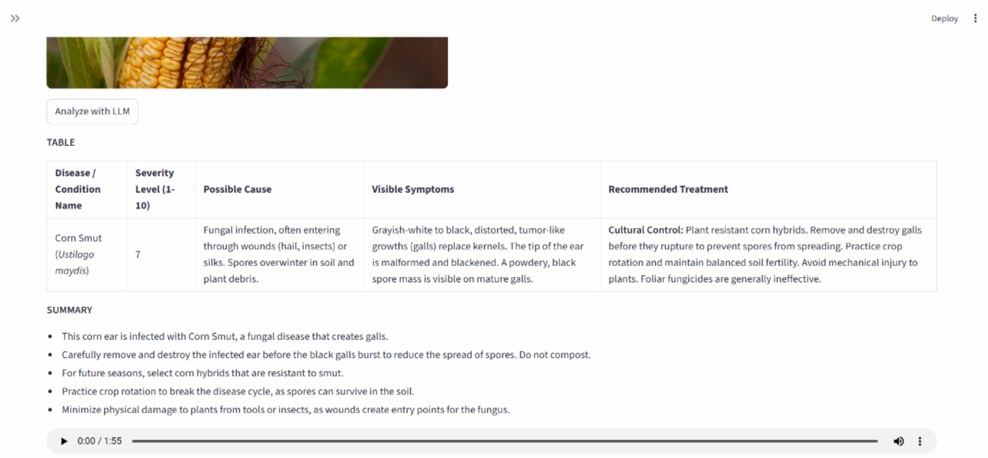

Figure 8. CropGuard AI disease diagnosis and advisory interface

CropGuard AI interface displaying a sample corn smut diagnosis, including disease severity, causal factors, visible symptoms, and recommended management actions, along with a bullet-point summary and audio advisory to support accessible, explainable guidance for farmers (Figure 8) .

4.2 Soil Health Prediction Results (SoilCare Agent): The diagnostic capability of the SoilCare Agent was further validated through a CNN-based visual analysis module designed for non-invasive soil assessment. By extracting spatial texture features and surface reflectance information from uploaded soil images, the model accurately classifies soil moisture conditions into Dry, Normal, and Wet categories.

Experimental evaluation demonstrated reliable classification performance with low-latency inference, indicating the suitability of the module for real-time field deployment and edge-based agricultural applications (Figure 9). The availability of an intuitive drag-and-drop image upload interface eliminates reliance on dedicated hardware sensors, enabling rapid and localized moisture diagnostics using commonly available imaging devices.

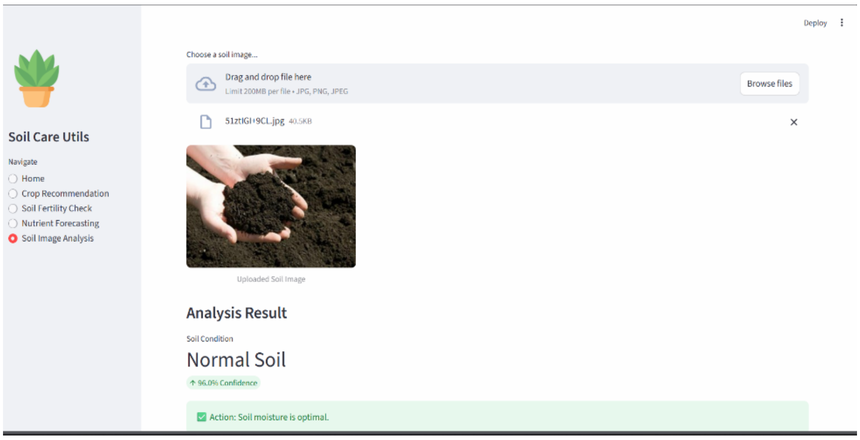

Figure 9. CNN-based visual soil analysis interface illustrating classification of soil moisture conditions from an uploaded soil image.

4.3. **Multi-Parametric Crop and Fertilizer Recommendation:** The crop and fertilizer recommendation module was evaluated for its ability to integrate multi-dimensional soil nutrient profiles into actionable decision-support outputs. By jointly analyzing key input variables—namely Nitrogen (N), Phosphorus (P), Potassium (K), and soil pH—the machine learning model consistently generated agronomically valid crop recommendations along with corresponding fertilizer guidance. Experimental evaluation indicates that the system demonstrates high sensitivity to minor variations in soil parameters. For instance, marginal changes in pH levels or potassium concentration result in proportional adjustments in fertilizer dosage recommendations, highlighting the model's responsiveness to fine-grained nutrient dynamics. This behavior confirms that the system provides field-specific recommendations rather than generalized advisories.

As illustrated in Figure 10, the user interface effectively abstracts complex computational processes into an intuitive visualization, ensuring minimal latency between parameter input and recommendation output. This design supports rapid decision-making and enhances the practical applicability of the system in real-time agricultural settings.

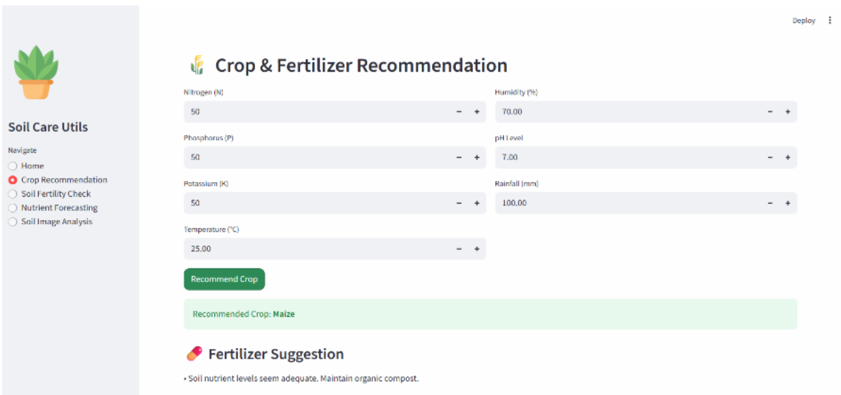

Figure 10. UI-driven output illustrating the computational mapping of soil nutrient data to crop and fertilizer recommendations.

4.4 Multi-parametric Soil Fertility and Crop Recommendation: The SoilCare Agent integrates key soil fertility parameters, namely nitrogen (N), phosphorus (P), potassium (K), and soil pH, to construct a comprehensive Soil Health Profile. The analytical engine applies threshold-based reasoning to classify nutrient availability and overall soil condition in a structured and interpretable manner. For instance, an input profile consisting of 50 mg/kg nitrogen, 40 mg/kg phosphorus, 40 mg/kg potassium, and a pH value of 6.5 is classified as Excellent, indicating balanced macronutrient levels and a neutral soil reaction suitable for a wide range of crops.

The computed results are presented through a color-coded visual interface, enabling rapid interpretation and immediate diagnostic feedback. This visualization abstracts complex analytical processes into an intuitive representation, thereby supporting efficient decision-making under field conditions.

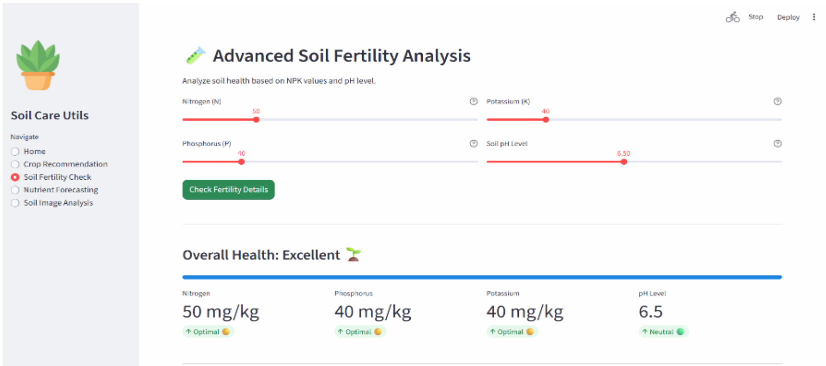

Figure 11. Multi-parametric soil fertility analysis interface showing NPK and pH inputs, overall soil health classification, and color-coded diagnostic feedback generated by the SoilCare Agent

Beyond soil health assessment, the system utilizes semantic reasoning combined with agronomic constraints to generate a Top-5 Crop Recommendation list. Rather than producing static or generic outputs, the model selects crops such as bush beans, carrots, lettuce, radishes, and zucchini based on biological compatibility with the evaluated soil profile (Figure 12). Each recommendation is accompanied by a concise ecological explanation—for example, the nitrogen-fixing capacity of legumes or the suitability of root crops under moderate nitrogen conditions—thereby promoting sustainable and informed soil management practices.

Furthermore, this multi-parametric reasoning framework enables the system to adapt recommendations dynamically as soil conditions evolve across successive cultivation cycles. By linking soil diagnostics with crop suitability logic, the SoilCare Agent supports both immediate decision-making and long-term soil fertility planning.

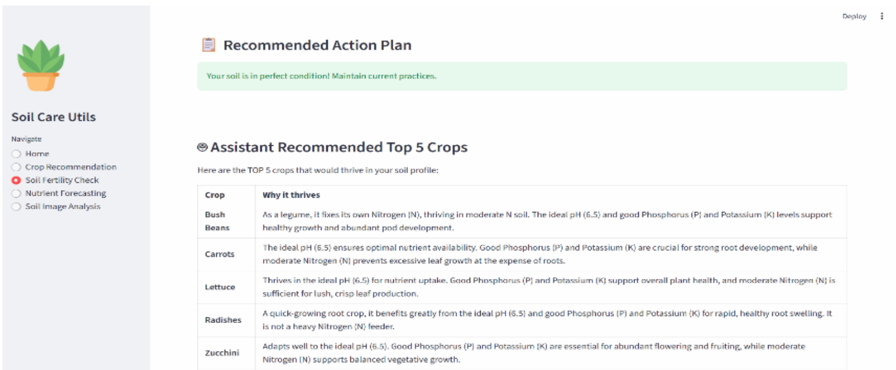

Figure 12. System-generated action plan and assistant-recommended top five crops with assistant-recommended top five crops with agronomic explanations based on the evaluated soil fertility profile.

4.5 Overall System Analysis and Discussion: The evaluation of the integrated framework demonstrates a successful convergence of computer vision and predictive analytics, creating a cohesive ecosystem for precision agriculture. By synthesizing the findings from CropGuard AI and the SoilCare Agent, the system effectively transforms raw data into actionable insights. A key strength of this architecture lies in its multimodal approach, which reduces dependence on any single data source and enhances the robustness of the diagnostic process. The CNN modules efficiently translate visual patterns from leaf and soil images into diagnostic categories, while the machine learning components process chemical soil parameters to generate field-specific advisories.

Furthermore, the system emphasizes interpretability and user accessibility by abstracting complex computational processes into intuitive, color-coded interfaces and plain-language explanations. By providing biological context for its recommendations, such as nutrient requirements or disease causative factors, the framework enhances user trust and supports informed decision-making, particularly for non-technical users. While the current validation establishes the functional reliability and logical consistency of the modules, the system remains adaptable for future enhancements, including more extensive quantitative benchmarking and the integration of diverse datasets. Overall, the results indicate that the proposed framework is a reliable and effective solution for intelligent crop monitoring and soil health management, with strong potential for real-world agricultural applications.

V CONCLUSION

This study presents a cohesive, machine learning-based architecture for crop health diagnosis and soil health optimization by integrating the functionalities of CropGuard AI and SoilCare Agent into a unified multimodal system. The proposed framework effectively bridges raw agricultural data with actionable decision support by employing deep learning for image-based disease detection and machine learning techniques for soil analysis. The results demonstrate that the integration of crop imagery, soil parameters, and user interaction enhances the system's ability to deliver reliable and context-aware insights. Unlike conventional approaches that rely on isolated analysis, the proposed system provides a comprehensive understanding of field conditions, enabling more informed and timely agricultural decisions. Furthermore, its real-time processing capability and user-friendly interface improve accessibility, making it suitable for practical deployment.

In countries like India, where agriculture plays a vital role in the economy, and many farmers depend on timely and accurate information, the significance of this is substantial. The proposed system has the potential to improve crop yield, reduce input costs, and promote sustainable farming practices by minimizing reliance on manual inspection and enabling data-driven decision-making. Additionally, its scalable and flexible architecture allows adaptation across diverse crops and varying climatic conditions.

In conclusion, the proposed multimodal framework represents a significant step toward intelligent and accessible precision agriculture. Future work may focus on incorporating larger and more diverse datasets, conducting extensive quantitative evaluation, and integrating advanced predictive analytics to further enhance system robustness and real-world applicability.

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