AGRI GENIUS: AI-POWERED MONITORING OF CROP HEALTH, SOIL CONDITION AND PEST RISKS USING MULTISPECTRAL/HYPERSPECTRAL IMAGING AND SENSOR DATA

Mr. L.N.V. Rao[1], HARINI SWARAJYAM NATTA[2], DAKINENI HEMA[3], ANAMDASU SHANMUKHA[4], ABDUL ASHRAF[5]

[1]Associate Professor, Dept. of CSE, V.K.R, V.N.B & A.G.K COLLEGE OF ENGINEERING, GUDIVADA

[2345]UG Students, Dept. of CSE,

V.K.R, V.N.B & A.G.K COLLEGE OF ENGINEERING, GUDIVADA

ABSTRACT

Modern agriculture requires intelligent monitoring systems to detect crop diseases, soil nutrient imbalance, and pest risks at early stages to ensure sustainable and high-yield farming. Traditional farming methods rely heavily on manual observation, which often results in delayed intervention and reduced productivity. To address these challenges, this research proposes AgriGenius AI, an intelligent agricultural monitoring framework that integrates Artificial Intelligence (AI), hyperspectral imaging, and sensor-based data analysis for precision agriculture.

The proposed system combines multiple machine learning and deep learning models to analyze diverse agricultural data sources. A Convolutional Neural Network (CNN) with transfer learning is used for plant disease detection from leaf images, achieving 78.36% accuracy with top-3 predictions and treatment recommendations. For soil analysis and crop recommendation, the XGBoost algorithm evaluates key soil parameters such as nitrogen (N), phosphorus (P), potassium (K), pH level, rainfall, and temperature to identify suitable crops for specific soil conditions.

Additionally, hyperspectral image analysis is performed using a 3D Convolutional Neural Network (3D-CNN) on benchmark datasets including Indian Pines and Salinas, achieving 99.46% classification accuracy for land-cover and vegetation monitoring. The system integrates data preprocessing, model training, prediction, and visualization through a centralized dashboard, supported by Explainable AI (XAI) techniques for improved transparency.

Experimental results demonstrate that AgriGenius AI provides accurate crop health monitoring, soil-based crop recommendations, and hyperspectral land-cover classification. The proposed framework offers a scalable and intelligent solution for precision agriculture, enabling early disease detection and improved agricultural decision-making.

KEYWORDS:

Artificial Intelligence, Precision Agriculture, Plant Disease Detection, Hyperspectral Imaging, Convolutional Neural Networks (CNN), 3D Convolutional Neural Networks (3D-CNN), Crop Recommendation System, XGBoost, Remote Sensing, Smart Farming, Agricultural Monitoring.

I INTRODUCTION

The agricultural sector is currently undergoing a digital transformation, moving away from traditional manual methods toward data-driven precision farming.AgriGenius AI represents a significant advancement in this evolution, offering an AI-powered monitoring solution for **crop health, soil condition, and pest risks**.By integrating advanced technologies such as **multispectral and hyperspectral imaging** with sensor intelligence, the platform provides a comprehensive view of the agricultural landscape that is often invisible to the naked eye.

The primary motivation behind this system is to optimize resource management and maximize yields through **Explainable AI**. Traditional farming often relies on reactive measurestreating a crop only after symptoms of disease or nutrient deficiency become visually obvious. Agri Genius AI changes this paradigm to a proactive one.

It monitors crop stress and predicts pest risks early, allowing for targeted interventions that reduce the unnecessary use of fertilizers and pesticides.

Technically, the system is designed as a sophisticated end-to-end pipeline. It facilitates the entire machine learning lifecycle:

Data Acquisition: Users can load diverse datasets including plant leaf images, soil CSV data, and complex hyperspectral datasets like **Indian Pines** and **Salinas**.

Data Preparation: The system automates preprocessing tasks such as normalization, resizing, and splitting data into training and validation sets to ensure high-accuracy results.

Advanced Modeling: It employs specialized models for different tasks, including **3D-CNNs** for hyperspectral classification, **XGBoost** for soil-based recommendations, and **CNNs** for plant disease detection.

ActionableOutputs:Beyond simple classification, the system provides a **User Dashboard**that deliversspecific recommendations, such as identifying a "Tomato Target Spot" and suggesting removal of infected leaves or application of fungicide.

Agri Genius AI serves as a bridge between high-level data science and practical field application. By providing detailed metricssuch as **Accuracy,**

Precision, Recall, and F1-score and visual tools like **Confusion Matrix heatmaps**, the platform ensures that its predictions are transparent and reliable for the end-user.

II RELATED WORK

Recent advancements in artificial intelligence and remote sensing technologies have significantly improved agricultural monitoring systems. Researchers have explored various machine learning and deep learning techniques to detect plant diseases, analyze soil nutrients, and monitor crop health. One of the widely studied areas is plant disease detection using image processing and deep learning models. Convolutional Neural Networks (CNN) have been widely used to classify plant leaf images and identify diseases with high accuracy. Studies have shown that CNN-based models can effectively recognize plant diseases from large image datasets and support early disease detection in crops.

Another important research area is hyperspectral imaging for agricultural monitoring. Hyperspectral images capture hundreds of spectral bands, allowing researchers to analyze detailed information about vegetation health, soil moisture, and crop stress conditions. Deep learning models such as 3D Convolutional Neural Networks (3D-CNN) have been applied to hyperspectral datasets like Indian Pines and Salinas to classify different land-cover types. These models analyze both spatial and spectral features of the data and have shown high accuracy in crop and vegetation classification tasks.

In addition to image-based approaches, machine learning algorithms have also been widely used for soil nutrient analysis and crop recommendation systems. Algorithms such as Random Forest, Support Vector Machines (SVM), and XGBoostanalyze agricultural datasets containing parameters like nitrogen (N), phosphorus (P), potassium (K), pH level, rainfall, and temperature. These models help predict suitable crops for specific soil and climatic conditions, enabling better resource management and improved agricultural productivity.

Although these techniques have shown promising results, many existing systems focus on individual tasks such as plant disease detection or crop recommendation. Therefore, there is a need for an integrated intelligent system that combines plant health monitoring, soil nutrient analysis, and hyperspectral image classification to provide comprehensive decision support for modern agriculture.

III LITERATURE REVIEW

Recent research in smart agriculture has focused on applying artificial intelligence and deep learning techniques to monitor crop health and improve agricultural productivity. One important area of study is plant disease detection using Convolutional Neural Networks (CNN). Researchers have demonstrated that CNN models can effectively classify plant leaf images into different disease categories by learning visual patterns from large image datasets. Image preprocessing techniques such as resizing, normalization, and feature extraction play an important role in improving the accuracy of these models. Studies show that CNN-based models can detect diseases such as Tomato Target Spot and other plant infections with high reliability, while also providing confidence scores for predicted classes.

Another significant research area is the use of hyperspectral imaging (HSI) for agricultural monitoring. Hyperspectral images contain hundreds of spectral bands, allowing researchers to capture detailed spectral information that is not visible in normal RGB images. Several studies have used 3D Convolutional Neural Networks (3D-CNN) to process hyperspectral datasets such as Indian Pines and Salinas. These models analyze both spatial and spectral features of the data, enabling accurate land cover classification and detection of plant stress conditions. Research findings indicate that hyperspectral image analysis can achieve very high accuracy in identifying crop types, soil conditions, and vegetation patterns, making it an important tool for precision agriculture.

In addition to image-based analysis, machine learning techniques have also been applied to soil nutrient analysis and crop recommendation systems. Algorithms such as Gradient Boosting and XGBoost are widely used for analyzing agricultural datasets that contain parameters like nitrogen (N), phosphorus (P), potassium (K), pH levels, rainfall, and temperature. These models help in predicting suitable crops for specific soil and climatic conditions. Previous studies have shown that machine learning-based crop recommendation systems can significantly improve farming efficiency and reduce resource wastage by guiding farmers toward optimal crop selection.

IV EXISTING SYSTEM

The current landscape of agricultural monitoring largely depends on traditional and manual methods to evaluate crop health and soil conditions. Although these approaches have been widely used for many years, they often lack the efficiency, accuracy, and speed required for modern large-scale farming practices. Farmers generally rely on manual observation and experience to identify problems in crops, which can sometimes lead to delayed detection of diseases or nutrient deficiencies. As a result, crop losses may occur before appropriate actions are taken.

One of the most common techniques used in traditional agriculture is **manual scouting**, where farmers or agronomists physically walk through fields to inspect plants for signs of pests, diseases, or stress. While this approach provides direct observation, it is time-consuming and may not be practical for large agricultural areas. Additionally, the accuracy of this method depends heavily on the farmer’s experience and ability to recognize early symptoms.

Another widely used method involves **standard RGB imaging**, where farmers use digital cameras or mobile phones to capture images of crops. These images only record the visible spectrum (Red, Green, and Blue), which limits the ability to detect early plant stress or nutrient deficiencies that are not visible to the human eye. Therefore, such methods may fail to identify underlying problems at an early stage.

Physical soil testing is also commonly performed to analyze soil nutrients and fertility levels. In this process, soil samples are manually collected and sent to laboratories for chemical analysis. Although this method provides accurate results, it often requires several days or weeks to obtain the final report. This delay can affect timely decision-making related to crop management and fertilization.Due to these limitations, most traditional agricultural practices follow a **reactive management approach**, where corrective actions such as pesticide spraying or fertilizer application are implemented only after visible crop damage appears. This delayed response can reduce crop yield, increase production costs, and negatively impact overall farm productivity.

DISADVANTAGES

Traditional agricultural practices face several limitations that affect productivity and sustainability. One major issue is the **delayed detection of plant diseases and pest infestations**. In many cases, farmers identify problems only after visible symptoms appear on crops, which often means the disease has already spread and caused significant damage. Additionally, most farmers rely on **standard RGB cameras or visual inspection**, which can only capture information in the visible spectrum. However, many early indicators of plant stress, such as changes in chlorophyll levels or moisture content, occur in spectral ranges that are not visible to the human eye, making early detection difficult.

Another challenge in traditional agriculture is the **dependence on manual inspection**, which can lead to human error and inconsistent diagnosis. Disease identification and crop health assessment often depend on the farmer's experience and knowledge, which may vary from person to person. As a result, incorrect identification of diseases can lead to improper treatment methods. Furthermore, soil management practices also face limitations because farmers typically apply fertilizers uniformly across the entire field without precise soil nutrient analysis, leading to inefficient resource usage and potential environmental damage.

In addition to these issues, traditional farming systems often lack **predictive capabilities and automation**. Most existing methods focus only on identifying current crop conditions rather than predicting future risks such as pest outbreaks or crop suitability based on environmental factors. Continuous monitoring of large agricultural fields also requires significant labor and time, making it expensive and difficult to manage. These limitations highlight the need for advanced technologies and intelligent systems that can provide accurate monitoring, early disease detection, and data-driven decision-making in modern agriculture.

V PROPOSED SYSTEM

The **Agri Genius AI system** is an advanced artificial intelligence–based framework designed to overcome the limitations of traditional agricultural monitoring methods. Unlike manual scouting that depends on human observation, this system integrates deep learning, machine learning, and hyperspectral imaging to analyze crop health and soil conditions more effectively. The system follows a structured workflow that includes data loading, preprocessing, model training, and prediction generation. By analyzing plant leaf images and agricultural datasets, the system can detect crop diseases and environmental stress at early stages, even before visible symptoms appear. Hyperspectral imaging allows the system to process high-dimensional spectral data, enabling accurate monitoring of plant health, soil conditions, and land cover patterns.

In addition to disease detection, the system provides **intelligent decision support** for farmers through explainable artificial intelligence techniques. Instead of only providing classification results, the platform generates clear risk explanations and pest-risk alerts categorized as low, medium, or high. Furthermore, the system includes a soil analysis module that evaluates important parameters such as nitrogen (N), phosphorus (P), potassium (K), pH level, and climatic conditions. Using a machine learning model such as XGBoost, the system recommends the most suitable crops for a particular soil environment. This integrated approach helps farmers make informed decisions, optimize resource usage, and improve agricultural productivity.

ADVANTAGES

The proposed **Agri Genius AI system** provides several advantages over traditional agricultural monitoring methods by enabling **early detection and prevention of crop diseases and pest risks**. Using advanced deep learning and hyperspectral imaging techniques, the system can identify crop stress and disease symptoms at an early stage, often before they become visible to the human eye. This allows farmers to take timely preventive measures and reduce potential yield losses. The system also achieves **high technical accuracy** by utilizing advanced machine learning models, providing reliable predictions for plant disease detection, soil analysis, and hyperspectral image classification.

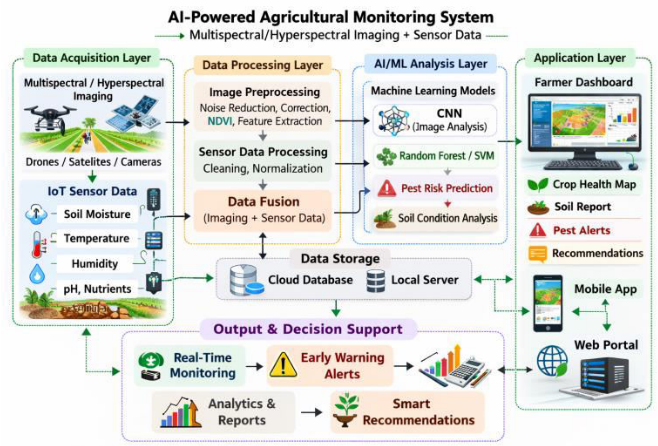
In addition, the system supports **precision resource management and intelligent decision-making**. By analyzing soil nutrients such as nitrogen, phosphorus, and potassium along with environmental factors, the platform recommends suitable crops and optimized fertilizer usage, helping reduce chemical waste and environmental impact. The system can also identify multiple land-cover classes using hyperspectral datasets, enabling large-scale agricultural monitoring. Furthermore, the platform features a **user-friendly graphical dashboard** with visual outputs such as heatmaps and performance metrics, making complex data easy to understand. Its scalable architecture allows the system to process large datasets, making it suitable for both small farms and large agricultural operations.

VI METHODOLOGY

The proposed **Agri Genius AI system** follows a structured methodology to analyze plant health, soil nutrients, and land-cover patterns using artificial intelligence techniques. The process begins with **data acquisition**, where different agricultural datasets are collected, including plant leaf images for disease detection, soil datasets containing parameters such as nitrogen (N), phosphorus (P), potassium (K), pH, rainfall, and temperature, and hyperspectral datasets like Indian Pines and Salinas for land-cover analysis. These datasets provide important information about crop conditions, soil fertility, and environmental factors required for accurate agricultural monitoring.The dataset is then divided into training and testing subsets to evaluate model performance and ensure that the trained models generalize well to unseen data.After data collection, the system performs **data preprocessing** to improve the quality and consistency of the datasets. Plant images are resized and normalized to ensure uniform input for deep learning models, while soil datasets are cleaned by handling missing values and scaling numerical features. For hyperspectral datasets, preprocessing techniques such as normalization and patch extraction are applied to convert the spectral cubes into a suitable format for model training. These preprocessing steps help remove noise, standardize the data, and enhance the performance of the learning models.In the **model development and prediction phase**, different machine learning and deep learning algorithms are trained to perform specific tasks. Convolutional Neural Networks (CNN) are used for plant disease detection from leaf images, while the XGBoost algorithm analyzes soil parameters to recommend suitable crops. Additionally, a 3D Convolutional Neural Network (3D-CNN) is used to classify land-cover types from hyperspectral images. Once trained, the models generate predictions that are displayed through a user-friendly dashboard, providing farmers with clear insights, risk alerts, and recommendations for improving crop management and agricultural productivity.

VII SYSTEM MODEL

SYSTEM ARCHITECTURE

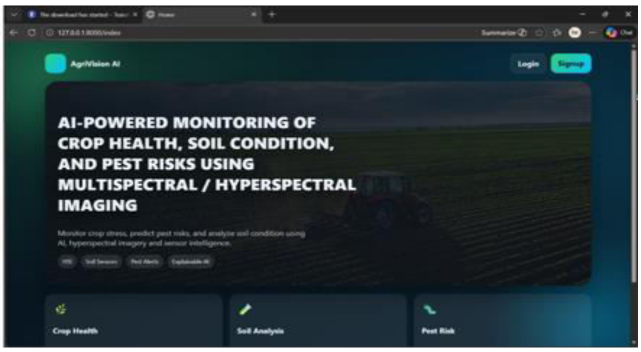


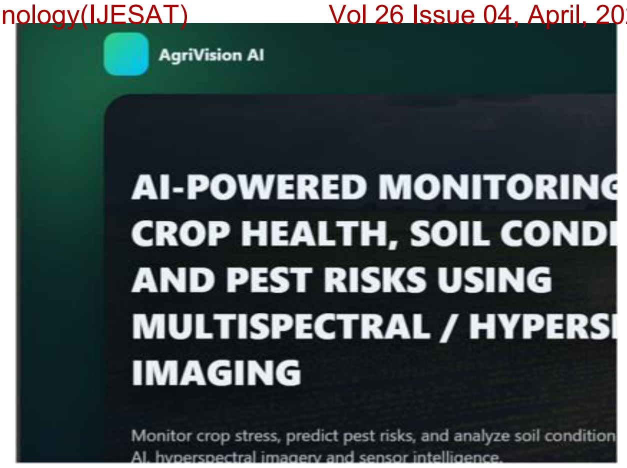
VIII RESULT AND DISCUSSIONS

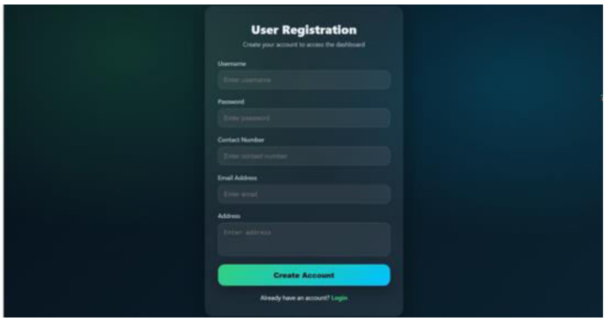
The experimental results demonstrate the effectiveness of the proposed **Agri Genius AI system** in analyzing agricultural data and providing accurate predictions. The plant disease detection module, implemented using a **Convolutional Neural Network (CNN)** model, successfully classifies leaf images into multiple disease categories. The model processes resized and normalized images and provides **top-3 predictions with confidence scores**, allowing users to understand the probability of each disease class. Performance evaluation metrics such as **accuracy, precision, recall, and F1-score** indicate that the CNN model is capable of reliably identifying plant diseases and generating appropriate pest-risk alerts for early intervention.

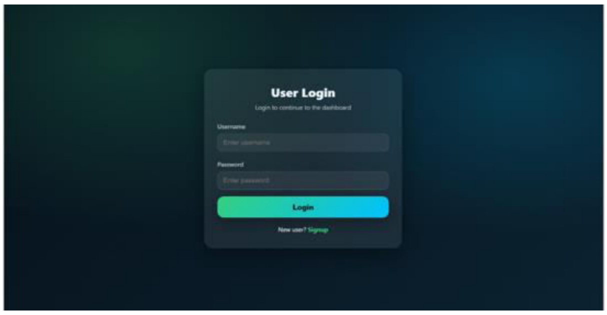
The **soil nutrient analysis module** uses the **XGBoost machine learning algorithm** to analyze parameters such as nitrogen (N), phosphorus (P), potassium (K), pH level, rainfall, and temperature.Experimental evaluation indicates that the XGBoost model achieved very high accuracy (close to 100%) on the training dataset while recommending suitable crops based on soil nutrient parameters and environmental conditions.This high level of accuracy demonstrates the effectiveness of gradient boosting techniques in handling structured agricultural data. The system helps farmers select the most appropriate crops and fertilizer strategies, which can improve crop yield while reducing unnecessary chemical usage.

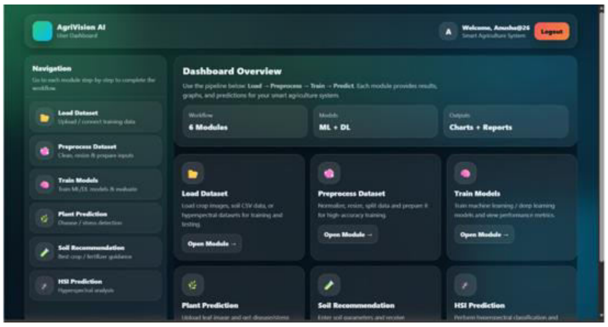
The **hyperspectral image classification module** uses a **3D Convolutional Neural Network (3D-CNN)** to analyze high-dimensional spectral datasets such as the Indian Pines dataset. The model processes spectral-spatial cubes and classifies different land-cover categories with an accuracy of **99.46%**, demonstrating its capability to capture detailed environmental patterns that are not visible in standard RGB images. The results are visualized using confusion matrices, accuracy graphs, and heatmaps displayed on the system dashboard. Overall, the results confirm that the integration of CNN, XGBoost, and 3D-CNN models provides an efficient and reliable framework for intelligent agricultural monitoring and decision support.

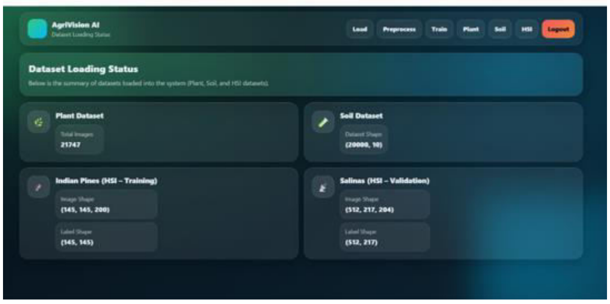


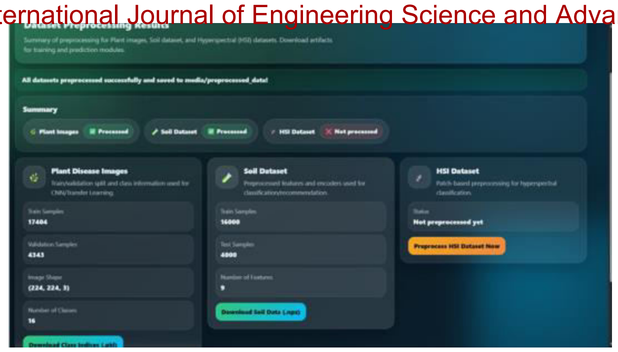


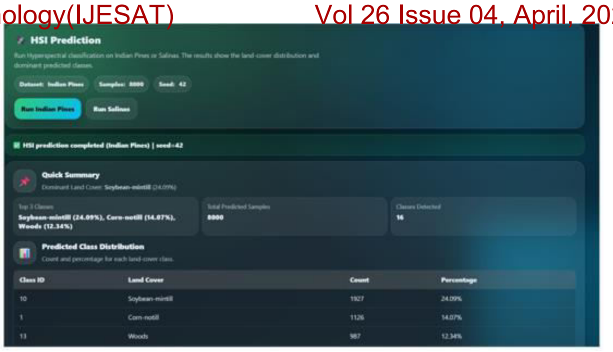


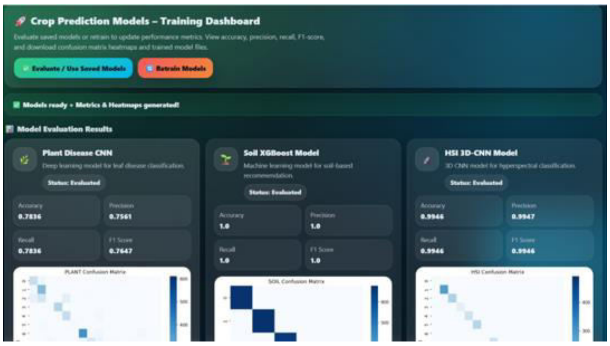


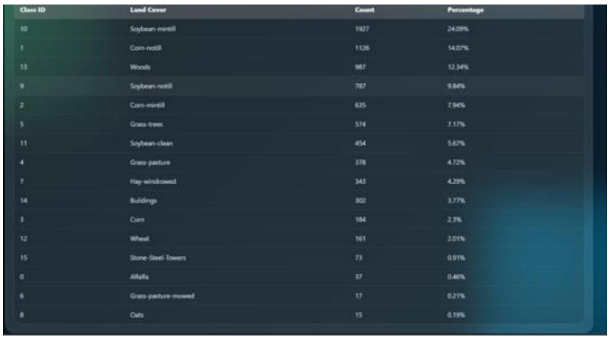




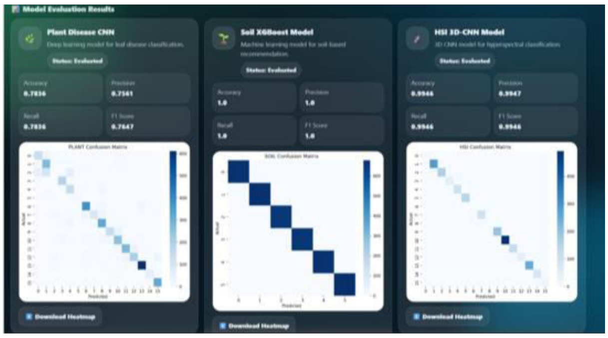








Class ID	Land Cover	Count	Percentage
10	Soybean-mintill	1927	24.09%
1	Corn-notill	1126	14.07%
13	Woods	987	12.34%
9	Soybean-notill	787	9.84%
2	Corn-mintill	635	7.94%
5	Grass-trees	574	7.17%
11	Soybean-clean	454	5.67%
4	Grass-pasture	378	4.72%
7	Hay-windrowed	343	4.29%
14	Buildings	302	3.77%
3	Corn	184	2.3%
12	Wheat	161	2.01%
15	Stone-Steel-Towers	73	0.91%
0	Alfalfa	37	0.46%
6	Grass-pasture-mowed	17	0.21%
8	Oats	15	0.19%



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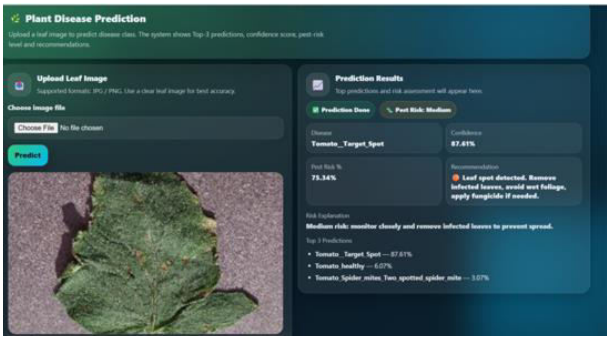

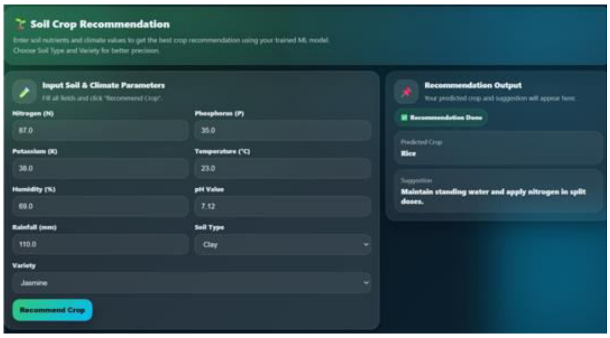

IX CONCLUSION

The proposed **Agri Genius AI system** presents an intelligent and integrated framework for improving agricultural monitoring and decision-making using advanced artificial intelligence techniques. By combining deep learning, machine learning, and hyperspectral image analysis, the system effectively analyzes plant health, soil nutrients, and land-cover patterns. The use of a Convolutional Neural Network (CNN) enables accurate detection of plant diseases from leaf images, while the XGBoost algorithm provides reliable crop recommendations based on soil nutrient parameters. In addition, the 3D-CNN model applied to hyperspectral datasets allows precise classification of land-cover types, enabling detailed agricultural analysis.The experimental results demonstrate the effectiveness of the proposed approach, achieving high performance in multiple modules of the system.The soil recommendation model achieved **very high prediction accuracy**, while the hyperspectral classification model achieved **99.46% accuracy**, showing the capability of the system to analyze complex agricultural data with high precision. By providing early detection of crop diseases, soil analysis, and intelligent recommendations, the system supports better resource management and helps farmers make informed decisions for improving crop productivity.

Overall, the Agri Vision AI framework contributes to the development of **smart and sustainable agriculture** by integrating modern AI technologies into a user-friendly platform. The system reduces reliance on manual monitoring, improves prediction accuracy, and supports efficient agricultural practices. In the future, the framework can be further enhanced by integrating real-time IoT sensors, larger agricultural datasets, and cloud-based deployment to support large-scale farming applications and real-time agricultural monitoring.Future research may also explore the integration of satellite imagery, drone-based monitoring systems, and real-time IoT sensor networks to further enhance large-scale agricultural monitoring and predictive analytics.

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