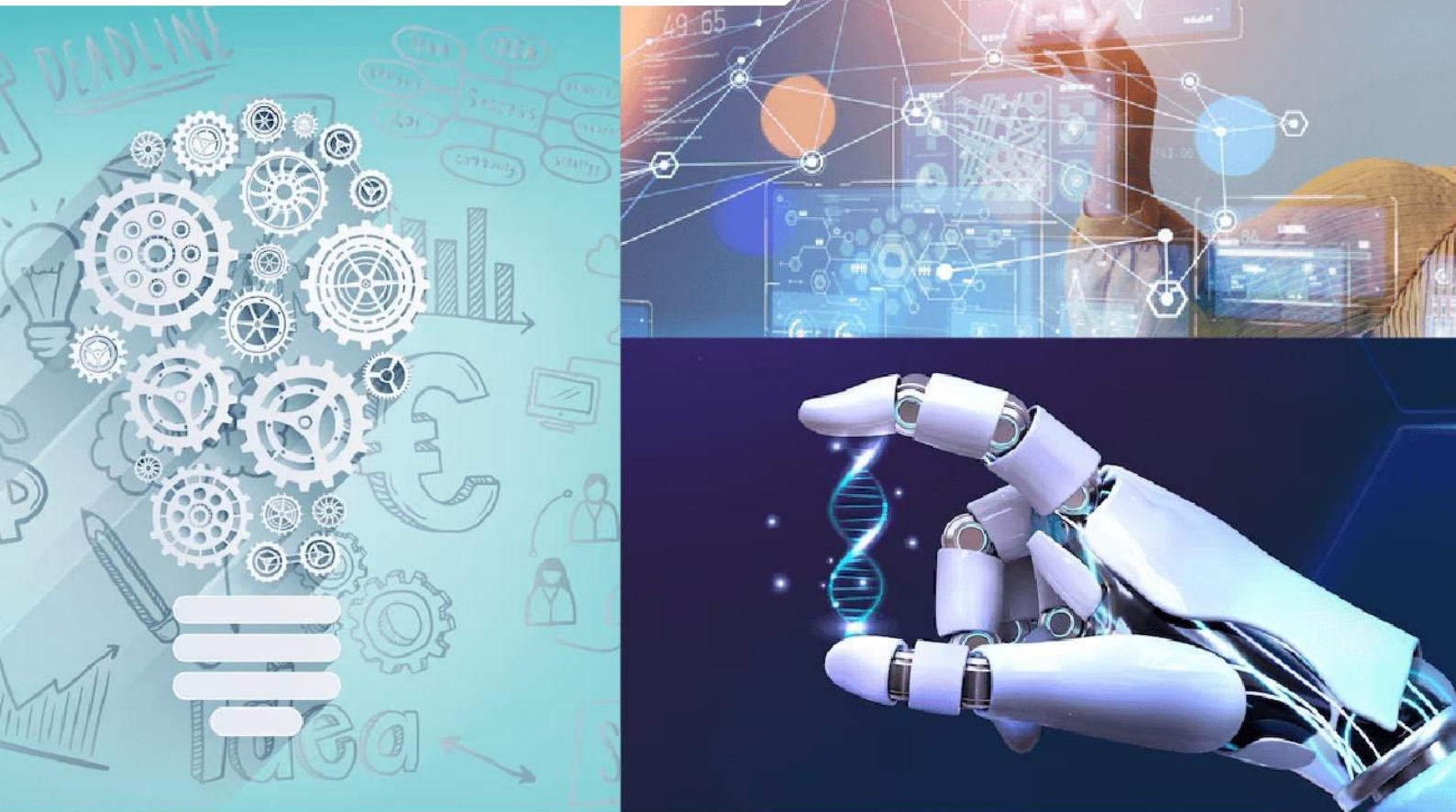




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AI-Based Approach for Crop Recommendation and Plant Disease Detection

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ABSTRACT: Even with worsening climate shifts and degrading soil conditions, modern agriculture increasingly relies on intelligent digital systems [13], [15]. This work presents an AI-based approach for crop recommendation and plant disease detection using deep learning and machine learning techniques [10], [14]. A ResNet-based model is used for disease detection, achieving high accuracy on PlantVillage datasets [1], [3]. Crop recommendation is performed using KNN based on soil and environmental parameters, while Random Forest is used for fertilizer prediction [10], [11]. The integrated system provides accurate and practical decision support for farmers.

KEYWORDS: Artificial Intelligence, Crop Recommendation, Plant Disease Detection, Machine Learning, Precision Agriculture

I. INTRODUCTION

Climate change, soil degradation, and unpredictable environmental conditions are increasingly affecting agricultural productivity worldwide [13]. Farmers face significant challenges such as irregular rainfall patterns, temperature fluctuations, declining soil fertility, and the emergence of new plant diseases, all of which negatively impact crop yield and quality [12], [15]. Traditional farming practices, which rely heavily on experience and generalized recommendations, often fail to adapt to rapidly changing environmental conditions, leading to inefficient decision-making and reduced profitability [14].

In recent years, advancements in artificial intelligence (AI) and machine learning (ML) have shown great potential in transforming traditional agriculture into a data-driven and precision-based domain [10]. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated high accuracy in detecting plant diseases using leaf images, enabling early diagnosis and prevention [1], [3]. Similarly, machine learning algorithms such as K-Nearest Neighbors (KNN) and Random Forest have been successfully applied to crop recommendation and fertilizer prediction based on soil nutrients and climatic conditions [11], [14].

However, most existing solutions operate as isolated systems, focusing either on disease detection, crop recommendation, or fertilizer analysis independently. This lack of integration limits their practical applicability, as farmers require a unified system that can provide comprehensive insights and actionable recommendations in real time [10]. Additionally, many systems lack user-friendly interfaces and fail to deliver understandable outputs for non-technical users.

To address these challenges, this paper proposes an integrated AI-based agricultural system that combines deep learning, classical machine learning, and generative AI techniques into a single framework. The system aims to provide accurate, efficient, and user-friendly decision support, enabling farmers to make informed choices related to crop selection, disease management, and resource optimization [12], [15].

II. LITERATURE REVIEW

2.1 Deep Learning for Plant Disease Detection

Several studies have demonstrated the effectiveness of deep learning techniques in plant disease detection. Convolutional Neural Networks (CNNs), including architectures such as AlexNet and ResNet, have been widely used to classify plant leaf diseases with high accuracy using datasets like PlantVillage [1], [3]. These models are capable of extracting complex visual features such as color, texture, and shape, enabling accurate multi-class classification.

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However, many existing models are trained on controlled datasets, which may limit their performance under real-world conditions. Variations in lighting, background noise, and image quality can significantly affect prediction accuracy [4]. To address these challenges, recent research has focused on developing lightweight and efficient models that can be deployed on mobile and edge devices without compromising performance.

2.2 Machine Learning for Crop and Fertilizer

Machine learning algorithms have been widely applied in agriculture for crop and fertilizer recommendation based on soil and environmental parameters. Techniques such as Decision Trees, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) analyze soil nutrients including nitrogen, phosphorus, potassium, pH, temperature, and rainfall to predict suitable crops [11], [14].

Among these methods, Random Forest has shown superior performance due to its ability to handle nonlinear relationships and reduce overfitting through ensemble learning [10]. Similarly, fertilizer recommendation systems utilize structured agricultural datasets to optimize nutrient usage and improve soil health. Despite their effectiveness, many of these models rely on limited datasets and static inputs, which can reduce their adaptability to dynamic environmental conditions.

2.3 Integrated and Smart Agriculture Systems

Recent advancements in smart agriculture have explored the integration of Internet of Things (IoT) sensors, weather APIs, and real-time monitoring systems to enhance agricultural decision-making [18]. These systems incorporate environmental parameters such as temperature, humidity, and rainfall forecasts to provide dynamic and location-specific recommendations.

While such approaches improve responsiveness, they often lack seamless integration with disease detection and soil analysis modules, resulting in fragmented advisory platforms [12]. Furthermore, most existing systems do not incorporate generative artificial intelligence to provide user-friendly and context-aware recommendations. This limits their accessibility, particularly for small-scale farmers who may not be familiar with technical outputs.

2.4 Research Gap and Motivation

Despite significant progress in applying artificial intelligence to agriculture, most existing systems focus on individual components such as disease detection, crop recommendation, or fertilizer analysis rather than providing a unified platform. The lack of integration between these components limits the effectiveness of current solutions in real-world farming environments.

Additionally, many systems lack intuitive interfaces and fail to provide clear, actionable insights for end users. The absence of conversational or generative AI further reduces accessibility and user engagement. Therefore, there is a strong need for an integrated agricultural system that combines deep learning, classical machine learning, and generative AI to deliver comprehensive, accurate, and user-friendly decision support.

III. METHODOLOGY

3.1 System Overview

The proposed system integrates deep learning, classical machine learning, and generative AI to support agricultural decision-making. It processes both image data (plant leaves) and tabular data (soil and environmental parameters). The system is designed as a modular architecture where each component performs a specific task while contributing to an overall intelligent farming assistant. User inputs are provided through a web interface, and processing is handled via a Flask-based backend with MongoDB used for data storage. External weather data is incorporated to enhance prediction accuracy.

3.2 Plant Disease Detection Using ResNet9

The plant disease detection module is developed using a modified ResNet9 architecture implemented in PyTorch. Deep learning models, particularly CNN-based architectures, are well-suited for image classification tasks due to their ability to automatically extract hierarchical features from raw input images [1], [3]. The model is trained on the PlantVillage dataset, which consists of labelled images of healthy and diseased plant leaves across multiple crop types.

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Before training, all input images undergo preprocessing steps including resizing to a fixed resolution, normalization of pixel values, and conversion into tensor format suitable for deep learning operations. These steps ensure consistency in data representation and improve model performance. The ResNet9 architecture incorporates residual connections, which help in mitigating the vanishing gradient problem and enable deeper network training without loss of information.

During training, the model learns distinguishing visual patterns such as colour variations, texture differences, and lesion characteristics associated with various plant diseases. The final classification layer uses a SoftMax activation function to output probability distributions across multiple classes. Experimental results show that the model achieves an accuracy of approximately 98–99%, indicating its effectiveness in identifying plant diseases under controlled conditions.

3.3 Crop Recommendation Using KNN

The crop recommendation module is implemented using the K-Nearest Neighbors (KNN) algorithm, a supervised machine learning technique used for classification tasks involving multidimensional data [11], [14]. The module recommends suitable crops based on soil nutrients and environmental conditions.

The input features include nitrogen (N), phosphorus (P), potassium (K), pH, temperature, humidity, and rainfall, which are essential for determining crop suitability. The dataset consists of labeled records representing crops and their corresponding soil and climatic conditions.

Before applying KNN, the data is preprocessed using normalization and feature scaling to ensure balanced contribution of all parameters. The algorithm identifies the ‘k’ nearest neighbors using Euclidean distance, with **k = 20** selected to balance bias and variance.

A weighted voting mechanism is used to improve prediction accuracy by giving more importance to closer neighbors. While the model achieves near-perfect accuracy on training data, its expected real-world accuracy is approximately 90%, consistent with similar agricultural systems.

3.4 Fertilizer Recommendation Using Random Forest

The fertilizer recommendation module is developed using the Random Forest algorithm, an ensemble learning technique known for its robustness and high performance in classification tasks involving structured data [10]. The purpose of this module is to recommend the most appropriate fertilizer based on soil nutrient composition and the selected crop.

The model takes input features such as nitrogen (N), phosphorus (P), potassium (K) levels, soil pH, and crop type. These factors are critical in determining the nutrient requirements of the soil and ensuring optimal crop growth. The dataset used includes both a smaller dataset with limited records and an expanded dataset containing a larger number of samples to improve generalization.

Random Forest works by constructing multiple decision trees during training and combining their outputs to produce a final prediction. Each tree is trained on a random subset of the data and features, which helps in reducing overfitting and improving model stability. The ensemble nature of the algorithm allows it to capture complex, nonlinear relationships between soil properties and fertilizer requirements.

When trained on a smaller dataset, the model achieves an accuracy of approximately 69.2%, reflecting the limitations of insufficient data. However, when trained on a larger dataset, the accuracy significantly improves to around 85–90%, demonstrating the importance of data availability in machine learning performance. The model effectively identifies patterns in soil nutrient deficiencies and maps them to suitable fertilizer recommendations.

IV. RESULTS AND DISCUSSION

The dataset used in this study was compiled from multiple agricultural datasets, including soil metrics, weather patterns, and a robust collection of symptomatic plant leaf imagery (e.g., PlantVillage dataset). The tabular data includes features such as Nitrogen (N), Phosphorous (P), Potassium (K) levels, temperature, humidity, pH, and rainfall. Additionally, the image dataset comprises high-resolution images of healthy and diseased crop leaves across various species, meticulously labeled for supervised learning.

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The system was implemented using Python-based machine learning and deep learning frameworks. The backend was developed using Flask, while the frontend interface was built using modern web technologies. Various libraries, including PyTorch and scikit-learn, were utilized for model development and evaluation.

Exploratory Data Analysis (EDA) revealed meaningful relationships between environmental factors and agricultural outcomes. Soil pH and nutrient levels were found to significantly influence fertilizer recommendations, while temperature and humidity played a crucial role in disease occurrence. These observations confirm the importance of using multi-dimensional data for accurate agricultural predictions.

Figure 1 illustrates the overall system context and data flow, highlighting the interaction between the central system and external services such as weather APIs and generative AI modules. This integration enables real-time data processing and enhances the adaptability of the system.

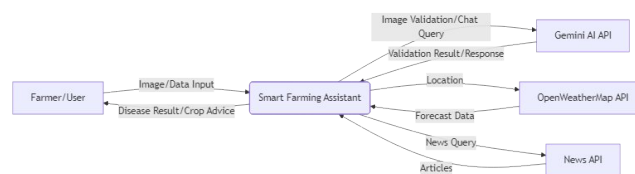


Fig. 1: System Context and API Integration

Figure 2 presents the feature importance analysis derived from the Random Forest model used for crop recommendation. The results indicate that environmental factors such as rainfall and humidity have a strong influence on crop prediction, while soil nutrients also contribute significantly. This demonstrates the model's ability to effectively capture the relationship between multiple agricultural parameters.

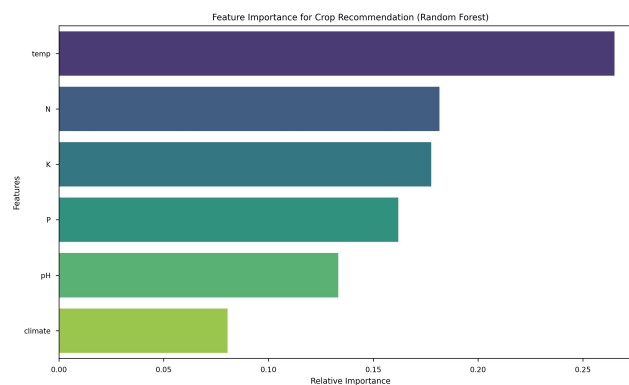


Fig. 2: Feature Importance from Random Forest Model

Figure 3 shows the training and validation performance of the ResNet9 model used for plant disease detection. The model achieves high accuracy with minimal overfitting, indicating strong generalization capability. The convergence of training and validation curves suggests that the model is well-optimized for classification tasks.

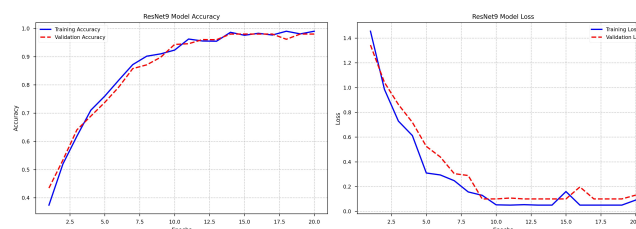


Fig. 3: ResNet9 Training Performance Metrics

Figure 4 demonstrates the disease analysis and recommendation interface, which provides actionable insights based on model predictions. In addition to identifying plant diseases, the system offers treatment suggestions and preventive measures. This enhances the practical usability of the system by bridging the gap between prediction and real-world application.

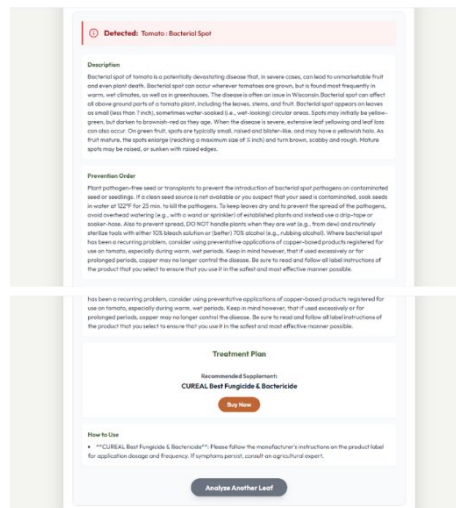


Fig. 4: Disease Analysis and Treatment Interface

V. CONCLUSION

This paper presented an integrated AI-based agricultural system designed to enhance decision-making in modern farming practices. By combining deep learning, machine learning, and generative AI, the proposed system provides a comprehensive solution for plant disease detection, crop recommendation, and fertilizer prediction. The use of a ResNet9-based model enables accurate identification of plant diseases, while KNN and Random Forest algorithms effectively analyze soil and environmental data to recommend suitable crops and fertilizers [1], [10], [11].

The integration of multiple AI techniques into a unified framework addresses the limitations of existing systems that operate in isolation. Furthermore, the inclusion of a generative AI-based module enhances usability by providing context-aware recommendations in natural language, making the system accessible even to non-technical users.

Although the system demonstrates strong performance, certain limitations remain. The reliance on limited structured datasets may affect generalization in diverse real-world conditions, and image-based detection may be influenced by environmental noise. Future work can focus on incorporating larger and more diverse datasets, integrating IoT-based real-time monitoring systems, and improving model explainability to increase user trust and adoption [18].

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