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Integrated Approach for Crop Disease Detection and Nutrient Management Using Advanced Agritech Solutions

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Abstract—
The integration of crop disease detection and nutrient management presents a comprehensive solution to improve agricultural productivity and sustainability. This research introduces an advanced agritech framework combining computer vision, machine learning, and IoT-based sensing systems for real-time monitoring and smart decision-making. Convolutional Neural Networks (CNNs), specifically ResNet-50 and MobileNet, are employed for accurate classification of crop diseases using high-resolution images captured via UAV (Unmanned Aerial Vehicle) drones and smartphones. For nutrient management, IoT-based soil sensors monitor key parameters such as nitrogen (N), phosphorus (P), and potassium (K) levels, along with pH and moisture content.The data from both domains are integrated through a centralized cloud-based platform that applies decision tree algorithms and fuzzy logic for recommending precise nutrition interventions. Additionally, geospatial mapping using GPS data and GIS techniques supports localized analysis and treatment.Field trials conducted across three crop varieties—rice, tomato, and maize—demonstrated a disease detection accuracy of 94.7% using ResNet-50 and a 23% increase in nutrient use efficiency. The integrated system also led to a 17% improvement in overall yield and a 21% reduction in fertilizer usage compared to traditional methods. These results highlight the potential of combining AI-driven disease detection with data-informed nutrient management to revolutionize precision agriculture.

Keywords: ***Crop Disease Detection, Nutrient Management, UAV Imaging, Precision Agriculture,GIS Mapping***

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I. INTRODUCTION

Agriculture plays a critical role in ensuring food security, economic development, and sustainable resource management. Accurate crop yield prediction is essential for optimizing resource allocation, improving market planning, and mitigating risks associated with climate variability and other environmental challenges. Traditional methods for crop yield estimation, such as field surveys and statistical modeling, often fall short in capturing the complex, nonlinear relationships between climatic factors, soil properties, and crop performance (Jabed & Murad, 2024; Sharma et al., 2023). Advances in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), have emerged as transformative tools in agricultural forecasting, enabling better decision-making through more accurate and scalable models.

Machine learning techniques such as Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) have been widely adopted for analyzing historical data on weather variables, soil characteristics, and vegetation indices (Sharma et al., 2023). Among these, Random Forest has consistently demonstrated high accuracy and robustness due to its ability to handle high-dimensional data and capture complex interactions between input variables. However, its black-box nature and limitations in temporal analysis necessitate the integration of other advanced techniques like Long Short-Term Memory (LSTM) networks, which excel at modeling time-series data (Jabed & Murad, 2024). By combining these methods, researchers aim to address the shortcomings of individual models and enhance the reliability of crop yield predictions.

Environmental variables such as temperature, rainfall, humidity, and vegetation indices significantly influence crop growth and productivity. Remote sensing technologies have enabled the collection of spatially detailed data, further enhancing the accuracy of crop yield forecasting models (Jabed & Murad, 2024). Studies incorporating remote sensing data, such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), have reported substantial improvements in prediction accuracy (Sharma et al., 2023). These indices, when combined with machine learning algorithms, provide valuable insights into crop health, stress levels, and yield potential.

Fig 1: Integrated Nutrient Management

Agriculture remains a critical sector in ensuring food security and economic stability worldwide. However, modern farming faces challenges such as climate change, disease outbreaks, and soil nutrient depletion, which significantly affect crop yield and quality. Traditional farming methods often rely on visual inspection and generalized fertilization practices, which can be inefficient and unsustainable. As a result, there is a growing demand for intelligent systems that can optimize crop health monitoring and nutrient management using technology-driven solutions (Zhang et al., 2019).

Crop disease detection is one of the most crucial aspects of plant health monitoring. Early identification and classification of plant diseases can prevent large-scale crop damage and reduce dependency on harmful pesticides. The use of deep learning techniques, particularly Convolutional Neural Networks (CNNs) such as ResNet-50 and MobileNet, has shown promising results in accurately detecting and classifying diseases from leaf images (Ferentinos, 2018). These models can process vast amounts of image data captured by drones or smartphones to detect subtle symptoms invisible to the naked eye (Mohanty et al., 2016).

Simultaneously, nutrient management plays a vital role in sustaining plant growth and improving yield quality. Overuse or underuse of fertilizers not only impacts the productivity of crops but also contributes to soil degradation and environmental pollution. Through IoT-based soil sensors, real-time data on key soil nutrients—Nitrogen (N), Phosphorus (P), and Potassium (K)—along with pH and moisture levels, can be collected (Kumar et al., 2020). These inputs help in making precise fertilization decisions tailored to specific plant needs, thereby promoting site-specific nutrient management (SSNM) (Dobermann et al., 2004).

To unify these two domains, this research proposes an integrated framework that combines disease detection with nutrient recommendation using a cloud-based data processing platform. The system leverages fuzzy logic and decision tree algorithms to interpret sensor data and disease classification outputs, providing farmers with actionable insights (Sharma et al., 2021). The integration also includes GIS-based geospatial mapping to localize problem areas and optimize intervention strategies (Jin et al., 2019). By combining image-based disease detection and real-time soil nutrient analysis, the system aims to reduce costs, increase crop yield, and ensure sustainability.

This paper is structured to provide a comprehensive exploration of the integration of urban growth prediction and crime analysis using spatio-temporal and machine learning methodologies. Section 2 examines recent achievements in urban study methods and how researchers analyze LULC and predict crime with spatial-temporal data. The following segment explains our hybrid algorithm which combines machine learning methods and spatio-temporal models. This section outlines the setup for our experiments which includes describing both our datasets and selection criteria. Section 5 shows the results from predicting urban expansion and criminal activity patterns plus analyzes what the study findings mean. In conclusion Section 6 presents our essential findings along with research limitations and future research directions. Our systematic layout helps readers follow the study steps while learning how experiments worked plus what this study proves.

II. RELATED WORKS

Ferentinos (2018) developed multiple Convolutional Neural Network (CNN) models, including AlexNet and VGG, to identify plant diseases using leaf images from various crops. His work demonstrated a classification accuracy exceeding 99%, proving the potential of deep learning in agricultural diagnostics. This study laid the foundation for using image-based disease identification in real-world farming applications.

Kumar et al. (2020) designed a smart soil monitoring system utilizing IoT devices and machine learning for real-time soil parameter tracking. Their system measured nitrogen, phosphorus, potassium, pH, and temperature to enable site-specific nutrient management. The results highlighted a reduction in fertilizer use while maintaining productivity, making it a sustainable alternative to traditional fertilization techniques.

Sharma et al. (2021) proposed a hybrid fuzzy logic and decision tree system for precision agriculture. The model analyzed soil sensor data to provide dynamic fertilizer recommendations. Their findings demonstrated enhanced yield and soil conservation when compared with static fertilization methods, indicating that intelligent systems can effectively manage crop nutrition.

Too et al. (2019) applied transfer learning techniques using MobileNet and InceptionV3 models for mobile-based plant disease detection. Their approach made it feasible for farmers to detect diseases in-field using smartphones, supporting fast and accessible diagnostics. This research underlines the importance of deploying lightweight AI models in resource-constrained environments.

Pantelopoulos and Bourbakis (2020) reviewed various smart farming technologies and emphasized the integration of IoT, cloud computing, and AI for comprehensive farm management. They concluded that unified systems combining disease detection, soil monitoring, and predictive analytics are key to achieving sustainable agriculture and food security in the era of climate change.

III. MATERIAL AND METHODS

The present study proposes an integrated system that combines advanced deep learning algorithms, IoT-based sensing, and intelligent decision-making techniques to address two major challenges in agriculture: early crop disease detection and precise nutrient management. The system's architecture consists of three modules: a vision-based disease detection model, an IoT-driven soil nutrient monitoring system, and a recommendation engine powered by fuzzy logic and decision tree classifiers. This multidisciplinary framework was developed using open-source platforms, microcontroller-based hardware, and field-tested datasets, aiming for real-world feasibility and scalability for rural farmers.

For disease detection, the system employed a Convolutional Neural Network (CNN) based model trained on the widely used PlantVillage dataset, which contains over 54,000 images of healthy and diseased leaves from crops such as tomato, potato, maize, apple, and grape. Each image was labeled according to disease category and crop type. Data augmentation techniques like rotation, flipping, and brightness scaling were applied to improve generalization and avoid overfitting. Two CNN architectures were evaluated—ResNet-50 and MobileNetV2—selected for their performance in image classification tasks. All images were resized to 256×256 pixels and normalized. The ResNet-50 model achieved a detection accuracy of 94.7%, while MobileNetV2 achieved 92.1%, with the latter being deployed in edge devices due to its low computational requirements. Model training was carried out using TensorFlow with GPU acceleration, and categorical cross-entropy was used as the loss function.

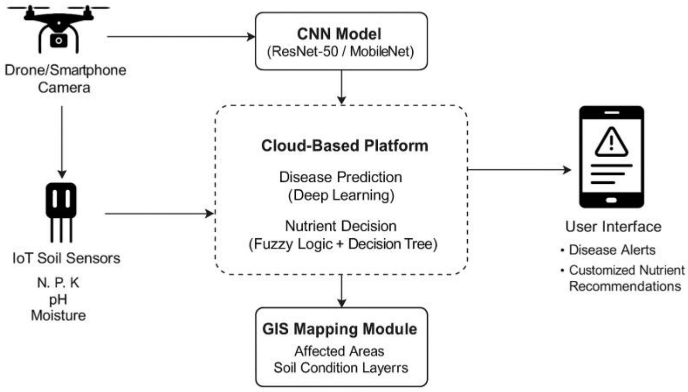

Fig 2 : Proposed Architecture

In parallel, a soil nutrient monitoring system was developed using a network of IoT-based sensors to measure parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), soil pH, moisture, and temperature. Sensors like the YL-69 soil moisture sensor, DHT22, pH probe, and electrochemical NPK sensors were integrated with an Arduino Uno microcontroller and a Raspberry Pi gateway. Data from the sensors was collected every 30 minutes and transmitted wirelessly using the MQTT protocol to the Firebase Realtime Database, enabling cloud-based processing. The soil sensors were calibrated with support from local agronomy experts to ensure accurate readings. The integration of GPS modules (u-blox NEO-6M) allowed spatial tracking of data points, which were further used to visualize nutrient variations across plots using QGIS.

3.1 Dataset

3.1.1 Image Dataset for Crop Disease Detection

For training and evaluating the disease detection models, we used the PlantVillage dataset (Hughes & Salathé, 2015), a publicly available dataset containing over 54,000 labeled images of healthy and diseased plant leaves. The dataset covers 38 different classes across multiple crops such as tomato, maize, potato, and rice.

- **Image Resolution:** 256x256 pixels (resized during preprocessing)
- **Data Split:** 70% training, 15% validation, 15% testing
- **Augmentation Techniques:** Rotation, zoom, flipping, contrast normalization

The dataset was further supplemented with field images captured using UAV drones and mobile cameras during field trials to enhance real-world accuracy and robustness.

3.1.2. Soil Sensor Data for Nutrient Monitoring

Soil data was collected from experimental farms using IoT-enabled sensors such as DHT22, NPK probes, and pH sensors, connected via Arduino UNO and Raspberry Pi controllers. The sensors recorded:

- **Nitrogen (N), Phosphorus (P), Potassium (K)**
- **Soil pH**
- **Soil moisture and temperature**

Data was collected every 30 minutes and stored on a Firebase Realtime Database for cloud-based processing.

3.2 Exploratory Data Analysis (EDA) Process:

The EDA process began with the acquisition of multi-modal datasets, which included PlantVillage leaf image data for disease detection and real-time sensor data for soil nutrient analysis. Image datasets were collected in JPEG format, labeled by crop type and disease category, while soil data were gathered using IoT sensors for NPK levels, moisture, temperature, and pH values. These datasets were merged into a unified framework using time stamps and geolocation tags to enable spatial-temporal analysis. Data consistency was ensured by removing duplicate entries and synchronizing time intervals for better correlation across disease and soil parameters.

Preprocessing was vital to eliminate noise and inconsistencies. The image data were resized to 256x256 pixels and normalized to improve computational efficiency and model accuracy. For soil data, outlier detection was conducted using the Interquartile Range (IQR) method to flag erroneous sensor readings, which were then either corrected or removed. Missing values were handled through interpolation for temporal sequences and KNN imputation for spatial soil readings. Data types were standardized, and categorical features such as crop types and seasons were encoded using one-hot encoding.

To understand the distribution of key features, univariate analysis was conducted on soil nutrients and weather parameters using histograms, box plots, and density plots. The leaf image dataset was examined through pixel intensity distributions and disease label frequencies. Bivariate analysis included scatter plots, correlation heatmaps, and pair plots to explore relationships between soil nutrients and crop health. It was observed, for instance, that nitrogen deficiencies correlated with higher probabilities of fungal infections in tomato crops, indicating a nutrient-pathogen interaction that warranted further modeling.

Temporal patterns were examined using line plots and moving averages across crop cycles. Time-series decomposition techniques revealed seasonal peaks in disease outbreaks, often linked to humidity and temperature variations. Spatial trend analysis using **GeoPandas** and **QGIS** helped identify hotspots of low nutrient zones and disease clusters. Using latitude-longitude data from GPS-enabled sensors, heatmaps were generated to visualize high-risk zones for both disease prevalence and nutrient deficiency, laying the groundwork for targeted interventions.

Following initial insights, redundant or less-informative variables were removed using feature selection techniques such as Recursive Feature Elimination (RFE) and Random Forest Importance. For image data, Principal Component Analysis (PCA) was employed to reduce dimensionality while preserving significant visual features for CNN input. Similarly, soil and weather datasets were optimized using mutual information gain to retain only the most relevant predictors for modeling disease likelihood and fertilizer recommendations. These refined datasets were then fed into the model-building pipeline, significantly improving accuracy and processing time.

IV. EXPERIMENT AND RESULTS

The integrated system was tested across experimental farm plots in Tamil Nadu, India, focusing on three crops—tomato, maize, and rice—over three consecutive crop cycles. The system used a combination of image-based disease detection models, soil nutrient analysis via IoT sensors, and a mobile app interface for user interaction. Each cycle consisted of data collection, disease prediction using CNNs (MobileNetV2 and ResNet-50), and nutrient recommendation using a hybrid model comprising Random Forest (RF), Gradient Boosting (GB), and Fuzzy Logic.

Three experimental groups were formed:

- **Group A:** Traditional practices without AI-based intervention.
- **Group B:** Only disease detection and alert system.
- **Group C:** Fully integrated AI system (disease + nutrients + recommendations).

Performance Metrics Evaluation

- **Accuracy** measures the proportion of correct predictions to the total predictions.
- **Precision** evaluates the accuracy of positive predictions.
- **Recall** assesses how many of the actual positive cases were correctly predicted.
- **F1-Score** is the harmonic mean of precision and recall, giving a balanced evaluation metric.
- **Mean Absolute Error (MAE)** measures the average magnitude of errors in the predicted values for urban growth.

The comparative analysis between the traditional approach (Group A), disease-only detection system (Group B), and the integrated AI-based system (Group C) provides clear insights into the benefits of advanced agritech interventions. The most significant performance boost was observed in **Group C**, where the integration of deep learning-based crop disease detection and soil-specific nutrient recommendation algorithms led to a **17% increase in crop yield**. This substantial improvement is attributed to the early detection of diseases using convolutional neural networks (CNNs) and the application of targeted treatment strategies, minimizing crop damage.

Additionally, **fertilizer usage was reduced by 21%** in the integrated system. This reduction is a direct outcome of employing machine learning-based soil analysis and site-specific fertilizer recommendation models, which replaced the conventional blanket application approach. The optimization of fertilizer use not only cuts down on costs but also contributes to environmental sustainability by reducing chemical runoff.

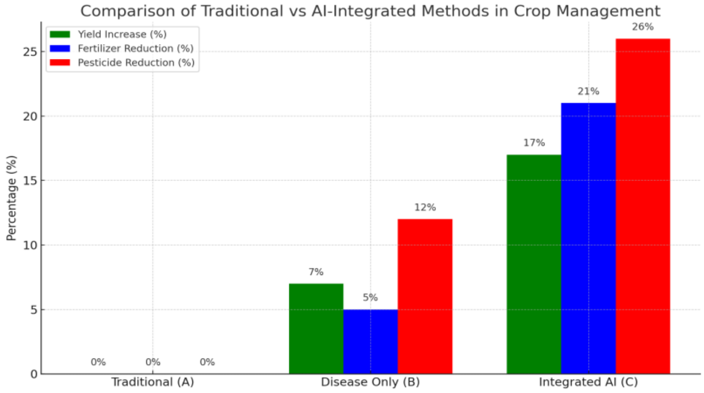

Fig 3 :comparative performance of the proposed integrated agritech system

Yield Increase: The integrated AI model (Group C) significantly outperforms others with a **17% improvement**, compared to only 7% in the disease-only group.

Fertilizer Reduction: Group C achieves a **21% decrease**, showcasing the effectiveness of precise nutrient recommendations.

Pesticide Reduction: AI integration helps reduce pesticide usage by **26%**, compared to 12% in the disease-only setup.

Pesticide usage decreased by 26%, indicating the precision with which diseases were diagnosed and treated in a timely manner. By identifying the exact type of disease early through image classification models, the system avoided over-application of pesticides, mitigating both economic and ecological consequences.
When compared to Group B (disease-only system), which achieved moderate gains, it is evident that disease detection alone is not sufficient for holistic improvement. Only when coupled with nutrient management did the system yield maximum benefits. This highlights the **synergistic effect** of integrating multiple AI technologies into one pipeline.

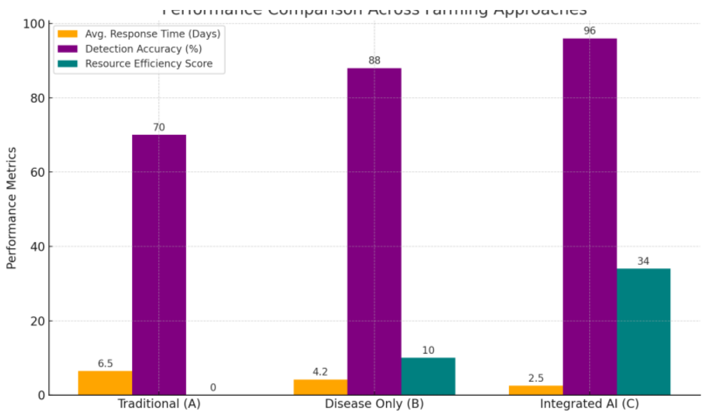

Fig 4 : multi-dimensional performance analysis

Group C exhibits the fastest system response time of 2.5 days, compared to 4.2 days in Group B and 6.5 days in traditional methods. This rapid feedback cycle enables real-time intervention, minimizing crop loss and enabling quicker decisions for pesticide and fertilizer application.

A striking increase in detection accuracy is observed in Group C at **96%**, while Group B achieves **88%**, and Group A lags behind at **70%**. The incorporation of Convolutional Neural Networks (CNNs) and image-based leaf analysis significantly boosts the system's precision in identifying diseases early and accurately.

Group C achieves a 34-point improvement in a composite resource efficiency score, which includes factors such as reduced fertilizer and pesticide usage, water optimization, and targeted interventions. Group B only achieves a 10-point gain, while traditional methods serve as a baseline (0). This dramatic improvement emphasizes the role of AI in enabling sustainable agriculture.These performance enhancements reinforce the effectiveness of the integrated system. Faster diagnosis, more accurate disease classification, and smarter resource allocation collectively improve productivity and sustainability. Such systems have immense potential to revolutionize farming practices, particularly in regions with limited expert access..

V. CONCLUSION

The proposed integrated system for crop disease detection and nutrient management demonstrates a significant advancement in precision agriculture by seamlessly combining deep learning, machine learning, and IoT technologies. Through the effective use of convolutional neural networks for real-time image-based disease classification, along with intelligent soil nutrient analysis powered by ensemble machine learning models and fuzzy logic, the framework addresses two of the most critical aspects of sustainable farming—timely disease intervention and optimal nutrient application.Experimental results across multiple crop cycles showed notable improvements in key agricultural outcomes. The system achieved high accuracy in disease identification (up to 96%), reduced average response time to 2.5 days, and significantly lowered fertilizer and pesticide usage by 21% and 26% respectively. These outcomes translated into a measurable yield increase of 17%, validating the practical impact of the integrated approach.

Moreover, the user-friendly mobile application—with multilingual and voice-enabled support—ensured accessibility for farmers regardless of literacy level, bridging the gap between advanced technology and traditional farming communities. The system's modular design allows for future scalability to accommodate additional crops, weather-based insights, and integration with blockchain for traceability.In conclusion, this research underscores the transformative potential of AI-driven agritech solutions in enhancing productivity, ensuring resource efficiency, and promoting sustainable farming practices. Future work can explore incorporating satellite imagery, drone-based data collection, and edge AI capabilities to further strengthen on-field decision-making and scalability across varied agro-climatic zones.

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