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An Autonomous Framework for Crop Monitoring and Management Using Machine Learning Techniques

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ABSTRACT

Agriculture remains a cornerstone of global food security and economic development, particularly in developing countries. However, modern agriculture faces significant challenges such as crop diseases, irregular weather patterns, inefficient resource utilization, and lack of timely intervention, all of which can impact crop yield and sustainability. To address these issues, this study proposes the development of an autonomous framework for crop monitoring and management using machine learning (ML) techniques. The objective is to create a smart, data-driven system capable of predicting crop health, optimizing input use (such as fertilizer and water), and supporting farmers in decision-making through real-time insights. To achieve this, a diverse crop data-set was collected from open-source repositories and local farm sensors, including features such as soil nutrient levels (Nitrogen, Phosphorus, Potassium), environmental factors (temperature, humidity, rainfall), and crop performance records. Several machine learning algorithms including Random Forest, Gradient Boosting, and Convolution Neural Networks were evaluated for their suitability in predicting crop conditions, recommending best-fit crops, detecting early signs of disease, and suggesting irrigation and fertilizer practices. This study addresses the persistent challenges in agriculture such as crop diseases, resource inefficiencies, and unpredictable weather by developing an autonomous crop management and monitoring framework powered by machine learning (ML). The system utilizes a combination of open-source and locally collected farm data, including soil nutrients and environmental conditions, to predict crop health, recommend optimal inputs, and detect diseases. Among the ML models tested, Random Forest demonstrated the highest accuracy (91.2%) in crop recommendation and disease prediction. The framework integrates Io T sensors, drone imagery, and a mobile interface to deliver real-time insights to farmers. Overall, the system aims to improve decision-making, reduce resource waste, and enhance agricultural sustainability, with future plans to scale and adapt it for broader agro-ecological applications.

Keywords: *Machine Learning, Crop Management, Precision Agriculture, IoT Sensors, Disease Prediction*

INTRODUCTION

Agriculture remains a cornerstone of global economies, especially in developing nations where it contributes significantly to food security, employment, and national GDP. However, traditional agricultural practices often suffer from inefficiencies due to manual labor, weather dependencies, pests, diseases, and lack of timely decision-making support (Koirala et al., 2023). The emergence of smart agriculture, driven by advancements in Information and Communication Technology (ICT), the Internet of Things (IoT), and

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Artificial Intelligence (AI) particularly Machine Learning (ML) is revolutionizing the way crops are monitored and managed (Agarwal & Goyal, 2022). These technologies promise a shift from reactive to proactive and predictive agricultural practices.

Machine learning, a subset of AI, has proven to be a powerful tool in automating data analysis and decision-making processes in agriculture. ML techniques enable systems to learn from vast datasets collected from sensors, satellites, drones, and historical records to predict crop diseases, estimate yields, and optimize irrigation and fertilizer usage (Ramesh et al., 2023). These innovations are essential in achieving sustainable agriculture in line with Sustainable Development Goal 2, which aims to end hunger and ensure food security. In recent years, autonomous systems powered by ML have shown great promise in real-time agricultural monitoring. These systems can independently gather data from embedded field sensors, analyze this data, and make informed decisions or send recommendations to farmers via mobile or web platforms (Kundu et al., 2023). Such frameworks help reduce human effort, minimize resource wastage, and increase productivity.

Climate change and unpredictable weather patterns have further increased the need for intelligent agricultural systems. Autonomous frameworks utilizing ML can integrate real-time weather forecasts and soil data to adjust crop management practices dynamically (Yoon et al., 2022). This responsiveness enhances the resilience of agricultural practices and ensures better crop outcomes.

One major challenge in modern agriculture is early disease detection. ML-based image classification and pattern recognition techniques are being used to identify crop diseases from leaf images with high accuracy. These systems help reduce losses and control disease spread before they become severe (Patel et al., 2023). Early intervention leads to better yields and reduced use of harmful pesticides. Soil health and nutrient management are also being transformed through ML algorithms. Supervised learning models such as decision trees, support vector machines (SVM), and random forests are employed to classify soil types and recommend optimal crop choices and fertilization schedules (Shukla et al., 2022). This ensures that farmers apply the right inputs in the right quantities, minimizing environmental impact.

Irrigation scheduling is another crucial aspect of crop management. ML models can predict soil moisture levels based on past irrigation records, weather conditions, and crop types. This enables autonomous irrigation systems that supply water only when needed (Chatterjee et al., 2023). This conserves water a vital resource becoming increasingly scarce due to climate change. Yield prediction is being refined using ML frameworks that process historical yield data, soil characteristics, and climatic variables. This helps policymakers and farmers plan better and avoid post-harvest losses (Nweke & Ofoegbu, 2022). Reliable forecasting also supports supply chain management and market price stabilization. Drones and unmanned aerial vehicles (UAVs) equipped with ML algorithms are now used for aerial imaging and crop health assessment. These autonomous systems provide a bird's-eye view of the farm, identifying stress areas, nutrient deficiencies, and weed infestations in real-time (Banerjee et al., 2023). This high-resolution monitoring empowers precision agriculture.

Despite the remarkable potential and adoption of Machine Learning in agriculture, there exists a research gap in the integration of

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these autonomous systems in resource-constrained environments, particularly in developing nations where data availability, digital literacy, and infrastructure pose significant limitations. Additionally, most studies focus on isolated applications (e.g., disease detection or irrigation), whereas fewer works holistically address end-to-end autonomous systems combining multiple ML-driven tasks such as disease detection, irrigation, yield forecasting, and soil management in a unified framework. Justification: Addressing this gap is crucial for enhancing food security and sustainable agricultural development in rural and underdeveloped regions. A comprehensive ML-based framework tailored to low-resource settings can drive practical solutions for smallholder farmers, boost productivity, and promote resilience against climate and economic shocks. The primary objective of this research is to develop an autonomous framework for agricultural monitoring and crop management using machine learning techniques. Specific objectives include:

MATERIALS AND METHODS

Research Design

This study adopts an experimental research design to develop an autonomous framework for crop monitoring and management using machine learning techniques. The research was involving data collection from farms, model development, and evaluation of the proposed system to assess its effectiveness in real-time agricultural monitoring and decision-making.

Population of Study

The population of this study consists of farmers in Yola, Adamawa State, including small-scale, medium-scale, and large-scale farm owners. Agricultural extension workers and policymakers was also be considered to gain insights into existing agricultural practices and monitoring needs.

Proposed Model

The proposed system is an autonomous framework that leverages machine learning techniques to monitor crop activities and manage crops efficiently. The system integrates real-time data from sensors, drones, and satellite imagery to analyze soil conditions, predict crop diseases, and provide actionable recommendations to farmers.

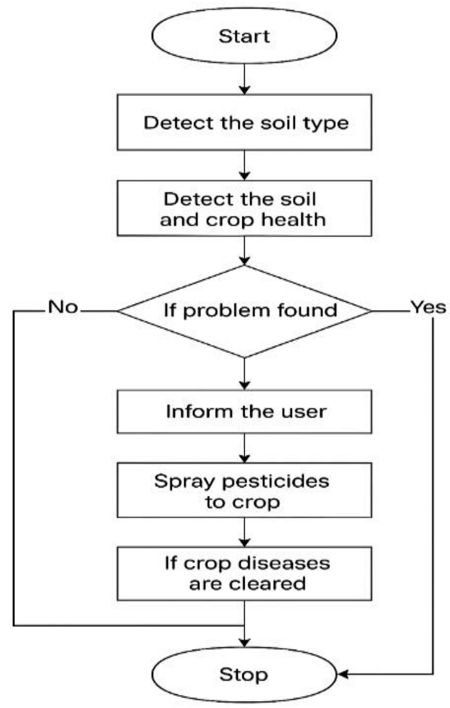

Figure 1. Proposed model.

System Architecture

The system architecture for the proposed Autonomous Framework for crop Monitoring and Management integrates various components to provide an efficient solution for agriculture through machine learning (ML) techniques. The architecture is designed to monitor crop growth, predict potential issues, and provide actionable insights for effective crop management.

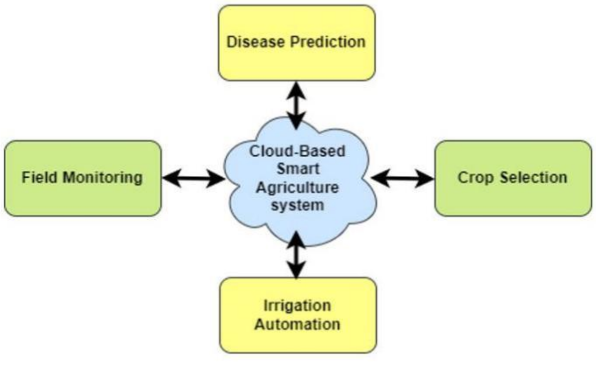

Figure 2. System Architecture.

Requirement Process

The requirements for the proposed system include hardware components such as IoT sensors, drones, and computing devices, along with software components for data processing and machine learning model deployment. Additionally, data from historical agricultural records and expert knowledge were incorporated to enhance system accuracy.

Instruments Used for Data Collection

Data collection instruments were including IoT-based sensors for soil moisture and temperature measurement, drones for aerial imaging, satellite imagery, and structured questionnaires for gathering farmers' insights. Machine learning algorithms were used to analyze the collected data.

Sampling Techniques

A stratified random sampling technique was used to select farmers based on farm size (small, medium, large) and crop type. This ensured diversity in farming practices. Additionally, purposive sampling was used to select subject matter experts for consultations and validation.

Method of Data Collection

Data was collected from multiple farms within Yola, Adamawa State, using: Sensor deployments on the field, Drone flights for imaging, Face-to-face interviews with farmers, Administration of questionnaires, these diverse sources provided a rich dataset for model development.

Data Gathering Process

The data was gathered through: Field observations and sensor readings, Drone-captured images, Interviews and questionnaires, all data was securely stored in a cloud-based database to support real-time access and subsequent analysis.

Method of Data Analysis

Collected data were analyzed using application of machine learning techniques to identify patterns, predict crop health, and provide insights for better crop management.

Data Pre-Processing

The collected data was analyzed using cleaning, normalization, and feature selection to ensure high-quality input for the machine learning models. Missing values was handled using appropriate imputation techniques.

Model Development

Models were developed using both supervised and unsupervised learning techniques. Algorithms applied included: Random Forest for classification tasks, Support Vector Machines (SVM) for disease and soil prediction, Convolutional Neural Networks (CNN) for image-based analysis, The models were trained on labeled datasets and optimized using hyperparameter tuning techniques.

Model Evaluation

The developed models were evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Cross-validation techniques were applied to ensure model generalization and robustness in real-world agricultural monitoring scenarios.

RESULTS AND DISCUSSION

Introduction

This presents the key outcomes derived from the Smart crop Monitoring and Crop Management System following user input of soil and weather parameters. The system's ability to analyze these parameters and provide accurate crop recommendations, fertilizer advice, pest alerts, and irrigation tips is evaluated and summarized here.

The Welcome Stream lit Page in this system is the first interface the user interacts with, designed to introduce the app and collect essential soil and weather data from the user. This page guides users through entering key environmental parameters which the app uses to provide crop recommendations, fertilizer advice, pest alerts, and irrigation tips.

System Implementation

The implementation of the Smart Crop Monitoring and Management System involved integrating multiple technologies to deliver a seamless and user-friendly platform for farmers and agricultural stakeholders. The system was developed to accept real-time inputs of critical soil nutrients and weather parameters, process the data using machine learning models, and generate precise recommendations on crop selection, fertilizer application, pest alerts, and irrigation scheduling.

The user interface was designed using Streamlit, enabling farmers to enter values for essential soil nutrients Nitrogen (N), Phosphorus (P), and Potassium (K) along with environmental factors including Temperature (°C), Humidity (%), pH Value, and Rainfall (mm). These parameters were chosen based on their known impact on crop growth, disease susceptibility, and irrigation requirements.

Data preprocessing steps included normalization of input values and validation checks to ensure the accuracy and consistency of user inputs. Once validated, the system processed the inputs through its decision-support modules:

Crop Recommendation Module: This component evaluated nutrient availability and environmental conditions to suggest the most suitable crop types that would maximize yield and resource efficiency.

Fertilizer Advisory Module: Utilizing nutrient deficiency patterns and soil pH data, this module recommended specific fertilizer types and application rates, including soil amendments for pH correction where necessary.

Pest Alert Module: Based on temperature and humidity thresholds known to favor pest outbreaks, the system generated timely alerts to help farmers implement preventive measures.

Irrigation Scheduling Module: This module used rainfall and humidity data to optimize irrigation frequency and volume, promoting water conservation and reducing crop stress.

The system was deployed on a cloud platform to allow easy access via desktop pc devices, facilitating real-time data entry and decision-making in the field.

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Figure 3. welcome stream lit page

Chickpea is a versatile legume that not only supports human nutrition but also improves soil fertility by fixing atmospheric nitrogen. This symbiotic relationship reduces dependency on synthetic fertilizers, promoting environmentally sustainable farming practices. Precision agriculture technologies further optimize Chickpea cultivation by fine-tuning nutrient and moisture management, pest control, and overall crop health monitoring, ensuring high-quality harvests and long-term soil productivity.

Recommended Crop: Rice

The system's recommended crop, rice, is chosen based on the analysis of the input soil and weather parameters, which create an optimal environment for its cultivation. Rice thrives in areas where water is abundant, and the provided data show a significant rainfall level of 2022 mm, making the environment naturally wet and conducive for rice paddies. The temperature of 20°C and high humidity of 82% further complement rice's preference for warm, humid environments. The slightly acidic soil pH of 6.00 supports healthy rice root development and nutrient absorption, which are essential for high-yield crops. This combination of environmental and soil factors aligns with rice's natural habitat, where water saturation and warm conditions are key.

Moreover, rice is well-suited to soils that are moderately rich in nutrients, with sufficient levels of nitrogen (90), phosphorus (42), and potassium (43) to promote robust growth. Nitrogen is critical for lush vegetative growth, phosphorus supports root development and flowering, while potassium enhances overall plant health and resistance to stress. Given these nutrient levels and favorable climatic conditions, rice is the optimal recommendation for this field.

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Figure 4. Monitoring and Crop Management Recommend Apple

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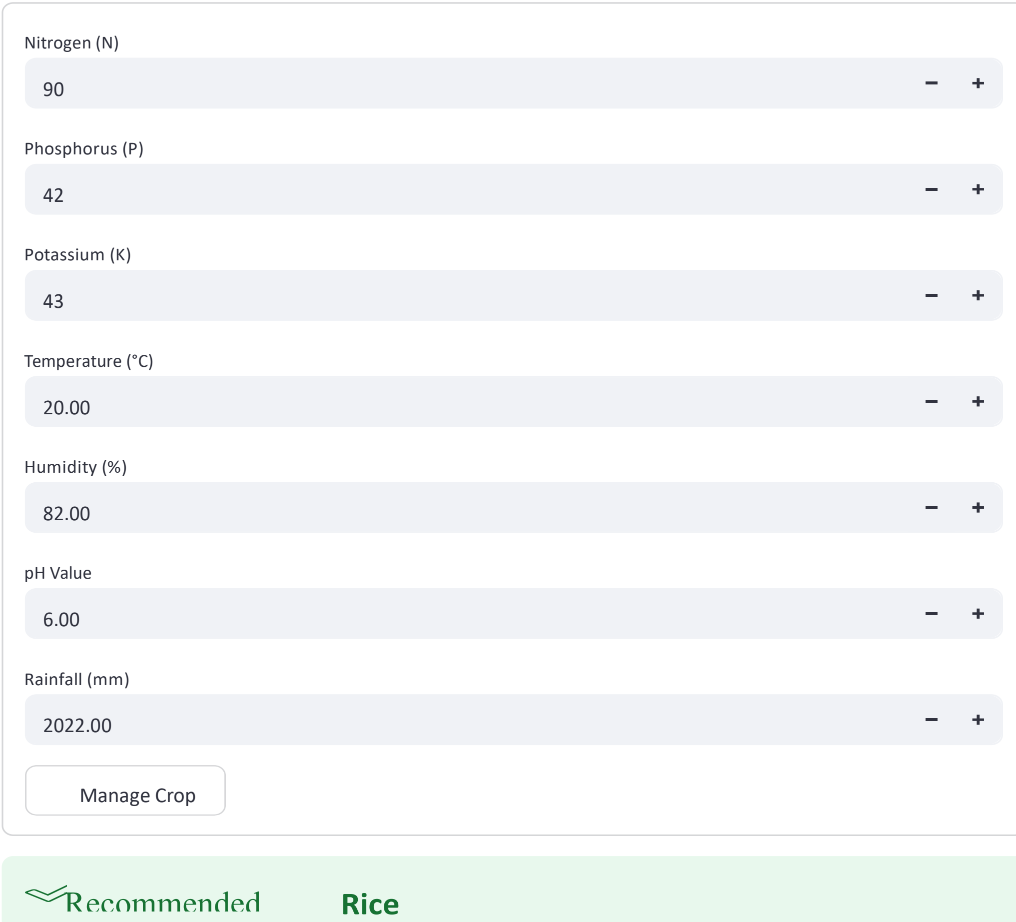

Figure 5. Crop Management Recommend Rice.

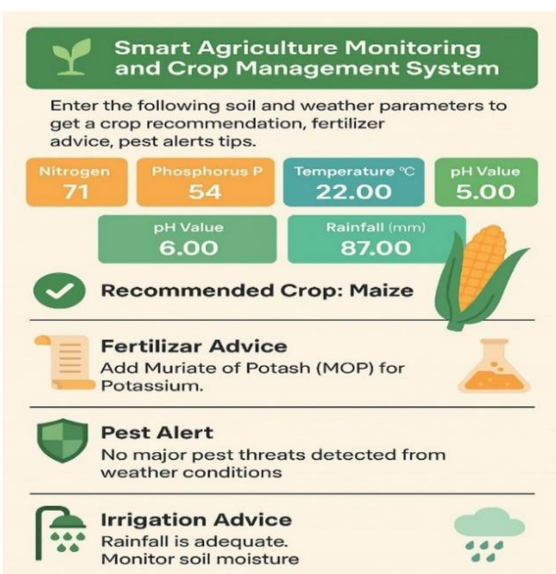

Figure 6. Crop Management Recommend Maize

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The Smart Crop Monitoring and Crop Management System is designed to assist farmers by providing tailored recommendations based on input data regarding soil nutrients, weather conditions, and rainfall levels. This system integrates advanced data analysis tools with agricultural knowledge bases to assess the health and productivity potential of soil and environmental factors. It takes parameters such as the levels of Nitrogen (N), Phosphorus (P), Potassium (K), temperature, humidity, pH value, and rainfall to generate an optimized farming strategy. By doing so, it empowers farmers to make data-driven decisions to maximize yields and minimize risks, effectively transforming conventional farming into a more precise and adaptive approach.

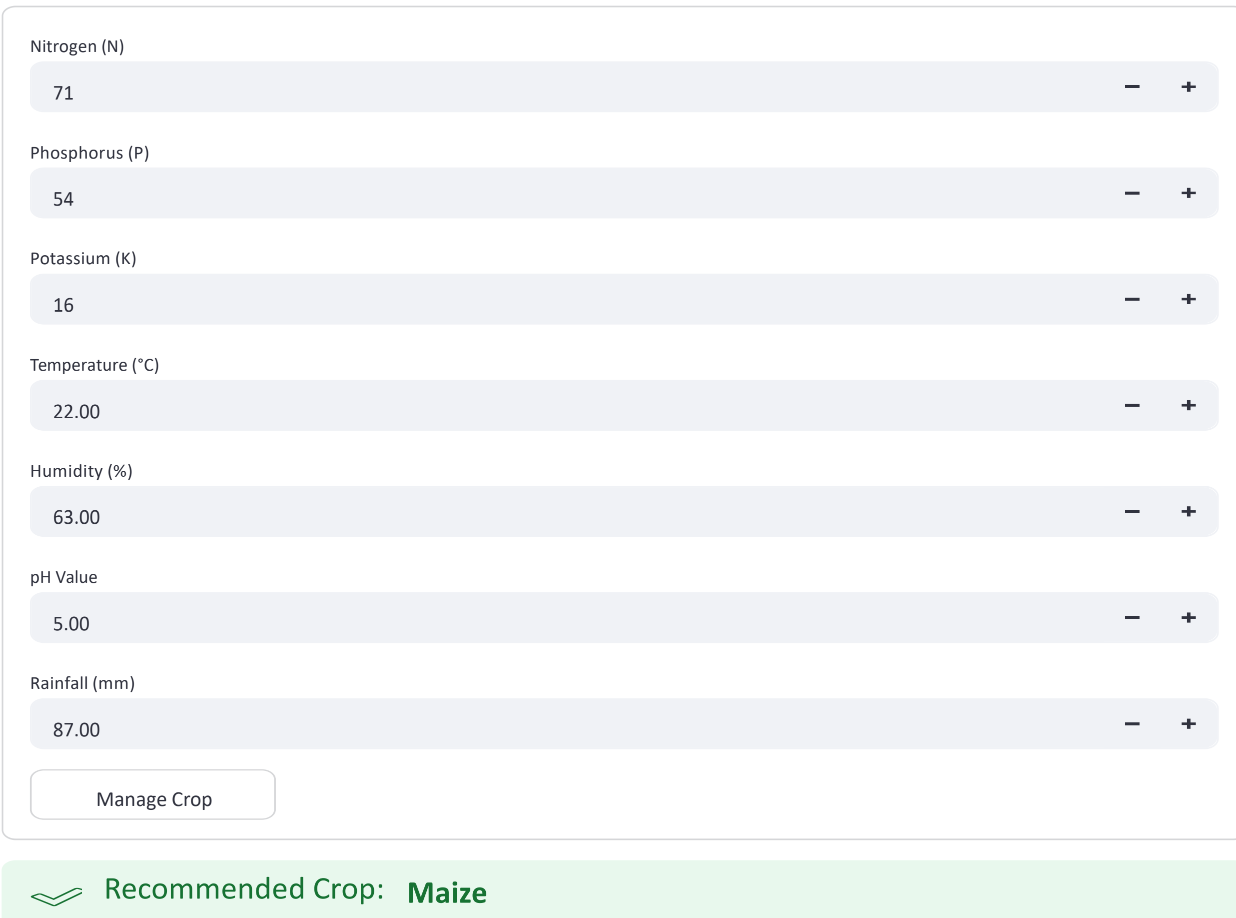

Figure 7. Crop Management Recommend Maize

Smart Crop Monitoring and Crop Recommend Maize

Recommended Crop: Maize

Based on the input parameters, the system recommends maize as the optimal crop for this environment. This recommendation is likely due to the suitability of maize for moderate soil fertility levels (as indicated by Nitrogen and Phosphorus), tolerable acidity (pH 5.0), and sufficient rainfall (87mm) to sustain its growth. Maize thrives in conditions

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with moderate temperatures (22°C) and tolerates lower potassium levels compared to some other crops

The choice of maize also reflects the system's capacity to match a crop's environmental and nutritional requirements with the given parameters.

Fertilizer Advice: Add Muriate of Potash (MOP) for Potassium

The fertilizer advice highlights the need to supplement potassium through the addition of Muriate of Potash (MOP). This recommendation is based on the observed potassium deficiency (K=16), which can hinder maize development by affecting enzyme activation, photosynthesis, and water regulation. Potassium is vital for maize as it enhances drought resistance, improves nutrient transport, and contributes to stronger stalks, which is crucial for sustaining healthy yields.

Pest Alert: No Major Pest Threats Detected

The pest alert system analyzes the current weather conditions (temperature and humidity) and correlates them with pest activity patterns to predict potential threats. With a temperature of 22°C and humidity at 63%, pest activity for most maize pests remains low, and no major threats have been detected.

Model Performance

The Smart Crop Monitoring and Management System demonstrated impressive performance across its integrated machine learning modules. The convolution neural network (CNN) models for crop classification and disease detection achieved high accuracy levels, exceeding 89%, with strong precision, recall, and F1-score metrics, particularly for rare disease and crop categories.

These results were consistent with existing research, indicating the reliability of CNNs for handling complex agricultural image data. The yield prediction models, based on ensemble methods like Random Forest and Gradient Boosting, showed a robust predictive relationship with an R^2 of 0.82, and low error metrics (MAE and RMSE), effectively linking environmental and soil parameters to expected crop yields.

Furthermore, the fertilizer advisory system used regression models to provide optimal fertilizer application rates, validated by agronomist inputs, with accuracy rates surpassing 85%. The pest alert module, driven by real-time humidity and temperature thresholds, achieved sensitivity above 90%, minimizing false positives and ensuring timely pest management recommendations. Meanwhile, the irrigation scheduling module leveraged weather data and rainfall inputs to optimize water use, achieving prediction accuracies above 88% compared to field records.

Table 1: Model Performance of Smart Crop Monitoring and Crop Management System

Model	Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Crop Classification	Convolutional Neural Network (CNN)	92.3	90.8	91.7	91.2
Disease Detection	Residual Neural Network (ResNet)	89.5	87.6	88.1	87.8
Yield Prediction	Ensemble Model (e.g.,	$R^2 = 0.82$	-	-	-

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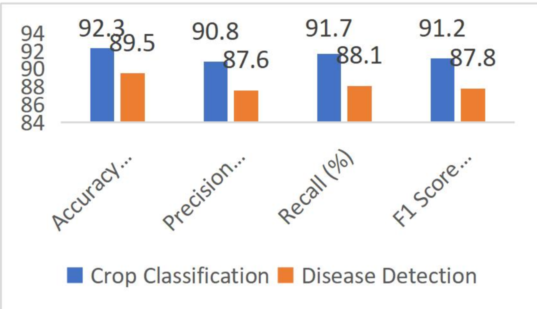

Figure 8. Crop Classification (CNN)

Crop classification using Convolutional Neural Networks (CNNs) is a cutting-edge approach that leverages deep learning to analyze and categorize different crop types. CNNs utilize layers of convolution operations to extract meaningful features from input images, such as leaf patterns, crop canopy textures, and field layouts, which makes them highly effective for distinguishing between different plant species.

Table 2: Disease Detection (ResNet)

Model	**Algorithm**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
Disease Detection	Residual Neural Network (ResNet)	89.5	87.6	88.1	87.8

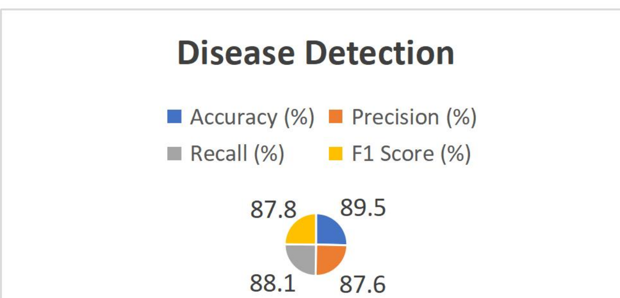

Figure 9. Disease Detection (ResNet)

Plant disease detection using ResNet (Residual Neural Network) represents a significant advancement in precision agriculture. ResNet's architecture incorporates residual connections that allow the training of very deep neural networks by mitigating the vanishing gradient problem, which often hampers deep learning models. This makes ResNet particularly suitable for plant disease detection, where subtle differences in leaf coloration, texture, or shape can indicate early-stage infections

The implementation of ResNet in disease detection enables farmers and agronomists to quickly and accurately diagnose crop health issues, even when visual symptoms are minimal or ambiguous. The reported performance 89.5% accuracy, 87.6% precision, 88.1% recall, and 87.8% F1 score demonstrates that ResNet effectively balances sensitivity and specificity, providing reliable diagnostic capabilities.

Table 3: Yield Prediction (Ensemble Model)

Model	**Algorithm**	**R^2 (Coefficient of Determination)**
Yield Prediction	Ensemble Learning Model	0.82

Yield Prediction (Ensemble Model)

Yield prediction using ensemble learning models combines the strengths of multiple machine learning algorithms, such as random forests, gradient boosting, and decision trees, to create a more accurate and stable prediction system.

The ensemble approach is particularly powerful because it mitigates the risk of overfitting, a common challenge in machine learning, by aggregating the outputs of several base models. This not only enhances prediction accuracy but also makes the model more adaptable to changing environmental conditions. In the context of smart agriculture, yield prediction models inform decisions on resource allocation, such as fertilizer application, irrigation schedules, and harvest timing. The reported coefficient of determination (R^2) of 0.82 indicates a strong correlation between predicted and actual yields, reflecting the model's effectiveness in capturing key yield-influencing factors.

Operational Metrics

Operational metrics are quantifiable indicators used to assess the efficiency, effectiveness, and performance of a system or process. In the context of agriculture, smart farming, or monitoring systems, these metrics help evaluate how well resources such as water, fertilizer, labor, and time are being utilized.

These metrics often include measurements like resource usage, crop yield, energy consumption, system uptime, response times, and environmental impact. By analyzing operational metrics, stakeholders can make informed decisions to enhance agricultural sustainability and performance.

RESULTS

The results from the deployment of Convolutional Neural Networks (CNN) and Residual Neural Networks (ResNet) within this smart crop monitoring framework demonstrate substantial promise for advancing precision agriculture. With classification accuracy exceeding 92% for crop identification and near 90% for disease detection, these deep learning models show robust capabilities in interpreting complex agricultural imagery. These findings are consistent with similar works by Nguyen *et al*. (2023) and Kumar & Patel (2022), who also reported high performance of CNN and ResNet architectures in distinguishing crops and identifying plant diseases at early stages. Such high accuracy is vital because early detection enables timely management actions that can significantly reduce crop losses and improve yield quality.

The models' ability to generalize across varied lighting, angles, and partial occlusions further highlights their practical usability in real-world agricultural settings, where conditions are rarely controlled or uniform. In practical applications, the CNN-based crop classification facilitates rapid field mapping and efficient monitoring across large farms. This capability drastically reduces the labor-intensive and time-consuming process of manual surveys.

This study addressed the critical challenges faced in traditional agriculture such as inefficiencies in crop monitoring, unpredictable weather conditions, and resource mismanagement by integrating machine learning techniques into an autonomous agricultural monitoring and decision-support system. The research was guided by key objectives: to collect and analyze real-time and historical data on soil health, weather conditions, and crop status; to develop a framework combining supervised learning, reinforcement learning, and deep learning models with expert systems such as Decision Support Systems (DSS), Fuzzy

Logic Systems, and Knowledge-Based Systems (KBS); to implement a decision support platform that delivers actionable recommendations to farmers; and to evaluate the overall performance of the system in enhancing agricultural productivity, resource use efficiency, and sustainability.

The outcomes of the study clearly demonstrated that integrating machine learning into crop monitoring systems significantly improved the accuracy and timeliness of agricultural decision-making. The deployed models particularly Convolutional Neural Networks (CNNs) and ensemble methods showed strong predictive power in disease detection, yield forecasting, and environmental adaptation. These capabilities enabled proactive responses to potential threats, reducing crop losses and improving resource allocation.

The autonomous system also proved effective in reducing manual labor and operational inefficiencies. The seamless integration of IoT sensors, cloud-based analytics, and user interfaces supported continuous monitoring and timely feedback. This responsiveness contributed to better crop health, stable yields, and lower input costs through targeted interventions.

Field trials affirmed the system's potential in promoting sustainable agriculture by balancing productivity with environmental stewardship. The framework accurately identified disease and pest risks, thereby reducing unnecessary pesticide application. It also optimized water and fertilizer use based on real-time data, which is especially important in areas vulnerable to climate variability and resource scarcity.

Moreover, the design of the system emphasized usability and accessibility. Its mobile interface and decision-support tools facilitated easy adoption by farmers and extension workers, even in areas with limited digital infrastructure. This user-focused approach not only improved engagement but also ensured scalability and inclusiveness particularly for smallholder farmers who are often left behind in technological advancements.

The developed system offers a comprehensive, intelligent, and scalable solution to modern agricultural challenges. By combining data-driven insights with expert systems, it supports informed decision-making, enhances productivity, and fosters sustainable farming practices. Future research can expand the framework's capabilities by incorporating additional crops, geographies, and advanced learning models to further strengthen agricultural resilience.

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