AI-Integrated Smart Agriculture System Using Autonomous Rover for Precision and Sustainable Farming

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***Abstract*— The goal of AI-driven Smart Agriculture through Fully Automated Agricultural Machines (AI-Integrated SMART Agriculture System Using Autonomous Rover for Precision and Sustainable Farming), is to increase yield in traditional agriculture by using integrated technology (AI) and advanced sensors connected to the internet, with the ability to move freely without human operators. By equipping a multi-sensor rover with multiple sensors (moisture, ph, DHT11 temperature, humidity, colour, and many others) and a high-resolution camera module, it will be possible to capture current field conditions, and accurately monitor soil quality, crop growth, and environmental conditions in real-time. The data collected through the rover will give the farmer a complete record of their agricultural activities, which will include the analysis of soil quality, crops' growth and environmental conditions over a period of time. Through the use of a CNN-based (Convolutional Neural network) model, each crop will have its own "leaf disease" detection and stress assessment model to find out if there is an infection and/or nutrient deficiency in the crop as soon as possible, so the farmer can take preventative action before too much time has passed. A K-Nearest Neighbors (KNN)-based and/or many other machine learning models will be used to classify and predict crop yield. In addition to the above, a LLM (Large Language Model)-based advisory system will be integrated to provide the farmer with a summary report of all the information received from the rover, and a recommendation for the most efficient methods of managing their resources (water and nutrients), as well as other general information related to the efficient and sustainable use of water, fertilizers, pesticides, and natural resources in the agricultural environment. In order to guarantee spatial precision and effective field coverage, data can be collected from several zones thanks to the autonomous rover's independent field navigation. This project creates a comprehensive precision agriculture framework that improves decision-making, decreases manual labor, conserves natural resources, and increases overall crop productivity by fusing AI-driven analytics, IoT-enabled sensing, computer vision, and autonomous navigation. This advances sustainable and technology-driven farming.**

Keywords— Precision Agriculture, Autonomous Rover, Machine Learning, IoT Sensors

I. INTRODUCTION

Agriculture continues to be the foundation of the global economy and is critical to providing food security for the ever-increasing global population. Most traditional methods of farming are dependent on manual observation, experience-based decision-making, and inefficient resource use, which often result in lower crop yields, greater operational costs, and harm to the environment. Additionally, other factors such as changing weather patterns, soil depletion, pest outbreaks, and lack of access to recent agricultural knowledge increase the obstacles farmers face in this technologically advanced age. Therefore, there is a tremendous need for intelligent, data-driven agricultural solutions to help improve efficiency of agriculture while promoting sustainable farming practices.

With the advancement of artificial intelligence (AI), Internet of Things (IoT), and autonomous robotics, a new era of agriculture is becoming possible. IoT-enabled devices allow for continuous monitoring of soil and other environmental conditions, machine learning and computer vision technologies can provide better assessments and predictions of crop health and the presence of diseases, and autonomous agricultural robots can efficiently gather vast amounts of data over large areas with little or no human input. The combination of these new technologies enables the development of intelligent agricultural systems which provide farmers with immediate data and practical solutions for achieving their best resource management and reduced labor needs and improved production rates.

In this regard, the suggested AI-Integrated Smart Agriculture System with an Autonomous Rover offers a thorough method for sustainable and precise farming. The system monitors crop conditions, detects plant diseases, forecasts production, and provides intelligent farming advice by combining multi-sensor data collecting, AI-driven analytics, and autonomous field navigation. The suggested approach is to provide farmers with precise, timely, and useful information by utilizing sophisticated machine learning models and intelligent advisory processes. This will help to improve productivity, sustainability, and resilience in contemporary agricultural operations.

II. Related Works

The research conducted by Sandeep Kumar and his colleagues through their work which appeared in the International Conference on Smart Technologies in Computing Electrical and Electronics (ICSTCEE) from 2020 to 2020. The researchers demonstrated through their study that plant disease monitoring requires implementation because it improves agricultural output. The results of manual plant observation systems show that they need extended times for observation yet produce a high frequency of incorrect outcomes. Their machine learning system implements its automated process to detect diseased leaf regions through image analysis and classification methods. The system achieved faster disease detection and better accuracy than traditional visual inspections while needing reduced manpower. The research team which included T. Priyaradhikadevi published their research findings in "Leaf Disease Detection Using Machine Learning Algorithm" to present their machine learning system which detects agricultural diseases at ICONSTEM 2023. The researchers analyzed the Plant Village dataset which included tomato grape apple and maize leaf images that had been categorized into healthy and sick groups. The researchers used Decision Tree and Gradient Boosting methods to extract texture and shape attributes from seven photographs which they used to perform classification tasks. The researchers demonstrated how machine learning models can improve crop loss prevention through early disease detection while maintaining high accuracy levels.

The researchers found that Deep Learning systems which utilize Convolutional Neural Networks (CNNs) outperformed traditional machine learning techniques because the systems automatically learned spatial and color characteristics without needing human help. In their ICESC 2021 presentation, "Leaf Disease Detection Using Deep Learning," Teemu Sahasra and his colleagues used CNN models to identify tomato leaf diseases. The researchers used an automatic disease classification system to detect diseases at an early stage while they used picture segmentation to identify infected regions. The deep learning model achieved high classification accuracy which enabled early treatment and improved crop health because it reduced the need for human work. The researchers developed their CNN-based Plant Leaf Disease Detection and Classification method which uses image processing and deep learning techniques at CSASE 2020 according to Marwan Adnan Jasim and Jamal Mustafa Al-Tuwaijari. The researchers built their model using the Plant Village dataset which contains more than 20,000 tomato and pepper and potato plant images. The system demonstrated that CNNs can correctly identify complex visual patterns, which allows them to detect diseases with high accuracy.

Kethsy Prabavathy and his research team presented their study "Plant Leaf Disease Detection using Machine Learning" at the International Conference on Applied Artificial Intelligence and Computing (ICAAIC) in 2023. The study used five different classifiers which consisted of K-Nearest Neighbor (KNN) Support Vector Machine (SVM) Decision Tree Random Forest and CNN classifiers. The researchers selected the most effective model by assessing its performance through two criteria: accuracy and computational efficiency after they applied pre-trained CNN models for feature extraction. The CNN model achieved the highest accuracy among all models which proves that deep learning models deliver better results than traditional machine learning methods. The authors demonstrated through their research that automated analysis of early detection systems leads to significant improvements in crop protection and agricultural productivity.

Amrita S. Tulshan and Nataasha Raul (2019) gave a presentation at ICCCNT 2019 titled "Plant Leaf Disease Detection using Machine Learning." Through their research work the scientists succeeded in better classification results by developing efficient methods for both image segmentation and data preparation. The authors demonstrated that machine learning algorithms should be integrated with agricultural management systems because this approach enables automated illness diagnostics and supports farmers who work on large-scale farms.

III. PROPOSED SYSTEM

The proposed system aims to develop an intelligent smart agriculture monitoring unit that uses Internet of Things devices and sensor technology and machine learning systems to deliver real-time assessments of crop health and environmental management capabilities. The system operates through hardware components which include a Node MCU (ESP8266) microcontroller that manages processing and communication and a DHT11 sensor that measures temperature and humidity and a soil moisture sensor that tracks soil conditions and a pH sensor that measures acidity levels and a camera module that takes leaf images for disease classification. The software requirements include the Arduino IDE for microcontroller programming and Thonny IDE for executing Python based machine learning models and cloud storage platforms for data visualization and remote monitoring.

The proposed system requires implementation because it gathers sensor data from field-based sensors which operate throughout its entire operational period. The Node MCU transmits processed sensor information to the cloud using its Wi-Fi connection. The Convolutional Neural Network (CNN) model analyzes leaf images to identify and classify plant diseases. The system uses control devices to maintain optimal crop conditions because it automatically activates fans and motors according to its analysis results. The system enables agricultural operations to become more sustainable while increasing productivity because it provides effective monitoring and early disease detection and reduces manual labor requirements.

A. Sensor Data Collection

The project starts from the location shown in Figure 3.5 which presents the initial system block diagram. The agricultural area receives multiple sensors which begin their installation process. The DHT11 sensor tracks temperature

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and humidity levels while the soil moisture sensor measures water content in the soil. The sensors distribute their monitoring function throughout the field as they establish multiple measurement locations. The Node MCU microcontroller functions as the primary processing unit that connects all sensors to gather real-time sensor data which will be used for future analysis.

B. Data Transmission to Cloud

The Node MCU microcontroller uses Wi-Fi connectivity to transmit environmental data which the sensors collected to a cloud-based platform. Data preservation through this procedure creates permanent stored information which researchers can access for historical analysis and current data review as shown in Figure 3.5: Block Diagram. The cloud functions as a single data repository which farmers can access through web or mobile interfaces to monitor temperature and humidity and soil moisture and crop status trends. The cloud-based system enables remote monitoring which helps farmers make quick decisions based on accurate information.

C. Data Transmission to Cloud

The project starts from the location depicted in Figure 3.5 which shows the initial block diagram of the system. The agricultural field receives its first set of sensors which begin their installation process. The DHT11 sensor tracks temperature and humidity levels while the soil moisture sensor measures water content in the soil. The sensors monitor the field through their ability to create various measurement points. The Node MCU microcontroller functions as the primary processing component that connects all sensors to gather real-time sensor information for future examination.

D. Automated Control Mechanism

The system operates through automated control which detects environmental changes while processing incoming data. The Node MCU automatically turns on the motor and fan to control temperature and humidity when any parameter, like soil moisture or temperature, departs from the ideal range specified in the system. The system operates through closed-loop control which maintains ideal agricultural conditions without requiring operators to perform manual tasks, as illustrated in Figure 3.5.

E. Leaf Disease Detection Using CNN

The system contains a camera module which enables the autonomous rover to capture high-resolution images of crop leafs. The system employs a Convolutional Neural Network (CNN) model which detects diseases through image analysis of Figure 3.5: Block Diagram. The CNN system examines the leaf photographs to identify various disease indicators which include bacterial spots and fungal infections and nutrient deficiencies. The process of identifying problems at an early stage helps to decrease crop yield losses while it enables farmers to take immediate corrective measures for maintaining healthy crops. The system achieves better operational performance through AI-based picture analysis technology, which improves both its accuracy and information processing capacity.

F. Actionable Insights and Decision Support

The technology provides farmers with smart decision-making tools which deliver practical insights through its system that combines sensor data with image analysis and automated control systems. The cloud platform displays data to users while it alerts them about health hazards and environmental issues which are shown in Figure 3.5. The information enables users to schedule their irrigation needs better and discover more efficient ways to use fertilizer while developing methods to protect against bugs and illnesses.

G. Continuous Improvement and Adaptation

The suggested system will undergo development through its continuous process of improvement and system updates. The system improves its algorithms through better performance and enhanced sensor precision and improved predictive abilities which result from the combined efforts of farmers and field data. The block 20 form shown in Figure 3.5 represents a scalable model which organizations can expand by integrating additional sensors to measure different variables including light intensity and nutrition concentration.

Fig 1 Block Diagram

The suggested smart agricultural system's flow diagram shows how sensors, embedded systems, cloud platforms, AI modules, and actuators collaborate to provide effective crop monitoring and management. provides a clear illustration of the system's complete workflow. Flow Chart, which offers a thorough comprehension of the data flow and the automated decision-making process of the system.

The Node MCU microcontroller powers up and connects to all of the sensors, actuators, and communication modules during the system's initialization phase. This initialization procedure, which is depicted at the start of guarantees that every component is operational and prepared for data collection. The analysis made it possible for the system to make decisions based off the corrective actions that would need to be performed if the Environmental Parameters were out of their optimal range. This is accomplished by the automatic operation of actuators (such as motors or fans or irrigation systems) to correct growing conditions whenever the parameters are out of the set range. The use of this automated feedback loop (as shown in Figure 3.6) reduces the amount of manual intervention required and also ensures that corrective actions are taken in a timely manner for crop stress factors.

The visualization and alerts provided to farmers will allow farmers to act upon the insight provided by the processed data along with system status and recommendations provided through either the cloud dashboard or mobile interface. The information provided to farmers enables them to make informed decisions about recommended interventions. The complete process shown in Figure 3.6 - Flow Chart continues to function as a continuous loop which monitors environmental parameters while it detects early disease and automatically manages environmental conditions. The closed loop operation of the entire system creates increased efficiencies in production, more efficient use of resources and more sustainable precision agriculture practices.

Fig 2 Flow diagram

IV.RESULT AND DISCUSSION

A Smart Agriculture System which operates through IoT and Sensor Networks and Artificial Intelligence technology has been created and tested in order to perform automated crop health monitoring and environmental parameter assessment. The Smart Agriculture System integrates data from multiple sensors which detect both physical plant health indicators and visual plant health indicators through machine learning and convolutional neural network (CNN) algorithms that identify plant diseases. The Smart Agriculture System development team utilized Thonny IDE as their integrated development environment (IDE) for both simulation work and coding activities. Thonny IDE provides an easy-to-use and efficient Python Development Environment (PDE) for integrating AI with hardware and communication protocols. The system trial proved that actual experiments could be conducted to collect sensor data in real time while preprocessing data for transmission through cloud services to a remote interface which used machine learning models to diagnose plant health by analyzing images of damaged plants. The research results showed that using deep learning models together with CNNs for plant image analysis provided better disease detection results than human agricultural inspectors used visual inspection methods. The following section provides a more in-depth assessment of the performance and results obtained during the testing and simulation of the Smart Agriculture System.

A. TRAINING AND VALIDATION PROCESS

The algorithm training used a dataset containing pictures of intact and damaged leaves from various crop species. The researchers used multiple data augmentation techniques which included both rotation and flipping and contrast modification to create additional data for their research and to improve model performance. The CNN model takes input images and its parameters are optimized through a learning process that repeats until it achieves its final state which is depicted in Figure 4.2-Training Process. The system training process displays both its implementation setup and its complete training procedure which shows all the training steps needed for system operation.

BACTERIAL SPOT ,EARLY BLIGHT ,LATE BLIGHT

DULEAM MOLD ,MOSAIC VIRUS ,SEPTORIAL LEAF SPOT

SPIDER MITES TWO-SPOTTED SPIDER MITE, TARGET SPOT, YELLOW LEAF CURL VIRUS

B. TRAINING DATA

The training used the Adam optimizer which operated at a learning rate of 0.001 for 50 epochs while processing data in groups of 32. The training process used the categorical cross-entropy function to evaluate prediction errors which served as the loss measurement. Figure 4.2: Training Process shows that both training and validation accuracy increased during all the epochs which demonstrates effective learning without significant overfitting. The model achieved stable performance through training and validation loss curves which showed convergence after approximately 30 epochs of testing.The results shown in Figure 4.2 demonstrate that the CNN model can accurately classify plant health conditions and detect early diseases with high effectiveness and reliability.

C. CLASSIFICATION REPORT

The testing process produces a classification report which assesses the trained model's ability to forecast various types of plant health issues. The model evaluation report presents essential performance metrics, which include precision and recall and F1-score and support, as the complete set of indicators that determine the model's performance. The testing process results demonstrated that the algorithm could successfully detect both healthy and diseased leaf samples through its different measurement techniques. The classification report shows that the proposed model produces accurate and dependable classification outcomes, which makes it appropriate for agricultural tasks that need real-time information processing. The deep learning method achieves this level of performance because it effectively detects diseases at an early stage and monitors crop health throughout smart farming operations.

Classification Report

	precision	recall	f1-score	support
0	0.90	1.00	0.95	28
1	0.91	0.97	0.94	31
2	1.00	1.00	1.00	58
3	1.00	0.98	0.99	91
4	1.00	1.00	1.00	61
5	0.94	1.00	0.97	49
6	1.00	0.98	0.99	51
7	0.99	0.97	0.98	134
8	0.99	0.97	0.98	88
9	1.00	1.00	1.00	96
accuracy			0.98	687
macro avg	0.97	0.99	0.98	687
weighted avg	0.98	0.98	0.98	687

Figure 3 CLASSIFICATION REPORT

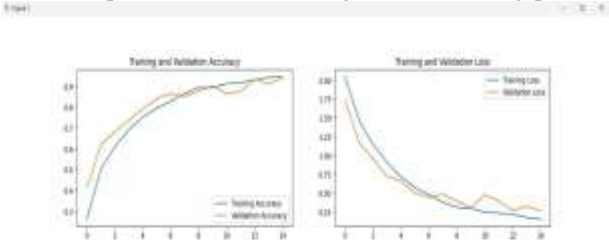
D. CONFUSION MATRIX ANALYSIS

The confusion matrix demonstrates which plant health status classes the model can predict and it displays the algorithm's classification ability through quantitative and visual measurement. The display of correct and incorrect predictions for each category enables a deeper understanding of model accuracy and possible misclassifications. The Confusion Matrix provides a complete view of this study by displaying how true positive and false positive and true negative and false negative values are distributed across all predicted classes. The model shows strong discriminative power because its predictions match real world labels. The system makes very few mistakes because it can only confuse diseased leaf samples that share similar color and texture characteristics.

Figure 4 CONFUSION MATRIX

E. VISUALIZATION OF TRAINING RESULTS

The accuracy/loss charts for training and validation provide essential information about how the CNN model performs during training and learning processes. The accuracy curve shows a persistent upward trend, as seen in Figure 4.5, Training and Validation Accuracy/Loss Plots, which demonstrates that the model operates at improved performance levels after each training period. The loss curve shows a continuous decline which proves that the optimization process achieves better results because it decreases prediction errors throughout the training period.



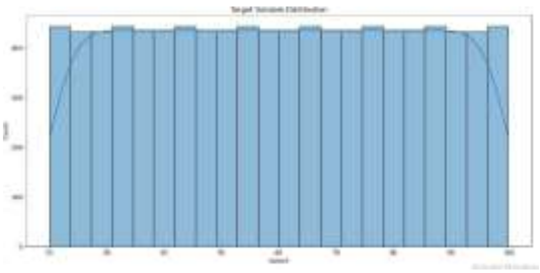
The model has achieved its final performance level after 30 epochs because the accuracy and loss curves reached their stable state. The network has acquired fundamental dataset characteristics which it now displays through its current performance level. The visual outcomes shown in Training and Validation Accuracy/Loss Plots demonstrate that the deep learning model achieved its optimal performance while handling the natural variability present in agricultural image datasets. The curves display smooth evolution because appropriate regularization and data augmentation methods were applied which resulted in minimal overfitting and strong generalization capabilities.

F. IMAGE DATASET AND OUTPUT VISUALIZATION

The training images contained samples of healthy leaves and leaves with slight infections and leaves from severely sick plants which were obtained from multiple crop types. The image preprocessing process used normalization and scaling methods to create standardized input proportions which applied to all images. The multiple dataset sources helped researchers improve model performance through better generalization capabilities. The system underwent testing through real-time photography which used the camera module during simulation. The algorithm achieved accurate plant health classification by processing soil pH and moisture and temperature sensor data which it displayed on the cloud dashboard. The proposed system can provide complete crop health assessments because the result visualization shows all system parameter checks. This development enhances precision agriculture methods while it reduces the requirement for human agricultural site inspections.

1. TARGET VARIABLE DISTRIBUTION

The distribution of the KNN model output is illustrated in Fig. 4.5, which presents a histogram of predicted target values along with a smoothed density curve



Target Variable Distribution of KNN Model

The results reveal a uniform and well-balanced distribution of predicted values across the target range of 20–100, indicating that the model does not exhibit bias toward specific output intervals. This balanced behavior suggests that the KNN model effectively generalizes across diverse input patterns without over-representing dominant ranges.

Such stability is particularly important in smart agriculture applications, where environmental parameters such as temperature, humidity, and soil moisture may vary dynamically. The uniform distribution demonstrates the model's capability to handle real-world variability and produce consistent predictions, thereby enhancing system reliability.

2) TRUE VALUES VS. PREDICTIONS ANALYSIS

The relationship between actual target values and the corresponding KNN predictions is shown in Fig. 4.6

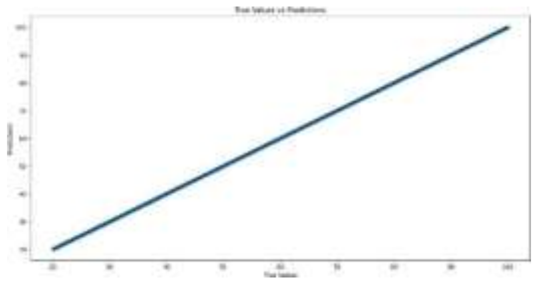


Fig. 4.6. True Values vs. Predictions for KNN Model

The plot exhibits a near-perfect linear correlation, with predicted values closely aligned to the ideal diagonal reference line. This strong linearity confirms that the KNN model achieves high prediction accuracy with minimal error deviation, reflecting excellent regression consistency. The low dispersion of points around the reference line in- dicates minimal residual error, demonstrating the model's ability to accurately capture underlying data relationships.

This performance validates the effectiveness of the chosen feature set and the suitability of KNN for refining prediction outputs in the proposed system.

Overall, the strong agreement between ground truth values and predicted outputs confirms that the KNN model reliably complements the CNN-based classification by providing accurate numerical estimation and decision refinement.

V.CONCLUSION

The Innovative AI-based Intelligent Agriculture System (IISAAS) will change the world of agriculture. By incorporating many different types of Sensors (including DHT11 Humidity/Temperature, PH, Soil Moisture, Color, etc.), along with an Advanced Convolutional Neural Network (CNN) for Disease Detection, Farmers will now have access to real-time, continuous quantitative data on the environment (including ambient temperature, humidity, soil moisture, and soil pH) and their Crops (including Plant Health, Color and Quality). The Autonomous Rover will provide increased Field Coverage and improved Mobility by allowing Farmers to collect Accurate and Live Data without the necessity of Manual Data Collection. This Real-Time Data will be processed via Machine Learning Algorithms (including K-Nearest Neighbors - KNN) that allow for an Accurate Yield Prognosis and Soil Classification; in addition to this, the Large Language Model (LLM)-based Advisory Module will provide Contextual Recommendations to Farmers, helping them make better decisions. When combined, these various components form the basis for a Completely Automated, Data-Driven Precision Agriculture System, resulting in Reduced Human Errors, Optimal Use of Resources and faster Adoption of Sustainable Agricultural Practices.

The Integration of IoT Devices with Cloud Computing for the purpose of Decision-Making based on AI/ML is a Significant Advance on the Road to Digitalizing Agriculture. By providing Real-Time Data to Farmers, this Project will ultimately allow for Improved Crop Productivity and Health through early Disease Detection and Control of the Environment and will support Farmers' Capacity to Make Better Decisions about Farm Operations.

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