Indian Journal of Multidisciplinary Research (IJOMR)
(Yearly, Blind Peer-Reviewed, Multidisciplinary Journal)
Home Page: https://ijomr.org

ISSN: 3048-8036 *(Online)*
July, 2026 Vol. 3 Issue 1
Page No: 267-279

Agri Vision: Soil Monitoring and Crop Recommendation System Using IoT and Machine Learning

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Received: 24.04.2026

Accepted: 07.07.2026

Published: 09.07.2026

Abstract

Agriculture remains a critical contributor to food security and economic stability; however, traditional soil testing practices and intuition-driven crop selection often result in inefficient resource utilization and reduced productivity. To overcome these challenges, this study introduces Agri Vision, a standalone Soil Monitoring and a crop recommendation framework that combines deep learning, machine learning, and IoT enabled sensing deployed on a Raspberry Pi platform. The developed approach identifies soil categories by analyzing images acquired through a USB camera, which are interpreted using a MobileNetV2 driven convolutional neural network, enabling accurate identification of seven soil categories. In parallel, soil parameters including moisture, pH, and temperature are captured through specialized sensing devices designed for accurate environmental measurement, interfaced through the MCP3008 analog-to-digital converter. The predicted soil class and sensor readings are combined and analyzed using a Random Forest model to recommend suitable crops for cultivation. A thkinter-based kiosk interface provides an intuitive user experience by supporting image capture, live sensor visualization, and instant result generation, along with email and quick response-based report delivery. All processing tasks are executed directly on the Raspberry Pi itself, enabling independent operation without internet access and ensuring reliable use in isolated and underserved farming regions. Experimental evaluation demonstrates high accuracy in soil classification and reliable crop prediction, validating the experimental outcomes confirm the practical viability of the developed system. Agri Vision provides an affordable and extensible framework for precision farming while also enabling future upgrades like soil nutrient analysis and intelligent irrigation automation.

Keywords: *Precision, Agriculture, Soil Monitoring, Crop Recommendation, Deep Learning, Internet of Things (IoT), MobileNetV2, Random Forest, Raspberry Pi*

Introduction

Agriculture remains a cornerstone of global food security, economic stability, and employment generation. In developing nations such as India, a large segment of the population continues to rely on agriculture either directly or indirectly, making agricultural productivity a matter of national importance (Gotlur et al., 2024; Vatin et al., 2024). Despite this significance, farming outcomes are frequently constrained by traditional practices that depend on manual assessment, experiential decision making, and irregular evaluation of soil conditions. Conventional soil analysis methods,

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including visual inspection and laboratory-based evaluations typically demand significant effort and time; while failing to accurately reflect the dynamic and location dependent conditions encountered in actual agricultural fields (Ananthi et al., 2017; Babu et al., 2020). These challenges often result in inefficient use of inputs, inappropriate crop selection, and increased vulnerability to climatic fluctuations.

Advancements in artificial intelligence, Internet of Things technologies, embedded systems, and edge computing have introduced fresh opportunities have emerged to support smarter farming choices. Precision agriculture now represents an evidence driven methodology that relies on ongoing observation, analytical intelligence, and efficient input management to increase yield quality while minimizing ecological harm (Ramesh et al., 2023; Kamilaris & Prenafeta-Boldú, 2018). Sensor networks and machine learning techniques enable real time assessment of soil and environmental parameters, allowing farmers to base decisions on objective measurements rather than intuition alone. With rising food demand, limited cultivable land, and increasing climate variability, the shift to- ward intelligent and data guided farming practices has become increasingly necessary (Li et al., 2015).

To overcome these issues, this study introduces Agri Vision, a self contained and portable system developed to assist farmers with intelligent soil analysis and crop selection. The solution brings together sensor based soil monitoring, image driven soil identification using deep learning, and predictive crop selection through machine learning, all implemented within a unified embedded framework. Implemented on a RaspberryPi4ModelB,Agri Vision performs sensor interfacing, image acquisition, model inference, and user interaction locally, eliminating reliance on cloud infrastructure or external controllers (Thangammal et al., 2024; Patel et al., 2021). Essential soil characteristics including moisture content, thermal conditions, and acidity levels are captured through properly calibrated sensing units, while soil category identification is performed by a MobileNetV2-based deep learning model using images acquired from the field. (Babalola et al., 2023; Kamilaris & Prenafeta-Boldú, 2018). The collected sensor readings and soil classification results are jointly analyzed through a Random Forest algorithm to identify crops best suited to the observed conditions, providing a flexible and economical approach for intelligent and sustainable farming (Singh et al., 2023).

Literature Review

The use of computational intelligence in agriculture has expanded significantly in response to the shortcomings of conventional farming and soil evaluation practices. Early agricultural decision support systems primarily relied on manual soil testing, laboratory based chemical analysis, and rule based expert systems (Ananthi et al., 2017; Babu et al., 2020). While these methods offered basic agronomic insights, they were often time, expensive, which makes them impractical for providing timely decisions in changing on-field agricultural scenarios. These limitations motivated researchers to investigate automated and data driven approaches to improve agricultural productivity and resource efficiency (Gotlur et al., 2024; Vatin et al., 2024).

With progress in artificial intelligence, deep learning techniques have become increasingly prominent in agricultural applications, particularly for image based analysis. CNNs have been widely adopted for soil and crop classification due to their capability to extract discriminative spatial features such as texture, color variation, and surface structure (Babalola et al., 2023; Kamilaris &

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Prenafeta-Boldú, 2018). Several architectures, including VGGNet, ResNet, and MobileNet, have demonstrated strong performance in soil classification tasks. Among these, MobileNetV2 has emerged as a preferred model for embedded deployment because of its lightweight architecture and reduced computational complexity, making it suitable for resource constrained platforms (Kamilaris & Prenafeta-Boldú, 2018). The use of transfer learning further improves model performance by allowing previously trained networks to be efficiently adapted to agricultural datasets with limited sample sizes (Alom et al., 2019).

Fig. 1 presents a comparative overview of traditional agricultural practices and existing smart agriculture solutions. The figure highlights that most existing systems focus on individual components such as IoT based soil sensing, image-based soil analysis, or machine learning driven crop recommendation. However, integrated offline embedded platforms that combine sensing, visual analysis, and intelligent decision making remain relatively limited. The proposed Agri Vision system addresses this research gap by unifying IoT sensing, CNN based soil classification, and machine learning based crop recommendation within a standalone Raspberry Pi platform.

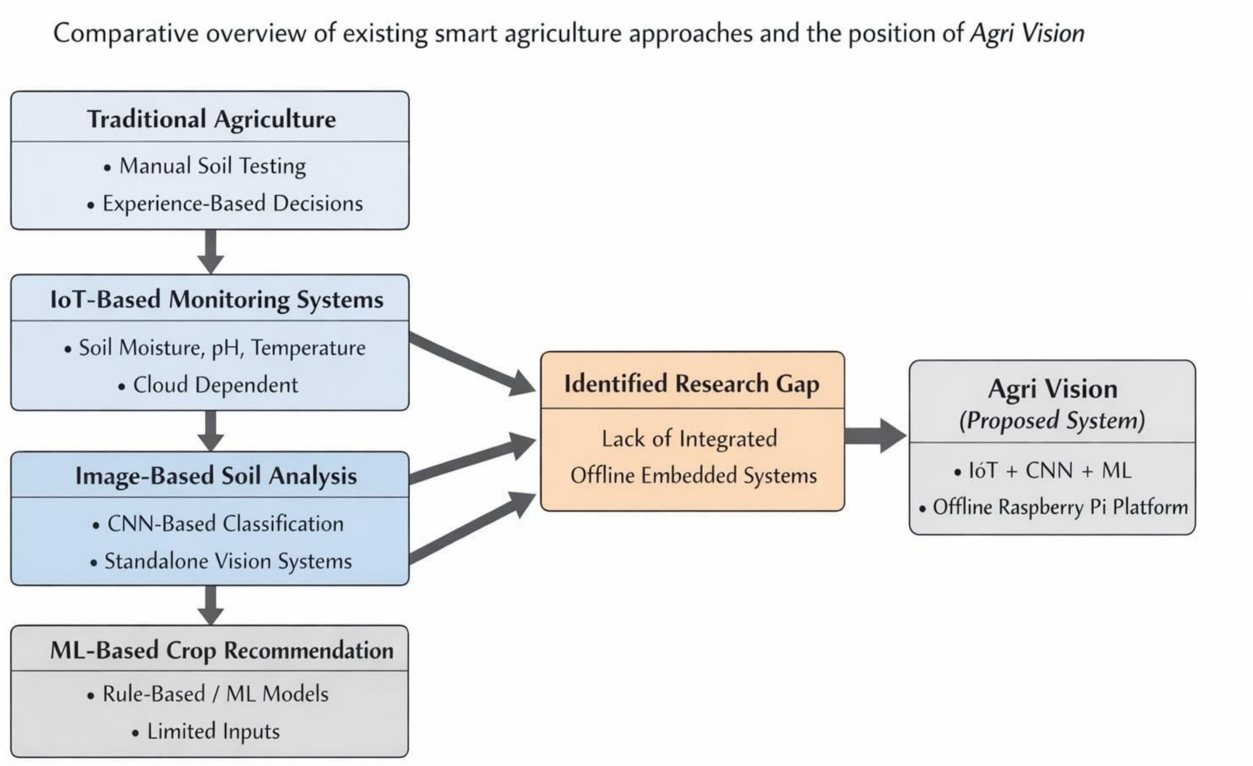

Fig.1.Comparative overview of existing smart agriculture approaches and the position of Agri Vision

IoT enabled soil monitoring solutions have been widely explored to enable continuous tracking of

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key soil attributes such as moisture content, temperature levels, and pH values. (Thangammal et al., 2024; Patel et al., 2021). Earlier implementations commonly relied on Arduino based controllers. These systems were commonly connected to cloud services to store and visualize data, which resulted in reliance on uninterrupted internet access and led to higher deployment and maintenance expenses. More recent studies have moved toward edge-based architectures built on Raspberry Pi platforms, where data is processed locally to minimize response delays and ensure dependable operation in geographically isolated farming regions (Ramesh et al., 2023; Li et al., 2015).

Data driven learning models have become central to modern crop advisory and yield forecasting research. Approaches including Support Vector Machines, Decision Tree methods, k-Nearest Neighbor classifiers, and ensemble-based Random Forest models have been widely tested on datasets composed of soil characteristics and environmental conditions. (Kavitha, 2023), (M. et al., 2023; Chaudhari et al., 2020). Within this group of techniques, Random Forest models have consistently shown superior effectiveness because they aggregate multiple decision trees, limit overfitting, and accurately capture complex nonlinear patterns commonly found in agricultural datasets (Singh et al., 2023). Despite these advances, fully integrated offline agricultural decision support systems remain scarce, motivating the development of the proposed Agri Vision platform.

Objectives of the Study

The primary objective of this research is to develop an intelligent and self-contained agricultural decision-support system capable of assisting farmers in soil assessment and crop selection through the integration of Internet of Things (IoT), deep learning, and machine learning technologies.

The specific objectives of the study are as follows:

1. To design and implement an IoT-enabled soil monitoring framework capable of measuring critical soil parameters such as moisture, pH, and temperature in real time.
2. To develop a lightweight deep learning model based on MobileNetV2 for accurate classification of soil types using field-acquired soil images.
3. To integrate sensor-derived soil characteristics and image-based soil classification results into a unified agricultural data profile.
4. To develop a machine learning-based crop recommendation model using the Random Forest algorithm for identifying suitable crops under varying soil conditions.
5. To evaluate the effectiveness, accuracy, and deployment feasibility of the proposed system in practical agricultural environments.

Methodology

The proposed Agri Vision system follows a multi-stage methodology integrating IoT sensing, deep learning, machine learning, and embedded computing technologies for intelligent soil monitoring and crop recommendation.

A. *Data Acquisition*

Soil information is collected through two independent sources. First, soil images are captured using a USB camera connected to the Raspberry Pi. Second, environmental parameters including soil moisture, pH, and temperature are measured using dedicated sensors. The analogy outputs of the moisture and pH sensors are converted into digital signals using the MCP3008 Analog-to-Digital Converter (ADC).

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B. *Data Preprocessing*

The acquired soil images are resized to 224 × 224 pixels and normalized before being supplied to the deep learning model. Sensor values are calibrated and normalized to eliminate measurement inconsistencies and ensure compatibility with the machine learning pipeline.

C. *Soil Classification Using Deep Learning*

A MobileNetV2-based Convolutional Neural Network (CNN) is employed to classify soil images into seven categories, namely alluvial soil, arid soil, black soil, laterite soil, mountain soil, red soil, and yellow soil. Transfer learning is utilized to improve classification performance while reducing computational requirements on embedded hardware.

D. *Sensor Data Integration*

The classified soil type is combined with real-time sensor measurements including moisture content, temperature, and pH. These attributes collectively form a feature vector representing the physical and environmental characteristics of the soil.

E. *Crop Recommendation Using Machine Learning*

A Random Forest classifier is trained using agricultural datasets containing soil properties and corresponding crop labels. During prediction, the model analyzes the integrated feature vector and recommends crops that are best suited to the observed soil conditions.

F. *User Interface and Edge Deployment*

The complete framework is deployed on a Raspberry Pi 4 Model B. A Tkinter-based graphical user interface enables users to capture soil images, monitor sensor readings, view soil classifications, and obtain crop recommendations. The generated results can also be shared through QR codes and email-based reports.

G. *Performance Evaluation*

The proposed system is evaluated using standard performance metrics including classification accuracy, validation loss, inference time, and end-to-end execution time. Experimental analysis is performed under offline operating conditions to validate suitability for deployment in rural and remote agricultural regions.

Proposed System Architecture

A. System Overview

The Agri Vision framework is conceived as an independent, field deployable decision support system that brings together IoT based soil sensing, image based soil analysis, and machine learning driven crop recommendations within a unified embedded architecture. The primary objective of the system is to deliver accurate and data driven agricultural insights directly at the field level while eliminating reliance on cloud services or laboratory dependent soil testing. The entire solution is built around a Raspberry Pi 4 Model B, allowing computations to be carried out at the edge with minimal delay and dependable operation even in rural or resource limited settings. The operational workflow of Agri Vision begins with the parallel acquisition of soil sensor data and soil images, as illustrated in Fig. 2. Soil parameters including moisture, temperature and pH are measured using dedicated sensors and digitized through the MCP3008 analog to digital converter before being processed locally on the Raspberry Pi (Ananthi et al., 2017), (Thangammal et al., 2024). Edge level processing enables real time analysis while avoiding dependency on cloud-based infrastructure (Patel et al., 2021; Li et al., 2015). Images of the soil surface are obtained through a USB camera

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and analyzed directly on the device using a MobileNetV2-based CNN model, specifically designed to operate efficiently on embedded systems with limited computational resources (Babalola et al., 2023; Kamilaris & Prenafeta-Boldú, 2018).The identified soil category is merged with the refined sensor readings to create a unified data profile that reflects both the observable appearance and the measured properties of the soil. This combined information is then provided to a Random Forest learning model, which analyzes complex patterns within the data to determine crops that best match the prevailing soil conditions (Kavitha, 2023; Singh et al., 2023). The final results are displayed through a Time-based graphic linter face that present sensor readings, soil classification outcomes, and recommended crops, with support for QR code and email based report generation (Ramesh et al., 2023). Since all computation is performed locally on the Raspberry Pi, the system operates entirely offline and is suitable for deployment in connectivity constrained agricultural regions.

B. *IoT Based Soil Parameter Acquisition*

Accurate measurement of soil conditions is essential for reliable and data driven agricultural decision making. In the proposed Agri Vision system, an IoT based sensing framework is employed to continuously monitor key soil parameters that directly influence crop growth and productivity. The system focuses on three critical parameters, namely soil moisture, temperature, and pH, which together provide a comprehensive indication of soil health and cultivation suitability.

Soil moisture is measured using a resistive moisture sensor that estimates water content based on variations in electrical conductivity between its probes. Continuous moisture monitoring supports effective irrigation management by preventing both water stress and excessive irrigation. Soil temperature is measured using a digital temperature sensor that provides stable reading across varying environmental conditions.

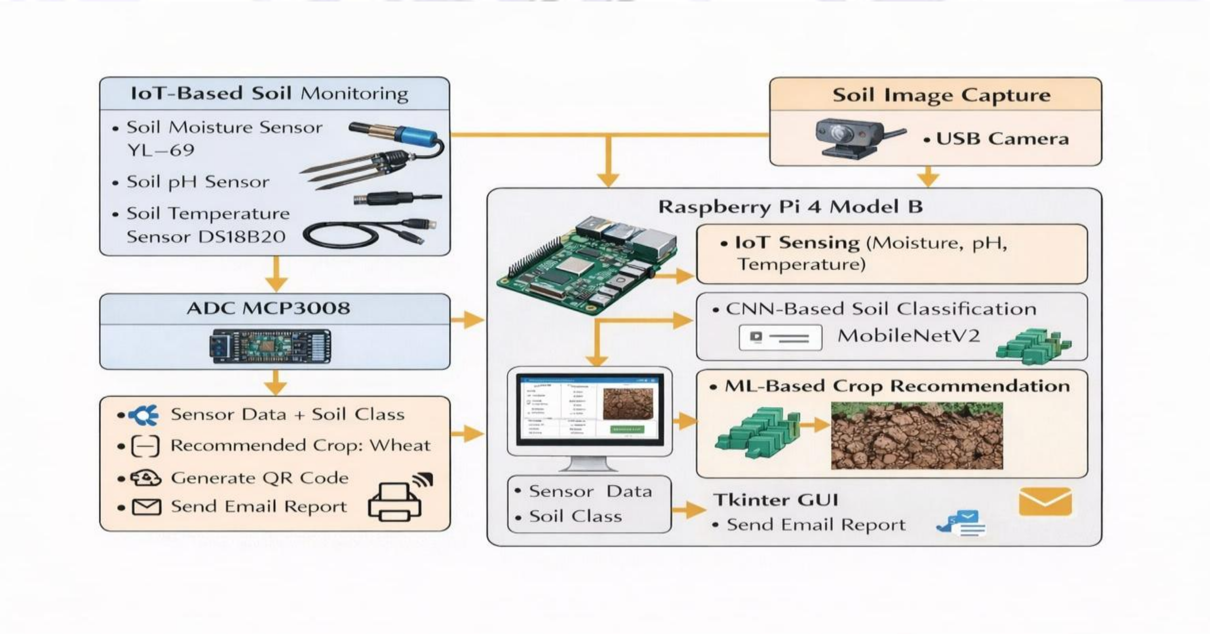

Fig.2.Overall architecture of the proposed Agri Vision system

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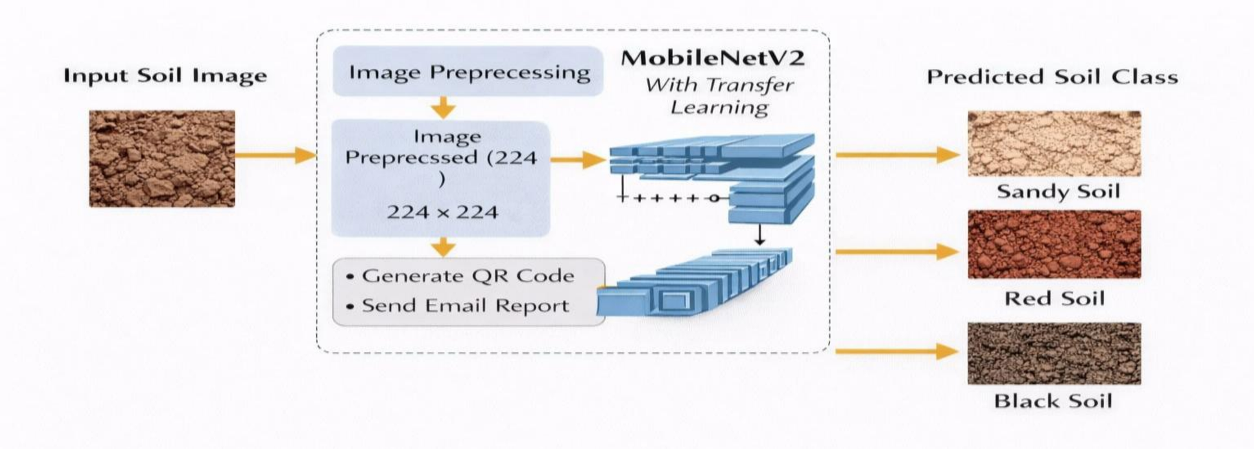

Fig.3.Soil image classification pipeline using Mobile NetV2

Temperature directly influences seed germination, microbial activity and nutrient availability. Soil pH is measured using an analog pH sensor to determine soil acidity or alkalinity, which significantly affects nutrient solubility and crop compatibility (Ananthi et al., 2017), (Babu et al., 2020).

Since the Raspberry Pi does not support direct analog input, the outputs from the moisture and pH sensors are interfaced through the MCP3008 analog to digital converter using the Serial Peripheral Interface protocol. The MCP3008 provides ten-bit resolution, enabling precise digitization of sensor signals suitable for further processing (Thangammal et al., 2024; Mohanraj et al., 2016). Sensor values are sampled at regular in Travels and calibrated to reduce noise and measurement drift.

The sensor outputs are handled directly on the Raspberry Pi, where the raw values are transformed and rescaled into consistent numerical ranges to ensure compatibility with sub- sequent machinal earning processing. The processed values are aggregated to form a structured feature vector representing real time soil conditions. This localized IoT based sensing approach ensures low latency operation, reduced deployment cost, and reliable performance in rural and connectivity constrained agricultural environments (Patel et al., 2021 Ray, 2017).

C. ***Crop Recommendation Using Machine Learning***

The final stage of the Agri Vision system is dedicated to identifying suitable crops by analyzing the combined outcomes of soil parameter sensing and image-based soil classification. The primary goal of this module is to recommend crops that are best aligned with the prevailing soil conditions, thereby improving agricultural productivity and reducing the likely- hood of crop failure. To accomplish this, the system adopts a supervised machine learning strategy that integrates real time sensor measurements with the predicted soil category.

A Random Forest classifier is employed as the crop recommendation model due to its robustness, scalability, and effectiveness in handling nonlinear relationships commonly observed in agricultural data sets. Training is carried out on an organized dataset that maps measured soil characteristics to their appropriate crop categories. Input features include the soil type predicted by the Convolutional Neural Network, soil moisture level, temperature, and pH value. Together, these features represent the key physical and chemical properties that influence crop growth and yield potential (Kavitha, 2023; Singh et al., 2023).

During the prediction phase, the trained Random Forest model evaluates multiple decision trees and

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determines the final crop recommendation through majority voting. This ensemble learning mechanism enhances generalization performance and minimizes overfitting when applied to real world agricultural conditions (Breiman, 2001). The recommended crop is presented to the user through the graphical interface and included in the generated report. By effectively combining heterogeneous data sources within a unified learning framework, the proposed system delivers reliable and data-driven crop recommendations that support informed and practical agricultural decision-making (Ramesh et al., 2023).

D. User Interface and Offline Execution

To ensure user friendliness and real-world applicability, Agri Vision includes a graphical interface that allows users to easily interact with the system's analytical components. The interface is implemented using the Tkinter framework and configured to operate in kiosk mode, allowing user stoper form soil analysis, observe live sensor readings, and view soil classification and crop recommendation outputs in real time. The interface is intentionally designed to be lightweight and responsive, ensuring smooth execution on resource constrained embedded hardware platforms (Thangammal et al., 2024; Ramesh et al., 2023).

A major advantage of this solution lies in its capability to operate independently without any reliance on network connectivity. All core operations, including sensor data acquisition, image preprocessing, deep learning inference, and machine learning based crop recommendation, are executed locally on the Raspberry Pi without dependence on cloud infrastructure or external servers. This offline capability enhances system reliability, lowers operational costs, and makes the solution well suited for deployment in rural and remote agricultural regions where internet connectivity is limited or unavailable (Patel et al., 2021; Li et al., 2015).In addition, the platform automatically creates scannable codes and delivers summarized results through electronic mail for convenient sharing and record keeping, enabling efficient sharing of results and simplified record maintenance in real world agricultural use cases (Ramesh et al., 2023).

Results and Discussion

A. Experimental Configuration

The Agri Vision framework was systematically evaluated to analyze its prediction accuracy as well as its practicality when implemented on embedded computing platforms. All deep learning and machine learning modules were developed using Python3.13.5.TensorFlow2.20.0wasutilizedfortrainingthe Convolutional Neural Network employed for soil image classification, crop selection component was developed using an ensemble learning approach implemented through the scikit- learn framework, and the learning process was executed on a high-performance system powered by an NVIDIA GeForce RTX 4060 Laptop GPU to ensure stable training behavior and accurate assessment of model effectiveness. (Babalola et al., 2023; Kamilaris & Prenafeta-Boldú, 2018).

After training, the optimized models were transferred to a Raspberry Pi 4 Model B to evaluate real time inference performance and overall system responsiveness under embedded computing constraints. The Raspberry Pi functioned as the core processing unit, handling sensor data acquisition, image preprocessing, model inference, and graphical user interface execution. All experiments were conducted under fully offline operating conditions to verify the suitability of the system for deployment in rural and connectivity constrained environments (Thangammal et al.,

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2024; Patel et al., 2021; Li et al., 2015).

The experimental evaluation employed two datasets, comprising a soil image dataset for visual soil classification and a structured agricultural dataset for crop recommendation. A comprehensive overview of the properties and composition of the data sets used in this study is provided in Table I within the Dataset Description subsection. The selected datasets support integrated evaluation of image-based soil classification and machine learning driven crop recommendation under practical operating conditions (Babalola et al., 2023; Singh et al., 2023; Breiman, 2001).

B. *Dataset Description*

The Agri Vision system employs two separate datasets to support the tasks of soil classification and crop recommendation. This work relies on two distinct data sources: one composed of soil photographs for appearance-oriented ground assessment, and another consisting of organized farming records applied for algorithmic crop selection. A combined outline of the data employed during performance analysis is presented in Table I.

The soil image dataset comprises seven distinct soil categories, including alluvial soil, arid soil, black soil, laterite soil, mountain soil, red soil, and yellow soil. The images were collected under diverse surface textures and illumination conditions to represent real-world agricultural scenarios. Prior to model training, all images were resized to a fixed resolution of 224×224 pixels and normalized to ensure uniform input

TABLEI
DATASET DESCRIPTION USED IN EXPERIMENTAL EVALUATION

Dataset	Description
Soil Image Dataset	Images representing seven soil categories
Number of Classes	Seven soil types
Image Resolution	224×224pixels
Data Augmentation	Rotation, scaling, brightness adjustment Crop
Dataset Type	Tabular agricultural dataset
Input Features	Soil pH, temperature, moisture, region
Target Label	Recommended crop

representation. Data augmentation methods were applied to enhance model robustness and improve generalization performance across varying soil conditions (Babalola et al., 2023; Kamilaris & Prenafeta-Boldú, 2018).

The dataset used for cultivation prediction is stored as a tabular file and includes measurements related to land conditions and surrounding climate, each linked to a corresponding suitable crop category. The input attributes include soil pH, temperature, moisture related measurements, and regional indicators relevant to crop growth. Preprocessing steps were performed to eliminate incomplete entries and apply normalization for consistent feature scaling. This data collection served both the learning and testing phases of the Random Forest model, which is particularly effective at capturing complex, non-linear patterns that frequently occur in agricultural scenarios (Singh et al., 2023; Breiman, 2001). The combined use of visual and tabular datasets enables a comprehensive analysis by integrating both physical and visual soil characteristics (Ramesh et al., 2023).

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C. *Performance Evaluation*

The effectiveness of the Agri Vision framework was assessed by examining its classification precision, response time during prediction, and the overall efficiency of system execution. Both analytical components the image driven prediction unit and the data-oriented decision engine—were systematically examined to verify their effectiveness for live, on field usage scenarios. The Convolutional Neural Network used for soil classification exhibited stable learning behavior and effective convergence during training. As demonstrated by the trends shown in Fig. 4, training and validation accuracy increased consistently across epochs while the corresponding loss values decreased steadily. The final validation accuracy achieved by the model was 87.85 percent with a of 0.2463, indicating good generalization capability and limited overfitting. When deployed on the Raspberry Pi 4 Model B, the model processed soil images within approximately one to two seconds per inference, demonstrating the feasibility of executing deep learning models on embedded edge devices. The crop recommendation module implemented using a Random Forest classifier achieved an overall prediction accuracy of 91.78 percent. Inference time for crop prediction remained below half a second, enabling near instantaneous recommendation generation. A consolidated summary of key performance metrics is presented in Table II. The complete analysis pipeline from sensor data acquisition to result visualization executed within six seconds, confirming reliable

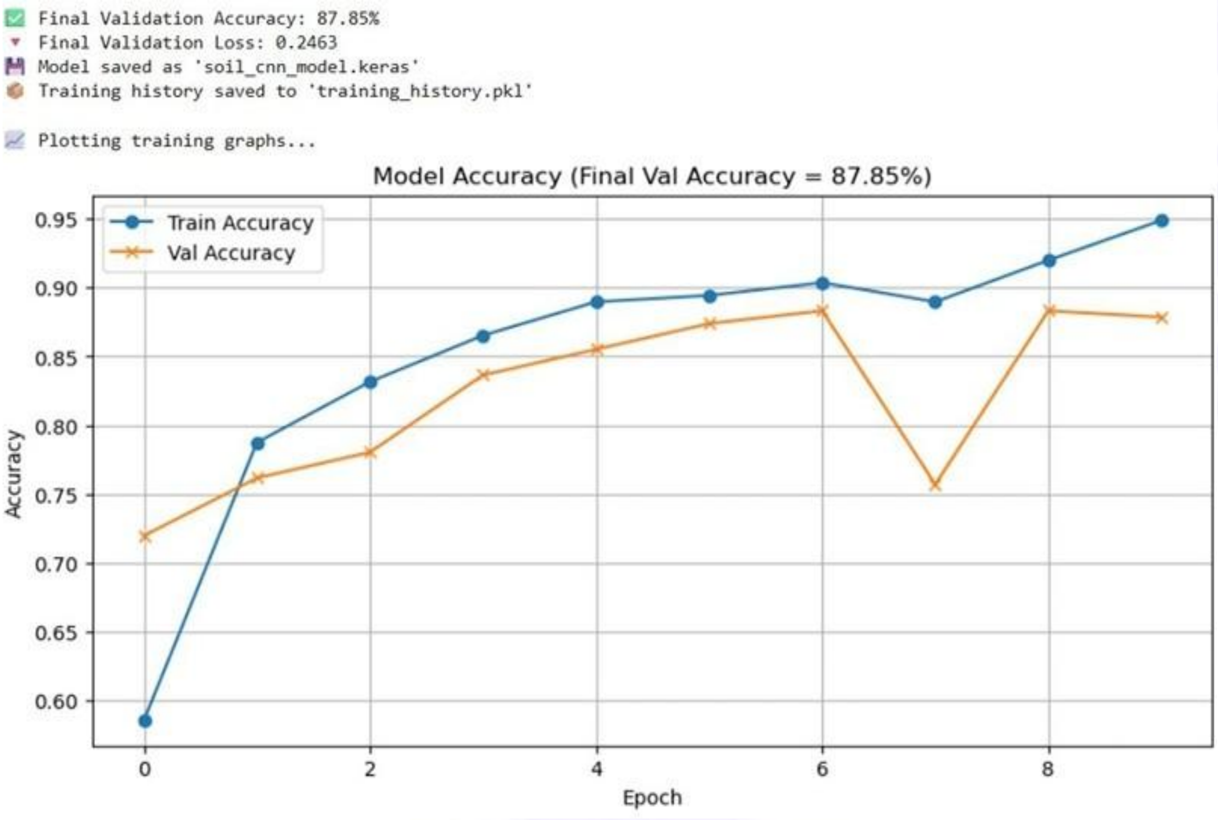

Fig.4.Training and validation accuracy curve softhe CNN based soil classification model

TABLEII
PERFORMANCE EVALUATION SUMMARY

Metric	Observed Performance
CNN Validation Accuracy	87.85percent
CNN Validation Loss	0.2463
Soil Classification	One to two seconds Crop
Inference Time	Recommendation
Accuracy	91.78 percent
ML Inference Time	Less than half a second
End to End Execution Time	Less than six seconds

And efficient system operation under real world deployment conditions (Singh et al., 2023; Breiman, 2001).

D. *Comparative Analysis and Discussion*

The proposed Agri Vision system offers clear advantages over traditional laboratory based soil analysis and cloud-dependent crop advisory solutions by combining IoT enabled soil sensing, image driven soil classification, and machine learning based crop recommendation within a single embedded platform (Gotlur et al., 2024; Thangammal et al., 2024). Conventional approaches typically involve delayed laboratory testing or static recommendation systems, which are often costly and difficult to access in rural regions (Ananthi et al., 2017; Babu et al., 2020). In contrast, Agri Vision provides automated, real-time decision support directly at the field level, enabling faster and more practical agricultural interventions.

As shown in Fig. 5, the graphical user interface integrates soil image capture, real-time sensor visualization, soil classification output, and crop recommendation results into a unified operational workflow. This consolidated interface improves usability and allows effective interaction even for users with limited technical expertise (Ramesh et al., 2023). The integration of visual soil characteristics with live sensor measurements results in more reliable predictions when compared to systems that rely on a single source of information (Babalola et al., 2023; Kamilaris & Prenafeta-Boldú, 2018).

Sample crop recommendation outcomes under different soil conditions are presented in Table III. The recommended crops are consistent with established agronomic suitability guide-lines reported in prior studies, there by validating the effectiveness of the proposed data fusion approach (Kavitha, 2023; Singh et al., 2023). Overall, the system achieves a balanced combination of accuracy, usability, and deployment feasibility, making it well suited.

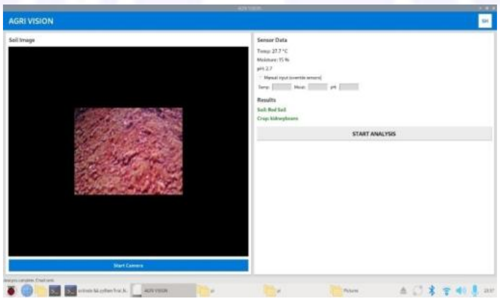

Fig. 5. Graphical user interface of the Agri Vision system during real-time operation

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TABLEIII
SAMPLE CROP RECOMMENDATION RESULTS

Soil Type	Moisture (%)	pH	Temperature(°C)	Recommended Crop
Black Soil	48	6.8	27	Cotton
Alluvial Soil	62	7.2	26	Rice
Red Soil	41	6.5	28	Groundnut
Laterite Soil	35	5.9	29	Cashew

for precision agriculture applications in rural and connectivity-constrained environments (Patel et al., 2021; Li et al., 2015).

Conclusion And Future Enhancements

This study presented Agri Vision, an integrated IoT, deep learning, and machine learning framework for real-time soil monitoring and crop recommendation on a standalone Raspberry Pi platform. The system achieved 87.85% soil classification accuracy. 91.78% crop recommendation accuracy with an end-to-end execution time of less than six seconds, demonstrating reliable offline operation. Compared with previous studies that focused on individual tasks or cloud-based processing. Agri Vision provides a unified, edge-based solution suitable for precision agriculture and rural deployment. Future work will incorporate NPK nutrient sensing, fertilizer recommendation, intelligent irrigation, weather-aware crop prediction, crop disease detection, and Explainable AI (XAI) to further improve accuracy, transparency, and practical applicability.

References

Gotlur, K., Kumar, R, Ram, S., Sanjeeva, P., Deepthi, P., Saeed, H., Asha, V., Kansal, L., & Praveen. (2024). Crop recommendation system and crop monitoring using IoT. *E3S Web of Conferences*. https://doi.org/10.1051/e3sconf/202450701063

Vatin, N., Joshi, S., Acharya, P., Sharma, R., & Rajasekhar, N. (2024). Precision agriculture and sustainable yields: Insights from IoT driven farming and the precision agriculture test. *BIO Web of Conferences, 86*.

Ananthi, N., Divya, J., Divya, M., & Janani, V. (2017). IoT-based smart soil monitoring system for agricultural production. In *Proceedings of the International Conference on Intelligent Agriculture and Research (TIAR)* (pp. 209–214). IEEE. https://doi.org/10.1109/TIAR.2017.8273717

Kavitha. (2023). Crop recommendation system using machine learning. *International Scientific Journal of Engineering and Management, 2*. https://doi.org/10.55041/ISJEM00457

Babu, G. R., Chellaswamy, C., Geetha, T. S., Raj, D. T., Venkatachalam, K., & Mulla, M. A. (2020). Soil test based smart agriculture management system. In *Proceedings of the 7th International Conference on Smart Structures and Systems (ICSSS)*. IEEE. https://doi.org/10.1109/ICSSS49621.2020.9202313

M., S. B., J., S. S., V., S., C., Y. K., & T., P. (2023). Crop Connect: An approach to crop recommendation. In *Proceedings of the 7th International Conference on Computation System*

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and Information Technology for Sustainable Solutions (CSITSS). IEEE. https://doi.org/10.1109/CSITSS60515.2023.10334150

Thangammal, C. B., Saai, P. M., Umar, M. T. N., S., N. S., & K., M. (2024). Agribot: An IoT and deep learning-based system empowering precision farming. In *Proceedings of the 2nd International Conference on Emerging Trends in Information Technology and Engineering (ICETITE)*. IEEE. https://doi.org/10.1109/ICETITE58242.2024.10493822

Patel, A., Pandey, K., Yadav, H., & Saraswat, P. (2021). IoT-based system for crop prediction and irrigation control. In *Proceedings of the IEEE 8th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*. IEEE. https://doi.org/10.1109/UPCON52273.2021.9667576

Chaudhari, A., Beldar, M., Dichwalkar, R., &Dholay, S. (2020). Crop recommendation and its optimal pricing using ShopBot. In *Proceedings of the International Conference on Smart Electronics and Communication (ICOSEC)*. IEEE. https://doi.org/10.1109/ICOSEC49089.2020.9215411

Babalola, E.-O., Asad, M. H., & Bais, A. (2023). Soil surface texture classification using RGB images acquired under uncontrolled field conditions. *IEEE Access, 11*, 67140–67155. https://doi.org/10.1109/ACCESS.2023.3290907

Ramesh, S., Vydeki, D., & Karthikeyan, R. (2023). Smart agriculture using IoT and machine learning. *International Journal of Engineering Research & Technology, 12*(3), 456–462.

Kamilaris, A., &Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture, 147*, 70–90.

Mohanraj, M., Ashokumar, K., & Naren, J. (2016). Field monitoring and automation using IoT in agriculture domain. *Procedia Computer Science, 93*, 931–939.

Barbedo, J. G. A. (2018). Factors influencing the use of deep learning for plant disease recognition. *Biosystems Engineering, 172*, 84–91.

Singh, R., Sharma, A., & Kaur, S. (2023). Crop recommendation system using supervised machine learning algorithms. *International Journal of Advanced Computer Science and Applications, 14*(2).

Li, S., Xu, L. D., & Zhao, S. (2015). The internet of things: A survey. *Information Systems Frontiers, 17*(2), 243–259.

Alom, M. Z., Taha, T. M., Yakopcic, C., et al. (2019). The history began from AlexNet: A comprehensive survey on deep learning approaches. *IEEE Computational Intelligence Magazine, 14*(4), 18–33.

Ray, P. P. (2017). Internet of Things cloud based smart farming: State of the art. *Journal of Ambient Intelligence and Smart Environments, 9*(4), 395–420.

Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32.

Howard, A., Sandler, M., Chu, G., et al. (2019). Searching for MobileNetV2. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*.