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AI-Enabled IoT for Precision Agriculture and Smart Crop Management

Tarun Badiwal[1]; Manish Jain[2]; Sandeep Jayswal[3]; Suresh Meena[4]

[1]Assistant Professor,Electrical Department Jagannath University
[2]Assistant Professor,Electrical Department Jagannath University
[3]Assistant Professor, Compucom Institute of Technology & Management, Jaipur
[4]Research Associate, Jagannath University

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Abstract: Agriculture is increasingly dependent on technologies that can improve productivity while reducing the consumption of water, fertilizers, pesticides, herbicides, labour and other resources. The five source chapters reviewed for this paper collectively describe the role of Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), computer vision, cloud computing and embedded systems in smart farming. The summarized work focuses on continuous sensing of soil and environmental parameters, automated irrigation, crop and weed monitoring, disease identification, yield prediction and decision support. The sources identify Artificial Neural Networks (ANNs), Deep Learning, Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs) as important approaches. A prototype architecture is also described using Arduino Mega 2560, Raspberry Pi, multiple sensors, Firebase and an Apache web server. In the disease-detection prototype, 295 leaf images were divided into training, validation and testing groups, and a CNN-based mobile application produced a reported confidence score of 0.97 for an example operation with an execution time of approximately 0.88 seconds. Overall, the reviewed material indicates that integrating IoT sensing with AI/ML can support real-time monitoring, resource optimization and faster agricultural decisions. However, Internet dependence, cybersecurity, system complexity, adoption cost, limited datasets and reduced accuracy for visually similar crop diseases remain important challenges.

Keywords: *Smart Agriculture; Artificial Intelligence; Internet of Things; Machine Learning; Deep Learning; CNN; ANN; Precision Agriculture; Automated Irrigation; Crop Disease Detection.*

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I. INTRODUCTION

Smart agriculture applies connected sensors, computing systems and intelligent algorithms to agricultural operations. The reviewed material describes IoT as a mechanism for connecting physical devices and sensors so that field information can be collected, transmitted, stored and used for control. AI and ML complement IoT by learning from historical or observed data and supporting decisions. The source material specifically proposes the combined use of IoT and ML to improve crop efficiency in water-limited regions and to continuously monitor temperature, humidity, soil moisture, pH and other environmental parameters.

The motivation for this technology is linked to increasing food demand, limited natural resources, variable climate conditions and the need to improve productivity from available land. The reviewed chapters emphasize that smart farming can reduce unnecessary interventions and support more informed decisions rather than simply replacing farmers.

➢ *Problem Statement*

Conventional farming practices may rely heavily on manual observation and fixed schedules for irrigation, pesticide application and crop monitoring. Such approaches can lead to inefficient resource use, delayed identification of crop problems and increased operational workload. The reviewed sources identify recurring challenges including crop diseases, weeds, inadequate irrigation management, pesticide control, soil and nutrient monitoring, changing weather conditions and the absence of sufficiently connected agricultural data.

➢ *Objectives of the Study*

- To study the application of Artificial Intelligence in agriculture for irrigation and the application of pesticides and herbicides.

- To evaluate automation approaches that use AI and intelligent sensing in agricultural operations.
- To study Machine Learning applications in IoT-based agriculture and smart farming.
- To monitor soil and environmental conditions using sensors and connected embedded systems.
- To support crop disease identification using image processing and deep learning.
- To improve resource utilization, particularly water, and reduce unnecessary agricultural interventions.

II. LITERATURE REVIEW

The reviewed chapters discuss several AI and ML techniques used in agriculture. Artificial Neural Networks are presented as models inspired by biological neural systems and are used for prediction and classification. Deep Learning extends neural-network approaches for complex data, while SVMs are described for classification, regression and clustering. The sources also discuss computer vision and CNNs for identifying plant diseases from leaf images.

The literature summarized in the sources covers species breeding and recognition, soil management, water management, yield prediction, harvest-quality assessment, disease detection, weed detection, animal production and animal welfare. Automated robots, drones, wireless sensor networks and IoT platforms are described as complementary technologies. These approaches move agriculture toward data-driven decision-making in which field observations can be collected continuously and used to trigger or recommend actions.

➢ *Major Applications of AI and IoT in Smart Agriculture*

Table 1 Major Applications of AI and IoT in Smart Agriculture

Application	Technology / Method	Purpose
Automated irrigation	IoT sensors, microcontroller, ML/decision rules	Monitor soil moisture and environmental conditions and control irrigation.
Disease detection	Computer vision, CNN, mobile/cloud system	Classify healthy and diseased leaves.
Weed detection	Computer vision, ML, robotics	Identify weeds and reduce unnecessary herbicide application.
Yield prediction	ANN, ML, computer vision	Estimate crop performance using agricultural and environmental data.
Soil management	Sensors, ML	Monitor soil moisture, temperature, pH and nutrient-related conditions.
Weather-based decisions	IoT sensing, AI/ML	Use environmental information for precautionary agricultural decisions.
Crop quality monitoring	AI, image analysis	Identify quality-related characteristics and reduce waste.
Livestock monitoring	AI classifiers and sensors	Support production and animal-welfare assessment.

III. PROPOSED INTEGRATED METHODOLOGY

Based on the five source chapters, an integrated smart-agriculture workflow can be summarized as follows: sensing → communication → cloud/database storage → data preprocessing → AI/ML analysis → decision/recommendation → actuator or farmer action → continuous monitoring.

- Sensing: collect temperature, humidity, soil moisture, pH, water-quality and related parameters.
- Communication: transfer sensor readings through embedded and wireless communication components.
- Storage: maintain field data in a cloud-backed database such as the Firebase-based architecture described in the source.
- Analysis: apply ML/DL models to detect patterns, predict conditions or classify crop images.
- Decision support: determine irrigation requirements, identify disease or suggest agricultural intervention.
- Actuation and monitoring: control irrigation equipment where appropriate and provide information through a web/mobile interface.

➢ *Prototype Architecture*

The prototype described in Chapter 4 uses Arduino Mega 2560 and Raspberry Pi as computing/control components. The sensing layer includes DHT22 for temperature and humidity, DS18B20 for temperature, pH sensing, gas-related sensing, turbidity and TDS-related measurements, along with soil and water monitoring components. Data are stored using Google Firebase, while an Apache web server is hosted on Raspberry Pi in the described architecture. The source further describes a mobile/cloud interface for remote monitoring and control.

➢ *Prototype Hardware and Software*

Table 2 Prototype Hardware and Software

Component	Role	Source-described use
Arduino Mega 2560	Microcontroller	Sensor interfacing and control.
Raspberry Pi	Edge computer/server	Data collection, storage/server functions and system coordination.
DHT22	Temperature/humidity sensor	Environmental monitoring.
DS18B20	Digital temperature sensor	Temperature measurement and water-system integration.

pH sensor	Soil/water chemistry	pH measurement.
HC-12	Wireless serial communication	Wireless data transmission.
Firebase	Cloud database	Real-time synchronized data storage.
Apache Web Server	Web service	Server-side access to stored information.
CNN + Android app	Disease identification	Leaf-image classification and farmer-facing detection interface.

➢ *Proposed a IoT Smart Agriculture Architecture*

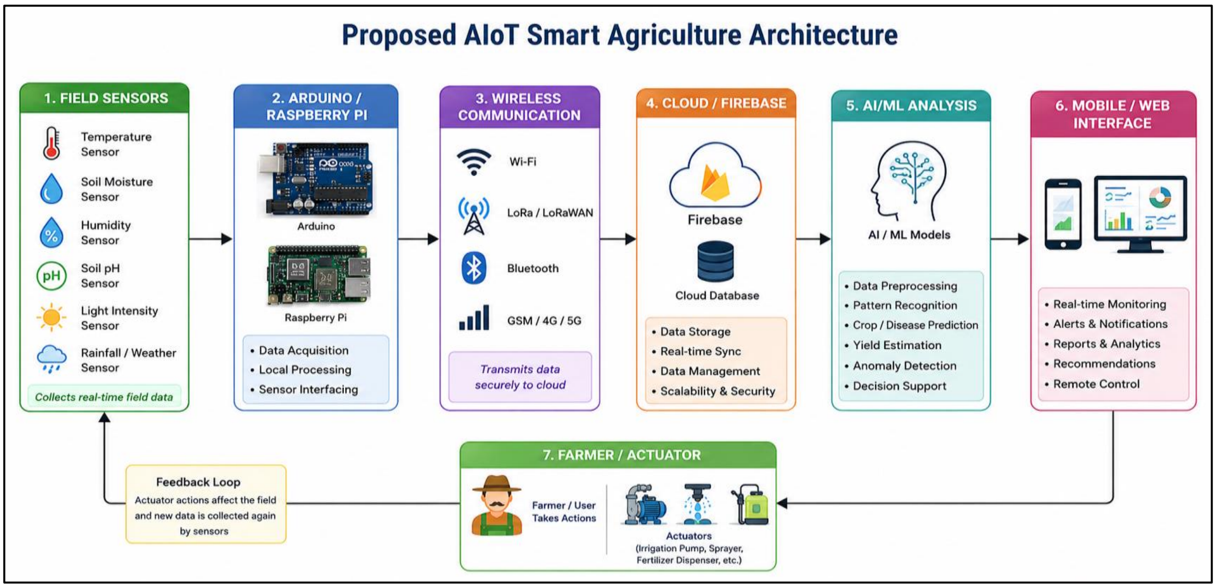

Fig 1 Proposed System Flow Based on the Reviewed Source Material.

➢ *Smart Irrigation Decision Flow*

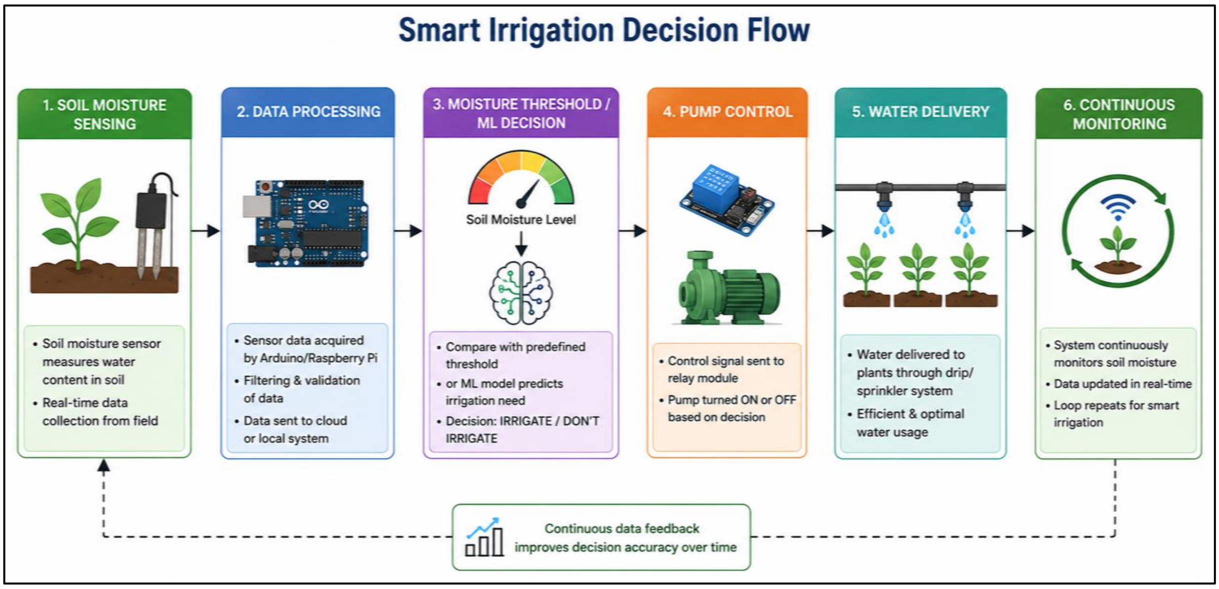

Fig 2 Proposed System Flow Based on the Reviewed Source Material.

IV. RESULTS AND DISCUSSION

The reviewed prototype results demonstrate the feasibility of collecting field information through distributed sensor nodes and making the information available through cloud and mobile interfaces. In the described IoT prototype, sensor nodes measure variables such as soil moisture, temperature, light and humidity. The collected readings can be used to determine where soil moisture is low and where irrigation should be directed. The architecture also supports remote access to records and control functions.

The prototype discussion further reports that humidity analysis can indicate conditions suitable for crops and inform the level of watering required. The source also describes automatic control of the irrigation motor based on predefined temperature and moisture limits, with a water-level sensor used to respond to excess water.

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For plant-disease detection, the source describes a CNN-based framework integrated with an Android application. The dataset contains 295 images divided into training (182), validation (78) and testing (36) images across five classes: apple scab, apple black rot, apple cedar apple rust, apple healthy and blueberry healthy. Image preprocessing and augmentation were used to reduce overfitting and positional bias. The reported mobile-app example produced a confidence score of 0.97 and completed the operation in approximately 0.88 seconds.

➢ *Dataset Distribution for the Disease-Detection Prototype*

Table 3 Dataset Distribution for the Disease-Detection Prototype

Class	**Training**	**Validation**	**Testing**	**Total**
Apple scab	50	18	9	77
Apple Black rot	32	14	6	52
Apple Cedar apple rust	30	19	8	57
Apple healthy	40	15	6	61
Blueberry healthy	30	12	6	48
Total	182	78	36	295

➢ *Interpretation of Results*

- IoT-based sensing supports continuous field observation instead of relying only on manual inspection.
- Cloud storage and mobile access allow farmers to view distributed field data and support remote decision-making.
- Automated irrigation can improve the timing of water delivery by responding to sensed conditions.
- CNN-based image analysis can provide rapid disease-classification assistance from leaf photographs.
- The reported confidence score and processing time show feasibility of the described prototype, but they should not be treated as a universal accuracy benchmark because the source does not provide a complete, independently validated performance study.

➢ *Summary of Reported Prototype Outcomes*

Table 4 Summary of Reported Prototype Outcomes

Prototype	**Input / Data**	**Technology**	**Reported Outcome**
IoT Field Monitoring	Soil moisture, temperature, humidity, light	IoT sensors + Raspberry Pi/Arduino + cloud	Remote monitoring and field-control support
Smart Irrigation	Moisture, temperature and water-level readings	Controller + sensors + pump	Irrigation can be controlled according to field conditions
Plant Disease Detection	295 leaf images	CNN + Android/cloud workflow	0.97 confidence reported for an example; ~0.88 s processing time
Cloud Data Management	Sensor readings	Firebase	Real-time synchronized data access

➢ *AI/ML Techniques and Agricultural Use*

Table 5 AI/ML Techniques and Agricultural Use

Technique	**Agricultural Task**	**Role**
Artificial Neural Network (ANN)	Prediction / classification	Learn patterns from agricultural data
Support Vector Machine (SVM)	Classification, regression, clustering	Separate or predict data classes
Convolutional Neural Network (CNN)	Plant disease detection	Classify leaf images
Deep Learning	Complex agricultural analysis	Learn high-level patterns from large datasets
Computer Vision	Weed/crop/disease identification	Extract information from images

- Note: The diagrams are simplified, editable representations synthesized strictly from the architecture and workflows described in the uploaded chapters; they are not reproduced copies of the source figures.

➢ *Advantages of the Integrated Approach*

- Improved monitoring of soil, climate and crop conditions.
- Potential reduction in unnecessary water, pesticide and herbicide use.
- Reduced dependence on repetitive manual field inspection.
- Faster identification of crop-health problems.
- Remote access to agricultural information through cloud/mobile systems.
- Better support for yield planning and resource allocation.
- A data foundation for future predictive and autonomous agricultural systems.

V. LIMITATIONS AND CHALLENGES

The source material identifies several limitations. Smart farming systems require reliable Internet connectivity, which can be a problem in rural and developing regions where network speed may be low. IoT systems also create

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security concerns because interconnected devices communicate over networks and may expose valuable data. The planning, development and maintenance of a large IoT system can be complex. Initial implementation costs can also be high, while farmer awareness and willingness to change traditional practices can affect adoption.

For crop-disease classification, the source notes that visually similar leaves can reduce accuracy. It specifically highlights the difficulty of distinguishing diseases in crops with common leaf characteristics. The small disease-image dataset described in Chapter 4 also means that broader field validation would be required before generalizing the reported prototype performance.

VI. FUTURE SCOPE

- Expand datasets using field-collected images and sensor readings from multiple locations and seasons.
- Evaluate multiple ML and deep-learning models using consistent validation metrics.
- Integrate weather forecasts with real-time sensor observations for improved irrigation decisions.
- Develop offline or low-connectivity modes for rural environments.
- Strengthen IoT security through device authentication, encrypted communication and access control.
- Integrate additional crop, soil, water and livestock sensors into a common platform.
- Develop more explainable AI recommendations so farmers can understand why an action is suggested.
- Conduct long-term field trials to quantify water savings, crop-yield changes and reduction in chemical inputs.

VII. CONCLUSION

This paper synthesizes five chapters covering smart farming, AI in agriculture, ML in IoT-based agriculture, an intelligent prototype architecture and the reported outcomes and limitations. The combined evidence from the uploaded material indicates that AI and IoT can transform agriculture from largely manual monitoring toward continuous, data-driven and partially automated decision-making. IoT sensors provide the field data required to observe soil and environmental conditions, while ML and deep-learning techniques can support prediction, classification and disease detection. The prototype architecture demonstrates how Arduino, Raspberry Pi, sensors, Firebase, web services and mobile applications can be combined for remote agricultural monitoring and control. The reported CNN experiment further demonstrates the feasibility of rapid leaf-disease identification using a mobile/cloud workflow.

At the same time, the reviewed material shows that successful deployment depends on reliable connectivity, security, affordable hardware, quality datasets, model validation and farmer adoption. Therefore, the most practical direction is not technology replacement of farmers, but technology-assisted farming in which sensing, AI/ML analysis and human decisions work together. Future research should focus on larger field datasets, stronger validation, secure low-cost IoT architectures and long-term measurements of water, chemical and productivity improvements.

- Note: The uploaded chapters contain internal numbered citations (for example, [1]–[175] and higher), but the complete bibliographic details for those cited works were not included in the supplied material. Accordingly, this summarized paper does not invent or reconstruct bibliographic entries that cannot be verified from the uploaded files.

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