Recent IOT-based Expert Systems and Deep Learning Methods in Smart Farming

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Abstract: IoT (Internet of Things) has been widely used in the agriculture industry, ranging from food production and management to irrigation planning, as well as the prediction and prevention of diseases in plants and vegetables. This paper presents a review study on the IoT infrastructure, including its three-level components: sensors, communication networks, and server-side data storage, along with the associated software packages. Various machine learning (ML) algorithms such as ANN, ensemble learning, deep learning, and SVM have been deployed for diverse purposes, including disease prediction, classification, and management of agro-products like corn, fruits, vegetables, and other plants. Domain-specific programs for disease detection and management in certain fruits, corn, and vegetables are also described. Expert systems integrated with IoT and ML now offer real-time, edge-deployed solutions capable of early disease detection with minimal latency. Communication technologies such as LoRaWAN, NB-IoT, and hybrid LPWAN-5G networks have enhanced connectivity in remote farmlands. Sensor technologies have evolved to include optical, hyperspectral, acoustic, weather, and soil sensors, enabling comprehensive crop monitoring. A IoT architecture combines these sensors with expert decision layers and lightweight edge models. Modern ML approaches, including convolutional neural networks, vision transformers, ensemble methods like Random Forests, and federated learning, enhance disease classification and yield prediction while preserving data privacy. Autonomous platforms such as drones and rovers now assist in detection and treatment, forming closed loop "sense-predict-act" systems with integrated farm management dashboards and mobile applications.

Keywords: IoT, Smart Farming, Deep Learning

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1. Introduction

"Smart farming" is an emerging concept that refers to managing farms using technologies like IoT, robotics, drones, and AI to increase the quantity and quality of products while optimizing the human labor required by production. IoT methodologies have been widely used in the agro industry and farming (Kuli et al., 2025).

In this paper, we describe various modern IoT infrastructures, including requisite devices, protocols, and information processing paradigms, along with their salient features. Machine Learning (ML) methods have been employed in the management of crop production, disease detection, and prediction in various agro-products such as corn, fruits, and vegetables. Various Expert Systems (ES) have been developed for the management and disease detection in vegetables, fruits, corn, wheat, rice, and pulses (Reddy et al., 2025). ES are domain-specific programs that mimic problem-solving strategies. We detail Machine Learning methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Ensemble Learning, and Deep Learning in the prediction and classification of diseases in agro-products (Sivakami & Karthikeyan, 2009).

Edge-deployed IoT systems with real-time analytics now enable early detection of diseases and pest infestations. Advanced communication networks like LoRaWAN, NB- IoT, and 5G hybrid LPWAN provide reliable connectivity across remote farmlands. Modern sensors—including hyperspectral imaging, thermal, acoustic, and soil nutrient sensors—allow for comprehensive monitoring of crops. AIoT frameworks integrate these sensors with expert decision layers and lightweight ML models for autonomous farm operations (Madiwal et al., 2025).

Federated learning and privacy-preserving ML approaches are increasingly used for multi-farm collaboration without sharing raw data. Autonomous drones and rovers assist in monitoring, spraying, and targeted treatment, creating closed-loop "sense-predict-act" systems that integrate with farm management dashboards and mobile apps (Mohammed, 2025).

2. IoT Infrastructure and Smart Farming

2.1. Infrastructure

In general, the IoT infrastructure comprises three interconnected information processing stages. The first stage consists of IoT services such as sensors at the lowest level and transmission and communication devices at the second level, with gateways like MQTT for communication and a back-end server having database mechanisms like MySQL and MongoDB.

At the cloud server side, protocols include MQTT, WebSocket, and HTTP. The recommended IoT communication technologies are RFID, NFC, WSN, Wi-Fi, and

Bluetooth. In the Expert System (ES) model, several experts from different domains of farming can share their opinions through IoT (Mateo-Fornés et al., 2021).
Agriculture sensors are utilized in intelligent farming practices. These sensors collect information that is useful to farmers in monitoring and improving crop performance in response to varying weather and environmental factors. Sensors can now be deployed on agricultural robots, drones, weather stations, and even autonomous ground vehicles.
Modern IoT frameworks integrate edge computing to process sensor data locally, reducing latency and enabling real-time decision-making. Advanced sensors now include hyperspectral cameras, thermal sensors, nutrient analyzers, and acoustic monitors, providing high-resolution data for precision farming.
Communication technologies have expanded to include LPWANs (LoRaWAN, NB-IoT) and hybrid 5G-LPWAN networks for reliable connectivity in remote areas. Cloud-based AI platforms now allow predictive analytics, anomaly detection, and automated alerts sent directly to farmer mobile apps. Integration with autonomous drones and robots enables targeted irrigation, fertilization, and pest control based on real-time sensor feedback (Miller et al., 2025).
An application of IoT in irrigation systems has been defined, in which several microcontrollers and moisture sensors are used. Data can be transferred to the IoT cloud using IoT gateways, and the updated results can be easily accessed on user mobile devices through dedicated applications. New systems now provide predictive irrigation schedules based on weather forecasts, soil health, and crop type, improving water use efficiency and crop yield (Morchid et al., 2024), as illustrated in Fig. 1.

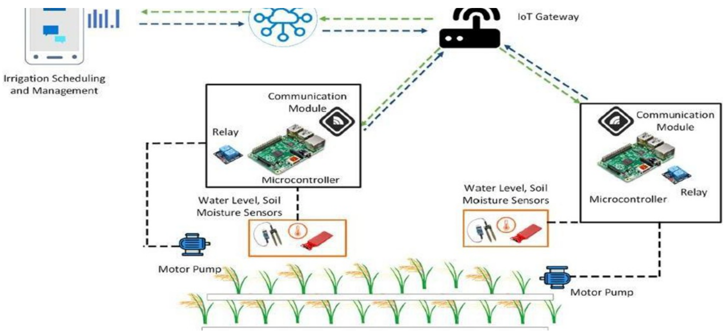

Fig1. Automated irrigation systems using internet of things. (Mohammed, 2025)

2.2. Expert Systems (ES) in Farming

Expert Systems (ES) are computer programs that mimic the problem-solving strategies of a domain expert. In agriculture, ES are increasingly used for crop management, pest and disease diagnosis, and precision farming, leveraging Artificial Intelligence (AI) methodologies. Various ES have been developed for the management and diagnosis of diseases in agricultural products, as discussed below:

In the state of Pennsylvania, GRAPE stands for "extended synonym for viticulture" and assists in grape cultivation decisions. COMAX is a resource for cotton farmers interested in Integrated Crop Management (ICM). To figure out which crops would thrive in a specific area, CROPLOT uses a rule-based expert system. Cucumbers are grown in a plastic tunnel using an Expert System.

In the orange-growing industry, CITEX serves as an Expert System for optimizing orange cultivation. CROPLOT was also applied in the GOSSYM procedure, representing the first practical integration of a simulation model with an expert system for farm management. Developed specifically for managing cucumber harvests inside plastic greenhouses, CUPTEX is an expert system for cucumber cultivation.

POMME (Apple Pest Orchard Management Expert System) was one of the first expert systems to incorporate expert decision-making for disease management in apple orchards, containing around 550 guidelines. AMRAPALIKA is an expert system developed specifically for identifying problems in Indian mangoes, including pests and infections. CPEST helps control coffee pests and diseases, especially in developing countries.

An Expert System called POMI assists in managing pests in apple orchards. SAGUIS is a system for developing individualized Agro- Advisory systems using IT; in Telugu, "Sagu" means "cultivation". Pulse Expert is a fully automated diagnostic tool that helps farmers and extension agents detect diseases in key pulse crops and recommend suitable controls, providing probabilities for each finding.

The University of Florida created DDIS, a remote diagnosis and identification system. Users can accomplish a wide range of tasks using this system. D-CAS is a sugarcane disease evaluation and management expert system. ICI Agrochemicals of England developed the multimedia computer program COUNSELLOR to combat pests and diseases in wheat. In Wisconsin, red pine stands can be damaged by pests and PREDICT is an expert system that identifies these issues.

PCEST is a tomato-specific pest control expert system focusing on both diagnosis and treatment. VEGES uses multiple programming languages to identify problems in six greenhouse crops: peppers, lettuce, cucumbers, beans, tomatoes, and aborigines. Various expert systems developed for different crops and agricultural applications are summarized in **Table 1**.

Table 1: ES in practice

ES Name	AI Methods / Components	Purpose & Uses
COMAX	Statistical analysis, rules and frame-based system	Provides information on integrated crop management in cotton.
CROPLOT	Rule-based expert system	Determines suitability of crops to given plots; used in cucumber production under plastic tunnels.
POMME	Rule-based model and DSS	Supports decision-making in fruit crop management (e.g., apples).
AMRAPALIKA	Rule-based expert system	Diagnoses pests, diseases, and physiological disorders in Indian mango crops.
CPEST	Rule-based expert system	Manages pests and diseases affecting coffee crops in developing countries.
DDIS	Rule-based and frame-based system	Assists in diagnosing and treating diseases of sugarcane.
COUNSELLOR	Rule-based model	Developed in England by ICI Agrochemicals to manage insect pests & diseases in wheat.
PCEST	Rule-based system with learning capability	Pest control expert system for tomato crops; diagnosis + treatment.
VEGES	Regression analysis and SVM for classification	Identifies pests, diseases, nutritional disorders in greenhouse vegetables.
CITEX	Rule-based model	Expert system for orange production management.
ESforRPD2	Rule-based / symptom-based rule engine; knowledge base; Waterfall paradigm, UML	Rice plant disease diagnosis (48 symptoms, 8 diseases).
Irrigator Pro / Automatic DSS for Irrigation	Regression & ML (Linear Regression, Random Forest, SVR); DSS architecture	Automatic irrigation scheduling and management; comparing learning techniques vs expert decisions.

2.3. Smart Farming (2025 Update)

With the help of the Internet of Things (IoT), the farm management concept of Smart Farming (SF) can help address the challenges associated with modern food production. The term “Smart Farm” refers to a system of crop cultivation and food production that integrates information and communication technologies (ICT) into farming tools, sensors, and machinery.

Smart Farm Technologies include soil moisture sensors, weather stations, drones, GPS-guided machinery, automated irrigation systems, and remote monitoring devices. The greatest benefit of these sensors is the massive amounts of data they can collect in real time, including soil quality, crop health, weather patterns, and water usage. While farmers possess deep knowledge of their fields, these sensors can detect early signs of stress, pest infestations, or nutrient deficiencies that might otherwise go unnoticed. By continuously monitoring farm conditions, these systems enable farmers to make data-driven decisions, improving efficiency, reducing costs, minimizing waste, conserving water, and increasing overall control over production. Additionally, the use of cloud computing, AI, and machine learning allows predictive analytics to optimize crop management and yield forecasting.With a projected world population of 9.7 billion by 2050, agricultural output is expected to rise by 69% between 2010 and 2050. To meet this demand, farmers will increasingly adopt IoT-enabled solutions, precision farming techniques, and automated systems to boost productivity sustainably. The use of IoT in agriculture is already widespread in several countries, and with India's rapid adoption of digital technologies in farming, smart farming is expected to become a mainstream practice across Indian agriculture by 2025 and beyond.

3. Machine Learning

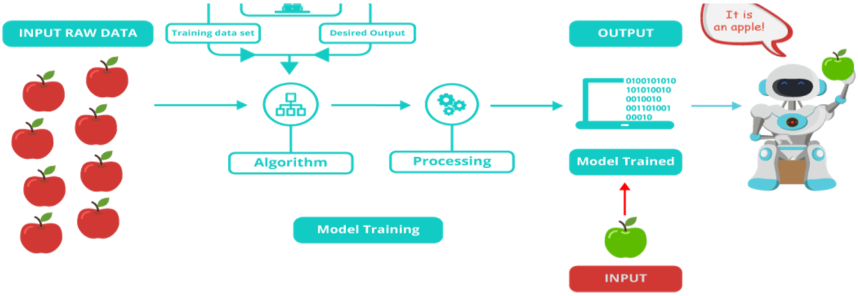

Fig 2: Machine Learning [2]

The fundamental concept and workflow of machine learning applied in smart farming are depicted in **Fig. 2**. Categorization of machine learning algorithms: The categorization of machine learning methods used in several areas of smart farming are shown in Fig3.Modeling the connection between two continuous variables can be done with simple linear regression. Predicting the value of a response variable from the value of a predictor variable is a common task.The goal of regression, and statistical modeling more generally, is to simulate the connection between an outcome (or response) variable and a set of predictors. Analysis of a Real-World Incident Modeling the yield of mechanically transplanted rice using an artificial neural network, with information about the transplanting parameters [8] and other factors as inputs.

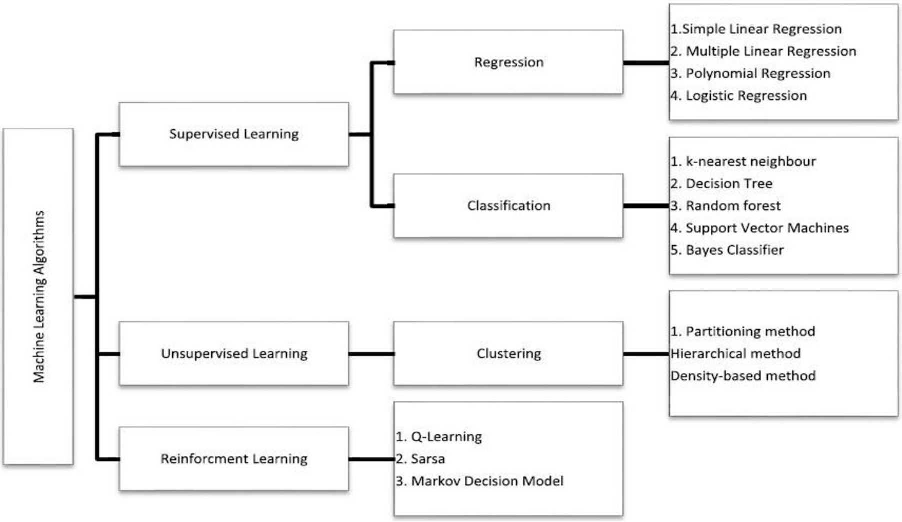

Fig3: Categorization of machine learning

The Regression model: The regression model shows how immensely the input parameters regulate the yield. The regression analysis ends up with an empirical equation containing a constant value and coefficients for relative inputs. The generated equation is as follows:

$$\text{Yield} = 761.77 + 7.451 \times SD - 1.310 \times SH - 4.574 \times M - 1.847 \times F$$

Where, SD= Seedling density, SH= seedling per hill, M = missing hill (%), F = floating hill (%).

The general workflow process for agricultural solutions using machine learning and AI—covering data collection, preprocessing, storage, and analytics—is shown in **Fig. 4**. The general workflow process for the agricultural solution using machine learning/ AI is required data collection from various resources such as sensors, pre-processing of the collected data can be done through machine learning methods. The real time data from various field of agriculture can stored in cloud servers through IoT gateways and can be easily available for further analysis as shown in Fig3.

4. Research so far in Smart Farming using Machine Learning Methods

There is tremendous research done so far in these areas. There are many machine learning methods such as ANN, ELM, CNN have been used for the prediction soil properties and weather condition and disease and weed identification.

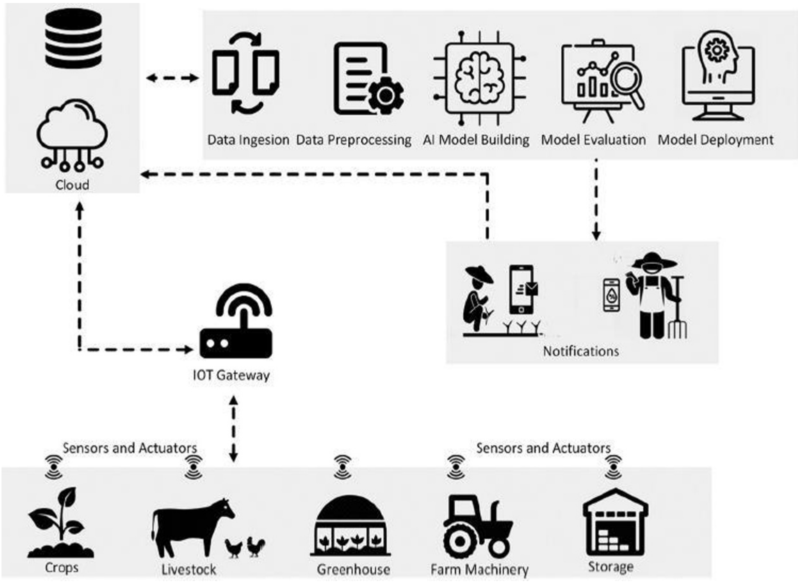

Fig4: Artificial intelligence/machine learning workflow for agricultural solutions [9]

The brief descriptions about research these are summarized in Table2. Various machine learning and deep learning algorithms used for disease and weed identification in agriculture are presented in **Table 3**.

Table2. Different DL algorithms for prediction of soil properties and weather conditions

DL Algorithm	**Purpose / Application**	**Key Features**	**Example Study / Reference (last 15 years)**
Artificial Neural Network (ANN)	Prediction of soil moisture, pH, and organic carbon content	Learns nonlinear relationships between soil parameters and spectral data	*Zhou et al., 2020 – Soil pH prediction using ANN based on hyperspectral data*
Convolutional Neural Network (CNN)	Soil texture, nutrient classification from satellite or drone images	Extracts spatial features from images	*Li et al., 2021 – CNN-based soil texture mapping using Sentinel-2 imagery*

Recurrent Neural Network (RNN)	Time-series soil moisture and temperature prediction	Captures temporal dependencies	*Rahmati et al., 2020 – RNN for soil moisture dynamics prediction*
Long Short-Term Memory (LSTM)	Prediction of soil moisture and evapotranspiration	Handles long-term temporal dependencies better than RNN	*Abbas et al., 2021 – LSTM model for soil moisture forecasting*
Autoencoder	Soil data dimensionality reduction and feature extraction	Learns compact soil representations	*Chen et al., 2019 – Autoencoder-based soil property prediction using hyperspectral data*
Hybrid CNN-LSTM	Predicting soil health indices and spatio-temporal changes	Combines spatial (CNN) and temporal (LSTM) features	*Feng et al., 2022 – CNN-LSTM for dynamic soil salinity mapping*
LSTM	Forecasting rainfall, temperature, and humidity	Strong in capturing sequential time-series weather data	*Bisht et al., 2021 – LSTM-based rainfall prediction in India*
Gated Recurrent Unit (GRU)	Predicting daily weather variables	Simplified RNN variant with less computational load	*Liang et al., 2020 – GRU for short-term weather forecasting*
CNN	Weather pattern recognition from satellite/radar images	Extracts spatial features from cloud or precipitation maps	*Shi et al., 2015 – CNN for precipitation nowcasting using radar data*
ConvLSTM	Spatiotemporal weather forecasting (rainfall, cloud movement)	Integrates CNN + LSTM for spatiotemporal modeling	*Shi et al., 2015 – ConvLSTM network for precipitation forecasting*
Transformer / Attention-based Models	Climate pattern detection and long-term weather forecasting	Captures long-range dependencies and global context	*Rasp et al., 2020 – WeatherBench using Transformer architectures*
Hybrid Models (CNN + BiLSTM / CNN + GRU)	Multivariate weather forecasting	Combines spatial and sequential learning	*Zhang et al., 2022 – CNN-BiLSTM for daily temperature prediction*

Table3: Different ML algorithms for disease and weed identification.

Algorithm / Family	**Application**	**Key features / why used**	**Representative study (year)**

Convolutional Neural Networks (CNNs) — (AlexNet / VGG / ResNet / GoogLeNet etc.)	Disease classification from leaf/rGB images; weed vs crop image classification	Strong image feature extraction; widely used with transfer learning on PlantVillage and field images. High accuracy for controlled images; easy to fine-tune.	Mohanty et al., *Using deep learning for image-based plant disease detection* (2016). (Frontiers)
Shallow / custom CNNs (lightweight nets)	On-device / real-time weed detection and grassy-weed classification	Lower compute footprint for embedded robotics / UAVs; suitable when dataset smaller or for edge deployment.	Yu et al., *Detection of grassy weeds in bermudagrass with deep convolutional neural networks* (2020). (Cambridge University Press & Assessment)
Fully Convolutional Networks (FCN) / Encoder–Decoder (semantic segmentation)	Pixel-wise crop/weed segmentation, stem detection for selective spraying	Pixel-level segmentation (semantic/instance)—enables selective treatment (spray only weeds). Works with sequential imagery.	Lottes et al., *Fully Convolutional Networks with Sequential Information...* (2018/2017). (ipb.uni-bonn.de)
K-means / unsupervised pretraining + CNN hybrids	Weed classification when labeled data limited	Unsupervised feature learning to bootstrap classification; helps when annotating is expensive.	Tang et al., *Weed identification based on K-means feature learning...* (2017). (ScienceDirect)
Transfer learning (pretrained ImageNet → fine-tune)	Both disease detection and weed classification	Reuses large-scale features; improves performance with small agricultural datasets.	Demonstrated widely (see Mohanty 2016) and many follow-ups. (Frontiers)
Multispectral / Hyperspectral CNNs	Disease detection and stress mapping using multispectral imagery	Uses spectral bands beyond RGB to detect early stress/disease not visible in RGB.	De Silva et al., *Multispectral Plant Disease Detection with Vision Transformers & CNN hybrids* (2023).

CNN + RNN / CNN + LSTM (spatio-temporal)	Time-series of field images (growth/disease progression); sequential UAV frames	Combines spatial feature extraction (CNN) with temporal modeling (LSTM) for progression/nowcasting.	FCN with sequential info (Lottes et al.) and other hybrid works. (ipb.uni-bonn.de)
Attention / Transformer / Vision Transformer (ViT) & hybrid ViT-CNN	Disease classification in-the-wild, robust to varied field conditions; multispectral/patch modeling	Self-attention captures global patterns; promising for complex, variable field images and multisensor fusion. Recent surge in 2021–2025.	De Silva et al. (2023) and recent ViT studies (2024–2025) on plant disease detection. (MDPI)
Ensemble & hybrid models (CNN + classical ML / multiple backbones)	Improve robustness across datasets and lighting; combine detectors + classifiers	Combines strengths of different models; reduces overfitting and domain shift effects.	Rakhmatulin et al., *Deep Neural Networks to Detect Weeds...* (2021) and comparative studies. (MDPI)
Lightweight / MobileNet / EfficientNet variants	Field deployment on mobile devices for farmer-level disease scouting	Efficiency for on-phone inference; good tradeoff between accuracy and latency.	Multiple studies applying MobileNet/EfficientNet for disease apps (see reviews). (Frontiers)

5. Conclusion

This study examined the three-tier IoT infrastructure in agriculture, comprising the sensor level for real-time monitoring of crops and environmental conditions, the communication and processing level involving gateways, cloud platforms, and data transmission, and the data storage level for long-term analysis and decision support. An IoT-based irrigation planning example illustrated how smart systems improve water-use efficiency and crop productivity. The study also reviewed Expert Systems (ES) as domain-specific tools that emulate expert decision-making, highlighting their successful application in disease detection and management across various crops. In parallel, the role of Machine Learning techniques—such as Artificial Neural Networks, Ensemble Learning, and Deep Learning—was discussed, emphasizing their growing importance in precision farming, crop management, and pest and disease prediction.

The findings indicate that integrating Expert Systems with IoT and AI/ML technologies significantly enhances modern agricultural practices by enabling data-driven decisions, predictive analytics, efficient resource utilization, and improved disease management. Such integration supports the development of sustainable and highly productive smart farming systems capable of addressing increasing global food demands. Looking ahead, emerging trends such as autonomous agricultural robots, AI-enabled drone surveillance, blockchain-based supply chain management, and edge-computing-driven real-time soil and climate analytics are expected to further advance precision agriculture and foster a fully connected, intelligent agricultural ecosystem by 2030.

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