AI-Driven ScarecrowAgriBot framework for enhanced agricultural sustainability

Alankritha SAMPATH[1], Rajarajeswari PEREPI[2*]

[1] School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu, India

sampath.alankritha2023@vitstudent.ac.in

[2*] Department of Software Systems, School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu, India

rajarajeswari.p@vit.ac.in (*Corresponding author)

Abstract: Modern agriculture is significantly influenced by Machine Learning (ML), Deep Learning (DL), Internet of Things (IoT), and Cloud Computing. Particularly in soil health monitoring, crop assessment, nutrient management and surveillance. This paper analyses 164 peer-reviewed research papers published from 2011-2025 with the aim of examining advanced methodologies, performance trends, and limitations in AI-based agricultural systems. The research insights reveal that ML and DL models demonstrated high accuracy in isolated tasks such as prediction of soil parameters, crop disease detection and identification of nutrient deficiency. The existing solutions remain fragmented, cloud- centric, and inaccessible to resource-constrained environments such as agriculture fields of smallholder farmers, especially with respect to wild-life intrusion deterrence. Based on these research gaps, this paper proposes a conceptual Scarecrow AgriBot framework that integrates edge-enabled, intelligent deterrence soil, crop monitoring, nutrient advisory and multilingual farmer interactions within a unified system. This Scarecrow AgriBot is a conceptual framework that serves as a literature-informed foundation for future prototype development and field-level evaluation.

Keywords: Soil monitoring, Crop health management, Nutrient deficiency, Precision agriculture, Scarecrow AgriBot.

1. Introduction

Agriculture acts as a major pillar of India's national economy, contributing to 18.2% of its Gross Domestic Product (GDP) and supporting two-thirds of the population. This includes 118.7 cultivators and 144.3 million agriculture labourers according to the NABARD 2021 report. This paper primarily focuses on issues related to soil degradation, erratic climate conditions and food insecurity in India, which are also prevalent in many countries like Asia, Africa and Latin America, creating a useful case study for broader applications. In India, erratic climate conditions such as heat waves, floods, droughts and cyclones have led to a significant crop loss of nearly 69 million hectares. In response, the farmers have adopted coping strategies such as acquiring loans, government insurance schemes and personal savings reported in the NABARD survey. Another significant barrier for sustainable Indian agricultural productivity is the depreciation of soil health. ICAR (Indian Council of Agriculture Research) and the International Zinc Association identified widespread single and multi-nutrient deficiency in 615 districts of 29 states from 242,827 soil samples in India (Shukla, et al., 2021). Micro and macro nutrient deficiencies such as Nitrogen (N), Phosphorous(P), Potassium(K), Zinc(Z), Iron (Fe) and Manganese (Mn) have negative impact on food quality, and soil fertility. Field intrusion and crop vandalism are persisting challenges in Indian agriculture, where most of the farmlands, have experienced frequent and severe crop damage, leading to financial loss and raising conflicts between humans and wildlife. Lack of monitoring and early warning systems, traditional mitigation techniques such as fencing and passive scarecrows provide limited protection for the crops. For tackling multifaceted issues and risks, there is a need for intelligent monitoring systems that use sensor networks. For developing an intelligent, cost efficient and contextually aware agriculture support system, a critical literature was analysed on soil monitoring, crop health management, nutrient management and surveillance. The main objective of this literature survey is to understand how these agricultural-based technologies can be thoroughly synthesized to inform the design of the proposed Scarecrow AgriBot framework for smallholder farmers. The uniqunss of the framework lies in its integration of intelligent wildlife

https://doi.org/10.33436/v36i1y202603

deterrence, through proposed scarecrow AgriBot functionality like soil monitoring, crop health management, nutrient management, and farmers native multilingual advisory support, a combination that has not been addressed in existing agriculture reviews or commercial platforms.

The rest of the paper is structured as follows: **Section 1** summarises the key challenges in Indian agriculture by accentuating the necessity of technical transformation. **Section 2** describes the methodology implemented for literature selection. **Section 3** proposes the framework for the Scarecrow AgriBot. **Section 4** presents the statistical insights from the literature review. **Section 5** discusses the effectiveness of the Scarecrow AgriBot and synthesizes the results into actionable insights. Finally, the References section provides a complete list of citations taken from scholarly and institutional sources.

1.1. Identified research gaps

R-Gap1. Lack of integrated platforms that combine soil analysis, crop recommendation, weather forecasting and surveillance functionalities tailored to local conditions.

R-Gap2. Limited real-time decision support that hasn't provided actionable insights in farmers' native languages, resulting in limited adoption of scientific recommendation.

R-Gap3. Insufficient socioeconomic targeting that doesn't integrate socioeconomic and agronomic recommendations, resulting in a poor uptake among small-scale and marginal farmers.

R-Gap4. Underexplored smart surveillance. While IoT-based monitoring exists, smart surveillance tools like the Scarecrow AgriBot that deter wildlife and alert farmers in real time have not been widely studied or implemented in India.

2. Literature review and methodology

This section examines the technological evolution of scarecrow systems, applications of ML and DL methodologies employed in agriculture by focusing on surveillance, soil monitoring, crop health analysis and nutrient deficiencies. For this purpose, a systematic process was adopted to confirm a structured and unbiased literature survey, curated from high-quality, impactful research databases, including IEEE Xplore, Scopus, Web of Science, ScienceDirect, ACM Digital, Springer and other authoritative institutional sources such as NABARD, ICAR, and ICRIST.

2.1. Methodology for literature selection

The selection of literature survey papers was curated based on specific keywords like soil monitoring, crop health management, ML/DL-based disease predictions and IoT-based intrusion detection in agriculture, from a pool of 5,000 papers. Through title screening, the number of papers was reduced to 877, followed by abstract screening, further reducing the number to 520 papers. After a complete paper evaluation, 164 papers were selected that applied ML, DL and IoT surveillance models to agricultural systems. This section's process is depicted in Figure 1. The multi-stage filtration process has directly informed the research questions and the development of the Scarecrow AgriBot. The duplicate, non-English papers which were conceptual and with no technical contribution, were excluded through the multi-stage filtration process.

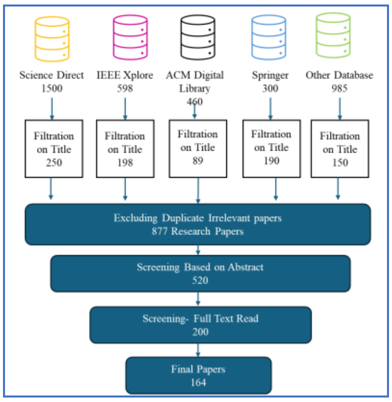


Figure 1. Literature selection and screening process from research databases, and other authoritative institutional sources (Author's own research)

2.2. Research hypotheses and key questions

A summary of the reviewed literature identified a few recurrent issues, which includes a lack of end-to-end integration between sensing, analytics and actionable interventions, inconsistent treatment of soil, crop and surveillance systems, limited real-time decision support customized to local farming contexts and understudied intelligent deterrence mechanisms for crop vandalism. The formulation of research questions was based on gaps identified from a systematic review of literature survey. RQ1 addresses R-Gap 4 and 1, with surveillance functionalities and deterrence mechanism tailored to agriculture conditions, whereas RQ2 and RQ4 together examine the existing technologies in soil, crop and nutrient management systems. Following R-Gap 2 and 3, which are limited to real-time decision support and socioeconomic with agronomic, recommendations are synthesized across the findings of these research questions. Adding up to domain specific technologies, various cross-cutting paradigms were explored in a literature survey like edge and fog computing to support real-time agricultural decision-making across multiple application domains.

2.3. Evolution of Scarecrow systems: from traditional to technological approaches

RQ1: How have modern technologies evolved and transformed traditional scarecrow systems for crop depredation deterrence?

The transition from traditional scarecrows to advanced deterrence systems spans several decades. Initial efforts centered on simple mechanical models and noisemakers, gradually evolving into systems that leverage electronics, automation and now intelligent computing technologies, are shown in Table 1 and the proposed Scarecrow AgriBot framework is depicted in Figure 2.

Table 1. Evolution of Scarecrow AgriBot systems from traditional to AI-assisted approaches (2003-2024)

Ref No.	Scarecrow Type	Application	Methodologies	Key Findings
Beringer, VerCauteren & Millspaugh (2003)	Animal-Activated Scarecrow (AAS)	Crop Depredation	Linear regression.	Unobtrusive and portable.
Nemtzov & Galili (2006)	Traditional Handmade Scarecrow	Crop Depredation	Manual fabrication and field deployment.	Birds adapted to the scarecrow over time.
Pornpanomchai et al. (2011)	Smart Scarecrow	Crop Depredation	Birds Detection using frame processing.	Struggled with similar birds, and clustered flying.

Richardson (2014)	Electronic Scarecrow	Crop Protection	Motion-triggered aversive sounds.	Frequent relocation caused wire damage..
Brown & Brown (2021)	URI Laser Scarecrow	Crop Protection	Automated laser motion and safety systems.	Protected plots: less bird damage compared to unprotected one.
Atikpakpa & Esabunor (2022)	Pseudorandom Sound Scarecrow	Crop Depredation	Pseudorandom number generator.	Scarecrow model with unique sound.
Mapari, Bhangale, Deshmukh et al. (2021)	Smart Scarecrow System	Crop Protection	Object detection	Monsoon rains affected sensor performance.
Mhandu, Musarurwa & Gudukeya (2023)	Solar-Powered Automated Scarecrow	Crop Depredation	Motion detection.	Promising system, not tested over an deployment period.
Rani, Bhaskar, Arshad et al. (2023)	AI-Based Scarecrow Man	Crop Protection	YOLOv3 object detection.	Tested on image datasets only.
Balaji et al. (2024)	Intelligent Scarecrow Surveillance System	Crop Protection	Transfer learning via MobileNet	Trained with 30 images per animal species.
Manz et al. (2024)	Laser Scarecrows	Crop Depredation	Multilevel mixed-effects models with Logit link.	Reduced likelihood of bird habituation.

In review of Table 1, scarecrow systems have shifted from manual deplyment to sensor integration and AI-Assited platforms. A censorious pattern accross this evolution has a recurring challenge of animal habituation, which is evident from (Nemtzov & Galili 2006) traditional handmade scarecrow to (Manz et al., 2024) laser-based scarecrow systems. Suggesting, with no single deterrance modality sustains long-term effectiveness. Futhermore, AI-based systems like (Rani et al., 2023) and (Balaji et al., 2024) demonstrated improved detection capabilities, but they remain validated only on image datasets rather than field conditions. The proposed Scarecrow AgriBot framework seeks to address these gaps by combining multi-modal deterrence with real-time advisory, though field-level reamains a future work.

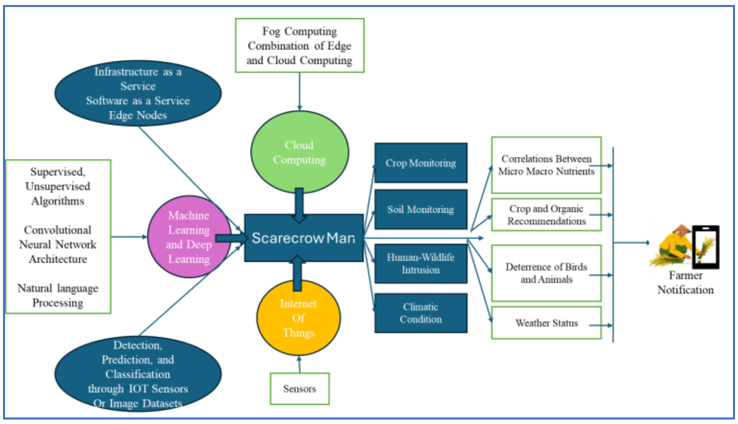


Figure 2. Technology components envisaged for the proposed scarecrow AgriBot framework (Author's own research)

2.4. Soil monitoring technologies and their relevance to the Scarecrow AgriBot

RQ2: What advanced technologies are integrated to optimise soil management practices?

Soil is an intricate natural resource on Earth that requires continual monitoring to maintain its fertility and productivity. In-terms for the proposed Scarecrow AgriBot, the advanced algorithms of IoT, ML and DL models, help in preserving the soil properties. The proposed framework envisages a sensor equipped platform that monitors soil continuously. In the proposed framework, ML and DL algorithms would processe soil data to predicts nutrient deficiencies and recommend approporiate fertilizers/lime for preserving the nutrients uptake in soil. This helps in preserving the physical and chemical properties of the soil. Table 2 summarises recent ML and DL models that can be integrated into the Scarecrow AgriBot System for advanced soil monitoring and management applications.

Table 2. Review of ML and DL models for potential integration into the proposed Scarecrow AgriBot for soil monitoring

Authors	Purpose	Learning Models and Datasets	Performance Metric	Relevance to the AgriBot
Ebrahimzadeh et al. (2023)	Pre-compression Stress	Random Forest (RF), Boosted Regression Tree; Sentinel-2 Root Mean Squared Error (RMSE)	RMSE: Decreased from 0.100 and 0.114 in Pedotransfer function	Sentinel-2 Satellite to derive Soil Properties
Seal & Sethia (2024)	Prediction of Soil Moisture	Neural Network (NN) Multilayer Perceptron (MLP); Very Near Infrared Rays (VNIR) by Cubert UHD-285	NN-MLP: RMSE:0.58 R^2 :97.47%	Hyperspectral Data from Cubert UHD-285
Huang et al. (2024)	Predicting Concentration of Cadmium	SVM, RF, NN	SVM: R^2 = 0.87	Fe-Mn Oxides, pH, Moisture Levels
Vibhute, Kale & Gaikwad (2024)	Soil Classification	Partial Least Squares Regression (PLSR), SVM; Multi-Hyper Spectral and Field Data	95.36 Accuracy	Soil Types: Regur, Lateritic, Sand Dunes
Mango, Narissara & Jaturong (2024)	Estimation of Soil Organic Carbon	SVM, Artificial Neural Network (ANN), PLSR Sentinel-2 data	ANN: RMSE:5.01and R^2:60%.	Sentinel-2 Data
Moharana et al. (2024)	Prediction of Soil Organic Carbon	XGBoost, RF, Cubist	Validation R^2:0.204 and RMSE: 0.213	Arid Soil Data

In review of Table 2, various ML and DL models such as RF, SVM, MLP and Gradient Boosting have been employed to predict soil parameters like salinity, organic carbon, heavy metal concentration and moisture. While learning-based spectral models perform well in soil classification tasks, RF-based models show high predictive accuracy for soil compression stress and carbon estimation. Together, these studies offer a strong basis for incorporating soil diagnostics into the Scarecrow AgriBot for applications involving real-time advice. Although RF and XGBoost consistently achieve high predictive accuracy in their respective studies. These results are not directly comparable, because they are derived from heterogenous datasets spanning from Indian arid soils, cadmium contaminated farm soils, and hyperspectral data experimented under various conditions. A notable gap across this Table 2 is the absences of multi-parameter, real-time field deployment, with most of the models validated through offline on curated datasets. That limits their capability to dynamic agricultural environments. These trade-offs reinforce the need of hybrid, edge-enabled soil diagnostics within the proposed framework rather than relying on single model architecture.

2.5. Crop Monitoring Technologies and their relevance to the Scarecrow AgriBot

RQ3: What modern technologies are used for detecting crop diseases and for monitoring plant health?

This section reveals advanced technologies for crop monitoring to detect disease and stress analysis. Below, Table 3 highlights the ML and DL models for integrating in the Scarecrow AgriBot for real-time crop surveillance. Recent studies in crop management highlight the utilization of technologies such as IoT sensors, ML, DL models and drones to smoothen the real-time monitoring. The proposed Scarecrow AgriBot framework is intended to integrate advanced models in detecting crop diseases, pest and nutrient deficiencies at very initial stages. In a future implementation, the system could generate alerts and recommendation to farmers via mobile notifications on nutrient applications on the field.

Table 3. Review of ML and DL models for potential integration into the proposed Scarecrow AgriBot for crop monitoring

Authors	Purpose	Learning Models and Datasets	Performance Metrics	Relevance to the AgriBot
Ahmyaw & Nuru (2019)	Maize Crop	Knowledge base Decision Tree (DT), (Ethiopia)	80.8% Accuracy	Supports Rule-based: nutrient deficiencies
Dey, Ferdous & Ahmed (2024)	Crop Horticulture	SVM, KNN, XGBoost, RF Dataset: (N: P: K)	99.09% XGBoost Accuracy	Suggest crops on sensor data
Gopi & Karthikeyan (2024)	Crop Recommendation and Yield Prediction	LSTM, Bidirectional Long Short-Term Memory (Bi-LSTM), Gradient Recurrsol salient Unit (GRU) 2000 images	98.45% R^2, RMSE, MAE	Forecast yield, Recommends crop
Thorat, Patle & Kashyap (2023)	Fertilizer and Insecticide Recommendation	Transition Probability Function (TPF)-CNN, KNN, ANN datasets: Pest 500 images;	90% TPF-CNN: Accuracy	Pesticide advisory system
Suma et al. (2019)	Leaf Disease	Classification and Regression Tree (CART), CNN, Dataset: leaf disease; 5000 images;	99.32% Accuracy	Enables vision-based detection of infected leaves in-field
Shabrina, Lika, & Indarti (2023)	Nematode Detection	EfficientNetV2M, Dataset: 957 microscopic images.	98.66% Accuracy	Useful for integrating lab feedback

As illustrated in Table 3, a broad spectrum of technologies from ML-based nutrient deficiency identification (Ahmyaw & Nuru, 2019) to UAV-enabled weed detection systems (Haq, 2022) has demonstrated strong performance in crop monitoring and management tasks. DL models excel at extracting and classifying image-based features and therefore dominate tasks such as weed recognition, crop disease detection and stress identification. However, the robustness of many high-performing models reported in the literature remains limited under practical environment conditions. Like, UAV-based with high-resolution imaging techniques are used, it increases detection accuracy and spatial coverage, but also increases the operational complexity, high energy consumption and cost. This ultimately prevents the smallholder farmers from using the technology or UAV on a large scale. To overcome this challenge, and for real-time analysis with cost efficient and minimal operational complexity, edge-based crop monitoring with lightweight architectures like MobileNet, EfficientNet and compressed CNN models can be used as a trade-off between accuracy and computational efficiency. Significantly, reported acuraries like 99.09% (Dey et al., 2024) and 98.45% (Gopi & Karthikeyan, 2024) should be cautiously interpreted, as results were obtained on curated benchmark dataset under controlled conditions, but they do not perform in open-field deployment with inconsistent lightning occulsion and seasonal changes.

2.6. Nutrient monitoring technologies and their relevance to the Scarecrow AgriBot

RQ4: How are advanced technologies applied in nutrient management strategies?

For sustainable agriculture, Nutrient management plays a vital role and primarily focuses on improving the availability of nutrients in crops by minimizing the environmental impacts. The literature survey highlights the significances of integrated organic and inorganic fertilizers called Integrated Nutrient Management, improving the soil fertility and crop yields. The proposed framework is designed to leverage these techniques by integrating ML and DL models to provide farmers with the appropriate recommendations for crop yield. State-of-the-art nutrient monitoring techniques were explored in this section and are summarized in Table 4.

Table 4. Reviewe of ML and DL models evaluated for nutrient deficiencydetection across multiple crops with performance metrics and relevance to the proposed Scarecrow AgriBot

Authors	Purpose	Learning Models and Datasets	Performance Metrics	Relevance to the AgriBot
Raju et al. (2023)	Nutrient Deficiency Detection	ANN, MobileNet; Plant leaf images;	MobileNet Accuracy: 98%	Real-time, lightweight image analysis
Navarro, Mateo & Manlises (2023)	Macro-Nutrient Deficiency-Onion	CNN, ResNet-50, VGG-16, Dataset: onion leafs (1000 images)	VGG-16 Accuracy: 85%	Pre-trained models for monitoring
Mkhatshwa & Daramola (2023)	Plant Disease and Nutrient Deficiency	VGG-16, Inception-13; Datasets: Rice, Groundnut, Banana;	F1 Score: 92%	Can use pre-trained models for multi-crop diagnostic models
Sindhuja et al. (2022)	Nutrient Deficiency in Rice	Image Classification-CNN, Adam, Soft Max Dataset: Rice (1156 images)	Accuracy: 98.75%	Can be integrated for surveillance and decision-making support
Han et al. (2023)	Nutrient Deficiency in Banana	ConvNeXtTiny; ReLU, CCE Loss; Dataset: PSFD-Musa	Accuracy 82.1%	Can process images on field via edge-AI
Talukder & Sarkar (2023)	Nutrient Diagnosis - Rice	Deep Ensemble CNN model,Transfer Learning, Rice (1156 images)	DensNet169: Accuracy: 96.66%	Ensemble logic for robust healthy insights

In review of Table 4, various ML and DL models like CNNs, MobileNet architecture, ensemble methods and IoT-based sensing have been applied for diagnosing nutrient deficiencies across different crops with high accuracies. When combined with edge computing and field-level sensing infrastructures, these techniques offer technological basis for real-time nutrient monitoring and decision-support systems. Still, the current methodologies focus on visual symptoms by ignoring the crop growth stages, soil properties and erratic climatic conditions, thus resulting in inaccurate recommendations across various field conditions. Furthermore, an analytical concern in this Table 4 is high classification accuraries like 98.75% (Sindhuja et al., 2022) and 98% (Raju et al., 2023) are of crop specific and dataset specific, the models were trained using rice and banana images. Most of the reviewed studies have not validated cross-crop generalisation and performance under field-level noise, suggesting that ensemble or transfer learning approaches are better suited for integration into the suggested framework than single-crop models.

2.7. Edge and fog computing and their relevance to the scarecrow AgriBot

In recent years, cloud-fog-edge has evolved in the agriculture sector by facilitating connectivity, latency, scalability, remote data storage, data capturing from various sources and weather prediction. Existing studies of Fog-Based Architecture demonstrates real-time irrigation control, crop monitoring and sensor data pre-processing, faster local decision-making by reducing the communication with cloud servers. Edge-based frameworks were applied for detecting real-time diseases by capturing the images and for monitoring, thus support critical situations in rural environments. However, due to model optimisation, limited computational resources and energy efficiency, few existing implementations face constraints.

3. Conceptual framework for Scarecrow AgriBot integration

This segment explores the core contribution of the proposed Scarecrow AgriBot by specifying the details of the architecture, data flow and novelty of the proposed system as shown in Figure 2. The proposed Scarecrow AgriBot is designed to addresse agricultural challenges by integrating soil, nutrient analysis, intrusion detection, and cropping patterns. The proposed framework responds to the challenges highlighted in Sections 2.1 to 2.7.

3.1. Components of the framework

1. Data Acquisition Layer: Incorporates sensors includes Low-cost NPK and moisture probes (operating at 3.3V–5V), PIR-based motion detectors, and a camera module like the Raspberry Pi Camera V2 are among the anticipated sensors. Depending on connectivity availability, data will be sent via LoRaWAN or Wi-Fi. The cost has declined with technological maturity and deployment of government subsidies could further reduce the financial burdens on farmers.

2. Edge Layer: Usage of edge computing can initially process, reduce data latency, filter data and enable real-time responses with low power and internet connectivity. The Raspberry Pi 4 (4GB RAM) and NVIDIA Jetson Nano are examples of potential edge platforms that provide enough processing power to run lightweight DL models like MobileNetV2 while running on a 5–10W power budget appropriate for solar-powered deployment.

3. Integration Layer: Incorporates ML and DL algorithms to analyse sensor and image data of crop, intrusion, nutrient deficiency, disease and pest. The MQTT protocol is intended for lightweight sensor data transmission between layers, and when connectivity allows, REST API calls to cloud services are used for model updates and data archiving.

4. Action Layer: Provides farmers with actionable alerts and suggestions in their native tongue through SMS or mobile application notifications. Deterrent responses, like audio-visual stimuli, are triggered locally at the edge layer without requiring cloud connectivity.

3.2. Data flow and interaction

The framework of the proposed Scarecrow AgriBot was designed with two-way communication as depicted in Figure 3. For instance, the sensor input signals flow to the edge systems, which then run analytics and return the alerts. The proposed architecture aims to reduce the end-to-end latency from sensor trigger to farmer alert by less than two seconds for intrusion events processed locally at the edge. Depending on network conditions, the estimated latency for nutrient and soil advisory queries involving cloud inference is between five and fifteen seconds. These results are also stored in a feedback loop for continuous model retraining based on real-world observations and seasonal dynamics. Coordination among the soil, weather and intrusion modules ensures real-time decision-making that adapts to environmental changes and threat profiles.

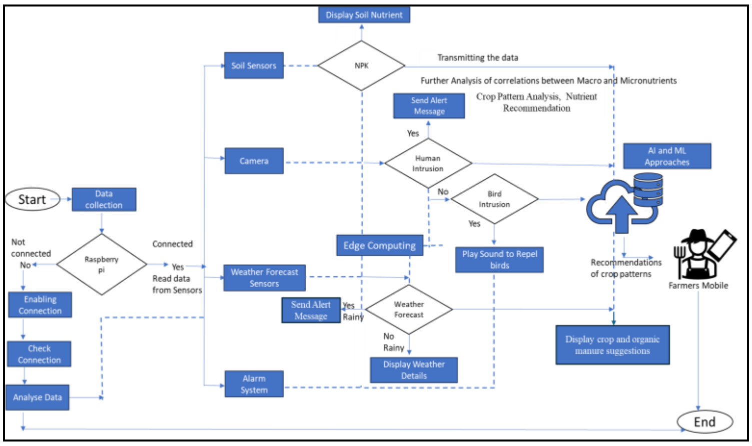


Figure 3. Proposed Conceptual data flow of the Scarecrow AgriBot framework showing two-way communication between the layers for real-time agricultural decision support (Author's own research)

3.3. Scope feasibility and validation considerations

The proposed Scarecrow AgriBot is presented as a conceptual and system-level integrated framework. The proposed framework's architectural design is completely defined with an underlying system concept that has been officially protected by grant approval and intellectual property registration. However, the focus of this paper is restricted to a literature-driven review and conceptual framework formulation. The study does not include hardware implementation, simulation-based testing or on-field experimental validations. Accordingly, no claims are made regarding deployment performance, energy efficiency, classification accuracy or operational robustness of the proposed framework. In this survey, multilingual interfaces of agricultural advisory systems through mobile applications were also explored. These interfaces include rule-driven natural language generation and voice-text-based recommendations/alerts for farmers that improves the accessibility with various linguistic backgrounds. The existing literatures also reveal that there is an improvement in adoption when recommendations are delivered to farmers in their native language.

3.4. Comparing Scarecrow AgriBot with smart agriculture platforms

Several review articles have examined ML, DL, and IoT applications in soil monitoring, crop disease detection, and precision farming separately. Nevertheless, none of the reviewed literature offers a cohesive conceptual framework that simultaneously integrates crop health monitoring, soil-nutrient advisory, wildlife deterrence, and multilingual farmer interaction into a single edge-enabled architecture. This distinguishes the proposed Scarecrow AgriBot from existing systems, which address these domains independently rather than integrated, farmer-centric system.

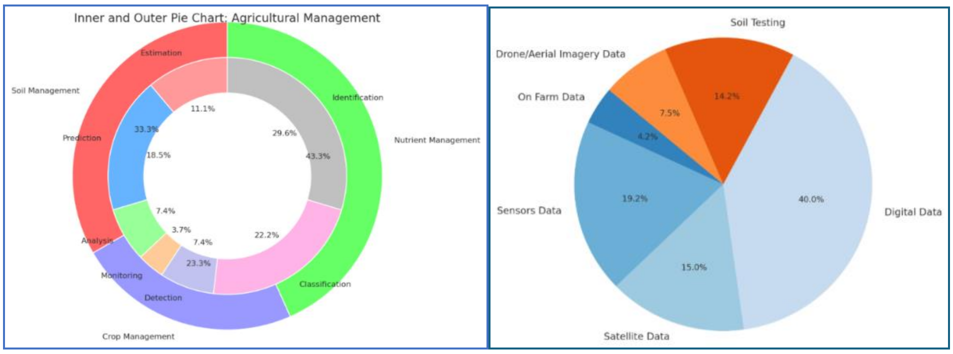
To support precision agriculture, several commercial and research-based platforms have been developed by integrating sensing, analytics, and advisory services. Prominent example includes "John Deere Operations Center, CropX, IBM Watson Decision Platform for Agriculture, Microsoft FarmBeats, and Climate FieldView". These platforms frequently target medium-large-scale commercial farms, mainly use Cloud-Centric architectures and concentrate on yield optimisation, farm management services, and large-scale data analytics. The Advanced Scarecrow, on the other hand, focuses on a low-cost, edge-enabled, and deterrence-aware architecture that is specifically designed for smallholder and marginal farmers shown in Table 5.

Table 5. Feature-wise comparison of the proposed Scarecrow AgriBot against established commercial smart agriculture platforms

Features	**Microsoft FarmBeats**	**CropX**	**Climate FieldView**	**Scarecrow AgriBot Framework**
Architecture	Cloud-Centric	Cloud	Cloud-Centric	Edge + Cloud
Focus On	Data Aggregation and Analytics	Soil Analytics	Yield and Farm Management	Integrated Surveillance and Advisory
Targeted Audience	Medium-Large	Commercial	Commercial	Small holder and Marginal farmers
Intrusion				Integrated Smart Deterrence
Edge Intelligence	Limited	Limited	Limited	Native Edge Intelligence
Language Support	Limited	Limited	Limited	Multilingual
Dependency	High	High	High	Low-Moderate
Cost effective	Subscription	Subscription	Subscription	Low-Cost

4. Research findings: trends and distribution in agriculture research

Existing studies reveal statistical data on utilization of various publicly available datasets in literature survey and ongoing research in various domains of agriculture as depicted in Figure 4. The statistics represent nutrient management in agriculture as dominant, with 43.3% of ongoing research in predicting, detecting and identification of nutrient deficiencies, and application of nutrient for yield improvement, followed by soil management, which accounts for 33.3% of ongoing research in soil fertility restoration, and crop management with 23.3% highlighting the ongoing research in stage-wise growth tracking with pest control and yield estimation, illustrated in Figure 4 as the outer circle of the pie chart. The inner circle of the chart illustrates the statistics of specific ongoing research such as identification, classification and prediction, representing 29.6%, 22.2% and 18.5% respectively, where identification and classification are shown as the dominant research with the role of computer vision and AI in diagnosis. Areas like monitoring account for 3.7%, indicating emerging needs, especially in continuous field tracking.



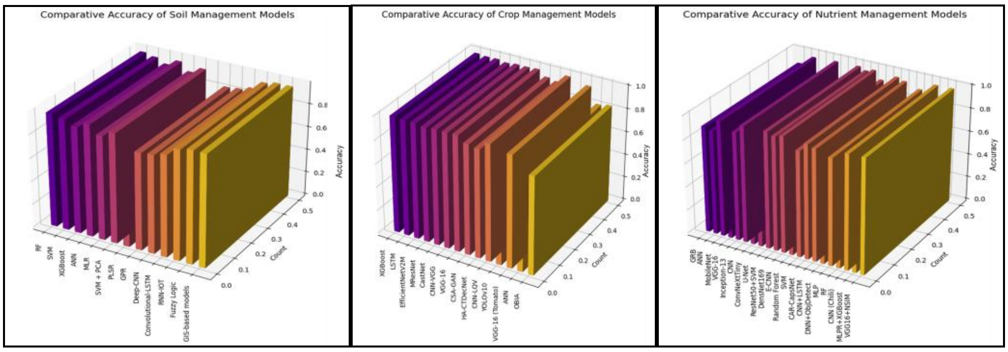
a) b)

Figure 4. Distribution of reviewed articles based on soil, crop, and nutrient: (a) Management, (b) Datasets (Author's own research)

4.1. Insights from soil, crop and nutrient management technologies

Soil management provides insight on predictive models with their performance across various soil parameters as summarised in Table 2. The literature also analyses multiple technologies, including ML, DL, geographic information systems (GIS) and real-time IoT-enabled soil monitoring systems. The model including RF, SVM and XGBoost shows a consistent performance by achieving accuracy of 97%, 94% and 98% respectively, depicted in Figure 5. Crop management provides insight on intelligent solutions like weed detection, growth prediction, disease and pests' detection depicted in Figure 5. The literature shows XGBoost as achieved highest accuracy of 99.09% for crop recommendation and yield prediction, followed by

EfficientNetV2M with 98.66% accuracy for identifying parasitic nematode infestations summarized in Table 3. Notably, in nutrient management high accuracies of 99.05% were seen in identifying the deficiencies in rice, banana and tomato crops using advanced pre-trained CNN models like ResNet, VGG-16 and InceptionV3, as depicted in Figure 5 and summarized in Table 4. It should be noted that, the accuracy figures shown in Figure 5 are derived from various studies with distinct dataset, experimental conditions and evaluation protocols. These comparisons should be interpreted carefully.



a) b) c)

Figure 5. Comparing accuracies of soil, crop, and nutrient management models: (a) Soil management models, (b) Crop management models, and (c) Nutrient management models
Note values are from independent studies with differing datasets and conditions (Author's own research)

4.2. Insights into smart agriculture implementations in developing countries

The studies report that the developing regions like Asia, Africa and Latin America use ML, remote sensing and IoT to address the same issues faced by India. The persistent challenge in over all Asia is soil degradation, according to (Yaseen et al., 2025). The research findings exhibit an extensive soil degradation, causing decline in food production, especially through nutrient imbalance, and yield loss due to soil erosion.

5. Conclusion and future scope

This literature survey has explored 164 reviewed papers on ML, DL, IoT and surveillance-based agricultural technologies. The literature survey reveals soil and nutrient management dominating the current research in agriculture domain, but practical integration of these technologies into farmer-centric systems remains limited. Most of these solutions were developed in isolation, incompatible and insufficient when tailored to local farming conditions. The proposed Scarecrow AgriBot fills these gaps by integrating crop surveillance, soil-nutrient advisory and intrusion detection within a modular, edge-enabled and multilingual architecture. To assess the efficiency and robustness of the Scarecrow AgriBot across various agro-climatic conditions and support for both smallholder and commercial farming systems, future work will focus on implementing the prototype with field-level validation and scalability assessment.

Authors contributions

Conceptualization: A.S., and R.P.; Data Curation: A.S.; Project administration: R.P.; Supervision: R.P.; Validation: R.P.; Writing—original draft: A.S.; Writing—review and editing: A.S., R.P. All authors have read and agreed to the published version of the manuscript.

Submission received: 07 August 2025; Revised: 15 January 2026; Accepted: 28 January 2026; Published: 31 March 2026.

REFERENCES

Ahmyaw, S. & Nuru, M. (2019) Knowledge Base System for Maize Crop Nutrients Deficiency Identification. *IOSR Journal of Computer Engineering.* (IOSR-JCE). 21(3), 21–26. https://doi.org/10.9790/0661-2103042126.

Balaji, V. S., Mahi, A. R., Anirudh Ganapathy, P. S., Manju, M. (2024) Scarecrow monitoring system: employing mobilenet ssd for enhanced animal supervision. *arXiv* [preprint] arXiv:2407.01435. https://arxiv.org/abs/2407.01435. [Accessed: 20th September 2024]

Beringer, J., VerCauteren, K. C. & Millspaugh, J. J. (2003) Evaluation of an Animal-Activated Scarecrow and a Monofilament Fence for Reducing Deer Use of Soybean Fields. *Wildlife Society Bulletin*. 31(2), 492-498. https://www.jstor.org/stable/3784330.

Brown, R. N. & Brown, D. H. (2021) Robotic laser scarecrows: a tool for controlling bird damage in sweet corn. *Crop Protection*. 146(4), 105652. https://doi.org/10.1016/j.cropro.2021.105652.

Dey, B., Ferdous, J. & Ahmed, R. (2024) Machine learning based recommendation of agricultural and horticultural crop farming in India under the regime of NPK, soil pH and three climatic variables. *Heliyon*. 10(3). https://doi.org/10.1016/j.heliyon.2024.e25112.

Ebrahimzadeh, G., Mahabadi, N.Y., Bayat, H. & MatinFar, H. (2023) Estimating pre-compression stress in agricultural Soils: Integrating spectral indices and soil properties through machine learning. *Computers and Electronics in Agriculture*. 215, 108393. https://doi.org/ 10.1016/j.compag.2023.108393.

Gopi, P. S. S. & Karthikeyan, M. (2024) Red fox optimization with ensemble recurrent neural network for crop recommendation and yield prediction model. *Multimedia Tools and Applications*. 83(5), 13159-13179. https://doi.org/10.1007/s11042-023-16113-2.

Han, K. A. M., Maneerat, N., Sepsirisuk, K. & Hamamoto, K. (2023, June) Banana plant nutrient deficiencies identification using deep learning. In *2023 9th International Conference on Engineering, Applied Sciences, and Technology (ICEAST), Vientiane, Laos.* IEEE, pp. 5-9.

Haq, M. A. (2022) CNN based automated weed detection system using UAV imagery. *Computer Systems Science & Engineering*. 42(2). https://doi.org/10.32604/csse.2022.023016.

Huang, B. Y., Lü, Q. X., Tang, Z. X. et al. (2024) Machine learning methods to predict cadmium (Cd) concentration in rice grain and support soil management at a regional scale. *Fundamental Research*. 4(5), 1196-1205. https://doi.org/10.1016/j.fmre.2023.02.016.

Mango, L., Narissara, N. & Jaturong, S. A. (2024) Estimating soil organic carbon using sentinel-2 data under zero tillage agriculture: a machine learning approach. *Earth Science Informatics*. 17(6), 5471-5486. https://doi.org/10.1007/s12145-024-01427-y.

Manz, S. T., Sieving, K. E., Brown et al. (2024) Experimental assessment of laser scarecrows for reducing avian damage to sweet corn. *Pest Management Science*. 80(3), 1547-1556. https://doi.org/10.1002/ps.7888.

Mapari, R., Bhangale, K., Deshmukh, L. et al. (2021) Agriculture protection from animals using smart scarecrow system. In *Proceedings of ICSCS 2021 - Soft Computing for Security Applications*. Singapore: Springer Singapore. pp. 539-551. https://doi.org/10.1007/978-981-16-5301-8_40.

Mhandu, M. M., Musarurwa, A. & Gudukeya, L. K. (2023, October) Design of a Solar Automated Scarecrow. In *Proc. IEOM Int. Conf. Smart Mobil. Veh. Electrif. Detroit, Michigan, USA.* pp. 440-451.

Mkhatshwa, J. & Daramola, O. (2023, November) Image-based identification of plant diseases and nutrient deficiency using interpretable machine learning. In *2023 Third International Conference on Digital Data Processing (DDP), Luton, UK.* IEEE. pp. 98-101.

Moharana, P. C., Yadav, B., Malav, L. C. et al. (2024) Regional prediction of soil organic carbon dynamics for intensive farmland in the hot arid climate of India using the machine learning model. *Environmental Earth Sciences*. 83(18), p. 529. https://doi.org/10.1007/s12665-024-11834-5.

Navarro, L. K. B., Mateo, K. C. H. & Manlises, C. O. (2023, October) CNN Models for Identification of Macro-Nutrient Deficiency in Onion Leaves (Allium cepa L.). In *2023 IEEE 5th Eurasia Conference on IOT, Communication and Engineering (ECICE).* IEEE. pp. 396-400.

Nemtzov, S. C. & Galili, E. (2006) A new wrinkle on an old method: successful use of scarecrows as a non-lethal method to prevent bird damage to field crops in Israel. In *Proceedings of the Vertebrate Pest Conference*, 22(22).

Pornpanomchai, C. et al. (2011) "Smart scarecrow." *2011 Third International Conference on Measuring Technology and Mechatronics Automation*, Vol. 3. IEEE, 2011.

Raju, S. H., Adinarayna, S., Prasanna, N. M. et al. (2023, October) Nutrient Deficiency Detection using a MobileNet: An AI-based Solution. In *2023 7th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC).* IEEE. pp. 609-615.

Rani, Y. A., Bhaskar, T., Arshad, M. & Allam, B. (2023, July) AI based scarecrow preventing from crop vandalization. In *2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC).* IEEE. pp. 1233-1238.

Richardson, M. R. (2014) *Efficacy of an Electronic Scarecrow on 4 Mammalian Crop-Raiders in Limpopo Province, South Africa*. Masters Theses & Specialist Projects. Paper 1400. http://digitalcommons.wku.edu/theses/1400 [Accessed: 20th September 2024].

Seal, S. & Sethia, D. (2023, October) Soil Moisture Prediction Using Deep Learning on Hyperspectral Data. In *Proceedings of the Third International Conference on AI-ML Systems*. pp. 1-8. https://doi.org/10.1145/3639856.3639861.

Shabrina, N. H., Lika, R. A. & Indarti, S. (2023) Deep learning models for automatic identification of plant-parasitic nematode. *Artificial Intelligence in Agriculture*. 7, 1-12.

Shukla, A. K., Behera, S. K., Prakash, C. et al. (2021) Assessing multi-micronutrients deficiency in agricultural soils of India. *Sustainability*. 13(16), p. 9136.

Sindhuja, V. R., Sobhana, M., Tejaswi, V. & Durgesh, P. (2022, February) Deep learning-based mobile application for nutrient deficiency identification of rice plants using ADAM Optimizer. In *2022 IEEE Delhi Section Conference (DELCON).* IEEE. pp. 1-6.

Suma, V., Shetty, R. A., Tated, R. F. et al. (2019, June) CNN based leaf disease identification and remedy recommendation system. In *2019 3rd International conference on Electronics, Communication and Aerospace Technology (ICECA).* IEEE. pp. 395-399.

Talukder, M. S. H. & Sarkar, A. K. (2023) Nutrients deficiency diagnosis of rice crop by weighted average ensemble learning. *Smart Agricultural Technology*. 4, p.100155.

Thorat, T., Patle, B. K. & Kashyap, S. K. (2023) Intelligent insecticide and fertilizer recommendation system based on TPF-CNN for smart farming. *Smart Agricultural Technology*. 3, p.100114.

Vibhute, A. D., Kale, K. V. & Gaikwad, S. V. (2024) Machine learning-enabled soil classification for precision agriculture: a study on spectral analysis and soil property determination. *Applied Geomatics*. 16(1), 181-190. https://doi.org/10.1007/s12518-023-00546-3.

Yaseen, U., Devnita, R., Nurbaity, A. et al. (2025) Soil erosion and food security in Asia’s most populous nations: a systematic review from China, India, and Indonesia. *Discover Soil*. 2(1), p. 60.

Alankritha SAMPATH is a Research Scholar at VIT, Vellore, with over three years of academic and research experience in Computer Science and Engineering, along with three years of industry experience. Her research interests focus on ML, DL, and NLP applications. She has published seven research papers in SCI, Scopus, and UGC-indexed journals, as well as in international conferences. She is also the holder of granted and published patents in agriculture AI-based systems. Her teaching philosophy emphasizes student-centered learning, practical problem solving, and the integration of emerging technologies into real-world applications.

Rajarajeswari PEREPI is an accomplished academician and researcher with over 24 years of teaching and research experience in Computer Science and Engineering. Her core expertise includes Software Engineering, Software Architecture, Cloud Computing, AI, IoT, Blockchain Technology, Data Mining, Game Theory, and Cyber-Physical Systems. She has published 35 research articles in reputed SCI, SCIE, and Scopus-indexed journals, authored multiple international books, and holds granted and published patents in intelligent systems and security applications. She has successfully completed UGC and AICTE-funded projects and is currently serving as Co-Principal Investigator for an ongoing ICMR-funded research project. She actively contributes to the academic community as an Editorial Board Member and Reviewer for leading international journals, including Springer and PLOS ONE, and has served as Session Chair, Advisory Committee Member, and FDP Coordinator for national and international conferences and faculty development programs. Her teaching philosophy emphasizes student-centric learning, real-time problem-solving, adaptability, fostering both academic excellence and practical competence among students.