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A Comprehensive Review Of AI-Driven Crop Recommendation Systems Using Deep Learning: Architectures, Datasets, And Future Research Directions

P Ayesha Barvin[1*], K Vignesh[2], M Jayalakshmi[3] and K Maharajan[4]

[1]Department of Computer Science and Engineering, Kalasalingam Academy of Research and Education, Srivilliputhur 626138, Tamil Nadu, India.
[2]Department of Computer Science and Engineering, Kalasalingam Academy of Research and Education, Srivilliputhur 626138, Tamil Nadu, India.
[3]Department of Computer Science and Engineering-Cyber Security, Ramco Institute of Technology, Rajapalayam 626117, Tamil Nadu, India.
[4]Department of Computer Science and Engineering, Kalasalingam Academy of Research and Education, Srivilliputhur 626138, Tamil Nadu, India.
Email: [1]r9923104006@klu.ac.in, Email: [2]vignesh.vkv2@gmail.com, Email: [3]jayalacsmi@gmail.com, Email: [4]maharajank@gmail.com
*Corresponding Author
P Ayesha Barvin, Department of Computer Science and Engineering, Kalasalingam Academy of Research and Education, Srivilliputhur 626138, Tamil Nadu, India.
Email: r9923104006@klu.ac.in , ORCID: 0009-0004-7804-449X

Abstract

Given how quickly AI as well as deep learning methods are developing, the modern-day agricultural sector has undergone many changes through the introduction of intelligence into the decision-making process. In particular, Crop Recommendation Systems (CRS) utilizing AI algorithms are among the useful solutions that help to boost productivity in the agricultural field. This review explores a number of studies dedicated to deep learning algorithms used to create crop recommendation systems, considering such aspects as architecture, dataset, methodological approaches, and future research areas. The research is conducted according to the PRISMA methodology, exploring relevant studies published between 2016 and 2026. CNN, LSTM, BiLSTM, GRU, Transformers, GNN, as well as hybrids like CNN-LSTM as well as CNN-Transformer are examples of deep learning models. Additionally, the study reviews existing agricultural datasets collected on the basis of soil parameters, climatic data, remote sensing, IoT, and satellite data. The study further considers some important problems that arise during implementation, including data sparsity, imbalance, lack of interpretability, computation limitations and cross-region generalizability problems. In addition to that, the study reviews some of the existing solutions to those problems, which include transfer learning, federated learning, explainable AI, TinyML and attention-based methods. It has been found out through the study that Transformer-based architectures and hybrid models perform much better than conventional ML models because of their ability to capture complicated space-time dependencies among agriculture-related variables. Lastly, the study identifies some potential areas where future research can take place in the domain of crop recommendations.

Keywords: Artificial Intelligence, Crop Recommendation System, Deep Learning, Precision Agriculture, CNN, LSTM, Transformer, Smart Farming, Remote Sensing, IoT, Explainable AI, Sustainable agriculture

1 Introduction

As the primary source of food, economic stability, as well as ecological balance worldwide, agriculture has been essential to human survival since the beginning of civilization. The demand for affordable, wholesome food will rise sharply as the world's population is predicted to reach 9.7 billion by 2050, placing tremendous pressure on agricultural operations to become more effective and productive [1]. However, current agriculture encounters many problems such as depleted soil quality, mineral deficiencies, soil degradation, water shortages and changing climate patterns. These issues adversely impact the stability of crop yields, hence endangering the world's food security in poorer nations where agriculture is their primary source of income [2].

Agriculture is still a very significant factor in the development of many developing countries, as it provides them with food sources, job opportunities and raw material inputs for millions of individuals [3]. But the conventional agricultural method depends heavily on human decision-making skills and past experiences, which sometimes yield suboptimal results due to constantly changing environmental factors. The challenge that farmers usually encounter is determining the best-suited crops according to their soil characteristics, weather conditions and seasons. This may cause poor output, ineffective resource usage and eventually, monetary losses. Thus, the need for intelligent decision support systems that can suggest crops according to the environment and soil conditions becomes imperative [4].

Recent advancements in AI have generated transformative opportunities for modern agriculture by using sophisticated systems for data-driven decision-making [5]. AI-driven agricultural systems may use extensive datasets including soil nutrient levels, meteorological conditions, precipitation patterns, and temperature variations to provide precise and pertinent crop recommendations. Figure 1 depicts many applications of AI in agriculture [6]. Artificial intelligence-driven technologies enable precision agriculture, as farmers can choose crops that fit perfectly with their environment, thus increasing their productivity. Some of the popular AI techniques include ANNs, CNNs, and RNNs [7]. They have shown high effectiveness when processing big amounts of structured data, include soil nutrient levels (nitrogen, phosphorus, potassium), pH indicators, humidity, precipitation, as well as temperatures to provide crop recommendations based on geographic locations [8]. Additionally, in order to develop highly accurate crop recommendation algorithms, recent research focuses on hybrid techniques that combine deep learning with information from IoT sensors, satellite photos, and climatic data sources.

Although there have been many advances made in this regard, yet certain difficulties exist in developing such robust AI-based recommendation systems. The most important among them include lack of agricultural data, lack of interpretability of models, variations in regional soils and weather, and deployment challenges in rural areas. Therefore, there is an increasing need for a review of studies that discuss deep learning algorithms used in crop recommendation applications [9]. With a focus on deep learning algorithms, this paper offers a comprehensive analysis of AI-based crop systems for recommendations. In order to conduct this review, recently published research articles were analyzed and discussed with respect to model types, datasets, and evaluation methods used in crop recommendation problems. Apart from the above factors, the review also focuses on future research challenges.

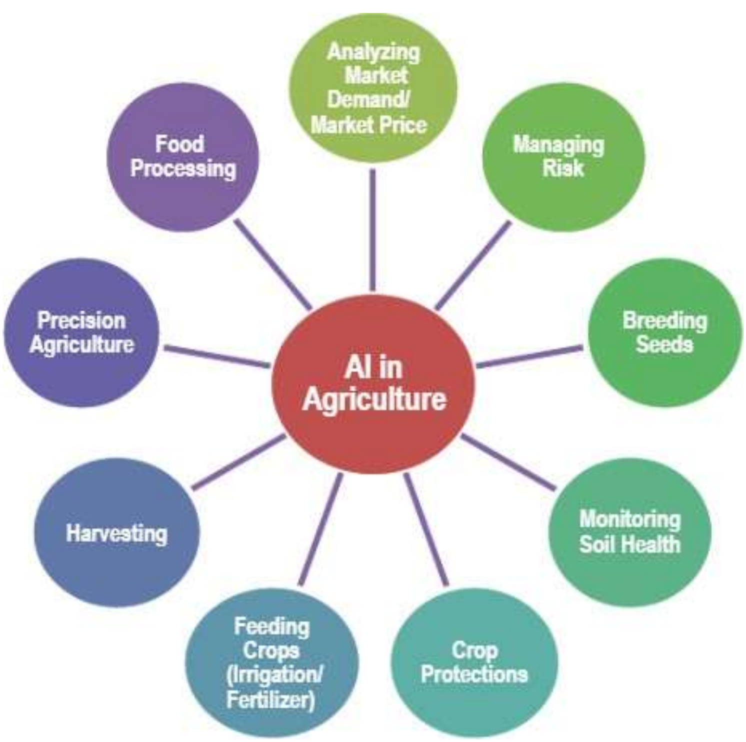

Figure 1: Applications of AI in Agriculture, Ref from [10]

2 Literature Review Methodology

2.1 Data Sources and Search Strategy

This review adheres to the PRISMA 2020 guideline to ensure a scientifically rigorous approach. An extensive literature search was carried out within five popular online academic databases, namely WoS, Scopus, IEEE Xplore, ScienceDirect and Google Scholar. The inquiry focused on articles written in English between January 2016 and December 2026.

The literature search was guided by carefully selected keywords relevant to crop recommendation systems and artificial intelligence technologies. The Boolean search string was structured as follows:

("crop recommendation" OR "crop selection" OR "crop prediction") AND ("deep learning" OR "neural network" OR "convolutional" OR "LSTM" OR "transformer") AND ("precision agriculture" OR "smart farming" OR "agricultural AI")

2.2 Inclusion and Exclusion Criteria

A study was selected if it met all four criteria:

(i) addressed AI-based algorithms related to crop recommendation or selection;
(ii) utilized one or more deep learning approaches or compared deep learning with machine learning;
(iii) presented quantitative results; and
(iv) was published in SCI-indexed publications or peer-reviewed IEEE/ACM conferences.

The exclusion criteria for this review are:
(i) if the study addressed disease detection or yield prediction alone without the crop recommendation part;
(ii) if it utilized rule-based expert systems without any learning component; or
(iii) if it was duplicate, preprint, or grey literature.

2.3 Study Selection Process

The selection of relevant studies followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, which provides a transparent and structured approach for systematic literature reviews. Four main steps made up the selection process: identification, screening, eligibility evaluation, and final inclusion.

In the identification phase, the preliminary search across all chosen databases yielded around 420 research papers pertaining to AI applications for agriculture. After removing duplicate records and applying language filters, approximately 310 articles remained for further evaluation. During the screening phase, the titles and abstracts of these publications were meticulously examined to assess their pertinence to crop systems of recommendations and AI-driven agricultural decision-making. Studies that were unrelated to crop recommendation or agricultural predictive models were excluded at this stage.

Following the screening process, approximately 84 research articles were selected for full-text examination during the eligibility stage. Each article was analyzed in detail to evaluate its methodological approach, models for deep learning or machine learning, datasets utilized, and its overall contribution to crop recommendation research. A final collection of 50 high-quality research was found and included in the thorough analysis provided in this review after all selection criteria were applied and studies that did not meet the inclusion standards were eliminated. The flowchart illustrating the identification, screening, and inclusion of studies for the systematic review (Figure 2).

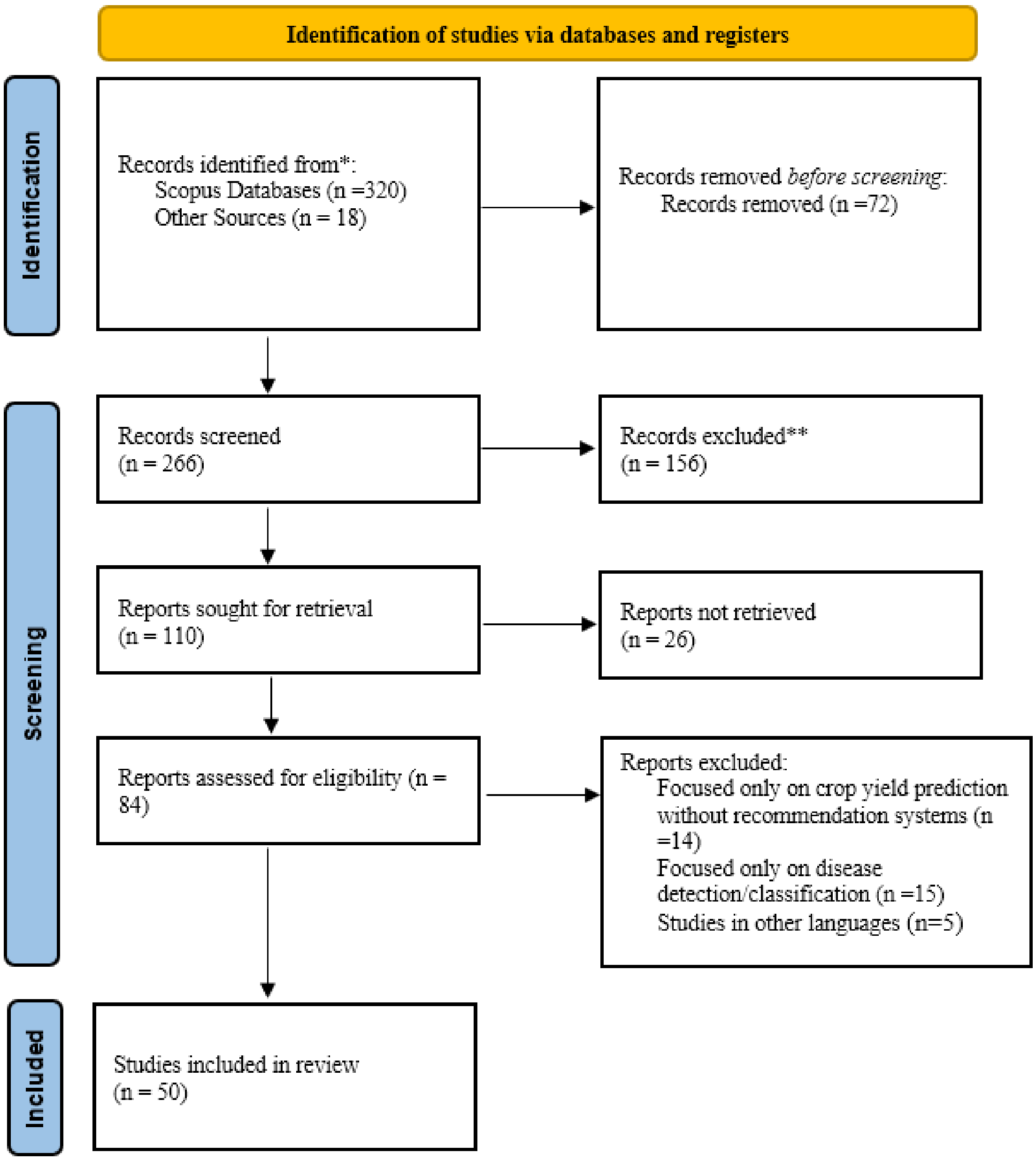

Figure 2: PRISMA Flow Diagram for the Proposed Systematic Review

2.4 Data Extraction and Analysis

To enable the comparison of the chosen articles systematically, key pieces of information were extracted from each research article. The name of the author or authors, the year the study was published, and the kind of machine learning or deep learning model used in the research paper are important facts that were taken from the publications, data sets and the input features, evaluation metrics used (accuracy/precision), and the outcomes of the evaluations.

These pieces of extracted information were important in enabling the identification of trends and developments in research as well as technology utilized in building crop recommendation systems. These pieces of information will be compiled and categorized accordingly in order to enable comparison across the selected research articles. This would also assist in identifying research gaps in the area.

3 Findings of the study

3.1 AI in Agriculture Background

AI technology has revolutionized agriculture from forecasting environmental effects to optimizing crop output and resource efficiency. Three significant uses of AI in agriculture are highlighted in this chapter: precision agriculture, machine learning, and agricultural robots (Figure 3).

AI has also been applied to precision agriculture, a technique that uses an improved sense of precision and command over conventional farming methods [11]. Large amounts of information have been collected through GPS and IoT in agricultural settings for precision agriculture [12], [13]. These datasets were used to extract information about the Heat, condition of the plants, fertilization, and moisture content of the soil. The AI system evaluates these datasets to provide useful recommendations to the farmers related to the planting, irrigation, and harvesting of crops. Based on these data, AI-powered devices can recommend how much water and fertiliser should be applied to the crops [14], [15].

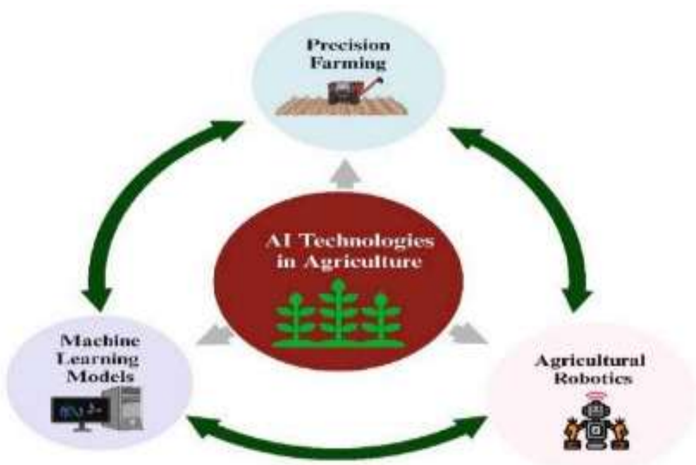

Figure 3: Schematic Representation of AI-Driven technologies in modern agriculture [15].

Figure 4 illustrates some of the different elements and outputs of the above technologies. At its core, In order to monitor a number of crucial characteristics, precision agriculture depends on real-time data gathering using GPS and Internet of Things devices, namely the status of the soil, climate patterns, and plant health [16], [17]. AI algorithms that support decision-making in the use of variable resources, such as optimized water, fertilizer, and pesticide treatments, are then fed the real-time data [18]. One of the primary results seen in the above chart is a reduction in overall operating costs, with inputs being applied only when necessary.

Figure 4: Components and benefits of precision farming: Leveraging real-time data and genomics for sustainable agriculture.

The implementation of agriculture robotics helps automate difficult labor-intensive tasks and minimize the involvement of human resource components while increasing efficiency [19]. There is an application of AI-enabled robots in such activities like harvesting and weeding of seeds [20][21]. Such robots can navigate through fields efficiently and can work continuously for 24 hours regardless of the weather conditions. Besides, besides increasing the speed at which activities are completed in agriculture, Robotics contributes to lowering human mistake rates and raising agricultural product quality standards [22]. To improve uniformity in quality of goods and cut down on waste, robot-based harvesters, for example, may be configured to gather only ripe fruits [23]. Through such innovations, AI is helping transform farming through improved intelligence, accuracy, and productivity in agriculture without the excessive consumption of resources. With time, there will be more revolutions in food production due to such changes. One revolution expected in agriculture globally is set to be triggered by such advancements in the near future.

3.2 Deep Learning Architectures in Crop Recommendation System

Deep learning's capacity has revolutionized CRS's potential by permitting the automated extraction of complex and non-linear feature representations from multi-dimensional agricultural datasets.

Unlike conventional machine learning methods that necessitate manually crafted features, deep neural networks facilitate the acquisition of hierarchical representations directly from data, including soil chemical composition, weather datasets, multispectral satellite imagery, and IoT sensor signals [24][25]. The integration of extensive agricultural data sources, advancements in GPU-based computational frameworks, and transfer learning in huge pre-trained deep neural network models has propelled Deep learning's use in agriculture [26][27].

CNNs remain the de facto state of the art solution for handling agricultural datasets characterized by spatiotemporal relationships. By means of successive convolutions, max-pooling operations, and nonlinear activation functions, CNNs generate increasingly complex representations of local spatial structures without explicit feature engineering [28]. When it comes to CRS jobs, pre-trained models like ResNet-50, VGG-16, EfficientNet, and DenseNet have been tailored using specific agricultural datasets to extract vegetation indices, soil textural properties, and plant canopy phenology markers from multispectral Sentinel-2 images [29][30]. Results from empirical evaluations suggest that CNN-based systems attain a classification accuracy range of 88% to 96% on highly-resolved time-series multispectral data sets with sufficient labeled examples. Singh & Sanodiya [31] showed that CNNs combined with transfer learning based on the ImageNet database greatly minimize the need for labeled training data to detect crop diseases, another sub-task in CRS. Nonetheless, CNNs are fundamentally restricted in their capacity to model temporal dependencies, which is necessary for understanding crop-climate seasonality.

A temporal model is crucial to CRS since the crop suitability is strongly associated with weather changes throughout the year. LSTM networks overcome the limitation of vanishing gradient of the vanilla recurrent network with a cell state-based gated mechanism which allows keeping agronomic information through long temporal sequences. LSTMs have been successfully used for modeling multi-year weather information, IoT-based soil moisture sequences and crop calendar events in CRS with 85-94% accuracy. Renukaradya et al. [32] utilized the temporal attention with LSTM to predict crop yield from district-level multiseasonal datasets from Karnataka with 92.4% accuracy.

BiLSTMs learn sequences in both temporal directions and capture past and future dependencies. The bidirectional encoding results in more enriched seasonal representation of data as achieved by Saini et al. [33] who predicted sugarcane yield from a combination of convolutional layers with BiLSTM achieving 94.6% accuracy. GRUs are an alternative to LSTMs with reduced computation requirements that combine multiple gates into one with 84–93% accuracy and faster training times [34], thus being well-suited for deployment at the edge due to bandwidth limitations in rural areas.

The Transformer architecture has shown excellent results in CRS by leveraging the use of multi-head self-attention systems to record long-range relationships among heterogeneous agri-data modalities without sequential dependencies. In CRS applications, Transformer encoders have been leveraged to integrate tabular data of soil chemistry with multiple time-series climate data through cross-attention mechanisms, leading to an effective multi-modal representation. Thilakarathne et al. [27] showed that cloud-based Transformer-based CRS frameworks exhibit a 94.1%

level of accuracy while being scalable for nationwide deployment via microservices architecture. The Vision Transformers (ViT) further leverages attention techniques in unprocessed multispectral images, where Sher et al. [35] found that CNN-GRU feature integration outperforms CNN alone for crop classification tasks, thereby supporting hybrid attention strategies. The accuracy reported in Transformer-based CRS literature ranges from 91-97%, which is the highest among all reviewed architectures.

The most common research direction is the fusion of complementary architectural abilities using hybrid approaches that can model both spatial and temporal aspects at the same time. CNN-LSTM combines the spatial information extracted by the convolution layer of CNNs on images or band series, which serves as the input sequence for LSTM units. Machichi et al. [29] showed that multi-input CNN-LSTM models could efficiently classify different cereal crops Using time series data from remote sensing. Bharti et al. [36] proved that CNN-LSTM is effective in predicting crop yields because Compared to individual designs, the hybrid model performs better. Finally, CNN-Transformer hybrid models use pre-trained visual backbones to extract spatial information efficiently and cross-modal alignment with attention with an accuracy of 91-97% on the surveyed multi-modal datasets.

The Graph Neural Networks (GNN) model provides a fresh way of thinking about relational representation based on structural dependencies among agriculture entities like crops, soil profile, climatic regions, and geographic regions in a heterogeneous graph with edges representing spatial, agronomic, and causative relations. The Graph Attention Networks (GAT) is an evolution of the fundamental GNN architecture that enables the model to learn attention values over edges in the neighborhood. An extensive study of the literature by Ayesha Barvin and Sampradeepraj [37] for the field of GNN-based CRS has confirmed that the relational bias helps improve cross-regional generalization in comparison with CNN or LSTM baselines. GNN-based studies achieve accuracies of 89-95% with impressive cross-regional transfer results.

GANs and VAEs function as data augmenters and feature compressors in CRS workflows rather than as classifiers. In the case of conditional GANs, we create realistic soil and weather data samples for classes having lesser representation owing to severe class imbalances inherent to crop recommendation datasets comprising predominantly staple crops [38]. Denoising autoencoders reduce the dimensionality of the high-dimensional data from sensors and spectral sources while retaining important discriminant features, as well as being insensitive to noise in the sensor data. The compressed latent space from autoencoders is then used as enhanced feature inputs to other classification algorithms [39].

Table 1. Comparative summary of deep learning architectures applied in crop recommendation systems (CRS). Accuracy ranges synthesised from reviewed literature (2019–2024).

Architecture	Category	Key Strength	Typical CRS Input	Accuracy Range (%)
CNN (ResNet/VGG/EfficientNet)	Spatial	Hierarchical feature extraction from imagery	Multispectral satellite images	**88-96**
LSTM	Temporal	Sequential long-range memory	Weather/IoT time-series	**85-94**
BiLSTM	Temporal	Bidirectional context encoding	Climate seasonal sequences	**87-95**
GRU	Temporal	Computationally efficient gating	Soil moisture streams	**84-93**

Architecture	Category	Key Strength	Typical CRS Input	Accuracy Range (%)
Transformer / ViT	Attention	Global dependency modelling	Multi-modal agri-data	**91-97**
CNN-LSTM Hybrid	Hybrid	Spatial + temporal fusion	Satellite + IoT sequences	**90-97**
CNN-Transformer	Hybrid	Multi-modal cross-attention	UAV imagery + climate	**91-97**
GNN / GAT	Graph-based	Relational crop-environment modelling	Crop-climate graphs	**89-95**
GAN / CVAE	Generative	Synthetic data for rare crops	Tabular / spectral data	**(Preprocessor)**
Autoencoder	Unsupervised	Compact feature representations	Sensor / spectral data	**80-91**

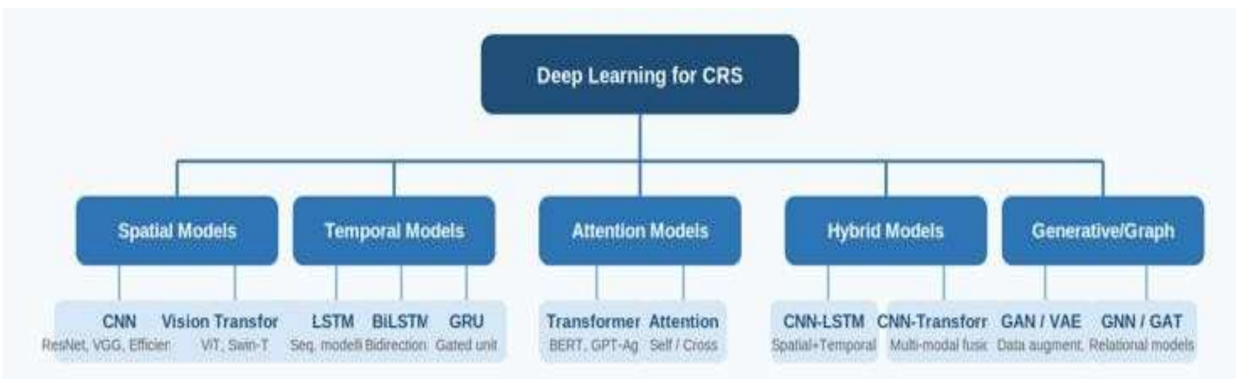

Figure 5: Taxonomy of deep learning architectures employed in crop recommendation systems

3.3 Datasets Used in Crop Recommendation Systems

The ceiling of performance capability for deep learning CRS systems is examined fundamentally by the nature of the training information that it relies on. The data related to agriculture is naturally multi-modal, and includes table soil chemistry, continuous meteorology time series, Non-linear field survey data with high-dimensional remote sensing data. Quality issues related to agricultural data, including missing data points, class imbalance, geographic clustering and shallow temporality, remain consistent barriers to the generalization of models across all of the literature cited [40][41].

3.3.1 Benchmark Tabular Datasets

The Kaggle Crop Recommendation Dataset is the benchmark that has been used extensively in practice due to its ease of use and structured data format. This dataset comprises 2,200 records featuring soil macronutrient content (Nitrogen, Phosphorus, Potassium), pH level, temperature, humidity and rainfall in an entire year for 22 different crops. This benchmark allows quick prototyping and comparison of models [42]. Shams et al. [24] reached the accuracy rate of 99.27% on this dataset via Gradient Boosting coupled with SHAP explanation. Despite high performance rates and relatively small size of the dataset (2,200 records), as well as its specificity related to the Indian agro-climate region, this database suffers from being too narrowly focused. It represents only two types of land arable and non-arable. In addition, more than 60% of studies in review are built solely on this benchmark.

3.3.2 Satellite Remote Sensing Datasets

Datasets derived from satellites have been revolutionary in extending the feature set of CRS with continuous spatial and temporally dense observations of the condition of the surface of the earth. The satellite system of the European Space Agency, i.e., the ESA Sentinel-2 constellation, provides multi-spectral images in 13 bands at 10 to 60 meter resolution and with 5-day revisit frequency, thus allowing vegetation indices (NDVI, EVI, SAVI and Red-edge NDVI) as well as crop growth stage indices to be extracted. In all the reviewed articles that use the Sentinel-2 satellite, an improvement in terms of 4 to 9 percentage points in multi-class crop classification was observed compared to the tabular-only baseline, and according to Wang et al. [43], self-supervised pre-training on Sentinel-2 satellite time series data leads to a significant decrease in labeled data needs. Sentinel-1 SAR data adds the value of penetration through clouds and all-season monitoring necessary in tropical or monsoon climates [44].

3.3.3 Soil Property Databases

All CRS models employ information from worldwide soil systems of information on the chemical and physical properties of agricultural land. With a resolution of 250 meters, the ISRIC World Soil Grids 2.0 forecasts soil organic carbon content, pH, bulk density, proportion of clay, silt, sand content, as well as cation exchange capacity globally. In their review, Minasny et al. [45]describe a range of machine learning algorithms in soil sciences using SoilGrids data that can be applied to digital soil mapping relevant to feature engineering in CRS models. The FAO GAEZ v4 database includes classifications of soil suitability, land cover maps, and agro-climatic resource inventories [46].

3.3.4 IoT and Sensor Datasets

Agricultural IoT systems create data sets at high resolution and real-time soil and microclimate conditions of the agricultural farm with a temporal granularity ranging from seconds to minutes. However, data collected from the IoT systems are subject to missing values, sensor drifts, and inconsistencies, which need proper preprocessing. Hossain et al. [47] suggested a machine learning-based CRS-based Internet of Things soil monitoring device, which gave instant recommendations regarding fertilizers and crops through a sensor network on an agricultural farm. Furthermore, Gupta et al. [48] used IoT weather stations and big data analytics techniques to forecast crops using weather data with 93.5% accuracy.

3.3.5 Crop Yield and Farm Survey Records

Databases for agricultural census and longitudinal farm surveys are valuable sources of ground truth on crop choices, cultivation practices, and yield performance for supervised CRS models training. The ICRISAT Village Level Studies Database with 3-decade long data on crop production in semi-arid tropical villages of South Asia has been employed in reviewed studies for long-term temporal LSTM training [49]. With 54,309 labeled images of diseased plants (Penn State), the Plant Village dataset allows training a deep network for disease-aware CRS, which suggests crop types considering the associated risks of diseases [50]. The USDA NASS CropScape 30-meter annual cropland map provides pixel-level labels for CNN training for crop classification in the continental US [51].

Table 2. Key datasets utilised in deep learning-based crop recommendation system research.

Dataset / Source	Region	Temporal Coverage	Key Features	Primary Use in CRS
Kaggle Crop Recommendation Dataset	India	Static	N, P, K, pH, humidity, rainfall, temp (22 crops)	Classification benchmarking; used in >60% of reviewed studies
NASA POWER (v8+)	Global	1981 - present	Solar irradiance, wind, temp, precip (0.5° grid)	Climate feature engineering for temporal DL models

ESA Sentinel-2 MSI	Global	2015 - present	13 spectral bands, 10–60 m, 5-day revisit	Spatial CNN models; NDVI/EVI extraction
ESA Sentinel-1 SAR	Global	2014 - present	C-band SAR, all-weather crop monitoring	Cloudy-region crop mapping with CNN-RNN
ISRIC SoilGrids (v2.0)	Global	2020 update	pH, SOC, clay, BD at 250 m resolution	Soil feature extraction for DL input layers
FAO GAEZ v4	Global	2021 release	Agro-climatic resources, crop suitability zones	Spatial-contextual modelling with GNNs
ICRISAT Village Level Studies	South Asia	1975-2014	Crop yields, rainfall, socio-economic data	Multi-year temporal LSTM training
PlantVillage (Penn State)	Multi-region	2019 - present	54,309 labelled plant disease images	Transfer learning for disease-aware CRS
Dataset / Source	Region	Temporal Coverage	Key Features	Primary Use in CRS
AgriSense IoT (proprietary)	Multi-region	Real-time	Soil moisture, temp, EC, pH from field nodes	IoT-driven LSTM/GRU recommendation models
USDA NASS CropScape	USA	2008 - present	30 m annual crop type maps	Training data for CNN crop classifiers

3.4 Challenges

Despite the advances achieved, deep learning CRS translation from prototype to agricultural advisories encounters a range of interconnected obstacles associated with technology, society and infrastructure. This section presents a detailed examination of the major challenges highlighted within reviewed literature [52]-[54].

Deep learning models' efficacy is intrinsically reliant on the volume as well as quality on their training information. Data shortage for minor and localised cultivars, geographic concentration in data-abundant regions (India, United States, China) and lack of temporal depth, restricting modelling of climate change over decades, is a persistent issue [55]. Over-representation of staple crops (rice, wheat, maize) within the training set creates an inherent prediction bias which is overlooked by accuracy indicators. The use of SMOTE algorithm oversampling, focal losses and class weighting resulted in up to 7% increases in accuracy for minority crops across reviewed papers [56], [57]. Missing data from equipment failure produces intrinsic bias that cannot be solved through imputation techniques, especially when there is a correlation between missingness and environment conditions [58].

One major barrier to deep learning models' acceptance in agriculture is their black-box character. The users will hardly follow recommendations provided by the system that cannot be questioned even though it exhibits high performance. For instance, Lundberg & Lee's [53] SHAP methodology for feature attribution was applied by Shams et al. [24] in their CRS pipelines, finding that rainfall, soil pH and soil temperature are the strongest features driving recommendations. Nonetheless, less than 30% of papers under consideration present any kind of model explanation or feature attribution at all [59]. Explanation mechanisms introduced ex post are far from accurately representing the inner workings of models, which warrants future research on intrinsically explainable models.

The high-performance training of DL algorithms requires access to GPUs which are not available in the restricted environments where most small-scale farming in developing countries is conducted. Although methods like knowledge distillation, quantisation, pruning, and TinyML approaches are being researched in the context of deploying these models in edge-computing scenarios, their implementation is still limited to date. Limited connectivity in rural areas calls for offline-capable edge-deployable models able to process the collected sensor data without having cloud connectivity [57].

Typically, most CRS algorithms are validated using the same geographical and temporal data sources used during training, which provides overly optimistic performance estimates. Generalisation across different regions is not often considered, yet is essential to achieve scalable application [60]. For instance, Paudel et al. [61] showed that the cross-regional accuracy decreased by 8% to 15% for Europe-based crop yield prediction. Temporal generalisation constitutes another important challenge, in that models trained using historical climate data might make consistently biased decisions when presented with a new climate.

Table 3. Summary of key challenges and evidence-based mitigation strategies in DL-based CRS.

Challenge	Description	Mitigation Strategies
Data Scarcity	Limited labelled data for minor/regional crops; geographic concentration in India and USA	Transfer learning, GANs, federated data sharing, open datasets
Class Imbalance	Staple crops over-represented; rare crop accuracy severely degraded	SMOTE, focal loss, class-weighted training, GAN augmentation
Model Interpretability	Black-box DL models reduce farmer trust and regulatory acceptance	SHAP, LIME, attention maps, prototype-based networks [R11]
Challenge	Description	Mitigation Strategies
Temporal Generalisation	Historical climate calibration fails under shifting climate regimes	Continual learning, domain adaptation, CMIP6 climate projections
Computational Constraints	GPU-intensive training prohibits edge/mobile deployment in rural areas	TinyML, knowledge distillation, ONNX Runtime, pruning
Spatial Generalisation	Models trained locally fail across diverse agro-ecological zones	Federated learning, GNN relational inductive bias, leave-one-region-out CV
Missing/Noisy IoT Data	Sensor drift, power failures produce systematic missingness	Denoising autoencoders, robust imputation, attention masking
Privacy & Data Governance	Farmers reluctant to share field data without transparency guarantees	Differential privacy, federated learning, blockchain audit trails

4 Conclusion

One of the most promising technical advancements in precision agriculture is AI-based crop recommendation systems, which provide clever methods for raising crop production, efficient use of resources and sustainable agriculture. In this review, various developments in deep learning-based CRS technologies were evaluated extensively, including major neural network architectures, popular benchmark datasets and implementation issues. Results show that GNNs, CNNs, LSTMs, Transformers, as well as hybrid models are much more powerful than traditional ML algorithms because of their capability to recognize complex agricultural patterns. Furthermore, the importance of combining satellite images, IoT sensors data, weather information, and soil properties within the context of integrated recommendation schemes was emphasized as well. Among all the methodologies examined, transformer-based models as well as hybrid deep learning methods demonstrated the highest accuracy, particularly when handling large and diverse agricultural data. Nevertheless, although there have been numerous developments in the field, there are still many unsolved problems such as the lack of good data, insufficient model interpretability, computational restrictions and poor cross-region applicability.

It is crucial for the future works to develop trustworthy AI models which could be trusted by farmers and facilitate their agricultural decisions. Edge computing, federated learning, multimodal data fusion, and recommendation systems with the ability to adapt to different climates are going to dominate the field in the near future. Integrating AI technology with blockchain, IoT, remote sensing and cloud-edge computing is going to contribute greatly to building intelligent agricultural ecosystems. In conclusion, AI-based crop systems of recommendations hold a great deal of promise to address the issue of food security in the next decades.

5 References

[1] K. Pawlak, “The Role of Agriculture in Ensuring Food Security in Developing Countries : Considerations in the Context of the Problem of Sustainable Food Production,” Sustainability, vol. 12, no. 13, p. 5488, 2020.

[2] S. D. Aslam, S., Bakr, M. A., & Khan, “Segmentation of Agricultural Fields in Aerial Imagery Using Enhanced Deep Learning Models,” in In 2024 19th International Conference on Emerging Technologies (ICET), 2024, pp. 1-6.

[3] M. Ullah, “Deep Learning Based Models for Paddy Disease Identification and Classification : A Systematic Survey,” IEEE Access, vol. 12, no. June, pp. 100862-100891, 2024.

[4] E. A. Goud and V. Rathikarani, “A Review on Deep Learning-Based Crop Disease Detection and Fertilizer Recommendation Systems for Smart Agriculture,” Curr. Agric. Res. J., vol. 13, no. 3, pp. 697-710, 2025.

[5] N. Khan, R. L. Ray, G. R. Sargani, M. Ihtisham, and M. Khayyam, “Current Progress and Future Prospects of Agriculture Technology : Gateway to Sustainable Agriculture,” Sustainability, vol. 13, pp. 1-31, 2021.

[6] Y. Chen, J. Kuang, D. Cheng, and J. Zheng, “AgriKG : An Agricultural Knowledge Graph and Its Applications,” Springer Nat. Switz., vol. 2, pp. 533-537, 2019.

[7] A. J. Khan, M. A. Bakr, and S. D. Khan, “Vegetation Detection Using UAV Imagery with Deep Learning Segmentation Models,” in 2024 19th International Conference on Emerging Technologies (ICET), 2024, pp. 1-6.

[8] N. Tantalaki, S. Souravlas, and M. Roumeliotis, “Data-Driven Decision Making in Precision Agriculture : The Rise of Big Data in Agricultural Systems Data-Driven Decision Making in Precision Agriculture :,” J. Agric. Food Inf., vol. 20, no. 4, pp. 1-37, 2019.

[9] M. Jayalakshmi, K. Maharajan, K. Jayakumar, and G. Visalaxi, “Novel Deep-Learning Approaches for Future Computing Applications and Services,” in Simulation and Analysis of Mathematical Methods in Real-Time Engineering Applications, pp. 247-271, 2021.

[10] M. Pradesh, “Application of artificial intelligence (ai) in agriculture: an indian perspective,” Soil Heal. Manag., vol. 5, no. 2, pp. 9-11, 2022.

[11] E. M. B. M. Karunathilake, A. T. Le, S. Heo, and Y. S. Chung, “The Path to Smart Farming : Innovations and Opportunities in Precision Agriculture,” Agriculture, vol. 13, pp. 1-26, 2023.

[12] R. K. Singh and G. S. Member, “AgriFusion : An Architecture for IoT and Emerging Technologies Based on a Precision Agriculture Survey,” IEEE Access, vol. 9, pp. 136253-136283, 2021.

[13] M. Jayalakshmi and M. Kaliyanandi, “Revolutionizing Precision Agriculture Using Artificial Intelligence and Machine Learning,” in Data Science for Agricultural Innovation and Productivity, pp. 110-126, 2024.

[14] B. B. Gupta and F. Colace, Handbook of Research on AI and ML for Intelligent Machines and Systems. IGI Global, 2023.

[15] M. Jayalakshmi and V. Gomathi, “Sensor-Cloud Based Precision Agriculture Approach for Intelligent Water Management,” Int. J. Plant Prod., vol. 14, no. 2, pp. 177-186, 2020

[16] N. Aijaz, H. Lan, T. Raza, M. Yaqub, R. Iqbal, and M. Salman, “Artificial intelligence in agriculture : Advancing crop productivity and sustainability,” J. Agric. Food Res., vol. 20, no. September 2024, 2025.

[17] K. E. Ukhurebor, C. O. Adetunji, O. T. Olugbemi, W. Nwankwo, A. S. Olayinka, C. Umezuruike, and D. I. Hefft, “Chapter 6 - Precision agriculture: Weather forecasting for future farming,” in Intelligent Data-Centric Systems, A. Abraham, S. Dash, J. J. P. C. Rodrigues, B. Acharya, and S. K. B. T.-A. I. Pani Edge and IoT-based Smart Agriculture, Eds. Academic Press, 2022, pp. 101-121.

[18] M. Jayalakshmi, K. S. Vamsi, K. D. D. Reddy, K. P. Chand, and K. M. Feroz, “Empowering Farmers: A Real-Time Bidding System with Integrated Machine Learning,” in Proc. 2024 Int. Conf. Sustain. Commun. Networks Appl. (ICSCNA), IEEE, pp. 1058-1064, 2024.

[19] A. Castrignanò, G. Buttafuoco, R. Khosla, A. Mouazen, D. Moshou, and O. Naud, Agricultural Internet of Things and

Decision Support for Precision Smart Farming. Academic Press, 2020.
[20] M. Bilal, F. Rubab, M. Hussain, S. Adnan, and R. Shah, “Agriculture Revolutionized by Artificial Intelligence : Harvesting the Future,” Biol. Life Sci. forum, vol. 30, no. 11, pp. 1-6, 2024.
[21] T. Wang, X. Xu, C. Wang, Z. Li, and D. Li, “From Smart Farming towards Unmanned Farms : A New Mode of Agricultural Production,” Agriculture, vol. 11, p. 145, 2021.
[22] M. Saiful, A. Mahmud, M. Shukri, Z. Abidin, and A. A. Emmanuel, “Robotics and Automation in Agriculture : Present and Future Applications,” Appl. Model. Simul., vol. 4, pp. 130-140, 2020.
[23] R. Barth, “Vision Principles for Harvest Robotics: Sowing Artificial Intelligence in Agriculture.” 2018.
[24] M. Y. Shams, S. A. Gamel, and F. M. Talaat, “Enhancing crop recommendation systems with explainable artificial intelligence: a study on agricultural decision-making,” Neural Comput. Appl., vol. 36, no. 11, pp. 5695-5714, 2024.
[25] P. Muruganantham and S. Wibowo, “A Systematic Literature Review on Crop Yield Prediction with Deep Learning and Remote Sensing,” 2022.
[26] S. A. Bhat, “Big Data and AI Revolution in Precision Agriculture : Survey and Challenges,” IEEE Access, vol. 9, pp. 110209-110222, 2021.
[27] L. P. Farming, “A Cloud Enabled Crop Recommendation Platform for Machine Learning-Driven Precision Farming,” Sensors, vol. 22, no. 16, 2022.
[28] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” Adv. Neural Inf. Process. Syst., vol. 25, 2012.
[29] M. A. Machichi, O. Bourja, O. Lahlou, Y. Zennayi, F. Bourzeix, I. H. Houmma, and R. Hadria, “Crop mapping using supervised machine learning and deep learning : a systematic literature review,” Int. J. Remote Sens., vol. 44, no. 8, pp. 2717-2753, 2023.
[30] M. Sher, N. Minallah, and J. Frnda, “Elevating Crop Classification Performance Through CNN-GRU Feature Fusion,” IEEE Acc, vol. 12, no. August, 2024.
[31] R. S. R. Singh and R. K. Sanodiya, “Zero-Shot Transfer Learning Framework for Plant Leaf Disease Classification,” IEEE Access, vol. 11, pp. 143861-143880, 2023.
[32] A. B. Renukaradya, N. D., Rao, K. G., & Jayachandra, “Classification and Estimation of Crop Yield Prediction in Karnataka using LSTM with Attention Mechanism.,” Int. J. Intell. Syst. Appl. Eng., vol. 12, no. 3, pp. 89-96, 2024.
[33] P. Saini, B. Nagpal, P. Garg, and S. Kumar, “CNN-BI-LSTM-CYP: A deep learning approach for sugarcane yield prediction,” Sustain. Energy Technol. Assessments, vol. 57, p. 103263, 2023.
[34] H. B. Patel, K., & Patel, “Multi-criteria Agriculture Recommendation System using Machine Learning for Crop and Fertilizesrs Prediction .,” Curr. Agric. Res. Journal, vol. 11, no. 1, 2023.
[35] M. Sher, N. Minallah, J. Frnda, and W. Khan, “Elevating Crop Classification Performance Through CNN-GRU Feature Fusion,” IEEE Access, vol. 12, pp. 141013-141025, 2024.
[36] S. Bharti, P. Kaur, P. Singh, C. Madhu, and N. Garg, “Crop Yield Prediction Using CNN-LSTM Model,” in 2022 IEEE Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), 2022, pp. 1-5.
[37] P. A. Barvin and T. Sampradeepraj, “Crop Recommendation Systems Based on Soil and Environmental Factors Using Graph Convolution Neural Network : A Systematic Literature Review,” Eng. Proc., vol. 58, no. 1, p. 97, 2023.
[38] M. Javaid, A. Haleem, I. H. Khan, and R. Suman, “Understanding the potential applications of Artificial Intelligence in Agriculture Sector,” Adv. Agrochem, vol. 2, no. 1, pp. 15-30, 2023.
[39] D. Elavarasan and P. M. D. Vincent, “Crop Yield Prediction Using Deep Reinforcement Learning Model for Sustainable Agrarian Applications,” IEEE Access, vol. 8, pp. 86886-86901, 2020.
[40] M. Hasan, M. A. Marjan, M. P. Uddin, M. I. Afjal, S. Kardy, S. Ma, and Y. Nam, “Ensemble machine learning-based recommendation system for effective prediction of suitable agricultural crop cultivation,” Front. Plant Sci., vol. 14, p. 1234555, 2023.
[41] J. Zhang and G. Liu, “Effects of control sequence optimisation on the performance of bivariate fertiliser applicator,” Comput. Electron. Agric., vol. 192, p. 106594, 2022.
[42] S. K. Apat, J. Mishra, K. S. Raju, and N. Padhy, “An Artificial Intelligence-based Crop Recommendation System using Machine Learning,” vol. 82, no. May, pp. 558-567, 2023.
[43] J. Wang, Y. Zhong, A. Ma, Z. Zheng, Y. Wan, and L. Zhang, “LoveNAS: Towards multi-scene land-cover mapping via hierarchical searching adaptive network,” ISPRS J. Photogramm. Remote Sens., vol. 209, pp. 265-278, 2024.
[44] S. Asam, U. Gessner, R. Almengor, M. Wenzl, J. Kriese, and C. Kuenzer, “Mapping Crop Types of Germany by Combining Temporal Statistical Metrics of Sentinel-1 and Sentinel-2 Time Series with LPIS Data,” Remote Sens., vol. 14, no. 3, p. 2981, 2022.

[45] B. Minasny, T. Bandai, T. A. Ghezzehei, Y.-C. Huang, Y. Ma, A. B. McBratney, W. Ng, S. Norouzi, J. Padarian, Rudiyanto, A. Sharififar, Q. Styc, and M. Widyastuti, “Soil Science-Informed Machine Learning,” Geoderma, vol. 452, p. 117094, 2024.

[46] J. P. Ghizoni Teive, R. C., Roesler Rese, A. L., & Parreira, “An Intelligent System for Operators Performance Multicriteria Evaluation of Distribution Networks,” Appl. Artif. Intell., vol. 36, no. 1, 2022.

[47] M. D. Hossain, M. A. Kashem, and S. Mustary, “IoT Based Smart Soil Fertilizer Monitoring And ML Based Crop Recommendation System,” in 2023 International Conference on Electrical, Computer and Communication Engineering (ECCE), 2023, pp. 1-6.

[48] R. Gupta, A. K. Sharma, O. Garg, K. Modi, S. Kasim, Z. Baharum, H. Mahdin, and S. A. Mostafa, “WB-CPI: Weather Based Crop Prediction in India Using Big Data Analytics,” IEEE Access, vol. 9, pp. 137869-137885, 2021.

[49] S. K. S. Durai and M. D. Shamili, “Smart farming using Machine Learning and Deep Learning techniques,” Decis. Anal. J., vol. 3, p. 100041, 2022.

[50] A. Singh and A. K. Bhamboo, “Crop Recommendation and Disease Detection Using Deep Neural Networks,” in 2022 IEEE 6th Conference on Information and Communication Technology (CICT), 2022, pp. 1-5.

[51] F. Feng, M. Gao, R. Liu, S. Yao, and G. Yang, “A deep learning framework for crop mapping with reconstructed Sentinel-2 time series images,” Comput. Electron. Agric., vol. 213, p. 108227, 2023.

[52] B. B. Sinha and R. Dhanalakshmi, “Recent advancements and challenges of Internet of Things in smart agriculture: A survey,” Futur. Gener. Comput. Syst., vol. 126, pp. 169-184, 2022.

[53] S. M. Lundberg and S.I. Lee, “A Unified Approach to Interpreting Model Predictions,” in Advances in Neural Information Processing Systems, 2017, vol. 30.

[54] D. Dahiphale, P. Shinde, K. Patil, and V. Dahiphale, “Smart Farming : Crop Recommendation Using Machine Learning with Challenges and Future Ideas,” no. July, pp. 1-13, 2025.

[55] D. B. Johnston, K. G. Pembleton, N. I. Huth, and R. C. Deo, “Comparison of machine learning methods emulating process driven crop models,” Environ. Model. Softw., vol. 162, p. 105634, 2023.

[56] P. S. S. Gopi and M. Karthikeyan, “Red fox optimization with ensemble recurrent neural network for crop recommendation and yield prediction model,” Multimed. Tools Appl., vol. 83, no. 5, pp. 13159-13179, 2024.

[57] S. Iniyan, M. S. Raja, R. Srinivasan, C. Santhanakrishnan, and A. Srinivasan, “Crop and Fertilizer Recommendation System Applying Machine Learning Classifiers,” in 2023 International Conference on Emerging Research in Computational Science (ICERCS), 2023, pp. 1-6.

[58] P. Sharma, “AI-Enabled Crop Recommendation System Based on Soil and Weather Patterns,” pp. 184-199, 1989.

[59] R. Ed-daoudi, A. Alaoui, B. Ettaki, and J. Zerouaoui, “A Predictive Approach to Improving Agricultural Productivity in Morocco through Crop Recommendations,” Int. J. Adv. Comput. Sci. Appl., vol. 14, no. 3, pp. 199-205, 2023.

[60] M. Rashid, B. S. Bari, Y. Yusup, M. A. Kamaruddin, and N. Khan, “A Comprehensive Review of Crop Yield Prediction Using Machine Learning Approaches With Special Emphasis on Palm Oil Yield Prediction,” IEEE Access, vol. 9, pp. 63406-63439, 2021.

[61] D. Paudel, H. Boogaard, A. de Wit, M. van der Velde, M. Claverie, L. Nisini, S. Janssen, S. Osinga, and I. N. Athanasiadis, “Machine learning for regional crop yield forecasting in Europe,” F. Crop. Res., vol. 276, p. 108377, 2022.