International Journal of Applied Resilience and Sustainability, Volume 2, Issue 3, May 2026, pp. 176-207

International Journal of Applied Resilience and Sustainability

Journal homepage: https://deepscipub.com/ijars

Artificial intelligence for sustainable agriculture: A review of machine learning and deep learning techniques for crop growth and yield prediction

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Article Info:
Received 26 March 2026
Revised 27 April 2026
Accepted 05 May 2026
Published 15 May 2026

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Abstract

The climate change, the lack of resources, soil decline, the population growth, and food security have put additional pressure on agriculture, which poses an urgent necessity to improve the accuracy and sustainability of systems of crop growth and crop yield projections. Machine Learning and Deep Learning are types of Artificial Intelligence that have become a groundbreaking method to overcome these issues in Sustainable Agriculture and Precision Agriculture. It is a PRISMA-based literature review of recent advances in Crop Growth Prediction and Crop Yield Prediction based on data-driven farming strategies with the emphasis on the research published in the age of Smart Farming, Digital Agriculture, and Climate-Smart Agriculture. The literature review was systematic in terms of tackling literature connected to machine learning, deep learning, remote sensing, UAV imagery, satellite imagery, Internet of Things sensors, and Agricultural Big Data to predictive modeling in agriculture. Typically used algorithms are Random Forest, Support Vector Machine, Gradient Boosting, Ensemble Learning, Convolutional Neural Network, Long Short-Term Memory, Reinforcement Learning, Transfer Learning, and Vision Transformer architectures. The results mean that Deep Learning-based architecture, in general, and hybrid CNN-LSTM and multimodal architectures in particular, are typically more successful in Crop Yield Prediction than classical statistical approaches, especially with the inclusion of weather, soil, vegetation index, and remote sensing data.

Keywords: Crop yield prediction, Machine learning, Deep learning, Precision farming, Predictive analytics, Big data.

1. Introduction

The alarming growth in population, climatic changes, decreasing soil fertility, water shortages, labour shortages as well as rising food demand is putting under a macro transformation the agricultural industry. The conventional types of agriculture do not suffice anymore to guarantee the Adequacy of Food Security and Agricultural Sustainability in the areas where they experience unreliable weather patterns and diminishing natural resources [1]. Here, the Artificial Intelligence has come out as one of the most promising technologies in enhancing the decision-making in Sustainable Agriculture. By applying Machine Learning, Deep Learning, Predictive Analytics, and Agricultural Informatics the farmers and agricultural stakeholders will be able to make decisions about the agriculture selection, irrigation, fertilization, disease outbreaks, and harvest predictions more precisely. The determination of Crop Growth and Crop Yield has gained prominence due to its significance in the food supply chain, stability of food markets, resource utilization and rural livelihoods. Latest trends in Precision Agriculture, Smart Farming, and Digital Agriculture have given impulse to use intelligent technologies capable of processing enormous amounts of agricultural data on-the-fly.

https://doi.org/10.70593/deepsci.0203007

The most significant applications of Artificial Intelligence in the field of agriculture are Crop Growth Prediction and Crop Yield Prediction since they enable proactive farm management and minimize uncertainty related to production in the agricultural sector. Proper estimation of yields facilitates farmers to optimize Precision Irrigation, fertilizer application, pests, labor preparation, and harvesting time. Over the past few years, with the growing provision of Agricultural Big Data services by the Remote Sensing platform, UAV Imagery, Satellite Imagery, weather stations, soil sensors, and the Internet of Things devices, there has been the development of new opportunities to use data to develop farming. More popular machine learning models like Random Forest, Support Vector Machine, Gradient Boosting, Decision Trees, and Ensemble Learning have also been employed to determine complicated interactions among climatic, environmental, and agronomic sources. Simultaneously, Convolutional Neural Network, Long Short-Term Memory, Deep Neural Networks, and hybrid CNN-LSTM models have shown to be quite successful in predictive tasks, particularly where dealing with high-dimensional image data and time series information are involved. They can be more effective than traditional statistical methods in Climate-Smart Agriculture and Precision Farming because such methods are able to capture nonlinear trends in crop growth and development.

The current research environment suggests a booming trend in application of Artificial Intelligence in modeling crops and soil analysis, optimization of resources and managing crops sustainably. Research has demonstrated that when machine learning and deep learning are used to combine various data types (vegetation indices, weather data, soil samples, and topographical data, and remote sensing data) their ability to predict yields substantially improves [1-2]. Recent research also highlights the importance of increasing Time Series Forecasting, Multimodal Learning, Reinforcement Learning and Transfer Learning to enhance the flexibility of predictive systems to multiple crops and climatic conditions. The emergence of Vision Transformer models and hybrid AI architectures is becoming an exciting option to the conventional Convolutional Neural Networks (CNNs) since they can interpret large volumes of spatial data with increased efficiency. Additionally, the Explainable Artificial Intelligence, Federated Learning, and Edge AI are gaining momentum as they will resolve the issue surrounding the transparency, privacy, and computational efficiency alongside real-time deployment in the rural agricultural setting. The emergent technologies can enhance the strength of Agricultural Decision Support Systems and allow larger scale farming methods that are more localized and resilient to climate changes.

Although these breakthroughs have been undertaken, there are still major research gaps to be filled. Most of the current research on the topic utilizes particular crops, regions, or short-term data, thereby not providing predictive models on the broader range of agricultural settings. Benchmark datasets, and standardized evaluation measures as well as uniform procedures of comparing Machine Learning and Deep Learning models in Crop Yield Prediction are still lacking. Moreover, numerous researchers focus on accuracy of the models at the expense of other aspects such as interpretability, computational cost, data quality, scalability, and applicability to smallholder farmers. Advanced Deep Learning algorithms remain a black-box and, as such, their current application in agriculture raises significant questions about transparency and trust especially when making high-stakes decisions. Another problem of significance is the geographic bias, a significant percentage of available studies focus on developed nations; a lot of the world’s destitute areas of agriculture exist in Asia, Africa, and Latin America and are underrepresented. Little is also known regarding on how crop genomics, socio-economic aspects, climate forecasting, and market intelligence can be incorporated in predictive models. Additionally, the application of Artificial Intelligence in agriculture is yet to be limited by digital divide, infrastructure, and accessibility of multilingual advisory systems to farmers.

In the light of these difficulties, the aim of this literature review is to present a synthesis of the body of work of both the actual implementation of the models and the methodology of Machine Learning and Deep Learning in relation to Crop Growth Prediction and Crop Yield Prediction in Sustainable Agriculture. The PRISMA framework is used to conduct an organized search to impressively identify, assess, and evaluate the most recent studies in this field [3-5]. The overview of the major algorithms, data sources, model, performance, and application is conducted in accordance with the Precision Agriculture, Resource Optimization, Climate Resilience, and Sustainable Crop Management. It also features new advancements like Explainable Artificial Intelligence, Federated Learning, Edge AI, Vision Transformer, foundation models, and multimodal predictive systems. Besides this review, the significant limitations and missing research links in the existing literature are identified with suggesting the future orientation of more inclusive, more interpretable and scalable AI-based agricultural systems. Through the incorporation of the latest advancements in Digital Agriculture, Remote Sensing, Internet of Things and Agricultural Decision Support Systems, this paper has added to the research literature on the possibilities of Artificial Intelligence being used to create resilient, efficient and sustainable systems of food production in the future.

The review also discloses new trends that include Explainable Artificial Intelligence, Federated Learning, Edge AI, multimodal learning, and Agricultural Decision Support Systems to enhance transparency, privacy, and scalability and real-time implementation at the farm level. Even with the considerable improvements made, there are still issues of data quality, model interpretability, computational complexity, geographic bias, and uptake by smallholder farmers. In general, AI can lead to significant changes in the field of Food Security, Resource Optimization, Precision Irrigation, and Sustainable Crop Management with the introduction of intelligent and climate -resistant agricultural systems.

2. Methodology

To achieve transparency, reproducibility, and rigor in interpreting evidence on artificial intelligence use in sustainable agriculture, and with particular attention to machine learning (ML) and deep learning (DL) algorithms to identify crop growth and yield predictions, this systematic literature review was carried out as per the Preferred Reporting Items to Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. An intensive, systematic search plan was implemented in four significant scientific databases — Scopus, Web of Science, IEEE Xplore, and PubMed — and included publications that revolved around the latest and pertinent developments in the fast-evolving interchange between AI and precision farming, 2019-2025. The Boolean search strings employed across Scopus and Web of Science were constructed using a combination of controlled vocabulary and free-text terms, including: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "convolutional neural network" OR "random forest" OR "support vector machine") AND ("crop yield prediction" OR "crop growth" OR "yield forecasting" OR "crop production") AND ("sustainable agriculture" OR "precision agriculture" OR "smart farming"); additionally supplemented with strings such as ("remote sensing" OR "IoT" OR "satellite imagery") AND ("crop monitoring" OR "yield estimation") AND ("machine learning" OR "deep learning"), and ("ensemble learning" OR "transfer learning" OR "LSTM" OR "transformer model") AND ("agriculture" OR "farming") AND ("yield prediction" OR "growth modeling"). Identical search terms were modified to work in IEEE Xplore and PubMed in their intending syntax. To be included in the study, the studies had to: (1) be published in English journals or conference proceedings; (2) directly use ML or DL algorithms to predict crop yield or growth; (3) be within the 20192025 publication period; and (4) use empirical results or model-based performance analysis. Articles were filtered out as review articles that made no contribution to data synthesis, livestock exclusively based studies, solely traditional statistical tools with no AI integration, or full-text articles that were not available. The intial database search revealed an overall number of 1,847 records (Scopus: 612, Web of Science: 487, IEEE Xplore: 493, PubMed: 255). After the elimination of 374 duplicate records, title and abstract-screening of 1,473 records were performed and 1,089 records were left out because they did not satisfy the predetermined inclusion criteria. Then 384 full-text reports were pursued to be retrieved, and 21 of them were not possible to retrieve. Out of 363 eligible articles, 189 articles were eliminated because they lacked enough details of the methodology (n=74), were on non-AI methods (n=37) or did not have the full text available (n=20). Finally, 174 new articles were added to the final review that resulted in a synthesis of 174 articles to pursue research goals of this article.

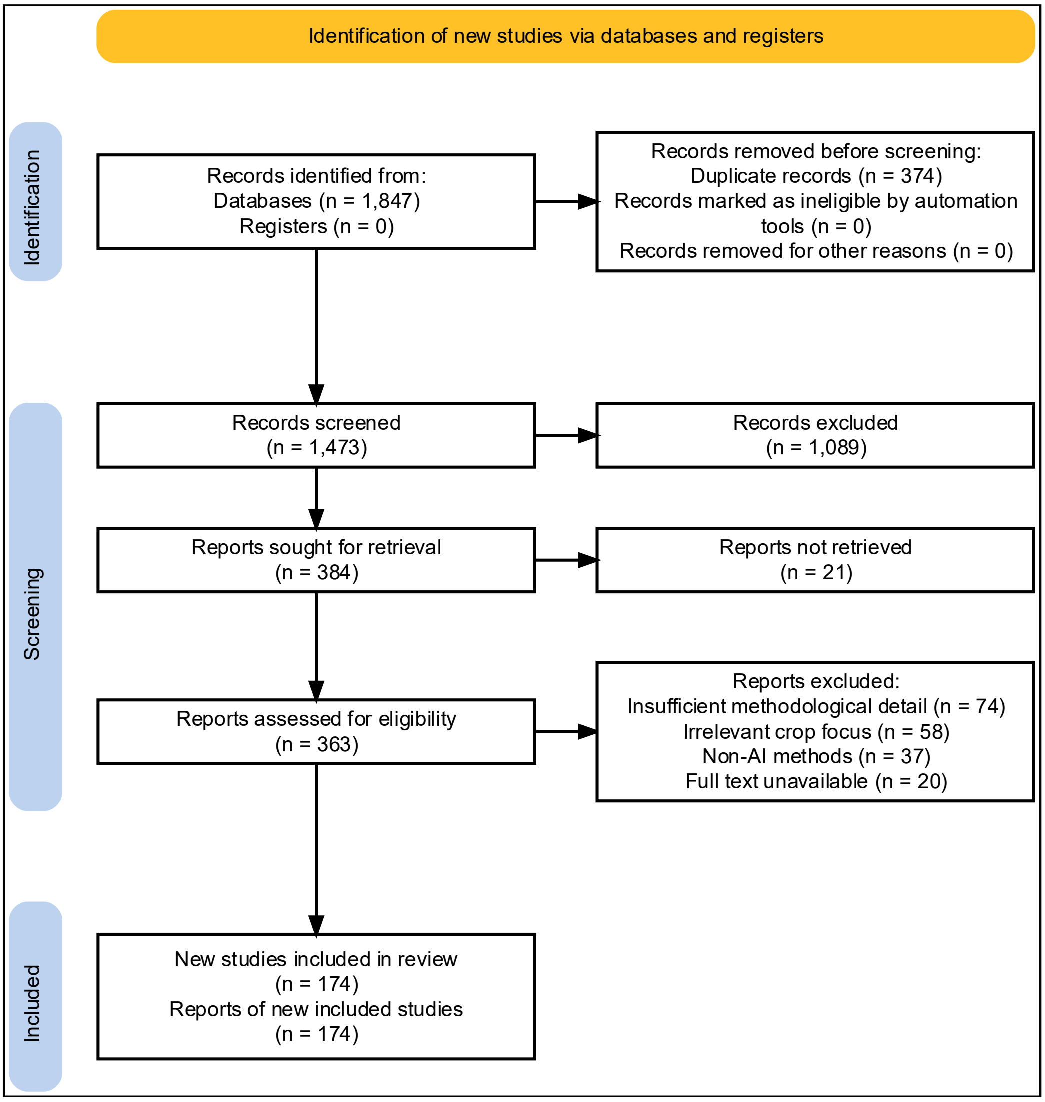

Fig. 1 PRISMA Framework

3. Results and discussions

3.1 Artificial intelligence techniques

Machine Learning in Precision Agriculture

Due to its capacity to operate on large volumes of heterogeneous agricultural data and generate very precise predictions pertaining to Crop Growth Prediction and Crop Yield Prediction, Machine learning has been one of the most actively used techniques of AI in Sustainable Agriculture. The conventional methods of agricultural decision making mostly relate to experience and past trends of farmers, as well as searching the fields manually, which is inadequate in fast changing farm conditions with climate variations, soil erosion, variable rainfall, and augmenting pests [6-8]. Machine Learning helps in turning agricultural data into predictive data by revealing latent interrelationships between variables like rain, humidity, soil nutrients, temperature, vegetation indices, irrigation regimes, fertilizer application, and crop phenology. Planting, irrigation, nutrient management, disease prevention, and harvest timing are all used by Machine Learning models in Precision Agriculture and Smart Farming. The growing supply of Agricultural Big Data, remote Sensing, Internet of Things, UAV Imagery, Satellite Imagery, and agricultural farm management data and systems have also boosted the implementation of Machine Learning in Data-Driven Farming and Climate-Smart Agriculture.

Random Forest for Crop Yield Prediction

One of the most popular algorithms utilized in Crop Yield Prediction with the help of Machine Learning is the Random Forest due to its high accuracy, strength, and capacity to be used with nonlinear relations in agricultural data. Random Forest is especially useful in the cases where the variables in the agricultural part are highly dependent and contain quantitative and nominal data. Multiplying decision trees, the algorithm enhances the ability to predict and decreases overfitting, which makes it very appropriate to Sustainable Crop Management and Resource Optimization. Random Forest has found a wide range of applications in agriculture, where it has been implemented to predict crop yield related to climatic conditions, soil moisture, rainfall, vegetation indices, nutrient content, and remote measurements. It can also be used in Soil Health Monitoring, land suitability analysis, crop classification and drought assessment. Its ability to be incorporated more extensively with geospatial analytics, vegetation indices, and satellite imagery has further served to make it more useful in Precision Farming and Agricultural Decision Support Systems.

Support Vector Machine and Kernel-Based Learning

Another method of Artificial Intelligence common in Precision Agriculture is Support Vector Machine due to its capability to operate effectively with small datasets and high-dimensional landmarks of agriculture. SVM can be efficiently applied in the classification of crop conditions, crop yield prediction, detection of pest outbreaks and detection of plant diseases [9]. The Support Vector Machine is able to model these nonlinear relationships between environmental variables and crop performance with the help of kernel functions. Support vector machine has been highly effective in Sustainable Agriculture as far as it is incorporated with remote sensing data, UAV Imagery, weather data and soil properties. It is also extensively used in classification of crop type, estimation of maturity of crop, detection of weeds and analysis of nutrient deficiency. Support Vector Machine can use smaller datasets with accuracy, thereby it can be useful in areas where infrastructure of data collection on agriculture is still at the low end.

Gradient Boosting, XGBoost, LightGBM, and CatBoost

Gradient Boosting techniques have become one of the most effective in Crop Growth Prediction and Crop Yield Prediction since they are improved by trial and error to achieve a better performance. Among them, XGBoost, LightGBM, and CatBoost are the most relevant to the field of Agricultural Informatics as they are highly efficient to use in terms of computation and have great predictive performance. XGBoost finds many applications in forecasting crop yields, rainfall, and irrigation requirements and in disease outbreaks, due to its ability to handle multifaceted agricultural data with low preprocessing. LightGBM is gaining a repute with large-scale agricultural components due to its capability in training with better speed and minimum memory usage thus, it is viable in Agricultural Big Data and real-time farming analytical applications. The popularity of CatBoost is due to its ability to deal with categorical variables that are common in agriculture like type of crop, soil and how it is being managed. Gradient Boosting methods are now typically deployed in Intelligent Farming System and Agricultural Decision Support Systems due to the accuracy, scalability and interpretability of predictive models.

Deep Learning and Neural Networks in Agriculture

Due to the capability to learn difficult patterns automatically on structured and unstructured agricultural data, Deep Learning has gained more and more significance in the Crop Modeling and Crop Yield Prediction domains. As opposed to conventional Machine Learning methods that rely extensively on Feature Engineering, Deep Learning models have the benefit of providing end users with the means to directly convert raw data sources, i.e., pictures, sensor readings and time-series weather data, into useful information [7,9-10]. The applications of Deep Neural Networks are especially valuable in Precision Agriculture since it is able to handle vast amounts of data collected by Remote Sensing, UAV Imagery, and Satellite Imagery, as well as Internet of Things devices. Deep learning has demonstrated high benefits of detecting concealed spatial and temporal correlations among agricultural variables resulting in improved estimations of crop growth, yield, irrigation demand, and soil fertility. The adoption of Neural Networks is changing how agricultural systems monitor crops, predict risks and optimize inputs and this is attributed to the rising application of Neural Networks in Smart Farming and Digital Agriculture.

Convolutional Neural Network for Image-Based Crop Analysis

Due to its better capabilities to process image-based data of agriculture, Convolutional Neural Network has turned out to be one of the most significant approaches of Deep Learning in the field of Sustainable Agriculture. Application CNN models The CNN models are employed to detect an increase in crop diseases, identify weeds, perform a count of fruits, phenotyping of plants, classify soil texture, ID the maturity of crops, and forecast yields based on UAV Imagery and Satellite Imagery. Precision Agriculture has risen dramatically with the integration of Convolutional Neural Network and Remote Sensing, this has contributed towards the farmers being in a position to identify the stress, nutrient deficiencies, and disease symptoms at the early stage of the crop. Vegetation indices, e.g., NDVI, EVI, and SAVI, can also be implemented in CNN-based architectures to enhance the performance of Crop Growth Prediction and Crop Yield Prediction. New advancements in Vision Transformer and hybrid CNN-Vision Transformer architectures continue to improve the capacity of image-based systems to high-resolution agricultural image processing with higher levels of spatial awareness.

Long Short-Term Memory and Time Series Forecasting

Long Short-Term Memory has established itself as a state-of-the-art Deep Learning technique in Time Series Forecasting in agriculture due to its capability to learn long-term interactions in sequential agricultural data. The LSTM models can be applied particularly to study the weather pattern, the soil moisture tendency, crop development cycle, variation of rain, and irrigation timetable [1,11-14]. Given that the productivity of agriculture is extremely sensitive to time, LSTM models take advantage in Crop Yield Prediction and Climate Resilience research. The LSTM networks will be able to handle sequence of temperature, precipitation, humidity, evapotranspiration and vegetation index data to predict crop performance in the future. Hybrid CNN-LSTM-based architectures are rapidly gaining user interest since they integrate the ability to process the image information of CNN with the behavior of time prediction of LSTM. These models are very efficient in Digital Agriculture since the ability to combine Remote sensing and UAV Imagery with weather projections and IoT sensor readings into a single predictive model is available.

Reinforcement Learning for Precision Irrigation and Resource Optimization

Reinforcement Learning is a new Artificial Intelligence method and it is becoming significant in Precision Irrigation, fertilizer optimization, greenhouse management and autonomous agricultural systems. As compared to the conventional supervised training approaches, Reinforcement Learning is concerned with sequential decision-making of dynamical environments. In Sustainable Agriculture, reinforcement learning models can find the most favorable irrigation regime, nutrient application rate, rate of pesticide application, and harvesting time, through constantly learning about the environment. Reinforcement Learning is especially useful in Climate-Smart Agriculture since it allows the management of the farm to adapt to uncertain climatic conditions. Reinforcement Learning carries full integration with Internet of Things devices, smart irrigation systems and Agricultural Robotics is facilitating a more efficient use of water, fertilizers and energy. With the growing water shortage and environmental issues, Reinforcement Learning will become a prominent technology in terms of Resource Optimization and Sustainable Crop Management.

Transfer Learning and Multimodal Learning

Application Transfer learning has gained relevance in the agricultural setting as numerous areas do not have extensive, high-quality labeled datasets to train Artificial Intelligence models. Transfer Learning allows a model that was trained on one type or aagricultural dataset or crop to be reconfigured to another crop, region or environmental condition with minimum retraining [13,15-17]. This method minimizes the computation cost, training time, and data necessities which makes it very apt to smallholder farming systems and underdeveloped nations. Transfer learning specifically applies to crop disease detecting, plant phenotyping, and crop classification based on UAV Imagery and Satellite Imagery. Similarly, Multi-modal Learning is also becoming a very promising sub field in Agricultural Informatics since it involves bringing together various data sources like weather information, soil characteristics, sensor images, remote sensing images and farm management documents into one predictive model. Multimodal Learning enhances Crop Growth Prediction and Crop Yield Prediction through a more comprehensive grasping of the agricultural systems and the interactions with the environment.

Vision Transformer and Generative Artificial Intelligence

One of the latest and most promising Deep Learning architectures to analyze agricultural images is Vision Transformer since it has better performance on large-scale image data and long-range spatial contexts. Vision Transformer is unlike Convolutional Neural Network in that it can process entire image patches at the same time which makes it more efficient in classifying crops, disease detection, land-use mapping, and yield estimation using high-resolution Satellite Imagery and UAV Imagery. Convolutional Neural Networks are also made to perform more effectively by using Vision Transformer models which in turn advance the work of crop monitoring systems in Precision Agriculture. Moreover, a novel generation of artificial intelligence (Generative Artificial Intelligence) and Autoencoders are becoming key methods to produce synthetic agricultural information, address gaps in sensor inputs, enhance image quality, and strengthen predictive learning. Simulation of crops, farming digital twins, and realistic training dataset generation to detect diseases and predict yield can be aided by generative AI.

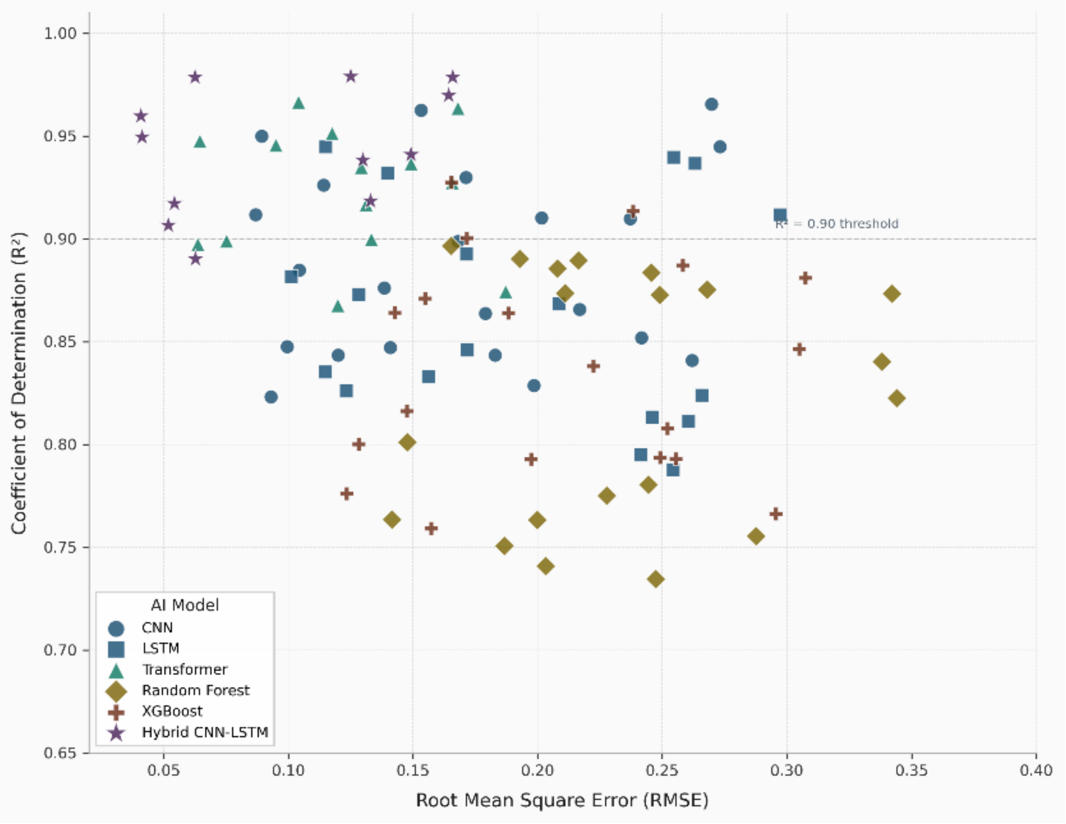

Fig. 2 Predictive Accuracy vs. Error Across AI Model Families

Fig. 2 shows scatter plot presents a comparative evaluation of six major AI model families, including CNN, LSTM, Transformer, Random Forest, XGBoost, and the emerging Hybrid CNN-LSTM architecture, across two fundamental regression performance metrics: Root Mean Square Error (RMSE) on the horizontal axis and the Coefficient of Determination (R^2) on the vertical axis. Each model family occupies a visually distinct region of the plot, reflecting its characteristic trade-off between predictive accuracy and error magnitude. Hybrid CNN-LSTM and Transformer-based architectures cluster toward the upper-left quadrant, indicating superior predictive capability with lower error, a finding consistent with recent literature demonstrating the advantage of attention mechanisms and temporal-spatial feature fusion in complex agricultural environments. Traditional ensemble methods such as Random Forest and XGBoost occupy the lower-right region, confirming their comparatively higher RMSE and lower R^2

when applied to spatially heterogeneous crop data. A horizontal reference dashed line at $R^2 = 0.90$ serves as an interpretive threshold, distinguishing high-fidelity models from moderate performers. This visualization supports the growing research consensus that architecturally sophisticated deep learning models are progressively outperforming classical machine learning approaches for crop yield prediction tasks involving multisource remote sensing inputs.

Explainable Artificial Intelligence and Interpretable Models

Explainable Artificial Intelligence has gained more and more importance in Sustainable Agriculture as most Deep Learning models are black-box systems offering a scarce transparency of their predictions. Policymakers, farmers and other stakeholders in agriculture need models that can be interpreted to provide answers to questions like why a specific model was produced to predict a given crop yield, recommend irrigation or diagnose an illness [18-20]. An Explainable Artificial Intelligence, i.e., SHAP, LIME, feature importance analysis and attention mechanisms are increasingly added to the Machine Learning and Deep Learning models, in order to enhance trust, accountability and acceptance. Explainable Artificial Intelligence is especially valuable in Agricultural Decision Support Systems since it allows users to learn the relative impact of climatic variables as well as soil properties, the use of fertilisers, and the management practices applied to crops on the final prediction results. Policy decisions around Food Security, Climatic and Sustainable crop management can also be assisted by the interpretable AI models.

Federated Learning and Edge AI in Smart Farming

Facilitated by Mobile computing, Federated Learning and Edge AI are recent technologies aiming to tackle significant issues surrounding data privacy, connectivity, and computational efficiency in Digital Agriculture. The federated Learning model allows two or more farms, institutions or agriculture organizations to collectively learn Machine Learning models without the exchange of raw data hence maintaining privacy and ownership of data. It is also a very valuable method when working in an agricultural setting where there is a possibility that data is divided over geographical areas, products, and agricultural systems. Edge AI, however, allows Artificial Intelligence models to operate directly on local machines, like drones, sensors, tractors, and smartphones, not using cloud computing to such an extent. Edges AI is particularly useful in sparsely populated rural regions with a weak internet connection as it enables important real-time crop surveillance, illness indication, and irrigation regulation, and predetermines crop yields. Federated Learning co-operating with Edge AI is likely to enable Intelligent Farming Systems that are scalable, privacy-preserving, and decentralized.

Hybrid Models and Future AI Directions in Agriculture

Hybrid Models are gaining more grounds in Sustainable Agriculture since they integrate the advantages of various and multiple Artificial Intelligence methods to enhance the precision and generalizability of the predictions. As an illustration, CNNLSTM networks combine both image and time-series model, whereas the RF-XGBoost model combines tree-based and boosting approaches to learning [19,21-22]. Hybrid systems incorporating Machine Learning, Deep Learning, Remote Sensing, and Internet of Things data as well as geospatial analytics and crop simulation models are showing high competence in Crop Growth Prediction and Crop Yield Prediction. The future of Artificial Intelligence in agriculture is projected to be more multimodal architectures, foundation models, Generative Artificial Intelligence, digital twins, and self-supervised learning techniques. Other topics in the future research are expected to include energy-efficient AI, privacy assuring analytics, climate adaptive, multilingual advisory systems, and inclusive technologies in smallholder farmers. Such advances should enhance the Food Security, Agricultural Sustainability, Climate Resilience and Sustainable Crop Management as well as empower more adaptable, ad hoc and resilient agricultural systems.

3.2 Artificial intelligence methods

Machine Learning Methods in Precision Agriculture

Machine Learning approaches have become core to Precision Agriculture since they enable the manipulation of complex agricultural data, and transformation into actionable predictions to be used in Crop Growth Prediction and Crop Yield Prediction. Agricultural systems create very diverse information on weather stations, soil sensors, Internet of Things, UAV Imagery, Satellite Imagery, farm records, and Remote Sensing platforms. Statistics used in the past may be unable to capture nonlinear connections among the variables that include rainfall, soil nutrients, a variety of crops, frequency of irrigation, pressure exerted by pests, and vegetation indices. Diagnosing hidden patterns in multidimensional data sets and enhancing agricultural decisions, Machine Learning techniques provide an answer to this issue. Some of the most common are now Random Forest, support vector machine, decision trees, boosting with gradients and Ensemble Learning; they are capable of working with high-dimensional agricultural data and can provide a high predictive performance. More recent reviews indicate that Machine Learning techniques are becoming more commonly combined with geospatial analytics, Agricultural Big Data, and Agricultural Decision Support Systems to enhance Sustainable Agriculture and Climate-Smart Agriculture.

Random Forest and Decision Tree Methods

One of the most widely usedMachine learning algorithms in the Crop Yield Prediction is Random Forest since it is able to handle structured agricultural data and decreases the chances of overfitting. Random Forest is an algorithm that takes several decision trees and merges the outputs of the trees and thus it is very suitable when one has nonlinear relationships among weather variables, soil conditions, fertilizer use, crop variety and vegetation indices [11,23-25]. The Decision Tree models also come in handy as they are easy to interpret in rules of prediction which can be comprehended by farmers and agricultural planners. Applications These techniques have found wide application as Soil Health Monitoring, land suitability analysis, crop classification, irrigation scheduling, and yield estimation. Random Forest has become especially significant since it can as well rank the relative importance of various agricultural features and therefore researchers can see which agricultural features have the strongest impact on crop productivity. Research always indicates that the Random Forest is particularly effective in those data sets that have temperature, rainfall, soil type and vegetation measures. Nonetheless, highly sequential agricultural observations e.g. long-term weather patterns may be challenging to deal with using Decision Trees and Random Forest, leading to a renewed idea of hybrid and recurrent models.

Support Vector Machine and Kernel-Based Methods

The other popular AI tool in Sustainable Agriculture is Support Vector Machine since it only requires smaller datasets to perform efficiently and is also capable of dimensional variables in the agricultural field. Machine predicting of Crop Growth, Crop Yield, weed, disease, and crop classification Support Vector machine is appropriate to predict nonlinear correlations between crop growth variables and factors and predict crop growth; therefore, it is suitable across support of all three aspects of crop growth analysis: Crop Growth Prediction, Crop Yield Prediction, and weed identification, disease detection, and crop classification. Support Vector Machine is especially useful in areas where the data used in agriculture are scarce due to the fact that they may perform exceptionally in predictive accuracy even in cases where few data points are observed. SVM is typically used with weather information, soil characteristics, crop life-cycle data and Remote Sensing data to categorize the agricultural environment and predict crop production. Kernel-based methods can be particularly advantageous in instances where agricultural variables have non-linear interactions, i.e., how rainfall, temperature, nutrient availability and crop maturity relate. Despite the good performance with small and medium scale datasets, Support Vector Machine may suffer deteriorated performance with extremely large and/or very high-dimensional image based agriculture data.

Gradient Boosting, XGBoost, LightGBM, and CatBoost

Gradient Boosting has turned out to be one of the most effective Artificial Intelligence techniques in Crop Yield Prediction since it minimizes overall error in the prediction through combination of several weak learners. XGBoost, LightGBM, and CatBoost have now gained particular power in Agricultural Informatics due to their capability to effectively handle vast agricultural data and reach very high predictive accuracy [26-28]. XGBoost is frequently employed in Smart Farming since it has the ability to characterize shrewd connections amid soil humidity, temperature, hydroxyl, watering techniques, and crop health cues. LightGBM is becoming popular due to its ability to train faster and also using less memory, it is applicable to Agricultural Big Data and farm analytics via large scale. CatBoost is especially appropriate in cases where the agricultural data have categorical variables like soil type, crop type, irrigation type or management technique. Such techniques are finding application in Precision Irrigation, Resource Optimization and Agricultural Decision Support Systems since they are both highly accurate and fairly interpretable in comparison to deep neural networks. The use of hybrid methods such as a combination of Random Forest, XGBoost, and Bagging Regressors is increasing as well due to its ability to enhance resistance to various crops as well as weather conditions.

Deep Neural Networks and Artificial Neural Networks

Digital Agriculture often makes use of Deep Neural Networks and Artificial Neural Networks as they are able to capture nonlinear relationships of agricultural variables in a highly detailed manner. In comparison to traditional Machine Learning algorithms, which heavily rely on Feature Engineering, Neural Networks are able to learn the hidden representations of raw agricultural data automatically. The models are effective in particular when used with high-dimensional data that is a composite of weather conditions, Remote Sensing images, soil nutrients, crop record, and Internet of Things sensor feeds. ANNs have found extensive application in Crop Modeling, yield prediction and irrigation control due to their ability to cope with large sets of interacting variables. DNNs are especially applicable to Climate-Smart Agriculture as they may discover subtle relations between crop performance and the evolving environments. The new studies also indicate that the Deep Neural Networks could be optimized further with the help of the genetic algorithm, which would automatically adjust the hyperparameters and enhance the forecasting performance in agro technologies.

Convolutional Neural Networks for Image-Based Agriculture

Convolutional Neural Networks are one of the most significant Deep Learning tools applied in agriculture since it can make analysis of UAV Imagery, Satellite Imagery, hyperspectral images, and photos of plants with great accuracy. The applications of CNNs have been extensively used in detecting crop diseases, identifying weeds, counting fruits, classifying soil texture, phenotyping plants, plant maturity, and Crop Yield Prediction [29-32]. They are especially simple to use in Precision Agriculture since they are able to notice visual signs of plant stress, nutrient deficiencies, and disease symptoms even before they turn noticeable with the naked eye. The accuracy of a crop monitoring system is usually enhanced by incorporating CNN models in conjunction with vegetation indices e.g. NDVI, EVI and SAVI. To track field variability and maximize fertilizer and irrigation, they are often also used in conjunction with Remote Sensing technologies. Other more recent advances include integrating CNN with recurrent networks or Vision Transformers to learn calls in both space and time of agricultural images.

Long Short-Term Memory and Gated Recurrent Unit Models

Gated Recurrent Unit and Long Short-Term Memory models Time Series Forecasting models are very popular since they are able to identify long-term dependencies in agricultural data. Temporal factors have a significant effect on crop performance by affecting rainfall patterns, seasonal temperature changes, irrigation, evapotranspiration and soil moisture. LSTM and GRU are thus very efficient in Crop Growth Prediction and Crop Yield Prediction since they are able to handle time-based sequences of observations in the agricultural industry. Common uses of LSTM models to previous weather data, vegetation data, soil moisture, and crop progress stage are used to predict the yield data in the future. GRU formulations have been commonly used in resource-limited settings since they are computationally lighter with a good predictive accuracy. Hybrid CNN-LSTM and CNN-GRU networks are also becoming very common since they may handle both sequential and image-based agricultural data at the same time. These hybrid approaches are especially significant in Climate Resilience research since those imply that researchers will be able to evaluate how the alterations of weather conditions affect the crop productivity across the seasons.

Vision Transformer and Vision-Language Models

Vision Transformer has become one of the most promising Deep Learning systems to analyse agricultural images due due to the ability to capture longer spatial correlations than Convolutional Neural Networks. Vision Transformer treats a sequence of patches as an image, instead of using only local convolution filters, enabling it to detect larger spatial features in crop fields [31,33-35]. Applications of this technique in crop classification, disease identification, land-use mapping, weed identification and yield prediction have gained broad use of high-resolution Satellite Imagery and UAV Imagery. The recent research also shows the increasing pressure on multimodal transformer architectures that can incorporate both the visual Remote Sensing data and meteorological data and soil variables. Spatial, multimodal, and temporal transformer layers are incorporated in other models (like MMST-ViT) to enhance prediction in varied climatic conditions. Vision-Language Models, foundation models like CLIP are also coming to agriculture as they are capable of integrating image knowledge with textual farm records, agronomic reports and advisory systems. It is anticipated that the future of Digital Agriculture will rely heavily on these approaches since they will help realize more generic and transferable agricultural intelligence.

Transfer Learning, Self-Supervised Learning, and Foundation Models

Transfer Learning is gaining relevance in agriculture since most farming areas do not have big labelled data to train state-of-the-art Artificial Intelligence systems. Transfer Learning enables the process of adapting pre-trained models into new crops, regions or agricultural conditions using relatively small quantities of new data. It is particularly handy when there is limited data collection in developing countries and smallholder agriculture systems. Another method that has become significant is Self-Supervised Learning as models can learn useful representations on unlabeled agricultural data, and then be fine-tuned on specific tasks. Such approaches incur lower annotation cost, and enhance model performance in crop disease detection, crop classification, and yield forecasting. The application of Foundation Models as a significant research direction is gaining popularity due to its ability to be trained on very large multi-modal agricultural images, and subsequently perform a plethora of downstream tasks. Transfer Learning, Self-Supervised Learning and foundation models will complement each other and lead to increased scalability, adaptation to specific domains and overall generalizability of agricultural Artificial Intelligence systems.

Reinforcement Learning for Precision Irrigation and Resource Optimization

Reinforcement Learning is a new Artificial Intelligence approach, which emphasizes a serial decision-making process when there is uncertainty. Precision Irrigation, fertilizer management, greenhouse control and autonomous farm operation are some of the other applications of Reinforcement Learning in agriculture [36-38]. These models learn through environmental interaction and continuous re-adjustment of decisions as a result of feedback. Reinforcement Learning is especially applicable in Climate-Smart Agriculture since it is able to optimally distribute water, control pesticides and nutrient utilization, and pick up time to harvest crops in changing climatic conditions. In theory, the Reinforcement Learning systems will be able to decide how and when to irrigate the land using weather predictions, the moisture content, and the stage of growing the crops. Such an approach is also gaining significance in Agricultural Robotics where autopilot tractors, drones, and robotic harvesting systems are supported. Reinforcement Learning thus has great promise to Resource Optimization and Sustainable Crop Management in water scarce and climatic varied environments.

Explainable Artificial Intelligence and Interpretable Methods

Explainable Artificial Intelligence has grown in importance due to the fact that often Deep Learning systems act as black-box models that give little information about prediction generation. Farmers, policymakers, and agricultural stakeholders are more likely to speak to farmers with open, transparent explanations before they believe yield forecasts, irrigation guidelines, or crop illnesses. SHAP, LIME, feature importance ranking, attention maps, and counterfactual explanations and explainable Artificial Intelligence are all methods aimed at enhancing transparency and accountability. The techniques allow determining the strongest variables affecting crop performance and include rainfall, soil fertility, vegetation indices or irrigation patterns. Explainable Artificial Intelligence of Agricultural Decision Support Systems is also essential as it can enhance farmer acceptance and heighten business acceptance of AI-capable technologies. Recent studies stress that explainability is necessary to enhance trust, as well as to remedy ethical issues of fairness, accountability, and transparency in Sustainable Agriculture.

Federated Learning, Edge AI, and Digital Twins

The next approaches to privacy, connectivity and real-time processing in Smart Farming are Federated Learning and Edge AI which are newer Artificial Intelligence approaches. Federated Learning allows several farms/institutions to train common Machine Learning models without sharing data with one another, ensuring the privacy of data, although cooperative learning does occur [1,39-41]. This is exceptionally useful in the agricultural field since agricultural information is likened to being more divided with regions and crops combined with management systems. Edge AI enables Machine Learning and Deep Learning models to run directly on local devices in drones, smartphones, tractors and field sensors. It minimizes the reliance on cloud infrastructure and creates an opportunity to make decisions quicker in rural areas where the internet is not as widespread. Digital Twins are also developing interest since they have the ability to produce virtual reproductions of the farms, crops, irrigation systems, and soil conditions. These computerized models enable the researchers and farmers to model various agrarian conditions and also optimize the management approaches and then apply them in the actual field. Combining Federated Learning, Edge AI, and Digital twins into Intelligent Farming Systems is likely to generate more flexible, decentralized, and resilient systems.

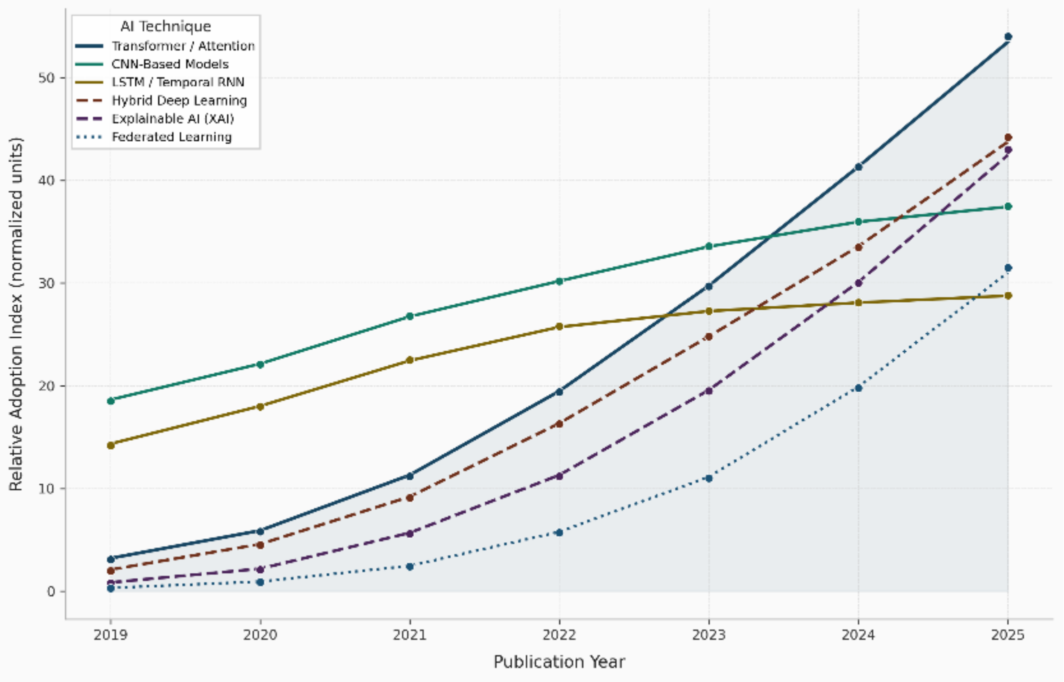

Fig. 3 Temporal Adoption Trends of AI Techniques in Agricultural Research (2019-2025)

Fig. 3 explains multi-series line plot traces the normalized adoption index of six prominent AI paradigms in agricultural research publications from 2019 to 2025, capturing a critical period of methodological transformation driven by data availability and computational advances. Transformer-based and hybrid deep learning models display the steepest upward trajectories, mirroring broader trends in computer vision and natural language processing that have progressively been adapted for remote sensing and phenotypic data analysis in precision agriculture. Explainable AI (XAI) and Federated Learning exhibit exponential growth from near-zero baseline values, reflecting the urgency of model interpretability in stakeholder-facing agricultural applications and the need for privacy-preserving learning across distributed farm data networks. CNN-based models and LSTM architectures, while showing sustained and substantial adoption, display a degree of plateauing consistent with their maturation as established methodologies. The light blue shading under the Transformer trend underscores its dominant upward momentum and positions it as the most citation-active methodological frontier. This longitudinal view serves as a roadmap for researchers seeking to align their contributions with high-impact, rapidly evolving methodological currents in AI for sustainable agriculture.

Hybrid Models and Future Artificial Intelligence Methods

Hybrid Models are gaining prominence since they can integrate the advantages of various Artificial Intelligence approaches to enhance Crop Growth Prediction and Crop Yield Prediction. CNN-LSTM models are image-based learning models that are used to combine with the temporal forecasting models, whereas the Random Forest-XGBoost model models are an ensemble learning model that is used to combine with boosting strategies. Combining Remote Sensing, Internet of Things sensor devices, geospatial analytics, weather forecasting, and crop simulation models into one predictive structure through hybrid systems can be achieved. Recent research has revealed that hybrid models tend to work better than standalone procedures since they may be able to capture spatial, temporal and environmental relationships. Other upcoming trends are Generative Artificial Intelligence, Autoencoders, multimodal transformer systems, and agriculture digital twins. Generative artificial intelligence can be used to generate synthetic agricultural data, improve the image quality, complete missing sensor values, and facilitate scenario-based crop simulation. Future studies will adopt energy efficient Artificial Intelligence, privacy protective analytics, multilingual advisory systems, climate adaptive models that can assist in sustaining Food Security and Sustainable Agriculture in both the developed and the developing countries.

3.3 Artificial intelligence technologies

Internet of Things and Smart Sensor Networks

Internet of Things has also emerged to be one of the pillar technologies in Sustainable Agriculture in the sense that it allows gathering of real-time environmental, climatic and crop related data to farms. Smart sensor networks are able to dedicate continuous observation to soil moisture, soil temperature, nutrient level, humidity, pH, rainfall, solar radiation and wind speed, as well as crop health [42-44]. With these Internet of Things devices, a lot of Agricultural Big Data is produced, which can be analyzed using a Machine Learning and Deep Learning system to enhance Crop Growth Prediction and Crop Yield Prediction. Smart Farming systems based on IoT are especially useful, as it minimizes the use of manual field inspection and makes it possible to make decisions based on data in large-scale agricultural fields. Precision Irrigation systems are becoming integrated with smart sensors that enable water to be only applied when required and in the appropriate quantity. Precision Fertilization (identifying the lack of nutrients and optimally applying the fertilizer) is supported by IoT as well. Subsequently, Climate-Smart Agriculture, Resource Optimization and Sustainable Crop Management are becoming dependent on the Internet of Things.

Artificial Intelligence of Things and Connected Farming Systems

Artificial Intelligence of Things sometimes AIoT is the combination of Artificial Intelligence and Internet of Things infrastructure to develop smart agricultural systems with the ability to sense, learn, and respond in real-time. AIoT employs automated Machine Learning models with sensor data collection capabilities to detect crop stress, optimize irrigation, predict yields, and detect pest outbreaks without 24/7 human monitoring. By utilizing AIoT devices in Precision Agriculture, connected farming systems are achieved, in which drones, tractors, irrigation devices, weather stations, and soil sensors exchange data with each other to enhance efficiency. Large-scale farming settings are particularly significant as AIoT ruoty telefermentet and could be utilized to automate daily farm operations and cut labor expenses. Using AIoT in Digital Agriculture will become more popular in the future, and Agricultural Decision Support Systems will become capable of scaling their operations, and establishing more resilient food production frameworks, able to react to changing climatic variability and adapt to shifting market dynamics.

Remote Sensing, Satellite Imagery, and UAV Imagery

Remote Sensing technologies can be discussed as one of the most popular Artificial Intelligence technologies used in Crop Growth Prediction and Crop Yield Prediction as they offer large-scale data on the health of vegetation and soil moisture, canopy structure, and land-use patterns. Monitoring the conditions of crops with Satellite Imagery of platforms like Sentinel, Landsat and MODIS is typically required to view the advancement over time, whereas the UAV Imagery can capture detailed information on the field level [45-46]. Using these technologies, researchers and farmers can compute various vegetation indices, including NDVI, EVI, SAVI, and crop water stress indices necessary to Precision Agriculture and to Sustainable Agriculture. UAV Imagery is mostly applied in the detection of pest infestations, nutrient deficiencies, water stress, and disease manifestations before proliferating to the rest of the field. Combining Remote Sensing and Deep Learning with Geospatial Analytics is enhancing the capabilities of Smart Farming systems to provide precise yield predictions and optimize farm management processes.

Hyperspectral Imaging and Geospatial Analytics

Hyperspectral Imaging has become a potent Digital Agriculture tool since it records data in hundreds of spectral bands that enables crop health, soil structure, soil moisture and soil nutrient-status to be analyzed in finer details. Hyperspectral Imaging is also able to detect subtle physiological transformations in crops not seen by the human eye in contrast to traditional RGB imagery. Geospatial Analytics is increasingly used together with this technology to map variability across fields, identify regions of stress, and aid variable-rate application of water, fertilizer and pesticides. Hyperspectral Imaging is particularly relevant to Precision Agriculture since it allows detecting earlier the disease and pests, as well as salinity problems and nutrient deficit. Hyperspectral data, once combined with the Artificial Intelligence, can greatly enhance Crop Modeling, Soil Health Monitoring, and Resource Optimization. Such technologies are also coming to play more and more in the Climate Adaptation practices since they promote more efficient exploitation of the scarcely available agricultural inputs.

Cloud Computing, Fog Computing, and Agricultural Big Data

Cloud computing is another critical technology in Smart farming since it offers scalable storage, data processing and compute capabilities to process Agricultural Big Data. IoT equipped farms with drones and Remote Sensing devices produce enormous amounts of data that cannot be effectively handled to local devices [18,47-49]. Machine Learning can examine weather predictions, agricultural growth, soil situations and market trends in real-time using cloud platforms. Fog Computing is a complement to Cloud Computing, moving the data processing nearer to the source, and this also decreases the latency and response time to the time-sensitive agricultural tasks, like irrigation scheduling and pest detection. Cloud Computing and Fog Computing are particularly significant to Precision Agriculture as it can give farmers a chance to view clever suggestions without having to have sophisticated computing facilities on-site. Such technologies will have even more significant roles in Agricultural Informatics and Digital Agriculture as farms become more and more data-intensive.

Edge AI and Real-Time Farm Intelligence

Edge AI is the application of Artificial Intelligence models to local devices like sensors, drones, smartphones, irrigation system, tractor and agricultural robots. In stark contrast to cloud-based systems, Edge AI is able to analyze farm data in real-time without relying fully on internet connectivity. It is useful especially in the rural farming setting due to unfavorable or unstable internet connections. Edge AI could facilitate instant reaction to stress of crops, pest infestations, irrigation requirements and equipment malfunctions. Edge AI is applied to optimize Sustainable Agriculture by facilitating quicker and more efficient decision-making and requiring less time to transmit vast amounts of agricultural data to cloud servers. It finds an ever-increasing application in Precision Irrigation, crop disease detection, livestock monitoring, and autonomous farming systems. Everything becoming more energy-efficient and less expensive, Edge AI will definitely become a main part of Smart Farming and Climate-Resilient Agriculture.

Agricultural Robotics and Autonomous Farming Systems

Agricultural robotics AGR is gaining momentum on changing the way farms are run by automating intensive, repetitive, and time intensive activities. Precision Agriculture is adopting autonomous tractors, robotic harvesters, drone sprayers, autonomous weeders, and robotic planting systems as a more cost-effective way to enhance productivity and lower labor costs [50-52]. Agricultural robots are able to navigate the fields, weed, apply fertilizers, spray pesticides and harvest crops with little human interference. These technologies are vital in areas that have shortages of labor and increasing costs of production. The integration of the Computer Vision and Deep Learning with Robotics Vision Systems allow the agricultural robots to detect crop rows, weed and crops, and keep track of the health of the crops. Agri Robotics are becoming more integrated with IoT sensors, Edge AI, and Reinforcement Learning to produce more advanced Autonomous Farming systems, which can continuously adapt to evolving field conditions.

Computer Vision and Crop Monitoring Systems

Computer Vision technologies are gaining more significance within the agricultural sphere since they enable farms to process visual data located in images and videos without contributing to the interpretation. Some of the applications of Computer Vision systems include crop disease detection, weed identification, counting fruits, plant phenotyping, livestock monitoring, and crop maturity assay. The models are commonly based on Convolutional Neural Networks, Image Transformer networks, and segmentation models to make visual decisions about crops and agricultural landscapes. Computer Vision-powered Crop Monitoring Systems can conduct real-time monitoring of the size and condition of crops and allow identifying diseases outbreaks, nutrient deficiencies, and environmental stresses earlier. Computer Vision coupled with UAV Imagery and Satellite Imagery is helping to make predictions of Crop Yield and Crop Growth much more accurate in Precision Agriculture.

Digital Twins and Virtual Agricultural Systems

Digital Twins Digital Twins have turned out to be one of the most promising Smart Farming technologies due to the representation of the farms, crops, irrigation systems, soil conditions and weather dynamics on a virtual level. Such digital models enable farmers and researchers to test the situation in agriculture in the simulation before putting them in real practice [53,54]. The effects of irrigation time, the use of fertilizers, pest attacks, and climate changes on crops can be tested using Digital Twins. Digital Twins in Precision Agriculture are helpful in making positive decisions ahead of the time that a problem can happen in that they enable farmers to leverage the opportunities located in the Digital Twin to manage what is most likely to happen to them. More advanced Agricultural Decision Support Systems that can respond and predict in real time are being developed by integrating Digital Twins with Remote Sensing, Internet of Things devices and Machine Learning. In the future, Digital Twin technology is likely to have a significant impact in the areas of Climate Resilience, Sustainable Crop Management, and Food Security.

Federated Learning and Privacy-Preserving Agriculture

Federated Learning is gaining relevance in Digital Agriculture, as it enables sharing of the development of Artificial Intelligence models between various farms, research centers and agricultural companies without exchanging raw data. This technology is especially topical since agricultural data is often spread out in various regions, crops, and management systems. Federated Learning enables the sharing of training of Machine Learning models without compromising data privacy or ownership. In Crop Yield Prediction, it is possible to use Federated Learning to enhance the accuracy of a model by learning under a variety of agricultural conditions, across various locations. Such technology is particularly applicable to Precision Agriculture since it does not bear the risk of having a centralized data storage site but enables analytics which protect privacy. Federated Learning will gain even more significance as governments and agricultural bodies emphasize more on data safety, privacy of farmers, and developing new trends in collaboration.

Explainable Artificial Intelligence and Human-AI Collaboration

Explainable artificial intelligence is a growing important technology since numerous systems of Machine Learning and Deep Learning trace to black boxes which reveal limited details regarding the way forecasts are created. Until AI advances in this area provide explanations that are very clear to farmers and other stakeholders in the agricultural sector, they may not trust their recommendations on issues concerning irrigation, fertilizer application, control of plant diseases and prediction of yields [55-57]. Explainable Artificial Intelligence approaches focus on feature importance analysis, feature attention and SHAP values and LIME to enhance interpretability. Human-AI Collaboration is emerging as a dominant idea in Sustainable Agriculture as farmers will be inclined to accept AI systems when they are capable of comprehending and justifying predictions. Policymakers can also use explainable Artificial Intelligence to figure out the most crucial factors to crop productivity and environmental sustainability. Due to this, explainability will probably become a largely important part of future Agricultural Decision Support Systems.

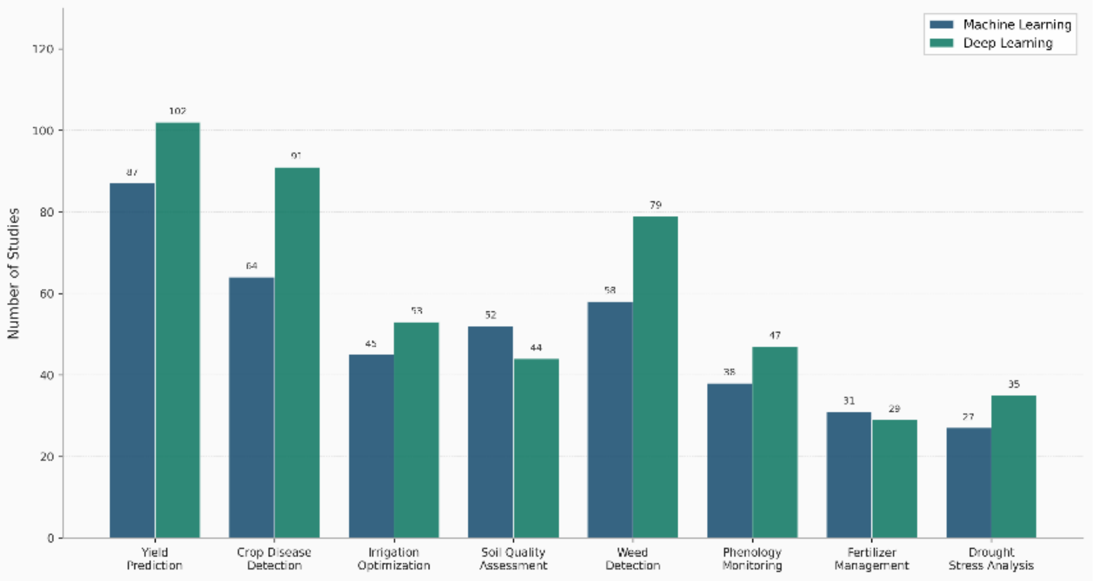

Fig. 4 Distribution of ML vs. Deep Learning Studies Across Agricultural AI Applications

Fig. 4 visualizes grouped bar chart provides a quantitative breakdown of the reviewed literature according to the specific agricultural application addressed, stratified by whether the study employed classical machine learning or deep learning methodologies. Yield prediction dominates the publication landscape for both paradigms, underscoring its central importance to food security and agricultural decision support systems. Crop disease and weed detection show strong deep learning prevalence, attributable to the visual nature of these tasks that directly benefits from convolutional feature extraction. Irrigation optimization and soil quality assessment exhibit a more balanced distribution between ML and DL, reflecting the diversity of sensor modalities and input feature types used in soil-plant-water system modeling. Phenology monitoring and fertilizer management represent comparatively underexplored domains, highlighting research gaps with high potential for future contribution. The annotation of exact study counts above each bar enhances readability and reproducibility, while the clean dual-color scheme preserves visual clarity across multiple categories. This figure provides a panoramic overview of how AI techniques are deployed across the breadth of sustainable agriculture challenges addressed in recent literature.

Foundation Models, Vision-Language Models, and Generative Artificial Intelligence

Some of the latest technologies that determine the future of agriculture are the Foundation Models, Vision-Language Models, and Generative Artificial Intelligence. Based on very large multimodal agricultural datasets containing images, weather data, soil and sensor measurements, and farm documents, Foundation Models are able to learn. The models can in turn be scaled to various bottom-end functions, including detecting disease, predicting the yield, classifying crops, and even studying the soil. The Vision-Language Models can be used to combine textual data with agricultural images, which will enable farms to produce smarter advisory systems and multilingual agricultural support systems. Generative AI can produce synthetic images of agriculture, fill gaps in sensor data, enhance the quality of data, and model future crop development scenarios in response to altered climatic conditions. These technologies are likely to make huge contributions to Digital Agriculture since they enable larger, transferable, and more generalized Artificial Intelligence systems to Sustainable Agriculture.

3.4 Artificial intelligence models

Decision Tree Models for Crop Growth Prediction

Decision Tree models also rank as some of the first models of Artificial Intelligence applied in Sustainable Agriculture since they offer simple, interpretable and rule-based to predict Crop Growth Prediction and Crop Yield Prediction. The agricultural data in these models are grouped into branches according to rainfall, temperature, type of soil, presence of nutrients, humidity, frequency of irrigation and so on [58,59]. The decision tree models are especially applicable in Agricultural Decision Support Systems as they are simple to comprehend and clarify to farmers, agronomists and policymakers. Their interpretability is significant in Smart Farming as the users frequently need to understand why a crop is trending to deliver a good or poor performance in certain circumstances. Applications of Decision Tree models include crop selection, soil fertility classification, irrigation-scheduling, pest-detection and land-suitability. Nevertheless, single Decision Trees can be unstable and prone to overfit especially in large and complex agricultural data thus, many researchers have started considering other classes of ensemble methods like the Random Forest and the Gradient Boosting that make more dependable predictions.

Random Forest Models in Precision Agriculture

One of the most popular Machine learning models in Precision Agriculture is the Random Forest, which is better at making more accurate predictions due to its ability to use several Decision Trees together as a single framework that can be used as one. Random Forests models can process nonlinear agricultural relationships and high volumes of data with weather records, soil characteristics, vegetation indices, irrigation programs as well as crop management procedures, making them extremely effective. Applications of these models include Crop Yield Prediction, Soil Health Monitoring, crop classification, and disease detection. Random Forest would particularly be useful since it can prioritize the relative importance of the agricultural variables, thus assisting the researcher to understand what variables have the greatest impact on crop productivity. Research indicates that random Forest works exceptionally well when structuring agricultural data and where the feature type is either mixed. It has also wide interconnections with Remote Sensing, Satellite Imagery, and UAV Imagery to monitor and predict analytics fields. Random Forest has continued to be one of the most desirable models in Sustainable Agriculture since it gives good performance without compromising its interpretability and computing capacities.

Support Vector Machine Models

SVMs are often utilized in Crop Yield Prediction due to the fact that it is very effective with smaller agricultural data sets and can effectively model very discrete relationships between factors in crop growth. In these models, the agricultural classes are separated with the help of kernel functions and complex patterns among the nutrients of the soils, weather variables, crop phenology, and vegetation indices are identified [3,60-61]. SVM has found extensive use in classifying crops, identification of weeds, diagnosis of diseases, soil testing and prediction of yields. One of the greatest advantages of

Support Vector Machine is that it has a high predictive accuracy when the agricultural data sets are small or, in other words, when there are numerous predictors as compared to the number of observations. This renders the model especially practical in developing countries where extensive datasets of farms might not be on offer. Nevertheless, the Support Vector Machine models can be computationally infeasible with a vast number of image samples or a lengthy time-series dataset, thereby constraining their applicability in Smart Farming (heavy) of data.

Gradient Boosting, XGBoost, LightGBM, and CatBoost Models

Gradient Boosting models have become one of the most effective predictive models in Digital Agriculture as they enhance prediction performance through the combination of numerous weak learners, which are produced in an iterative process. Gradient Boosting Models that are typically used in Crop Yield Prediction and Precision Irrigation include XGBoost, LightGBM and CatBoost. Its popularity among agriculture and research application lies in XGBoost being able to handle large quantities of agricultural data and can also be used to detect intricate interactions between weather, soil, and crop variables. LightGBM is not as frequently used due to its choices of quicker training times and reduced memory usage that are commonly needed in large-scale agricultural environments. CatBoost also works well with the agricultural datasets of categorical variables, i.e. the soil type, the type of crop and the type of irrigation. These models have shown high predictive statistics in the use in rainfall prediction, suitability of crops, pest, and optimization of irrigation. They are being incorporated more into Agricultural Decision Support Systems since they compromise forecasting with moderate decipherability. XGBoost, especially, is becoming one of the most popular models in Smart Farming because of its scalability and strength.

K-Nearest Neighbor and Naïve Bayes Models

The simplified Artificial Intelligence Models (K-Nearest Neighbor and Naïve Bayes models) are still useful in the Agricultural Informatics, especially when there are smaller datasets to be addressed, which address the classification tasks. K-Nearest Neighbor is a predictive approach used to forecast crops using similarity between close-by agricultural data, which is used in crop recommendation systems, soil classification, and disease detection [62-64]. Naive bayes is commonly applied to crop suitability analysis, pest classification and yield prediction, as it has the ability to make probability estimates assuming independent features. These models are not as powerful as ensemble techniques or Deep Learning Models, but they are not pointless since they are easy to pursue and computationally efficient. The more recent research notes that with a set of structured environmental variables (rainfall, humidity, nutrients in the soil, temperature) added to it, Naïve Bayes can be surprisingly effective in crop yield prediction. The models are particularly useful in agricultural settings that have low resources and the computational infrastructure is not very large.

Artificial Neural Networks and Deep Neural Networks

Deep Learning Models based on Artificial Neural Networks and Deep Neural Networks have emerged, as they can model nonlinear and highly complex relationships in agriculture to be used in Sustainable Agriculture. It should also be remembered that the traditional Machine Learning Models used used to need manual Feature Engineering; on the other hand, the Neural Networks can automatically extract hidden patterns out of the raw data. ANNs have been very popular in Crop Dynamics, Soil Crop Health, irrigation prediction, and Crop Yield Projection because they are able to simultaneously process multiple environmental factors. Deep Neural Networks also allow incorporation of many hidden layers that enable the models to learn more abstract and rich relationships among agricultural variables. These are particularly helpful with Agricultural Big Data, Remote Sensing data, and big climate data. The studies are growing in the use of Artificial Neural Networks and Deep Neural Networks as more suitable methods of yield prediction because they offer a more efficient means of dealing with interactions of weather variability and the crop type, along with the soil and farm management techniques.

Convolutional Neural Network Models

Convolutional Neural Network architectures rank among the top-value Deep Learning Models in Precision Agriculture as they are axiomatically structured in the exhibition of images on agricultural data. The CNN models have been utilized to detect crop diseases, classify weeds, count fruits, phenotype eligible plants, predict crop maturity, and predict yields based on UAV Imagery and Satellite Imagery [19,65-67]. They are very effective in detecting stress and nutrient deficiencies, as well as disease symptoms that are early affecting crops, due to the ability to detect spatial pattern of agricultural images. CNN models are commonly combined with Vegetation Indices like NDVI and EVI to enhance the effectiveness of Crop Growth Prediction. Circumstantial changes in CNN architectures have now made possible the capability of applying multispectral and hyperspectral imagery to the field level to enhance the accuracy of irrigation, fertilization and pest management policies. Combinations between CNN models and either recurrent or transformer-based models are also increasingly employed with the aim of enhancing their capacity to combine both spatial and temporal information in agriculture.

Long Short-Term Memory and Recurrent Neural Network Models

Specifically, Long Short-Term Memory and Recurrent Neural Network models are useful in the agricultural sector since they are set to handle sequential and Time Series Forecasting data. The productivity of agriculture greatly depends on the long-term weather cycles, the cycles of rainfalls, irrigation times, soil moisture variations, developmental stages of crops, etc. The advantages of LSTM models are in the fact that they are capable of recalling long-term dependencies in the example of agricultural sequences and forecasting future crop results basing on historical data. RNNs are also applicable to sequential agricultural data, but tends to suffer more from vanishing gradient issues with long time horizons. The LSTM and Gated Recurrent Unit models are thus more often utilized in the field of Crop Yield Prediction, Precision Irrigation, drought forecasting, and Climate Resilience analysis. The use of hybrid CNN-LSTM frameworks is gaining more significance as they integrate image-based learning with time-series forecasting to develop more all-encompassing and precise agriculture prediction frameworks.

Vision Transformer and Foundation Models

The models based on Vision Transformers are becoming one of the most promising alternatives to the Convolutional Neural Networks due to their ability to effectively use the long-range spatial relationships in agricultural images. Vision Transformer models in contrast to CNNs handle image as a sequence of patches which enables them to detect larger spatial relationships in crop fields [68-70]. Such models find more uses in crop classification, disease detection, yield estimation, and land-use mapping with high-resolution Satellite Imagery and UAV Imagery. The Foundation Models also have a growing availability since they can be trained on high multimodal agricultural data and fine-tuned to individual downstream tasks, including Crop Yield Prediction, Soil Health Monitoring, and crop recommendation. Recent applications to geospatial foundation models show that these models can produce high-resolution intra-field yield forecasting via the use of satellite measurements and the time domain. It is predicted that the application of the Vision Transformer and Foundation Models is rapidly growing due to their enhanced scalability, transferability, and performance of other crops and climates, as well as agricultural regions.

Ensemble Learning and Hybrid Models

Ensemble Learning Models make use of the result of several predictive algorithms to enhance the general accuracy and stability of the agricultural forecasts. They are especially applicable in Crop Yield Prediction since no single model proves to be the best in all agricultural data and climatic conditions. Ensemble Learning models commonly pool Decision Trees, Random Forest, XGBoost, Neural Networks and Support Vector machine so as to get various patterns in the data to be reflected. The Hybrid Models are gaining more importance since they combine the subdivide strengths of various algorithms. An example is CNN-LSTM models that fuse image analysis with time-series prediction and Random Forest-XGBoost models that fuse ensemble learning with gradient boosting. Precision Agriculture Hybrid Models are particularly effective due to its abilities to process many types of data at the same time, such as weather, soil condition, Remote Sensing images and market trends. Recent reviews highlight that in agricultural applications, the hybrid and ensemble models tend to be superior to standalone models since they minimize prediction error and enhance consistency in overall performance across different farming systems.

Explainable Artificial Intelligence Models

The importance of Explainable Artificial Intelligence Models is on the rise due to the fact that most sophisticated Deep Learning Models have a black-box nature that offers limited information aiding in the process of making predictions. In agriculture, policymakers and farmers tend to insist on transparency prior to implementing AI-produced recommendations touching upon the choice of crops, irrigation, fertilization, and predictions of the harvest [71-73]. Explainable Artificial Intelligence models rely on such tools as SHAP values, LIME, attention mechanisms, and feature importance analysis to answer the question of why some predictions are made. Such models are especially useful in Agricultural Decision Support Systems since they assist users to determine the relative repercussion of rain that falls, temperature, soil nutrients, frequency of irrigation and vegetation indices. Due to its capability to enhance trust and accountability, as well as user adoption, explainability is becoming a key aspect in Sustainable Agriculture. Recent studies are accumulating more and more evidence to point to the future prominence of Explainable Artificial Intelligence as the center of the future of Climate-Smart Agriculture and Food Security as it enables agricultural decisions to be made transparently and with evidence underlying them.

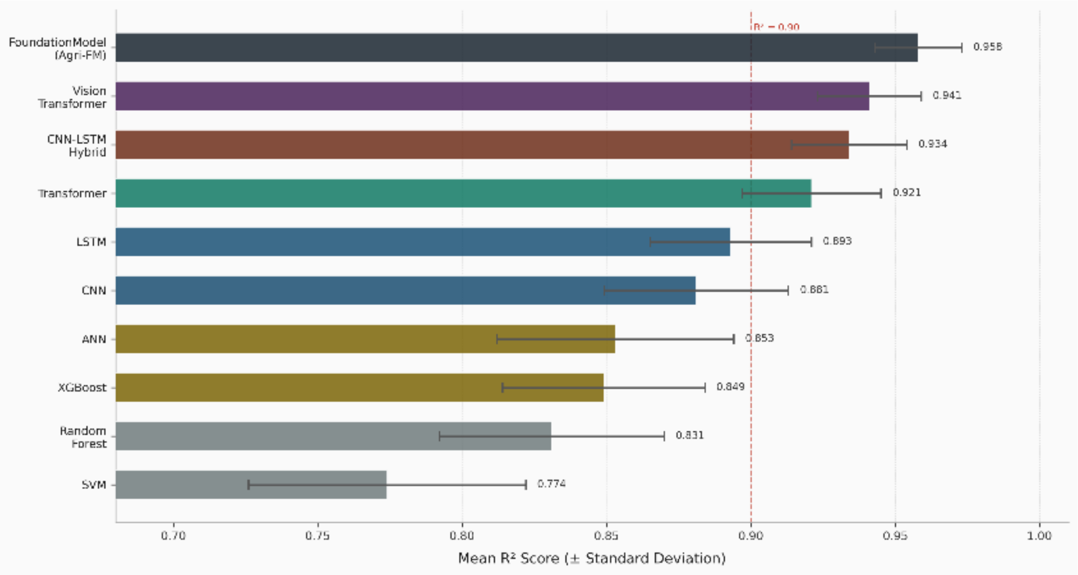

Fig. 5 Mean R² Performance with Variability Across AI Model Architectures

Fig. 5 presents mean R² scores alongside their associated standard deviations for ten AI model architectures arranged in ascending order of predictive performance, spanning from Support Vector Machines to the newly emerging Agricultural Foundation Models (Agri-FM). The arrangement reveals a clear performance hierarchy, with foundation models and Vision Transformers achieving mean R² values exceeding 0.94, far surpassing traditional kernel-based and linear approaches. The narrowing of error bars as model sophistication increases is a particularly important trend: Agri-FM and Vision Transformer models display notably low variability (SD approximately 0.015 to 0.018), suggesting greater generalizability across crop types, geographic regions, and growing seasons. A vertical dashed red line at R² = 0.90 provides an interpretive benchmark, with advanced architectures consistently exceeding this threshold. This figure is particularly relevant for researchers conducting benchmarking studies or meta-analyses, as it synthesizes cross-study performance variation in a statistically rigorous and visually accessible format. The inclusion of exact R² values to the right of each bar further supports its utility as a quick-reference performance summary for model selection in applied crop yield forecasting contexts.

Federated Learning, Edge AI, and Future Models

Federated Learning and Edge AI are the future of Artificial Intelligence Models in Smart Farming as it overcomes the issue of data privacy, connectivity, and real-time decisions. Federated Learning allows farms and agricultural organizations to collectively train Machine Learning Models without accessing raw data, maintaining privacy and control of sensitive agricultural data. Edge AI enables predictive algorithms to execute at local hardware, like drones, tractors, sensors and smartphones, without being fully dependent on cloud infrastructure. Such technologies have a particular use in the realm of rural agriculture where the Internet connection might not be reliable. Predicted Future Artificial Intelligence Models It is believed that Federated Learning, Edge AI, Multimodal Learning, and Generative Artificial Intelligence will also be integrated in future Artificial Intelligence models to develop more responsive, scaled, and decentralized farming systems. Some of the emerging agricultural applications are multilingual advisory systems, climate adherent crop selection systems, and AI-based decision support systems suited to smallholder farmers. Such tendencies show that in the future Intelligent Farming g Systems will be increasingly based on privacy safeguarding, locally fitting, and highly flexible Artificial Intelligence Models.

3.5 Artificial intelligence applications

Crop Growth Prediction and Crop Yield Prediction

Crop Yield Prediction and Crop Growth Prediction are the most frequented uses of Artificial Intelligence in Sustainable Agriculture since they have a direct affect on the profitability of farms, Food Security and the resilience to climatic conditions. Using variables like the rainfall, soil nutrients, temperature, humidity, vegetation indices, and irrigation schedules, AI models can estimate the crop growth stages, the biomass accumulation, flowering periods, and yields anticipated [50,74]. Remote Sensing, Internet of Things sensors, UAV Imagery and Satellite Imagery are gaining traction with Machine Learning and Deep Learning techniques to offer real-time yield predictions at field and regional ranges. Specifically, crop yield prediction systems are valuable due to the fact that they enable farmers to maximize planting time, application of fertilisers, labor usage and harvesting. Recent trends in Precision Agriculture indicate that hybrid AI systems which could integrate the random forest, Convolutional Neural Network, and Long Short-term memory architectures can enhance accuracy in predicting even in the presence of drought and water stress conditions. The combination of field-level satellite imagery like Sentinel-2 and multimodal predictive frameworks is also advancing AI-driven yield prediction to be even more accurate.

Precision Irrigation and Water Management

One of the most valuable uses of Artificial Intelligence is Precision Irrigation since the water shortage turns out to be one of the critical issues of Climate-Smart Agriculture. AI-driven irrigation implements based on weather predictions, soil moisture detectors, evapotranspiration information and development stages of the crops to decide when and how much water is required to be sprayed. Such systems have the potential to save a lot of water waste and also retain/ enhance crop production. Machine Learning models like the Random Forest and Reinforcement Learning are increasingly being applied in the optimization of irrigation hour schedules, providing real-time environmental information. The new technologies of Edge AI and Internet of Things are also making localized irrigation control in rural regions with poor connection a possibility. In the recent studies, scientists have found that the implementation of AI-driven smart irrigation devices will allow cutting agricultural water use by 10-30 percent, and that intelligent weather stations and localized monitoring systems can enhance irrigation control as well as mitigate losses of crops due to extreme weather elsewhere.

Soil Health Monitoring and Nutrient Management

An interesting use of Artificial Intelligence is Soil Health Monitoring, as soil fertility directly influences crop productivity and Sustainability of Agriculture over the long term. Artificial intelligence tools can determine the soil type, pH, moisture ratio, nutrient content, organic carbon, and salinity in the soil to determine the deficiencies and prescribe appropriate corrective actions . The application of Soil-based Machine Learning models to make predictions about the needs of nitrogen, phosphorus, and potassium is rapidly increasing because, in this way, farmers can implement Precision Fertilization practices that can minimize wastage, thus enhancing input efficiency. One of the sensor systems is the Internet of Things sensors that enable constant control over the state of soil, and Deep Learning software is capable of combining the information base with the data on weather and crop development to create an individualized use of nutrients. Applications in AI-based soil analysis are gaining particular significance in such areas as the excessive consumption of fertilizers led to a decline in soil quality and decreased sustainability in the productivity of farms.

Crop Disease Detection and Pest Management

One of the applications of Artificial Intelligence that have had the most significant impact is Crop Disease Detection and Pest Management due to the high percentage of crop losses globally attributed to pests and diseases. The plant images can be analyzed using Convolutional Neural Networks, Computer Vision systems, and Vision Transformer to detect disease, nutrient deficiency, pest infestation and crop stress. These systems are being applied more and more in conjunction with UAV Imagery, methods using multispectral and hyperspectral sensing technology to enable an early warning system prior to the visible damage getting out of hand. Pest management systems managed by AI can also predict the chances of outbreak occurrences depending on the temperature, humidity, rainfall as well as the crop growth cycle. This allows the farmers to only use pesticides where needed, causing only minimal harm to the environment and limited costs of production. Applications of AI in identifying diseases would be of great value, as it helps accelerate intervention procedures, enhance crop resilience, and provide effective integrated pest management programs.

Weed Detection and Precision Spraying

Another significant use of Artificial Intelligence is Weed Detection since weeds will compete with crops over nutrients, water, and sunlight, which inhibits yield potentials. Detection of crops and weeds in growing fields can be made using Computer Vision systems alongside the Deep Learning algorithms to identify the ones that need herbicides and only those infected . More and more, agricultural drones, robotic weeders and autonomous tractors incorporate precision spraying technologies to minimize the use of herbicides and pollute the environment. Such systems can be particularly helpful in Precision Agriculture since they enable site-specific weed control and save on inputs. Weed recognition with artificial intelligence (AI) also enhances efficiency in labor since it is automated where many people would have been required to inspect each one. Image classification and sensor-based weed management systems are becoming much more prevalent in Smart Farming due to their ability to minimize chemical addiction and aid in Sustainable Crop Management.

Precision Fertilization and Resource Optimization

Precision Fertilization is a new application of Artificial Intelligence that can optimize the time of fertilizer use, place, and amount. Using AI models will analyze the soil properties, nutrient requirements of crops, and weather trends and suggest variable-rate nutrient management plans based on this. This enhances the efficiency of the fertilizers and lowers the ecological climate of the nutrient leaking, polluting groundwater, and the emission of green house gases. Machine Learning, geospatial analytics, and resource data fusion become more commonly used together in Resource Optimization applications to help optimize the use of water, fertilizers, seeds, pesticides, and energy. The technologies are gaining additional significance since farmers are now confronted with increasing input prices and growing environmental regulations. The use of AI to optimize resources resources will be critical in supporting Climate Resilience and Sustainable Agriculture through waste reduction and enhancing the profitability of the farms.

Crop Monitoring and Remote Sensing Applications

One of the fastest-evolving applications of Artificial Intelligence is Crop Monitoring as it lets farmers obtain continuous data concerning the health of crops, variability of fields, and environmental factors.

The most common kinds of Remote Sensing technologies, Satellite Imagery, UAV Imagery, and hyperspectral sensors are extensively utilized to measure crop vigor, leaf area index, canopy temperature, soil moisture, and vegetation indices: NDVI and EVI [2,17-19]. Crop monitoring systems that use AI will be able to detect spots with drought, pests, nutrient shortages, or disease before the effects become noticeable to the farmers. This is making such systems increasingly more precise with developments in Geospatial Analytics, Vision Transformer models and multispectral imaging. The fact that the AI Crop Monitoring market is continually growing is attributable to the demand related to predatory analytics and real-time agricultural smarts.

Smart Greenhouses and Controlled Environment Agriculture

Greenhouses are another important use of Artificial Intelligence in the form of Smart Greenhouses due to the fact that it offers a high rate of control in growing crops. Greenhouse systems that are powered by AI incorporate sensors, automation, predictive analytics to control temperature, humidity, light intensity, nutrient supply, and carbon dioxide levels. These are highly beneficial to crops that have high value like vegetables, fruits, and flowers due to the fact that yield consistency is enhanced and resource-wastage minimized. Ventilation, irrigation, and shading can also be optimized by artificial intelligence considering the real-time situations in the environment. The use of Reinforcement Learning and Edge AI in automation of greenhouse, is getting more popular since the systems can dynamically adjust to various conditions without the need that humans be constantly present to control it. The role of smart greenhouse technologies is likely to increase as urban agriculture, vertical farming, and resilience to climatic changes in food production grow.

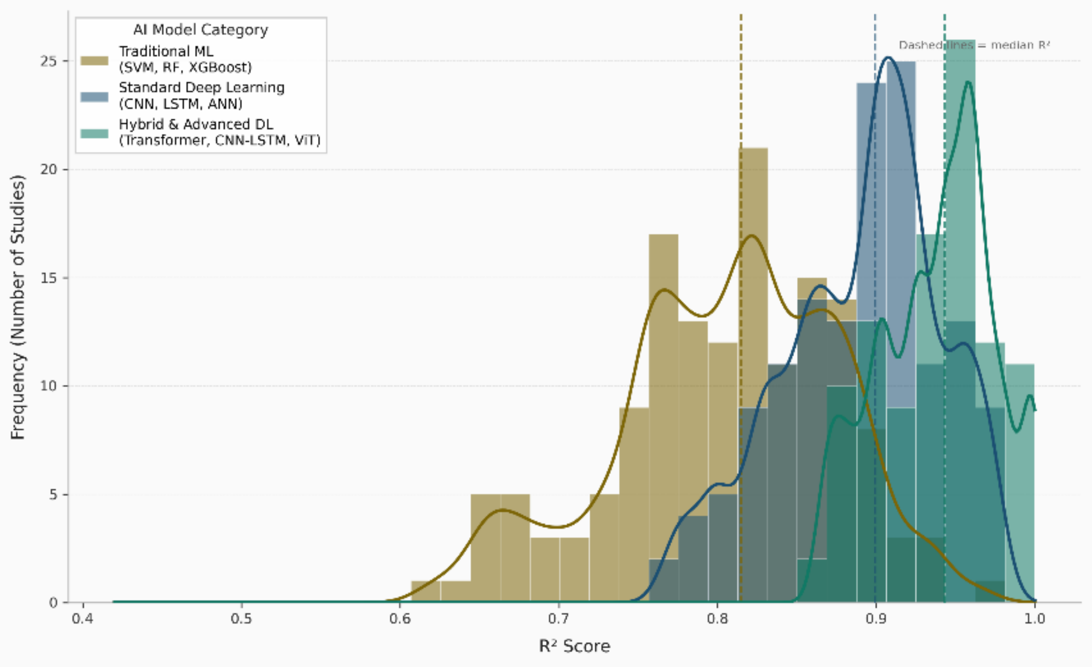

Fig. 6 Distribution of R² Scores Across AI Model Categories

Fig. 6 shows overlapping histogram with superimposed Kernel Density Estimation (KDE) curves illustrates the distributional characteristics of R² scores reported across the reviewed literature, disaggregated into three model categories: Traditional ML (SVM, RF, XGBoost), Standard Deep Learning (CNN, LSTM, ANN), and Hybrid and Advanced Deep Learning (Transformer, CNN-LSTM, Vision Transformer). The distributional shift from left to right across the three categories is unmistakable, with Traditional ML studies concentrated around R² values of 0.75 to 0.87, Standard DL studies peaking near 0.88 to 0.93, and Hybrid and Advanced DL studies showing a tight, right-skewed distribution centered above 0.93. Vertical dashed lines representing category-level median R² scores reinforce these inter-group differences and provide summary statistics without obscuring the underlying distributional shape. The smooth KDE curves superimposed over the frequency bars allow for a cleaner inference of modal performance across large bodies of literature, accommodating the inherent heterogeneity of agricultural datasets and experimental conditions. This figure directly supports the central argument of the review that architectural advancement in AI correlates with measurable, statistically consistent improvements in crop yield and growth prediction accuracy, and it provides a compelling visual foundation for future meta-analytic and bibliometric investigations in this domain.

Agricultural Robotics and Autonomous Farming

Autonomous Farming Systems and Agricultural Robotics are fast revolutionizing the workings of farms by automating labor-intensive and repetitious tasks. Planting, harvesting, weeding, pruning, spraying and sorting Agricultural products are becoming more commonly done by AI-controlled robots [87-89]. Drones, autonomous tractors, robotic weeders and harvesting machines can perform tasks more precisely, and with less manpower. Such technologies are particularly crucial where there is labor shortage and increased farm wages. Robotics systems can often be used with Computer Vision, sensor fusion, Reinforcement Learning and Edge AI to traverse fields, inspect crop conditions, and execute tasks independently. We will see a much higher adoption of AI-powered robotics as it helps to not only boost productivity but also limit the waste production of inputs and make farms more efficient.

Agricultural Decision Support Systems and Multilingual Advisory Platforms

With Agricultural decision support systems on the one hand becoming more important, they give the farmers valuable advice on which specific crops to cultivate, whether to irrigate their farms, fertilizer type to use, when to control weeds and when to harvest their crops among others. The systems utilize the integration of Machine Learning, weather forecasts, soil data, Remote Sensing information and market intelligence to aid in making better decisions. In particular, Multilingual Advisory Systems play a vital role in, say, India since local feeding recommendations may be needed by farmers, in regional languages. New programs like the Bharat-VISTAAR, and ANNAM.AI are showing the impact of how Artificial intelligence can aid personalised, data-based farming advices to millions of farmers. These systems encompass systems that combine weather brains, crop sensors, pest predictors and government farming records to give hyperlocal suggestions. Multilanguage artificial intelligence systems will have a key role to play in enhancing the uptake of Digital Agriculture by the smallholder farmers.

Supply Chain Optimization and Post-Harvest Management

Artificial Intelligence is progressively used outside the farm to enhance Supply Chain Optimization and Post-Harvest Management. The AI systems have the ability to predict demand, optimal transportation pathways, waste minimization of food and enhanced storage of agricultural items . Predictive analytics would know the optimal harvest, transportation, and market delivery timings and minimize losses after harvesting and enhance profits. Images and Computer vision are also being applied to grade produce quality, sort fruits and vegetables and also identifying spoilage during storage and transportation. AI has become more associated with blockchain Agriculture and traceability systems to promote food safety, transparency, and consumer trust. The technologies are particularly gaining significance since post-harvest losses are another significant challenge in the world food systems.

Generative Artificial Intelligence, Digital Twins, and Future Applications

The upcoming phase in AI applications in agriculture is generative Artificial Intelligence, Digital Twin, and multimodal systems. Generative AI can generate the synthetic agricultural data, enhance the image quality, the gaps in sensor data, or simulate the future crop conditions in shifting climatic conditions. The diffusion models and generative frameworks are especially relevant to detect the crop disease, improve the performance of remote sensing, and enhance the agricultural images. Digital Twins can be used to build virtual models of farms, crops, irrigation systems, and soil conditions that can be used by both researchers and farmers to test various management strategies before applying them to actual fields. Applications in the future are planned to involve integrating Generative Artificial Intelligence, Federated Learning, Edge AI, Vision-Language Models, and Digital Twins in generating more responsive, privacy-conscious, and climate-resilient farms. The technologies will also play the main role in the future Smart Farming systems since they will enhance predictive precision, minimize the risk, and facilitate prolonged Agricultural Sustainability.

4. Discussion

The results of this literature review show that Artificial Intelligence has grown to be more than an auxiliary analytical instrument but a key technology in the Sustainable Agriculture, Precision Agriculture, and Smart Farming. The fast development of the Machine Learning and Deep Learning applications in Crop Growth Prediction and Crop Yield Prediction evidences that agriculture is becoming more and more data-driven and technology-intensive . The Artificial Intelligence models are replacing traditional statistical techniques due to their ability to model nonlinear relationships between climatic variables, soil properties, crop genetic makeup, irrigation, and vegetation indices at a significantly more accurate rate. Random Forest, Support Vector Machine, Gradient Boosting, Convolutional Neural Network, Long Short-Term Memory, Vision Transformer, and combined CNN-LSTM models have continuously been demonstrated to be effective in predictive analytics against crop growth and yield estimation. The availability of Internet of Things, Remote Sensing, UAV Imagery, Satellite Imagery, farm management platforms, and hence Agricultural Big Data have further increased the rate of Digital Agriculture and Agricultural Informatics. Current research even points out that AI systems are not only rising beyond yield forecasting but also extending to full-fledged Agricultural Decision Support Systems that can be used to assist in the scheduling of irrigation, managing fertilizer usage and pest control as well as optimizing real-time resources.

Table 1. Artificial Intelligence Techniques for Crop Growth and Yield Prediction

Sr. No.	Application	Techniques / Methods / Models	Key Challenge	Future Direction
1	Crop Yield Prediction	Random Forest, XGBoost, ANN	Data variability	Hybrid multimodal models
2	Crop Growth Prediction	LSTM, GRU, CNN-LSTM	Temporal uncertainty	Long-term seasonal forecasting
3	Soil Health Monitoring	SVM, Decision Tree, IoT	Limited soil data	Sensor-based real-time analytics
4	Precision Irrigation	Reinforcement Learning, IoT	Water scarcity	Autonomous irrigation systems
5	Crop Disease Detection	CNN, Vision Transformer	Limited labeled images	Foundation models
6	Weed Detection	Computer Vision, CNN	High field variability	Autonomous robotic weeders
7	Pest Prediction	Deep Learning, Weather Analytics	Climate uncertainty	Hyperlocal pest forecasting
8	Fertilizer Optimization	XGBoost, Sensor Data Fusion	Nutrient imbalance	Variable-rate fertilization
9	Crop Recommendation	Explainable AI, SVM	Regional bias	Personalized advisory systems
10	Climate Resilience	LSTM, Geospatial Analytics	Extreme weather events	Climate-adaptive models
11	Remote Sensing-Based Yield Estimation	CNN, Satellite Imagery	Cloud cover limitations	Optical-radar data fusion
12	Smart Greenhouses	Reinforcement Learning, Edge AI	Energy costs	Fully autonomous control systems
13	Agricultural Robotics	Computer Vision, Edge AI	High deployment cost	Affordable farm robots
14	Supply Chain Forecasting	Predictive Analytics, ML	Market volatility	Integrated farm-to-market systems
15	Precision Fertilization	Random Forest, IoT	Overuse of chemicals	Sustainable nutrient management
16	Crop Classification	Vision Transformer, CNN	Mixed cropping systems	Multispectral image fusion
17	Yield Simulation	Hybrid Models, Digital Twins	Model complexity	Real-time digital twins
18	Farm Advisory Systems	Explainable AI, NLP	Low farmer trust	Multilingual AI advisory systems
19	Resource Optimization	Ensemble Learning, IoT	Resource inefficiency	Autonomous decision support
20	Weather Forecasting	Time Series Forecasting, LSTM	Prediction errors	Hyperlocal forecasting systems
21	Drought Prediction	Geospatial Analytics, ML	Sparse climate data	Integrated climate monitoring
22	Crop Phenotyping	UAV Imagery, CNN	Limited field coverage	Automated field phenotyping

23	Food Security Planning	Predictive Analytics, AI	Regional disparities	National-scale forecasting systems
24	Yield Mapping	Remote Sensing, GIS	Spatial inconsistency	High-resolution field analytics
25	Autonomous Farming	Robotics, Edge AI	Infrastructure cost	Human-AI collaborative systems

The comparative evidence indicates that the Machine Learning models, including the ones of suitability like the Random Forest, XGBoost, LightGBM, and Support Vector Machine can be efficiently utilized with structured agricultural data, which included weather conditions, soil types, actions of crop management, and the indices of vegetation. They tend to be used as the commonly preferred models since they provide excellent predictive ability, incumbent with moderate interpretability, as well as being computationally fast. Deep Learning models are however trending to overtake the established Machine Learning practices in high-dimensional data sets including Satellite Imagery, UAV Imagery, hyperspectral images and Time Series Forecasting information. Convolutional neural networks are especially useful at detecting crop diseases, identifying weeds, crop type classification, and predicting yields based on images, whereas the Long Short-Term Memory and Gated Recurrent Unit networks show improved ability to capture time variations related to rainfall, irrigation, temperature variations, and crop phenology. The recent increase in the usage of hybrid models integrating CNN, LSTM, Random Forest and Gradient Boosting reflects the necessity to have more comprehensive frameworks that will be able to combine spatial and temporal agricultural data. The most promising avenue is using hybrid systems since they offer increased robustness in terms of various crops, climates, and production systems.

A second notable discussion area is that the future of Artificial Intelligence in Sustainable Agriculture is becoming more adaptive, decentralized and explainable systems. Explainable Artificial Intelligence is becoming significant since the more farmers and other people in the agricultural sector will believe in predictive systems when they know the reason behind the creation of a particular recommendation or forecast [3,39-41]. SHAP, LIME, attention mechanisms and feature importance ranking are some of the methods that have found their way into Agricultural Decision Support System to enhance transparency and accountability. Meanwhile, Federated Learning and Edge AI are becoming highly valuable solutions as they minimize privacy, connectivity and scalability issues in the countryside farming setting. Federated Learning gives multiple farms and organizations the ability to train Machine Learning models in collaboration without exposing raw data, and Edge AI allows local processing of crop images, irrigation signals, and disease detection outcomes on devices like drones, smartphones, and sensors. It is anticipated that these technologies will gain greater significance in smallholder farming systems whereby cloud networks are likely to be restricted, along with data sharing. The studies indicate that federated systems are capable of very high predictive accuracy and also the cloud dependency and response time is minimized greatly.

Table 2. Challenges, Opportunities, and Future Research Directions in Artificial Intelligence for Sustainable Agriculture

Sr. No.	Challenge	Opportunity	Emerging Technology	Future Research Direction
1	Limited labeled agricultural data	Transfer Learning	Foundation Models	Few-shot agricultural learning
2	Poor model interpretability	Explainable AI	SHAP, LIME	Transparent prediction systems
3	Data privacy concerns	Federated Learning	Decentralized AI	Secure collaborative learning
4	Weak rural connectivity	Edge AI	On-device inference	Offline smart farming tools
5	Climate variability	Climate-Smart Agriculture	Digital Twins	Adaptive risk forecasting
6	High computation cost	Efficient AI Models	TinyML	Low-power farm devices
7	Regional bias in datasets	Inclusive AI	Localized training	Diverse geographic datasets
8	Smallholder exclusion	Human-AI Collaboration	Advisory Platforms	Farmer-centered design
9	Low image quality	Generative AI	Diffusion Models	Synthetic data generation
10	Cloud cover in satellite data	Radar-Optical Fusion	Sentinel-1 and Sentinel-2	Multi-source remote sensing
11	Missing sensor values	Autoencoders	Imputation Models	Robust data reconstruction
12	Poor scalability	Multimodal Learning	Unified Data Platforms	Integrated farm intelligence
13	High infrastructure costs	Robotics-as-a-Service	Agricultural Robotics	Affordable automation
14	Weak crop model transferability	Domain Adaptation	Transfer Learning	Cross-region deployment

15	Limited crop diversity in research	Genomic AI	DNA Foundation Models	Climate-resilient breeding
16	Uncertain weather patterns	Time Series Forecasting	LSTM, GRU	Hyperlocal climate prediction
17	Delayed farmer response	Real-Time Analytics	IoT and Edge AI	Immediate field intervention
18	Fragmented farm records	Agricultural Informatics	Blockchain Agriculture	Integrated data sharing
19	Lack of benchmark datasets	Standardization	FAIR Data Principles	Reproducible agricultural AI
20	Overreliance on black-box models	Explainable Models	Attention Mechanisms	Trustworthy AI systems
21	Limited multilingual support	NLP Systems	Vision-Language Models	Regional language advisories
22	Sparse phenotypic data	Geospatial Analytics	UAV Imagery	Field-level crop monitoring
23	High labor shortages	Autonomous Farming	Smart Robotics	Semi-autonomous agriculture
24	Weak integration of genomics	Biological AI	Plant Foundation Models	Precision breeding systems
25	Limited sustainability metrics	Sustainable AI	Carbon-aware AI	Environmentally efficient models

There are also emerging trends that Remote Sensing, Satellite Imagery, UAV Imagery, geospatial analytics, and Digital Twins are emerging as core technologies of the next-generation crop monitoring and yield projections. Machine Learning and Deep Learning systems are starting to be combined with Sentinel-2 imagery, radar-optical data fusion, vegetation indices, and process-based crop growth models to better field-level yield estimates. Digital Twins are especially significant since they enable farmers to model their irrigation plans, fertilizer plans, disease outbreaks and weather risks prior to making field decisions. The growing convergence of Digital twins with Machine Learning, IoT, and smart irrigation devices will probably transform Precision Agriculture by allowing to simulate, optimize, and manage risks in real-time. Simultaneously, with the advent of foundation models, multimodal learning, Vision-Language Models, and Generative Artificial Intelligence, novel avenues of exploration are becoming feasible in future research. Such models have the capability to learn on very large farming datasets (that encompass text, imagery and weather data, genomic data, and sensor streams) to generate more general and transferable agricultural intelligence systems. Future Advances Climate-responsive crop development and better crop genetics: The use of DNA-based foundation models in plant biology and breeding can also open new avenues in future climate-sensitive crop development and in enhancing crop genetics.

With all these developments, however, there are still serious gaps in research. Numerous studies are still based on region-specific databases, and it is challenging to extrapolate the models of Machine Learning and Deep Learning within other geographies, types of crops, and other climatic regions. Many aspects of Crop Yield Prediction research still lack benchmark datasets, uniform evaluation metrics and cross-regional validation frameworks. Moreover, Deep Learning models cost is relatively high to compute, labeled agricultural data is scarce, and has no user-friendly interfaces, which are obstacles to widespread implementation. They should be investigated using multimodal learning models, privacy-aware analytics, low-power porous Artificial Intelligence (EAI), climate-sensitive crop models, and multilingual advisory systems, which have the potential to be used by both the commercial farms and smallholder farmers. The future of Artificial Intelligence in Sustainable Agriculture will probably not only be based on technical performance but also on the level of accessibility, transparency, affordability, and the capability to facilitate resilient and just food systems.

5. Conclusions

The PRISMA-based literature review illustrates that Artificial Intelligence has emerged to be one of the most powerful technological factors behind Sustainable Agriculture, specifically Crop Growth Prediction and Crop Yield Prediction. The results confirm the fact that both on Machine Learning and Deep Learning technologies are becoming more suitable than traditional statistical tools due to their advanced capacity to handle nonlinear, complex and multidimensional agricultural data. Models including random forest, support vector machine, gradient boosting, convolutional neural network, long short-term memory, and deep neural networks, ensemble learning, and hybrid CNN-LSMT networks have demonstrated good predictive results across crop types, climatic zones, and agricultural environments. The addition of Remote Sensing, UAV Imagery, Satellite Imagery, weather, soil characteristics, vegetation indices, Internet of Things sensor networks, and other technologies has made predictive systems more accurate and reliable in Precision Agriculture and Smart Farming.

Another aspect mentioned in the review is the fact that the future of Agricultural Informatics is moving into more intelligent, adaptive and real-time decision making systems. Older versions like Explainable Artificial Intelligence, Federated Learning, Edge AI, Transfer Learning, Vision Transformers, and Multimodal Learning have become potentially the main research focus since they tackle some of the most enduring shortcomings of the existing forecasting models. Explainable Artificial Intelligence has the potential to enhance trust, transparency and accountability among farmers, and Federated Learning provides privacy-preserving collaborative learning across distributed agricultural data. Likewise, Edge AI will be able to assist with low-latency crop health and yield prediction in resource-limited and rural settings, minimizing the need to use cloud services and improving response to environmental stressors. Such innovations will greatly enhance Agricultural Decision Support Systems and climate-resilient agricultural strategies in the future.

Another intriguing observation is that Artificial Intelligence is also being correlated with more sustainable sustainability goals, such as the Food Security, Climate Resilience, Resource Optimization, Soil Health Monitoring, Precision Irrigation, and Sustainable Crop Management. Instead of displacing the farmers, AI-based systems are becoming collaborative technologies to assist in making more effective decisions, minimizing wastage of inputs, enhancing water and fertilizer use and productivity during varying climatic conditions. This is particularly more applicable in areas where labor lacks, weather is unpredictable and agricultural factors are scarce. The increased use of autonomous system, predictive analytics and AI-enhanced farm management systems is indicative that agriculture is shifting towards a more data-focused and technology-enhanced form of production.

Nevertheless, as successful as the results were, there are a number of research gaps that have not yet been addressed. Numerous current research works are based on limited datasets that are restricted to the geographical area and type of crops, thus reducing the ability to generalize across different geographical areas, crops, and climatic regions. Lack of benchmark datasets, data imbalance, limited transparency of black-box models, and underrepresentation of smallholder farming systems are significant obstacles to large-scale adoption. To advance future research, the creation of open-access agricultural data, models that are interpretable, energy efficient, standard assessment metrics, and frameworks that are geographically accommodative and can be implemented in both developed and developing countries should be an ongoing goal in future research. More attention should be also paid to the incorporation of genomics, climate forecasting, soil health, market intelligence, and socio-economic factors in the predictive frameworks. With over time, a combination of Artificial Intelligence, Digital Agriculture, foundation models, and next-generation sensing technologies, could create highly adaptive agricultural ecosystems which can enhance productivity, sustainability, and resilience on a global scale.

Conflict of interest

The authors declare no conflicts of interest.

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