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Review article

Applications of machine learning and deep learning in agriculture: A comprehensive review

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ABSTRACT

The digitalization of agriculture has increasingly integrated artificial intelligence (AI), machine learning (ML), and deep learning (DL) to address the challenges arising from population growth, climate change (CC), and resource limitations. This study provides a comprehensive review of the potential applications of AI techniques across various stages of agricultural production, with a particular focus on innovations that align with climate-smart agricultural practices. The review encompasses research conducted from 2018–2024, emphasizing the use of ML and DL in areas such as crop selection, land monitoring and management, water, soil and nutrient management, weed control, harvest and post-harvest practices, pest and insect management, and soil management. The findings underscore that ML and DL facilitate the analysis of complex datasets, enabling data-driven decision-making, reducing reliance on subjective expertise, and improving farm management strategies. Despite challenges such as data availability, model interpretability, scalability, security concerns, and user interface design, which hinder the widespread adoption of ML and DL methodologies, collaborative efforts among stakeholders can help overcome these barriers. This review concludes that ongoing advancements in ML and DL present significant opportunities to enhance agricultural productivity, sustainability, and resilience. By leveraging data-driven insights and innovative technologies, the agricultural sector can transition toward more efficient, environmentally sustainable, and economically viable practices, contributing to global food security and environmental preservation.

1. Introduction

Agricultural experts and scientists are dealing with the challenge of sustainable agriculture due to various threats, including rising food and energy prices, climate change (CC), ongoing exhaustion and depletion of natural resources, a significant reduction in freshwater availability, and the predicted population growth [1–5]. Agriculture is key to global food security and economic prosperity, constituting 6.4% of the total GDP and serving as a significant livelihood for millions worldwide [6]. The United Nations' Food and Agriculture Organization (FAO) projects a 70% surge in worldwide food demand by 2050, driven by population growth and changing consumption patterns linked to rising incomes in many countries [7,8]. These shifts in demand exert significant pressure on food systems. Despite sufficient global food production, widespread malnutrition persists, affecting 500 million individuals, while over 821 million suffer from hunger. [9,10]. Urbanization trends indicate that two-thirds of the population will reside/live in urban areas, with substantial growth predicted in several regions [11]. This demographic shift, coupled with an estimated 473 million individuals projected to join the middle class in India and Nigeria, presents a formidable challenge to achieving sustainable development goals (SDGs), notably eradicating hunger. By 2030, meeting 40% of water demands may prove challenging, and 20% of agricultural land potentially degraded [12]. Considering impending resource constraints, farmers must embrace sustainable practices to enhance productivity [13]. The three-billion-ton annual increase in wheat production and a more than 200% rise in meat production, primarily driven by improved yields, are necessary to fulfill the global population's expected demands by 2050 [14,15]. Accomplishing these targets mandates scaling up agricultural infrastructure and deploying

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advanced technologies. However, the feasibility of achieving these objectives in an environmentally sustainable and socially equitable approach remains uncertain [10,12]. Addressing these challenges requires a substantial and swift transformation in farm operations, emphasizing innovation adoption [13]. Agricultural stakeholders are increasingly motivated to integrate cutting-edge technologies to optimize harvest yields [5,16]. Agri-technology and precision farming, now encompassed under digital agriculture, have emerged as innovative scientific disciplines leveraging data-concentrated methodologies to enhance agricultural efficiency while mitigating environmental influence [17,18]. The modern agriculture landscape uses many sensors to generate data, offering insights into dynamic interactions between crops, soil, weather conditions, and machinery performance. This Big data enables more informed and expedited decision-making processes [19].

The integration of computers into agriculture was documented in 1983 [20]. Since then, several methods, from decision support systems and databases, have been used to address agricultural difficulties. Over the past decade, Artificial Intelligence (AI), deep learning (DL), and encompassing machine learning (ML) have emerged [21]. With High-performance computing and large data technologies, ML and DL have revolutionized the analysis of data-rich agricultural environments [21]. ML, defined as the scientific discipline enabling machines to learn without explicit programming, has been found to have applications across diverse scientific domains [22]. In agriculture, ML and DL hold promise for unraveling complex processes, quantifying trends, and understanding intricate relationships within operational contexts [19]. By using the power of these algorithms, agricultural stakeholders can optimize resource distribution, modify interventions, and mitigate risks, thereby fostering sustainable agricultural practices [22]. ML models are classified into four classes based on the input type or feedback accessible to the learning mechanism. Firstly, in supervised learning, the system receives inputs with their corresponding desired outputs from a 'supervisor/operator.' The objective is for the system to discern a general rule that can map inputs to outputs effectively [23]. Secondly, in unsupervised learning, algorithms operate independently without any provided labels, tasked with discovering inherent structures within the input data. Unsupervised learning can either be a standalone objective to unveil concealed patterns within the data or facilitate feature learning [24]. Meanwhile, semi-supervised learning blends supervised and unsupervised learning by training models with labeled and unlabeled data, such as Generative Adversarial Networks [25]. Lastly, reinforcement learning is a process where a computer program interacts with a changing environment [26].

ML has recently been utilized in agriculture to tackle challenges like CC, population growth, resource degradation, crop management, and yield predictions [27,28]. Precision agriculture, which influences ML, aims to enhance productivity, ensure environmental safety, and promote sustainability by focusing on efficient resource management, ecosystem preservation, service development, and advanced technology implementation [19]. In agriculture, the most employed ML algorithms in image processing include Decision Trees (DTs), Random Forest (RF), ANNs, Support Vector Machines (SVM), k-nearest Neighbors (KNN), and Naïve Bayes. RF is an observed ML algorithm comprising multiple decision trees created employing random vectors. It addresses classification and regression tasks, improving accuracy as the number of trees increases. Unlike single decision trees, RFs randomly determine the root and split feature nodes, effectively reducing the risk of overfitting and handling missing values and categorical data [4]. DTs are frequently employed as straightforward classifiers, arranging examples by their feature values to assign classifications. [29]. The DT consists of nodes and branches, in which each node denotes a classification example, and every branch represents the possible value the node could acquire [30]. It is sometimes possible to guess the class label for a set of input attributes, which can be challenging due to complex factors not considered in the analysis. Bayesian classifiers model probabilistic associations among attributes and the class label, addressing these complexities [31]. ANNs are inspired by biological neural networks and consist of direct and interconnected nodes, recognized as connectionist systems. Every link is weighted and transmits signals between nodes. Each node processes the signal before being passed to the next, with the outcome of every neuron determined through a non-linear function of its inputs. Learning in ANNs involves adjusting the weights to improve signal strength and accuracy [3,21]. SVM is another supervised learning model for classification that separates examples of distinctive classes in vector space with an evident gap. New samples are mapped into the vector space. Their labels are allotted based on their position relative to the gap. The kernel technique allows SVMs to perform non-linear classification efficiently [32].

DL, a specialized area within ML, holds significant promise for transforming the agriculture sector [33]. DL classification is presented in Fig. 3. It offers enhanced accuracy and efficiency in monitoring crop development, forecasting yields, and detecting plant diseases [34]. It extends ML by utilizing hierarchical functions for data transformation, facilitating multi-level data representation. A notable advantage lies in its feature-based learning, enabling the automatic extraction of diverse features from input datasets [21,35]. DL excels in solving complex problems efficiently due to its utilization of intricate models, enabling extensive parallelization [35]. DL encompasses diverse components such as convolutions, pooling layers, fully connected layers, gates, memory cells, activation functions, and encode/decode schemes, which vary depending on the employed network architecture, including Unsupervised Pre-trained Networks, CNNs, DNNs, and RNNs [21,36,37]. CNN stands out for its hybrid or semi-supervised nature, particularly adept in computer vision and visual object recognition tasks. While CNNs automatically learn filters and capture spatial features from images, challenges such as overfitting and the demand for extensive training data persist [38]. RNN, also hybrid or semi-supervised, excels in discerning patterns and predicting future developments, leveraging memory across time intervals. Despite their effectiveness, RNNs encounter hurdles like the complexity of training and gradient-related issues [36,39]. DNNs in agriculture revolutionize farming practices. These networks analyze vast datasets to enhance crop monitoring, predict yields, and detect plant diseases with unprecedented accuracy [40,41]. DNNs offer efficient solutions for optimizing agricultural productivity and sustainability by automatically extracting features from input data [42]. Transfer learning has emerged as a powerful tool in agricultural applications, particularly where datasets are limited. In various studies, DL architectures like GoogLeNet, AlexNet, and VGGNet have been fine-tuned to achieve impressive results in plant identification and disease classification tasks [43–45]. For example, VGG-19 attained a classification accuracy of 98.7% in distinguishing sugar beet and potato images under varying light conditions [46]. DenseNet outperformed other architectures with a testing accuracy of 99.75% in plant disease classification experiments. Despite these successes, a common limitation is the reliance on pre-trained weights from general-purpose datasets like ImageNet, prompting further inquiry into the potential benefits of fine-tuning agricultural-specific data to enhance model performance [47]. In another study, the efficacy of DL was demonstrated in automating disease detection on fruits via an automatic sorting machine. The system's performance was enhanced by using a deep autoencoder [48]. Furthermore, a fully CCN model was employed on hyperspectral images for crop virus detection using a tractor-shaped system equipped with a push broom [49].

Past studies showed potential applications of ML and DL in agriculture, but CC and other challenges still need to be addressed, requiring climate-smart sustainable practices and advanced technologies to ensure agricultural productivity and sustainability [50]. This study systematically reviews research from 2018 onward on the application of ML and DL in agricultural production, categorizing advancements into nine critical areas: crop selection, land monitoring, water and soil, nutrient management, weed control, insect and pest management, disease management, harvest practices, and climate impact assessment.

Each category reflects a vital aspect of the agricultural lifecycle, where AI technologies enhance efficiency and sustainability. The review highlights how AI models optimize decision-making, resource allocation, and threat mitigation while addressing challenges like CC. Key contributions include analyzing ML/DL applications in precision agriculture, a comparative evaluation of algorithmic performance, and insights into future trends and limitations for climate-smart farming.

2. Materials and methods

This research adopts the Systematic Literature Review (SLR) methodology, guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework [51]. Recognized for its application across diverse fields, including agriculture, environmental sciences, public health, and technological integration, PRISMA ensures a robust and transparent approach to systematically identifying, analyzing, and synthesizing relevant literature [52].

The framework comprises four fundamental stages: identification, where studies are located; screening, to exclude irrelevant works; eligibility, involving detailed evaluation; and inclusion, which finalizes the selection of studies for analysis (see Fig. 1). This structured process enhances the credibility and reproducibility of the review, ensuring comprehensive coverage of the research domain.

2.1. Literature identification

The identification phase involved a comprehensive search across several academic databases, including IEEE Xplore, ScienceDirect, Web of Science, Springer, and the Multi-disciplinary Digital Publishing Institute (MDPI). Google Scholar was also a supplementary source to ensure extensive coverage of relevant literature. These databases were selected for their wide-ranging scope and relevance to the study's objectives.

The search strategy utilized Boolean operators and selected keyword combinations to ensure comprehensive retrieval of relevant studies. Specific search terms included: "machine learning" AND "agriculture", "deep learning" AND "crop yield prediction", "artificial neural networks" AND "agriculture", "smart agriculture" AND "deep learning", as well as variations such as "ML applications in agriculture" AND "crop prediction models", "ANNs in agricultural management", "precision agriculture" AND "AI", "data-driven farming" AND "machine learning", "crop management" AND "artificial intelligence", "AI-based crop modeling" AND "deep learning", and "sustainable agriculture" AND "machine learning".

The search was confined to titles, abstracts, and keywords to enhance retrieval accuracy and relevance, ensuring the identification of studies that addressed the integration of ML, DL, and ANNs within the agricultural domain.

2.2. Research questions

This review was structured to address the following key research questions (RQs):
RQ-1: What ML and DL methodologies have been applied to various stages of agricultural production?
RQ-2: In what ways have ML and DL approaches impacted agricultural research and practices?
RQ-3: How effective are ML and DL techniques in addressing agricultural challenges?
RQ-4: What datasets have been utilized in these studies, and how are they structured?
RQ-5: What are the limitations and gaps in the current body of research?

2.3. Study screening and eligibility

2.3.1. Inclusion criteria

Peer-reviewed journal articles published between 2018 and the present were selected for this review. The rationale for choosing this timeframe is that 2018 marked a surge in research interest and advancements in the application of ML and DL in agriculture, driven by the increasing availability of big data, computational resources, and domain-specific studies. This period captures significant insights into ML and DL methodologies, datasets, and outcomes in agriculture, reflecting the field's most relevant and impactful developments.

2.3.2. Exclusion criteria

Duplicate records and articles not published in English and focused on climate prediction, given its distinct and expansive scope requiring separate analysis. Non-peer-reviewed sources, conference proceedings, and grey literature.

2.4. Data extraction and synthesis

The identified articles were systematically categorized into nine thematic domains to effectively organize the findings (see Fig. 2). These domains include crop selection, land monitoring and management, water and nutrient management, soil management, weed, insect, and pest management, disease detection and management, harvest and post-harvest practices, and crop yield prediction. While the domain of climate impact assessment was identified as significant, it was excluded from this review due to its expansive scope, which warrants a separate, focused analysis.

2.5. Quality control

To ensure the reliability and validity of the study selection process, abstracts were reviewed for relevance to the research questions. Screening criteria were rigorously applied, including removing duplicate entries and non-English publications.

3. Results and discussion

This section presents case studies of the applications of ML and DL models, as illustrated in Fig. 3, across various stages of agricultural processes. The analysis highlights the integration of these advanced ML and DL techniques to optimize decision-making and enhance efficiency throughout the agricultural lifecycle.

3.1. Land monitoring and management

Agricultural Land is essential for food production and ecological regulation [53]. Its evaluation involves analyzing soil, topography, climate, and other factors to match land attributes with crop requirements [54]. Poor management can lead to soil pollution and erosion [55]. Recent advancements in ML and DL have enabled more sustainable and precise agricultural land management [53,56,57]. These models manage large datasets, offer significant benefits, and present vulnerabilities [14]. Precision agriculture, which relies on data analytics and ML, highlights the need for robust data security to prevent data manipulation or misuse, given the large data volumes and potential economic impact [58]. ML addresses complex, nonlinear problems with diverse datasets, enhancing decision-making and reducing reliance on user expertise. DL further advances these applications by transforming datasets through hierarchical data representation and automated feature extraction, providing more accurate classification and analysis [59]. Efficient land evaluation is crucial for policymakers to promote sustainable agricultural resource use. The general mechanism for implementing these ML and DL methods is shown in Fig. 4.

Table S1 presents the applications of these methods in agricultural land monitoring and management. For example, Li, Liu et al. (2023) integrated multimodal data into Google Earth Engine to assess land quality in Guangdong Province, China, finding that RF outperformed DNN models for predicting land quality, particularly in paddy fields [44]. Azadnia et al. (2022) developed a CNN-based smartphone

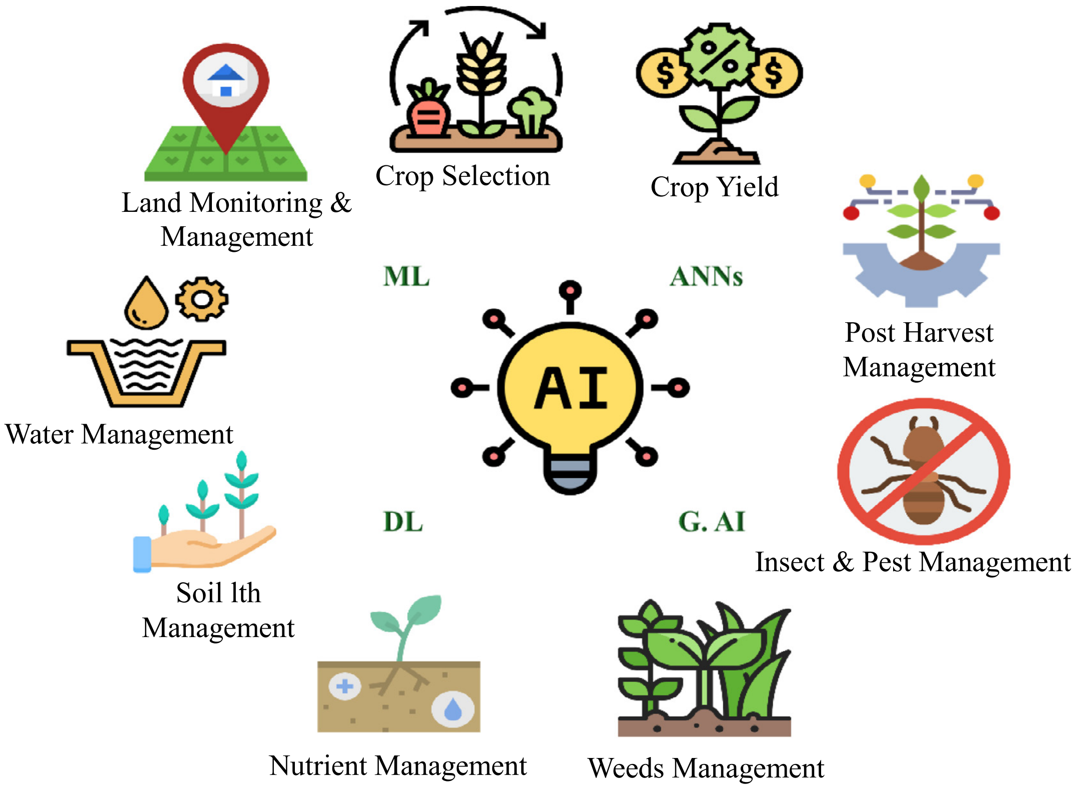

Fig. 1. Applications of artificial intelligence (ML and DL models) in agriculture.

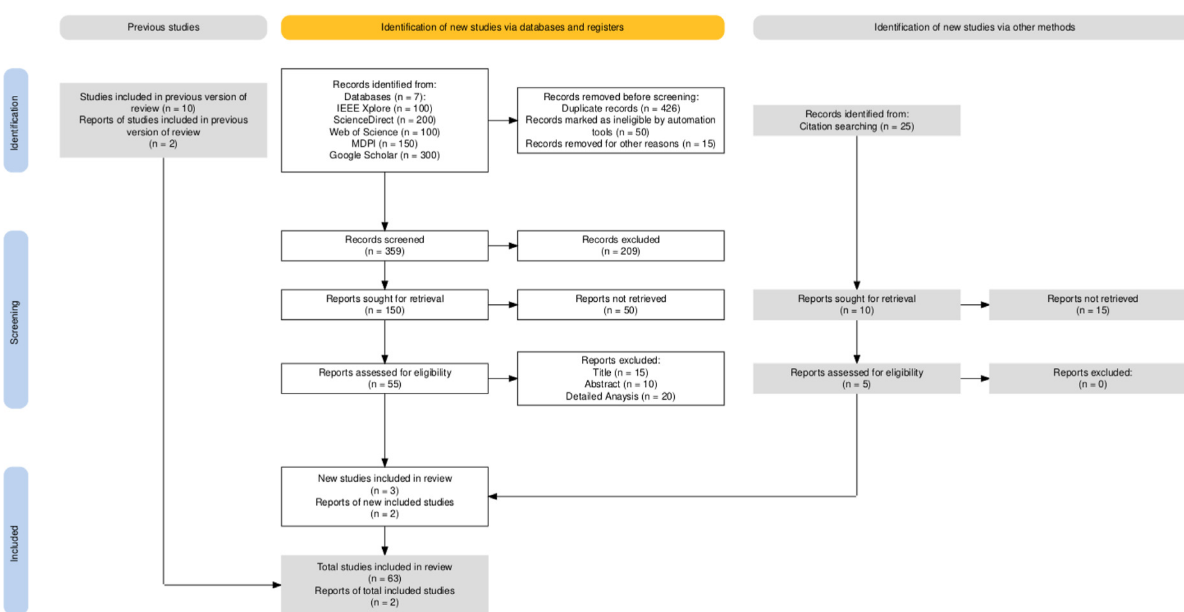

Fig. 2. Complete criteria (PRISMA) and design for a detailed systematic review.

system for soil texture classification, achieving high accuracy and offering a quick, cost-effective alternative to traditional methods [53]. Singh et al. (2022) used U-Net and RF models to map agricultural land usage types with Sentinel-2 facts, with U-Net showing superior performance [56]. Sarma, Das et al. (2022) combined IoT and AI for continuous monitoring and automated decision support in tomato farming, utilizing VGG16 CNN for effective disease classification [57]. Lastly, El Hoummaidi, Larabi et al. (2021) employed UAVs and DL for mapping agriculture in Dubai, achieving high vegetation cover accuracy with an integrated object detection and geospatial analysis workflow [60]. These advancements highlight the potential of DL and ML in enhancing agricultural productivity and decision-making through proper land monitoring and evaluation.

3.2. *Agricultural water management*

Globally, approximately 85% of freshwater resources are allocated to the agricultural sector, primarily driven by the increasing demand

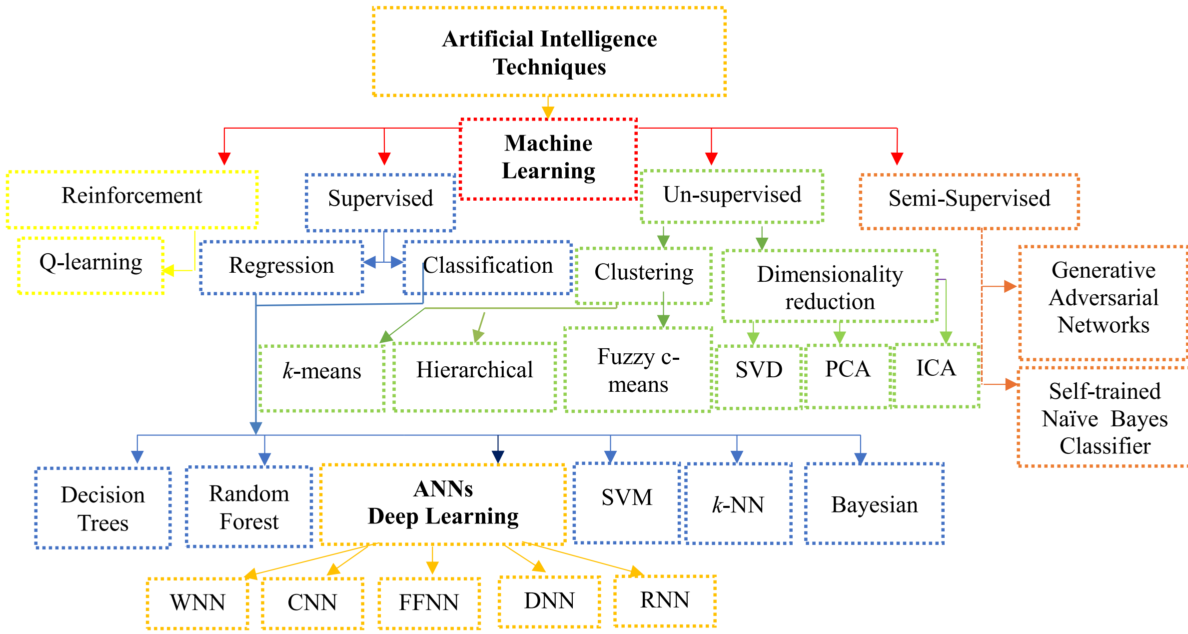

Fig. 3. Artificial intelligence classification, comprising machine and deep learning [21].

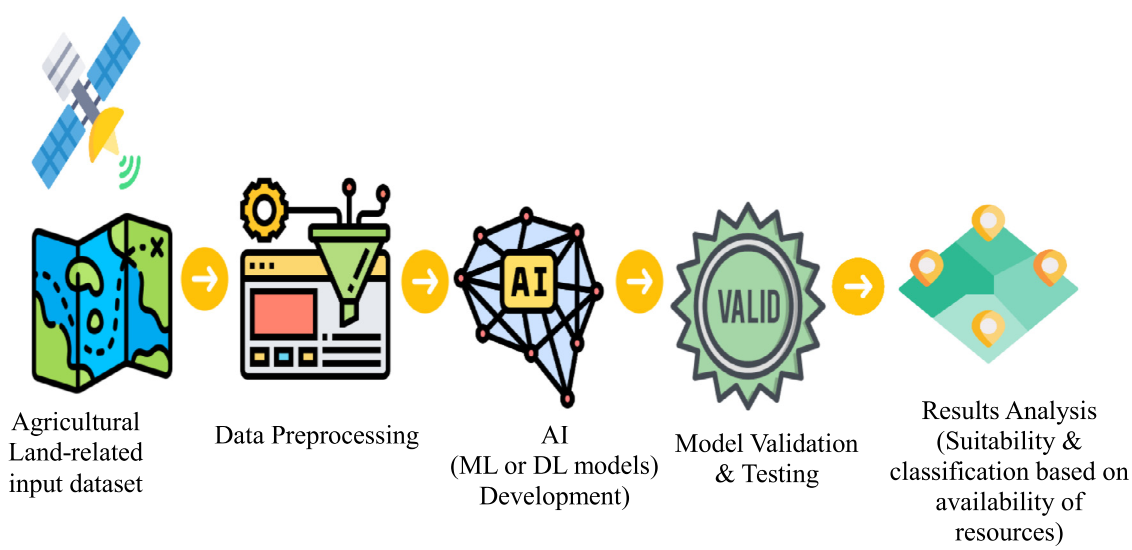

Fig. 4. The overall mechanism of land monitoring and management processes through ML and DL.

for food due to population growth expansion [61]. However, traditional irrigation practices face significant challenges, including low water-use efficiency and productivity. Moreover, CC and global warming disrupt rainfall patterns, further exacerbating water availability issues [62,63]. Crop's water requirements and physiological processes exhibit seasonal variations influenced by environmental factors like weather.

In contrast, controlled environments such as greenhouses offer some regulation, and open-field cultivation farms struggle with managing these variables [64,65]. Adaptive management approaches and precision irrigation systems are essential to address these challenges. Recent advancements in ML and DL methods have revolutionized the extraction of geospatial features from remote sensing imagery, enabling more efficient and precise analysis [66]. ML and DL models have found applications across various domains [67].

Fig. 5 illustrates how ML and DL models enhance agricultural water management by integrating data from numerous sources like satellites, drones, or ground sensors. Satellite images provide large-scale soil moisture and crop health data, while drones capture high-resolution images to monitor crop conditions, including stress and moisture levels. Ground sensors measure specific soil and plant parameters like moisture and temperature. This data is fed into a central processing unit utilizing ML and DL models to analyze and interpret the information. The models output valuable insights such as soil moisture estimation, evapotranspiration, soil water modeling, prediction, estimation of plant water stress, and status identification. These outputs help in precise irrigation scheduling, efficient water use, and timely interventions to prevent crop loss. Thus, the integration of advanced algorithms and diverse data sources leads to optimized water management, improved crop health, and enhanced farm management.

Many ML and DL methods have been applied to agricultural water management, highlighting promising outcomes with some limitations (Table S2). For example, Raei et al. (2022) employed U-Net with ResNet-34 for various irrigation types in Idaho, achieving high accuracy rates in training, validation, and test data, although imbalanced training data and increased computational time with larger image sizes posed challenges [68]. Ferreira and da Cunha (2020) utilized RF,

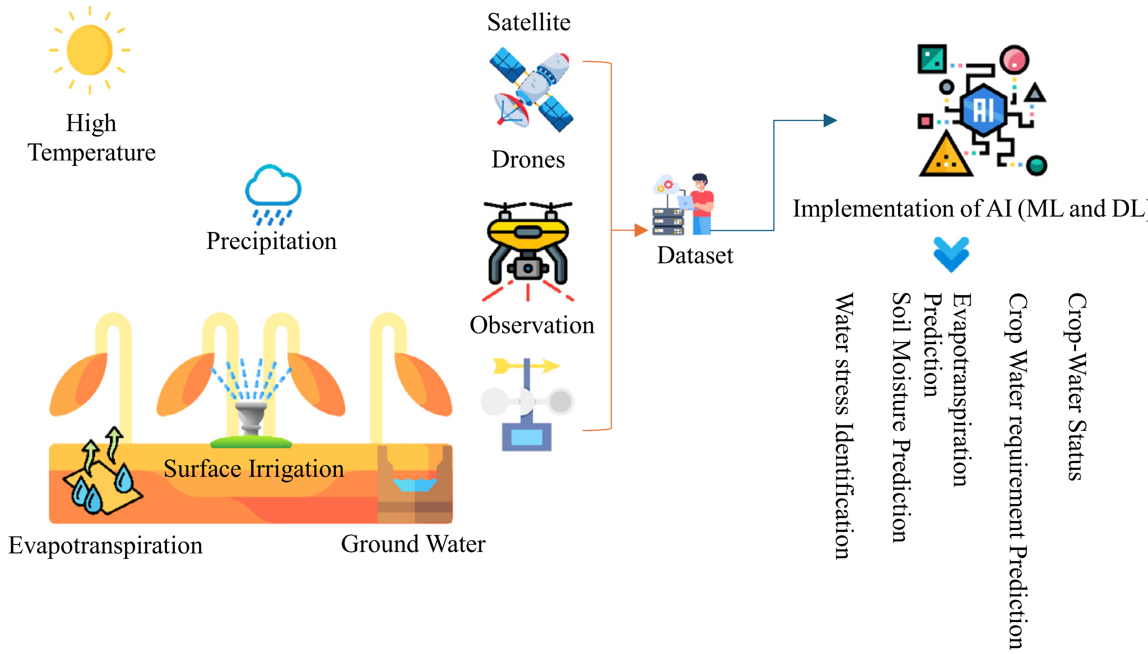

Fig. 5. Schematic representation of water management by ML and DL.

CNN ANN, and XGBoost for general irrigation, reporting significant improvements in performance metrics, yet performance varied based on data availability and climatic conditions [69]. Elbeltagi et al. (2020) utilized a DNN to forecast evapotranspiration for wheat, achieving high correlation coefficients between actual and predicted values but with limitations in geographical scope and future projections based on specific scenarios [70]. Yu et al. (2020) developed ResBiLSTM to predict soil water content in summer maize, demonstrating high forecast precision among different growth phases but with decreased accuracy over longer prediction times and focusing on a specific region and crop [71]. Finally, Malakar et al. (2021) applied FNN, RNN, and LSTM for groundwater trend forecasting, showing LSTM's superiority in performance metrics, yet constrained by data availability and limited to specific regions with similar conditions as those studied in India [72]. These studies highlight the potential of ML and DL techniques in agricultural water management while underscoring the need to address various challenges for broader applicability and robustness. Further research is needed to develop robust remote sensing-based ML and DL models capable of addressing these challenges and extending beyond the conventional scope of center pivot irrigation.

3.3. Crop selection

Accurate predictions enable the government to formulate short- and long-term policies to minimize food scarcity or plan import–export strategies for the agricultural division [73,74]. Several investigations on the prediction of suitable crops depend on various environmental factors, soil conditions, and regional climates to enhance crop identification and yield forecasting [75–77]. Predicting the most appropriate crops for cultivation has become a crucial aspect of modern agriculture, with ML and DL models contributing to these predictions [78]. In today's technological and data-driven landscape, the agricultural division can significantly assist by applying ML and DL techniques. Key techniques in this area include feature selection and classification [75]. Various factors, including weather, soil type, conditions, and management of crop methods, are considered to infer the potential crops in a specific region [79]. In current years, numerous DL techniques have been explored for crop prediction due to their nonparametric nature, allowing them to adapt to complex data associations and uncover hidden patterns [80]. Unlike conventional statistical methods, DL provides flexibility and has shown significant power in developing AI applications across diverse fields, including agriculture, finance, medicine, and technology [81].

Recent studies have highlighted diverse applications of ML and DL techniques in optimizing crop selection strategies (Table S3). For example, a study employed a variety of ML models, including RF, CNN, KNN, DT, Naïve Bayes, SVM, Logistic Regression, and XGBoost, to recommend suitable crops such as kidney beans, rice, maize, and several fruits like papaya and mango [75]. Using a dataset comprising 2200 examples with parameters like nitrogen, phosphorus, potassium levels, temperature, soil pH, humidity, and rainfall, the models assisted farmers in making informed decisions based on environmental conditions. However, the study was limited to the crops included in their dataset [82]. Another study utilized RF and SVM models with Sentinel-2 Multi-Spectral Instrument (MSI) and Google Earth Engine (GEE) for crop classification, achieving high accuracy rates but within a specific geographical area [83]. A study employed a DL-based Long Short-Term Memory (LSTM) network on Sentinel-2 imagery to map staple crops like rice, wheat, and sugarcane with 93.77% accuracy within four weeks of sowing, benefiting smallholder farms despite challenges in crop diversity [84].

Similarly, a study utilized RNN, RF, and ANN to optimize crop selection (rice, cotton, chili, soybean, maize) based on soil characteristics and weather parameters. The research proposed predictive models for sowing times and suggested integrating IoT devices to enhance data precision. This approach aims to improve agricultural efficiency and yield prediction in varying environmental conditions [85]. These studies underscore the potential of ML and DL in precision agriculture, emphasizing their strengths and current limitations in broader application contexts.

3.4. Soil management

Arable land is a crucial natural asset facilitating agricultural activities, serving as a foundation for ensuring food security, fostering sustainable economic growth, and upholding societal equilibrium and coherence [86]. For agricultural lands, soil organic matter or moisture and nitrogen content are elemental soil attributes that delineate soil quality and substantiate plant growth [87]. Estimating these soil properties is important for ecosystem management, encompassing soil quality assessments, CC mitigation, and long-term predictive modeling, facilitating proactive measures to uphold and enhance soil quality [88]. Consequently, regularly monitoring these properties is indispensable for effective agricultural soil management [89]. Farmers traditionally assess soil quality and health before planting to inform agricultural practices, relying on various indicators and indices due to the impracticality of direct measurement [90]. Conventional methods analyze numerous indicators through costly laboratory analyses, impacting crop profitability [91]. In previous years, Remote sensing evolved as a potent tool for swiftly acquiring extensive crop data, offering valuable insights for crop managers [92]. In agriculture, Remote sensing applications include estimating soil quality indicators, particularly those associated with chemical fertilizers like nitrogen, phosphorus, and potassium, and biological indicators like organic matter content [93]. Recently, ML and DL models have shown significant promise in soil management, revolutionizing traditional approaches by offering advanced predictive capabilities and insights [94,95]. ML techniques, like RF, KNN, and SVM, have been used to analyze soil properties, predict soil health indicators, and accurately classify soil types [53]. DL models, including CNN [96] and LSTM networks [53], have enabled the assessment of complex soil datasets, such as soil texture and moisture content, leading to more precise predictions and improved decision-making in agricultural practices. These ML and DL models have been applied across diverse regions and crops, offering tailored solutions for soil management. Despite their successes, challenges remain, including the requirement for large and diverse datasets, model interpretability, or scalability.

Table S4 compiles numerous studies on soil-related management across different regions and crops. For example, a study utilized RF and SVM in farmlands across the USA or Canada, predicting soil health metrics and tillage status from microbiome data [89]. In another study, researchers applied CNN, ANN, SVM, RF, and KNN in West Azerbaijan Province, Iran, successfully predicting soil texture with high accuracy [53]. Similarly, LSTM networks, ANN, AutoRegressive with Exogenous Inputs (NARX), Fuzzy Rule Neural Network (FRNN), and Multivariate Regression Tree were implemented in an olive grove in Tuscany, Italy, developing a simulated soil moisture sensor for cost-effective and reliable monitoring [96]. In Xiangzhou, Hubei Province, China, RF, Entropy Weight (EW), and Backpropagation Neural Network (BPNN) were employed to assess farmland quality and spatial distribution [86]. In Tamil Nadu, India, a study utilized Deep Neural Network Regression (DNNR), which effectively predicted soil quality and provided insights for soil resource management [97]. All reviewed studies highlighted the benefits and limitations of employing ML and DL in soil management. Moreover, integrating ML and DL models into existing soil management practices requires collaboration among researchers, farmers, and policymakers to ensure practical implementation and adoption.

3.5. Crop nutrient management

Accurate crop nutritional assessment is essential for effective farm management to prevent damage from nutrient imbalances, aligning with precision agriculture to reduce financial waste and environmental impacts [98]. Agricultural nutrient management aims to protect and enhance soil properties, which are crucial for maintaining crop health and productivity [99]. In developing countries, excess and land use constraints have reduced soil fertility. Utilizing micronutrients in soil management can improve productivity, helping experts and farmers inform findings about soil and crop environmental management [100]. Additionally, computational tools for nutrition monitoring can support farmers without expert access. Technological advancements have significantly enhanced the productivity and efficiency of various agriculture industries. Innovations such as “big data”, “data analytics”, “AI”, “The Internet of Things”, “erosion modeling”, “smart farming”, “ML”, and “DL” have revolutionized the field [101]. Digital soil mapping uses numerical models to map soil variations geographically and temporally based on observations and environmental variables [102]. Integrating AI models is progressively becoming crucial for ensuring the sustainability of smart agriculture initiatives [59,103–105]. Diverging from conventional farming practices, smart farming leverages sophisticated technological innovations to enhance productivity and alleviate labor burdens. Through the application of AI, smart farming endeavors to automate soil and crop management tasks, drawing inspiration from human problem-solving and learning methodologies [106]. Accurate evaluation of current crop nutritional status and nutrient needs is vital in efficient farm management, influencing environmental sustainability and economic viability [104]. Nutrient imbalances can precipitate yield reductions, suboptimal resource utilization, a decline in soil organic carbon content, and related challenges. Precise diagnosis offers multifaceted benefits to farmers, encompassing enhanced yields, refined fertilizer recommendations, and augmented revenue. ML and DL emerged as a prominent technology proficient in recognizing intricate patterns within extensive datasets, thereby facilitating direct prediction from provided data [21,36]. ML and DL algorithms exhibit efficacy in yield prediction by assimilating variables such as fertilizer rates, genetic information, and environmental parameters [28,107–110]. Simultaneously, in nutrient management, harnessing ML and DL models enables the combination and extrapolation of previously unexplored datasets, thereby enhancing the understanding of agricultural systems and nutrient requirements. This approach facilitates the integration of economic considerations into decision-making frameworks [58,61,105].

Table S5 gives a complete overview of ML and DL models utilized for nutrient management across various crops globally. In a study on tomato crops, RF, SVR, and ANN techniques applied to soil samples from diverse regions enhanced soil nutrient prediction and improved crop yield forecasting [111]. Similarly, research on lettuce, watercress, lettuce, green peppers, kale, tomatoes, and collard greens employed a Linear SVM with Semi-Bolstered Re substitution Error estimation, achieving optimal plant growth through nutrient concentration regulation [104]. A study concerning rice cultivation implemented CNN models, leading to significant cost reduction and high accuracy in soil nutrient deficiency detection using aerial imagery data [105]. In another investigation focused on cabbage, DNN with the Levenberg–Marquardt algorithm demonstrated strong predictive accuracy for soil nutrients, albeit with the need for further research on broader crop applications [112]. Moreover, Ensemble ML and DL methods exhibited high accuracy in soil nutrient and pH classification, presenting an effective tool for enhancing agricultural productivity [113]. However, challenges such as limited datasets, computational resource requirements, and the need for further research on diverse crop applications remain pertinent across these studies.

3.6. Weed control management

Weeds threaten rice yield considerably, resulting in substantial economic losses and compromising crop quality [114,115]. Throughout various stages of growth, crops are susceptible to weed interference. Weeds compete with crops for basic requirements like water, sunlight, and nutrients. [116]. Timely weed management interventions mitigate potential crop yield losses by up to 34% and contribute to reducing pest and disease incidences [117]. Weed infestations cause significant economic costs, including yield losses and increased production expenses, as evidenced by findings of yield reductions ranging from 19% to 56% [118]. Traditional weed management heavily relies on herbicides, raising concerns about environmental sustainability and food safety [119]. While herbicides enhance crop yields by targeting specific weed species and reducing labor, their indiscriminate use leads to resistant weed populations and harmful residues in soil and water systems [120]. Despite their effectiveness in enhancing crop yields, herbicides raise concerns regarding environmental sustainability and food safety due to herbicide-resistant weed populations and residue persistence [121]. The random use of herbicides poses risks to aquatic life, human health, non-target plants, and aquatic life, necessitating more eco-friendly and precise weed management strategies [122]. Consequently, there is a pressing need for more exact and eco-sustainable weed management approaches. AI models offer promising alternatives by providing precise, environmentally friendly approaches to weed control [115]. Innovative approaches to weed management, driven by ML, DL, and advanced technologies, are crucial for mitigating environmental harm and ensuring agricultural sustainability. AI applications aim to reduce herbicide use, enhance efficacy, and minimize residue presence, promoting a more eco-conscious approach to weed control [123]. DL models, trained on extensive datasets, excel in differentiating between weeds and crops in complex environments, driving advancements in precision agriculture [124]. Beyond weed management, AI optimizes resource allocation, notably in herbicide application, land use, and labor efficiency, which is vital for addressing challenges like population growth and soil degradation [125]. As agriculture transitions towards AI-driven practices, new employment opportunities emerge, reinforcing the resilience of agricultural systems [126].

To address how ML and DL methods enable precision weeding technologies to tackle site-specific weed management in the 21st century, a review of 10 articles was conducted. Table S6 provides a comprehensive overview of studies employing ML and DL techniques for weed management across various crops worldwide. In one study focusing on corn and soybean crops, image classification and object detection methods achieved impressive accuracy rates for identifying weed species, with specific models such as VGG16 and YOLOv3 demonstrating high-performance [114]. Another investigation on bermudagrass utilized Deep CNN models to detect and discriminate specific weed species effectively, showcasing potential applications for precision herbicide application systems [127]. Similarly, ML methods, including RF, SVM, and KNN, demonstrated promising results in weed detection for Chilli cultivation, highlighting the potential for increased accuracy by adopting DL algorithms [128]. Moreover, studies on lettuce and various crops employed ML and DL techniques to enhance weed coverage estimation and precision agriculture practices. For example, ML and DL models like SVM, YOLOv3, and Mask R-CNN achieved high precision in crop recognition and weed coverage estimation, improving agricultural productivity [129].

Additionally, various DL frameworks were evaluated for real-time weed detection and classification, with Faster R-CNN and YOLOv3 being compared for their performance in target detection tasks [130]. However, these studies encountered common limitations such as dataset imbalance, the need for further research on diverse crop applications, and challenges associated with precise weed localization and herbicide spraying. Despite these challenges, the outcomes emphasize the potential of ML and DL techniques in revolutionizing weed management practices across different agricultural contexts.

3.7. Prediction of crop yield

Predicting crop yields has become increasingly vital due to growing concerns about food security [108]. Predicting crop yields is crucial for addressing food crises by evaluating food availability for the growing global population [131]. Enhancing crop yields is vital, as about 820 million people face food insufficiency. The United Nations aims to eradicate hunger and promote sustainable agriculture by 2030, while the FAO projects a 60% increase in food demand by 2050 [132]. Accurate crop yield prediction is essential for developing strategies to meet these goals [133]. Crop yield depends on soil characteristics, environmental conditions, nutrient application, and field management, with environmental factors being particularly variable and influential [134]. Understanding the relationships among these factors and developing a mathematical model to represent them is essential. Timely field updates and informed decisions on irrigation, climate adaptation, and soil nutrition can enhance yield and minimize environmental impact [135]. Crop yield prediction might be done in many ways. Traditionally, crop yield models simulate and predict production under various conditions yet struggle with accurate input parameter estimation and forecasting in complex scenarios [136]. Previous yield prediction methods have been limited by a focus on specific lines and single environmental variables, restricting their applicability [137]. Linear models offer an alternative but often fail to capture biological complexities and site-specific weather variations [138]. While methods like ARIMA excel in time series forecasting, they fail to predict climate extremes crucial for agricultural outcomes [139]. To address this issue, the advancement of the ML and DL models has overcome these challenges. ML enhances yield prediction by analyzing diverse attributes within datasets [108]. ML models are trained on past outcome datasets, with parameters calculated during training and tested on historical data for performance evaluation [75–77]. These models can be descriptive or predictive, with predictive models using past knowledge for future events. ML aids yield prediction and decision-making throughout cultivation, utilizing algorithms like multivariate regression and decision trees [140]. DL utilizes ANNs to construct probability models from raw data, which is useful for crop performance prediction under varying climates [133]. Deep Neural Networks (DNNs) enable complex operations resembling human cognitive processes [133]. Currently, several ML and DL models are applied to predict the yield of different crops worldwide. Table S7 presents a detailed overview of studies utilizing ML and DL models for crop yield prediction across diverse regions and crops worldwide. In a study conducted in China focusing on rice cultivation, LSTM outperformed RF and LASSO regression in yield prediction, demonstrating the significance of satellite vegetation indexes and meteorological data [141].

Similarly, research in Rajasthan, India, employed ML methods such as RF and Gradient Descent for multiple crops, showcasing their potential to assist farmers with crop selection and yield prediction [108].

Moreover, a study in the Netherlands, Germany, and France utilized an ML workflow to predict yields at a regional level for various crops, providing a baseline for further optimizations [103]. Furthermore, investigations in major winter wheat production regions in China explored the efficacy of RF, DNN, and LSTM models, highlighting the scalability and accuracy of these models in capturing yield variations [133]. In India, ML and DL models based on SVM and LSTM/RNN achieved high accuracy in predicting suitable crops for given conditions, offering valuable insights for farmers [142]. Similarly, studies in Atlantic Canada [131] and Southern India [28] employed ML and DL techniques to predict potato and paddy yields, respectively, demonstrating the usefulness of proximal sensing data and environmental parameters. Moreover, research in North America focused on soybean cultivation employed LSTM RNN models with temporal attention mechanisms, showcasing enhanced interpretability and valuable insights for plant breeders [131]. Additionally, investigations in Finland employed CNN-LSTM and 3D-CNN models to predict wheat, barley, and oats yields, leveraging UAV data for intra-field scale predictions [143]. These studies highlight the potential of ML and DL models in revolutionizing crop yield prediction across various crops and regions, albeit with challenges such as data limitations, model interpretability, and the need for further validation and refinement.

3.8. Pest and disease management

Insect pests are a significant cause of crop damage globally, leading to substantial agricultural losses. Effective prevention and control of these pests are crucial for reducing such losses [144]. A critical criterion for implementing pest control measures is accurately detecting and classifying insect pests, which involves identifying various species and estimating their populations for targeted pest management [145]. Due to the continuous and costly nature of monitoring, there has been an increasing interest in automatic insect pest recognition systems in recent years [146]. Pest monitoring has traditionally relied on experts or technicians to manually identify insect pests, which is a subjective, labor-intensive process and unsuitable for large-scale applications [147]. The availability of devices with cameras and internet connectivity has made computer vision technology a promising solution for automatic pest monitoring in modern agriculture, significantly enhancing the efficiency of monitoring processes [148]. Cutting-edge technologies such as ML and DL have significantly enhanced the efficacy and accuracy of plant disease detection and management systems [149]. Numerous studies have been conducted in the ML domain to identify and mitigate plant diseases, employing conventional ML techniques such as RFs, SVM, fuzzy logic, K-means clustering, and CNN, among others. In agricultural research, ML methodologies identify, classify, and predict crop diseases and plant stress phenotyping. Unlike genomics-based approaches that rely on the precise identification of molecular constituents, ML techniques in plant disease research often leverage automated platforms, including drones and ground-based robots equipped with sensors, to gather continuous data from agricultural fields.

Traditionally, data is extracted from high-resolution images or sensor readings and pre-processed to eliminate irrelevant information. Spatial data about plant diseases is crucial for pre-processing and selecting appropriate ML algorithms, enhancing the model's predictive performance. ML methods are indispensable for detecting and diagnosing plant diseases in agricultural settings [150,151]. DL models, such as CNNs, have demonstrated considerable success across diverse domains within computer vision [152]. These applications include but are not limited to traffic detection, medical image recognition, scenario text detection, expression recognition, and face recognition [153]. The emergence of ML and DL for plant diseases and pest detection signifies a significant advancement in academic research and holds immense potential for widespread commercial adoption. Despite this progress, there remains a noticeable gap in the literature regarding comprehensive and detailed discussions about these methodologies.

Table S8 presents the performance of DL and ML methods for plant disease and pest detection, evaluated across numerous studies, highlighting both achievements and limitations. A custom-designed 2D-CNN achieved a high accuracy of 96.94% in detecting stem bleeding disease, leaf blight disease, and pest infection by Red palm weevil in coconuts, outperforming other models like MobileNet (82.10%) and InceptionResNetV2 (81.48%). However, this study was limited by a small dataset and focused on only four specific diseases [150]. Another study used Faster R-CNN, SSD MobileNet, and BP neural networks to identify agricultural pests such as aphids and red spiders, achieving a remarkable 99.0% accuracy with Faster R-CNN. Despite this, it was constrained to just five pest classes and emphasized the need for future expansion and real-time detection capabilities [152]. An improved AlexNet model was applied to various crop diseases, particularly in fragrant pears, obtaining an average recognition accuracy of 96.26%, with a minimum of 91% on other datasets. The study indicated that further research is necessary to gauge better disease severity and effective treatment areas [151]. ML models like SVM, RF, and SGD, along with deep learning models such as Inception-v3, VGG-16, and VGG-19, were compared for citrus leaves. VGG-16 yielded the highest accuracy at 89.5%, while RF performed the least at 76.8%, highlighting the limited scope of the dataset and the comparative algorithms [154]. A study on apple leaves used deep neural networks to classify various damages, including pear leaf blister moth and mildew, demonstrating superior performance and phenology alignment with field data. However, data scarcity was a significant limitation, suggesting using citizen science and drones to enhance data collection [155]. For the cereal crops, Rouabah et al. (2022) applied Random Trees (RT), RF, and Linear Models (LM) to predict crop performance in various cereal crops using data from 28 fields. RF provided the best accuracy, while RT offered better interpretability, but non-linear models were excluded due to residual misdiagnosis.

Similarly, Kasinathan et al. (2021) utilized ANN, SVM, KNN, NB, and CNN to detect insect pests in corn, soybean, and wheat using 225 and 1397 image datasets. The improved CNN performance through image pre-processing and augmentation, addressing the limitation of small dataset sizes. These studies collectively underscore the promise of advanced ML and DL techniques in agricultural applications while also pointing out the need for larger, more diverse datasets and the incorporation of real-time detection systems.

3.9. Harvest and post-harvest management

Post-harvesting involves the immediate separation of plants from the ground, contingent upon their maturity. Significant post-harvest losses occur due to wastage and damage during harvesting, impacting food quality and safety [156]. In recent years, there has been a rise in computer vision applications in industry, aiding in natural capital mapping, crop monitoring, and precision farming. Researchers are actively minimizing losses and recognizing their impact on food safety and quality throughout the post-harvest system, including handling, storage, and transportation [157]. Effective post-harvest treatment plays a critical role in determining the quality of crops for fresh consumption and processing them into food products [158]. Computer vision offers valuable insights for extending the shelf life of food products, often using biodegradable films, which are cost-effective and environmentally sustainable. These systems minimize wastage and contribute significantly to environmental conservation [159,160]. ML and DL have evolved in recent years, expanding beyond tech to revolutionize agriculture. These techniques optimize harvest timing and post-harvest strategies using vast data [161], enhancing decision-making and sustaining productivity [162]. In harvest management, ML algorithms can analyze soil conditions, crop health, and weather forecasts to determine the optimal crop harvest timing. By identifying the most favorable conditions for harvest, farmers can maximize yields while minimizing losses due to factors such as inclement weather or pest infestations [163].

Furthermore, DL algorithms are being utilized to improve post-harvest management practices, such as storage and distribution. Advanced image recognition systems powered by DL can accurately assess the quality of harvested produce, sorting them based on factors like size, ripeness, and any signs of damage or disease. It enables farmers to implement targeted storage and transportation methods, ensuring crops reach markets optimally and minimizing waste along the supply chain. Integrating ML and DL into harvest and post-harvest management represents a significant advancement in agricultural technology. By harnessing the power of data-driven insights, farmers can optimize their operations, increase productivity, and contribute to more sustainable and efficient food production systems [164]. As these technologies evolve, the potential for innovation in agriculture remains boundless, promising a future where feeding the world's growing population is feasible and environmentally responsible.

Several studies have investigated the application of ML and DL methods in agriculture, particularly during the harvesting and post-harvesting stages (Table S9). Melesse et al. (2022) utilized a Deep CNN to monitor the quality of bananas, achieving a remarkable 99% prediction accuracy based on thermal images of bananas categorized into four classes. However, the study's generalizability to other fruits was questioned, highlighting a dependency on thermal imaging technology [161]. Azadnia et al. (2023) employed Inception-V3, ResNet-50, and CNN models for classifying the ripeness level of Hawthorn fruit, reporting high accuracy rates ranging from 99.63% to 100%. Nonetheless, the study underscored the need for a specific imaging setup and large datasets for effective model training [165]. Zhou et al. (2022) utilized Mask Region CNN (Mask R-CNN) to detect bruises on strawberries, achieving high F1 scores for both whole bruise detection and severity classification. However, concerns were raised regarding the dependency on specific lighting conditions, such as UV light, which could lead to false detections in adjacent severity categories [166]. Patil et al. (2023) applied CNNs to predict the quality of grapes, including ripeness and size, with a reported accuracy of 100%. Despite this high accuracy, areas for improvement were identified, such as enhancing model performance and developing a real-time prognostication system [167]. Finally, Ashtiani et al. (2021) employed various CNN architectures for the ripeness classification of mulberries, achieving promising accuracy rates exceeding 98%. Nonetheless, the study highlighted the need for a larger, labeled dataset for training and sensitivity to lighting conditions [164]. Overall, while these studies demonstrate the potential of ML and DL methods in agriculture, they also underscore the importance of addressing limitations related to dataset size, model generalizability, and sensitivity to environmental factors for broader applicability and effectiveness in real-world scenarios.

3.10. Discussion

ML and DL offer transformative potential in addressing agricultural challenges, ranging from crop selection to post-harvest management. While this study provides a comprehensive analysis of AI applications, as the reviewers emphasized, it is crucial to delve deeper into practical case studies, adoption barriers, and model scalability and data quality implications.

The suitability of specific AI techniques for agricultural tasks is evident through numerous case studies. For example, DL models like CNNs and RNNs have shown exceptional utility in soil texture classification and disease detection due to their ability to process complex datasets and uncover hidden patterns. The deployment of CNN-based systems for soil analysis has demonstrated high classification accuracy and significant cost-effectiveness compared to traditional laboratory methods [45]. However, these models are often limited by their reliance on high-quality input data, which can be scarce in resource-constrained settings. Hybrid ML-DL systems integrating data from satellite imagery and ground sensors in water management have proven invaluable for irrigation scheduling and soil moisture prediction [71]. Nevertheless, the scalability of such solutions remains a concern, particularly when extending their application to diverse geographical regions with varying agricultural practices.

Despite these successes, the extent of adoption in practical agricultural settings varies significantly. Precision agriculture platforms like Climate Field View and John Deere Operations Center have incorporated ML to optimize resource allocation, yet their penetration in smallholder farming remains limited due to inflated costs and technological barriers. For example, in high-income countries, DL models have been integrated with IoT systems for real-time monitoring and automated decision-making in greenhouse environments, significantly improving water-use efficiency and yield forecasts [69]. However, low-income regions often lack the infrastructure to support such advanced systems, underscoring the need for more accessible technologies tailored to these contexts.

A critical aspect influencing the scalability and generalization of ML and DL models is their adaptability across crops, regions, and farming systems. Studies have highlighted that models trained on region-specific data often struggle to generalize to other contexts, a limitation exacerbated by the variability in crop physiology and climatic conditions. For example, RF models designed for paddy fields in China outperformed DNNs in land quality prediction but faced challenges when applied to non-paddy agricultural systems [44]. Similarly, while DL models such as LSTMs have excelled in crop yield predictions in controlled environments, their accuracy diminishes when applied to heterogeneous, real-world conditions [133,141]. Addressing these challenges requires the development of more robust models that can accommodate diverse datasets and integrate region-specific parameters.

The reviewers have rightly pointed out the impact of data quality on the performance of AI models. Data scarcity and poor-quality datasets significantly impede the effectiveness of ML and DL in agriculture. For instance, studies on pest detection using CNNs have shown reduced accuracy when training datasets were limited or imbalanced [146]. Moreover, incomplete datasets can lead to erroneous predictions in nutrient management, as demonstrated by ML models that underperformed due to missing soil fertility parameters [113]. These challenges highlight the critical need for robust data pre-processing techniques and data augmentation strategies to enhance model reliability. Collaborative efforts between researchers, policymakers, and farmers to establish standardized data collection protocols could mitigate these issues, fostering more accurate and scalable AI solutions.

Computational demands and infrastructure requirements further constrain the scalability of AI models. DL architectures, such as DenseNet and ResNet, which have achieved remarkable results in disease classification, require high-performance computing resources and extensive training datasets [165]. Such requirements are often unattainable for smallholder farmers in developing countries, necessitating the development of lightweight models optimized for low-resource environments. Federated learning, which allows decentralized training of models across multiple devices, offers a promising avenue for addressing these challenges while maintaining data privacy and security.

In terms of practical applications, this review underscores the transformative potential of AI in optimizing resource use and enhancing decision-making. For example, predictive models for nutrient management, such as ANN-based systems, have demonstrated significant cost reductions in fertilizer application and improved crop productivity [104]. However, their reliance on continuous data inputs from IoT devices underscores the importance of integrating these technologies with farming systems to ensure seamless data flow and actionable insights.

Furthermore, the ethical and social implications of AI adoption in agriculture warrant careful consideration. While ML and DL models have the potential to reduce labor costs and increase productivity, their implementation could exacerbate existing inequalities in access to technology, particularly in low-income regions. Initiatives aimed at democratizing AI, such as open-source platforms and capacity-building programs for farmers, are essential to ensure equitable access to these technologies.

4. Conclusion and recommendations

The integration of ML and DL in agriculture represents a pivotal advancement in addressing global challenges such as food insecurity, climate variability, and resource constraints. This comprehensive review evaluates the application of these technologies across various agricultural processes, including crop selection, land monitoring and management, water, soil, and nutrient management, pest and disease control, and post-harvest management. The findings underscore the role of ML and DL in facilitating data-driven decision-making, which enhances precision in agricultural practices and improves resource efficiency.

However, despite significant progress, several challenges remain, including the lack of multimodal datasets and difficulties related to model scalability, interpretability, and real-time application. To address these limitations, the development of robust datasets that integrate satellite imagery, IoT sensors, and climate forecasts is crucial. Also, transfer learning techniques could help mitigate data scarcity, particularly in regions with limited agricultural data. Future research should prioritize integrating ML/DL models with IoT systems to enable real-time analytics, thus enhancing decision-making and resource allocation.

The synergistic potential of ML and DL technologies in agriculture is still underexplored. Certain domains, such as yield prediction and pest management, have shown mixed results, suggesting that the effectiveness of these models is context-dependent. Therefore, an interdisciplinary approach involving agronomists, data scientists, and policymakers is essential to optimize these models for diverse agricultural applications.

Moreover, designing intuitive interfaces and scalable frameworks is crucial for improving usability among non-expert stakeholders, thereby promoting broader adoption. While ML and DL have transformative potential for advancing sustainable agriculture, overcoming the existing challenges will require collaborative efforts and innovative methodologies. This review emphasizes the need for future research to develop scalable, secure, and interpretable solutions that ensure AI technologies substantially contribute to global food security and environmental sustainability.

Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
CC	Climate Change
FAO	Food and Agriculture Organization
SDGs	Sustainable Development Goals
ANNs	Artificial Neural Networks
RF	Random Forest
DTs	Decision Trees
SVM	Support Vector Machines
KNN	k-Nearest Neighbors
GAN	Generative Adversarial Networks
CNN	Convolutional Neural Networks
RNN	Recurrent Neural Networks
DNN	Deep Neural Networks
IoT	Internet of Things
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
GEE	Google Earth Engine
MSI	Multi-Spectral Instrument
NARX	Nonlinear AutoRegressive with eXogenous inputs
BPNN	Back Propagation Neural Network
DNNR	Deep Neural Network Regression

CRediT authorship contribution statement

Muhammad Waqas: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Adila Naseem:** Formal analysis, Methodology, Validation. **Usa Wannasingha Humphries:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition. **Phyo Thandar Hlaing:** Validation, Visualization, Writing – review & editing. **Porntip Dechpichai:** Formal analysis, Investigation, Methodology, Writing – review & editing. **Angkool Wangwongchai:** Conceptualization, Investigation, Supervision, Writing – review & editing.

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Declaration of competing interest

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.grets.2025.100199.

Data availability

Data used to support the study's findings can be obtained from the corresponding Author upon request.

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