Discover Food

Review

Yield prediction, pest and disease diagnosis, soil fertility mapping, precision irrigation scheduling, and food quality assessment using machine learning and deep learning algorithms

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Abstract
The growing demand for food grains amidst resource constraints necessitates advancements in crop management. Artificial intelligence, particularly machine learning and deep learning, is revolutionizing agricultural practices by enabling data-driven, precise, and sustainable solutions. This review synthesizes advancements in artificial intelligence applications across key domains, including crop yield prediction, precision irrigation, soil fertility mapping, insect pest and disease forecasting, and foodgrain quality assessment. Artificial intelligence algorithms efficiently process vast datasets from unmanned aerial vehicles, ground vehicles, and satellites, enabling precise and timely interventions. Artificial intelligence-driven tools automate pest detection and classification, optimize irrigation with minimal human input, generate high-resolution soil fertility maps, and enhance foodgrain quality assessment through rapid defect and contaminant detection. Artificial intelligence-powered precision irrigation integrates real-time soil moisture data and weather predictions for optimized water usage. Similarly, artificial intelligence-driven soil fertility mapping not only enables high-resolution assessments but also facilitates real-time monitoring of nutrient dynamics, supporting sustainable land management. In pest and disease detection, artificial intelligence systems combining image processing and real-time analytics demonstrate promise for early intervention. Artificial intelligence integration into foodgrain quality assessment leverages hyperspectral imaging and predictive models to enhance grading, adulteration detection, and contaminant screening, contributing to food safety and market competitiveness. Furthermore, advancements in transfer learning and data augmentation have improved artificial intelligence adoption in regions with limited datasets. While artificial intelligence technologies promise to boost agricultural productivity and sustainability, their efficacy and scalability hinges on data quality, diversity, and availability.

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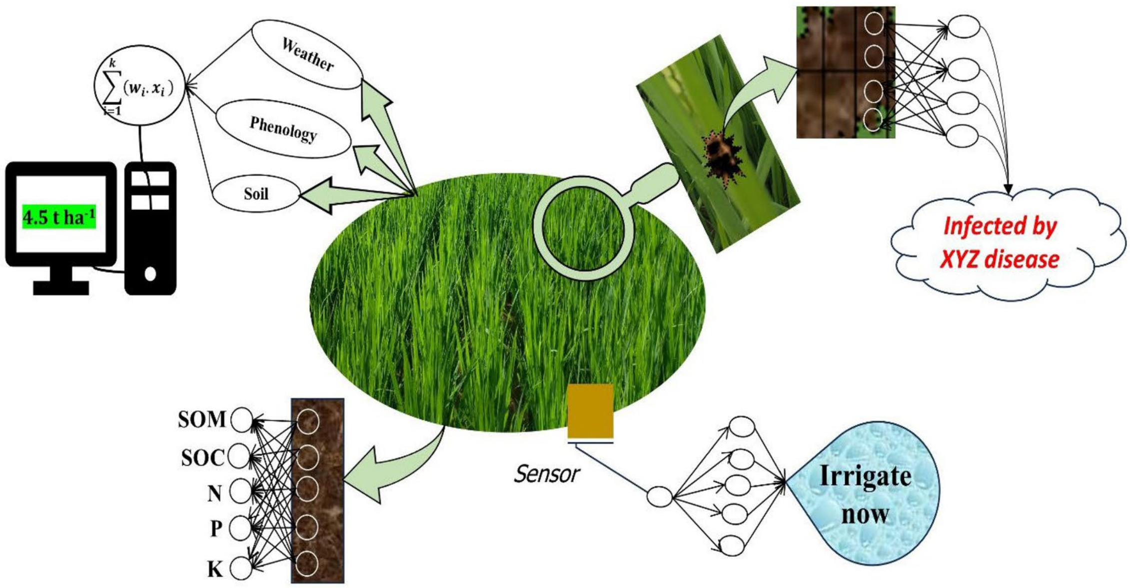
Graphical Abstract



Keywords Artificial intelligence · Nutrient management · Soil moisture · Crop protection · Yield forecasting

1 Introduction

Food security remains a critical priority for nations worldwide, as it underpins societal stability and well-being [1]. However, this goal is increasingly threatened by rapid population growth, diminishing natural resources, and the intensification of biotic and abiotic stresses to crops, which collectively widen the gap between foodgrain production and demand [2]. Addressing resource scarcity and ensuring sustainable agricultural productivity requires innovative solutions. Recent advancements in technology offer promising opportunities to bridge this gap. [3]. The adoption of cutting-edge tools like artificial intelligence (AI), machine learning (ML), deep learning (DL), and the Internet of Things (IoT) has transformed traditional agricultural practices. The integration of AI in agriculture improves input use efficiency, optimizing resource allocation while boosting crop yields [4–6]. IoT-based systems enable precise crop monitoring and management, ensuring better utilization of scarce resources [7, 8].

Furthermore, ML and DL provide huge opportunities for real-time analysis of crop growth, health, and productivity, supporting strategic decision-making to achieve sustainable food security [9]. Integrating these technological advancements with climate-resilient agricultural practices not only addresses present challenges but also lays the foundation for long-term sustainability [10]. Data-driven predictive models and model-based crop monitoring and disease forecasting are helping agricultural decision-making by enabling informed strategies for optimal resource allocation. These approaches not only reduce cultivation costs but also enhance crop yields, addressing critical aspects of agricultural sustainability [11]. ML and DL- models are emerging as powerful alternatives to traditional statistical models as they effectively handle nonlinearity and complexity in the data while delivering precise results [12–14]. By leveraging these innovations, agriculture can evolve to meet the growing demand for food while conserving resources and mitigating environmental impacts.

Forecasting crop yield is highly important for ensuring food security, particularly in the region where production is likely to drop [15]. The advanced yield predictions at local and regional levels empower stakeholders to anticipate potential shortfalls and adopt timely adjustments in cultural practices to mitigate the impact of reduced yield [16]. The pre-harvest yield prediction is equally essential for planning harvest operations, logistics, and storage, significantly minimizing post-harvest losses and wastage of farm products [17, 18]. Furthermore, the advancement in ML and DL models has expanded the capability of large spatial-scale yield prediction, offering a scalable solution to address global food security challenges [19].

Insect pests and diseases are major threats to agricultural productivity, causing an estimated loss of 20–40% in global production and becoming a major challenge to attaining and maintaining food security [20]. Early diagnosis of plant diseases and pest infestations is crucial, as timely intervention can prevent further spread, minimize yield loss, reduce pesticide usage, lower production costs, and promote environmental sustainability. Moreover, early detection helps preserve the quality of harvested produce, safeguarding market value and consumer trust [21]. Although human sight and cognition are potential tools for detecting and understanding disease symptoms and pest damage, decision-making based on visual observation is often subjective, prone to cognitive bias, and limited by individual expertise [22, 23]. Laboratory analyses can provide precise diagnosis but are time-intensive and may delay necessary actions. ML and DL algorithms address these limitations by quickly and accurately detecting insect pests and plant diseases before they cause severe yield loss [24, 25]. Advanced imaging techniques, such as visible, thermal, near-infrared, and hyperspectral-based imaging, further enhance the capability of AI models by providing rich, detailed inputs for analysis [26].

Another important threat to sustainable agriculture is the declining availability of irrigation water, driven by increasing competition from other sectors and excessive groundwater extraction [27, 28]. Agriculture accounts for over 50% of freshwater use, with Asia being a significant contributor. However, irrigation efficiency in the region remains substantially lower than in developed countries, posing a critical challenge to water resource sustainability [29, 30]. Advanced irrigation systems, such as IoT- and sensor-based irrigation, have emerged as effective solutions for automated water management for various crops, drastically reducing water wastage. By integrating real-time soil moisture data with AI that predicts weather patterns, precise irrigation scheduling becomes feasible, ensuring optimal water use and minimizing losses [31–33]. The increasing affordability of sensors, combined with increasing digital literacy and mobile phone usage among farmers, has further accelerated the adoption of these technologies in many regions [34].

In addition to water management, sustainable agriculture faces challenges related to low nutrient use efficiency, high fertilizer costs, and environmental impacts, like eutrophication and greenhouse gas (GHG) emissions. Addressing these issues necessitates faster, more accurate, and spatially detailed soil testing methods, surpassing the limitations of traditional approaches [35, 36]. Conventional soil nutrient analysis is often labor-intensive, time-consuming, and restricted to point-based measurements [37]. AI powered by ML and DL algorithms offers a transformative approach to accurately predicting soil nutrient levels with greater efficiency. By analyzing complex spectral data, ML and DL can detect soil nutrient deficiencies, enabling timely and precise corrective measures [38]. This advancement not only enhances nutrient use efficiency but also reduces environmental impacts, paving the way for more sustainable agricultural practices.

Ensuring the quality assessment of food grains, especially cereals, millets, and pulses, is critical for maintaining food safety, obtaining premium prices, and detecting adulteration. Traditional methods for quality assessment, which involve assessing parameters such as grain color, moisture, and pest infestation, are often costly, labor-intensive, and time-consuming. Moreover, these methods frequently suffer from inconsistent results [39]. To address these limitations, rapid, non-destructive, and accurate analytical techniques are needed. Spectral and hyperspectral imaging, combined with ML and DL algorithms, has emerged as a powerful tool for efficient preprocessing, feature extraction, and image modeling, enabling quick and reliable quality assessment of food grains [40, 41].

Achieving maximum yield, ensuring better quality produce, advanced insect pest and disease forecasting, and yield prediction are paramount to securing global food security. However, crop productivity is influenced by precise crop management strategies, such as precision irrigation, nutrient management, and effective pest and disease diagnosis. The advancement in AI presents significant opportunities for making timely, efficient, and precise decisions in these aspects. Therefore, an attempt was made to summarize recent research on the application of ML and DL in crop yield prediction, pest and disease monitoring, precision irrigation, soil fertility testing, and food quality evaluation. The primary objectives include assessing the feasibility of AI for these purposes, identifying the most suitable and accurate ML and DL algorithms, and highlighting the barriers to large-scale AI adoption in commercial agriculture. Additionally, this review examines different kinds of datasets used in these applications and their preprocessing methods to offer insights into the current state of AI-driven agricultural solutions.

2 Methodology

An extensive search was performed from online databases such as ResearchGate, Google Scholar, IEEE Xplore, and ScienceDirect to collect the research and review articles on the application of ML and DL concepts concerning crop yield prediction, pests and diseases detection, precision irrigation, soil fertility, and foodgrain quality assessment. The keywords used for the search are "machine learning", "deep learning", "yield prediction", "pest and disease detection", "image analysis", "precision irrigation", "soil fertility", "organic carbon", "food grain quality assessment", "neural network", "support vector regression", "random forest", and "convolution neural network". Articles relevant to this review were screened manually. Among the selected papers, the papers concentrated on state-of-the-art ML and DL approaches to predict crop yield, detect insect pests and disease, precision irrigation, soil fertility evaluation, and assess foodgrain quality are examined completely and their key findings are discussed in tabular form (Fig. 1). The country-wise number of literature reviewed in this study is illustrated in Fig. 2.

3 Yield prediction

Many researchers have used numerous approaches to predict crop yield at different scales. ML models make better predictions of crop yields by learning underlying patterns and relationships in the input data [42]. Artificial neural network (ANN), support vector regression (SVR), random forest (RF), and XGBoost are the most preferred ML models, while convolution neural network (CNN), long-short term memory (LSTM), and deep neural networks (DNN) are the commonly used DL models for yield prediction [43–46]. The accuracy of these models largely depends on the selection of input variables that significantly influence yield. Incorporating ML and DL models with both crop management and remote sensing data can enhance the predictive capability of these models [47]. Similarly, the integration of remote sensing, weather, and soil datasets into ML frameworks provides robust yield prediction even in smallholder farms [48].

However, the performance of a model often varies by location, crop type, and data availability. For example, a model that performs better for a location or crop may not offer better performance for another location or crop. Therefore, exploring different models with varying functional forms is essential to identify the best-fit model for a specific crop

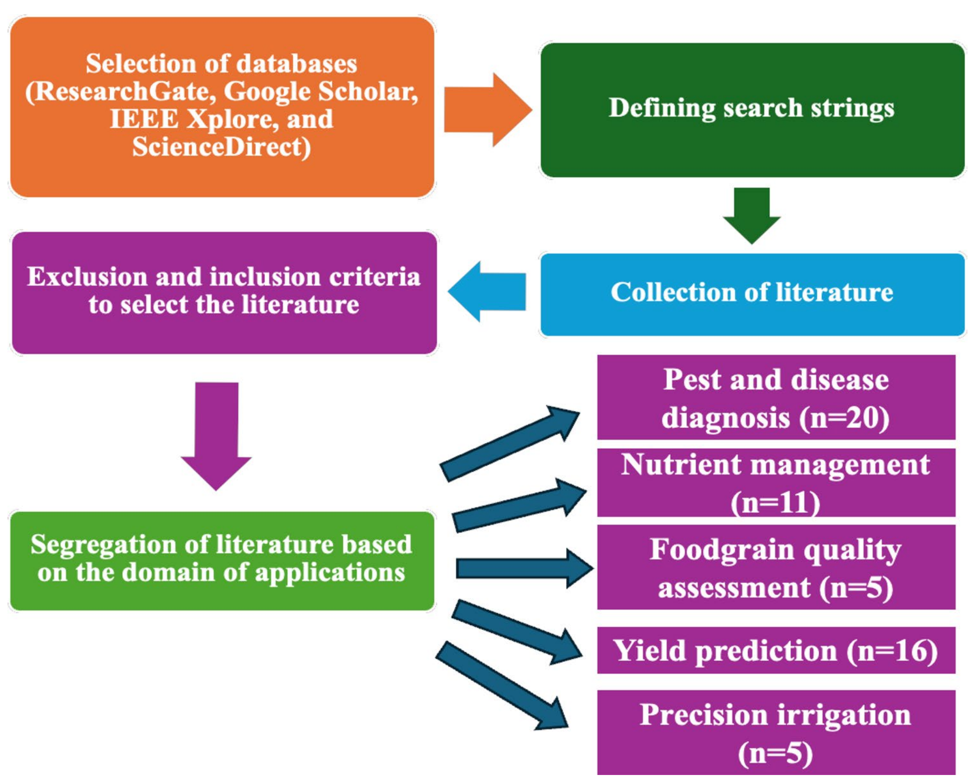


Fig. 1 Overall methodology followed in the literature screening and selection

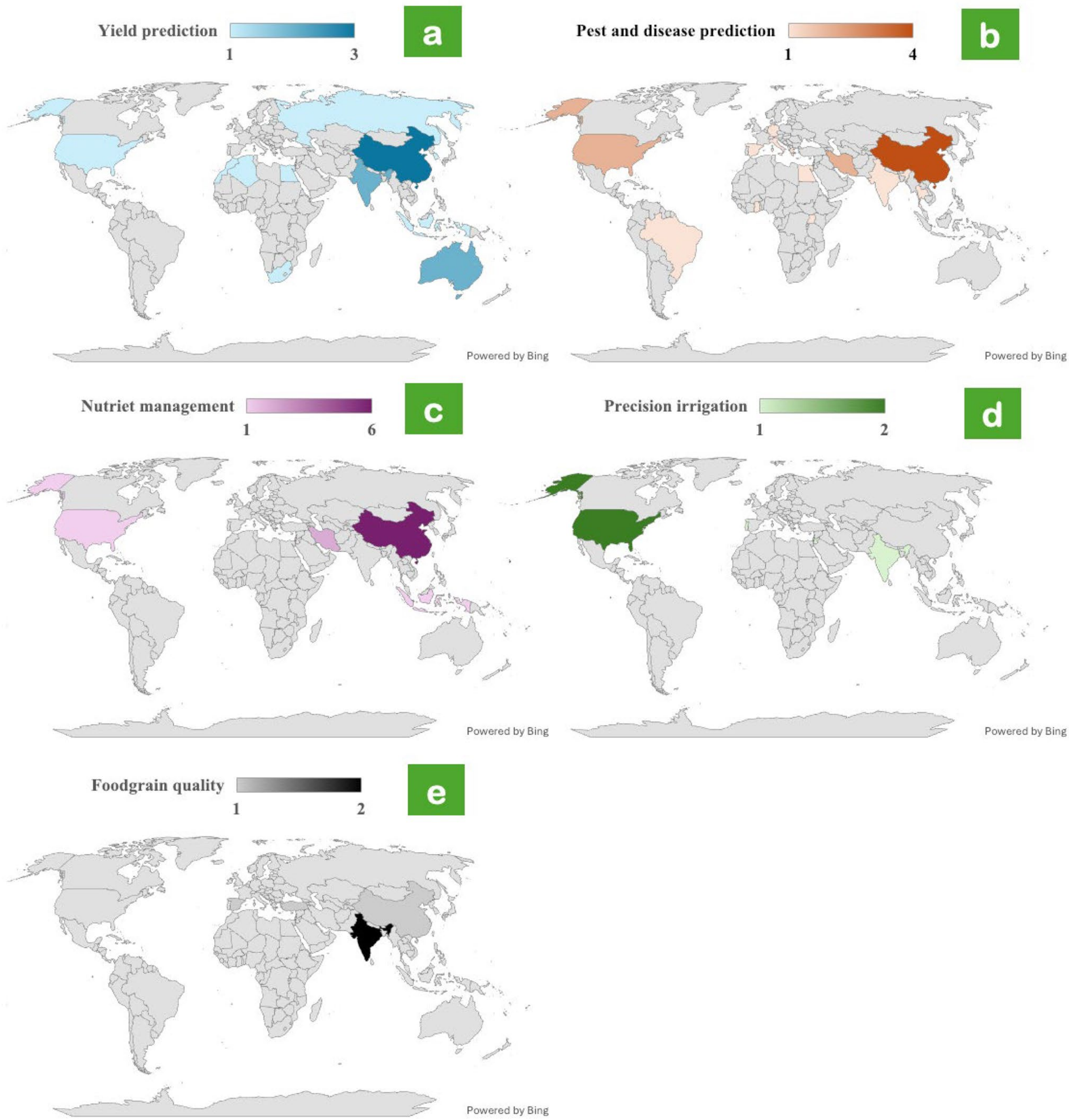


Fig. 2 Country-wise representation of the number of literatures concerning **a)** Yield prediction **b)** Pest and disease prediction **c)** Nutrient management **d)** Precision irrigation **e)** Food grain quality reviewed in this manuscript

and region [49]. A best-fitted model effectively learns the patterns from training datasets and delivers satisfactory performance on new data [50]. The proportion of training and testing datasets is subjective and can influence model outcomes. Random splitting is preferable to ensure that both recent and historical data are well-represented in training and testing datasets [51]. Typically, 70 to 80% of the data is allocated for model training, while the remaining 20–30% is reserved for validation of the fitted models. The summary of the few research studies on ML and DL-based prediction of crop yield is discussed in Table 1.

Table 1 Summary of research studies related to ML and DL models for crop yield prediction

Crop	Study Area	Models/Algorithms used	Input data	Training & validation data split	Model evaluation parameters	Conclusion	References
Wheat and chickpea	Moree in New South Wales, Australia	XGBoost	Data on weather, soil data and satellite imagery	80:20	RMSE and concordance correlation coefficient	The outputs derived from mechanistic models can be used as input to data-driven ML models to increase predictive performance by capturing complex patterns and relationships	[52]
Wheat	125 wheat farmers' fields in Morocco covering diverse soil, climatic conditions and crop management practices	MR, RF and APSIM-wheat	Soil, climatic and cultural practices along with remotely sensed leaf area index	Two-third: one third	RMSE, NRMSE and R^2	ML models are consistent in identifying the most influencing factors on yield. They are easier and more useful for mid-term regional prediction	[53]
Maize	Henneman, South Africa	MR, multilayer perceptron, DT, and RF	Twenty-four georeferenced soil and agronomic data and remotely sensed vegetative indices	80:20	MAPE, RMSE and R^2	The high prediction accuracy was obtained from the RF model. The inclusion of remotely sensed vegetative indices improved the performance of the model	[54]
Wheat	Hebei Province in North China Plain	LSTM and LGBM	Climate and satellite data	70:30	RMSE and R^2	LSTM using near-infrared reflectance outperformed LGBM for wheat yield prediction	[55]
Wheat	Tongshan experimental station in Xuzhou City, Jiangsu province, China	GPR, SVR, RFR, DT, Lasso, and GBRT	Ten vegetation indices that indicate crop growth state are obtained from UAV multispectral images	75:25	MAE, RMSE and R^2	The GPR model using extremely strong correlated vegetation indices predicts farm-scale crop yield accurately which is highly valuable for farm-scale crop management	[56]

Table 1 (continued)

Crop	Study Area	Models/Algorithms used	Input data	Training & validation data split	Model evaluation parameters	Conclusion	References
Durum wheat	Two Provinces in Algeria namely Constantine and Setif 1	SVR, RF, Extreme Learning Machine, ANN, DNN	Weather variables	70:30	RMSE, MAE, MAPE, R^2 and MBE	DNN and RF models perform well for durum wheat yield prediction. Data augmentation by merging small data from two locations increases the model performance	[57]
Soybean	9 states of the United States of America	XGBoost, and ML and DL hybrid models viz. CNN-DNN, CNN-XGBoost, CNN-RNN and CNN-LSTM	Weather and soil-related parameters	NA	MSE, RMSE, MAPE and R^2	CNN-DNN model performs better with low RMSE, MSE and MAE and high R^2. The XGBoost model also performs better with less execution time	[58]
Spring wheat	Forest-steppe zone of Western Siberia	Two methods of constructing decision trees viz. Classification and Regression Tree and Conditional Inference method	Qualitative factors such as the level of intensification, remoteness of culture from steam and tillage system and quantitative climatic factors such as the sum of effective air temperatures and precipitation	80:20	MAE, RMSE and R^2	The decision tree algorithms using qualitative and climatic parameters provides high precision for yield prediction	[59]
Rice	Udham Singh Nagar district of Uttarakhand in India	ELNET, RF, MARS, SVR, LRSS, KNN, XGBoost, ANN and Cubist	Optical and Synthetic Aperture Radar (SAR) data in combination with crop biophysical parameters	80:20	Willmott index of agreement, MBE, RMSE and R^2	ML models such as XGBoost, ELNET, SVR, ANN and RF using remote sensing and biophysical parameters are helpful for informed decision-making on resource management for enhancing food security	[60]

Table 1 (continued)

Crop	Study Area	Models/Algorithms used	Input data	Training & validation data split	Model evaluation parameters	Conclusion	References
Rice	Korea	Hybrid structure of LSTM and one-dimensional CNN	Vegetation indices sensed through MODIS, transplanting date, solar radiation and temperature	Six years data for model training and one year data for validation	Nash–Sutcliffe model efficiency, RMSE and R^2	Crucial factors for predicting rice yields are water-related index and maximum temperature for North Korea and vegetation indices and geographic variables for South Korea	[61]

ANN-artificial neural network, CNN-convolution neural network, DNN-deep neural network, DT-decision tree, ELNET-Elastic net, GBRT-gradient boost regression tree, GPR-gaussian process regression, KNN-K-nearest neighbours, Lasso-least absolute shrinkage and selection operator, LGBM-light gradient boosting machine, LRSS-Linear regression with stepwise selection, LSTM-long short term memory, MAE-mean absolute error, MAPE-mean absolute percentage error, MARS-Multivariate adaptive regression splines, MBE- mean bias error, MR-multiple Regression, MSE-mean square error, NRMSE-normalized root mean square error, RF-random forest, RMSE-root mean square error, R^2-coefficient of determination, SVR-support vector machine regression, XGBoost-Extreme gradient boost

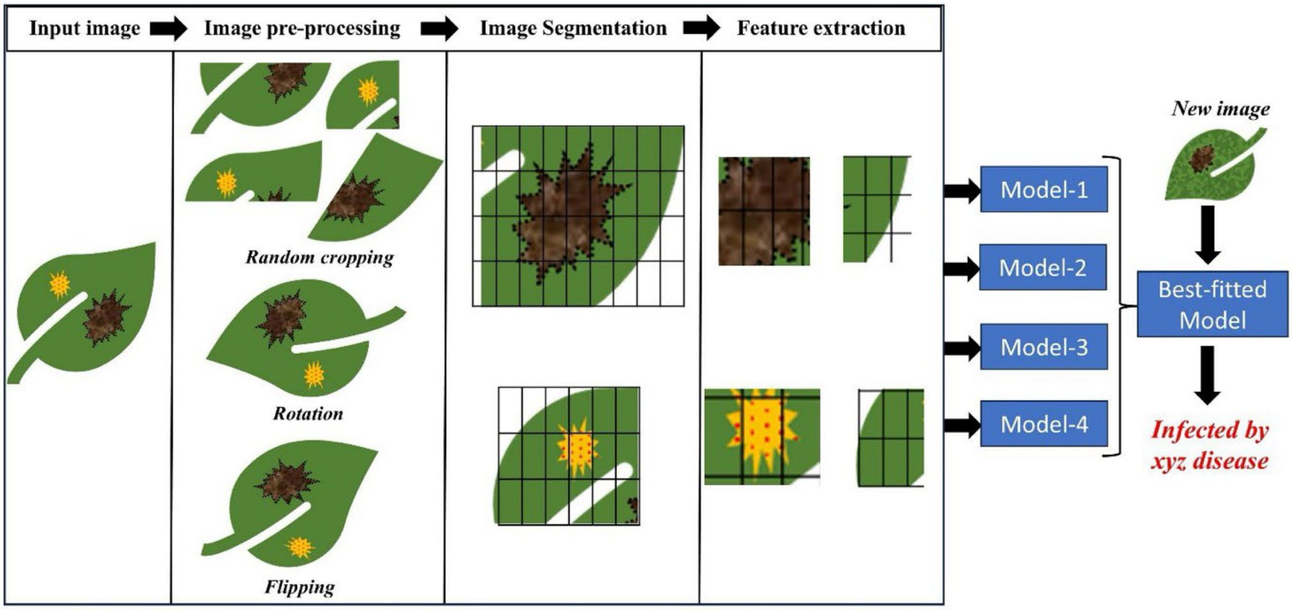


Fig. 3 Steps involved in pest and disease diagnosis

4 Pest and disease diagnosis

Each plant disease infestation produces a distinct visual damage on the plant parts such as leaves, stems, flowers, grain, fruit, while each pest species exhibits unique characteristics such as shape, size, and color pattern. These distinguishing features can be effectively captured in digital images, offering a valuable dataset for analysis [62]. The electromagnetic spectrum emitted by objects across different wavelengths provides additional information that can be recorded and analyzed to detect plant health issues [63]. Digital image processing, combined with model-based approaches, enables the accurate diagnosis and differentiation of pests and diseases [64]. The integration of ML techniques further enhances this process, offering significant potential for early-stage detection and classification of diseases and pests. ML and DL algorithms automate feature extraction, making them ideal for cost-effective crop disease and pest detection, classification, and prediction [65]. These models are trained using labelled image datasets, with their detection and classification accuracy validated against testing sets. Typically, the model-based detection and classification process consist of four key steps, viz. image acquisition, image pre-processing, segmentation, feature extraction, and classification [66]. These steps are crucial for transforming raw image data into actionable insights (Fig. 3).

4.1 Image acquisition

The first step in the process is image acquisition, which involves capturing high-resolution images of both infected and healthy plant leaves. For optimal results, images should be taken under natural lighting conditions using a high-resolution digital camera. To increase dataset diversity, the multipatch technique is used, splitting captured image into several smaller patches [67]. Data-augmentation techniques, such as random cropping, scaling, rotation, noise injection, and translation, are applied to expand small datasets and improve model performance. Additionally, open-access repositories like PlantVillage, which hosts over 50,000 curated images of healthy and infected crop leaves serve as valuable resources for training datasets [68].

4.2 Image pre-processing

Images captured in field conditions often contain complex backgrounds, multiple leaves, and varying lighting conditions, which can hinder model accuracy [69]. Preprocessing these images is an important step to remove undesired distortion and enhance quality, enabling models to effectively learn the patterns of symptoms. The process typically involves clipping the images to focus on the region of interest, applying smoothing filters such as the Gaussian filter to reduce noise, and performing image enhancement to improve contrast [70].

4.3 Segmentation

In the image segmentation process, the pixels with similar color and brightness values are grouped to isolate the targeted regions, such as infected areas on diseased leaves. This step ensures that only relevant areas are analyzed for disease. Among segmentation techniques, the k-means clustering algorithm is commonly used due to its effectiveness in grouping similar pixels [71].

4.4 Feature extraction

Feature extraction simplifies the learning process by identifying critical features in the input images that the classification models can process. Techniques like the Histogram of Oriented Gradients (HoG) analyze the gradient distribution of edges oriented in various directions, enabling robust feature detection [72]. Other commonly used algorithms include Scale Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF), which extract essential features even in varying image conditions.

4.5 Classification

In the classification stage, predefined features, corresponding to healthy, non-healthy, and disease-specific patterns are used to train ML or DL algorithms. These models compare the color and texture variations in input images with predefined feature sets, classifying the leaves as either healthy or infected. For infected leaves, the models further determine specific diseases based on symptom patterns [73].

CNN has become a vital algorithm in pattern recognition in image processing [74]. A hybrid DL system that combines segmentation and classification capabilities can effectively identify infected regions on leaves and determine the specific disease [75]. When the training dataset includes all possible symptom variations of a disease, DL models handle classification challenges efficiently, ensuring robust disease identification [76]. Model performance is typically evaluated using standard object detection metrics, such as accuracy, precision, recall, and F1-score [77]. A detailed review of selected research papers on pest and disease detection and monitoring is discussed in Table 2.

In the field condition, fully automated pest detection without traps remains a significant challenge since many pests tend to reside on the undersides of leaves. Pheromone-based glue traps provide a practical solution, where pests are attracted and captured, and their images are recorded using a digital camera mounted above the trap [93]. However, this approach is less effective for pests that inflict damage during their larval stages. Accurate pest classification presents another challenge, as visual similarities between target and non-target pests can lead to misclassification [94]. To address this, models must be trained on extensive datasets containing wide diverse conditions to attain high precision [95, 96]. Data augmentation techniques, such as varying insect orientations and scales, are particularly beneficial for enhancing model performance in pest detection tasks [97]. Integration of remote sensing with ML and DL models has demonstrated high accuracy and efficiency in pest and disease monitoring, offering a scalable solution for agricultural management [98].

5 Soil nutrient level detection using ML and DL algorithms

The major processes involved in AI-based soil nutrient diagnosis are presented in Fig. 4. It begins with the collection of spectral data from sources such as satellites, UAVs, and spectrometers, alongside ground-truth soil samples to provide essential reference nutrient values for training and validating AI models. Preprocessing steps are then applied to the spectral data to remove noise and calibrate it with ground-truth nutrient values, ensuring accuracy and reliability. Key spectral features are subsequently extracted to focus on nutrient-specific information. Techniques like band selection and PCA are employed to isolate the spectral bands most strongly correlated with specific soil nutrients. Using this refined dataset, algorithms like RF, SVM, and XGBoost are trained. These models are optimized through hyperparameter tuning, and validated using robust cross-validation techniques and metrics such as R^2 and RMSE. Once validated, these models predict nutrient levels, producing nutrient distribution maps that guide precision soil management practices

Table 2 Research studies concerning the application ML and DL models to diagnose pests and diseases in crops

Context	Crop	Pest/Disease	Models/Algorithms used	Input used	Results	References
Diseases detection	Rice	Bacterial leaf rot, brown spot, hyspa, leaf spot, leaf burn, leaf streak, brown spot, sheath rot, tungro, and blight	Deep Spectral Generative Adversarial Neural Network	Images of rice leaf diseases and healthy leaves were collected from publicly available in nine disease categories	The proposed algorithm provided a substantial accuracy with significant improvement in the learning rate and a decreasing false rate compared to the other models	[78]
Disease identification	Rice	Bacterial leaf blight, rice blast and brown spot	VGG16-CNN	Diverse datasets of rice leaf images	VGG16 algorithm demonstrated remarkable efficacy in distinguishing the rice leaf diseases	[79]
Disease identification	Rice	Rice panicle neck blast, rice false smut, rice leaf blast, and rice stem blast	A novel approach named RiceNet which is executed in two steps viz. YoloX to detect the diseased parts of rice and Siamese Network to identify the rice disease patch	200 RGB colour rice leaf images with complex backgrounds were captured from field experiments	The proposed RiceNet model approach achieved a high accuracy with great detection speed for the identification of rice diseases	[80]
Disease detection	Tomato	6 different diseases	DWT + PCA and GLCM + CNN	Leaf images captured from the field	DWT + PCA + GLCM extracts the leaf samples informative features, and CNN distinguishes disordered leaves from normal leaves. The proposed model detected disordered leaves with an accuracy of 99.6%	[81]
Weather-based disease forecasting	Rice	Rice blast disease	Five different classification models viz. Multilayer Perceptron, SVM, Naive Bayes, Decision Tree, and K-Nearest Neighbors	Rice blast disease occurrence and weather data were collected from official records	Classification algorithms in association with feature selection algorithms improve prediction performance	[82]
Rice and wheat leaf diseases recognition	Rice and wheat	Bacterial blight, brown spot, and Leaf blast in rice and leaf rust and powdery mildew in wheat	Multi-task transfer learning model	Rice leaf disease images were collected from public datasets in UCI machine learning database and wheat leaf disease images were obtained from Internet	The proposed algorithm recognizes rice and wheat leaf diseases quickly and accurately	[83]

Table 2 (continued)

Context	Crop	Pest/Disease	Models/Algorithms used	Input used	Results	References
Pest recognition	Citrus	Citrus Leaf miner, Sooty Mold, and Pulvinaria	Ensemble classifier of deep CNN with three diversity levels at classifier level, feature level, and data level	1774 citrus leaf images	The proposed approach outperformed other competing CNN algorithms for the recognition of pests with an accuracy of 99.04%	[84]
Detection and classification of insects	Field crops	33 insect classes	ANN, SVM, KNN, NB, and CNN	Wang and Xie dataset	CNN model provided the highest success rate in classifying the insects	[85]
Disease detection	Potato	Potato Late Blight	RF and PLS-DA	Contact leaf reflectance was obtained using a high-spectral-resolution field spectroradiometer	Both PLS-DA and RF identified similar spectral features for blight discrimination during all disease stages	[86]
Diseases identification	Maize	Gray leaf spot, healthy, leaf blight, rust	SCNN-KSVM and SCNN-RF	Plantvillage, a public plant disease database	Shallow CNN along with classical ML classification algorithm is highly suitable for simpler plant disease identification	[87]
Disease detection	Wheat	Wheat rust	*v*-SVR, BRT, RFR and GPR	Hyperspectral reflectance data of healthy and diseased leaves captured from field experiment	*v*-SVR outperformed other ML algorithms for the identification of wheat leaf rust at low, medium and high leaf area index	[88]
Disease recognition	Tea	Tea anthracnose, Tea brown blight, Tea netted blister blight, Exobasidium vexans Massee and Pestalotiopsis	SLIC with SVM	1308 digital image samples with five common diseases	SLIC extracts plant leaf disease saliency maps that help identify the leaf disease efficiently	[89]
Disease identification	14 plants	26 diseases	Deep CNN architectures viz. VGG 16, Inception V4, DenseNets with 121 layers and ResNet with 50, 101 and 152 layers	Images of healthy and diseased leaves obtained from plantVillage	DenseNets architecture of CNN provides a high-accuracy for plant leaves image-based disease identification	[90]
Diseases detection	25 plant species	58 distinct diseases	Five CNN algorithms	87,848 photographs collected from openly available databases	CNN algorithms can be employed for leaf images-based plant disease detection and diagnosis. Particularly, a high success rate was attained with the VGG architectures of CNN	[91]

Table 2 (continued)

Context	Crop	Pest/Disease	Models/Algorithms used	Input used	Results	References
Image processing-based counting of insects	Rice	Planthoppers	Three layers of detection involving an AdaBoost classifier using Haar features in the first layer, SVM classifier based on the HOG features in the second layer and the threshold judgment of the three features in third layer	Rice planthoppers images on rice stems was captured using a handheld device	The proposed method provides an easy, rapid and accurate assessment of rice planthoppers population density in paddy fields	[92]

BRT-boosted regression trees, CNN-convolutional neural network, DWT-discrete wavelet transform, GLCM-grey level co-occurrence matrix, GPR-gaussian process regression, HOG-histogram of oriented gradient, PCA-principal component analysis, PLS-DA-partial least squares discrimination analysis, RFR-random forests regression, SCNN-KSVM-shallow CNN with kernel SVM, SCNN-RF-shallow CNN with random forest,, SLIC-simple linear iterative cluster, SVM-support vector machine, VGG-visual geometry group and *ν*-SVR-support vector regression

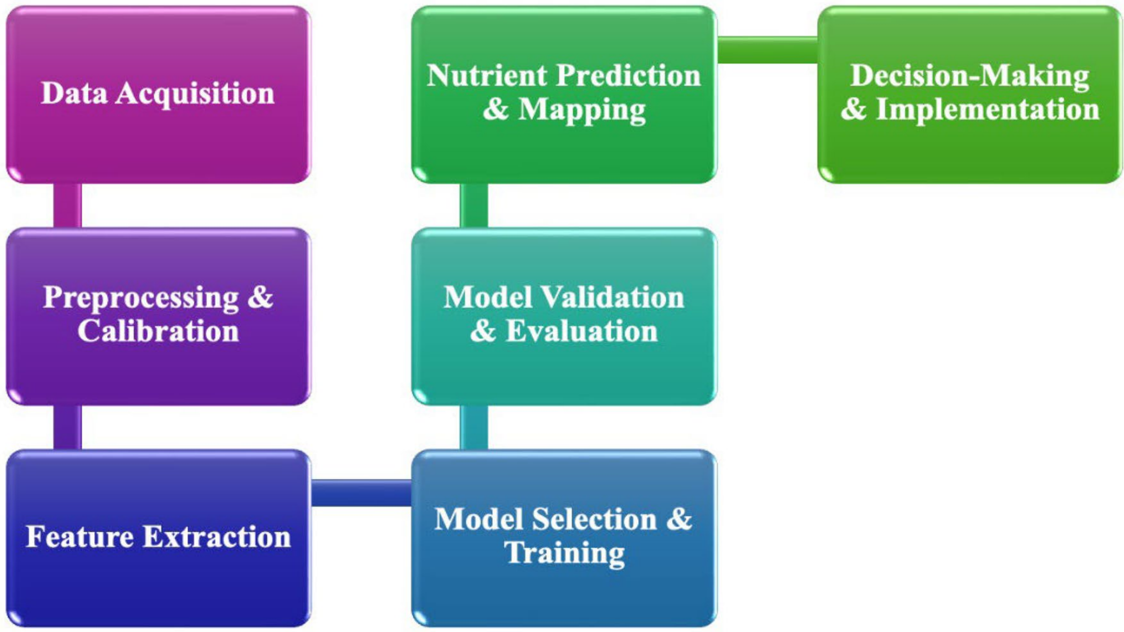


Fig. 4 Major steps involved in soil nutrient level detection using ML and DL algorithms

like variable-rate fertilization. Continuous feedback and data from field applications are used to refine model accuracy and adaptability over time.

Pairing appropriate AI algorithms with spectral data significantly enhances the predictive accuracy of soil nutrient levels, a crucial aspect of effective soil management and sustainable agriculture. Our review of previously published research reveals that RF and SVR are among the most effective algorithms, particularly for predicting soil organic matter (SOM) and soil organic carbon (SOC). These algorithms consistently achieve high R^2 values. highlighting their robustness in handling spectral data across diverse sources [99–101]. Additionally, the Gradient Boosting Regression Tree (GBRT) algorithm has proven to be highly effective for multi-nutrient prediction (N, P, K). With its ability to achieve high ratio of performance to deviation (RPD) values, GBRT is well-suited for applications that require complex nutrient assessments [102]. Additionally, AI algorithms have shown their capability to effectively process diverse spectral datasets, including satellite and UAV data, to predict soil nutrient levels with remarkable precision (Table 3).

However, the choice of spectral data source significantly influences the accuracy of soil nutrient predictions. For example, Sentinel-2 and spectrometers have demonstrated superior accuracy in nutrient prediction when combined with advanced ML algorithms such as RF [103]. On the other hand, data from Landsat-8 showed comparatively lower predictive performance, indicating its limited applicability for soil nutrient assessment in certain contexts [102]. Compared to satellite data, UAV systems offer rapid, and highly accurate assessments, making them ideal for real-time, field-scale monitoring, a key advantage for precision agriculture applications. Most studies prioritize predicting SOC and SOM, essential indicators of soil health (Table 3). Very few studies have been attempted for multi-nutrient prediction. The multi-nutrient modeling approach could provide a holistic understanding of soil nutrient status, enabling timely nutrient management interventions.

6 Precision irrigation scheduling using AI

The essential steps in AI-based irrigation water scheduling are outlined in Fig. 5. The process begins with data collection, where real-time soil moisture data, along with historical weather, crop type, and field condition data from sensors and climate sources, is gathered. Preprocessing ensures data quality through cleaning, normalization, and calibration. Feature engineering then identifies critical variables, such as soil moisture levels and crop growth stages to enhance model accuracy. In model training, ML models (e.g., LSTM, Q-Networks) are selected and trained using historical data to recognize irrigation patterns. Validation follows, assessing model reliability with metrics like accuracy and RMSE.

Table 3 Performance of different machine learning and deep learning algorithms in predicting soil nutrient levels focusing on the use of various spectral sources

Spectral source	AI-algorithm	Nutrient	Performance	References
GaiaSorter-dual camera	PLSR	SOC	R^2 0.61	[101]
Landsat-8	GBDT	SOC	R^2 0.147	[102]
Sentinel-2	RF	SOM	R^2 0.445	[103]
Spectrometer	SVM	SOC	R^2 0.32	[99]
Spectrometer	Cubist	SOC	R^2 0.35	[100]
Sentinel-2	XGBoost	SOC	R^2 0.84	[104]
Spectrometer	GBRT	N, P, K	GBRT with RPD 2.64, 3.93 and 2.38 for N, P and K, respectively	[105]
SVR	AisaFenix sensor	P, K, Ca, Mg, Cl, SOM	R^2 0.87	[106]
CART	UAV	N, SOC	Overall Accuracy 87%	[107]
RF	Prisma	SOM	R^2 0.92	[108]
Stepwise multiple regression	MODIS	SOM	R^2 0.725	[109]
RF	ASD field spectrometer	SOM	R^2 0.838	[110]

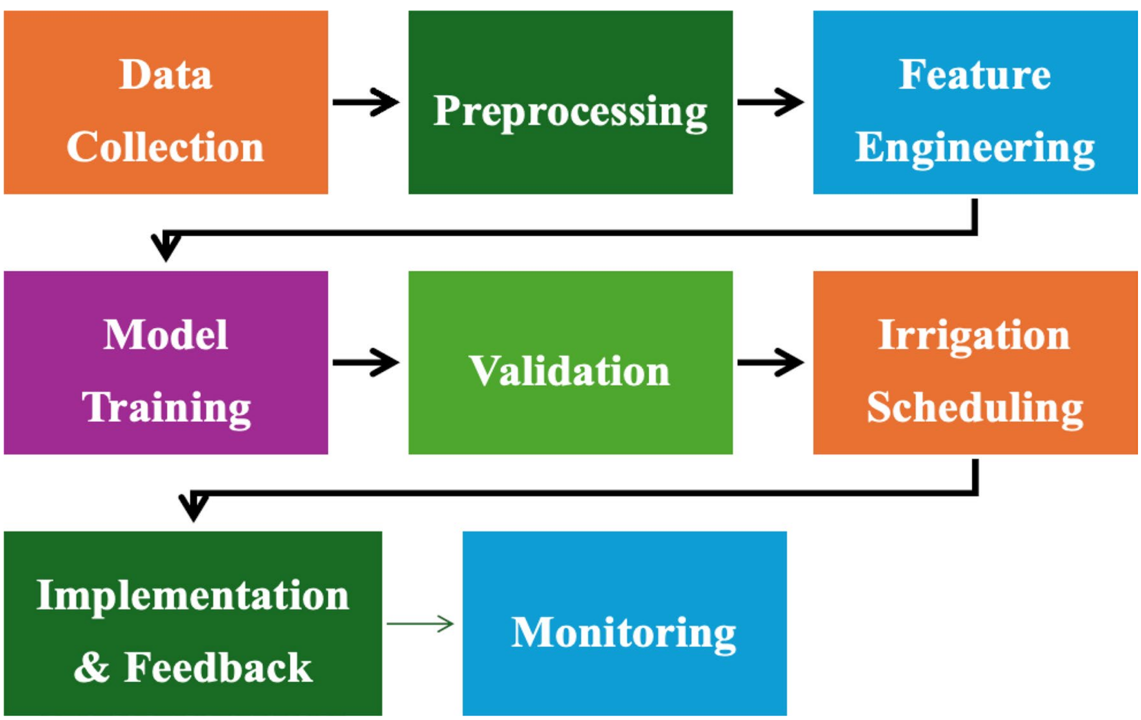


Fig. 5 Major steps involved in AI-based irrigation scheduling

For irrigation scheduling, real-time schedules are generated based on predicted water requirements, integrating current weather forecasts. During implementation and feedback, these schedules are applied in the field, and continuous feedback from new data refines the model. Finally, monitoring allows for adjusting schedules based on field responses, optimizing water efficiency over time.

The application of AI in irrigation has led to substantial water savings across various crops. For instance, [111] documented a 43% reduction in water usage for farmland irrigation, while [31] reported approximately 30% savings for potato crops. Notably, [112] observed a 74% reduction in runoff for turfgrass irrigation using a Radial Basis Function Support Vector Machine (RBF-SVM) model. It underscores AI's potential to minimize water pollution risks from agricultural runoff, especially in crops requiring precise water control. AI models not only improve water-use efficiency but also enhance profitability in crops like maize and wheat [113]. ML models have achieved 97.8% accuracy in predicting soil humidity and temperature, facilitating real-time, precision irrigation [114].

The K-Nearest Neighbor (KNN) algorithm predicts crop water requirement based on crop growth stage with an accuracy of 97.4% and proposes an automated irrigation model that can improve water productivity [115]. Adaboost models achieved 71% accuracy in rice water demand forecasting [32], and Deep Q-Networks achieved 20–30% water savings in tomato irrigation [116], both demonstrate AI's potential for crop-specific, efficient water management solutions tailored to environmental conditions. Overall, AI models can be utilized to optimize water use, improve irrigation scheduling, and increase economic returns across a variety of crops. The AI-based irrigation scheduling in different crops along with its benefits is summarized in Table 4.

7 Foodgrain quality assessments using AI

AI applications are revolutionizing foodgrain quality assessments by enabling rapid, accurate identification of high and low quality food products. Various ML and DL algorithms have assessed characteristics like color, texture, and kernel integrity across different grains. For wheat quality assessment, ML algorithms such as SVM, KNN, multilayer perceptron (MLP), and Naive Bayes (NB) have been used effectively to differentiate good and poor-quality grains. SVM, in particular, demonstrated a high accuracy of 93.46% in wheat quality classification based on color and texture features [117]. In contrast, DL approaches, such as the bidirectional long short-term memory (BiLSTM) algorithm, achieved even higher accuracy (99.5%) in distinguishing sunn pests (*Eurygaster integriceps*) affected wheat grains [118].

For maize kernel inspection, [119] developed an automatic inspection machine for maize kernel inspection via two-sided image capture and analysis. Using the CNN-based ResNet model, this system accurately classifies detective maize kernels as poor quality. This system processes approximately 500 g of maize kernels (around 1,250 kernels) in just 25 s, allowing for high-throughput and efficient defect detection. Similarly, advancements in AI have significantly improved adulteration detection in rice varieties. Estrada-Pérez et al. [120] employed CNNs to analyze thermographic images captured during cooling, effectively identifying adulterated rice samples and demonstrating that CNNs can be applied to non-visible quality traits. Similarly, pulse quality and impurity detection are facilitated by the FoodExpert mobile application, which uses the RF classification algorithm to sort pulses into quality grades and detect synthetic dye adulterations based on image data. This tool achieved 96% accuracy in pulse grading and 94% accuracy in identifying dye adulterations [121].

8 Limitations in using ML/DL algorithms

Conceptually ML/DL algorithms reproducibly mimic the biological human nervous system. However, the solutions they produce depend solely on the information with which the system is trained. These algorithms may produce misleading results when the ground reality is poorly represented by the input information [122]. These models may induce bias when irrelevant data, inappropriate pre-processing, lack of diversity, and imbalance in the data [123]. Especially, in pattern detection and classification problems like pest and disease detection, the accuracy and reliability of results are particularly sensitive to the prepossessing of images. The reliability and stability of the ML/DL models heavily depend on the size, quality, and diversity of the training data [124, 125].

ML and DL models require a large and more accurate dataset on weather and other environmental variables during crop season to find the best-performing model [126, 127]. Particularly, DL models require large amounts of data to provide stable performance and they generally exhibit poor performance with small datasets [128–130]. The availability of quality and long-term data is a constraint, especially for developing countries. However, artificial data augmentation techniques help deal with the problem of limited data availability to some extent [131]. Further, the transfer learning approach is helpful in this regard, in which models that are already trained on general global datasets can be utilized. Such models can be tuned to perform specific tasks by training considerably smaller and available problem-specific datasets [132].

Most of the ML and DL models are like "black boxes" [133]. Particularly, the DL structure consists of many hidden layers with numerous neurons per layer that perform multiple nonlinear transformations to produce a close to accurate level of precision for prediction. However, the interpretability of such models is a technically challenging issue, and virtually

Table 4 AI-based irrigation in different crops for saving water and increasing returns

Crop	AI models	Input data	% saving & income	References
Farmland and arable crop	Long Short-term Memory	Soil moisture and weather data	43% water saving compared to conventional irrigation	[111]
Potato	LSTM	Soil moisture, weather data, irrigation	Approximately 30% water saving	[31]
Rice	Adaboost	Weather and soil variables	71% accuracy in predicting rice water demand	[32]
Maize, wheat and soybean	Q-Network, Deep Q-Network	AquaCrop simulations, and weather data	Higher net return for maize and wheat, second highest for soybean	[115]
Rice	Deep Q-Network	Rainfall forecast and water depth in the field	Irrigation scheduling saved 23 mm water per hectare	[33]
Tomato	Deep Q-Network	Climate data, irrigation amount, total soil water in profile	20–30% saving of irrigation water	[116]
All crop	Decision Tree	sensors measure the humidity and temperature in the soil every ten minutes	Accuracy 97.8%	[114]
Turfgrass	Radial Basis Function—Support Vector Machine	Synthetic data generated through the Monte-Carlo (MC) technique	Reduced runoff by 74%	[112]

impossible to see what is inside [134, 135]. However, the limitation of non-interpretability of ML/DL models can be ignored if the primary objective is just prediction [136].

The researchers need to have a solid knowledge of the working principle of ML/DL concepts to choose the appropriate algorithm for the problem under study. These analyses are generally performed using high-end coding software. Therefore, it is required to have good programming skills to avoid implementation errors [137]. Computer hardware with a high processing power is an obvious requirement to process large datasets by such a complex algorithm in reasonable timescales without any technical issues [138].

9 Potential future directions

Generally, the models are trained using observed historical data. However, it is important to incorporate dynamic updating mechanisms in the models to update the parameters to the latest available data. In field conditions, the plants are often infected by multiple diseases and the infected leaves exhibit the symptoms of different diseases. Therefore, to diagnose symptom-wise diseases, the models are to be trained in such a way as to capture the symptom patterns of each disease. The algorithms are to be trained in such a way that the results produced by them are less sensitive to extreme cases. The development of more transparent, interpretable, and accountable algorithms is the need of the hour. Integrating domain knowledge with algorithms is desirable to improve the practical utility of the models. It is highly important to design the algorithms to account for ethical considerations too.

10 Conclusions

AI applications in yield prediction, pest and disease diagnosis, soil fertility assessment, precision irrigation, and food quality have shown transformative potential for sustainable agriculture. In yield prediction, AI algorithms provide accurate forecasts based on climate, soil, and crop growth data, empowering farmers and policymakers to make proactive decisions to enhance productivity. The pest and disease diagnosis models enable early and precise detection, reducing crop loss and minimizing pesticide use. Soil fertility assessment benefits from ML techniques that analyze different spectra quickly with higher spatial and temporal resolution, helping farmers apply nutrients precisely where needed, improving nutrient use efficiency, soil health, and preventing fertilizer-associated pollution. AI-driven precision irrigation models process real-time soil moisture and weather data, ensuring optimal water usage and significantly conserving water resources while maximizing crop growth. Lastly, AI tools for food quality assessment leverage imaging and ML algorithms to sort grains, detect adulterations, and ensure high-quality produce reaches consumers. Together, these advancements underscore AI's critical role in enhancing efficiency, sustainability, and profitability in modern agriculture, laying the foundation for more resilient and resource-efficient farming systems.

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Declarations

Competing interests The authors declare no competing interests.

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