Integrative
Plant Biotechnology
ISSN: 3007-2735 (Online), 3007-2727 (Print)

Review Article

Role of AI and Big Data for Managing Plant Stress in Smart Agriculture

Warda Ghaffar[1], Qalb e Abbas Qaseem[1], Ghulam Mustafa[1], Muhammad Sarwar Khan[1], Rimsha Riaz[1*]

[1]Centre of Agricultural Biochemistry and Biotechnology, University of Agriculture, Faisalabad, 38040, Pakistan.

ABSTRACT

Artificial intelligence (AI) and big data have greatly transformed plant stress management practices in smart agriculture. Conventional stress management approaches have many limitations regarding precision, efficiency, and scalability, which are being resolved using modern digital technologies. Machine learning (ML) and deep learning are advanced AI techniques that can easily analyze diverse data from images, sensors, and multi-omics. These assist in early stress identification, classification, and prediction of future risks associated with stress. ML models (both supervised and unsupervised) have the ability to accurately classify the stress types. Computer vision technology is widely used in agriculture and helps in conducting timely decisions by detecting morphological and spectral alterations in plants. Big data facilitates unraveling complex mechanisms underlying plant stress through integrative multi-omics. Various AI-driven predictive models have also been applied in forecasting insect pests and disease outbreaks. Furthermore, AI and big data are revolutionizing agriculture through precision fertilization and irrigation, robotic spraying technology and AI-integrated farm management information systems. Thus, AI and big data have significantly advanced conventional methods in plant stress management.

Keywords: Artificial intelligence, Computer Vision, Multi-omics, Machine Learning, Plant stress, Precision agriculture, Smart agriculture

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***Correspondence**
Rimsha Riaz
rimsha.riaz@uaf.edu.pk

Article History
Received: November 18, 2025
Accepted: December 06, 2025
Published Online: December 21, 2025

Cite this article
Ghaffar, W., Qaseem, Q., Mustafa, G., Khan, M. S., & Riaz, R. (2025). Role of AI and Big Data for Managing Plant Stress in Smart Agriculture. Integrative Plant Biotechnology, 3, 351–360.

INTRODUCTION

Agriculture plays a central role in global food security, but it faces several challenges that compromise crop productivity. Climate change, reduction in groundwater resources, labor issues, rapidly growing global population and biological stress are some of the reasons in lowering crop yield. Both biotic and abiotic factors are involved in plant stress. Abiotic factors include drought, salinity, extreme temperatures, flooding and nutrient deficiencies (Kelbessa *et al.*, 2023). These are responsible for reducing crop yield by more than 50% in major crops, with drought alone responsible for decreasing 34% of global crop yield. Soil salinity has deteriorated approximately 20% of irrigated land and is a key factor in land degradation (Phour and Sindhu, 2023). The severity of these stress factors is increasing under climate change and poses serious risk to agriculture. On the other hand, biotic stress arises from pests (insects, nematodes, rodents), pathogens (fungi, bacteria, viruses) and weeds. These stresses are responsible for reducing 20-40% crop yield (Garoma *et al.*, 2024). For example, fungal diseases like wheat rust and rice blast destroy crops across many developing regions. The annual crop losses due to plant diseases are over 220 billion, whereas losses due to insect pests exceed 70 billion (Garoma *et al.*, 2024; Mahmoud, 2021).

https://doi.org/10.55627/pbiotech.003.04.1702

Conventional stress management strategies, such as selective breeding, chemical application and irrigation, play an important role in mitigating plant stress. However, these approaches have some limitations such as delayed response, inefficient use of resources, costly and environment unfriendly (Zuckerman *et al.*, 2024). Data collection and recordkeeping through traditional techniques depend on manual and paper-based methods but these are laborious and time-consuming during field surveys and data interpretation. Further, these also lack precision and scalability that are required to manage stress in large and diverse agricultural landscapes (Basir *et al.*, 2024; Rimpika *et al.*, 2023).

These challenges can be resolved by adopting smart agricultural procedures. These are the combination of traditional agronomic knowledge and advanced digital technologies. Remote sensing, Internet of Things (IoT) devices, sensors, robotics and decision-support systems are frequently used digital technologies in smart agriculture (Ameer *et al.*, 2024). In this context, artificial intelligence (AI) and big data analytics are becoming increasingly significant in plant stress management. Machine learning (ML) and deep learning are two models of AI technologies that are important in early stress management. These look for complex patterns of diverse data to detect, classify and predict future outbreaks. These assist in timely crop management practices from sowing to harvesting by managing fertilizer and irrigation applications, observing insect pest infestations and monitoring crop health throughout the growing season (Javaid *et al.*, 2022). Similarly, big data also supports decision making based on wide range of data retrieved from various sources like past data, weather forecast, sensors and satellite images, etc. Together AI and big data analytics is leading towards smart and precise agriculture that leads towards generation of climate resilient crop varieties (Saggi and Jain, 2022). Studies have explored applications of various AI methods in agriculture, few have critically examined the integrated use of AI, big data and multi-omics in managing plant stress within a unified smart agriculture framework. This review addresses this gap by summarizing recent literature (2020-2025), providing a comprehensive and critical overview of how these technologies help to transform plant stress management.

AI AND BIG DATA TECHNIQUES FOR PLANT STRESS DETECTION

Plant stress identification and management are revolutionized through advanced AL tools. Agriculture 5.0 represents a new era that integrates all AI approaches, smart sensors and high-performance computing to transform conventional farming. AI technologies can easily recognize early symptoms of stress and give a signal for timely actions while big data techniques can increase decision-making by collecting and analyzing heterogeneous data. Their effective integration in essential to increase productivity, reduce operational costs and minimize environmental impact (Taha *et al.*, 2025). Figure 1 presents workflow involving different AI and big data techniques exploited in smart agriculture for stress detection. The process starts with the collection of data through sensors, UAVs and satellite imaging. It is followed by big data preprocessing which includes data cleaning, normalization and finally data storage in cloud platforms. AI models e.g., CNN and LSTM are then applied for feature extraction, classification, and prediction. Finally, smart actions are inducted through robotic systems or decision-providing tools.

Smart Sensor Technologies

Modernization in smart sensor technologies has transformed plant monitoring systems. These enable real time assessment and accurate examination of plant health under changing environment. Integration of AI, advanced biosensors and Internet of Things (IoT) programs greatly help in collecting, analyzing and monitoring data regarding plant health and foster identification of early problems before appearing visible symptoms (Shajari *et al.*, 2023). These smart sensors facilitate in assessing both abiotic and biotic factors. Further, it helps in timely decision of crop management by detecting nutrient content, moisture, irrigation and pest infestation in field, hence optimizing and reducing wastage of agricultural resources (Yin *et al.*, 2021). Following sensors are frequently used in imaging, monitoring and assessing farms:

Imaging sensors

These sensors take clear pictures of plants to identify changes in color, shape, stress symptoms and nutrient deficiencies. RGB cameras, multispectral cameras and thermal cameras have recently been used. Nowadays, RGB cameras are affordable for researchers to capture and measure visible light reflected by plants (López-García *et al.*, 2022).

Soil and environmental sensors

Soil sensors are used to measure moisture content of soil, often referred to as soil moisture sensor or meter. These are useful in gardening, farming and experimental fields which help people decide when and how much plants need water to keep plants healthy.

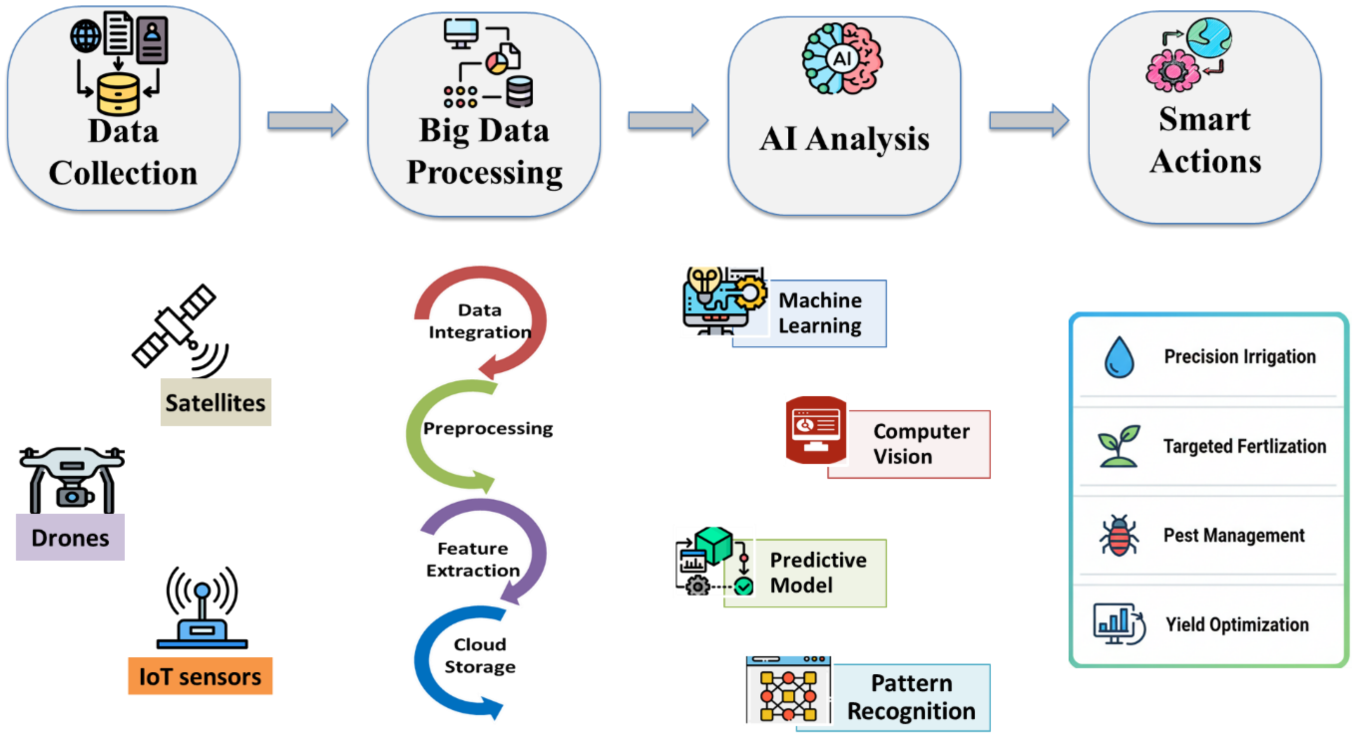

Figure 1. Workflow of AI-driven smart agriculture shows the progression from data collection to big data processing, AI-based analysis and the resulting smart actions.

Soil sensor detects soil health and fertility levels by measuring pH, electrical conductivity, and organic matter. Volumetric soil moisture sensors, tensiometers and crop health sensors are some types of soil sensors used in smart agriculture for better outlook (Xing and Wang, 2024; Santosh *et al.*, 2024).

Weather and environmental sensors identify how climate and soil conditions affect plant fitness. Soil moisture sensors, temperature sensors, humidity sensors, light sensors and wind sensors are operated to observe plant condition. Remote sensing technology is applied in fields through platforms such as satellites, aircraft and unmanned aerial vehicles to achieve better efficiency, cost-effectiveness, and high-throughput way to monitor crops (Fuentes-Peñailillo *et al.*, 2024; Kouadio *et al.*, 2023).

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Unmanned aerial vehicles (UAVs)

UAVs are high-resolution camera sensors that capture detailed images depending on flying height. Drones have been widely used in scientific research for several years with the benefits of flexible time and cloud-free data collection for monitoring crop health. The use of drones in agriculture and satellite imagery has revolutionized crop monitoring. This information enables early identification and shortage of nutrients, that allows real-time assessment of crop health, growth stages, and potential issues by facilitating timely interventions to protect crops (Ruwanpathirana *et al.*, 2024). The combination of UAV imagery and machine learning has been applied to accurately estimate the numbers of plants of various crops to detect weed seedlings in cultivation fields. The proposed methods in the literature have utilized machine learning techniques that provide high accuracy output for detecting individual plants in UAV imagery; thus, the quantification of field plant density can be accurately measured (Haq, 2022; Bouguettaya *et al.*, 2022). Considering that farmers have broad fields, monitoring plant density with UAV will be a challenging task.

MACHINE LEARNING FOR SMART AGRICULTURE

Machine Learning (ML) is a promising approach to interpret dynamic multi-omics data under stress conditions. It helps with prompt decision making by identifying, quantifying and predicting stress signals. ML autonomously learn by reading patterns provided in images and environmental symptoms which then allows its models or algorithms to interpret large datasets. It is widely applied in academic and industrial setups to visualize data and reduce data dimensionality (Shoaib *et al.*, 2024). ML and AI together have revolutionized agriculture sector by revealing novel insights within biological data that is obtained under various conditions. It greatly enhances crop quality and reduces the waste of agri-resources. However, its interpretation is highly dependent on quality of data (Ryan *et al.*, 2023).

Learning Approaches for stress detection

ML is classified into supervised and unsupervised learning approaches. Supervised learning (SL) uses a labeled training data set for model training and makes predictions for an unlabeled test data set, whereas Unsupervised learning (UL) uses an unlabeled data set to both train a model and find relationships within the data (Yu *et al.*, 2025). Both learning approaches are split into two further branches. SL into classification and regression whereas UL into clustering and data dimensionality reduction (DR). Both are implemented through different model representations. Supervised learning models, such as support vector machines (SVM), random forests (RF), decision trees (DT), k-nearest neighbors (KNN), and artificial neural networks (ANN), dominate the field due to their ability to classify known stress types with high accuracy (Phongying and Hiriote, 2023). Unsupervised methods, such as hidden Markov models (HMM) and partial least squares discriminant analysis (PLS-DA), are utilized for more exploratory analysis, especially where labeled data is limited and have been used to classify stress types (Yu *et al.*, 2025) . Under field conditions, stress symptoms can be easily identified from field images using advanced deep learning approaches. Selection techniques and feature extraction can significantly improve these approaches and help in development of next-generation models. ANNs can also be used to learn features from images, videos and sensors. Using these, stress symptoms on plants can be easily highlighted from varied data. Thus, this early identification is crucial for initiating prompt crop protection measures (Upadhyay, 2024; Sushma Sri *et al.*, 2023).

AI-DRIVEN PREDICTIVE MODELS

AI-driven decision systems and diagnostic tools are transforming agricultural management by converting complex data into valuable insights for farmers, agronomists and researchers. These systems integrate images' data with ML and deep learning algorithms to diagnose infected plants and give suggestions for further treatment and even predict future risks. AI-based systems are faster, more accurate and have data-driven recommendations. It can also analyze the historical and real-time data to develop predictive models that can efficiently anticipate pest outbreaks (Padhiary *et al.*, 2024). As discussed in the smart sensor section, UAVs provide high-resolution spatial data that feed predictive models for early stress detection, forecasting pest infestation and real-time crop health monitoring. Farmers may reduce risks and make proactive decisions by forecasting. Farmers can predict the best planting window, therefore lowering the vulnerability of their crops to bad weather, by investigating past weather patterns and current soil data.

Table 1. Comparative analysis of AI-based methods and their applications in smart agriculture.

Methods	Type	Strengths	Limitations	Applications
Support Vector Machines	Supervised ML	High accuracy for classifying small data	Cannot efficiently deal with complex large data	Efficient use in stress detection and classification
Random Forest	Supervised ML	Robust in handling and interpreting missing data	Give less accurate analysis with imbalanced data	Suitable for abiotic stress prediction using environmental data
Artificial Neural Networks	Supervised ML/ Deep Learning	Highly flexible and can learn complex patterns	Requires large data, difficult to interpret due to overfitting	Applicable for recognizing stress symptoms and overall crop health analysis using multi-omics data
Convolutional Neural Networks	Deep Learning	Good for image processing with high spatial accuracy	Needs large, labeled images for interpretation	Stress symptoms are detected visually and guide about respective pests and disease
Long Short-Term Memory	Deep Learning	Detects temporal dependencies and ideal for time-series prediction	Needs large datasets, difficulty in training	Help in forecasting weather patterns and predicting stress timing
K-Nearest Neighbors	Supervised ML	Simple with no requirement of complex parameters, good for low-dimensional studies	Computationally expensive for large datasets; sensitive to noise	Better for experimental use rather than real-world
Decision Trees	Supervised ML	Easy to understand and interpret	Not good for continuous variables due to overfitting	Applied in rule-based decision systems with limited resources
Hidden Markov Models	Unsupervised ML	Handles sequential data	Requires assumptions, often oversimplify real-world variability	Helpful in detecting disease progression under changing climate
Partial Least Squares Discriminant Analysis	Unsupervised ML	Works well with complex data	Less effective for complex patterns	Helps in classifying stress through integrative multi-omics approaches
YOLO	Deep Learning	Real-time detection with high accuracy	Need to train data, limited in small object detection	Drones used in pest monitoring and weed identification

It also gives farmers the capacity to keep ahead of difficulties and make data-informed decisions by optimizing agricultural output and resilience (Won *et al.*, 2023). These are critical enablers of smart agriculture that help to uncover traits that enhance crop productivity, sustainability and resilience. Their integration with IoT, genomics and AI is transformative in meeting future food security (Kazi, 2024; N Al-Wesabi *et al.*, 2022). While all these AI techniques offer diverse expertise, their suitability for stress detection varies depending on type of data, resource availability and application goals. Table 1 describes the main characteristics, strengths, limitations, and agricultural applications of some important AI methods used in smart agriculture for managing plant stress.

Computer vision in Plant Stress Detection

Computer vision is a foundation revolutionary AI technology in climate smart agriculture. It utilizes AI and ML algorithms to process and interpret visual information and facilitate agriculturists' vision capabilities. Considering plant stress detection, these computer vision systems capture alterations in morphology, texture and color of plants' images and then analyze them to indicate specific plant stress (Ruby *et al.*, 2024). One of the primary applications of computer vision in agriculture is leaf-level analysis as many types of stress manifest first on leaves, in the form of discoloration, wilting, or abnormal growth patterns.

RGB, thermal and hyperspectral imaging are commonly used, their integration with computer vision algorithms further help in detecting early stress symptoms. Thermal imaging is effective in identifying water stress by detecting changes in the canopy temperature. Changes in canopy temperature are basically associated with reduced transpiration. Hence, agriculture enters an era with computer vision where the visual world becomes a rich source of data and knowledge which improves or enhances farming by elevating productivity and minimizing losses (Renó *et al.*, 2024).

BIG DATA ANALYTICS FOR UNDERSTANDING PLANT STRESS RESPONSES

Plants being immobile are continuously facing environmental stresses which affect plant growth and development. Plants have innate immune system to protect themselves from stress but the way they respond is not easy to understand as they involve complex mechanisms. Traditional methods unable to study core pathways involved in such conditions. Therefore, the analysis and interpretation of such huge datasets require advanced tools and approaches. Here, big data analytics provides a solution to solve these complexities underlying plant stress (Huang and Jin, 2022). It helps in exploring hidden insights and relationships by collecting, processing and analyzing diverse data. For example, during investigation of plant stress, data is collected from multiple sources, i.e., smart sensor data, omics data and image data. A dynamic framework is required to manage these datasets and handle their volume and veracity.

Integrative multi-omics is an example of big data analytics to interpret molecular interactions. Under stress conditions, transcriptomic data will indicate specific genes that are upregulated or down regulated while metabolomics provide information about changes in osmolytes levels during stress. These integrative approaches are helpful in identifying stress responsive genes that can be used further in marker assisted breeding or engineering climate resilient varieties. Real-time stress monitoring and predictive modeling allow for proactive management decisions. But dealing with heterogenous data in big data analytics is a serious issue that must be addressed by adopting cloud computing resources, open-source databases and collaborations (Tinte *et al.*, 2021; Zhou *et al.*, 2022).

APPLICATIONS FOR SMART AGRICULTURE MANAGEMENT

Precision irrigation and fertilization continuously progress with the development of science and technologies and always a trending research topic for researchers and scientists. It’s a need of time to achieve green and efficient global agriculture. It’s a modern type of agriculture that is supported by information technology and management system to determine the optimal time of irrigation and fertilization with help of AI (Fuentes-Peñailillo *et al.*, 2024). Use of sensors, IoT devices, data analytics, and AI to deliver water and nutrients at the right time and in the right amount, optimizing crop yields. This method called variable rate application minimizes waste, prevents soil degradation, and increases overall farming efficiency and sustainability. Simultaneously, changes in environment are a threat to pests and diseases are more prominent problems. But new innovations are addressing these issues (Nyéki and Neményi, 2022). With the help of AI, it is easy to identify and predict the pest and diseases.

Robotic sprayers are another form of automated pest control. These ground-based robots are equipped with sensors and GPS systems to navigate fields autonomously and apply pesticides in targeted areas. Integrating AI with Farm Management Information Systems (FMIS) creates smart farming solutions that leverage data for better decision-making, improved efficiency and higher crop yields. This integration involves combining AI algorithms with data from IoT sensors and other sources to enable automated monitoring, predictive analytics, pest and disease detection, resource optimization and automated farm equipment (Dayana *et al.*, 2024; Maraveas, 2022). Table 2 shows some applications of AI in detecting stress and crop management in various crop plants for sustainable agriculture.

CHALLENGES AND FUTURE PERSPECTIVES

Agriculture faces many hurdles including lack of irrigation systems, extreme weather conditions, lowering groundwater levels, massive food wastage, diseases and pest infestations to crops. Biggest threat to farmers is loss in crop yield due to pests and natural disasters. It happens often due to lack of timely information. Even though AI and big data analytics offer many benefits, there are still many complications that need to be considered.

Table 2. AI-driven approaches for stress detection and management in crop systems for smart agriculture.

Crop	Stress Type	Application Area	Tools Used	Findings	References
Triticum aestivum	Drought, Heat, Salinity	Precision irrigation and stress detection	Hyperspectral Imaging, UAVs, IoT Sensors, CNN, LSTM	Saved 10-30% irrigated water by early detection of water and salinity stress	Sharma *et al.*, 2025
	Drought	Integrated multi-omics	ANN, Bayesian Learning, RF, Deep Learning, Multi-Omics Data	Predicted drought resilience using AI/ML ensemble models	Le Roux *et al.*, 2024
Zea mays	Drought	Integrated multi-omics	Random Forest, Deep Learning, Multi-Omics	Predicted drought tolerance traits by integrating genomics and phenomics data	Sheoran *et al.*, 2022
	Drought, Heat, Salinity	Precision irrigation and stress detection	UAVs, ML, UNet, Hyperspectral Imaging	Mitigated yield loss through timely intervention, significant water use efficiency	Rajwade *et al.*, 2023
	Pest, Disease	Integrated pest management	UAVs, YOLO, Edge-AI Pest Traps	Improved monitoring and targeted control of pests and diseases	Adetunji *et al.*, 2023
Oryza sativa	Drought, Heat, Salinity	Precision irrigation and stress detection	IoT sensors, DL, Remote Sensing	Improved water management and monitoring under temperature and water stress	Kamarudin *et al.*, 2021
	Drought, Salinity	Omics-Driven stress-responsive gene prediction	SVM, GWAS, Transcriptomics, Feature Selection	Identified key genes and molecular markers linked to salt and drought resistance	Ali *et al.*, 2024
Gossypium hirsutum	Water Stress	Smart irrigation scheduling	Satellite Imagery, Remote Sensing, ML Models	Improved irrigation decisions and water use efficiency	Chen *et al.*, 2020
Abelmoschus esculentus	Salinity	High-throughput stress phenotyping	Hyperspectral Imaging, Deep Learning Segmentation, ML Regression	Found strong correlation between hyperspectral profile and salinity response in 13 genotypes	Gill *et al.*, 2022
Glycine max	Biotic and Abiotic	Early stress detection and monitoring	CNN, SVM, High-Throughput Imagery	Early and accurate classification of multiple stresses	Gou *et al.*, 2024
Solanum tuberosum	Drought, Pest, Disease	Integrated stress and pest management	CNNs, UAVs, YOLO, Robotic Vision	Optimized pesticide application timing and quantity by reducing false positives	Gülmez, 2025
Solanum lycopersicum	Insects	AI-driven pest detection	UAV Drone Imagery, CNN, YOLOv5, YOLOv10	Detected pests attack with up to 96% accuracy	Raza *et al.*, 2023
Citrus × sinensis	Insects	AI-driven pest detection	UAV Drone Imagery, CNN, YOLO Models	Mapping insect infestations in orchards with high accuracy	Zhu *et al.*, 2024

Technologies such as smart sensors, drones and GPS-guided instruments are expensive and make it difficult for smaller farms to afford investment and need further study. Quality problems like data points that don't fit into normal patterns, inaccurate or inconsistent data, repeated entries and missing values make data interpretation difficult. Data collection is tedious due to varying conditions in different places and harvesting of crops only once or twice a year. Poor quality data (due to weather, soil or pests) makes it hard to train accurate AI models (Polwaththa *et al.*, 2024). High cost of AI tools and maintenance is another barrier. Smart machines are expensive and need frequent updates. AI and ML tools must be of good quality to execute large scale data to work well, it's important to invent new ways to deal with hardships that are still big challenges in the field. Security challenges in precision farming are one of the biggest threats that can hurt farmers and others involved. Unauthorized access to private data, financial losses and fear of misuse of data make farmers less willing to use AI and digital tools (Vilar-Andreu *et al.*, 2024).

Adopting techniques in agriculture and food systems can be a game changer especially in era of increasing world's population. AI and smart tools greatly help in achieving sustainable farming by increasing crop yield, using fewer resources, predicting diseases and pests, and conserving environment. Using open-source platforms can make AI tools cheaper and more accessible. These tools can help with crop disease detection, surveying soil health and weather forecasting. Faster development of technologies will make a huge modification in farmer's life. With the right tools, farmers can predict problems before they happen. AI-powered sensors, big data and robotics can collect real-time data from the field, be installed in harvesting equipment, help improve the efficiency of farming operations and will ultimately support yield prediction and planning. Thus, AI can help us grow more food with fewer resources, making farming sustainable.

AUTHOR CONTRIBUTIONS

Rimsha Riaz and Wardah Ghaffar conceptualized and drafted the manuscript. Qalb e Abbas Qaseem made table and figure and edited manuscript. Ghulam Mustafa, Muhammad Sarwar Khan reviewed and supervised the writeup.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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