PLANT SCIENCE TODAY
Vol 12(sp4): 01–10
https://doi.org/10.14719/pst.8159

eISSN 2348-1900

REVIEW ARTICLE

Artificial intelligence: Concepts, importance and future perspectives in agriculture

Bhumika Sharma[1], Vani Mahindru[1], Reetika Sharma[2], Vikas Abrol[1], Riya Kalsotra[1], Aakash Saini[1], Shruti Kumari[1], Stanzin Khenrab[1], Maanik[2] & Peeyush Sharma[1*]

[1]Division of Soil Science & Agricultural Chemistry, Sher-e-Kashmir University of Agricultural Sciences & Technology of Jammu, Jammu 180 009, Jammu & Kashmir, India

[2]Division of Fruit Science, Sher-e-Kashmir University of Agricultural Sciences & Technology of Jammu, Jammu 180 009, Jammu & Kashmir, India

*Correspondence email - dr.pabrol@gmail.com

Received: 10 March 2025; Accepted: 20 August 2025; Available online: Version 1.0: 24 November 2025

Cite this article: Bhumika S, Vani M, Reetika S, Vikas A, Riya K, Aakash S, Shruti K, Stanzin K, Maanik, Peeyush S. Artificial intelligence: Concepts, importance and future perspectives in agriculture. Plant Science Today. 2025;12(sp4):01–10. https://doi.org/10.14719/pst.8159

Abstract

The United Nations World Population Forecast-2022 suggests that the Indian population could reach 1.668 billion by 2050. Consequently, the demand for increased food production and employment opportunities is also rising. Traditional farming practices alone may not be adequate to address these future challenges. As a result, novel automated technologies like artificial intelligence (AI) are being introduced into agriculture. AI can unravel the potential to sustain the human health. It also promises food security and employment opportunities for increasing population. Recently, the agriculture sector has increasingly embraced the use of AI. The fundamental idea behind integrating AI into agriculture lies in its adaptability, superior performance, precision and cost-efficiency. Using sensors, drones and satellite imagery, AI helps farmers monitor and manage fields with unparalleled accuracy by detecting anomalies and nutrient deficiencies in soil. It also provides real-time recommendations for precise irrigation, fertilization and pesticide application. AI finds application in various areas such as weather prediction and automatic adjustment of machinery for identifying diseases or pests. These advancements contribute to reduced water and pesticide usage, precise herbicide application, soil fertility preservation and enhanced farming efficiency. Despite these benefits, access to AI for small-scale farmers is limited due to lack of practical experience with new technologies and high initial cost. Therefore, the government needs to create awareness about machine learning by various schemes and training programs to improve the utilization of AI in farming practices. This review discusses the impacts, advantages, limitations and future prospects of AI in agriculture, with a focus on ensuring the sustainability of food production, water management and environmental conservation.

Keywords: artificial intelligence; intelligent sensors; precision agriculture; robotics; start-ups

Introduction

Agriculture is the principal industry in many nations worldwide. As the population is growing at an alarming rate, it will reach up to 9.7 billion people from 7.5 billion people. It is expected that there will be lesser land under cultivation by 2050 and there will be greater demand placed on the land. Farmers will consequently have to do more with less. The same analysis indicates that food output needs to increase by 60 % to feed the extra two billion people by 2050.

Agriculture has a vital role in the economies of emerging countries and contributes greatly to the economic prosperity of established ones. The expansion of agriculture has resulted in a significant rise in the per capita income of rural population. In countries like India, approximately 50 % of the workforce is engaged in agriculture, contributing about 18 % to the national GDP. Enhancements in the agricultural domain will promote rural development, subsequently augmenting the national revenue generation. The incorporation of AI into agriculture has ushered in a new era of productivity, precision farming and sustainability. AI is an approach to create intelligent software that learns from human knowledge to think, learn and solve the problem. Thus, as a technology in the agriculture sector advances, artificial intelligence (AI) is becoming more prevalent. Artificial Intelligence can empower farmers to maximize crop yields by timely management of weeds, soil nutrients and irrigation (1). It can assist farmers in minimizing environmental risks and optimizing resource utilization by accessing data from several sources.

Another critical challenge facing global agriculture is climate change, which poses serious risks to food systems worldwide. Climate change is marked by higher temperatures, lower agricultural productivity, heightened presence of pests and diseases and declining soil health, which stem from shifts in rainfall patterns, more frequent extreme weather events and rising sea levels. In the recent past, the agriculture industry has been more severely affected by climate change. Between 2010 and 2039, India could experience a national decline in important agricultural yields of up to 9 %, which would only get worse with time. AI can play a crucial role in developing climate-resilient agricultural strategies to mitigate these and ensure food security.

Artificial intelligence (AI) has a rich history, beginning in the 1950s when John McCarthy coined the term at the Dartmouth Conference, sparking early exploration into computational problem-solving and symbolic reasoning. Artificial intelligence (AI), a branch of computer science that simulates human cognition such as learning, reasoning and perception, has evolved significantly since its inception in the 1950s. Coined by John McCarthy at the Dartmouth Conference, the term marked the beginning of an era exploring computational intelligence. The 1950s-60s saw the development of programs like the Logic Theorist, simulating human problem-solving. The 1970s-80s introduced expert systems like MYCIN and DENDRAL, designed to mimic human decision-making in specific domains. However, the 1980s-90s brought the "AI winter", marked by reduced interest and funding due to unmet expectations. Revival occurred in the 1990s-2000s with advances in computational power, algorithms and the rise of machine learning, particularly neural networks. The 2010s to the present have seen the dominance of deep learning, revolutionizing tasks like image and speech recognition. Fig. 1 shows a timeline depicting the evolution of artificial intelligence. Today, AI continues to evolve with applications in numerous fields, though ethical concerns about bias, privacy and job displacement remain pressing challenges. Despite cycles of hype and disillusionment, AI remains a driving force in technological innovation and societal transformation.

Types of AI

Artificial intelligence can be broadly classified into two primary categories-based on capabilities and functionalities. These classifications help in understanding the current and potential scope of AI development. A flowchart (Fig. 2) visually summarizes these distinctions.

AI can be classified into two main types based on capabilities and functionalities. "Type-1", based on capabilities, includes "Narrow AI" (or Weak AI), which specializes in specific tasks without operating beyond its domain, like Apple's Siri; "General AI", which aims to perform intellectual tasks on par with humans but remains in the research phase; and "Super AI", a theoretical concept where machines surpass human intelligence, capable of independent reasoning and decision-making. "Type-2", based on functionalities, includes "Reactive Machines" that respond to present conditions without memory, like IBM's Deep Blue; "Limited Memory AI", which temporarily stores past data to inform decisions, exemplified by self-driving cars; "Theory of Mind AI", which seeks to understand human emotions and social interactions but is still under development; and "Self-Awareness AI", a speculative frontier envisioning machines with consciousness and emotions, which currently does not exist.

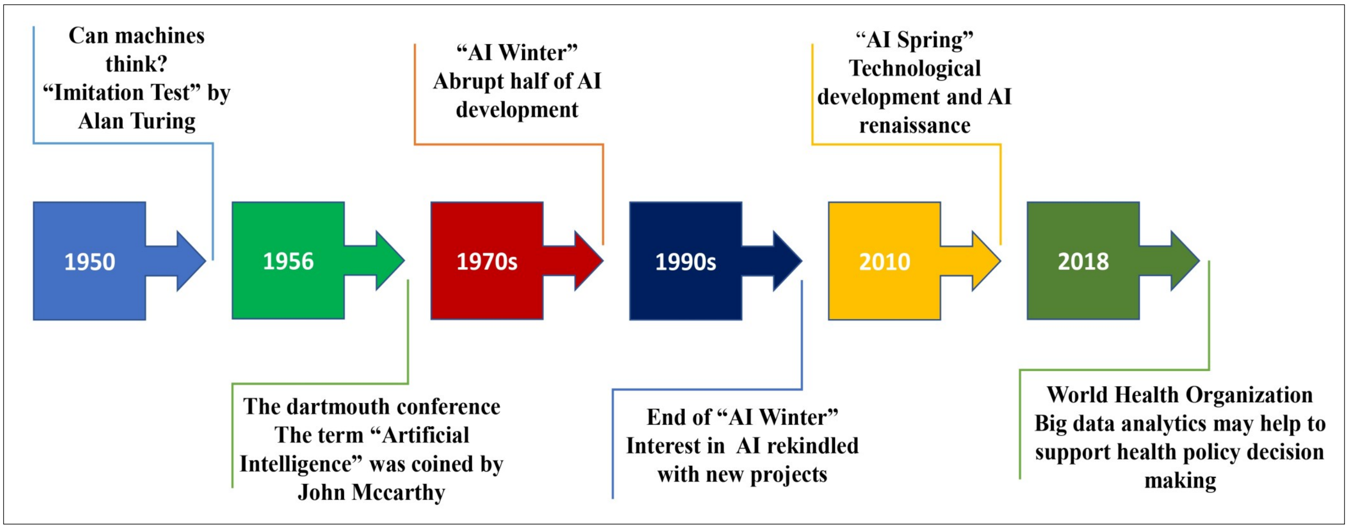

Fig. 1. A timeline depicting the evolution of artificial intelligence (2).

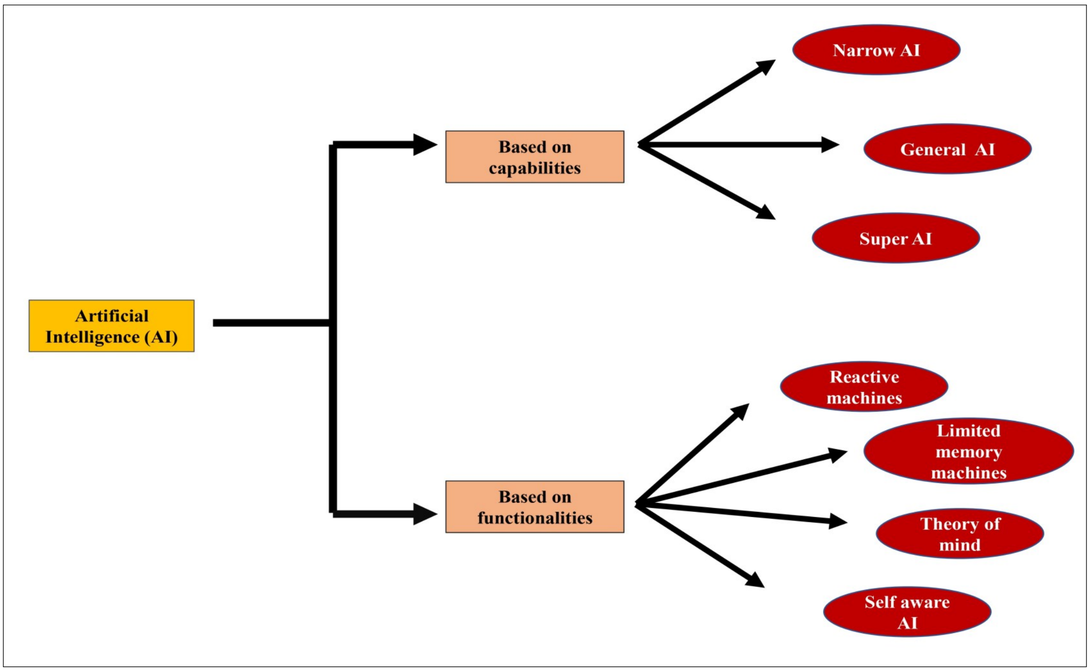

Fig. 2. Types of artificial intelligence.

Applications of AI in agriculture

AI-driven technologies contribute to enhance productivity across diverse sectors and address challenges encountered by various industries, including agriculture as shown in Fig. 3. These technologies contribute to improving yield, irrigation management, soil analysis, crop monitoring, weed control and establishment of crop in the agriculture sector (3). Agricultural robots present a notable application of AI within the industry, providing valuable solutions. The issues facing the agriculture business are a result of the growing worldwide population. Nevertheless, AI presents promising solutions. AI-driven technological innovations empower farmers to maximize their output while minimizing input, enhance the standard of their output and accelerate time-to-market for harvested crops. To precisely evaluate important aspects like weed detection, yield estimation, crop quality evaluation and more, advanced computer-based systems have been created.

AI has made notable contributions to the agricultural sector in several ways as follows:

Crop monitoring and regulation

AI aided by diverse sensors like PrecisionHawk, John Deere See & Spray, Plantix, IBM Watson Decision Platform for Agriculture, Taranis, CropX, Prospera etc, serves as a caretaker for crops on the farm, overseeing their health and growth. It advises farmers on optimal timing for planting, watering and harvesting to maximize crop yield. Essentially, it functions as a knowledgeable farm advisor, optimizing productivity and ensuring farmers reap the rewards of their efforts.

Efficient farming through smart techniques

AI enhances farming efficiency by assisting farmers in optimizing the usage of resources like fertilizer and pesticides, ensuring they're applied in precise amounts neither excessive nor inadequate. This minimizes waste while promoting healthier crop growth. It is comparable to having a highly skilled specialist in the field, precisely managing environmental variables to optimize plant growth and maximize food production.

Farming automation

AI coordinates various machines such as tractors and drones, which autonomously handle tasks like planting seeds, weed removal and crop spraying. These machines perform their duties with precision and efficiency, streamlining operations and enhancing overall productivity.

Livestock surveillance

AI utilizes advanced sensors and intelligent data analysis to ensure the well-being and contentment of livestock. If any issue arises, it promptly notifies the farmer, enabling proactive care and smooth farm operations. It is comparable to an intelligent system that continuously monitors and responds to field conditions in real time for the animals, ensuring their welfare while optimizing farm performance.

Weather and price forecasting

Using AI-driven weather forecasting tools like Random Forest, Support Vector Machines, XGBoost, Temporal Fusion Transformer, Google Earth Engine, Microsoft Azure FarmBeats, Climate FieldView, Taranis, Agremo etc, farmers gain insights into weather patterns, enabling informed decisions regarding crop selection, seed planting and harvest planning. Price forecasting provides farmers with valuable information on crop prices in the coming weeks, aiding in maximizing profitability.

Crop health monitoring

The type and nutritional content of the soil have a major impact on crop quality. However, with increasing deforestation, soil degradation has become a pressing concern, making it challenging to assess soil quality accurately. Soil health monitoring focuses on evaluating nutrient levels, organic matter content and overall soil fertility to guide appropriate fertilizer and soil management strategies. To address these challenges, AI powered tools like Plantix, developed by PEAT, offer support not only in assessing soil conditions but also in plant disease detection. Plantix allows farmers to take pictures of their crops, using AI-bases image recognition to diagnose plant illness, pest infestation and nutrient deficiencies. This helps farmers make informed decision to enhance crop quality and productivity through timely interventions.

Agriculture robotics

Robotics is extensively utilized across various industries, particularly in manufacturing, for executing intricate tasks. Presently, many AI companies like Agrobot, Blue river, TartanSense, Agnikul Cosmos

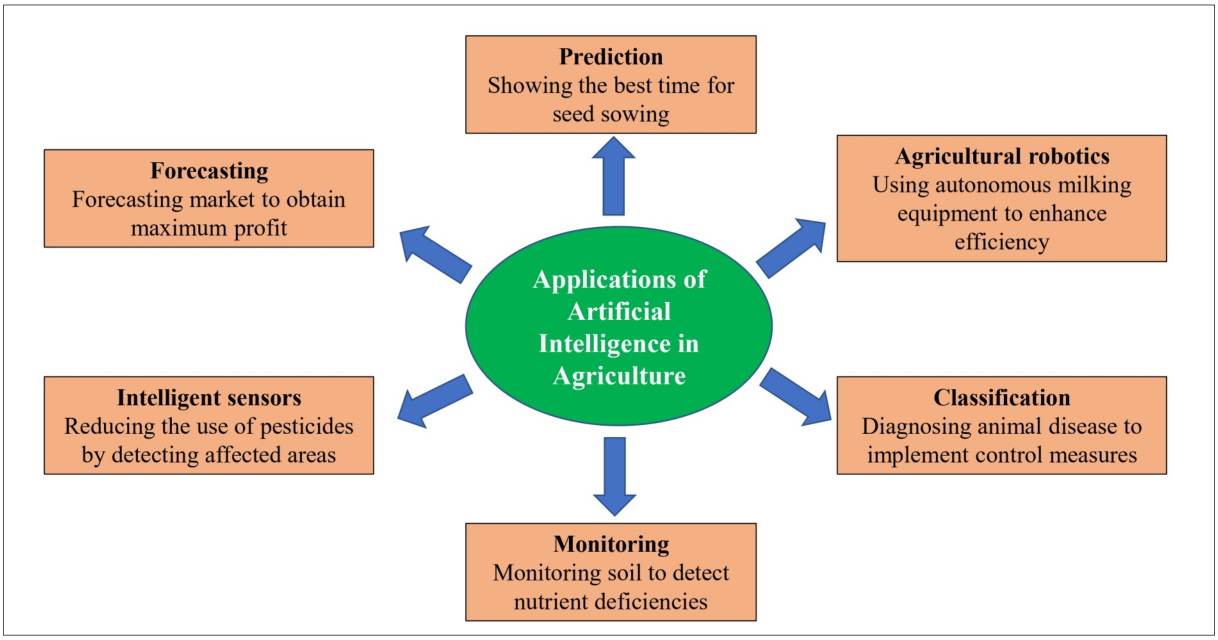

Fig. 3. AI applications in digital agriculture.

(Agri Division), Farms2Fork Technologies, Vyomika Space and Agri-Tech etc are designing robots specifically for the agricultural sector. These AI-driven robots are engineered to undertake a variety of farming tasks efficiently. They are skilled in crop quality assessment, weed detection and management and faster crop harvesting than humans.

Intelligent spraying

AI sensors equipped with computer vision enable precise weed detection and localization in agricultural fields. Systems such as Blue River Technology's See & Spray leverage this capability to apply herbicide selectively, significantly reducing chemical usage and minimizing crop exposure. The adoption of such AI-driven sprayers enhances resource efficiency, lowers input costs and contributes to improves crop quality.

Diagnosing diseases in crops

AI driven predictions allow for detection of plant diseases, enabling g timely and targeted intervention that minimize crop losses and reduce labor intensity. As part of diagnostic process, plant images are pre-processed using computer vision techniques to differentiate between healthy and affected regions. After identification, these regions can be isolated and forwarded to diagnostic laboratories for further analysis. Additionally, this approach supports the identification of pest infestation, nutrient deficiencies and other physiological disorders in crops.

Precision farming

Precision farming emphasizes the principles of applying right input at the right place, at the right time, offering data driven and controlled approach that reduces reliance on labour-intensive practices through automation. A key aspect of precision farming is the detection of plant stress-both biotic (e.g., diseases, pests) and abiotic (e.g., drought, salinity, nutrient deficiencies) through the analysis of high-resolution images and sensor derived data. These datasets, often collected via satellite imagery. UAVs and IoT- based sensors, serve as inputs for machine learning models, enabling accurate identification of stress symptoms in crops.

AI techniques used in agriculture

A wide array of artificial intelligence techniques has been applied to manage soil conditions, improve productivity and reduce environmental harm in agriculture, as summarized in Table 1. Management-oriented modeling (MOM) is designed to reduce nitrate leaching by generating multiple practical management strategies. It evaluates each strategy using a simulator and selects the optimal option based on user-defined criteria. MOM employs the *hill-climbing* strategy for global search and *best-first* for tactical decision-making, enabling efficient navigation through decision paths (4, 5).

Another soil management tool, the Soil Risk Characterization Decision Support System (SRC-DSS) includes three phases: acquiring knowledge, conceptualizing design and implementation. It supports decision-makers in identifying potential soil risks and adopting sustainable practices (6). Artificial neural network (ANN) is used to predict soil texture (sand, clay and silt) by combining hydrographic characteristics from digital elevation model (DEM) with features obtained from existing low-resolution soil maps (7). A sophisticated neural network, known as a higher-order neural network (HONN), is coupled with a remote sensing device to analyze and predict changes in soil moisture levels (8).

Crop management, starting from sowing and extending through growth monitoring, harvesting and storage, encompasses actions aimed at enhancing agricultural product growth and yield. Gaining a deep understanding of crop varieties in relation to their preferred soil types and seasonal timing can greatly increase production. Precision crop management (PCM), a strategy in agriculture tailored to allocate crop and soil inputs based on field-specific demands, aiming to maximize the profit while preserving the ecosystem. Nevertheless, PCM faces challenges due to the absence of up-to-date and thorough data on crop and soil conditions (9). To address water shortfalls arising from soil conditions, weather patterns, or insufficient irrigation, farmers must integrate diverse crop management approaches. It's advisable to prioritize flexible crop management systems guided by decision-making rules. Key considerations for selecting cropping alternatives include timing, severity and predictability of drought conditions (10).

A comprehensive grasp of atmospheric pattern aids in decision-making, which leads to increase in crop yield and improved quality (11). PROLOG leverages weather data, machinery capacities, workforce availability and knowledge about authorized and prioritized operators and equipment to evaluate the efficiency of a farming system. Furthermore, it forecasts crop output, total revenue and net earnings for both specific fields and the entire farm (12). The crop prediction approach utilizes the evaluation of various soil and atmospheric factors to predict the most appropriate crop. These factors encompass soil characteristics such as type, pH level, nutrient levels, OC, soil depth, as well as climatic conditions like temperature, rainfall and humidity (13).

Demeter is an automated speed-rowing machine controlled by computer, incorporating a duo of video cameras alongside a global positioning sensor for navigation purposes. It can strategize harvesting operations across an entire field, implementing its plan by cutting crop rows, navigating to cut subsequent rows, adjusting its position within the field and identifying any unexpected obstacles (14). Utilizing AI in cucumber harvesting incorporates several components of the robot's hardware and software. Rainfall data and weather variables specific to each field can be employed at individual locations. Modifying the parameters of artificial neural networks (ANNs) impacts the precision of rice yield forecasts. When managing smaller datasets, it's essential to employ fewer hidden nodes and decrease the learning rates during the optimization process for the model (15).

To achieve optimal agricultural yield, disease control measures are imperative as plant and animal diseases significantly hinder yield improvement. Multiple factors contribute to the development diseases, impacting both plants and animals. These factors may include genetics, soil composition, rainfall, drought, wind, temperature variations and others. Table 1 outlines the various applications of AI in disease management. The Explanation Block (EB) offers a succinct grasp of the rationale utilized by the core of the expert system (16). The system employs a novel approach to rule advancement using fuzzy logic to make intelligent deductions for managing crop diseases. Furthermore, there's integration of a text-to-speech (TTS) converter to facilitate a text-to-voice user interface, improving interactive functionalities on the web for live interactions (17).

Weeds consistently reduce the expected profits and yields for farmers. As per a report, if weed infestations are not controlled, there could be a 50 % decline in yield for dried corn crops and dried

Table 1. AI techniques used in agriculture.

Management	Techniques	Application in agriculture	Constraints	References
Soil Management	Management-oriented modelling (MOM)	Minimizes nitrate leaching and increases yield	Needs a specific timeframe and pertains solely to nitrogen	(5)
	Fuzzy Logic: Soil Risk Characterization Decision Support System (SRC-DSS)	Can categorize soil according to related risks	Requires extensive data sets; only a limited number of instances were analyzed	(6)
	DSS	Decrease erosion and sedimentary yield	Needs extensive datasets for training	(34)
	ANN artificial neural network	It can predict soil enzyme activity effectively and accurately classify soil structure	It only assesses a limited number of soil enzymes and prioritizes classification over enhancing soil performance	(35)
	ANN	It has the capability to predict the average soil temperature monthly	It only considers temperature as a determinant of soil functionality	(36)
	ANN	It predicts soil texture	It necessitates extensive datasets for training and faces limitations in certain implementation areas	(37)
	ANN	Able to predict soil moisture	Over time, the accuracy of predictions may diminish due to the unpredictability of weather conditions	(7)
	ANN	It can estimate soil nutrient levels following erosion events	Its estimation is limited to NH_4 only	(38)
Crop Management	ROBOTICS-Demeter	It can harvest a maximum of 40 hectares of crops	Costly: Consumes significant amounts of fuel	(14)
	CALEX	Can create recommendations for scheduling crop management tasks	Takes time	(39)
	PROLOG	Eliminates farm tools that are used less frequently from the farm	Location-specific	(12)
	ROBOTICS	Achieves an 80 % success rate in crop harvesting	Low efficiency in picking speed and accuracy	(40)
	FUZZY Cognitive Map	Forecast cotton yield and enhance crop quality for decision-making in management	It is relatively slow	(41)
	ANN and Fuzzy Logic	Decreases the presence of crop-damaging insects	Demonstrates difficulty distinguishing between crops and weeds	(42)
	ANN	Can accurately predict rice yield	Takes a lot of time and is only suitable for specific climate	(15)
Disease Management	FL & TTS converter	Addresses plant pathogenic problems promptly	Requires a high-speed internet connection. Utilizes a voice-based interface for multimedia interactions	(43)
	Rule-Based Expert, Data Base (DB)	Produces precise outcomes within the tested conditions	Ineffectiveness of database implementation on a large scale	(16)
	Fuzzy Logic (FL), Web GIS	Cost effective, eco-friendly	Ineffectiveness arises from the dispersed distribution of data, leading to delays in locating and disseminating information. The data's whereabouts are dictated by a mobile browser.	(44)
	FL Web-Based, Web-Based Intelligent Disease Diagnosis System (WIDDS)	Provides accurate and rapid responses to crop disease characteristics	Its effectiveness is constrained by the need for internet connectivity. The extent of its power remains uncertain, given that only four seed crops were considered	(17)
	ANN, GIS	95 % accuracy	Dependent on internet connectivity, which may be inaccessible to certain rural farmers	(45)
	FuzzyXpest	High precision in forecast, offers pest information to farmers, bolstered by internet connectivity	Internet dependent	(46)
	ANN	Has above than 90 % prediction rate	Does not eradicate infections or diminish their impact	(47)

Weed Management	Smart sprayer hardware	Registers the precise location of weeds and applies spray directly to the target	Following detection, a heading angle must be calculated to accurately determine the object's geographic location on the ground	(48)
	Optimization using invasive weed optimization (IVO), ANN	Cost-efficient with improved performance	Difficulty in adapting to new data	(49)
	Mechanical Control of Weeds. ROBOTICS. Sensor machine learning	Saves time while effectively eliminating resistant weeds	Costly. Continuous use of heavy machinery can diminish soil productivity over time	(50)
	UAV, GA	Capable of swiftly and effectively monitoring weeds	Lacks significant control over weeds and comes with a high cost	(27)
	Saloma expert system for evaluation, prediction & weed management	High rate of adaptation and accuracy in prediction	Necessitates extensive data and expertise in utilization	(51)
	Support Vector Machine (SVM), ANN	Swiftly identifies crop stress to facilitate timely site-specific remedies	Only identifies low nitrogen levels	(52)
	Digital Image Analysis (DIA), GPS	Achieves accuracy and success rates exceeding 60 %	It took four years to achieve success, making it a time-consuming process	(28)
	UAV unmanned aerial vehicle	Rapidly detects weeds at a high rate	It's quite costly and demands extensive human expertise	(53)
	Learning Vector Quantization (LVQ), ANN	Quickly identifies weeds with a high recognition rate	The AI's performance was influenced by the method of data input utilized	(54)

beans (18). Weed competition leads to an approximately 48 % decrease in wheat yield (19, 20). At times, these losses could elevate to as much as 60 % (21). Research investigating weed effect on soybean cultivation revealed yield reductions ranging from 8 % to 55 % (22). Research on loss of yield in sesame crops attributes approximately 50 % to 75 % (23). Variations in yield loss can be linked to the length of time crops are subjected to weed presence and the spatial diversity of weed distribution (24-26). As indicated by the WSSA report (Weed Science Society of America), these effects encompass flooding during hurricanes, resilience of certain weed species to wildfires, potential for causing irreversible liver damage if ingested and their ability to outcompete plants or crops by vying for sunlight, water and nutrients. Some weeds possess toxicity and can induce allergic reactions, posing potential threats to public health. Table 1 provides a condensed overview of the applications of AI in weed management.

A system can use images from drones to divide images into parts, calculate and change plant indexes into a binary format, find crop rows, adjust settings for optimization and create a classification model. Using a crop row detection algorithm helps to tell the difference between crop and weed pixels because they look similar in images, especially since crops are usually in rows.

This addresses a common issue encountered in differentiating between crops and weeds (27). Weed control in crops like sugar beet, maize, winter wheat and winter barley often utilize modern techniques such as utilizing digital image analysis from UAVs (drones) for online weed detection, computer-driven decision-making and GPS-guided patch spraying (28).

Furthermore, numerous studies focusing on artificial intelligence were conducted, encompassing a variety of applications and methodologies. A new leaf wetness detection system was developed, employing color imaging of a reference surface and Convolutional Neural Network for detecting leaf wetness duration, a method rooted in artificial intelligence (29). This system underwent testing at two distinct field locations throughout the strawberry growing season, positioned approximately 5 meters away from the strawberry fields. Comparative analysis with manual observations revealed a high level of accuracy in the system's results. Additionally, the predicted labels were cross-referenced with data from the Strawberry Advisory System (SAS). In a related study, a method was presented for detecting plant diseases and infections using transformers, showcasing better performance than current cutting-edge studies (30).

In the study "Smarter Robotic Sprayer System for Precision Agriculture", the authors created an intelligent and unique electric sprayer that can be mounted on a robotic platform and is able to function independently in a variety of challenging environments, including steep inclines and rough terrain (31). To lower losses during pesticide application and lower chemical residues in the soil, the system was tested in actual steep-slope vineyards. The leaf density is determined by the sprayer's crop sensing system using Support Vector Machine (SVM) classifier. The controller in charge of regulating the airflow, water flow rate and water density of the sprayer can utilize this density as a benchmark value. The accuracy score of the leaf density classifier ranges from 80 % to 85 %, according to its results.

The performance of the Precision Robotic Sprayer (PRYSM) was validated by analyzing the size and dispersion pattern of water droplets produced during spraying. These parameters serve as indicators of spray uniformity, coverage efficiency and droplet drift control, which are critical for effective and precise application of agrochemicals.

Mean Weight Diameter (MWD) is a widely accepted indicator of soil aggregate stability and plays a vital role in assessing soil structure and erosion potential. However, unlike other routine soil parameters such as pH, organic matter, or texture, MWD is not commonly measured in standard soil testing due to its labour-intensive and time-consuming procedures.

Remote sensing technologies have shown promising results in agricultural mapping, with spatial crop classification achieving an accuracy of up to 87 % (32). This enables farmers to identify field variability, optimize input allocation and plan precision interventions. Additionally, aerial digital photography using model airplanes has been employed to assess crop biomass and nitrogen status, offering a cost-effective and flexible platform for real-time field monitoring (33).

Challenges and limitation

Many individuals view AI as a commodity relevant solely to digital realms, overlooking its potential applications in physical farming tasks. This perception often stems from a lack of understanding of AI tools, particularly among those outside of the tech industry. Consequently, adoption of AI in agriculture has been sluggish. Despite the long history of advancements in farming, many farmers are more accustomed to traditional methods. The majority have likely not engaged with systems incorporating AI technology.

Lack of practical experience with new technologies

The level of technological advancement in the agricultural industry varies across different regions worldwide. While some areas can fully leverage the boons of AI, in nations where modern agricultural technology is not yet widespread, challenges persist. Technology firms seeking to establish a presence in these emerging agricultural markets must adopt a proactive strategy. To overcome this, technology providers must not only deliver innovative solutions but also invest in farmer training, support services and capacity-building initiatives.

Disinclination to embrace new technologies and processes

Lack of awareness often leads to hesitancy in adopting new technologies, making it challenging for farmers to fully embrace AI, despite its clear benefits. Resistance to innovation and reluctance to try new methods hinder the advancement of farming practices and overall profitability in the sector. It's important for farmers to recognize that AI is simply a more refined version of existing technologies for processing field data. Encouraging adoption of AI among agriculture workers requires providing resources, incentives and training from both the public and private sectors. Governments also need to establish regulations to reassure workers that AI technology is not a threat. Awareness programs, incentives and regulatory support can help bridge this attitudinal gap and encourage gradual adoption.

High initial investment cost

A significant drawback of integrating artificial intelligence into agriculture is the substantial upfront expenses involved. Developing and deploying AI systems demand considerable financial investment, posing a barrier for small-scale farmers and agricultural enterprises. According to a World Economic Forum report, the cost of AI implementation in agriculture can vary widely, ranging from tens of thousands to millions of dollars, contingent on system complexity and operational scale. This financial burden can impede farmers' adoption of AI technology, particularly in developing nations where access to capital is limited. Nevertheless, it's crucial to acknowledge that despite the initial costs, the long-term advantages of AI in agriculture, such as enhanced efficiency, increased yields and reduced labor expenditures, can outweigh these financial challenges.

Limited access to small scale farmers

The utilization of Artificial Intelligence (AI) in agriculture presents opportunities for industry transformation, yet it also carries drawbacks. One significant disadvantage is the limited accessibility for small-scale farmers. The cost associated with implementing and maintaining AI technology often exceeds the financial capabilities of many small-scale farmers, creating a barrier to adoption. Consequently, a digital divide emerges between large-scale and small-scale farmers, with the former enjoying the benefits of AI while the latter are left at a disadvantage. This disparity can deepen existing inequalities within the agricultural sector and impede the advancement of sustainable agricultural practices. Therefore, it is imperative to explore avenues to enhance the accessibility and affordability of AI technology for small-scale farmers, ensuring that its potential benefits are accessible to all.

Huge upfront cost

While artificial intelligence (AI) can offer cost savings in the long run, the initial investment can be significant. This may present challenges for many agribusinesses and farms, especially smaller-scale growers and those in developing countries, making the current feasibility of AI adoption uncertain. However, as technology advances, the cost of implementing AI in agriculture is anticipated to decline. Additionally, businesses have the opportunity to seek support from alternative funding sources such as private investments or government grants.

Dependency on technology and expertise

While AI can offer valuable insights and guidance, it necessitates a high level of technical proficiency for operation and maintenance. Farmers without the requisite skills may struggle to utilize AI effectively, leading to dependency on external experts or service providers. Relying on AI technology can be expensive and time-intensive, particularly for small-scale farmers who don't have the means to invest in such technology. Furthermore, the use of AI may diminish traditional farming skills and knowledge as farmers increasingly rely on technology for decision-making. This trend could have enduring consequences for the sustainability and resilience of agricultural systems, particularly in regions where traditional farming practices prevail.

AI start-ups in agriculture

Prospera, founded in 2014 in Israel, offers intelligent, cloud-based solutions for efficient farming by collecting extensive field data on soil, water and aerial imagery, utilizing its Prospera device equipped with various sensors and computer vision technology. Similarly, Blue River Technology, established in California in 2011, develops advanced agricultural machinery that employs AI, computer vision and robotics to recognize plants and optimize farming strategies, thereby reducing costs and chemical usage. FarmBot presents an open-source CNC precision farming system that allows users to autonomously grow crops using a physical robot and software package, all manageable via a web application. In India, Fasal is focused on providing cost-effective sensors for real-time data and insights to small-scale farmers, aiming to democratize precision farming through AI-driven tools. Lastly, One Soil offers a software solution that leverages machine learning and computer vision to help farmers monitor crops, detect field issues, access weather forecasts and calculate fertilizer rates, enabling informed agricultural decisions.

Future scope

The future of artificial intelligence in agriculture is highly promising, offering solutions to some of the sector's most pressing challenges. In the near term, AI is expected to drive the widespread adoption of precision farming technologies, including smart irrigation systems, automated pest detection and real-time soil monitoring. These innovations can significantly reduce input costs, enhance yields and mitigate environmental impacts. In the long term, AI may facilitate the development of climate-resilient crop varieties and intelligent decision-support systems that integrate genomic, weather and soil data for tailored agricultural management. The integration of AI with biotechnology, IoT and remote sensing can usher in a new era of sustainable, data-driven farming. However, to realize this potential, it is essential to address existing limitations related to data availability, algorithm refinement and affordability. With continued advancements in computing, stronger institutional support and inclusive policy frameworks, AI is well-positioned to enhance agricultural resilience, productivity and global food security in the coming decades.

Conclusion

Artificial Intelligence (AI) has the potential to revolutionize agriculture by enhancing productivity, sustainability and decision-making efficiency. Through AI-driven tools such as sensors, drones and predictive models, farmers can monitor soil health, weather patterns and irrigation need with greater precision. However, limitations including insufficient infrastructure, high initial costs and low awareness impede widespread adoption. Addressing these barriers through targeted research, institutional support and collaborative frameworks is essential to realizing AI's transformative impact on modern agriculture.

Acknowledgements

We acknowledge individuals who provided technical assistance or writing support. Additionally, we extend gratitude to department chairs who offered general support. We are grateful for their contributions.

Authors' contributions

BS and VM contributed to material collection, organization and design. RS and AS were responsible for reference collection. SK[1], SK[2] and M participated in the study design and contributed to reviewing related papers and the manuscript. VA and PS conceived the study, drafted and edited the manuscript and coordinated the work. All authors read and approved the final manuscript. [SK[1]-Shruti Kumari; SK[2]- Stanzin Khenrab].

Compliance with ethical standards

Conflict of interest: Authors declare no conflict of interests to declare.

Ethical issues: None

References

1. Dutta S, Rakshit S, Chatterjee D. Use of artificial intelligence in Indian agriculture. Food and Scientific Reports. 2020;1(4):65-72.
2. Bellini V, Cascella M, Cutugno F, Russo M, Lanza R, Compagnone C, et al. Understanding basic principles of artificial intelligence: a practical guide for intensivists. Acta Bio Medica: Atenei Parmensis. 2022;93(5). https://doi.org/10.23750/2Fabm.v93i5.13626
3. Kim Y, Evans RG, Iversen WM. Remote sensing and control of an irrigation system using a distributed wireless sensor network. IEEE Transactions on Instrumentation and Measurement. 2008;57(7):1379-87. https://doi.org/10.1109/TIM.2008.917198
4. Dara R, Hazrati Fard SM, Kaur J. Recommendations for ethical and responsible use of artificial intelligence in digital agriculture. Frontiers in Artificial Intelligence. 2022;5:884192. https://doi.org/10.3389/frai.2022.884192
5. Li M, Yost RS. Management-oriented modeling: optimizing nitrogen management with artificial intelligence. Agricultural Systems. 2000;65(1):1-27. https://doi.org/10.1016/S0308-521X(00)00023-8
6. López EM, García M, Schuhmacher M, Domingo JL. A fuzzy expert system for soil characterization. Environment International. 2008;34(7):950-8. https://doi.org/10.1016/j.envint.2008.02.005
7. Zhao Z, Chow TL, Rees HW, Yang Q, Xing Z, Meng FR. Predict soil texture distributions using an artificial neural network model. Computers and Electronics in Agriculture. 2009;65(1):36-48. https://doi.org/10.1016/j.compag.2008.07.008
8. Elshorbagy A, Parasuraman K. On the relevance of using artificial neural networks for estimating soil moisture content. Journal of Hydrology. 2008;362(1-2):1-8. https://doi.org/10.1016/j.jhydrol.2008.08.012
9. Moran MS, Inoue Y, Barnes EM. Opportunities and limitations for image-based remote sensing in precision crop management. Remote Sensing of Environment. 1997;61(3):319-46. https://doi.org/10.1016/S0034-4257(97)00045-X
10. Debaeke P, Aboudrare A. Adaptation of crop management to water-limited environments. European Journal of Agronomy. 2004;21(4):433-46. https://doi.org/10.1016/j.eja.2004.07.006
11. Aubry C, Papy F, Capillon A. Modelling decision-making processes for annual crop management. Agricultural Systems. 1998;56(1):45-65. https://doi.org/10.1016/S0308-521X(97)00034-6
12. Lal H, Jones JW, Peart RM, Shoup WD. FARMSYS-a whole-farm machinery management decision support system. Agricultural Systems. 1992;38(3):257-73. https://doi.org/10.1016/0308-521X(92)90069-Z
13. Dahikar SS, Rode SV. Agricultural crop yield prediction using artificial neural network approach. International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering. 2014;2(1):683-6.
14. Pilarski T, Happold M, Pangels H, Ollis M, Fitzpatrick K, Stentz A. The demeter system for automated harvesting. Autonomous Robots. 2002;13:9-20. https://doi.org/10.1023/A:1015622020131
15. Ji B, Sun Y, Yang S, Wan J. Artificial neural networks for rice yield prediction in mountainous regions. The Journal of Agricultural Science. 2007;145(3):249-61. https://doi.org/10.1017/S0021859606006669
16. Balleda K, Satyanvesh D, Sampath NV, Varma KT, Baruah PK. Agpest: An efficient rule-based expert system to prevent pest diseases of rice & wheat crops. In: 2014 IEEE 8th International Conference on Intelligent Systems and Control (ISCO); 2014. p. 262-8. https://doi.org/10.1109/ISCO.2014.7103957
17. Kolhe S, Kamal R, Saini HS, Gupta GK. A web-based intelligent disease-diagnosis system using a new fuzzy-logic based approach for drawing the inferences in crops. Computers and Electronics in Agriculture. 2011;76(1):16-27. https://doi.org/10.1016/j.compag.2011.01.002
18. Neil Harker K. Survey of yield losses due to weeds in central Alberta. Canadian Journal of Plant Science. 2001;81(2):339-42. https://doi.org/10.4141/P00-102
19. Khan M, Haq N. Wheat crop yield loss assessment due to weeds. Sarhad Journal of Agriculture (Pakistan). 2002;18(4):449-53. https://doi.org/10.1016/j.cropro.2018.01.007
20. Fahad S, Hussain S, Chauhan BS, Saud S, Wu C, Hassan S, et al. Weed growth and crop yield loss in wheat as influenced by row spacing and weed emergence times. Crop Protection. 2015;71:101-8. https://doi.org/10.1016/j.cropro.2015.02.005

21. Rao AN, Wani SP, Ladha JK. Weed management research in India-an analysis of past and outlook for future. Monograph. DWR, Jabalpur; 2014.

22. Datta A, Ullah H, Tursun N, Pornprom T, Knezevic SZ, Chauhan BS. Managing weeds using crop competition in soybean [*Glycine max* (L.) Merr.]. Crop Protection. 2017;95:60-8. https://doi.org/10.1016/j.cropro.2016.09.005

23. Mruthul T, Halepyati A S, Chittapur BM. Chemical weed management in sesame (*Sesamum indicum* L.). MSc Thesis. College of Agriculture, Raichur: University of Agricultural Sciences; 2015.

24. Swanton CJ, Nkoa R, Blackshaw RE. Experimental methods for crop –weed competition studies. Weed Science. 2015;63(SP1):2-11. https://doi.org/10.1614/WS-D-13-00062.1

25. Jha P, KumarV, Godara RK, Chauhan BS. Weed management using crop competition in the United States: A review. Crop Protection. 2017;95:31-7. https://doi.org/10.1016/j.cropro.2016.06.021

26. Milberg P, Hallgren E. Yield loss due to weeds in cereals and its large -scale variability in Sweden. Field Crops Research. 2004;86(2-3):199-209. https://doi.org/10.1016/j.fcr.2003.08.006

27. Pérez-Ortiz M, Gutiérrez PA, Peña JM, Torres-Sánchez J, López-Granados F, Hervás-Martínez C. Machine learning paradigms for weed mapping via unmanned aerial vehicles. In: 2016 IEEE symposium series on computational intelligence (SSCI); 2016. p. 1-8. https://doi.org/10.1109/SSCI.2016.7849987

28. Gerhards R, Christensen S. Real-time weed detection, decision making and patch spraying in maize, sugarbeet, winter wheat and winter barley. Weed Research. 2003;43(6):385-92. https://doi.org/10.1046/j.13653180.2003.00349.x

29. Patel AM, Lee WS, Peres NA. Imaging and deep learning based approach to leaf wetness detection in strawberry. Sensors. 2022;22(21):8558. https://doi.org/10.3390/s22218558

30. Parez S, Dilshad N, Alghamdi NS, Alanazi TM, Lee JW. Visual intelligence in precision agriculture: exploring plant disease detection via efficient vision transformers. Sensors. 2023;23(15):6949.

31. Baltazar AR, Santos FN, Moreira AP, Valente A, Cunha JB. Smarter robotic sprayer system for precision agriculture. Electronics. 2021;10(17):2061. https://doi.org/10.3390/electronics10172061

32. Nema S, Awasthi MK, Nema RK. Spatial crop mapping and accuracy assessment using remote sensing and GIS in Tawa command. International Journal of Current Microbiology and Applied Sciences. 2018;7(5):3011-8. https://doi.org/10.20546/ijcmas.2018.705.350

33. Hunt ER, Cavigelli M, Daughtry CS, Mcmurtrey JE, Walthall CL. Evaluation of digital photography from model aircraft for remote sensing of crop biomass and nitrogen status. Precision Agriculture. 2005;6:359-78. https://doi.org/10.1007/s11119-005-2324-5

34. Montas HU, Madramootoo CA. A decision support system for soil conservation planning. Computers and Electronics in Agriculture. 1992;7(3):187-202. https://doi.org/10.1016/S0168-1699(05)80019-5

35. Tajik S, Ayoubi S, Nourbakhsh F. Prediction of soil enzymes activity by digital terrain analysis: comparing artificial neural network and multiple linear regression models. Environmental Engineering Science. 2012;29(8):798-806. https://doi.org/10.1089/ees.2011.0313

36. Levine ER, Kimes DS, Sigillito VG. Classifying soil structure using neural networks. Ecological Modelling. 1996;92(1):101-8. https://doi.org/10.1016/0304-3800(95)00199-9

37. Bilgili M. The use of artificial neural networks for forecasting the monthly mean soil temperatures in Adana, Turkey. Turkish Journal of Agriculture and Forestry. 2011;35(1):83-93. https://doi.org/10.3906/tar-1001-593

38. Behrens T, Förster H, Scholten T, Steinrücken U, Spies ED, Goldschmitt M. Digital soil mapping using artificial neural networks. Journal of Plant Nutrition and Soil Science. 2005;168(1):21-33. https://doi.org/10.1002/jpln.200421414

39. Plant RE. An artificial intelligence based method for scheduling crop management actions. Agricultural Systems. 1989;31(1):127-55. https://doi.org/10.1016/0308-521X(89)90017-6

40. Van Henten EJ, Hemming J, Van Tuijl BA, Kornet JG, Meuleman J, Bontsema J, et al. An autonomous robot for harvesting cucumbers in greenhouses. Autonomous Robots. 2002;13(3):241-58. https://doi.org/10.1023/A:1020568125418

41. Papageorgiou EI, Markinos AT, Gemtos TA. Fuzzy cognitive map based approach for predicting yield in cotton crop production as a basis for decision support system in precision agriculture application. Applied Soft Computing. 2011;11(4):3643-57. https://doi.org/10.1016/j.asoc.2011.01.036

42. Yang CC, Prasher SO, Landry JA, Ramaswamy HS. Development of a herbicide application map using artificial neural networks and fuzzy logic. Agricultural Systems. 2003;76(2):561-74. https://doi.org/10.1016/S0308-521X(01)00106-8

43. Mudgil M, Kumar A. A brief survey on the applications of artificial intelligence and machine learning in agriculture. International Journal of Mechanical Engineering. 2021;6. https://doi.org/10.56452/2021SP-8-021

44. Jesus JO, Panagopoulos TH, Neves AL. Fuzzy logic and geographic information systems for pest control in olive culture. In: 4th IASME/WSEAS International Conference on Energy, Environment, Ecosystems & Sustainable Development, Algarve, Portugal; 2008 Jun 11.

45. Liu G, Yang X, Ge Y, Miao Y. An artificial neural network-based expert system for fruit tree disease and insect pest diagnosis. In: 2006 IEEE International Conference on Networking, Sensing and Control. IEEE; 2006. p. 1076-9. https://doi.org/10.1109/ICNSC.2006.1673301

46. Siraj F, Arbaiy N. Integrated pest management system using fuzzy expert system. In: Proceedings of Knowledge Management International Conference & Exhibition (KMICE). Legend Hotel Kuala Lumpur, Malaysia. Universiti Utara Malaysia, Sintok; 6-8 June 2006. p. 169-76.

47. Wang X, Zhang M, Zhu J, Geng S. Spectral prediction of *Phytophthora infestans* infection on tomatoes using artificial neural network (ANN). International Journal of Remote Sensing. 2008;29(6):1693-706. https://doi.org/10.1080/01431160701281007

48. Partel V, Kakarla SC, Ampatzidis Y. Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. Computers and Electronics in Agriculture. 2019;157:339-50. https://doi.org/10.1016/j.compag.2018.12.048

49. Moallem P, Razmjooy N. A multi-layer perception neural network trained by invasive weed optimization for potato color image segmentation. Trends in Applied Sciences Research. 2012;7(6):445-55. https://doi.org/10.3923/tasr.2012.445.455

50. Brazeau M. Fighting weeds: can we reduce, or even eliminate, herbicides by utilizing robotics and AI. North Wales: Genetic Literacy Project; 2018.

51. Stigliani L, Resina C. SELOMA: expert system for weed management in herbicide-intensive crops. Weed Technology. 1993;7(3):550-9. https://doi.org/10.1017/S0890037X00037337

52. Karimi Y, Prasher SO, Patel RM, Kim SH. Application of support vector machine technology for weed and nitrogen stress detection in corn. Computers and Electronics in Agriculture. 2006;51(1-2):99-109. https://doi.org/10.1016/j.compag.2005.12.001

53. López-Granados F. Weed detection for site-specific weed management: mapping and real-time approaches. Weed Research. 2011;51(1):1-1. https://doi.org/10.1111/j.1365-3180.2010.00829.x

54. Yang CC, Prasher SO, Landry J, Ramaswamy HS. Development of neural networks for weed recognition in corn fields. Transactions of the ASAE. 2002;45(3):859. https://doi.org/10.13031/2013.8854

Additional information

Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

Reprints & permissions information is available at https://horizonepublishing.com/journals/index.php/PST/open_access_policy

Publisher's Note: Horizon e-Publishing Group remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Indexing: Plant Science Today, published by Horizon e-Publishing Group, is covered by Scopus, Web of Science, BIOSIS Previews, Clarivate Analytics, NAAS, UGC Care, etc

See https://horizonepublishing.com/journals/index.php/PST/indexing_abstracting

Publisher information: Plant Science Today is published by HORIZON e-Publishing Group with support from Empirion Publishers Private Limited, Thiruvananthapuram, India.