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DOI
10.1016/j.cpb.2025.100476

Publication date
2025

Document Version
Final published version

Published in
Current Plant Biology

Citation (APA)
Kusumavathi, K., Konatala, R., Lal, P., Sarkar, S., Banerjee, H., Bandopadhyay, P., Sethi, D., & Upendar, K. (2025). Artificial intelligence for fostering sustainable agriculture. *Current Plant Biology*, *42*, Article 100476. https://doi.org/10.1016/j.cpb.2025.100476

Current Plant Biology 42 (2025) 100476

Contents lists available at ScienceDirect

Current Plant Biology

journal homepage: www.elsevier.com/locate/cpb

Artificial intelligence for fostering sustainable agriculture

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ARTICLE INFO

Keywords:
Artificial intelligence
Drones
Robots
Sensors
Sustainable agriculture

ABSTRACT

Agriculture intensification has a paradoxical effect, as it increases food production and productivity by increasing farmer's return on investment while instantaneously posing a serious threat to long-term sustainability like depletion of resources, soil degradation, water scarcity and finally environmental pollution. All these challenges have flickered concerns about the quality of life. To bash all these concerns, the precise and judicious use of agricultural inputs is necessary. Bespoke solutions (Site-Specific) tailored to specific problems can optimize resource utilization while minimizing negative impacts. Integrating advanced technologies like automation by the use of sensors, drones and robotics guarantees solutions in the context of availability and efficiency of agricultural labour decline. This technology-driven approach can reform agriculture. So, the holistic approach of using technological advancements with sustainable practices is necessary for a long-term ecological balance with enhancement in productivity. The integration of driven solutions allows farmers to obtain real-time insights into soil health, water availability and nutrient status facilitating sustainable farming practices. The main goal of this manuscript is to review the applications of AI in agriculture for crop monitoring with sustainable use of resources such as soil, water, and nutrients, as well as to elevate food production with better quality maintenance. This article scrutinizes the findings of several researchers to get a brief outline of the subject of the recent execution of automation in agriculture and compares it with conventional methods followed by the farmer.

1. Introduction

Intensive transformation and landscaping can reduce biodiversity, pollute air and water sources, and put human and animal health at risk [1–3]. Agriculture faces critical challenges, including climate change, water scarcity, environmental degradation, and dependence on conventional energy sources [1]. Sustainable agriculture is an agricultural practice that permanently meets the essential conditions of environmental health, economic viability, and social equity while ensuring long-term productivity and resource conservation [4,5].

A key challenge for the agriculture industry is feeding a rapidly growing population. There is growing consensus that transforming the global food system is essential to ensure safe and nutritious food for all while maintaining ecological balance within the earth's limit [6,7]. An estimate reveals that nearly 10 billion people by 2050 will boost demand for food, with about 3 billion more mouths to feed than there were in 2010 [8]. India is the most populous country surpassing China, but the biggest drawback for India is that it projects 17 per cent of the world's population and constitutes only 2.2 per cent of the world's land mass [9]. Globally about 720–800 million people are suffering from food insecurity [10]. Moreover, the use of natural resources in recent days has been highly stressed as 25 % of all farmland is highly degraded [11] and about 80 % of deforestation is driven by agriculture globally [12]. In India, the national average soil erosion is estimated at 21 tons per hectare per year. This loss can be directly attributed to anthropogenic interventions such as deforestation and intensive agricultural practices [13]. Agriculture is the most water-intensive sector, accounting for 70 % of global freshwater use, while the industrial sector consumes 22 % and domestic use makes up 8 %, significantly impacting freshwater availability [14]. Over 25 % of the world's population and 40 % of global

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https://doi.org/10.1016/j.cpb.2025.100476
Received 15 September 2024; Received in revised form 23 March 2025; Accepted 24 March 2025
Available online 25 March 2025

agricultural production depend heavily on unsustainable groundwater extraction [15].

Climate change, accompanied by increased emissions of green house gases (GHG), is to blame for declining agricultural productivity [16].The top six countries with GHG emissions in 2022 were China, the United States, India, the EU27, Russia, and Brazil [17]. Globally these six countries constitute 50.1 % of the global population, 61.2 % of Gross Domestic Product [18], 63.4 % of fossil fuel consumption [19] and 61.6 % of GHG emissions. In 2022, India, the world's third-largest GHG emitter, accounted for a 5 % rise in emissions compared to 2021, the highest relative increase globally [17]. Food waste across the globe has reached an enormous scale, and India holds the second position with 68, 760,163 tonnes of total food waste per year after China [20,21]. All the above-mentioned challenges leadto poverty and hunger, as India is already classified in the "serious category" on the Global Hunger Index (GHI) severity scale [22]. As such, a worldwide agricultural transformation is needed to switch from conventional to modern automated approaches [23].

A dramatic transformation in technological progress has been noticed with the advent of artificial intelligence (AI) in all industrial sectors across the globe [8,24]. Agriculture, on the other hand, being the least digitized, fueled the growth and commercialization of agro-technologies [8]. Inevitably, AI seems to be a separate realm for agriculture. Agriculture harnesses natural resources to sustain the global population by producing food [25]. On the other side, AI is acutely entangled with automated systems, multifaceted communications, modeling, and decision-making approach [26]. Women are more engaged in agriculture than men due to male migration for better livelihoods. With fewer youth in farming and small farms becoming unviable, de-peasantization is pushing many into agricultural labour, impacting future food production [27]. Training youth in AI-driven agriculture using sensors, drones, and robotics can transform the industry, enhancing efficiency and sustainability. Farmers should keep a close eye on climatic, ecological, and geographic factors to ensure sustainable agricultural production and economic survival in the face of a highly competitive and globalizing sector. Farming is one of the oldest and arguably most important human pursuits, as well as one that entails a huge mixture of choices, complexity, and ambiguity, along with qualms like variation from season to season and weather, cost of farming equipment, degradation of soil, cropping feasibility, smothering by weeds, crops, crop damage due to pests and diseases, and variable climates. Hence, it's vital to assess the application of AI in agriculture with regard to soil, crop, disease, and pest management.

AI-powered farming solutions enable farmers to be more productive with fewer resources, improve crop quality, and provide a quick go-to-market (GTM) strategy for crops. Innovation is integral to conquering the challenges, and India has been on a rising trajectory over the past several years from a rank of 81 in 2015–40 in 2023 [28].

This implies that, relative to its gross domestic product (GDP), India grew 8.15 % YoY over the fiscal 2023–2024 [29].The domain of modern agriculture tackles colossal challenges where conditions cannot be over simplified to propose a universal solution. Agriculture4.0:" The Future of Farming Technology, "issued by the World Government Summit in 2018, spotlights assimilating budding technologies such as the Internet of Things (IoT), artificial intelligence, blockchain, data analytics, big data, etc. for the best possible resource use and amplifying the production of agricultural practices [30]. Accuracy and robustness are two factors for AI [31] that facilitate depicting the complicated details of each situation on the farm and coming up with an outcome that suits well for a particular problem [8]. The indigenous way of arming is no longer capable of feeding the burgeoning population [7]. The problem of increased demand has only one solution: intensifying agricultural practices and in the long run, the land remains unproductive. Automation can be replaced with the intensification of agricultural practices to fulfill the needs of the global population safely [32].

The use of digitalization caused humans to surpass the threshold level of thought process and attempt to combine their natural human brains with an artificial one [33]. Consequently, an entirely new field has been created called 'Artificial Intelligence' (AI). Precisely, AI represents "intelligent behaviour" puzzled by human experts in the expansion of certain responsibilities [34]. AI is tools enable machines to think and suggest algorithms for forecasting unforeseen troubles or occurrences to resolve the issues in the agricultural field not only with precision but also by estimating resolutions for improving crop productivity while maximizing resource utilization and preservation [35]. The AI also used in the plant biotechnology for solving several issues like metabolomics, transcriptiosome, pharmacogenetics, and functional and structural genomics [36,37]. Next-generation AI and Big data also reported for using in crop breeding programs [38,39]. The main goal of this manuscript is to review the applications of AI in agriculture for crop monitoring with sustainable use of resources such as soil, water, and nutrients, as well as to elevate food production with better quality maintenance. This article scrutinizes the findings of several researchers to get a brief outline on the subject of the recent execution of automation in agriculture and compares it with conventional methods followed by the farmer.

2. Bibliometric analysis

For bibliometric analysis on the theme, data from Scopus was extracted and the analysis was done in Biblioshiny using R-software package. For extraction of data the search engine used was "Artificial Intelligence" and "Sustainable agriculture" OR "Artificial Neural Network". Total of 738 documents were extracted and later the data retrieved was screened and unwanted data was eliminated. Later using the inclusion criteria and eliminating unwanted articles, the data was analyzed in Biblioshiny. Different types of analysis were conducted like number of publications, citation over time, prolific authors, etc., which is presented in the subsequent section. The study period for bibliometric analysis was taken as last 23 years when the topic accentuated (Fig. 1).

Publication on artificial intelligence in agriculture very few, till 2016 from 2002, thereafter it was increased slowly and a sudden spike in publications after 2019 which adheres to the fact that both sustainable agriculture and artificial intelligence have trend in the recent decade (Fig. 2). The highest (20.2 %) number of publications concerning to artificial intelligence was on computer science followed by engineering (15.1 %), agriculture and allied (12.5 %), environmental science (5.6 %), social science (5.6 %), energy (4.8 %) mathematics (4.6 %), decision science (4.3 %), business management (3.4 %), Earth and planet (3.3 %) and others (15.4 %) (Fig. 3). The highest frequency of word is "artificial intelligence" followed by "sustainable development". Decision support systems, agriculture robots etc. were among the other most frequently used keywords (Fig. 4). The highest volume of contributions towards publication related to AI was in China followed by India, USA, Italy and Spain (Fig. 5). The highest number of publications as well as collaborative publications (multi-country publications) was higher in India followed by the China, USA and Germany (Fig. 6).

3. Types of artificial intelligence

Artificial Intelligence is broadly divided into two categories viz based on capability and functionality and also further classified (Fig. 7).

3.1. Classification based on capability

Artificial Narrow Intelligence (ANI), also known as weak artificial intelligence, accomplishes a single narrow task with inadequate capabilities [40]. Its usage is exponentially increasing and has become a part of our lives. Google Maps, Google Assistant, Image and Facial Recognition Systems, Google Translate, Amazon Alexa, and Apple Siri are examples of ANI [41]. Artificial General Intelligence (AGI) teaches computers to think and act like humans [40]. This kind of intelligence is mainly helpful in overcoming dilemmas, planning, and decision-making under uncertain situations, but the time taken to accomplish tasks is more than that of artificial super intelligence (ASI) [42]. Artificial super intelligence (ASI) is more advanced and makes computers or machines superior to humans in ways like being wiser, smarter, and more creative [42]. This type of intelligence revolutionizes human actions before they even occur. So many people are agonizing over the changes it wishes to bring about in human society.

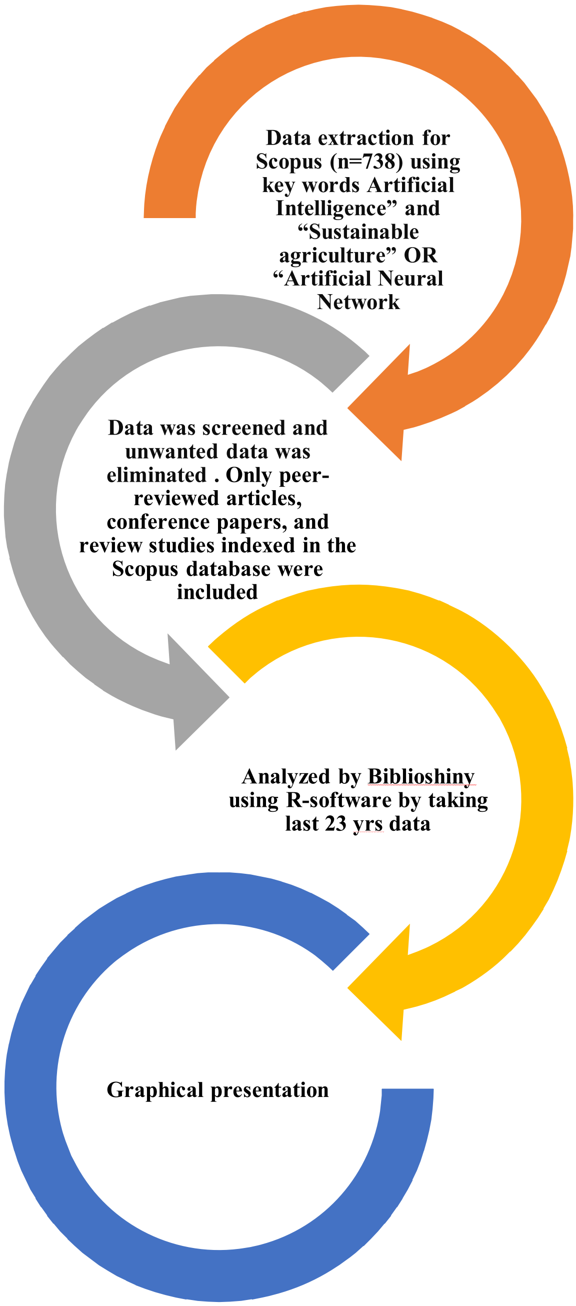

Fig. 1. Flow-Chart represents the data extraction and analysis.

3.2. Classification based on functionality

The simplest form is the reactive machine, as it deals with existing data and not previous cumulative data [43]. It reacts to the recent situation, hence the nomenclature. Limited memory deals with acquired past data to accomplish an action, and the experience gained is limited. The theory of mind has the skill to react and is full of emotions, which permits machines to be aware of human behaviour. Self-Awareness: The entity of self-awareness in machines is still imaginary. A self-aware AI would have human-level awareness, but through sophisticated investigations, it may turn out to be the most advanced form of AI proven to humankind.

3.3. Digital appliances used in agriculture

The introduction of AI to agriculture will be enabled by other technological advances, including robotics, the availability of sensors and cameras, drone technology, and even wide-scale internet coverage on geographically dispersed fields. Various AI technologies are embedded in digital appliances like sensors, drones, and robotics in agriculture to make it more comfortable and precise with the least amount of effort from humans when compared to the manual method of farming.

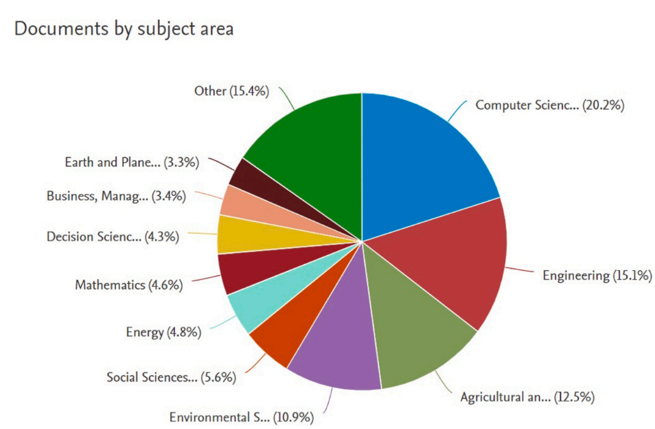

Fig. 3. Publications regarding artificial intelligence on subject area.

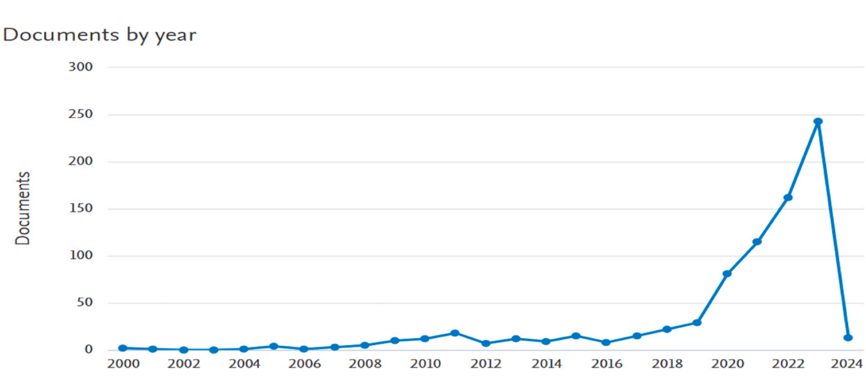

Fig. 2. Publication per year from2002 to2024 (till08.01.2024).

Fig. 4. Word cloud map on the theme of studies.

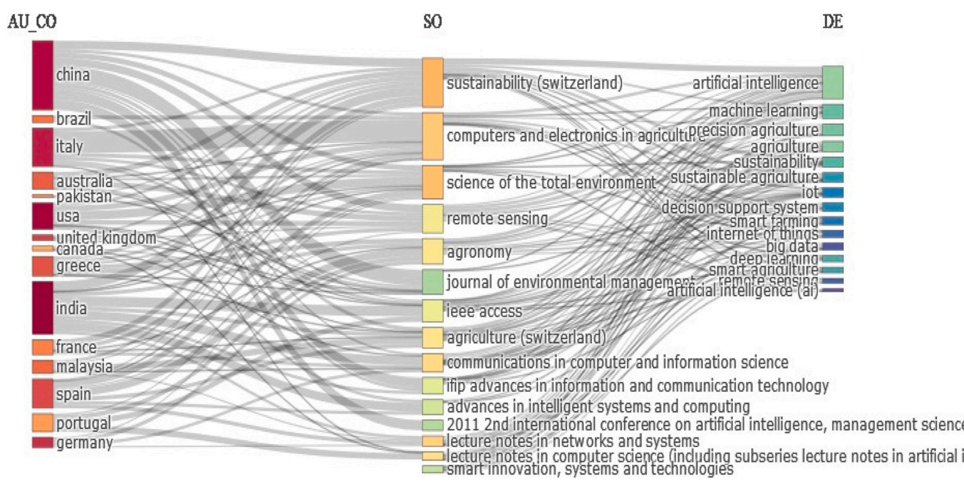

Fig. 5. Sankey graph for author countries, sources and keywords.

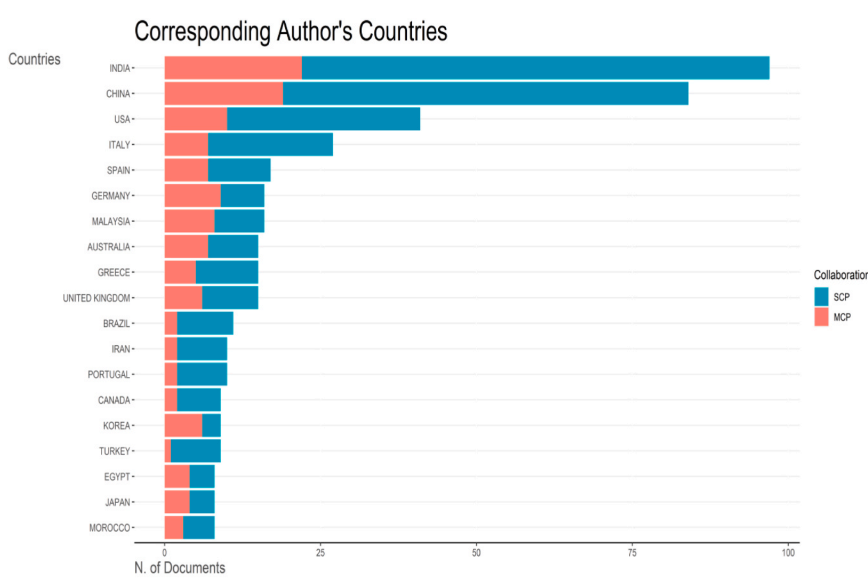

Fig. 6. Corresponding author country (single and multi-country publications).

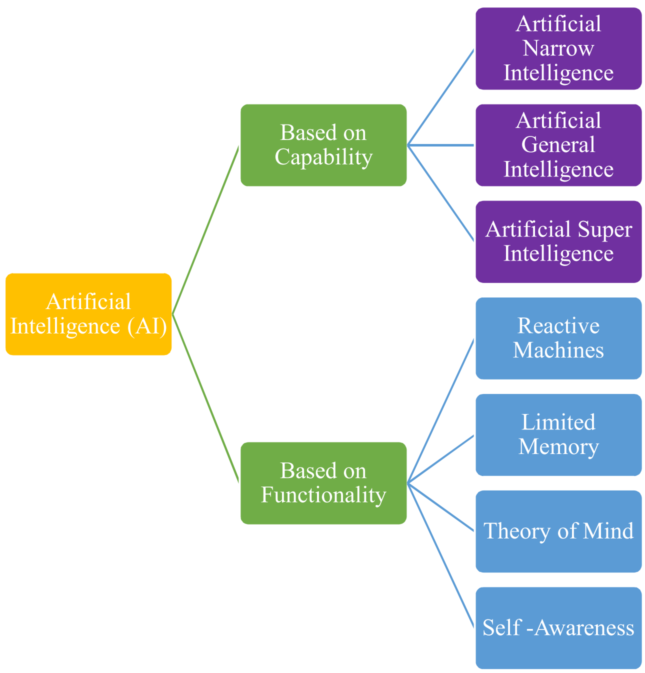

Fig. 7. Classification of Artificial Intelligence.

3.3.1. Sensors

Sensors play a decisive role in this technological revolution [44]. It's simply "a device that counters a physical stimulus (as heat, light, sound, pressure, magnetism, or a particular motion) and diffuses an impulse (as for measurement or operating a control). In other words, it is a trouble-free and tiny device that detects natural world conditions such as motion, heat, or light and converts the data into an analogue or digital representation. Innovations result in the development of new sensors that are more precise, and have lower dimensions and costs, but do not sacrifice performance. A new generation sensor called 'smart' was developed by suing recent technologies which are capable of wireless communication from remote areas [45]. Farmers can predict calamities caused by both biotic and abiotic factors by using smart sensors in agriculture; thereby, they can sustain resources, protect crops from environmental impact or disaster, and finally increase productivity. Some sensors, like WeedSeeker, are used for spot spray systems aimed at the selective application of herbicides, GreenSeeker is used for plant health and vigour in terms of NDVI readings, and ultrasonic sensors are used for spraying boom height control. Today, all the machinery used in the agriculture sector, like tractors, sprayers, bailers, and combines, is endowed with sensors for measuring different parameters that fall into navigation, guidance, and obstacle avoidance using GPS and inertial sensors such as gyroscopes and accelerometers for control (e.g., speed, height of spray booms or other tools above the ground). Performance monitoring such as harvested crop quantity, condition, or rate of seed dispersal. Soil moisture is measured using several sensors for irrigation water management [46]. Fabbri et al. [47] conducted an experiment entitled "Sustainability Assessment of the Green Seeker N Management Tool: A Lysimetric Experiment on Barley" to evaluate the application of a specific sensor-based N rate for Italian barley production and compare it with conventional N management. Sensor-based N fertilization rate (RF) tanks showed a higher NDVI than conventional fertilization (CF) at the senescence stage, and crops did not require additional N. The NDVI values are directly proportional to the levels of N. The reduction of NDVI is due to lower absorption of radiation in the visible region, which occurs mainly because of low chlorophyll content. The ultimate reason for all these is low N levels supplied to crops. As a result, the lack of nitrogen in control tanks caused crop yellowing and stunted vegetative growth. The use of a SPAD meter in conjunction with Green seeker to determine the threshold color of rice leaves in terms of NDVI and SPAD value at which N-fertilizer should be applied for increased yield and N use efficiency [48]. In this manner, the application of sensors in agriculture can revolutionize production by facilitating real-time environmental detection, and enhancing sustainability through efficient resource conservation, including water and agricultural inputs such as nutrients and herbicides.

3.3.2. Drones

The drone revolution is nothing but "an eye in the sky for agriculture." Drones are the farming of the future, and by fine-tuning the implementation of drone technology, a miracle can be accomplished in the drone sector. As the agricultural sector renews, the adoption of drone technology is anticipated to increase significantly. Understanding how to use this technology wisely is essential, as it can enhance efficiency and save time for farmers. According to projections, the global agricultural drone market will reach $5.7 billion by 2025, growing at a 35.9 % CAGR. A drone, also known as an unmanned aerial vehicle (UAV), is a robotic vehicle and flying device that can be controlled remotely using autopilot and GPS coordinates. The device also has normal radio controls and can be piloted manually in case of an adverse situation. The major components of a drone are the chassis, propellers, motors, electronic speed controller (ESC), flight controller, radio receiver, and battery. A list of remotely piloted aircraft (RPA) systems is given in Table 1. According to Nuijten et al. [49], unmanned aerial systems (UAS) along with digital aerial photo grammetry and object-based image analysis (OBIA) methods enable effective crop productivity analysis. The template matching and multi-resolution image segmentation (MIRS) resulted in 99.8 and 85.4 per cent accuracy with respect to crop detection and well-delineated main crop areas, respectively. Drones in agriculture are helpful in soil and field analysis, crop monitoring, planting, spraying agrochemicals, preparing for weather glitches, geo-fencing and avoiding the overuse of chemicals. The major drawbacks to the usage of drones are internet connectivity issues, weather dependence and the need for knowledge and skill.

3.3.3. Robotics

The term "robot" was first used in 1923, and thereafter, it has made epic advancements in various fields, including agriculture. Agricultural robotics is the logical proliferation of automation technology into biosystems [50]. A robot consists of moving parts and sensors, but AI helps in processing the program environment by enabling it to understand and do things on its own. The major components of robots are the manipulator, control system, power supply, end effector, and sensors.

Table 1
List of some remotely piloted aircraft (RPA) systems along with their specifications.

Name of RPA	Manufacturer name	Max. take-off Weight (kg)	Max. attainable height (ft)
Look Out VTOLRPAS	Throttle Aerospace Systems Private Ltd	1.99	400
Patang	Skylark Drones Pvt Ltd	1.9	1000
A200	Asteria Aerospace Pvt Ltd	1.9	200
Insight	AaravUnmanned Systems Pvt Ltd	3.6	400
Ninja	Idea Forge Technology Pvt Ltd	1.98	400
Agribot UAV (AGUAV)	IoTech World Avigation Pvt Ltd	23.2	33
PrionMk3	UAVE Limited	42.88	12100
Starlite	Hubblefly Technologies Pvt Ltd	1.92	9842

*VTOLRPAS: Vertical Take-Off and Landing Remotely Piloted Aircraft; UAV: Unmanned Aerial Vehicle

The primary task of a robot in agriculture is seeding, planting, weeding, spraying, and monitoring, while the secondary task deals with mobility, steering, navigation, and manipulation (Fig. 8). Indian researchers have developed various kinds of robotic vehicles for agricultural operations (Table 2).

3.4. Machine learning and deep learning

Machine learning (ML) uses mathematical and statistical tools for exploring and analyzing the data. Machine learning is of three types: supervised, unsupervised, and reinforcement learning. Supervised learning works by mapping variables, combining previously tagged information with previous input specifics to produce a preferred output variable. Bayesian networks, decision trees, and regression analysis are some of the algorithms used in supervised learning [52–54]. Unsupervised learning works on unlabeled data devoid of previous knowledge of input and output variables. This learning employs the clustering technique, which involves grouping data based on similarity. Machine learning is also known as reinforcement learning or semi-supervised learning, which explores innovative actions to put on more particulars as compared to exploiting information already assembled. In a nut shell, it combines supervised and unsupervised learning. Algorithms, like Q-learning and deep Q- learning, are used in semi-supervised learning [52]. The ML algorithm can be used a step ahead to visualize the effect of important soil properties on rice yield and the accumulated local effect (ALE) plot has been used to find out an important property that is influencing paddy yield [55]. The concept of machine learning makes computers assume and act with minimum human interference, whereas deep learning makes computers cogitate utilizing structures modeled with human intelligence and makes machines learn things the same as humans. It is a sub-set of AI and also a model of machine learning. The main idea of deep learning is to mimic human brains. However, ML and DL require more computing power and naturally need less ongoing human interference. The DL employs a multi-neural network architecture called" deep neural networks, "which are fostered to acclimatize large volumes of amorphous data. Some of the DL algorithms utilized in science and engineering fields are recurrent neural networks (RNN), artificial neural networks (ANN), and convolutional neural networks (CNN). The way these algorithms represent data varies, such as numbers in ANN, images in CNN, and time series in RNN.

3.5. Advantages and disadvantages of artificial intelligent robots

Robots, in general, use a variety of applications based on their working behaviors. Robots can sense and respond by using AI

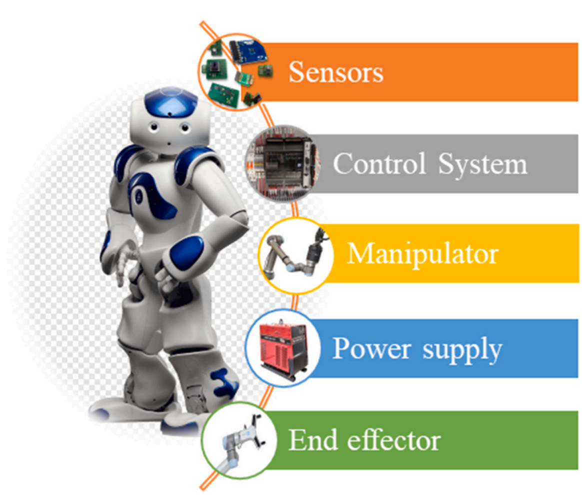

Fig. 8. Components of Robot.

Table 2
Various kinds of robotic vehicles for agricultural operations.

Vehicle/ Place	Name of the Developer	Applications
Pneumatic actuated gripper	TNAU	Graspingandreleasingtheplugtypeseedling. transplantingrateis20–25 seedlings/minute
Robotic rice pellet seeder	TNAU	Robotic rice pellet seeder
Robotic precision Planter	IARI	Has wireless control through micro-processor using a Wi-Fi module. The total time for completion of one block is 3 min 40 s.
Grobomac	Bangalore	Detection and harvesting of Cotton balls
Robotic arm	IIT Kharagpur	Cotton picking based on 3D Machine vision techniques,

Source: Adapted from Jyoti et al# [51]
*TNAU: Tamil Nadu Agricultural University; IARI: Indian Agricultural Research Institute; IIT: Indian Institute of Technology

technology, as their functions are pre-programmed for rapid detection and task performance. The sensors and ML technology used in robots can inspect elements with the help of AI techniques and detect mistakes. Predictive capability and process enhancement are the main features of robots. The ability to improve speed and efficiency as exhibited by robots plays a vital role in any field or environment. The robots can perform any task and overcome any obstacle in any environment. Robots can assist customers and answer their questions in various locations such as airports, hotels, and shops, just like human service agents. These machines have a high maintenance cost, and the uploading of a programme requires changing requirements. The procedures to reinstate the missing code or data are time-consuming and cost-effective. Storage, access, and retrieval of data are not as effective as humans. They can perform repetitive tasks for longer periods, but they do not get better with an experience like humans do. "AGRIBOT" is a sensor- and vision-based autonomous seed sowing machine [56]. The "BoniRob" is an autonomous field robot platform that has been used with an automatic soil penetro meter and GIS-based documentation [57]. Soil properties can be measured by "APP," which has been illustrated and authenticated in both laboratory and field experiments. The "BoniRob" in combination with the "PenetrometerApp" is used for soil property measurement. Umarkar and Karwankar [58] demonstrated that an automated seed-sowing Agri bot provides approximately 93 % accuracy regarding seed placement.

3.6. Impact of artificial intelligence (AI) in agriculture

The essence of farming always involves strategies for increasing crop production without sacrificing quality. Productive farms exhibit maximum utilization of natural resources like soil, water, and air and allocate natural resources for the future to deal with formidable challenges like climate change, labors shortages, urbanization leading to shrinkage of land for farming, poor soil fertility of the available land, declining water resources, etc. Any agricultural monitoring system must include crop identification, classification among various crop types, and crop health grade assessment. Accuracy and robustness achieved through the use of AI technologies are critical in this farming perspective, as they direct the way for precise use of natural resources and ultimately bring about a massive change in the field of agriculture [59]. It instantly facilitates the transition of millions of farmers in a country from site-specific advisory services to customized and site-based precise advisory services. Henceforth, Artificial Intelligence (AI) is considered a game changer in the field of agriculture. AI in agriculture avoids chores and boredom for many agricultural operations, and that time can be remunerated for creative AI innovations to outstrip human capabilities.

The knowledge of detecting threshold limits of crop stress factors is decisive for identifying crop growth and assessing the expected crop yield [60]. The application of artificial intelligence in agriculture protected the farming scenario, thereby increasing crop productivity on a large scale. According to Ennouri et al. [61], the major key challenges in the agricultural sector are to prepare the soil to cultivate, select the crop and seed according to the location, and finally harvest, which is becoming increasingly challenging due to climate change. Every plant requires precise soil nourishment. Plants suffer from a lack of basic nutrients such as nitrogen, phosphorous, and potassium, which results in low crop productivity. Artificial Intelligence- based technological recommendation has enabled farmers to produce supplementary output with reduced input and even improved output quality, ensuring quick go-to-market for yielded crops. The farmers will be operating 75 million connected devices by 2020. The average farm is anticipated to generate an average of 4.1 million data points per day by 2050 [8]. Crop protection against various weeds, pests, and diseases also plays a vital role, and faulty agriculture practices may lead to an increase in the cost of cultivation. Agricultural losses caused by diseases after harvest can be disastrous. Therefore, the foremost activity is to go through AI applications in agriculture forsoil and crop management.

3.6.1. *Soil management*

Both a soil description and a soil classification are essential for precise soil management. The description of soil represents the physical nature and state of the soil, whereas soil classification deals with the severance of soil into different groups, and each one has equivalent characteristics and potential behavior. An integral part of agricultural activities is soil management, as soil acts as a reservoir of nutrients, water, minerals, and diversified microbes. The health and productivity of the "cornerstone of life" or "magic carpet" (soil) beneath our feet help us attain the climate and biodiversity targets, build a clean and circular economy, reverse biodiversity loss, and protect human health.

Balanced applications of both organic sources in large quantities and inorganic sources in small quantities are very important for sustaining soil health. The application of organic materials like compost and manure improves the soil's quality, porosity, and aggregation, preventing soil crust formation. Soil-test-based fertility management is a valuable tool for building up the productivity of agricultural soils that have extremes in spatial variability. International Business Machines (IBM) created a micro-fluidic chip inside a card that performs chemical analysis of soil and an AI-driven machine vision algorithm that estimates the colorimetric test value better than the normal human eye. An artificial neural network (ANN) estimates field capacity and soil moisture content [62]. An artificial neural network (ANN) model forecasts soil texture information using characteristics derived from existing coarse-resolution soil map sand hydrographic parameters derived from a digital elevation model (DEM) [63]. Higher-order neural networks (HONN) are useful for understanding soil moisture flux [64]. Support vector machines (SVM) were the first statistic-all-earning theory foundations to be introduced [65]. Soil mean weight diameter predicted by machine learning tactics [66]. Sarkar et al. [67] reported that the soil risk characterization decision support system (SRC-DSS) is useful for identifying contaminated soils. The AI technologies can also be useful for estimating biological parameters like soil enzyme activity. ANN a better predictor or than multiple linear regression (MLR), and a digital terrain model-(DTM) attached to ANN has been discovered, resulting in better mapping of soil enzyme activity [68]. The Extreme Learning Machine (ELM) technique is useful not only for sorting but also for prophesying soil fertility indices and pH levels in the north-central lateritic region of Kerala, India [69].

3.6.2. *Crop management*

Crop management begins with seed sowing and continues with examining growth, harvesting, storage, and supply. Physical monitoring of large farms by farmers is highly impossible, and it can absolutely bed one using computer vision systems. Crop monitoring by AI technologies is very much required, thereby reducing human interventions in practice. The application of AI technologies is further explained concerning different crop management practices like sowing, nutrient and weed management, pest and disease management, and harvesting.

3.6.2.1. Sowing. Lack of awareness and faulty practices due to the poor literacy of farmers are soem of the reasons for climate change, which makes farmers extremely vulnerable to crop loss. As such, the sowing date is considered a key factor for farmers to have fruitful harvests. Very often, sowing is completely dependent on rain. If sowing is not done at the optimum time, it results in huge losses due to the costs incurred for seeds, fertilizers, and land preparation. In this context, digital agriculture aided by advanced technologies like AI will truly benefit millions of farmers. Microsoft collaborated with the International Crops Research Institute for the Semi- Arid Tropics (ICRISAT) in Telangana, India, to develop an AI sowing app that proved and escorted farmers to 30 % higher yields (Fig. 9) by notifying farmers of optimal sowing dates based on weather, soil, and other indicators. The best part is that farmers do not need to spend money installing sensors in fields or purchasing smart phones; all they need is a mobile device that can receive text messages [70]. A precision seeder equipped with a Real-Time Kinematic Global Positioning System (RTKGPS), optical seed detectors, and a data logging system are found to be effective in high-precision seed position mapping in sugar beet fields [71].

3.6.2.2. Nutrient management. The primary causes of lower nutrient use efficiency (NUE) are a) insufficient synchronism between fertilizer N and crop requirement, b) homogeneous nutrient applications for spatially variable topography that frequently varies in crop nutrient need, and c) temporary variability of crop nutrient requirement. Management-oriented modeling (MOM) is an effective tool for checking nitrogen leaching [72]. The ANN model can estimate soil nutrients but is restricted to only NH_4 after erosion. Song and He [73] stated that the efficacy of a developed system was improved by joining an expert system with an artificial neural network for estimating the nutrient status of crops. Lemmon [74] developed an expert system called "Cotton Management Expert (Comax)" and also expanded his contributions by developing a micro-computer-friendly programme entitled "Gossym" that reinforces the utilization of Comax. Comax and Gossym are jointly employed for simulating cotton crop growth [75]. Above all, COMA is used for retaining nitrogen content in fields, scheduling irrigation, and growth in the cotton crop. Tremblay et al. [76] developed a field-and crop-specific fuzzy inference system (FIS) to predict optimum N fertilizer rates.

3.6.2.3. Water management. Irrigation is one of the most labour-intensive agricultural processes. Application of water to the field should follow the 4 R's for sustainable water use, proper plant growth and development devoid of pests and diseases, and overcoming over utilization of water resources. Saxena et al. [65] stated that around 70 % of the world's fresh-water is used for irrigating crops; hence, the

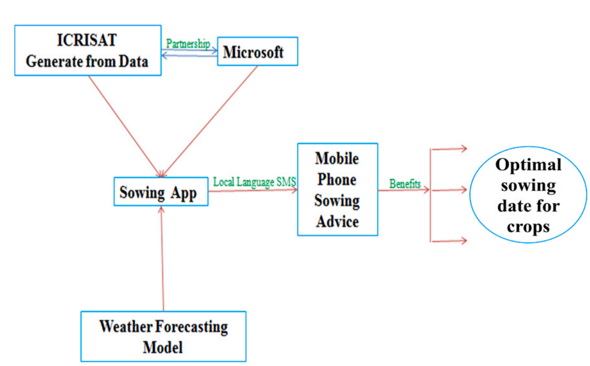

Fig. 9. Schematic representation of AI sowing app helping farmers as suggested by ICRISAT.

consciousness of AI leading to automation would have a big impact on saving water loss in agriculture. The manual irrigation based on soil water measurement was replaced by automatic irrigation scheduling techniques, and plant evapotranspiration, which is dependent on various atmospheric parameters and crop factors, was taken into consideration while implementing self-directed irrigation machines. Water from various sources is available to the crop, but water losses occur. The sensor in the root zone detected the water stress, and irrigation is recommended (Fig. 10).

A neuro drip irrigation system was developed by using ANNs to predict the spatial distribution of water in the subsurface [77]. An estimation of soil moisture in paddy fields using less meteorological data was made possible with two ANN models [78]. Maier and Dandy [79] implemented neural networks to predict and forecast water resource variables. Arvind et al. [80] developed a model using an Arduino micro-controller and database Zig Bee technology for analyzing the water requirements of a crop planted in a field for its entire lifecycle. Different researchers have used different algorithms for irrigation management in crop fields, as presented in Table 3.

An automated irrigation system with an Arduino micro-controller for reducing manpower and time spent in the process of irrigation was developed by Jha et al. [75]. Dai et al. [92] developed an ANN model for predicting the response of crops to soil moisture and salinity but considered only soil temperature and texture as factors. Plant [93] developed CALEX, which helps in scheduling guidelines for crop management activities, but the shortcoming is that it takes time. Lal et al. [94] implemented PROLOG, which removes less-used farm tools from the farm and is location-specific. A smartphone application named Cotton Smart Irrigation App (Cotton App) [95] and IGdroid [96] were developed to schedule irrigation in the cotton crop and other crops. Bartlett et al. [97] developed Water Irrigation Scheduling for Efficient Application (WISE), a smartphone application for better use of water resources. Perea et al. [98] implemented a multiplatform application for precision irrigation scheduling for the strawberry production sector in 2016, using both PC and Android devices. Bluleaf, a smartphone irrigation scheduling tool by Saab et al.[99], uses crop, soil, weather, and irrigation system data to support farmers in the water application process and scheduling irrigations. ANN feed-forward and back-propagation technologies to optimize the water resources in a smart farm is developed by Dela Cruzetal[100].

3.6.2.4. Weed management. The major concern for the farmers in the

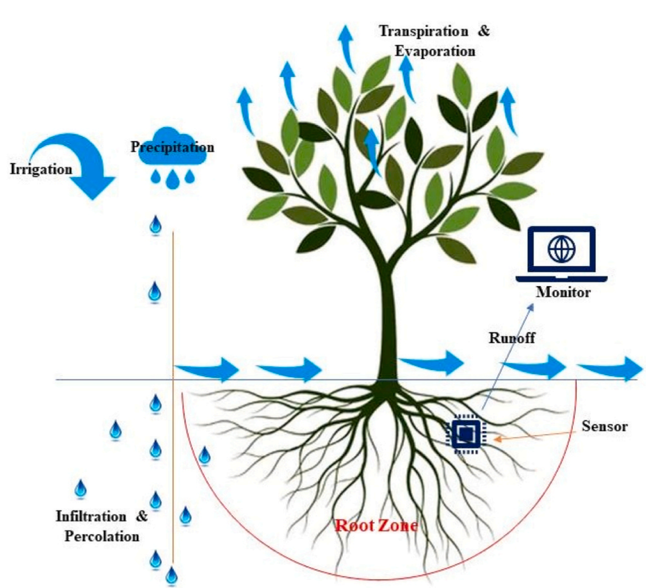

Fig. 10. Water inflow and losses and detection of water stress by sensor.

Table 3
Use of Artificial Intelligence for water management by different algorithm.

Sl. No.	Algorithms	Method of evapotranspiration/ desired calculation	Advantages/ results	References
1.	PLSR and other regression Algorithms	Evapotranspiration model	Increased efficiency and economic feasibility	[81]
2.	ANN		Prediction of ETo using weather variable to decide irrigation scheduling	[82]
3.	Artificial Neural Network based control system	Evapotranspiration mode	Automation	[83]
4.	Fuzzy Logic	FAO Penman Monteith method	Optimization	[84]
5.	ANN (multilayer neural model), Levenberg Marquardt, Back propagation	Penman-Monteith method	Evaporation decreased due to schedule and savings observed in water and electrical energy	[85]
6.	ANN	Penman-Monteith equation and Hargreaves equation	Estimation of ETo using daily data on solar radiation, humidity, temperature and wind speed.	[86]
7.	Fuzzy Logic	Fuzzy logic irrigation algorithm	Experimental results verification. Can be applied to home gardens and grass	[87]
8.	Machine Learning Model	Decision Trees, Random Forest, Neural Networks, and Support Vectors Machines	Adaptive irrigation management using machine learning to predict the time of the day for irrigation using the air-soil humidity and temperature, the current time of the day, wind speed, and direction data.	[88]
9.	ANNFeed Forward, Back propagation	MATLAB Neural Network	Optimization of water resources in a smart farm	[89]
10.	Fuzzy Logic Controller	Penman–Monteith method	Drip irrigation prevents wastage of water and evaporation	[90]
11.	Machine Learning Algorithm	Sensors, Zigbee, Arduino microcontroller	Prediction and tackle drought situations	[80]

(*continued on next page*)

Table 3 (*continued*)

Sl. No.	Algorithms	Method of evapotranspiration/ desired calculation	Advantages/ results	References
12.	Machine Learning Model	KNN, GND, SVM, ANN, DT	The top two models are ANN and KNN, which have an accuracy of 90 % and 98 %, respectively	[91]

field is reducing the interface between crop and weed. Now-a-days, weeds are alarming as they are silent robbers of water, nutrients, sunlight, and space and thus compete with crops, thereby declining in yield and crop quality. The competitiveness of crops and weeds, plant and weed populations, time of surfacing weeds relative to crops, duration of weed presence, and propinquity of weeds relative to crops are the factors responsible for weeds reducing crop yield. Proper application of herbicides with the right quantity, selectivity of herbicides, method, and timing of application is very important for weed management; otherwise, it not only destroys the crop yield but also creates disturbance in the environment and humans. Weed infestations are often a distributed non- uniformly in agricultural fields. Site-specific weed management plays a vital role in the growth and development of weeds varying temporally and spatially to reduce environmental and economic costs. The manual way of applying herbicides may not be accurate, so the use of embedded AI technologies can sort out the issue. Weeds can be detected with the aid of image analysis and neural networks with a precision of > 75 % [101]. The difference between the weedy crop and the desired crop is striking. Möller [102] reported that a convolutional neural network (CNN) equipped with many algorithms could identify weeds in a crop. Pasqual [103] developed a rule-based expert system for recognizing and removing weeds in crops such as oats, barley, triticale, and wheat. Machine learning (ML) algorithms such as ANN, decision trees, deep learning, and instance-based learning are used for simulating efficient models for weed detection [104]. With Learning Vector Quantization (LVQ), ANN has a high weed identification rate with a short processing time [105]. Digital Image Analysis (DIA), GPS contained > 60 % accuracy, and a success rate of four years was obtained, so the major drawback with this model is time consumption [106]. Saloma, is an expert system for weed management evaluation and forecasting [107]. Its benefits include a high adaptation rate and a high prediction level, but its drawback is that it requires big data and usage expertise. Some sensors that primarily focus on very few specific spectral bands (one or two) are called optoelectronic sensors [108]. Identification of weeds in sugarcane crops could be performed by using the fuzzy real-time classification algorithm (FRTCA) [109]. VGG16 and VGG19 are convolutional neural network (CNN) architectures, and both vary in the number of weighted layers in the model (in the case of VGG16 and VGG19) implemented for semantic demarcation of oilseed rape images composed of a complex field condition with excessive weeds. The process of computation in VGG-19 takes more time and is more expensive because it contains excessive parameters that make the generated network less suitable for real-time applications than VGG-16. As a result, Abdalla et al. [110] concluded that the VGG-16 encoder model outperforms the VGG-19 encoder model for semantic demarcation of oil seed rape images derived from a complex field situation with high weed pressures.

3.6.2.5. Pest management. Environmental protection can be achieved by decreasing pesticide usage. The two important factors for a healthy crop stand in precision farming are the timely identification and classification of crop pests and diseases and their management. Delays in the above-mentioned activities may result in pest population and infestation crossing threshold levels in a large portion of the field, resulting in a reduction in crop yield. Some pathogens become dormant in the soil after the harvest of the preceding crop, but they aggravate with the succeeding crop as they act as hosts. Exact inspection of the field is critical in rescuing from pathogens. Alalm and Nasr [111] stated that, with the aid of artificial intelligence, information is gathered to use pesticides exactly where affected plants are located. The Fuzzy Xpest provides pest information for farmers with high precision in forecasting, but it is internet-dependent [112]. The FL/TTS converter has been developed by Kolhe et al. [113] to resolve plant pathological problems swiftly, but it requires high-speedinternet and utilizes a voice service as its multimedia interface. Li and Chao [72] evaluated the amalgamation of convolutional neural networks (CNN) and generative adversarial networks (GAN) compared with a regular CNN approach for the identification of crop pests and plant leaves. In regular CNNs, lack of recollection causes an imbalance between old and new tasks, and they are limited to single tasks, whereas the combination of CNN and GAN can outperform regular CNNs because can gather knowledge and ease forgetting. On the other side, Li and Chao [72] stated that CNN is relatively easy to access, while the generative adversarial network (GAN) is unstable, hard to train, and certainly requires experience. The TEAPEST and Tea object-oriented expert systems were applied to 65 fields and obtained almost acceptable results [114]. The Tea Radial Basis Function Networks Modified TEAPEST, proposed by Banerjee et al. [115], detects pests with an accuracy of 99.99 %, which is superior to TEAPEST, i.e., 90 %. A major drawback is that it only identifies the three main pests of the tea crop and is restricted to only tea and not all cash crops. Pasqual and Mansfield [116] developed the general crop rule-based expert system PEST (Pest Expert System) for the identification and control of insects. AnMLP (Multi-Layer Perceptron) neural model was used for detecting granary weevil in stored wheat grains by x-ray images of damaged wheat kernels [117]. Microsoft, in alliance with United Phosphorus Limited (UPL), is manufacturing a pest risk prediction API that leverages AI and machine learning to indicate in advance the risk of potential pest attacks based on the weather conditions and crop growth stage. Pest attacks are predicted as high, medium, or low [118]. Kramers et al. [119] designed the expert system EXSYS for diagnosing flower bulb diseases, pests, and non-parasitic disorders.

3.6.2.6. Disease management. Various agricultural producers are struggling to overcome the risks caused by diseases incrop fields. Diseases are of major concern to the farmers. Proper experience and proficiency at the right time are necessary to notice a sick plant and take the necessary steps for recovery. Biotic and abiotic factors are responsible for the incubation of diseases in crops. In such a scenario, having keen knowledge about the causative influence of disease and its management is a big question in large-scale farming. BEA [120] reported that to overcome the losses incurred due to diseases, integrated disease control management is necessary but is time-consuming and costly (Weed Science Society of America). This solution can also be replaced with a computer-aided system to make it possible in a more precise manner. Hence, it is a prerequisite for AI applications to control diseases and their management [121,122]. The study of AI applications for detecting diseases of different crops has been presented in Table 4. For disease prediction based on leaf wetness duration, a fuzzy logic-based model was implemented. To begin, the image segment of the leaf image was pre-processed into three parts: the background, the diseased part, and the healthy part. Then the cropped, diseased part was sent to remote labs for further diagnosis. Sasaki and Suzuki [123] developed an automatic diagnosis system for plant disease using genetic programming. Balleda et al. [124] created a computer vision system (CVS), a genetic algorithm (GA), and an artificial neural network (ANN) that are multitasking and fast but have dimension-based detection, which may affect good species. Munirah et al. [125] created an expert system for disease detection based on a rule-base that was faster, more cost-effective, and

Table 4
Different studies using AI for detecting diseases of different crops.

Sl. No.	Crop	Disease	Proposed Model/ Application Name	References
1	Rice	Tungro, Blast, Brown spot and Bacterial blight	Random Forest + Naive Bayes + SVM	[141]
		Bacterial leaf blight, Sheath blight, Leaf blasts, Leaf smut and Brown spots	Random Forest Classifier and R-CNN with VGG− 16	[142]
		Hispa, Leaf Blast and Brown spot	You Only Look Once (YOLO) v5	[143]
			ResNet34	[144]
		Leaf Smut, Brown Spot, Bacterial Leaf Blight	CNN with 15-layer architecture	[145]
			A hybrid CNN (Inception ResNet)-SVM model	[146]
		Red blight, Rice blast, *Aphelenchoides besseyi*, Leaf smut, Bacterial leaf streak, Bacterial leaf blight, Brown spot and Rice sheath blight	GoogLeNet (E-Inception module)	[147]
		Tungro, Brown spot and Bacterial blight	A vulture-based Automatic Graph Neural Network (VAGNN) was proposed for RLDC	[148]
		Leaf Smut, Brown spot and Bacterial blight	Naïve Bays, K-Nearest Neighbor, Random Forest, Decision Tree, Linear Regression	[149]
		Sheath spot, Grassy stunt virus, Brown spot, Sheath rot, False smut, yellowing motel, Sheath, Leaf scald, Eyespot, Blast, tungro virus, kernel smut, Footrot, Leaf smut, Sheath blight, ragged stunt, Bacterial leaf streak, Crown sheath rot, Flag leaf sheath, Powdery mildew, Bacterial blight, Narrow brown leaf spot, and Pecky rice (kernel spotting)	VGG− 16 and Google Net	[150]
		Leaf Smut Bacterial Leaf Blight and Brown spot	DenseNet169-MLP	[151]
		Neck blast, Hispa, Tungro, Bacterial blight, False smut, Blast, Brown spot and Stemborer	RDD_CNN model (automated Rice Disease Diagnosis System (RDDS))	[152]
		Rice blast, Brown spot and Bacterial leaf blight		[153]
		Hispa, Leaf Blast and Brown spot	E-crop doctor (app) and a user-friendly chatbot (docCrop)	[154]
		Leaf smut, Bacterial leaf blight and Brown spot	Optimal Weighted Extreme Learning Machine (CNNIROWELM) and Inception with ResNet v2 based on Convolutional Neural Network	[155]
		Rice leaf blast, Brown spot and Rice Hispa damage	Depthwise separable neural network with Bayesian optimization (ADSNN-BO)	[156]
		Sheath Blight	Back propagation (BP) neural network	[157]
		Sheath rot, Brown spot, Bacterial blight and Leaf blast	DNN-JOA	[158]
	Wheat	Brown rust (Leaf rust), Yellow rust(Stripe rust) and Black rust (Stem rust	Efficient Net B4	[159]
		Fungal Diseases like Powdery mildew, rust and septoria	FCM technique called marker and mask-based membership filtering (M3FCM) which is faster and more reliable	[160]
		Fusarium head blight		[161]
	Corn	Northern maize leaf blight	CEMLB-YOLO	[162]
		Common rust Blight disease and Gray leaf spot	3D-DCNN-EOS	[163]
		Gray Leaf Spot, Blight and Common Rust	AlexNet-Inception	[164]
		Gibberella stalk rot, Anthracnose leaf blight, Northern corn leaf spot, Eyespot, Anthracnose stalk rot, Southern rust	NPNet− 19	[165]
		Fungal Foliar disease, Northern Leaf Blight/ Turcicum Leaf Bligh	Attention U-Net	[166]
		Northern Corn Leaf Blight, Gray Leaf Spot and Common Rust	Deep convolutional neural network (CNN) model	[167]
		Eyespot, Puccinia-sorghi, Southern rust, Healthy Samples, Exserohilumturcicum, PDD DB with Downy mildew, Northern leaf blight, Cercospora-zeaemaydis	The Deep clustering (RDC) algorithm integrates the efficacy of convolutional autoencoder models with local structure preservation constraints and regularization techniques.	[168]
		Rust, Gray spot and Leaf spot	CNN model	[169]

time-consuming. A comparison was done between the performance of machine learning (ML) and deep learning (DL) methods to notice and recognize crop diseases [126] like citrus plant leaf disease [127] and tomato diseases [128]. Kolhe et al. [113] implemented the FL Web-Based, Web-Based Intelligent Disease Diagnosis System (WIDDS), which has good accuracy and responds rapidly to the nature of crop diseases, but requires the internet and is limited to four seed crops. The hop plant rule-based expert system named Corac was developed by Mozny et al. [128] for identifying downy mildew, hop aphids, and weevils. The fuzzy inference system uses the "IF…THEN" condition type, which predicts plant disease based on weather data [129]. The POMME was used in the apple scab disease cycle model [130]. The grading of leaf diseases can be done accurately by using a fuzzy inference system [131]. The SMH method (Support Vector Machine, Maximally Stable Extremely Regions, and Histograms of Oriented Gradient Method) proposed by Liu et al. [132] is used for detecting aphid attacks on wheat crops. Chung et al. [133] proposed a method to identify three-week-old rice seedlings infected with Bakanae disease, which is caused primarily by the fungus *Fusarium fujikuroi*. Convolutional neural networks (CNN) generate digital images depicting soybean diseases [134]. A computer vision method was used for automatic detection of disease-causing organisms for leaf spot in rice by using the MCW (Marker-Controlled Watershed) algorithm and the SLIC algorithm (Simple Linear Iterative Clustering) [135]. Border/Interior Classification (BIC), histogram, and WDH (Wavelet

Decomposed Color Histogram) for evaluation of the detection of diseases in soybean leaves [136]. Sun et al. [137] investigated and concluded that the DBN (Deep Belief Network) model provided the best results in recognizing the fungal colonies in rice. K-means segmentation algorithm was developed in a system by Al-Hiary [138] and Al Bashish et al. [139] For wheat disease diagnosis, a web-based expert system was developed by Khan [140].

3.6.2.7. Harvesting. Harvesting the produce at the right time is very crucial for farmers to get the desired output and continue the food supply chain, and this activity is going wrong due to faulty practices like early or delayed sowing and due to weather abnormalities, and in the worst scenario, the entire crop goes to waste due to climate change. All of these factors point to the adoption of AI technology for harvesting at the optimal time. NITI Ayog, the Government's policy think tank, collaborated with IBM to create a crop yield prediction model that uses artificial intelligence (AI) to provide real-time advice to farmers in some Indian states. The Gobasco is an artificial intelligence-based platform that helps with procurement optimization and yield prediction solutions for the agriculture sector [170]. An expert system, "PRITHVI," based on fuzzy logic using MATLAB as a user interface module useful for increasing soybean production was developed in Rajasthan, India [171]. Snehal and Sandeep [172] developed an ANN model for the prediction of crop yield, capturing weather as a factor for crop yield. An expert system was designed by Landry [173] to control potato storage environments. Papageorgiou et al. [174] developed a fuzzy cognitive map for predicting cotton yield and improving crop decision management, but it is relatively slow. The ANN model can accurately predict rice yield, but it is time-consuming and limited to a particular climate [175]. Ayed and Hanana [55] stated that different ML algorithms can be used for crop yield prediction, such as the Bayesian network, regression, decision tree, clustering, deep learning, and ANN. The hyperspectral datasets and the AlexNet CNN deep learning model were used to classify the strawberry fruits into early-ripe and ripe stages [176]. Bargoti and Underwood [177] used R-CNN in fruit detection in orchards by keeping the VGG-16 NET with its 13 convolutional layers and also the ZF network, which has 5 convolutional layers. A multi-layered feed-forward ANN (MLFANN) was developed by Singh and Prajneshu [178] for detecting the yield of the maize crop by keeping algorithms like GDA (gradient descent algorithms) and CGDA (conjugate gradient descent algorithm), which are simulated in MATLAB using the neural network toolbox.

4. Conclusion

The agricultural industry has been facing several challenges, including a shortage of labour, efficient irrigation systems, weeding, plant monitoring, etc. To overcome all these challenges, the use of modern technology for sustainable farming through efficient resource utilization remains a great necessity. Undoubtedly, artificial intelligence, being a revolutionary innovation, brings prosperity to Indian agriculture. Plant surveillance is also no longer a burden. Artificial Intelligence (AI) is reforming agriculture by enhancing competence, productivity, and sustainability. The advanced technologies such as computer vision, machine learning, and predictive analytics, AI facilitates precise decision-making in crop management, pest control, soil health monitoring, and resource optimization. It facilitates smart farming practices by automating labour-intensive tasks, decreasing input wastage without compromising on quality. Additionally, AI-driven innovations like drones, robotics, and IoT-based sensors are renovating traditional farming into a data-driven industry. AI can provide cheaper solutions, and a digital economy like India has a great chance to easily adapt AI technologies.

CRediT authorship contribution statement

Konathala Kusumavathi, Ramesh Konatala and Smritikana Sarkar: Conceived idea, collections of review and writing manuscript; Hirak Banerjee, Pintoo Bandopadhyay, Priyanka Lal and Debadatta Sethi: Writing manuscript and revision of manuscript; Konga Upendra and Debadatta Sethi: Revision of manuscript. All authors contributed critically and gave final approval for publication.

Declaration of Competing Interest

There is no conflict of interest

Data availability

The data that has been used is confidential.

References

[1] A.A. Mana, A. Allouhi, A. Hamrani, S. Rehman, I. el Jamaoui, K. Jayachandran, Sustainable AI-based production agriculture: exploring AI applications and implications in agricultural practices, Smart Agric. Technol. 7 (2024) 100416, https://doi.org/10.1016/j.atech.2024.100416.

[2] M. Betts, C. Wolf, W.J. Ripple, B. Phalan, K.A. Millers, A. Duarte, S.H.M. Butchart, T. Levi, Global forest loss disproportionately erodes biodiversity in intact landscapes, Nature 547 (2017) 441–444, https://doi.org/10.1038/nature23285.

[3] X. Qi, Y. Fu, R.Y. Wang, C.N. Ng, H. Dang, Y. He, Improving the sustainability of agricultural land use: an integrated framework for the conflict between food security and environmental deterioration, Appl. Geogr. 90 (2018) 214–223, https://doi.org/10.1016/j.apgeog.2017.12.009.

[4] R. Roy, N.W. Chan, An assessment of agricultural sustainability indicators in bangladesh: review and synthesis, Environmentalist 32 (2012) 99–110, https://doi.org/10.1007/s10669-011-9364-3.

[5] S. Liu, Towards a sustainable agriculture: achievements and challenges of Sustainable Development Goal Indicator 2.4.1, Glob. Food Secur. 37 (2023) 100694, https://doi.org/10.1016/j.gfs.2023.100694.

[6] W. Willett, J. Rockström, B. Loken, M. Springmann, T. Lang, S. Vermeulen, T. Garnett, D. Tilman, F. DeClerck, A. Wood, M. Jonell, M. Clark, L.J. Gordon, J. Fanzo, C. Hawkes, R. Zurayk, J.A. Rivera, W. De Vries, L. Majele Sibanda, A. Afshin, A. Chaudhary, M. Herrero, R. Agustina, F. Branca, A. Lartey, S. Fan, B. Crona, E. Fox, V. Bignet, M. Troell, T. Lindahl, S. Singh, S.E. Cornell, K. S. Reddy, S. Narain, S. Nishtar, C.J.L. Murray, Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems, Lancet 393 (2019) 447–492, https://doi.org/10.1016/S0140-6736(18)31788-4.

[7] L.C. Stringer, E.D.G. Fraser, D. Harris, C. Lyon, L. Pereira, C.F.M. Ward, E. Simelton, Adaptation and development pathways for different types of farmers, Environ. Sci. Policy 104 (2020) 174, https://doi.org/10.1016/j.envsci.2019.10.007.

[8] T. Talaviya, D. Shah, N. Patel, H. Yagnik, M. Shahd, Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides, Artif. Intell. Agric. 4 (2020) 58–73, https://doi.org/10.1016/j.aiia.2020.04.002.

[9] Government of India. Press Information Bureau. Ministry of Health and Family Welfare. (2024).⟨https://pib.gov.in/PressNoteDetails.aspx?NoteId= 151925&ModuleId= 3&reg= 3&lang= 1⟩. Accessed on 22nd March 2025.

[10] A.A. Mana, A. Allouhi, A. Hamrani, S. Rehman, I. el Jamaoui, K. Jayachandran, Sustainable AI-based production agriculture: exploring AI applications and implications in agricultural practices, Smart Agric. Technol. 7 (2024) 100416, https://doi.org/10.1016/j.atech.2024.100416.

[11] T. Viju, A. Nambiar, C.M. Firoz, Sustainable land management strategies, drivers of LULC change and degradation: an assessment of Malappuram Metropolitan region, Kerala, India, in: U. Chatterjee, B. Pradhan, S. Kumar, S. Saha, M. Zakwan (Eds.), Water, Land, and Forest Susceptibility and Sustainability, Volume 2: Insight Towards Management, Conservation and Ecosystem Services, Elsevier, 2023, https://doi.org/10.1016/C2022-0-01959-0.

[12] FAO), (2021). FRA 2020 Remote Sensing Survey. Brows on 31.08.2024.

[13] M. Cavallito, A study illustrates for the first time the extent of the phenomenon in India. For 3 percent of the area, the situation is defined as "catastrophic" according to the new classification. Re soil Foundation, Regenaration for a clean and healthy soil. (2024). ⟨https://resoilfoundation.org/en/environment/india-soil-erosion-risk/⟩.Accessed on 23rd March 2025.

[14] E. Aivazidou, N. Tsolakis, E. Iakovou, D. Vlachos, The emerging role of water footprint in supply chain management: a critical literature synthesis and a hierarchical decision-making framework, J. Clean. Prod. 137 (2016) 1018–1037.

[15] E. Levintal, M.L. Kniffin, Y. Ganot, N. Marwaha, N.P. Murphy, H.E. Dahlke, Agricultural managed aquifer recharge (Ag-MAR)—a method for sustainable groundwater management: a review, Crit. Rev. Environ. Sci. Technol. 53 (3) (2023) 291–314.

[16] M. Al-Raeei, Artifcial intelligence for climate resilience: advancing sustainable goals in SDGs 11 and 13 and its relationship to pandemics, Discov. Sustain. 5 (2024) 513, https://doi.org/10.1007/s43621-024-00775-5.
[17] Crippa, M., Guizzardi, D., Pagani, F., Banja, M., Muntean, M., Schaaf E., Becker, W., Monforti-Ferrario, F., Quadrelli, R., Risquez Martin, A., Taghavi-Moharamli, P., Köykkä, J., Grassi, G., Rossi, S., Brandao De Melo, J., Oom, D., Branco, A., San-Miguel, J., Vignati, E., GHG emissions of all world countries, Publications Office of the European Union, Luxembourg (2023), doi:〈10.2760/953332JRC134504〉.
[18] WB, data of GDP PPP, (constant 2017 international $) (expressed in 1000 US dollar, and adjusted to the Purchasing Power Parity of 2017) for 1990–2022, World Bank (2023), Last access: July 2023..
[19] E.I., Energy Institute, 2023 Statistical Review of World Energy, (2023). 〈https://www.energyinst.org/statistical-review〉. Last access: 23 March 2025.
[20] UNEPFoodWasteIndexReport2021.〈https://www.unep.org/resources/report/unep-food-waste-index-report-2021〉.
[21] S.S. Priya, S.K. Dixit, S. Kabiraj, M.S. Priya, Food waste in Indian households: status and potential solutions, Environ. Sci. Pollut. Res. 30 (2023) 124401–124406, https://doi.org/10.1007/s11356-023-31034-1.
[22] K. von Grebmer, J. Bernstein, W. Geza, M. Ndlovu, M. Wiemers, L. Reiner, M. Bachmeier, A. Hanano, R. Ní Chéilleachair, T. Sheehan, C. Foley, S. Gitter, G. Larocque, H. Fritschel, Global Hunger Index: The Power of Youth in Shaping Food Systems. Bonn: Welthungerhilfe (WHH), Concern Worldwide, Dublin, 2023.
[23] H.C.J. Godfray, T. Garnett, Food security and sustainable intensification, Philos. Trans. R. Soc. B Biol. Sci. 369 (2014) 20120273, https://doi.org/10.1098/rstb.2012.0273.
[24] V. Kakkad, M. Patel, M. Shah, Biometric authentication and image encryption for image security in cloud framework, Multiscale Multidiscip. Model. Exp. Des. (2019) 1–16, https://doi.org/10.1007/s41939-019-00049-y.
[25] T. Feng, R. Xiong, P. Huan, Productive use of natural resources in agriculture: The main policy lessons, Resour. Policy 85 (2023) 103793, https://doi.org/10.1016/j.resourpol.2023.103793.
[26] S. Abbasi, A.M. Rahmani, Artificial intelligence and software modeling approaches in autonomous vehicles for safety management: a systematic review, Information 14 (2023) 555, https://doi.org/10.3390/info14100555.\.
[27] R. Chand, J. Singh. Workforce Changes and Employment. NITI Aayog Discussion Paper (2022). NITI Aayog Government of India New Delhi March 2022.
[28] WIPO) (2023). Global Innovation Index 2023: Innovation in the face of uncertainty. Geneva: WIPO. DOI:〈10.34667/tind.48220〉.
[29] IEO). (2024). Deloitte Global Economics Research Center. August 2024.
[30] M. De Clercq, A. Vats, A. Biel, Agriculture 4.0: The future of farming technology. In Proceedings of the World Government Summit, Dubai, United Arab Emirates, (2018)11–13. 〈https://www.bollettinoadapt.it/wp-content/uploads/2019/12/OliverWyman-Report_English-LOW.pdf〉. Browsed on 21.02.2025.
[31] S. Khan, S. Tsutsumi, T. Yairi, S. Nakasuka, Robustness of AI-based prognostic and systems health management, Annu. Rev. Control 51 (2021) 130–152, https://doi.org/10.1016/j.arcontrol.2021.04.001.
[32] N. Tsolakis, T.S. Harrington, J.S. Srai, Leveraging automation and data-driven logistics for sustainable farming of high-value crops in emerging economies, Smart Agric. Technol. 4 (2023) 100139, https://doi.org/10.1016/j.atech.2022.100139.
[33] J. Fan, L. Fang, J. Wu, Y. Guo, Q. Dai, From brain science to artificial intelligence, Engineering 6 (2020) 248–252, https://doi.org/10.1016/j.eng.2019.11.012.
[34] B.A. King, T. Hammond, J. Harrington, Disruptive technology: economic consequences of artificial intelligence and the robotics revolution, J. Strateg. Innov. Sustain. 12 (2017) 53–67, https://doi.org/10.33423/jsis.v12i2.801.
[35] B. Panahi, R. Hamid, H.M.Z. Jalaly, Deciphering plant transcriptomes: Leveraging machine learning for deeper insights, Curr. Plant Biol. 41 (2024) 100432, https://doi.org/10.1016/j.cpb.2024.100432.
[36] G.S. Patel, A. Rai, N.N. Das, R.P. Singh. Smart Agriculture: Emerging Pedagogies of Deep Learning, Machine Learning and Internet of 5ings, 1st edition, CRC Press, Boca Raton, FL, USA, 2021.
[37] A. Holzinger, K. Keiblinger, P. Holub, K. Zatloukal, H. Müller, AI for life: Trends in artificial intelligence for biotechnology, N. Biotechnol. 74 (2023) 16–24, https://doi.org/10.1016/j.nbt.2023.02.001.
[38] Y. Zhang, G. Huang, Y. Zhao, X. Lu, Y. Wang, C. Wang, X. Guo, C. Zhao, Revolutionizing Crop Breeding: Next-Generation Artificial Intelligence and Big Data-Driven Intelligent Design, Engineering (2024), https://doi.org/10.1016/j.eng.2024.11.034.
[39] M.A. Farooq, S. Gao, M.A. Hassan, Z. Huang, A. Rasheed, S. Hearne, B. Prasanna, X. Li, H. Li, Artificial intelligence in plant breeding, Trends Genet. 40 (10) (2024) 891–908, https://doi.org/10.1016/j.tig.2024.07.001.
[40] B. Zohuri, F. Behgounia, Application of artificial intelligence driving nano-based drug delivery system. A Handbook of Artificial Intelligence in Drug Delivery (Eds. Philip, A., Shahiwala, A., Rashid, M. and Faiyazuddin, M.). (2023) pp 145-212.〈https://doi.org/10.1016/C2020-0-03058-6〉.
[41] M.B. Hoy, Alexa, Siri, Cortana, and More: an introduction to voice assistants, Med. Ref. Serv. Q. 37 (1) (2018) 81–88, https://doi.org/10.1080/02763869.2018.1404391.
[42] K.M. Stiefel, J.S. Coggan, The energy challenges of artificial superintelligence, Front. Artif. Intell. 6 (2023) 1240653, https://doi.org/10.3389/frai.2023.1240653.
[43] N. Joshi, 7 Types Of Artificial Intelligence. Forbes. Retrieved November 7, (2020), 〈https://www.forbes.com/sites/cognitiveworld/2019/06/19/7-types-of-artificialintelligence/?sh= 3ca817eb233e〉.
[44] M. Javaid, A. Haleem, R.P. Singh, S. Rab, R. Suman, Significance of sensors for industry 4.0: Roles, capabilities, and applications, Sens. Int. 2 (2021) 100110, https://doi.org/10.1016/j.sintl.2021.100110.
[45] P. Rajak, A. Ganguly, S. Adhikary, S. Bhattacharya, Internet of Things and smart sensors in agriculture: scopes and challenges, J. Agric. Food Res. 14 (2023) 100776, https://doi.org/10.1016/j.jafr.2023.100776.
[46] P. Barapatre, J.N. Patel, Determination of soil moisture using various sensors for irrigation water management, Int. J. Innov. Technol. Explor. Eng. (IJITEE 8 (7) (2019) 576–582.
[47] C. Fabbri, M. Napoli, L. Verdi, M. Mancini, S. Orlandini, A.D. Marta, A sustainability assessment of the greenseeker n management tool: a lysimetric experiment on Barley, Sustainability 12 (2020) 7303, https://doi.org/10.3390/su12187303.
[48] S. Halle, S. Biswal, Effect of real time nitrogen management on yield attributes of direct seeded rice by using SPAD meter and greenseeker, Preprints (2021) 2021060047, https://doi.org/10.20944/preprints202106.0047.v1.
[49] R.J.G. Nuijten, L. Kooistra, G.B. De Deyn, Using Unmanned Aerial Systems (UAS) and Object-Based Image Analysis (OBIA) for Measuring Plant-Soil Feedback Effects on Crop Productivity, Drones 3 (2019) 54, https://doi.org/10.3390/drones3030054.
[50] K.P. Karthik, R.P. Chandra, Overv. Agric. Robots (2014). 〈http://www.yuvaengineers.com/an-overview-of-agricultural-robots-p-koteswara-karthik-p-ravi-chandra〉.
[51] B. Jyoti, N.S. Chandel, K.N. Agrawal, Application of Robotics in Agriculture: An Indian Perspective, 8th Asian-Australasian Conference on Precision Agriculture (8th ACPA-19) from 14-17 October, 2019 at Punjab Agricultural University (PAU), Ludhiana, Punjab Agricultural University (PAU), Ludhiana (2020).
[52] R.B. Ayed, M. Hanana, Artificial Intelligence to Improve the Food and Agriculture 591 Sector, J. Food Qual. (2021) 5584754, https://doi.org/10.1155/2021/5584754.
[53] P. Whig, P. Sharma, N. Aneja, A.A. Elngar, N. Silva, Artificial Intelligence and Machine Learning for Sustainable Development: Innovations, Challenges, and Applications, CRC Press, 2024, https://doi.org/10.1201/9781003497189.
[54] A. Gamage, R. Gangahagedara, S. Subasinghe, J. Gamage, C. Guruge, S. Senaratne, T. Randika, C. Rathnayake, Z. Hameed, T. Madhujith, O. Merah, Advancing sustainability: The impact of emerging technologies in agriculture, Curr. Plant Biol. 40 (2024) 100420, https://doi.org/10.1016/j.cpb.2024.100420.
[55] S. Garnaik, P.K. Samant, M. Mandal, T.R. Mohanty, S.K. Dwibedi, R.K. Patra, K. K. Mohapatra, R.H. Wanjari, D. Sethi, D.R. Sena, T.B. Sapkota, J. Nayak, S. Patra, C.M. Parihar, H.S. Nayak, Untangling the effect of soil quality on rice productivity under a 16-years long-term fertilizer experiment using conditional random forest, Comput. Electron. Agric. 197 (2022) 106965, https://doi.org/10.1016/j.compag.2022.106965.
[56] P.V. Santhi, N. Kapileswar, V.K.R. Chenchela1, V.S. Prasad, Sensor and Vision based Autonomous AGRIBOT for Sowing seeds. International Conference on Energy, Communication, Data Analytics and Soft Computing (2017) 242-245. 〈https://doi.org/10.1109/ICECDS.2017.8389873〉.
[57] C. Scholz, K. Moeller, A. Ruckelshausen, Automatic Soil Penetrometer Measurements and Gis Based Documentation with the Autonomous Field Robot Platform BoniRob, International Society of Precision Agriculture, 2014.
[58] S. Umarkar, A. Karwankar, Automated seed sowing agribot using Arduino, Int. Conf. Commun. Signal Process. (2016) 1379–1383, https://doi.org/10.1109/ICCSP.2016.7754380.
[59] D.K. Pandey, R. Mishra, Towards sustainable agriculture: harnessing AI for global food security, Artif. Intell. Agric. 12 (2024) 72–84, https://doi.org/10.1016/j.aiia.2024.04.003.
[60] R. Luciani, G. Laneve, M. JahJah, Agricultural monitoring, an automatic procedure for crop mapping and yield estimation: the great rift valley of Kenya case, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 12 (7) (2019) 2196–2208, https://doi.org/10.1109/JSTARS.2019.2921437.
[61] K. Ennouri, S. Smaoui, Y. Gharbi, M. Cheffi, O.B. Braiek, M. Ennouri, M.A. Triki, Usage of artificial intelligence and remote sensing as efficient devices to increase agricultural system yields, J. Food Qual. (2021) 6242288, https://doi.org/10.1155/2021/6242288.
[62] P. Bhattacharya, P. Pramanik, M. Ray, P. Krishnan, Comparison of artificial neural network and multi-linear regression for prediction of field capacity soil moisture content, J. Agric. Phys. 18 (2) (2018) 173–180.
[63] Z. Zhao, T.L. Chow, H.W. Rees, Q. Yang, Z. Xing, F.R. Meng, Predict soil texture distributions using an artificial neural network model, Comput. Electron. Agric. 65 (1) (2009) 36–48, https://doi.org/10.1016/j.compag.2008.07.008.
[64] A. Elshorbagy, K. Parasuraman, On the relevance of using artificial neural networks for estimating soil moisture content, J. Hydrol. 362 (1-2) (2008) 1–18, https://doi.org/10.1016/j.jhydrol.2008.08.012.
[65] A. Saxena, T. Suna, D. Saha, Appl. Artif. Intell. Indian Agric. (2020). 〈https://www.researchgate.net/publication/341736064〉.
[66] P. Bhattacharya, P.P. Maity, M. Ray, N. Mridha, Prediction of mean weight diameter of soil using machine learning approaches, AgronomyJournal 113 (2) (2020) 1303–1316, https://doi.org/10.1002/agj2.20469.
[67] A. Sarkar, P.P. Maity, A. Mukherjee, Appl. AI Soil Sci., Food Sci. Rep. 2 (2) (2021) 38–39.
[68] S. Tajik, S. Ayoubi, F. Nourbakhsh, Prediction of soil enzymes activity by digital terrain analysis: comparing artificial neural network and multiple linear regression models, Environ. Eng. Sci. 29 (8) (2011) 798–806, https://doi.org/10.1089/ees.2011.0313.

[69] M.S. Suchithra, M.L. Pai, Improving the prediction accuracy of soil nutrient classification by optimizing extreme learning machine parameters, Inf. Process. Agric. 7 (1) (2020) 72–82, https://doi.org/10.1016/j.inpa.2019.05.003.
[70] K. Fernandes, Artificial intelligence in agriculture in India, CSR J. (2020). ⟨https://thecsrjournal.in/artificial-intelligence-in-agriculture-in-india⟩.
[71] H.W. Griepentrog, M. Norremark, H. Nielsen, B.S. Blackmore, Seed mapping of sugarbeet, Precis. Agric. 6 (2005) 157–165, https://doi.org/10.1007/s11119-005-1032-5.
[72] Y. Li, X. Chao, ANN-Based Continual Classification in Agriculture, Agriculture 10 (2020) 178, https://doi.org/10.3390/agriculture10050178.
[73] H. Song, Y. He, Crop nutrition diagnosis expert system based on artificial neural networks.Third International Conferenceon Information Technology and Applications (ICITA'05) Sydney, NSW. 1 (2005)357–362.
[74] H. Lemmon, Comax: an expert system for cotton crop management, Science 233 (4759) (1986) 29–33, https://doi.org/10.1126/science.233.4759.29.
[75] K. Jha, A. Doshi, P. Patel, M. Shah, A comprehensive review on automation in673agriculture using artificial intelligence, Artif. Intell. Agric. 2 (2019) 1–12, https://doi.org/10.1016/j.aiia.2019.05.004.
[76] N. Tremblay, M.Y. Bouroubi, B. Panneton, S. Guillaume, P. Vigneault, C. Belec, Development and validation of fuzzy logic inference to determine optimum rates of N for corn on the basis of field and crop features, Precis. Agric. 11 (2010) 621–635, https://doi.org/10.1007/s11119-010-9188-z.
[77] A.C. Hinnell, N. Lazarovitch, A. Furman, M. Poulton, A.W. Warrick, Neuro-Drip: Estimation of subsurface wetting patterns for drip irrigation using neural networks, Irrig. Sci. 28 (6) (2010) 535–544, https://doi.org/10.1007/s00271-010-0214-8.
[78] C. Arif, M. Mizoguchi, B.I. Setiawan, R. Doi, Estimation of soil moisture in paddy field using Artificial Neural Networks, Int. J. Adv. Res. Artif. Intell. 1 (1) (2012) 17–21, https://doi.org/10.14569/IJARAI.2012.010104.
[79] H.R. Maier, G.C. Dandy, Neural networks for the prediction and forecasting of water resources variables: a review of modeling issues and applications, Environmental Modeling & Software (2000)101–124. ⟨https://doi.org/10.1016/S1364-8152(99)00007-9⟩.
[80] G. Arvind, V.G. Athira, H. Haripriya, R.A. Rani, S. Aravind, Automated irrigation with advanced seed germination and pest control, 2017 IEEE Technol. Innov. ICT Agric. Rural Dev. (TIAR) (2017), https://doi.org/10.1109/tiar.2017.8273687.
[81] S. Choudhary, V. Gaurav, A. Singh, S. Agarwal, Autonomous crop irrigation system using artificial intelligence, Int. J. Eng. Adv. Technol. 8 (5S) (2019) 46–51.
[82] N.K. Nawandar, N. Cheggoju, V. Satpute, ANN-based model to predict reference evapotranspiration for irrigation estimation. Proceedings of the International Conference on Recent Trends in Machine Learning, IoT, Smart Cities and Applications, Springer, Singapore, 2020, pp. 671–679, https://doi.org/10.1007/978-981-15-7234-0_63.
[83] S.M. Umair, R. Usman, Automation of irrigation system using ANN based controller, Int. J. Electr. Comput. Sci. 10 (2) (2010) 45–51.
[84] P.J. Kia, A.T. Far, M. Omid, R. Alimardani, L. Naderloo, Intelligent control based fuzzy logic for automation of greenhouse irrigation system and evaluation in relation to conventional systems, World Appl. Sci. J. 6 (1) (2009) 16–23.
[85] N. Karasekreter, F. Başçiftçi, U. Fidan, A new suggestion for an irrigation schedule with an artificial neural network, J. Exp. Theor. Artif. Intell. 25 (1) (2013) 93–104.
[86] M.S.P. Subathra, C.J. Blessing, S.T. George, A. Thomas, A.D. Raj, V. Ewards, Automated intelligent wireless drip irrigation using ANN techniques. Advances in Big Data and Cloud Computing, Springer, Singapore, 2018, pp. 555–568, https://doi.org/10.1007/978-981-13-1882-5_49.
[87] A.R. Al-Ali, M. Qasaimeh, M. Al-Mardini, S. Radder, I.A. Zualkernan, ZigBee-based irrigation system for home gardens. 2015 International Conference on Communications, Signal Processing, and Their Applications (ICCSPA'15). (2015) ⟨https://doi.org/10.1109/iccspa.2015.7081305⟩.
[88] A. Glória, J. Cardoso, P. Sebastião, Sustainable irrigation system for farming supported by machine learning and real-time sensor data, Sensor 21 (2021) 3079, https://doi.org/10.3390/s21093079.
[89] J.R. Dela Cruz, R.G. Baldovino, A.A. Bandala, E.P. Dadios, Water usage optimization of smart farm automated irrigation system using artificial neural network,"in Proceedings of the 2017 5th International Conference on Information and Communication Technology (ICoIC7), (2017) pp. 1–5, Melaka, Malaysia. ⟨https://doi.org/10.1109/ICoICT.2017.8074668⟩.
[90] K. Anand, C. Jayakumar, M. Muthu, S. Amirneni, Automatic drip irrigation system using fuzzy logic and mobile technology, 2015 IEEE Technol. Innov. ICT Agric. Rural Dev. (TIAR) (2015), https://doi.org/10.1109/tiar.2015.7358531.
[91] T. Jain, P. Garg, P.K. Tiwari, V.K. Kuncham, M. Sharma, V.K. Verma, Performance prediction for crop irrigation using different machine learning approaches. Examining the Impact of Deep Learning and IoT on Multi-Industry Applications, IGI Global:Hershey, PA, USA, 2021, pp. 61–79, https://doi.org/10.4018/978-1-7998-7511-6.ch005.
[92] X. Dai, Z. Huo, H. Wang, Simulation of response of crop yield to soil moisture and salinity with artificial neural network, Field Crops Res. 121 (3) (2011) 441–449, https://doi.org/10.1016/j.fcr.2011.01.016.
[93] R.E. Plant, An artificial intelligence based method for scheduling crop management actions, Agric. Syst. 31 (1) (1989) 127–155, https://doi.org/10.1016/0308-521X(89)90017-6.
[94] H. Lal, J.W. Jones, R.M. Peart, W.D. Shoup, FARMSYS-A wholefarm machinery management decision support system, Agric. Syst. 38 (3) (1992) 257–273, https://doi.org/10.1016/0308-521X(92)90069-Z.
[95] G. Vellidis, V. Liakos, J. Andreis, C. Perry, W. Porter, E. Barnes, K. Morgan, C. Fraisse, K. Migliaccio, Development and assessment of a smartphone application for irrigation scheduling in cotton, Comput. Electron. Agric. 127 (2016) 249–259, https://doi.org/10.1016/j.compag.2016.06.021.
[96] D.F. Rodrigues, C.D.G.C. de Almeida, The Irrigation Scheduling IGdroid Tool, Irrig., Botucatu, Edição Espec. 01 (2014) 21–28, https://doi.org/10.12702/ii.inovagri.2014-a054.
[97] A. Bartlett, A. Andales, M. Arabi, T. Bauder, A smartphone app to extend use of a cloud-based irrigation scheduling tool, Comput. Electron. Agric. 111 (2015) 127–130, https://doi.org/10.1016/j.compag.2014.12.021.
[98] R.G. Perea, I.F. García, M.M. Arroyo, J.R. Díaz, E.C. Poyato, P. Montesinos, Multiplatform application for precision irrigation scheduling in strawberries, Agric. Water Manag 183 (2016) 194–201, https://doi.org/10.1016/j.agwat.2016.07.017.
[99] M.T.A. Saab, I. Jomaa, S. Skaf, S. Fahed, M. Todorovic, Assessment of a Smartphone Application for Real-Time Irrigation Scheduling in Mediterranean Environments, Water 11 (2) (2019) 252, https://doi.org/10.3390/w11020252.
[100] M.J. Aitkenhead, I.A. Dalgetty, C.E. Mullins, A.J.S. McDonald, N.J.C. Strachan, Weed and crop discrimination using image analysis and artificial intelligence methods, Comput. Electron. Agric. 39 (3) (2003) 157–171, https://doi.org/10.1016/S0168-1699(03)00076-0.
[101] J. Möller, Computer vision – a versatile technology in automation of agriculture machinery. 21st Annual Meeting Bologna, EIMA Int. (2010) 1–16, https://doi.org/10.52151/jae2010474.1423.
[102] G.M. Pasqual, Development of an expert system for the identification and control of weeds in wheat, triticale, barley and oat crops, Comput. Electron. Agric. 10 (2) (1994) 117–134, https://doi.org/10.1016/0168-1699(94)90016-7.
[103] K. Liakos, P. Busato, D. Moshou, S. Pearson, D. Bochtis, Machine learning in agriculture: a review, Sensors 18 (8) (2018) 2674, https://doi.org/10.3390/s18082674.
[104] C.C. Yang, S.O. Prasher, J. Laundry, H.S. Ramaswamy, Development of neural networks for weed recognition in corn fields, Am. Soc. Agric. Biol. Eng. 45 (3) (2002) 859–864, https://doi.org/10.13031/2013.8854.
[105] R. Gerhards, S. Christensen, Real-time weed detection, decision making and patch-spraying in maize, sugar beet, winter wheat and winter barley, Wiley Online Libr. 43 (6) (2003) 385–392, https://doi.org/10.1046/j.1365-3180.2003.00349.x.
[106] L. Stigliani, C. Resina, Seloma: Expert system for weed management in herbicide-intensive crops, Weed Technol. 7 (3) (1993) 550–559.
[107] K. Upendar, K.N. Agrawal, K.S. Vinod, The role of sensing techniques in precision agriculture. Machine Vision for Industry 4.0, CRC Press, 2022, pp. 63–78, https://doi.org/10.1201/9781003122401-3.
[108] M. Sujaritha, S. Annadurai, J. Satheeshkumar, S.S. Kowshik, L. Mahesh, Weed detecting robot in sugarcane fields using fuzzy real time classifier, Comput. Electron. Agric. 134 (2017) 160, https://doi.org/10.1016/j.compag.2017.01.008.
[109] A. Abdalla, H. Cena, L. Wana, R. Rashid, H. Wenga, W. Zhoue, Y. Hea, Fine-tuning convolutional neural network with transfer learning for semantic segmentation of ground-level oilseed rape images in a field with high weed pressure, Comput. Electron. Agric. (2019), https://doi.org/10.1016/j.compag.2019.105091.
[110] M.G. Alalm, M. Nasr, Artificial intelligence, regression model, and cost estimation for removal of chlorothalonil pesticide by activated carbon prepared from casuarinas charcoal, Sustain. Environ. Res. 28 (3) (2018) 101–110, https://doi.org/10.1016/j.serj.2018.01.003.
[111] F. Siraj, N. Arbaiy, Integrated Pest Management System Using Fuzzy Expert System. Knowledge Management International Conference & Exhibition, Kuala Lumpur, Malaysia, (2006) June 6–8.
[112] S. Kolhe, R. Kamal, H.S. Saini, G.K. Gupta, An intelligent multimedia interface for fuzzy-logic based inference in crops, Expert Syst. Appl. 38 (12) (2011) 14601, https://doi.org/10.1016/j.eswa.2011.05.023.
[113] Ghosh, R.K. Samanta, Teapest: an expert system for insect pest management In Tea, Appl. Eng. Agric. 19 (5) (2003) 619–625, https://doi.org/10.13031/2013.15309.
[114] G. Banerjee, U. Sarkar, I. Ghosh, A radial basis function network based classifier for detection of selected tea pests, Int. J. Adv. Res. Comput. Sci. Softw. Eng. 7 (5) (2017) 665–669.
[115] G.M. Pasqual, J. Mansfield, Development of a prototype expert system for identification and control of insect pests, Comput. Electron. Agric. 2 (4) (2003) 263–276, https://doi.org/10.1016/0168-1699(88)90002-6.
[116] P. Boniecki, H. Piekarska-Boniecka, K. Świerczyński, K. Koszela, M. Zaborowicz, J. Przybył, Detection of the granary weevil based on x-ray images of damaged wheat kernels, J. Stored Prod. Res. 56 (2014) 38–42, https://doi.org/10.1016/j.jspr.2013.11.001.
[117] A. Bagchi, Artif. Intell. Agric. (2018). ⟨https://www.mindtree.com/sites/default/files/201804/Artificial%20Intelligence%20in%20Agriculture.pdf⟩.
[118] M.A. Kramers, C.G.M. Conijn, C. Bastiaansen, EXSYS, an expert system for diagnosis flower bulb diseases, pests and non-parasitic disorders, Agric. Syst. 810 (1998) 57–85, https://doi.org/10.1016/S0308-521X%2898%2900046-8.
[119] BEA, 2018. Value Added by Industry as a Percentage of Gross Domestic Product, available at:⟨https://apps.bea.gov/iTable/iTable.cfm?ReqID= 51&step= 1#reqid= 51&step= 51&isuri= 1&5114=a&5102= 5⟩.
[120] A. Jafar, N. Bibi, R.A. Naqvi, A. Sadeghi-Niaraki, D. Jeong, Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations, Front. Plant Sci. 15 (2024) 1356260, https://doi.org/10.3389/fpls.2024.1356260.

[121] A. Singla, A. Nehra, K. Joshi, A. Kumar, N. Tutej, R.K. Varshney, S.S. Gill, R. Gill, Exploration of machine learning approaches for automated crop disease detection, Curr. Plant Biol. 40 (2024) 100382, https://doi.org/10.1016/j.cpb.2024.100382.
[122] Y. Sasaki, M. Suzuki, Construction of the automatic diagnosis system of plant disease using genetic programming which paid its attention to variety, ASAE paper 031049 (2003)1-13. doi: ⟨10.13031/2013.13718⟩.
[123] K. Balleda, D. Satyanvesh, N.V.S.S.P. Sampath, K.T.N. Varma, P.K. Baruah, Agpest: An Efficient Rule-Based Expert System to Prevent Pest Diseases of Rice & Wheat Crops. 8th International Conference on Intelligent Systems and Control, Coimbatore, India, (2014) January 10–11.
[124] M.Y. Munirah, M. Rozlini, Y.M. Siti, An Expert System Development: Its Application on Diagnosing Oyster Mushroom Diseases. 13th International Conference on Control, Automation and Systems, Gwangju, South Korea (2013). ⟨https://doi.org/10.1109/ICCAS.2013.6703917⟩.
[125] A. Singla, A. Nehra, K. Joshi, A. Kumar, N. Tuteja, R.K. Varshney, S.S. Gill, R. Gill, Exploration of machine learning approaches for automated crop disease detection, Curr. Plant Biol. 40 (2024) 100382, https://doi.org/10.1016/j.cpb.2024.100382.
[126] K. Joshi, S. Hooda, A. Sharma, H. Sonah, R. Deshmukh, N. Tuteja, S.S. Gill, R. Gill, Precision diagnosis of tomato diseases for sustainable agriculture through deep learning approach with hybrid data augmentation, Curr. Plant Biol. 41 (2024) 100437, https://doi.org/10.1016/j.cpb.2025.100437.
[127] R. Sujatha, J.M. Chatterjee, N. Jhanjhi, S.N. Brohi, Performance of deep learning vs machine learning in plant leaf disease detection, Microprocess. Microsyst. 80 (2021) 103615, https://doi.org/10.1016/j.micpro.2020.103615.
[128] M. Mozny, J. Krejci, I. Kott, CORAC, hops protection management systems, Comput. Electron. Agric. 9 (1993) 103–110, https://doi.org/10.1016/0168-1699(93)90001-H.
[129] V. Tilva, J. Patel, C. Bhatt, Weather based plant diseases forecasting using fuzzy logic. Nirma University International Conference on Engineering (NUiCONE). (2013)1–5. ⟨https://doi.org/10.1109/NUiCONE.2013.6780173⟩.
[130] J. Roach, R. Virkar, C. Drake, M. Weaver, An expert system for helping apple growers, Comput. Electron. Agric. 2 (2) (1987) 97–108, https://doi.org/10.1016/0168-1699(87)90020-2.
[131] S.S. Sannakki, V.S. Rajpurohit, V.B. Nargund, A. Kumar, P.S. Yallur, Leaf disease grading by machine vision and fuzzy logic, Int. J. Comp. Tech. Appl. 2 (5) (2011) 1709–1716.
[132] T. Liu, W. Chen, W. Wu, C. Sun, W. Guo, X. Zhu, Detection of aphids in wheat Fields using a computer vision technique, Biosyst. Eng. 141 (2016) 82–93, https://doi.org/10.1016/j.biosystemseng.
[133] C.L. Chung, K.J. Huang, S.Y. Chen, M.H. Lai, Y.C. Chen, Y.F. Kuo, Detecting Bakanae disease in rice seedlings by machine vision, Comput. Electron. Agric. 121 (2016) 404–411, https://doi.org/10.1016/j.compag.2016.01.008.
[134] N. Bevers, E.J. Sikora, N.B. Hardy, Soybean disease identification using original field images and transfer learning with convolutional neural networks, Comput. Electron. Agric. 203 (2022) 107449, https://doi.org/10.1016/j.compag.2022.107449.
[135] L. Han, M.S. Haleem, M. Taylor, A novel computer vision-based approach to automatic detection and severity assessment of crop diseases. In: 2015 Science and Information Conference (SAI), (2015) 638–644. ⟨https://doi.org/10.1109/SAI.2015.7237209⟩.
[136] S. Shrivastava, S.K. Singh, D.S. Hooda, Soybean plant foliar disease detection using image retrieval approaches, Multimed. Tools Appl. (2016) 1–28, https://doi.org/10.1007/s11042-016-4191-7.
[137] K. Sun, Z. Wang, K. Tu, S. Wang, L. Pan, Recognition of mould colony on unhulled paddy based on computer vision using conventional machine-learning and Deep learning techniques, Sci. Rep. 6 (2016) 37994, https://doi.org/10.1038/srep37994.
[138] H. Al-Hiary, Fast and accurate detection and classification of plant diseases, Int. J. Comput. Appl. 17 (1) (2011) 31–38, https://doi.org/10.5120/2183-2754.
[139] D. Al Bashish, M. Braik, S. Bani-Ahmad, Detection and classification of leaf diseases using K-means-based segmentation and Neural-networks-based classification, Inf. Technol. J. 10 (2) (2011) 267–275, https://doi.org/10.3923/itj.2011.267.275.
[140] S.F. Khan, S. Razzaq, K. Irfan, F. Maqbool, A. Farid, I. Illahi, T. ul amin, "Dr. Wheat: a Web-based expert system for diagnosis of diseases and pests in Pakistani wheat." In Proc. of the World Congress on Engineering, London, UK (2008).
[141] K.M. Sudhesh, V. Sowmya, P.K. Sainamole, O.K. Sikha, AI based rice leaf disease identification enhanced by dynamic mode decomposition, Eng. Appl. Artif. Intell. 120 (2023) 105836, https://doi.org/10.1016/j.engappai.2023.105836.
[142] V. Rajpoot, A. Tiwari, A.S. Jalal, Automatic early detection of rice leaf diseases using hybrid deep learning and machine learning methods, Multimed. Tools Appl. 82 (23) (2023) 36091–36117, https://doi.org/10.1007/s11042-023-14969-y.
[143] N. Mishra, J. Seetha, A.G.D. Kumar, S. Menon, A. Ravuri, Design an ant lion-based Yolo-V5 model for prediction and classification of paddy leaf disease, Int. J. Intell. Syst. Appl. Eng. 11 (6s) (2023) 599–612.
[144] A. Stephen, A. Punitha, A. Chandrasekar, Designing self attention-based ResNet architecture for rice leaf disease classification, Neural Comput. Appl. 35 (9) (2023) 6737–6751, https://doi.org/10.1007/s00521-022-07793-2.
[145] G. Parasa, M. Arulselvi, S. Razia, Identification of diseases in paddy crops using CNN, Int. J. Intell. Syst. Appl. Eng. 11 (6s) (2023) 548–557.
[146] S. Jain, R. Sahni, T. Khargonkar, H. Gupta, O.P. Verma, T.K. Sharma, T. Bhardwaj, S. Agarwal, H. Kim, Automatic rice disease detection and assistance framework using deep learning and a chatbot, Electronics 11 (14) (2022) 2110, https://doi.org/10.3390/electronics11142110.
[147] L. Yang, X. Yu, S. Zhang, H. Zhang, S. Xu, H. Long, Y. Zhu, Stacking-based and improved convolutional neural network: a new approach in rice leaf disease identification, Front. Plant Sci. 14 (2023), https://doi.org/10.3389/fpls.2023.1165940.
[148] V. Rajasekhar, G. Arulselvi, K.S. Babu, Optimization-based auto-metric graph neural network framework for rice leaf disease classification, Int. J. Intell. Syst. Appl. Eng. 11 (6s) (2023) 563–575.
[149] S.K. Rai, Singh, Is banded leaf and sheath blight a potential threat to maize cultivation in Bihar? Int. J. Curr. Microbiol. Appl. Sci. 7 (11) (2018) 671–683, https://doi.org/10.20546/ijcmas.2018.711.080.
[150] R. Yakkundimath, G. Saunshi, B. Anami, S. Palaiah, Classification of rice diseases using convolutional neural network models, J. Inst. Eng. (India) Ser. B 103 (4) (2022) 1047–1059, https://doi.org/10.1007/s40031-021-00704-4.
[151] R.P. Narmadha, N. Sengottaiyan, R.J. Kavitha, Deep transfer learning based rice plant disease detection model, Intell. Autom. Soft Comput. 31 (2) (2022) 1257–1271, https://doi.org/10.32604/iasc.2022.020679.
[152] S.V. Vasantha, S. Samreen, Y.L. Aparna, Rice disease diagnosis system (RDDS), Comput. Mater. Contin. 73 (1) (2022), https://doi.org/10.32604/cmc.2022.028504.
[153] K.S. Archana, S. Srinivasan, S.P. Bharathi, R. Balamurugan, T.N. Prabakar, A.S. F. Britto, A novel method to improve computational and classification performance of rice plant disease identification, J. Supercomput 78 (6) (2022) 8925–8945, https://doi.org/10.1007/s11227-021-04245-x.
[154] D.J. Chaudhari, K. Malathi, Detection and prediction of rice leaf disease using a hybrid CNN-SVM Model, Opt. Mem. Neural Netw. 32 (1) (2023) 39–57, https://doi.org/10.3103/S1060992X2301006X.
[155] V.G. Krishnan, M.V. Saradhi, G. Dhanalakshmi, C.S. Somu, W.G. Theresa, Design of M3FCM based convolutional neural network for prediction of wheat disease, Int. J. Intell. Syst. Appl. Eng. 11 (2s) (2023) 203–210.
[156] Y. Wang, H. Wang, Z. Peng, Rice diseases detection and classification using attention based neural network and bayesian optimization, Expert Syst. Appl. 178 (2021) 114770, https://doi.org/10.1016/j.eswa.2021.114770.
[157] Y. Lu, Z. Li, X. Zhao, S. Lv, X. Wang, K. Wang, H. Ni, Recognition of rice sheath blight based on a backpropagation neural network, Electronics 10 (23) (2021) 2907, https://doi.org/10.3390/electronics10232907.
[158] S. Ramesh, D. Vydeki, Recognition and classification of paddy leaf diseases using optimized deep neural network with Jaya algorithm, Inf. Process. Agric. 7 (2) (2020) 249–260, https://doi.org/10.1016/j.inpa.2019.09.002.
[159] S. Nigam, R. Jain, S. Marwaha, A. Arora, Md.A. Haque, A. Dheeraj, V.K. Singh, Deep transfer learning model for disease identification in wheat crop, Ecol. Inf. 75 (2023) 102068, https://doi.org/10.1016/j.ecoinf.2023.102068.
[160] U.A. Bukar, M.S. Sayeed, S.F.A. Razak, S. Yogarayan, O.A. Amodu, R.A. R. Mahmood, A method for analyzing text using VOSviewer, MethodsX 11 (2023) 102339, https://doi.org/10.1016/j.mex.2023.102339.
[161] M.B. Almoujahed, A.K. Rangarajan, R.L. Whetton, D. Vincke, D. Eylenbosch, P. Vermeulen, A.M. Mouazen, Detection of fusarium head blight in wheat underfield conditions using a hyperspectral camera and machine learning, Comput. Electron. Agric. 203 (2022) 107456, https://doi.org/10.1016/j.compag.2022.107456.
[162] S. Leng, Y. Musha, Y. Yang, Feng, CEMLB-YOLO: efficient detection model of maize leaf blight in complex field environments, Appl. Sci. 13 (16) (2023) 9285, https://doi.org/10.3390/app13169285.
[163] R. Sowmyalakshmi, T. Jayasankar, V.A. PiIllai, K. Subramaniyan, I. A. Pustokhina, D. A. Pustokhin, K. Shankar, An optimal classification model for rice plant disease detection, Comput. Mater. Contin. 68 (2) (2021) 1751–1767, https://doi.org/10.32604/cmc.2021.016825.
[164] K. Balasubramanian, Feature analysis and classification of maize crop diseases employing AlexNet-inception network, Multimed. Tools Appl. 83 (9) (2024) 26971–26999, https://doi.org/10.1007/s11042-023-16467-7.
[165] M. Nagaraju, P. Chawla, Maize crop disease detection using NPNet-19 convolutional neural network, Neural Comput. Appl. 35 (4) (2023) 3075–3099, https://doi.org/10.1007/s00521-022-07722-3.
[166] C.K. Rai, R. Pahuja, Northern maize leaf blight disease detection and segmentation using deep convolution neural networks, Multimed. Tools Appl. 83 (7) (2023) 19415–19432, https://doi.org/10.1007/s11042-023-16398-3.
[167] Md.A. Haque, S. Marwaha, C.K. Deb, S. Nigam, A. Arora, Recognition of diseases of maize crop using deep learning models, Neural Comput. Appl. 35 (10) (2023) 7407–7421, https://doi.org/10.1007/s00521-022-08003-9.
[168] Y. Resti, C. Irsan, A. Neardiaty, C. Annabila, I. Yani, Fuzzy discretization on the multinomial naïve bayes method for modeling multiclass classification of corn plant diseases and pests, Mathematics 11 (8) (2023) 1761, https://doi.org/10.3390/math11081761.
[169] H. Yu, J. Liu, C. Chen, A.A. Heidari, Q. Zhang, H. Chen, M. Mafarja, H. Turabieh, Corn leaf diseases diagnosis based on K-means clustering and deep learning, IEEE Access 9 (2021) 143824–143835, https://doi.org/10.1109/ACCESS.2021.3120379.
[170] D. Manaware, Artificial Intelligence: A New Way to Improve Indian Agriculture, Int. J. Curr. Microbiol. Appl. Sci. 9 (3) (2020) 1095–1102.
[171] A. Prakash, A.S. Rathor, G.S.M. Thakur, Fuzzy Based Agriculture Expert System for Soyabean. International conference on computing sciences WILKES100-ICCS2013, Jalandhar, Punjab, (2013) pp. 1–13. ⟨https://doi.org/10.13140/2.1.1765.0567⟩.
[172] S.S. Snehal, S.V. Sandeep, Agricultural crop yield prediction using artificial neural network approach, Int. J. Innov. Res. Electr., Electron., Instrum. Control Eng. 2 (1) (2014) 683–686.

[173] J.A. Landry, E.R. Norris, Expert system for the control of potato storage environments, Appl. Eng. Agric. (2001) 839–844, https://doi.org/10.13031/2013.6837.
[174] E.I. Papageorgiou, A.T. Markinos, T.A. Gemtos, Fuzzy cognitive map based approach for predicting crop production as a basis for decision support system in precision agriculture application, Appl. Soft Comput. 11 (4) (2011) 3643–3657, https://doi.org/10.1016/j.asoc.2011.01.036.
[175] A. Ji, Y. Sun, S. Yang, J. Wan, Artificial neural networks for rice yield prediction in mountainous regions, J. Agric. Sci. 145 (3) (2007) 249–261, https://doi.org/10.1017/S0021859606006691.
[176] Z. Gao, Y. Shao, G. Xuan, Y. Wang, Y. Liu, X. Han, Realtime hyperspectral imaging for the in-field estimation of strawberry ripeness with deep learning, Artif. Intell. Agric. 4 (2020) 31–38, https://doi.org/10.1016/j.aiia.2020.04.003.
[177] S. Bargoti, J. Underwood, Deep Fruit Detection in Orchards. IEEE International Conference on Robotics and Automation (ICRA) (2017) 3626–3633. ⟨https://doi.org/10.1109/ICRA.2017.7989417⟩.
[178] R.K. Singh, Prajneshu, Artificial neural network methodology for modeling and forecasting maize crop yield, Agric. Econ. Res. Rev. 21 (2008) 5–10.