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REVIEW ARTICLE

Reconnoitering Precision Agriculture and Resource Management: A Comprehensive Review from an Extension Standpoint on Artificial Intelligence and Machine Learning

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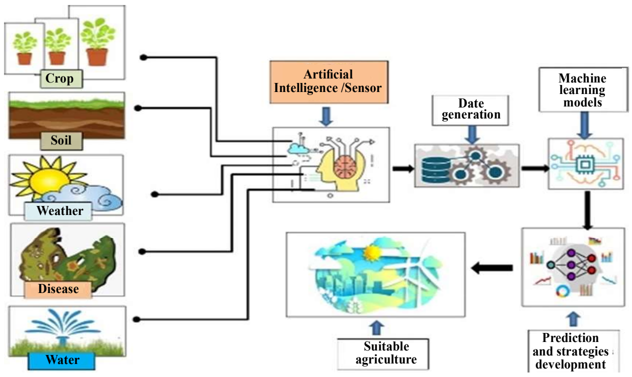
HIGHLIGHTS

- This article goes beyond a basic review, offering a detailed exploration of diverse AI/ML applications across different aspects of precision agriculture
- This focus on sustainability aligns with growing global concerns about resource depletion and climate change, making the paper relevant to a broader audience.
- The paper positions itself as a valuable resource for researchers and stakeholders interested in AI/ML in agriculture. This suggests it offers actionable insights and recommendations beyond just a theoretical overview.

GRAPHICAL ABSTRACT



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ABSTRACT

Introduction : The agriculture sector is a crucial driver of global economic growth, especially in the face of the increasing demand for food production to sustain a growing population. Traditional farming methods fall short of meeting these demands sustainably.

Context: In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as pivotal tools for agricultural management, promising higher productivity and profitability.

Objective: This systematic review provides a comprehensive overview of AI and ML applications, their utility, and algorithms in agriculture.

Content: AI and ML technologies empower autonomous learning and enhance decision-making processes. They facilitate smart monitoring of crops and soil, transforming agriculture by optimizing resource utilization both on and off the field. These technologies play a vital role in crop development and production, protecting crops from various biotic and abiotic threats. This review delves into a diverse range of AI applications in agriculture, including the use of sensors, robotics, and drones to improve agricultural operations. These innovations hold the potential to efficiently manage water, reduce the need for herbicides, pesticides, and fertilizers, and minimize manual labor, ultimately boosting productivity and enhancing crop quality. *Significance*: In a world where food security and resource efficiency are paramount, this review underscores the necessity of harnessing AI and ML for the advancement of precision agriculture and resource management.

Agriculture is one of the vital sectors of the Indian economy employing more than half of the Indian population. The global population is expected to reach around 10 billion by 2050 and to meet the demand, the agricultural sector is required to increase its production by 50 per cent compared to the year 2013 (FAO, 2017). Currently, the area for crop production is about 37.7 per cent of the total global area. It contributes significantly to the economic prosperity of developed countries as well as plays an active part in the economies of developing countries. The augmentation of agriculture has led to a significant increase in per capita income in the rural community and therefore, greater emphases need to be given to the agricultural sector. The development of the agricultural sector accelerates the growth and development of rural areas and transforms rural socio-economic scenarios (Shah *et al.,* 2019). Along with the advancement of knowledge, there has been a dramatic transformation in many industries (manufacturing, service, textile, food processing, etc.) around the globe (Kakkad *et al.*, 2019). Although agriculture is regarded as a relatively less digitized sector having the lesser application of information communication technologies, AI has already started to play a major role in everyday life, increasing our ability to solve problems in easier ways (Gandhi *et al.*, 2020). There are many examples of successful uses of AI in the agricultural sector. Plessen, M.G. (2019) designed a method of harvesting crops and introduced a vehicle routing for selecting different fields located at different places. With such promising technology, the agricultural workforces limited to only industrial sectors are now extending to other sectors. AI applications are spread in many sectors including physics, biology, computer science, mathematics, medicine, chemical science, engineering, etc.

Prospects of AI advancements in Indian agriculture : The future of Artificial Intelligence (AI) in India appears remarkably promising, poised to experience a significant transformation and growth trajectory. With the global AI market projected to surge at an impressive CAGR of 39.4 per cent, reaching approximately \$422.37 billion by 2028, India stands to play a pivotal role in this evolution. The nation's AI landscape is expected to flourish as well, with the market projected to expand at a CAGR of 20.2 per cent by 2025, according to the International Data Corporation (IDC, 2023), soaring from \$3.1 billion in 2020 to \$7.8 billion. As AI technologies continue to advance and become more accessible, the growth of AI in agriculture holds the promise of increased efficiency, reduced environmental impact, and improved food security. It has the potential to revolutionize traditional farming practices and contribute to the development of a more resilient and sustainable agricultural sector.

In a study, Jha *et al.* (2019) presented the AI implementation through a planned method for the identification of flowers, leaves and irrigation on the agricultural farm. The main idea of AI is to introduce technology that can function as a human brain (Parekh *et al.,* 2020). These technologies (software and smart programs) are developed by learning how our brains think, learn, make decisions and solve different types of problems. This software is provided with processed or readable data and these intelligent programs provide the required output for each valid input. Nowadays, major domains *viz*., machine learning (ML) and deep learning (DL) are at the heart of AI (Sukhadia *et al.,* 2020). AI deals with making intelligent programs as well as machines, while ML can learn things without being explicitly designed. On the other hand, DL deals with deep neural network learning (Kodali and Sahu, 2016). The main purpose of AI is to develop a problem-solving system that can include the use of an Artificial Neutral Network (ANN), which is a hardware (algorithm for processing) that is influenced by the intent and operation of the human brain (Shah *et al.,* 2020). It has an outstanding capability for self-documentation and adaptive learning. ANN has replaced several ongoing traditional methods that have developed in several fields including biology, computer science, physics, engineering, physiology, mapping, image processing, economics, medicine, etc. ANN goes through the learning process and adjusts the changes accordingly. Learning techniques can be broadly classified into two categories, supervised and unsupervised. In supervised learning, the machine algorithm is trained with well-labeled data while in unsupervised learning, the algorithm is trained with non-labeled data. The commonly used algorithms for supervised learning are Linear and Logistics regression, Random Forest, Support Vector Machine, Neural Network, etc. and in unsupervised learning, K-means clustering, Hierarchical clustering and Apriory algorithm are commonly used. In supervised learning, the desired output is given which is not provided in unsupervised learning.

AI-based systems have renovated today's agricultural sector to a new level. It has enhanced crop productivity and makes better on-time sensoring, cultural practices, processing and delivery. New technologies of AI systems applying robotics and drones have improved fabulous output in the agricultural sector. A variety of highly technical systems are programmed and designed to estimate many vital indicators such as detecting weed population, yield determination and status of crops (Liakos *et al.,* 2018). These computer-based hi-tech systems are used for AI-based irrigation, spraying, weeding and harvesting to improve production and lessen human labor. Various robotic AI soil detection techniques help to suggest efficient nutrient management (Wall and King, 2004). Temperature and moisture sensors significantly help in crop management and irrigation scheduling. The AI sensing systems are linked with GPS and the locations of these systems can be tracked with the help of Google Maps. Data from the systems are processed through an automated wireless protocol module and finally, the readings are displayed on the monitor screen incorporated with the machines to act according to response. The new AI spraying and weeding systems are implemented by using drones. AI-automated drones are being also used for yield mapping and detecting disease pests and other stress by using software programming and meeting with feed calculation and calibration. The framework of AI in agriculture is shown in Figure 1.

So far, several studies have been conducted on AI use in Agriculture. This systematic review was conducted to comprehensively assess and analyze the utilization of Artificial Intelligence and Machine Learning techniques in the context of precision agriculture and resource management. The study aims to provide insights into the current state, advancements, and potential applications of these technologies, contributing to a deeper understanding of their role in optimizing agricultural practices and sustainable resource utilization.

METHODOLOGY

The primary objective of this systematic review is to conduct a thorough and comprehensive evaluation of the deployment and analysis of Artificial Intelligence (AI) and Machine Learning (ML) methodologies within the domain of precision agriculture and resource management. The study endeavors to furnish comprehensive insights into the contemporary status, progression, and prospective implementations of these techniques, thereby augmenting the depth of knowledge concerning their pivotal role in enhancing agricultural methodologies and facilitating the sustainable utilization of resources. In this systematic review, a total of 325 studies were screened from the Web of Science database globally with the keywords "artificial intelligence, machine learning, agriculture, deep learning, image processing, sensors, robots, decision support systems, etc.". Out of that, 95 significant and useful studies were selected. AI tools were broadly classified into eight categories (Soil management, Crop management, Disease-pest management, Weeds management, Irrigation, Harvesting, Drone and Robotics) based on agricultural uses. Further, this paper reviews on importance and challenges of AI in agriculture and its scope in precision farming and natural resource management.

CONTENT

Applications of AI in the agriculture sector :

Soil management : Preparation of soil for cultivation is an important primary agricultural activity. It is well known that healthy soil can produce impressive yields and conserve soil resources. It is the use of operations, practices and treatments to improve soil performance. Heavy metal detection can be improved by integrating AI with a traditional soil survey (Kimpe and Morel,

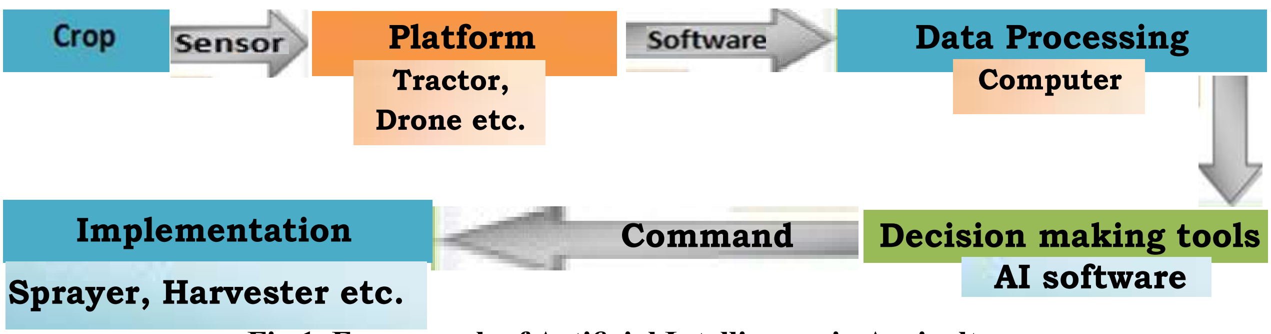

Fig 1. Framework of Artificial Intelligence in Agriculture

2000). The use of locally available compost and manure improves soil physical characteristics such as porosity, structure and aggregation. Organic matter presence in the soil also plays a vital role in preventing soil crust formation, soil nutrient storage and maintaining microbial diversity. Alternative tillage systems such as zero tillage or minimum tillage help to prevent soil physical degradation. Vegetables are prone to many soil-borne diseases that require control through proper soil management approaches (Abawi and Widmer, 2000). The degree of soil prone to degradation is much needed to implement future strategies. The application of AI such as management-oriented modeling (MOM) helps to increase nitrogen use efficiency as well as reduce nitrate pollution. The SRC-DSS model can characterize soils according to associated risks (Lopez *et al.,* 2008). Likewise, the Decision support system (DSS) model helps to detect erosion proneness and sediment yield in agricultural land. An artificial neural network (ANN) model helps to determine soil texture, structure, moisture, temperature, and nutrients, based on data obtained from existing on-time soil maps combined with hydrological characteristics derived from a digital elevation model (DEM) (Zhao *et al*., 2009). Another remote sensing device, a higher-order neural network (HONN) helps to estimate the dynamics of soil moisture. Some important AI techniques related to soil management are given in Table 1.

Crop management : Crop management began with sowing followed by growth monitoring and harvesting and ended with post-harvest storage. All these activities directly boost plant growth and yield. A better understanding of these activities in crop management helps to increase crop yield as well as improve the quality of products. AI-based precision crop management (PCM) is a farm management system developed to obtain required crop and soil resources according to farm needs to maximize profit without any negative effect on the surrounding environment.

The requirement of water and the presence of soil moisture helps to make correct decisions regarding crop cultivation resulting in higher production. Crop prediction methodology helps to choose the right crop by sensing different soil parameters such as soil texture, pH, soil nutrients, organic carbon, soil depth, soil temperature, precipitation, etc. (Snehal and Sandeep, 2014). A fully computer-operated speed rowing machine named "Demeter", equipped with a video camera and GPS, is capable of developing a plan for harvesting the whole farm and then applying its plan by cutting plants in rows, further processing and detecting undesirable obstacles in the field (Pilarski *et al.,* 2002). The application of AI in harvesting various crops including fruits and vegetables consists of the hardware and software of the robot including the auto-run vehicle, computer vision systems capable of developing 3D images of the fruits and vegetables and then a control system that operates the harvesting process. Location-specific precipitation data and weather parameters must be used. Proper calibration of ANN or CALEX parameters must be needed to obtain more accurate results. Table 1 consists of some AI techniques and their uses related to crop management.

Disease and pest management : Disease and pest management is essential to maximize agricultural production and ensure quality produce. Plant diseases and insect pests are regarded as very important restrictive factors of crop production. Various environmental factors affect the spread of these plant diseases and insect pests, which include genetic characteristics, type of soil, precipitation, temperature, wind, etc. Management of these factors in an unfavorable open environment is a huge challenge in the farming sector. To successfully control diseases and reduces losses, a grower must implement a suitable integrated disease management (IDM) or integrated pest management (IPM) strategy which consists of physical, chemical as well as biological control measures BEA (2018). These IDM or IPM models are time-consuming, hence there is a good scope to implement AI approaches along with IPM and IDM for plant-efficient disease and pest management. AI system "Computer vision system" (CVS) and "Genetic Algorithm (GA)" provides a dimension-based detection of disease samples in the field with high speed and also have multi-tasking ability, which greatly helps in the management of diseases. Another impressive AI system is "fuzzy logic", used for planning crop disease and insect management. It has also a "text to speech" (TTS) converter, which makes it even more user-friendly. Fuzzy expert provides pest information and its location-specific management (Kolhe *et al.,* 2011). It is also supported by internet services, advanced mapping and tracking of infested areas. Some applications of AI in disease-pest management are listed in Table 1.

Weed management : Improper weed management makes it unable to obtain an expected profit and yield.

Table 1. Applications of AI in the agriculture sector

AI Technique	Uses (References)
AI *in soil management*	
Fuzzy Logic: SRC-DSS	Can classify soil according to associated risks. (Lopez *et al.*, 2008)
ANN	Can predict soil enzyme activity. Accurately predicts and classifies soil structure, texture, moisture, temperature, nutrient erosion (Zhao *et al.* (2009)
HONN	Soil Moisture (Elshorbagy, A., Parasuraman, K., 2008)
AI based moisture analyzers	Precise temperature control (Hanson *et al.* (2007)
Satellite imagery	Spatial and multi-depth temporal soil temperature assessment (Singh *et al.* (2018)
Non-tuned data intelligent model	Soil temperature assessment (Sanikhani *et al*. (2018)
AI to map and model	Soil organic matter assessment (Ghorbani *et al.* (2019)
AI model	Soil fertility assessment (Kouadio *et al*. (2018)
Applications of AI *in crop management*	
Fuzzy Cognitive Map	Predict cotton yield and improve crop for decision management. (Papageorgiou *et al.* (2011)
ANN	Predicts crop yield. (Snehal, S.S., Sandeep, S.V. (2014)
SVM-based model	Chlorophyll assessment (Nieto *et al.* (2015)
Kernel of SVM model	Fertilizer management (Mustafa *et al.* (2004)
AdaBoost	Various crop management activities (Hassanijalilian *et al.* (2020)
SLFNs	Crop monitoring (O'Sullivan *et al.* (2019)
Regression tree technique	Predicting crop yield (Park *et al.* (2004)
AI *in disease-pest management*	
Web-based intelligent disease diagnosis system	Good accuracy, responds swiftly to the nature of crop diseases. (Kolhe *et al.* (2011)
Computer Vision System (CVS)	Works at a high speed. Can multitask. (Balleda *et al.* (2014)
Genetic Algorithm (GA)	Works at a high speed. Can multitask. (Balleda *et al.* (2014)
TTS Converter	Resolves plant pathological problems quickly (Kolhe *et al.* (2011)
CNN model	Disease detection (Selvaraj *et al.* (2019)
AI based intelligent system	Tea leaf disease detection (Ismail, M., Mustikasari (2013)
Deep neural networks-based system	Leaf disease identification (Sladojevic *et al.* (2016)
Deep Learning	Leaf disease detection (Hanson *at al.* (2017)
AI *in weed management*	
Optimization using invasive weed Optimization	Cost effective, enhanced performance (Moallem, P., Razmjooy, N. (2012)
Unmanned Ariel Vehicle	Can quickly and efficiently monitor weeds (Perez-Ortiz *et al.* (2016)
Digital Image Analysis, GPS	Has above 60%accuracy and success rate (Gerhards *et al.* (2003)
Sensor Machine Learning	Saves time and removes resistant weeds. (Brazeau, M. (2018)
Machine vision algorithm	Intra-row weeding (Bakker *et al.* (2006)
Color Based and texture based algorithms	Weed Detection (Sujaritha *et al.* (2017)
Data augmentation for image preprocessing	Weed Detection (Ngo *et al.* (2019)
Machine vision	Weed control in sugar beets (Astrand *et al.* (2002)
AI based smart sprayer	Precision weeding (Partel *et al*. (2019)

AI *in irrigation*	
Artificial Neural Network based control system	Automation (Kumar *et al.* (2022)
PLSR Algorithms	Increased efficiency and economic feasibility (EI-Hendawy *et al.* (2019)
AI-IoT Pivot Irrigation	Smart irrigation (Debauche *et al.* (2020)
Multilayer neural model	Evaporation decreased due to schedule and savings observed in water and electrical energy (Kolhe *et al.* (2011)
Machine Learning algorithm	Predict and tackle drought stress (Arvind *et al.* (2017)
Fuzzy logic controller with wireless sensors	Drip irrigation (Anand *et al.* (2015)
Multilayer Neural Model	Evaporation decreased (Karasekreter *et al.* (2013)
ANN (Feed Forward)	Water use in smart farm (Dela Cruz *et al.* (2017)
Zigbee	Experimental results verification (Al-Ali *et al.* (2015)
AI *in harvesting*	
Kinect v 2	Tomato harvesting (Yasukawa *et al.* (2017)
Mask R-CNN	Strawberry harvesting (Ge *et al.* (2019)
Matlab(k-nearest neighbor algorithm)	Apple harvesting (Davidson *et al.* (2017)
RealSense D435i, SSD algorithm	Mushroom harvesting (Rong *et al.* (2021)
Deep neural network (DNN)	Crop yield estimation (Kim *et al.* (2019)
CROO	Root crop harvesting (Alreshidi, E. (2019)
ZigBee protocol	lettuce harvesting (Chang *et al.* (2021)
AI base d soft gripper	Fruit harvesting (Navas *et al.* (2021)
Keras machine learning model	Harvesting (Horng *et al.* (2019)
AI *based drones in agriculture*	
DJI Phantom 3 Advanced UAV	Crop Monitoring, Mapping, and Spraying (Psirofonia *et al.* (2017)
Gyroscope and Accelerometer sensors	Pesticide Spraying (Garre, P., Harish, A. (2018)
Multispectral sensor	Crop Monitoring (Vega *et al.* (2015)
Arduino	Spraying Fertilizers and Pesticides (Pharne *et al.* (2018)
Multispectral camera	Remote Sensing (Xiang, H., Tian, L. (2011)
Spray motor	Pesticide Spraying (Yallappa *et al.* (2017)
Accelerometer and Gyroscope Sensors	Fertilizers and Pesticides application (Pharne *et al.* (2018)
Camera-cum-software system	Digital map (Reinecke, M., Prinsloo, T. (2017)
Hyper spectral Frame Camera	Monitoring leaf nitrogen (Zheng *et al.* (2016)
Bayesian information criterion	Remote sensing (Senthilnath *et al.* (2016)
AI *based robots in agriculture*	
MF-Scamp	Inspection, weeding and harvesting (Alexandratos, N., Bruinsma, J. (2015)
BoniRob	Physical and chemical weed control, measurement of soil compaction and to assist in plant breeding (Sorensen *et al.* (2007)
Agribot	Agricultural field works (Govin *et al.* (2001)
High-speed seedling transplanting robot	Transplanting (Hu *et al.* (2014)
Weed detecting robot	Weed detecting (Torres-Sospedra J, Nebot P. (2014)
Rose harvesting robot	Rose harvesting (Abarna, J., Selvakumar, A. (2015)
Pneumatic robot gripper	Brinjal harvesting (Blanes *et al.* (2015)

For many crops, more than 50 per cent loss in yield has been reported due to massive weed infestations (Datta *et al.*, 2017). The yield losses due to weed infestation largely depend on stages of crop growth, type of weeds, exposure period and management strategies (Swanton *et al.*, 2015). Weed population control with herbicides has been introduced over the decades. Even though, this management strategy costs a lot in lowering the profit of cultivation. Therefore, there is a need for an advanced weed control technique to minimize this loss of earnings. Auto-generated system developed consisting of unmanned aerial vehicles and imagery devices, which can convert the captured data into binary digits. Weed management can be done in several field crops including wheat, maize, rice and barley using drones connected with advanced computer-based decision-making systems and GPS-controlled spraying management. The drone can travel faster, be suitable for undulated topography, spray uniformly and save labor and time. Camera-incorporated robots (Kilter AS) and boom sprayers (DAT Ecopatch, AgriCon.) were introduced in crop fields for site-specific weed management (Gerhards *et al.*, 2022). Some important applications of AI for the control of weeds in agricultural fields are listed in Table 1.

Irrigation : The agriculture sector consumes more than $4/5^{th}$ of the water resources used on the planet, which is rising quickly with the ever-growing population. Therefore, the need for efficient technologies to minimize loss of water during irrigation has been of deep concern. Manual irrigation has a lot of difficulty over automated AI-operated irrigation systems. The evapotranspiration rate of plants depends on several environmental factors including growth stage, plant density, atmospheric humidity, solar radiation, wind speed and soil types, which must be taken into consideration while developing AI-based irrigation system. Types of equipment, such as fertility meter and pH meter are included in the system to monitor nutrient and pH status in the field. Automatic plant irrigators are set up on the field and connected via wireless systems to operate sprinkler or drip irrigation. Machine-to-machine technology (M2M) has been developed to communicate among different types of machinery placed on the field. Microcontrollers such as Arduino have been developed to check soil moisture levels and based on that turn ON/OFF the water source for irrigation. Primary devices like soil moisture meters, pH meters, nutrient meters and thermometers send digital signals to the main control system through wireless networks such as (Zigbee Gat *et al.,* 2016). GSM module-operated advanced soil moisture sensor alerts the farmer about the need for moisture through SMS in their mobile phone. Based on the information received, farmers can ON/OFF the water source by using SMS. Machine learning algorithms have been used to tackle drought situations in large farms. Like-wise robotics have been used to auto-irrigate crop fields, based on several sensors. Some AI techniques and their uses in irrigation are mentioned in Table 1.

Harvesting : Manual harvesting is usually practiced in India. Harvesting by hand is suitable for limited crops, such as cotton where the maturity of all pods never reaches at the same time in a plant (Reid *et al.,* 2001), hence selective manual harvesting of pods/fruits is necessary. Similarly, pulse crops matured at different times. Harvesting mature crops is a very crucial task to obtain quality yield. Mechanical selective harvesting requires advanced sensing technology, which is capable of gathering information on required parameters. The received information of the crop is processed by the microprocessor and based on the status of the crop plant or fruit/vegetable decision support system gives the command to the mechanical parts to harvest the crop, such as Kinect v 2 (Yasukawa *et al.,* 2017 and Mask R-CNN Ge, Y., *et al*., 2019) etc. The whole system can be divided into three divisions - sensor mechanism, harvesting mechanism and decision support system. AI-based machines can be operated at real-time data-sensing, data-processing and feeding the processed data for accurate harvesting. This type of advanced technology helps to solve labor shortages, reduce harvesting costs and maintain the quality of harvested crops. The AI-supported vehicle uses GPS, GIS and various vision sensors (such as Inverse-cam mechanism, Real Sense D435i etc) to collect information regarding certain threshold parameters of crops in the field (Rong *et al.*, 2021). Improved mechanical parts harvest the crops in bulk or selectively based on the signals received from the core system. In a modern farm, harvesting is further linked with other AI-based post-harvest activities like cleaning, grading, packing and cooling. Some important AI techniques related to harvesting are listed in Table 1.

Drone application : Drones are automatons unmanned aircraft that can be remotely controlled from a pre-determined distance. AI-based drone linked with GPS consists of several sensors. Drones are being used in agriculture for a range of operations including field monitoring, irrigation, weed detection, disease-pest management, disaster control and wildlife monitoring (Ahirwar *et al.*, 2019). Remote sensing with the use of drones for image capturing, processing and analysis is nowadays creating a massive impact on farming (Abdullahi *et al.*, 2015). Drone-based sprayers may be of different types, such as hydraulic energy sprayers, gaseous energy sprayers, centrifugal energy sprayers, kinetic energy sprayers etc. A simple drone sprayer includes a container, siphon, control valves, funnels, spray spouts and an AI-based digital system to detect liquid material requirements, apart from the mechanical parts of the drone. In the case of a hydraulic energy sprayer, the liquid materials are pressurized up to 40–1000 psi by utilizing a vacuum apparatus followed by a shootout through the spray spout. Gaseous energy sprayers have a blower to create a high-speed airflow, which pushes liquid toward the outlet of the spout. A centrifugal energy sprayer contains a fast-rotating tool, which turns the liquid material and forces it towards the outlet and forms droplets. Kinetic energy sprayers have a vibrating spout system that forms coarse droplets. Drones are gaining popularity among farmers as crop monitoring devices, such as DJI Phantom (Psirofonia *et al.,* 2017 and Arduino Pharne *et al.*, 2018), etc. Advanced sensors and imaging tools have come up with many new ways to boost yields and minimize damage. These drones have abilities to survey, data acquisition and automatically analysis is done by AI systems. Many Satellite-linked (GIS) drones have been used to look over and study large croplands and forests. This system also helps to process yield maps in a particular crop field. Nowadays, there are many emerging Indian drone manufacturing firms developed, especially dedicated to agricultural drones, such as Multiplex drones, Paras Aerospace, Krishi Vimaan, ASAP Agritech etc. A brother-sister from Kerala, India developed a UAV capable of increasing farmers' income by more than 40 per cent. Some advanced AI techniques and their uses related to drone application in agriculture are given in Table 1.

Robotics in Agriculture : Automation of agricultural activities is now in high demand to increase yield with the use of machinery and technology. In Asian countries, where farmers have small lands, the field of agricultural robotics focuses on developing multi-use small efficient robots in place of traditional large tractor-based machinery (Bisgaard *et al*., 2004). On the other hand, these systems have a low environmental impact as they minimize chemical use, energy consumption and inputs. Robots have specialized navigation tools such as GPS, map-based, landmark navigation and vision-based to work under control areas for farming. This technology is used for seed bed development, sowing, transplanting, re-seeding, plant counting, site-specific weeding, location-specific spraying, irrigation, etc. (Blackmore *et al.*, 2004). Robotic vehicles are currently used for harvesting fruits like tomatoes, cucumbers, apples, citrus, etc. Milking robots are getting attention in many countries. Robots such as MF-Scamp are mainly developed for inspection, weeding and harvesting (Alexandratos and Bruinsma, 2015). These GPS-connected robots have a four-wheeled or six-wheeled auto-moving system. Crops need to grow in rows and columns so that the robots can inspect, remove weeds and harvest crops accurately. The framework of agricultural robots is shown in Figure 2.

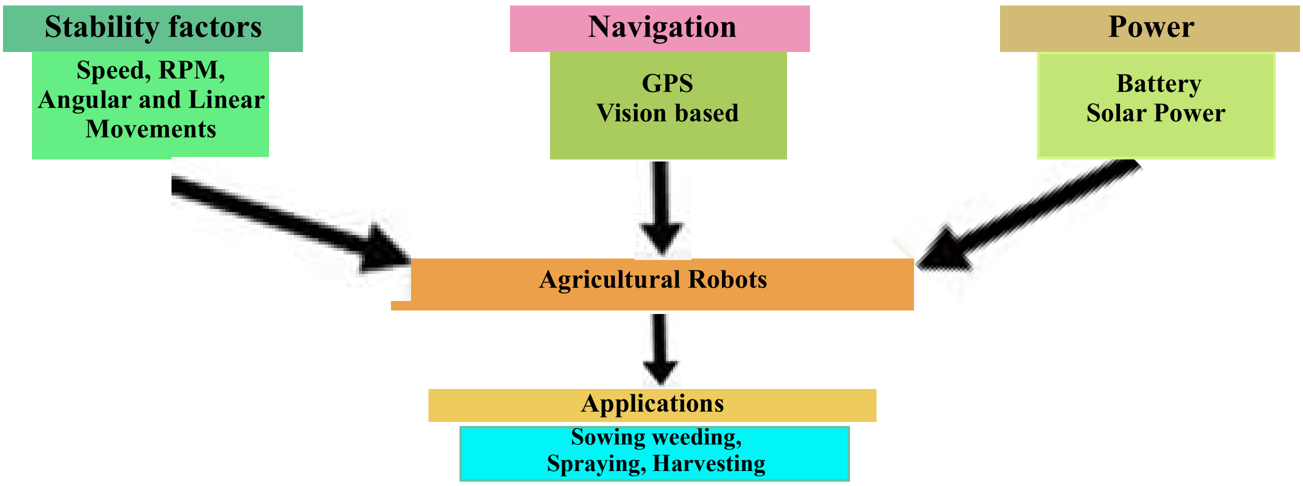

Fig 2. Framework of Agricultural robots

This crop canopy-based robot ISAAC-2 is designed to gather quickly precise information in the crop field to assess crop health and growth status. This advanced robot carries tools above the crop canopy and uses GPS to detect the accurate location of the plant. This robot offers automated crop survey, crop nutrient status, stress conditions and weed detection. BoniRob is another independently steerable multi-use robot designed for the application of physical and chemical weed control, measurement of soil compaction and to assist in plant breeding. These robots are well connected with satellite systems and can communicate with each other as well as farmers (Sorensen *et al.,* 2007). A robot developed by Stanford University called "Lettuce Bot" has a very advanced robotic system consisting of computer visualization and machine learning algorithms to inspect crops in the lettuce growing fields. It can detect weeds very close to lettuce plants followed by the release of a spray of herbicide or fertilizer. The CROPS robots can select harvest fruits after determining ripeness and also have the capability of target spraying towards foliage. This robot also consists of gripping, cutting and harvesting tools (Godwin *et al.*, 2001). Agribot developed by BIT Hyderabad, India (Gollakota *et al.*, 2011), is designed to higher the yield, increase the working speed, improve accuracy of tasks and reduce labor cost. It is used for harvesting, spraying, sowing and weeding. This robot has a camera for live vision of the crop field and GPS GPS-connected map module to operate agricultural operations on a specific land. Some important agricultural robots are listed in Table 1.

As stated in the budget of the Indian Government for 2022-23, the focus of the government will be on promoting drones in the Agricultural sector. For this purpose, a total of Rs 127 crore has been released for the purchase, demonstration and promotion of Kisan drones in agriculture through custom hiring centers and subsidy schemes of the government of India 2022 (Ministry of Agriculture & Farmers Welfare, 2023). 'Kisan' Drones will be promoted for crop assessment, digitization of land records and spraying of insecticides and nutrients. It can usher in a revolution as high-capacity drones can be used to carry vegetables, fruits, and fish to the market directly from the farms also (Beriya, 2022).

Artificial intelligence in precision agriculture and Natural resource management : Effects of climate change, scarcity of water, injudicious use of fertilizers and chemicals-based agriculture systems have forced us to rethink improving the resource use efficiency. Under changing hydro-climatic circumstances, agroecosystems must be reoriented to reduce stress on environmental resources while meeting rising socio-economic goals. Land degradation, hydro-climatic scarcity, food insecurity, greenhouse gas (GHG) emissions and poverty may all be mitigated by sustainable agriculture (Toor *et al.,* 2020). Due to the growing need for smart agriculture, there has been substantial growth and development in the field of crop estimation and prediction. The study of crop age status is critical for avoiding over-fertilization, determining the best time to harvest, and lowering production

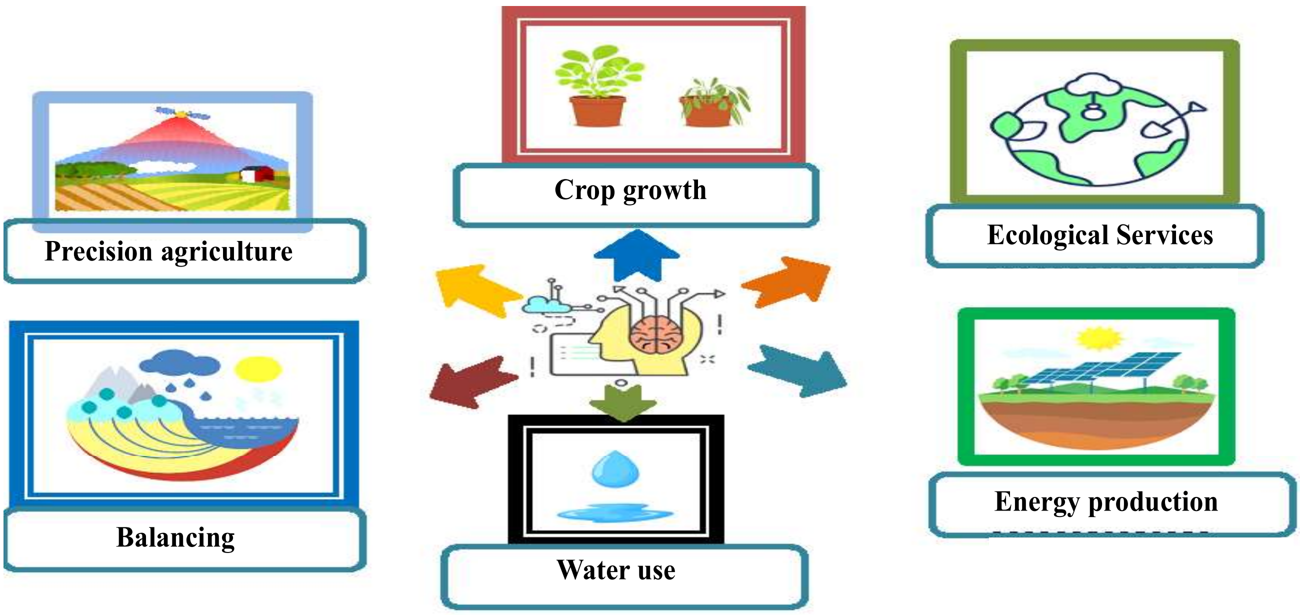

Fig 3. Use of artificial intelligence for precision agriculture

costs. In this arena, AI has a greater role to play. The image-based analysis combined with AI is useful in estimating category age in crops. AI has emerged as a critical component in addressing several environmental sustainability concerns, including sustainable agriculture, biodiversity, energy, and water management (Kwok, 2019) (Figure 3). Several applications have been reported in this area. In agriculture, AI-driven predictive models have shown promising results in predicting crop yields, disease outbreaks, and optimal planting times. Companies are leveraging AI to provide farmers with actionable insights for resource management and improved productivity.

It's important to note that the performance of AI predictions is continuously evolving as technology advances, more data becomes available, and algorithms become more sophisticated. While AI has achieved impressive levels of accuracy and efficiency in many areas, there are still challenges to overcome, including data quality, bias, and interpretability, that researchers and practitioners are actively working to address. To forecast ecosystem services, biodiversity research has created machine learning or natural language processing systems. Water resource conservation is progressively benefiting from AI applications and machine learning algorithms for prediction and optimization. Similarly, the energy domain emphasis lies in neural networks, expert systems, pattern recognition, and fuzzy logic models. Ensuring environmental sustainability requires vigilant monitoring of initiatives.

Future of agricultural supply chain management through blockchain technology, IoT and AI : The integration of Blockchain technology, AI and the Internet of Things (IoT) into agricultural supply chain management emerges as a transformative and innovative avenue, poised to harness the anticipated advancements of the forthcoming 6G technology. This visionary approach holds profound potential to reshape the agricultural industry, introducing heightened levels of transparency, traceability, and security throughout the intricate supply chain network (Feng *et al.*, 2020).

Recent research underscores the substantial capabilities of Blockchain's decentralized and immutable ledger system to effectively tackle the pressing challenges encountered by the sector. These challenges encompass a broad spectrum, ranging from imperative concerns like food safety and fraud prevention to the optimization of scarce resources. The amalgamation of Blockchain with IoT amplifies these advantages, as IoT systems gather data from diverse devices, including smart tags like RFID, NFC, barcodes, and more, as well as sensory data such as temperature and humidity. This data collection further bolsters traceability and enables better quality control, safety enhancements, optimized supply chain processes, and cost reductions, especially during product recalls (Frank, 2021).

With global economic interconnectivity intensifying, the importance of inter-organizational communication in supply chains is accentuated. The integration of Blockchain and IoT aligns seamlessly with this context, providing a sophisticated solution to challenges that span across industries. This strategic amalgamation not only augments the agricultural supply chain's robustness but also contributes to broader sustainability agendas.

Artificial Intelligence (AI) for vibrant Agricultural Extension Advisory Services (AEAS) : Agricultural extension advisory services (AEAS) play a crucial role in providing farmers with information, knowledge, and resources to enhance their productivity and livelihoods (Jankovic *et al.*, 2015). The integration of Artificial Intelligence (AI) in agricultural extension services has the potential to revolutionize the way information is disseminated, decision-making processes are optimized, and overall agricultural practices are improved (Deji *et al.,* 2023). In the changing global perspective, the recent extension advisory service demands extraordinary innovative strategies and approaches to overcome the more complex challenges ranging from food security and resource efficiency to climate change adaptation. The traditional extension advisory service mostly relied on human efficiency and field-level networking to render information to the farmers through field visits, demonstrations and training etc, but sometimes the valuable services lack timeliness, scalability and reach (Cherupelly, 2022). The integration of AI with AEAS promises to overcome these barriers and renders prodigious benefits to the client system. AI, encompassing machine learning, data analytics, and automation, can substantially enhance the efficacy of agricultural extension by harnessing the power of data, algorithms, and intelligent systems (Smith and Johnson, 2020). Chatbots and Large Language Models (LLMs) powered with AI can play a significant role in enhancing agricultural extension advisory services by providing interactive and personalized support to farmers (Bhuyan *et al.*, 2022).

Chatbots can provide instant responses to farmers' queries, allowing them to access information and assistance in real time. This is particularly useful for addressing urgent issues such as pest outbreaks or weather-related concerns (Ekanayak and Saputhanthri, 2020). Farmers can interact with chatbots through various platforms, including websites, messaging apps, and even simple feature phones. This increases the accessibility of extension services, especially in remote areas and can also deliver relevant information on a wide range of topics, including crop management practices, pest control, weather forecasts, and market prices. They can also guide farmers through various processes, such as crop planning or irrigation scheduling. Multilingual chatbots can cater to diverse linguistic preferences, ensuring that farmers from different regions can interact comfortably in their preferred languages. Chatbots can be used to collect data from farmers, such as crop types, land size, and agricultural practices. This data can be valuable for generating insights and tailoring extension services to specific needs.

Large Language Models (LLMs) can be used to build knowledge bases for agricultural information. Farmers can ask questions in natural language, and the model can retrieve relevant information from its extensive training data, LLMs can assist in generating informative content for extension services, including articles, guides, and tutorials (Tzachor *et al.*, 2023). This can help in expanding the range of available resources for farmers. By understanding the context of farmers' queries, LLMs can provide personalized recommendations based on their specific needs, location, and agricultural practices. LLMs can contribute to the development of interactive educational materials. This includes creating virtual training modules and simulations to educate farmers on best practices and new technologies. LLMs can process vast amounts of data to provide farmers with updates on agricultural policies, market trends, and relevant news, enabling them to make informed decisions.

Some examples of Chatbots and LLMs used for AEAS in India are:

Krishi Sakhi: Krishi Sakhi is an initiative by the Government of India that focuses on providing agricultural information and guidance to farmers, especially women (Patel and Sethi, 2021). While it may not explicitly mention the use of LLMs, it's common for such platforms to integrate chatbots or AI-driven assistants to enhance communication and support.

Agri Chat Bot (AgroStar): Agro Star, an agritech platform in India, provides Agri Chat Bot services Javaid *et al.* (2023). While it may not explicitly mention LLM integration, chatbots are often designed to understand and respond to user queries using advanced natural language processing techniques.

Hello Krishi: Hello Krishi is a mobile app that connects farmers with agricultural experts to get personalized advice. While the specific technologies used may not be detailed, such platforms often leverage chatbot-like interfaces to facilitate farmer-expert interactions.

Fasal Salah (IFFCO): Indian Farmers Fertilizer Cooperative (IFFCO) offers the Fasal Salah app, which provides personalized agricultural advice. While the exact technology stack may not be detailed, it's common for such platforms to incorporate AI-driven features like chatbots for user engagement.

Digital Green: Digital Green, a non-profit organization, has been using technology to provide extension services to farmers in India. While it may not explicitly mention chatbots or LLMs, it emphasizes the use of digital tools for disseminating agricultural knowledge.

Chat GPT: Generative AI like ChatGPT is useful in agricultural extension advisory services through the creation of chatbots for solving farmers' problems concerning crop production, marketing, disease management, etc. It also has the potential to provide customized recommendations to farmers for better decision-making.

Ama Krush: Ama Krush for farmers, user-centric artificial intelligence systems that deliver information to citizens are emerging as critical modalities for solving information asymmetry in governance. It is running successfully in Odisha.

Farmer CHAT: Generative AI startup Gooey.AI and global development organization Digital Green have come together to announce a revolutionary new product, Farmer CHAT, to address the needs of farmers on the frontlines of climate change and water security. It is a locally responsive farmer advisory service designed to facilitate real-time communication between governments and farmers on the frontlines of climate change and water security issues. It is a GPT4-based, multi-lingual artificial intelligence (AI) platform that empowers farmers and government extension agents with data-driven insights and decision-making tools to optimize crop management, reduce waste, and increase yields.

CONCLUSION

In conclusion, this systematic review underscores the significant strides that Artificial Intelligence (AI) and Machine Learning (ML) have made in revolutionizing precision agriculture and resource management. The synthesized findings highlight the efficacy of AI-driven techniques in enhancing agricultural practices, optimizing resource utilization, and promoting sustainability. Looking ahead, the future scope of research in this domain is promising and multifaceted. Expanding the frontiers of AI and ML applications, there is a compelling need to delve deeper into climate-resilient farming methodologies. Investigating advanced models for predictive analytics, coupled with the integration of diverse data sources, will enable precision decision-making even in dynamically changing environmental conditions. The exploration of ethical considerations surrounding AI in agriculture is paramount, ensuring responsible deployment and addressing societal concerns.

Furthermore, refining AI-powered robotics and automation systems for seamless integration into farm operations is pivotal. The potential of harnessing blockchain technology to bolster transparency, traceability, and trust across the agricultural supply chain warrants rigorous exploration. In light of these emerging avenues, interdisciplinary collaborations between agronomists, data scientists, technologists, and policymakers are imperative to drive forward the research agenda. By unraveling the intricacies of AI's role in precision agriculture and resource management, we pave the way for a more sustainable and resilient agricultural landscape, poised to address global food security challenges while respecting ecological balance.

Looking ahead, the future scope of research is expansive and exciting. One promising avenue is the integration of Blockchain in agricultural supply chain management, poised to capitalize on the upcoming 6G technology boom. This innovation promises heightened transparency, traceability, and security across the supply chain, addressing critical issues in the industry. Furthermore, the potential for Machine Learning algorithms, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF), holds great promise for crop yield forecasting. Additionally, there is potential for delving into the categorization of farming communities, modeling consumer behaviors, and deciphering the intricate dynamics of farmers' decision-making processes.

The integration of Chatbots with LMM plays a pivotal role in case of materializing robust, timely and trustworthy Agricultural Extension Advisory Services for sustainable agricultural development.

As we embark on this journey of exploration, interdisciplinary collaborations will be paramount. Agronomists, technologists, data scientists, and policymakers must work in unison to unravel the untapped potential in these research domains. By harnessing AI's capabilities and delving into these unexplored areas, we can chart a course toward a more sustainable, efficient, and equitable agricultural future.

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