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Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation

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A R T I C L E I N F O

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A B S T R A C T

The automation of all-terrain vehicles (ATVs) through the integration of advanced technologies such as machine learning (ML) and artificial intelligence (AI) vision has significantly changed precision agriculture. This paper aims to analyse and develop trends to provide comprehensive knowledge of the current state of ATV-based precision agriculture and the future possibilities of ML and AI. A bibliometric analysis was conducted through network diagram with keywords taken from previous publications in the domain. This review comprehensively analyses the potential of machine learning and artificial intelligence in transforming farming operations through the automation of tasks and the deployment of all-terrain vehicles. The research extensively analyses how machine learning methods have influenced several aspects of agricultural activities, such as planting, harvesting, spraying, weeding, crop monitoring, and others. AI vision systems are being researched for their ability to enhance precise and prompt decision-making in ATV-driven agricultural automation. These technologies have been thoroughly tested to show how they can improve crop yield (15-20%), reduce overall investment (25-30%), and make farming more efficient (20-25%). Examples include machine learning-based seeding accuracy, AI-enabled crop health monitoring, and the use of AI vision for accurate pesticide application. The assessment examines challenges such as data privacy problems and scalability constraints, along with potential advancements and future prospects in the field. This will assist researchers and practitioners in making well-informed judgments regarding farming practices that are efficient, sustainable, and technologically robust.

1. Introduction

Precision farming is a significant shift from traditional agricultural systems, utilizing contemporary techniques to enhance crop yield while minimizing resource consumption [1]. Precision agriculture is a data-driven method that utilizes various instruments like sensors, drones, GPS guidance systems, and machine learning algorithms [2] to analyse and address field variability. This strategy allows farmers to assess changes in crop health, soil composition, and moisture levels to make informed decisions tailored to specific sections of their farm [3]. Precision agriculture aims to enhance global food production by utilizing farm inputs such as fertilizer, pesticides, and water efficiently through real-time data collection and analysis to improve yield, efficiency, and environmental sustainability [4].

The progress in many agricultural areas has been sped up by the remarkable development of machine learning (ML) and Artificial Intelligence (AI) vision in agriculture [5]. Initially employed for crop monitoring and production prediction [6], machine learning techniques have since broadened to encompass a variety of agricultural applications. The applications utilize extensive datasets for predictive analytics and decision-making [7]. AI vision systems have reinvented pest identification, disease detection, and crop analysis, allowing for precise and prompt actions [8]. Autonomous vehicles and drones are already capable of doing intricate tasks such as planting, spraying, and harvesting in fields due to the combination of machine learning algorithms with artificial intelligence vision technology [9]. Rapidly advancing technologies offer scalable solutions for agriculture that optimize productivity, reduce environmental impact, and efficiently manage farm

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investment [10].

All-terrain vehicles (ATVs) are platforms that are flexible and responsive for incorporating new technology into farming operations, which makes them critical to the revolution in precision farming [11]. The vehicles can negotiate challenging terrain and perform precise, location-specific tasks due to their powerful navigation systems, sensors, and automation features [12]. ATVs let farmers perform certain tasks efficiently while minimizing crop damage and soil compaction by facilitating the use of various agricultural tools such as seeders, sprayers, and sensors [13]. ATVs equipped with machine learning and AI vision systems enable autonomous operations for tasks such as planting, harvesting, and monitoring. This technology enhances productivity and maximizes crop yield by optimizing farm-asset utilization [14,15]. Vehicles are essential for advancing precision farming by providing adaptable and nimble solutions to address the intricacies of contemporary agricultural practices.

The main goal of this review article is to offer a detailed analysis of the current status and recent advancements in incorporating machine learning (ML) and artificial intelligence (AI) vision technologies into all-terrain vehicle (ATV) systems for precision farming purposes. The paper provides an in-depth examination of machine learning and artificial intelligence vision applications [16,17] in ATV-based agricultural automation, focusing on crop harvesting and field activities. Several studies conducted to look how AI can help with agricultural problems like managing soil and crops and using expert systems to increase productivity [18,19]. These studies highlight the considerable potential of

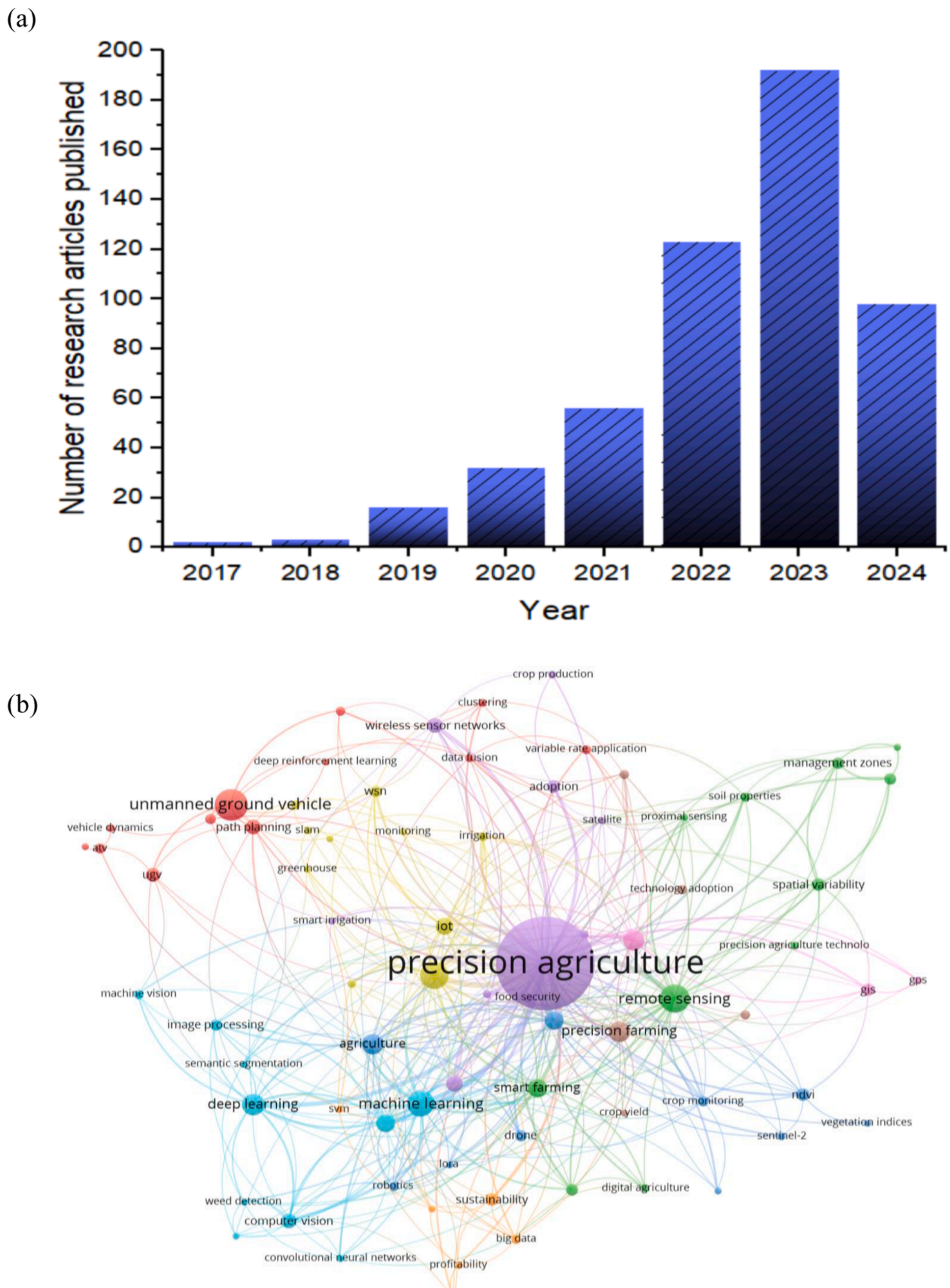


Fig. 1. (a) Trend of scientific publications in the Scopus database on AI/ML integrated ATVs for precision agriculture from 2017 to 2024 (till 8th May 2024); (b) The keyword network diagram based on 77 most occurring keywords out of 2998, with number of occurrences of a keyword being ≥ 5 (Based on 1055 publication accessed from Scopus database with keywords ‘ML in agriculture, AI vision, ATV, Precision Agriculture and unmanned ground vehicle’ (17th March 2024).

machine learning and artificial intelligence vision applications in ATV-based agricultural automation. The study aims to highlight the potential of these technologies to improve agricultural methods, efficient farm investment, increase crop productivity, and minimize environmental footprint [20].

Hence, the present review focuses on the current status of ML algorithms and AI vision in shaping modern-day agriculture. This review is expected to provide a thorough examination of the literature, current advancements, obstacles, and future paths regarding the incorporation of machine learning and artificial intelligence vision in autonomous terrain vehicle-driven precision farming systems. The aim is to offer guidance to academics, practitioners, and stakeholders to help them realize the potential applications and repercussions of these technologies in altering contemporary agricultural methods.

2. Literature review methodology

Though the research interest on 'AI-ML and Precision Agriculture' has been significantly increased in the last decade, there need to have a diversified look into these thrust area. Various scientific literatures are encompassed within the realm of science and are archived across multiple databases such as Google Scholar, Scopus, PubMed, and Web of Science (WoS). Among them, the authors of this review opted to utilize the Scopus due to their extensive peer-reviewed research publications and citations in this domain in various journals across the globe [21]. A literature search of published articles on AI-ML integrated ATV for precision agriculture showed that the scientific studies on this domain have an upward trend with a notable rising drift between 2017 and 2024 (till date) (Fig.1a). There has been about 2 fold increase in research publications each year from 2019 to 2023 and is expected to go much beyond this year and in the following years to come. This demonstrates the relevance of the topic for current research and publications. Thereafter, a bibliometric analysis was performed in VOS viewer following the methodology of Mukarram, Wandhekar [22]. A keyword network diagram (Fig. 1) constructed based on 77 most occurring keywords out of 2998 from a total of 1055 publications from Scopus database with the search keywords 'ML in agriculture', 'AI vision', 'ATV', 'Precision Agriculture 'and 'Unmanned surface vehicle' showed 9 clusters, indicating that integration of AI-ML in precision agriculture is a prime thrust area for research exploration. In the network, the keyword 'Precision Agriculture' is well connected that indicates the rising interest of researchers and stakeholders in deploying Precision agriculture for farm automation. In contrast, the keyword 'ATV' was found poorly connected with others keyword, raising concerns over the successful implementation of AI-ML models in these vehicles for carrying out on-field operations effectively. The primary reason could be complexity in understanding vehicle dynamics, implementing proper AI models for ground navigation at varying slopes and incompatibility of the developed model in reducing computational time. Implementation of multiple models with adaptive boosting algorithms are required to improve the model accuracy and also to reduce computational cost [23]. However, to keep the discussion focused and updated, an attempt was made to include only the most impactful research articles.

3. Machine learning in precision agriculture

Machine learning, a subset of artificial intelligence, is dedicated to establishing models and methods that enable computers to learn from data and improve without requiring explicit programming [24]. Machine learning involves developing mathematical models to analyse data patterns for the purpose of making predictions or decisions [25]. By iteratively examining historical data, these models identify patterns and enhance their precision as time progresses [26]. The typical process involves training the model on a dataset to uncover correlations between input features and output values. Unsupervised learning utilizes unlabelled data to identify concealed patterns, whereas supervised learning relies on labelled data [27,28]. Reinforcement learning utilizes interactions with the environment to learn how to attain specific goals [29]. Neural networks, decision trees, support vector machines, and clustering algorithms are machine learning methods utilized for data processing, pattern recognition, and autonomous prediction or decision-making [9].

3.1. Applications and benefits in farm automation

3.1.1. Sowing

Machine learning technology used in precision planting with automated all-terrain vehicles (ATVs) has improved farming methods by allowing for accurate and flexible planting techniques. These applications utilize machine learning algorithms to examine soil variability, historical yield data, and environmental conditions in order to enhance seed location and density [16]. Machine learning algorithms can optimize planting depths, spacing, and seed kinds for maximum crop output by analysing real-time data from sensors on automated ATVs [30,31]. The use of machine learning in precision planting using automated ATVs demonstrates how technology improves precision agriculture by refining planting procedures to promote efficiency and productivity. Artificial intelligence (AI) and machine learning (ML) improve the process of determining the optimal positioning of seeds, resulting in consistent growth of crops and increased productivity.

3.1.2. Harvesting

Machine learning algorithms incorporated into automated ATV systems assess various data sources, such as crop maturity indicators, weather patterns, and field conditions, to enhance harvesting operations [32]. The algorithms provide predictive modelling to identify the optimal timing for harvesting, ensuring that crops are harvested when they are at their highest level of maturity, thereby maximizing both yield and quality [33]. ATVs equipped with sophisticated sensors and vision systems can use machine learning to selectively detect, categorize, and harvest crops based on certain criteria helps minimize field loss and increase productivity [34]. Integrating machine learning with automated ATV systems for harvesting optimization demonstrates the potential to transform farming practices by ensuring timely and effective harvesting operations while maintaining crop quality and quantity.

3.1.3. Spraying

Machine learning algorithms are crucial for enabling accurate spraying and fertilizing operations in ATV automation, ushering in a new era of precise and efficient agricultural techniques. These algorithms are incorporated into automated ATV systems to utilize data from several sources, like soil composition, crop health indicators, and environmental conditions, for the efficient use of pesticides and fertilizers [35]. By utilizing machine learning methods like predictive modelling and pattern recognition, these systems can identify the most effective spraying and fertilizing approaches customized for specific sections of a field, reducing excess usage and guaranteeing precise application [36, 37]. AI-driven vision systems on ATVs are used for real-time crop monitoring, indicating regions needing treatment, and enabling precise, automated distribution of agrochemicals based on detected needs [38, 39]. The incorporation of machine learning algorithms in ATV automation for spraying and fertilizing activities demonstrates its ability to enhance better farm input management and reduce environmental harm in agriculture.

3.1.4. Weeding

Machine learning plays a crucial role in transforming weeding and pest control methods in agriculture during ATV operations. Incorporating machine learning techniques into ATV systems allows for the creation of advanced weed identification and classification models [39]. The models utilize data from sensors and camera systems to precisely distinguish between crops and weeds in real-time [40]. Machine learning-based pest detection systems integrated into automated ATV operations use environmental data to forecast and detect possible pest outbreaks, allowing for preventive actions in targeted pest management [41]. Machine learning in ATV operations enables automated decision-making for accurate weed management and insect control, which can reduce pesticide usage, improve crop health, optimize agricultural techniques, and minimize environmental impact.

3.1.5. Crop monitoring

Incorporating machine learning with all-terrain vehicle (ATV) automation has redefined crop monitoring and health evaluation, providing unparalleled understanding of field conditions and plant health. ATV-mounted sensors and imaging systems use machine learning algorithms to gather and analyse extensive data for evaluating crop health indicators like leaf colour, biomass, and disease symptoms [42]. These algorithms facilitate the development of prediction models for early disease detection, stress identification, and yield forecasting [43]. AI-powered image analysis systems on ATVs offer immediate evaluations of plant health and development, enabling prompt actions and specific management strategies [44]. Machine learning in ATV automation improves farmers' capacity to optimize yields and implement precision agricultural practices by enabling proactive decision-making through real-time crop health assessments [45].

3.2. Data collection and analysis techniques

Precision agriculture utilizes sensor technology to gather real-time data on field characteristics such as soil moisture, temperature, and nutrient levels [46]. Ground-based and wearable sensors offer detailed data that is essential for making accurate decisions in agricultural activities. Farmers can improve decision making and increase crop output by using these tools to monitor and change methods according to changing field conditions. Remote sensing and satellite photography provide a broad view, enabling the surveillance of extensive agricultural regions [47]. These technologies offer multispectral and hyperspectral data, allowing for the evaluation of vegetation health, crop stress, and general field conditions. Using satellite imaging helps spot patterns and anomalies and assess crop health on a large geographical scale. Drones are now important tools for collecting detailed aerial data in precision agriculture, providing high-quality imagery and data gathering capacities [48]. Drones with specialized sensors and cameras offer extensive and localized data on crops, soil, and topography, aiding in precision decision-making and focused interventions in farming methods.

Data fusion approaches combine data from several sources, such as sensors, satellites, drones, and weather stations [49]. By integrating these diverse data sources, a thorough comprehension of field conditions is achieved, which improves the precision and dependability of agricultural decision-making procedures (Fig. 2). Big data analytics in agriculture entails the processing and analysis of substantial amounts of data to get important insights [50]. Applying machine learning algorithms and data mining techniques to extensive agricultural data aids in recognizing patterns, forecasting trends, and enhancing farming methods to improve efficiency and sustainability.

In order to enhance agricultural decision-making processes, it is essential to integrate diverse data sources and utilize big data analytics in agriculture. By processing substantial amounts of data and applying machine learning algorithms, valuable insights can be gained, patterns can be recognized, trends can be forecasted, and farming methods can be improved for increased efficiency and sustainability [51]. This comprehensive approach allows for a deeper understanding of field conditions and ultimately improves the precision and reliability of agricultural practices.

3.3. Challenges and limitations

Challenges and constraints remain in precision agriculture despite its progress. Sophisticated technology can create challenges in terms of accessibility and pricing, which can hinder small-scale farmers from adopting it [52]. Interoperability difficulties among various systems and devices for data collection and analysis impede smooth integration, resulting in data silos and inefficiencies in decision-making processes [53]. Issues related to privacy in the acquisition and utilization of agricultural data, such as ownership and distribution rights, provide ethical and legal challenges [54]. Moreover, the difficulty of having skilled individuals who can effectively manage and understand intricate agricultural data persists [55]. Weather variability, especially uncertain conditions, impacts the dependability of prediction models and decision-support systems, creating obstacles for precise and timely

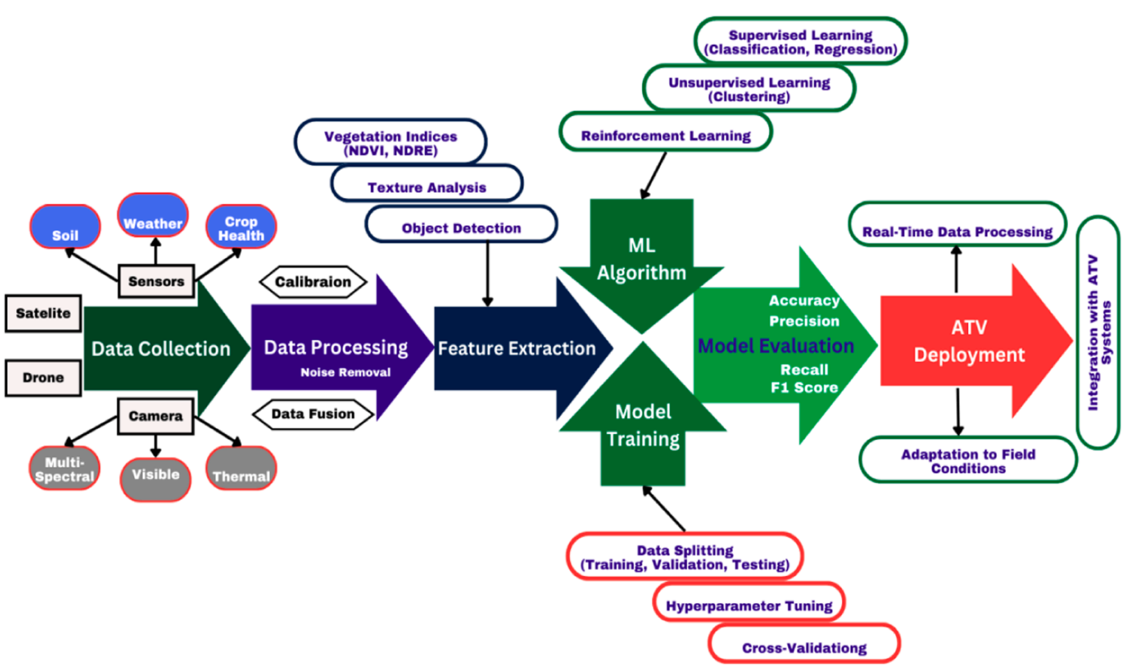


Fig. 2. Data collection and analysis for AI and ML to use in ATV.

interventions in agricultural practices [56]. To effectively adopt precision agriculture techniques on a large scale, we need to tackle problems related to technical accessibility, interoperability, data protection restrictions, talent gaps, and weather variability.

4. AI vision in agriculture automation

AI vision technology, an element of artificial intelligence, transforms agricultural automation by combining enhanced image capabilities with complex machine learning algorithms [57]. This combination enables robots to analyse visual information, allowing them to identify patterns, recognize irregularities, and make well-informed choices in agricultural environments [58]. AI vision systems in agriculture use complex algorithms to analyse various visual inputs, such as data from drones, cameras, and sensors. This processing power enables precise and efficient completion of activities including evaluating crop health, identifying diseases, and predicting yields with exceptional precision [59]. Integrating AI vision technology into agricultural automation provides farmers with valuable information about crop behaviour, allowing for precise interventions and better investing capabilities to enhance sustainability and productivity in agriculture [60,61].

4.1. Imaging and sensing technologies in agricultural automation

Imaging and sensing technologies are crucial for current agricultural automation, including advanced instruments that transform farming methods [62]. Technologies such as multispectral and hyperspectral photography, LiDAR, thermal imaging, and sensor arrays provide farmers with a detailed perspective of their fields [63]. Systems for multispectral and hyperspectral imaging collect data outside the visible spectrum, offering information on plant health, stress levels, and nutrient deficits [64]. LiDAR technology provides three-dimensional field mapping, assisting in terrain analysis and accurate topographical evaluations [65,66]. Thermal imaging sensors can identify changes in crop temperatures, enabling the early diagnosis of pests or diseases. These imaging and sensing technologies provide farmers with immediate and precise data that is essential for making educated decisions and carrying out specific agricultural actions [63,67].

4.2. Object detection and classification for precision farming

Object detection and classification are essential in precision farming, using advanced technology to identify and classify important factors for making agricultural decisions [9]. Precision farming utilizes object detection systems, typically driven by machine learning algorithms, to identify different components in agricultural environments such as crops, weeds, pests, and soil irregularities [80]. These systems use data from sensors, cameras, and drones to assess and categorize items in real-time, enabling specific interventions like selective spraying or weeding [81]. Convolutional neural networks (CNNs) are successful in accurately identifying and categorizing agricultural factors, allowing farmers to use precise and efficient farming methods [39,82]. Object detection and classification technologies play a crucial role in precision farming by helping farmers optimize implement use and improve crop management.

4.3. AI vision applications in crop health monitoring

AI vision applications in crop health monitoring are a major advancement in precision agriculture, providing exceptional abilities to evaluate and control crop conditions. The applications use advanced algorithms to interpret visual data from drones, sensors, and cameras, offering immediate insights into plant health indicators like chlorophyll levels, water stress, and disease symptoms [83]. AI models, such as CNNs, utilize deep learning to quickly and precisely detect anomalies, illnesses, and stressors in crops [84]. AI vision systems monitor crop health indicators to enable farmers to intervene promptly, take proactive steps to reduce risks, optimize nutrient use, and improve crop productivity [59,85].

4.4. Yield prediction and estimation using AI vision

AI vision technology for yield prediction and estimation is a revolutionary method in agriculture that provides important insights into crop productivity. AI vision systems, using machine learning algorithms, evaluate large amounts of visual data from field photos, drones, and sensors to predict agricultural yields with high precision [86]. The systems utilize advanced models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to analyze visual data, evaluate plant growth phases, and predict prospective yields by considering growth trends and environmental factors [87]. Farmers can optimize their farming techniques for increased production and profitability by using AI vision technology to estimate yields, which provides predictive capabilities for decision-making, investment allocation, and planning [59,88].

4.5. Automated decision-making with AI vision systems

AI vision systems in agricultural automation have significantly improved the speed and accuracy of important farm decisions. These systems utilize machine learning algorithms and image analysis to automate decision-making processes using real-time visual data gathered from agricultural sources like drones, cameras, and sensors [89]. AI vision systems use sophisticated algorithms, such as deep learning networks, to quickly process and analyze large volumes of visual data. This enables prompt and well-informed decision-making in areas such as crop management, disease control, and farm-asset allocation [9,62]. AI vision systems help farmers quickly adapt to field changes and monitor crop health, leading to more efficient and precise agricultural practices[90].

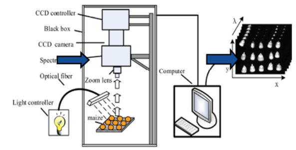
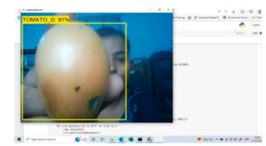
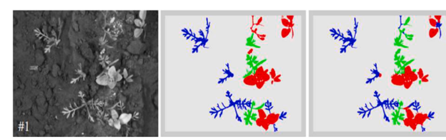
5. All-terrain vehicle automation for farming operations

By incorporating machine learning and AI vision into all-terrain vehicles (ATVs), precision agriculture is being transformed, enhancing on-field operations and allowing for exceptional accuracy in chores. ATVs are equipped with navigation systems and path planning algorithms that utilize machine learning approaches to handle challenging terrains and adjust to changing field conditions [91]. These systems use artificial intelligence vision to create real-time maps, recognize objects, and avoid obstacles as discussed in Table 1. This allows ATVs to autonomously navigate through different agricultural terrains by determining the best routes and performing accurate manoeuvres [92,93]. Combining machine learning and AI vision enables ATVs to carry out precise activities like planting, spraying, and harvesting (Fig. 3) with remarkable accuracy and efficiency [94]. This connection advances precision agriculture by enabling ATVs to autonomously perform tasks, maximizing input efficiency, and enhancing agricultural yield.

5.1. Planting operations

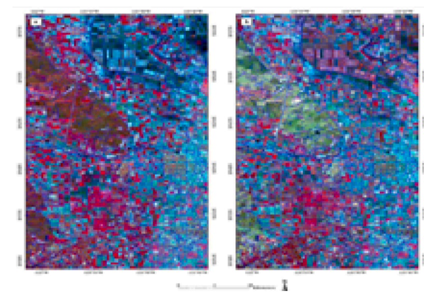
Machine learning algorithms included in seeding systems examine soil variability, historical yield data, and environmental conditions to optimize seed location and density, providing the best crop distribution [95]. AI vision technologies allow for accurate control of seeding depth and plant spacing by using advanced imaging systems to evaluate soil conditions and plant growth, ensuring consistent and optimal seed spacing [96]. This fusion of machine learning for seed placement optimization and AI vision for seeding depth control enhances farming practices by maximizing crop establishment and yield potential while minimizing capital investment waste, underscoring the potential of technology-driven precision agriculture [16].

Table 1
AI/ML-based approaches for performing various on-field agricultural tasks.

Agricultural Tasks	Crop/ system	Automation vehicle/ platform	Performance matrix	ML algorithms	Disadvantages /Limitations	Block diagram/ Mechanical setup/Analysis	References
Crop monitoring and growth assessment	Maize	Stand still imaging system	94.4	LSSVM	Limited diversity in data samples- not enough to prove the robustness of the model.		[68]
	Tobacco	UAV system	96.1	SVM	Feature extraction-needs improvement-to enhance performance efficiency	 Ariel view Analyzed image b-channel	[69]
	Tomato	BLYNK IOT	91	VGG with Tensor flow object detection API	Model performance decrease on Raspberry pi due to limited computational power.		[70]
Crop discrimination	Rice	Robot	98.2	SVM	Model's effectiveness may diminish on account of diverse factors like light intensity, different rice varities, weeds etc.		[71]
	Carrot	BoniRob robot	93.8	Random	Performance comparison has not been done with manual weeders	 Input image Ground truth Prediction *(Red: weed; Green: Crop)*	[72]
Harvesting	Apples	Robotic harvester	89	SVM	Error rate due to foliage occlusion-11 % and too high recognition execution time.		[73]

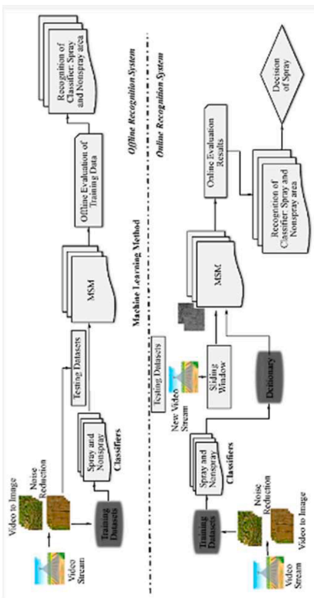
(*continued on next page*)

Table 1 (*continued*)

Agricultural Tasks	Crop/ system	Automation vehicle/ platform	Performance matrix	ML algorithms	Disadvantages /Limitations	Block diagram/ Mechanical setup/Analysis	References
	Broccoli	Tractor	95.2	SVM & KNN	Computational cost is bit high- can be reduced with adaptive boosting algorithms		[74]
Land covering	Almond	ASTER satellite system	91	SVM	A higher computational time and model complexity was reported.	 ASTER Satellite images	[75]
	Corn	ASTER satellite system	89	MLP			[75]
Disease detection	Strawberry	Mobile robot	97.7	SVM	Support vector distance from classification line -very low- increase sensitivity for errors		[76]
	Citrus	UAV system	93.3	SVM	ML model is not compared with DL model to justify the effectiveness.		[77]

(*continued on next page*)

Table 1 (*continued*)

Agricultural Tasks	Crop/ system	Automation vehicle/ platform	Performance matrix	ML algorithms	Disadvantages /Limitations	Block diagram/ Mechanical setup/Analysis	References
Spraying	Orchards	UAV based spraying system	70	MSM	Training and testing systems needs improvement with ANN and DL.		[78]
	Citrus	LiDAR based smart tree crop sprayer	84	CNN	Low accuracy (72 %) - for dead tree classification with more background noises		[79],

*SVM: Support Vector Machine; LSSVM: Least –squares Support Vector Machine; UAV: Unmanned aerial vehicle; VGG: Visual Geometry Group; API: Application programming Interface; KNN: K-Nearest Neighbour; ASTER: Advanced Space-borne Thermal Emission and Reflection Radiometer; MLP: multilayer perceptron; ML: machine learning; DL: Deep Learning; MSM: mutual subspace method; ANN: Artificial Neural Network; CNN: Convolutional Neural Network.

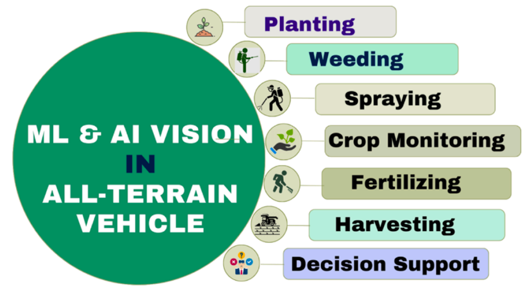


Fig. 3. Application of ML and AI vision in ATV.

5.2. *Harvesting automation*

Machine learning algorithms and AI vision technologies combine to change harvesting processes by providing predictive insights on the best harvesting schedule and accurate crop yield estimation. Machine learning algorithms use historical data and environmental variables to forecast the optimal period for harvesting by taking into account aspects such as crop maturity and weather conditions [97]. AI vision systems with advanced image analysis skills enable automatic crop detection and precise yield estimation by analysing visual data from drones, cameras, and sensors[98]. The combination of machine learning for predictive harvesting and AI vision for automated crop detection and yield estimation provides farmers with advanced capabilities for accurate crop yield predictions and efficient harvesting operations [99,100].

5.3. *Spraying and fertilizing*

AI vision technology enhances precision spraying methods, while machine learning algorithms transform fertilizer delivery by adapting to soil analysis. AI vision systems linked to spraying equipment like IOT-based sprayers [101] accurately identify and classify target areas, facilitating precision administration of pesticides or herbicides while reducing off-target impacts [102]. Machine learning algorithms analyse soil data from sensors and imaging systems to adjust fertilizer dispensing rates in real-time based on soil nutrient levels and crop needs, optimizing fertilizer application to enhance yield and minimize environmental impact [103]. Moreover, implementation of deep-learning algorithms for droplet detection and spray distribution have proved to be promising for designing smart sprayers [104]. However, the sophisticated procedures (as shown in Fig. 4) and algorithms limit their application to some extent for the farmers. The integration of AI vision for precise spraying and machine learning for adaptive fertilizer distribution represents a notable advancement, promoting enhanced efficiency and environmentally friendly farming methods [102,103,105].

5.4. *Weeding and pest control*

AI vision systems are becoming effective tools for identifying weeds and applying herbicides precisely, while machine learning algorithms are transforming pest detection and integrated pest management techniques. AI vision systems use sophisticated imaging technologies to evaluate visual data and differentiate between crops and weeds, enabling accurate identification for targeted herbicide administration [106]. Machine learning algorithms, trained on various datasets, may automatically detect pests by assessing environmental factors and pest indicators, which helps in implementing integrated pest management techniques [107]. Combining AI vision for identifying weeds and machine learning for detecting pests transforms tactics for controlling pests and weeds, providing farmers with more effective and ecologically friendly methods for maintaining crop health [9,108].

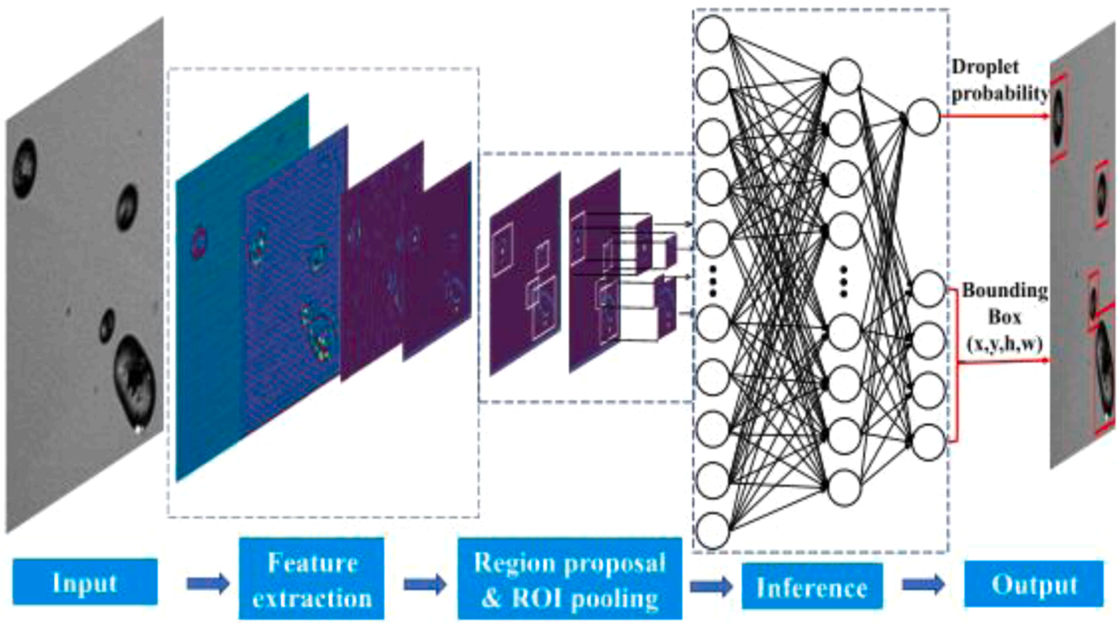


Fig. 4. The deep-learning pipeline for droplet detection in smart spraying system [104].

5.5. Crop monitoring and health assessment

Combining remote sensing with AI vision technology revolutionizes crop health monitoring, with machine learning assisting in disease diagnosis and stress analysis for proactive agricultural management. Remote sensing, using aerial photography and satellite data, along with AI vision systems, offers immediate information on crop health factors such as chlorophyll levels, moisture content, and general vegetative vigor [109]. Machine learning algorithms use pattern recognition and classification approaches to automatically detect diseases and analyse stress by interpreting multispectral data and discovering anomalies that indicate diseases or crop stressors [110]. Integrating remote sensing with AI vision and machine learning enhances farmers' ability to detect and address threats to crop health promptly, improving proactive agricultural strategies for optimal yield and investment management [111, 112].

5.6. Data integration and decision support systems

AI-driven data fusion approaches transform field analysis by combining diverse data sources, while machine learning algorithms are effective in providing decision support for optimal agricultural techniques. Data fusion approaches, enhanced by artificial intelligence, combine data from several sources, such as sensors, satellites, drones, and weather stations, to provide thorough field analysis [49,113]. Machine learning algorithms analyse the combined data to provide decision support systems for farmers using predictive modelling and optimization techniques [114]. These systems help in making well-informed decisions about when to plant, how to allocate farm assets, and which crop management strategies to use by using predictive analytics. This improves farm production and sustainability [115,116]. The combination of AI-driven data fusion and machine learning in decision support paves the way for precision agriculture, providing farmers with practical insights to enhance efficiency and sustainability in farming methods.

6. Practical applications

In the Midwest, an agricultural cooperative utilized AI vision systems in its ATVs to enhance seeding and planting operations [117]. The ATVs used machine learning algorithms to accurately plant seeds at ideal depths and densities according to soil variations and past yield information, leading to enhanced crop growth and consistency throughout the fields. California vineyards employed AI vision technology on their ATVs to detect weeds and target the application of herbicides [118]. Machine learning algorithms were used to distinguish between crops and weeds, enabling precise herbicide administration. This approach decreased the need for chemical and personnel expenditures while ensuring crop health. An extensive farm in the Great Plains area used AI vision technology in its ATVs to observe crop status instantly [119]. The ATVs used sophisticated imaging systems to record multispectral data and utilized machine learning for immediate analysis, allowing for early identification of stress causes and abnormalities. In Europe, an agricultural operation incorporated AI vision systems into its ATVs for accurate spraying and fertilizing [120]. The ATVs utilized machine learning algorithms to pinpoint regions needing pesticide or fertilizer application by analysing soil and crop health data, thus enhancing capital use efficiency and minimizing environmental harm. An agribusiness organization utilized AI vision and machine learning in their ATVs to forecast production and identify the best time for harvesting [16]. The ATVs used previous data and advanced image processing to properly predict agricultural yield and determine the optimal time for harvesting, thereby improving efficiency and maximizing crop output and quality.

7. Impact on efficiency, yield, and resource management

ML and AI vision enhance the process of determining the optimal positioning of seeds, resulting in consistent growth of crops and increased productivity. According to a study conducted by Avalekar, Patil [121], the use of AI-guided precision sowing resulted in a 15 % improvement in crop emergence rate compared to conventional approaches. The AI system analyzed soil moisture and temperature changes to identify the best depths for seed placement, ensuring even crop growth. Another study conducted by Javaid, Haleem [122], revealed that the implementation of AI-driven planting resulted in a 12 % improvement in agricultural productivity compared to traditional manual methods. The AI system improved crop yield by adjusting seed spacing according to soil quality, leading to higher plant density. Crop emergence rate and seedling establishment rate indicate how well seeds sprout and grow into plants. Using AI for precise seeding can improve seed growth rates and overall crop production compared to traditional methods.

AI and ML enable accurate herbicide application, reducing weed interference and promoting better crop growth. In a field experiment conducted by Márquez [123], the use of artificial intelligence (AI) to guide herbicide application led to a 40 % decrease in the amount of weed biomass when compared to the traditional method of human spraying. The AI system used machine learning algorithms to study weed characteristics and distribution patterns. This allowed the system to apply herbicides only where weeds were present, minimizing crop damage.

Research conducted by Corceiro, Alibabaei [108] demonstrated that the utilization of AI-driven weed detection resulted in a 35 % improvement in herbicide effectiveness when compared to traditional approaches. The AI system accurately recognized weed types and growth stages to determine the best herbicide doses. This led to a reduction in chemical usage and an improvement in crop health.

The utilization of AI technology for herbicide application can lead to enhanced weed control effectiveness and crop yield, hence demonstrating superior primary production in comparison to human spraying. ML and AI vision technologies are capable of identifying initial indications of agricultural stress, allowing for prompt actions to preserve crop health and optimize crop yields. Partel, Nunes [124] conducted a study in 2019 where they utilized AI vision technology to achieve a 20 % decrease in disease occurrence compared to traditional manual monitoring techniques. The AI system discovered disease indications early by studying spectral fingerprints and leaf reflectance patterns, enabling precise therapies. According to a field trial conducted by Maraveas, Piromalis [125], the use of AI-guided crop health monitoring resulted in a 25 % increase in yield compared to traditional approaches. The AI system combined satellite images and machine learning to identify nutrient deficiencies and water stress, enabling precise nutrition and irrigation management. The illness incidence rate and yield are used as performance measures. Utilizing AI technology to monitor crop health can lead to reduced disease rates and increased yields, demonstrating enhanced primary output in comparison to human monitoring techniques.

Precision spraying and fertilizing techniques have a significant impact on primary production. Chemical application can be optimized to minimize wastage and maximize nutrient uptake by crops through AI vision and ML applications. A study conducted by Danton, Roux [126] revealed that the use of AI-guided precision spraying resulted in a 50 % reduction in chemical usage when compared to manual spraying. The AI system utilized aerial imaging and weather data to analyze and subsequently modify spraying rates according to the density of the crop canopy, enhancing precision in chemical application. This adjustment aimed to reduce chemical drift and minimize the impact on the environment. By employing machine learning algorithms, a farm achieved a significant 40 % decrease in fertilizer consumption through the implementation of AI-guided precision fertilizing [127]. The AI system optimized fertilizer application rates by assessing soil nutrient levels and crop development patterns, resulting in reduced costs and nutrient runoff. The chemical utilization efficiency and nutrition absorption efficiency function as performance indicators. The utilization of AI-powered precision spraying and fertilization techniques may lead to increased efficiency, hence demonstrating enhanced primary production in comparison to manual methods.

The estimation of crop yield and the timing of harvest have a significant impact on primary production by use of AI vision and ML. It is possible to properly forecast crop output and select the most optimum timing for harvest, which helps to minimize losses and maximize the efficiency of the harvest process. According to a study conducted by Singh, Vaidya [128] in 2022, the use of AI or estimating crop output resulted in a 30 % reduction in post-harvest losses compared to traditional manual estimation methods. Through the analysis of meteorological data and historical patterns of crop production, the AI system successfully forecasted crop yields with precision, enabling the identification of the most opportune moment for harvesting. By implementing machine learning algorithms, a farm successfully improved its harvest efficiency by 50 % through the use of AI-guided optimization of harvest scheduling [129]. The AI system utilized crop maturity indicators and field circumstances to ascertain the most advantageous time for harvesting, hence maximizing crop production and minimizing losses in the field. The post-harvest loss percentage and harvest efficiency are used as measures of performance. The utilization of AI to estimate crop yield and optimize the timing of harvest can lead to reduced losses and increased efficiency, hence enhancing primary production compared to manual techniques.

Moreover, the implementation of AI and ML technologies in agricultural operations has had profound effects on decision-making and predictive capabilities. Many studies have emphasized the role of AI-driven predictive modelling in aiding farmers' decisions, enabling them to anticipate crop diseases and weather patterns [130,131]. This proactive approach has significantly reduced crop losses due to diseases and adverse weather conditions, leading to a 20–25 % decrease in crop loss rates [132]. Additionally, AI-driven decision support systems have facilitated better market predictions and optimized crop distribution, contributing to a more efficient supply chain and reducing post-harvest losses by approximately 15–20 % [133]. The integration of AI and ML technologies in decision-making processes within agriculture has not only improved operational efficiency but has also positively impacted the economic viability of farming practices.

8. Patents

Several products and technologies have been patented in recent years that are related to Precision Agriculture for production purposes and ML algorithms to control the crucial agricultural operations. A brief description of the most relevant patents is provided in the following section. Most patents related to ML algorithms are used to optimize the computational complexity of the task assigned (Table 2).

The patents cover various aspects of agricultural technology, including spectral image acquisition, real-time plant growth optimization, autonomous robots, intelligent robot systems, autonomous vehicle platform systems, autonomous farming systems, intelligent agricultural robots, digital blueprints for agricultural fields, crop yield prediction techniques, and computer-implemented methods for generating field data before agricultural harvesting machines operate in the field.

The US Patent (US10942113B2) describes about a method to acquire spectral images, normalize and process them, create a palette file, and generate a displayable false-color image. The US Patent (US20230409910A1) focuses on a system designed for optimizing indoor farm plant growth in real-time using inputs from sensors, such as image and environmental sensors. The system adjusts light exposure and other environmental factors to enhance plant growth through machine-learning analysis and image recognition. The Australian Patent (AU2017357645B2) includes an autonomous robot with a positioning subsystem, computer vision subsystem, control subsystem, quality control subsystem, and storage subsystem. The South Korean Patent (KR20190031391A) outlines an intelligent robot system capable of dynamically adjusting its height and width to accommodate various crop types and cultivation methods in open-field environments.

The European Patent (EP2855102B1) works on an autonomous vehicle platform system designed to apply fertilizer selectively between two rows of planted crops in agricultural fields. The US Patent (US11856882B2) focuses on an autonomous farming system that includes ground-based drones and unmanned aerial vehicles (UAVs) for farming steep terrain inaccessible to traditional farming equipment. The Chinese Patent (CN110692352A) is based on an intelligent agricultural robot equipped with key components for different growth stages of tomatoes, enhancing labor productivity and operational quality. The US Patent (CN112955000B) describes a system that creates a digital blueprint for agricultural fields using various digital inputs, such as pressure

Table 2
Patent title, code, and application of AI-ML in Precision Agriculture.

Title	Patent Code	Product/Design/ML Algorithm	Application(s)
• Methods, systems, and components thereof relating to using multi-spectral imaging for improved cultivation of cannabis and other crops	US10942113B2	Multi-spectral imager	Monitoring and assessing plant health
• AI-powered autonomous plant-growth optimization system that automatically adjusts input variables to yield desired harvest traits	US20230409910A1	ML model and sensors	ML for image recognition regulate light exposure for plant growth
• A robotic fruit picking system	AU2017357645B2	Autonomous robot	Fruit image analysis, picking/cutting, monitor fruit quality and Store.
• Intelligent agricultural robot system	KR20190031391A	Robot	Crop sowing, growth management, pest prevention, harvesting
• Robotic platform method for selectively applying fertilizer in an agricultural field	EP2855102B1	Autonomous vehicle	Smart fertilizer application.
• Autonomous robot system for steep terrain farming operations	US11856882B2	Drones and UAVs	Aids farming in steep terrains
• Intelligent agricultural robot and control method	CN110692352A	Robot and control method	Performs multiple functions of picking, fertilizing, pollinating, spraying.
• Computer-assisted farm operation using machine learning based seed harvest moisture prediction	CN112955000B	ML model	Digitally plans and predict product maturity, planting date, harvest date and plant location.
• Crop yield prediction method based on machine learning	CN110443420B	ML Algorithm	Crop yield prediction
• Agricultural harvesting machine control using machine learning for variable delays	US11641801B2	Computer-implemented method with ML algorithm	Predicting field data of harvesting machine

*UAVs: Unmanned aerial vehicle.

risk data, product maturity data, field location data, planting date data, and harvest date data. The US Patent (CN110443420B) works on a crop yield prediction technique leveraging machine learning, utilizing climate characteristics during specific crop growth phases to correlate with crop yield. The US Patent (US11641801B2) provides a computer-implemented method for generating field data before an agricultural harvesting machine operates in the field.

9. Challenges and future directions

9.1. Data privacy and security concerns

The introduction of AI and ML in agriculture brings up important issues regarding data privacy and security. Given that these technologies depend on extensive agricultural data, safeguarding data protection is essential. Various studies highlight the susceptibility of agricultural systems to cyber threats and data breaches [134,135]. Farmers and technology providers need to deal with issues related to data ownership, sharing, and access rights to protect sensitive information, promoting confidence and adherence to data protection laws [136].

9.2. Scalability and accessibility of technology

Despite the revolutionary powers of AI and ML, worries remain about the scalability and accessibility of these technologies in agriculture. Several researchers emphasize variations in technology adoption based on farm sizes and geographies [137,138]. To ensure scalability, it is important to tackle cost, infrastructure, and user-friendliness challenges in order to make these technologies available and affordable for small-scale farmers and various agricultural environments [139].

9.3. Emerging trends and potential innovations

Various developing trends and possible developments are currently shaping the landscape of AI and ML in agriculture. Research indicates that edge computing is becoming increasingly important in agriculture by allowing real-time data processing at the field level [140,141]. Furthermore, the incorporation of block chain technology is developing to guarantee data transparency and traceability throughout the agricultural supply chain [142]. AI-powered robotics and autonomous systems are becoming increasingly popular, offering prospects for improved efficiency and decreased reliance on human labour[143]. The referenced works illustrate current debates and investigations into the difficulties, possibilities, and potential future paths in the fields of data privacy, technology accessibility, and developing trends in AI and ML applications in agriculture.

10. Conclusion

The study highlights how ML and AI vision integrated into all-terrain vehicles (ATVs) revolutionizes various farming tasks and processes. It presents real-world case studies in several agricultural areas, such as precision sowing, weed identification, crop health monitoring, and decision support systems. AI technology in precision farming, such as automated seeding and targeted spraying utilizing AI vision in ATVs, has enhanced operational efficiency by precisely optimizing seed placement, minimizing chemical application, and reducing labor expenses. This application has shown a noticeable rise in crop yields, with reports indicating a substantial enhancement in yield for several crops. AI and ML technologies have improved farming methods by improving irrigation schedules and fertilization tactics using real-time data. These advancements have directly contributed to a 20–25 % increase in efficiency, a 15–20 % increase in yields, and a 25–30 % reduction in operational costs through intelligent investment in farming and reduced reliance on manual interventions. Also AI-driven decision support systems have significantly reduced crop losses due to diseases and weather conditions, resulting in a 20–25 % decrease in loss rates. The combined effects of AI and ML in agriculture highlight their significant influence by enhancing efficiency and encouraging sustainable asset management methods.

Growing research interests in the field shows future could further explore how to handle data privacy problems using strong encryption techniques and clear data-sharing structures. To ensure technology can grow and be easily used by many people, efforts must be made to lower costs, improve user interfaces, and create solutions specifically for small-scale farmers. Furthermore, investigating future trends like edge computing, block chain integration, and robotics in agriculture is necessary due to their potential transformational effects. Recommendations include fostering collaboration among stakeholders to facilitate knowledge sharing, allocating substantial funding for research and development, and implementing policies that not only promote technology adoption but also safeguard farmers' interests and data privacy. With a strong emphasis on inclusive, effective, and sustainable practices, this comprehensive analysis not only illuminates the current landscape but also charts a clear path for the future integration of AI and ML in agriculture.

Ethics statement

Not applicable: This manuscript does not include human or animal research.

CRediT authorship contribution statement

Mrutyunjay Padhiary: Conceptualization, Resources, Software, Writing – original draft. **Debapam Saha:** Data curation, Visualization, Formal analysis, Writing – original draft. **Raushan Kumar:** Investigation, Formal analysis, Writing – review & editing. **Laxmi Narayan Sethi:** Supervision, Validation, Writing – review & editing. **Avinash Kumar:** Supervision, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

[1] E. Karunathilake, et al., The path to smart farming: innovations and opportunities in precision agriculture, Agriculture 13 (8) (2023) 1593.
[2] M.T. Linaza, et al., Data-driven artificial intelligence applications for sustainable precision agriculture, Agronomy 11 (6) (2021) 1227.
[3] A.L. Case-Cohen, Understanding the Soil Health Knowledge of Farmers in the Yakima Valley, Evergreen State College, 2018.
[4] V. Gawande, et al., Potential of precision farming technologies for eco-friendly agriculture, Int. J. Plant Soil. Sci. 35 (19) (2023) 101–112.
[5] N.S. Redhu, et al., Artificial intelligence: a way forward for agricultural sciences. Bioinformatics in Agriculture, Elsevier, 2022, pp. 641–668.
[6] M. Rashid, et al., A comprehensive review of crop yield prediction using machine learning approaches with special emphasis on palm oil yield prediction, IEEe Access. 9 (2021) 63406–63439.
[7] I.H. Sarker, Data science and analytics: an overview from data-driven smart computing, decision-making and applications perspective, SN. Comput. Sci. 2 (5) (2021) 377.
[8] P. Batz, et al., From identification to forecasting: the potential of image recognition and artificial intelligence for aphid pest monitoring, Front. Plant Sci. 14 (2023) 1150748.
[9] T.A. Shaikh, T. Rasool, F.R. Lone, Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming, Comput. Electron. Agric. 198 (2022) 107119.
[10] M. Lezoche, et al., Agri-food 4.0: a survey of the supply chains and technologies for the future agriculture, Comput. Ind. 117 (2020) 103187.
[11] A. Roshanianfard, S.F. Ardabili, Autonomous Agricultural Vehicles: Concepts, Principles, Components, and Development Guidelines, CRC Press, 2023.
[12] S. Kumar, S. Mohan, V. Skitova, Designing and implementing a versatile agricultural robot: a vehicle manipulator system for efficient multitasking in farming operations, Machines 11 (8) (2023) 776.
[13] M.N. Tahir, et al., Application of unmanned aerial vehicles in precision agriculture. Precision Agriculture, Elsevier, 2023, pp. 55–70.
[14] I.D. Lawrence, R. Vijayakumar, J. Agnishwar, Dynamic application of unmanned aerial vehicles for analyzing the growth of crops and weeds for precision agriculture. Artificial Intelligence Tools and Technologies for Smart Farming and Agriculture Practices, IGI Global, 2023, pp. 115–132.
[15] B.S. Faiçal, et al., The use of unmanned aerial vehicles and wireless sensor networks for spraying pesticides, J. Syst. Architect. 60 (4) (2014) 393–404.
[16] E. Mavridou, et al., Machine vision systems in precision agriculture for crop farming, J. ImAging 5 (12) (2019) 89.
[17] S. Fountas, et al., AI-assisted vision for agricultural robots, AgriEngineering, 4 (3) (2022) 674–694.
[18] N.C. Eli-Chukwu, Applications of artificial intelligence in agriculture: a review. Engineering, Technol. Appl. Sci. Res. 9 (4) (2019).
[19] S. Mandal, et al., Adaption of smart applications in agriculture to enhance production, Smart Agric. Technol. (2024) 100431.
[20] McConnell, L.L., I.D. Kelly, and R.L. Jones, Integrating technologies to minimize environmental impacts. 2016.
[21] A. Sendros, et al., Blockchain applications in agriculture: a scoping review, Appl. Sci. 12 (16) (2022) 8061.
[22] S.A. Mukarram, et al., Global perspectives on the medicinal implications of green walnut and its benefits: a comprehensive review, Horticulturae 10 (5) (2024) 433.
[23] M.H. Saleem, J. Potgieter, K.M. Arif, Automation in agriculture by machine and deep learning techniques: a review of recent developments, Precis. Agric. 22 (6) (2021) 2053–2091.
[24] C. Janiesch, P. Zschech, K. Heinrich, Machine learning and deep learning, Electron. Mark. 31 (3) (2021) 685–695.
[25] X. Zhai, et al., Applying machine learning in science assessment: a systematic review, Stud. Sci. Educ. 56 (1) (2020) 111–151.
[26] I.H. Sarker, Machine learning: algorithms, real-world applications and research directions, SN. Comput. Sci. 2 (3) (2021) 160.
[27] N.V. Chawla, G. Karakoulas, Learning from labeled and unlabeled data: an empirical study across techniques and domains, J. Artif. Intell. Res. 23 (2005) 331–366.
[28] J. Bekker, J. Davis, Learning from positive and unlabeled data: a survey, Mach. Learn. 109 (2020) 719–760.
[29] G. Dulac-Arnold, et al., Challenges of real-world reinforcement learning: definitions, benchmarks and analysis, Mach. Learn. 110 (9) (2021) 2419–2468.
[30] W. Zhao, et al., Terrain analytics for precision agriculture with automated vehicle sensors and data fusion, Sustainability. 13 (5) (2021) 2905.
[31] Ashapure, A., et al. Unmanned aerial system based tomato yield estimation using machine learning. in Autonomous air and ground sensing systems for agricultural optimization and phenotyping IV. 2019. SPIE.
[32] T.J. Esau, et al., Artificial intelligence and deep learning applications for agriculture. Precision Agriculture, Elsevier, 2023, pp. 141–167.
[33] J. Xu, J. Meng, L.J. Quackenbush, Use of remote sensing to predict the optimal harvest date of corn, Field Crops Res. 236 (2019) 1–13.
[34] L. Benos, A. Bechar, D. Bochtis, Safety and ergonomics in human-robot interactive agricultural operations, Biosyst. Eng. 200 (2020) 55–72.
[35] A. Castrignanò, et al., Agricultural Internet of Things and Decision Support for Precision Smart Farming, Academic Press, 2020.
[36] C. Musanase, et al., Data-driven analysis and machine learning-based crop and fertilizer recommendation system for revolutionizing farming practices, Agriculture 13 (11) (2023) 2141.
[37] T. Thorat, B. Patle, S.K. Kashyap, Intelligent insecticide and fertilizer recommendation system based on TPF-CNN for smart farming, Smart Agric. Technol. 3 (2023) 100114.
[38] T. Talaviya, et al., Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides, Artif. Intell. Agric. 4 (2020) 58–73.
[39] T.A. Shaikh, et al., Machine learning for smart agriculture and precision farming: towards making the fields talk, Arch. Computat. Methods Eng. 29 (7) (2022) 4557–4597.
[40] M. Alam, et al., Real-time machine-learning based crop/weed detection and classification for variable-rate spraying in precision agriculture, in: 2020 7th International Conference on Electrical and Electronics Engineering (ICEEE), IEEE, 2020.
[41] C.-J. Chen, et al., An AIoT based smart agricultural system for pests detection, IEEe Access. 8 (2020) 180750–180761.
[42] M. Maimaitijiang, et al., Crop monitoring using satellite/UAV data fusion and machine learning, Remote Sens. (Basel) 12 (9) (2020) 1357.
[43] K.K. Singh, An artificial intelligence and cloud based collaborative platform for plant disease identification, tracking and forecasting for farmers, in: 2018 IEEE International Conference on Cloud Computing in Emerging Markets (CCEM), IEEE, 2018.
[44] A.J. Mathews, Object-based spatiotemporal analysis of vine canopy vigor using an inexpensive unmanned aerial vehicle remote sensing system, J. Appl. Remote Sens. 8 (1) (2014), 085199-085199.
[45] C. Prakash, et al., Advancements in smart farming: a comprehensive review of IoT, wireless communication, sensors, and hardware for agricultural automation, Sens. Actuat. A: Phys. (2023) 114605.
[46] U. Shafi, et al., Precision agriculture techniques and practices: from considerations to applications, Sensors 19 (17) (2019) 3796.
[47] M. Nolde, S. Plank, T. Riedlinger, An adaptive and extensible system for satellite-based, large scale burnt area monitoring in near-real time, Remote Sens. (Basel) 12 (13) (2020) 2162.
[48] R. Pathak, R. Barzin, G.C. Bora, Data-driven precision agricultural applications using field sensors and Unmanned Aerial Vehicle, Int. J. Precis. Agric. Aviat. 1 (1) (2018).
[49] V. Barrile, et al., Experimenting agriculture 4.0 with sensors: a data fusion approach between remote sensing, UAVs and self-driving tractors, Sensors 22 (20) (2022) 7910.
[50] S.A. Bhat, N.-F. Huang, Big data and ai revolution in precision agriculture: survey and challenges, IEEe Access. 9 (2021) 110209–110222.
[51] K.G. Liakos, et al., Machine learning in agriculture: a review, Sensors 18 (8) (2018) 2674.
[52] H.J. Smidt, O. Jokonya, Factors affecting digital technology adoption by small-scale farmers in agriculture value chains (AVCs) in South Africa, Inf. Technol. Dev. 28 (3) (2022) 558–584.
[53] S. Sun, et al., Data handling in industry 4.0: interoperability based on distributed ledger technology, Sensors 20 (11) (2020) 3046.
[54] R. Dara, S.M. Hazrati Fard, J. Kaur, Recommendations for ethical and responsible use of artificial intelligence in digital agriculture, Front. Artif. Intell. 5 (2022) 884192.

[55] J. Astill, et al., Smart poultry management: smart sensors, big data, and the internet of things, Comput. Electron. Agric. 170 (2020) 105291.
[56] K.E. Ukhurebor, et al., Precision agriculture: weather forecasting for future farming. AI, Edge and IoT-based Smart Agriculture, Elsevier, 2022, pp. 101–121.
[57] Y. Jararweh, et al., Smart and sustainable agriculture: fundamentals, enabling technologies, and future directions, Comput. Electric. Eng. 110 (2023) 108799.
[58] S. Subudhi, et al., Empowering sustainable farming practices with AI-enabled interactive visualization of hyperspectral imaging data, Meas.: Sens. 30 (2023) 100935.
[59] M. Hassan, K. Malhotra, M. Firdaus, Application of artificial intelligence in IoT security for crop yield prediction, ResearchBerg Rev. Sci. Technol. 2 (1) (2022) 136–157.
[60] P.R. Daugherty, H.J. Wilson, Human+ machine: Reimagining Work in the Age of AI, Harvard Business Press, 2018.
[61] S. Zhu, et al., Intelligent computing: the latest advances, challenges, and future, Intell. Comput. 2 (2023) 0006.
[62] S.O. Araújo, et al., Characterising the agriculture 4.0 landscape—Emerging trends, challenges and opportunities, Agronomy 11 (4) (2021) 667.
[63] F.Y. Narvaez, et al., A survey of ranging and imaging techniques for precision agriculture phenotyping, IEEE/ASME Trans. Mechatron. 22 (6) (2017) 2428–2439.
[64] T. Adão, et al., Hyperspectral imaging: a review on UAV-based sensors, data processing and applications for agriculture and forestry, Remote Sens. (Basel) 9 (11) (2017) 1110.
[65] M. Jaboyedoff, et al., Mapping and monitoring of landslides using LiDAR. Natural Hazards, CRC Press, 2018, pp. 397–420.
[66] M. Padhiary, L.N. Sethi, A. Kumar, Enhancing hill farming efficiency using unmanned agricultural vehicles: a comprehensive review, Trans. Indian Natl. Acad. Eng. 9 (2) (2024) 253–268.
[67] K.J. Evans, A. Terhorst, B.H. Kang, From data to decisions: helping crop producers build their actionable knowledge, CRC. Crit. Rev. Plant Sci. 36 (2) (2017) 71–88.
[68] M. Huang, et al., Classification of maize seeds of different years based on hyperspectral imaging and model updating, Comput. Electron. Agric. 122 (2016) 139–145.
[69] H. Xie, et al., Tobacco plant recognizing and counting based on svm, in: 2016 International Conference on Industrial Informatics-Computing Technology, Intelligent Technology, Industrial Information Integration (ICIICII), IEEE, 2016.
[70] M. Padhiary, et al., Efficient Precision Agriculture with Python-based Raspberry Pi Image Processing for Real-Time Plant Target Identification, Int. J. Res. Anal. Rev. 10 (3) (2023) 539–545.
[71] B. Cheng, E.T. Matson, A feature-based machine learning agent for automatic rice and weed discrimination, in: International Conference on Artificial Intelligence and Soft Computing, Springer, 2015.
[72] S. Haug, et al., Plant classification system for crop/weed discrimination without segmentation, in: IEEE Winter Conference on Applications of Computer Vision, IEEE, 2014.
[73] W. Ji, et al., Automatic recognition vision system guided for apple harvesting robot, Comput. Electric. Eng. 38 (5) (2012) 1186–1195.
[74] K. Kusumam, et al., 3D-vision based detection, localization, and sizing of broccoli heads in the field, J. Field. Robot. 34 (8) (2017) 1505–1518.
[75] J.M. Peña, et al., Object-based image classification of summer crops with machine learning methods, Remote Sens. (Basel) 6 (6) (2014) 5019–5041.
[76] M. Ebrahimi, et al., Vision-based pest detection based on SVM classification method, Comput. Electron. Agric. 137 (2017) 52–58.
[77] S.K. Sarkar, et al., Towards autonomous phytopathology: outcomes and challenges of citrus greening disease detection through close-range remote sensing, in: 2016 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2016.
[78] P. Gao, et al., Development of a recognition system for spraying areas from unmanned aerial vehicles using a machine learning approach, Sensors 19 (2) (2019) 313.
[79] V. Partel, L. Costa, Y. Ampatzidis, Smart tree crop sprayer utilizing sensor fusion and artificial intelligence, Comput. Electron. Agric. 191 (2021) 106556.
[80] S.I. Hassan, et al., A systematic review on monitoring and advanced control strategies in smart agriculture, IEEe Access. 9 (2021) 32517–32548.
[81] A. Pretto, et al., Building an aerial–ground robotics system for precision farming: an adaptable solution, IEEe Robot. Autom. Mag. 28 (3) (2020) 29–49.
[82] H.S. Abdullahi, R.E. Sheriff, Introduction to deep learning in precision agriculture: farm image feature detection using unmanned aerial vehicles through classification and optimization process of machine learning with convolution neural network. Deep Learning for Sustainable Agriculture, Elsevier, 2022, pp. 81–107.
[83] H.M. Abdullah, et al., Present and future scopes and challenges of plant pest and disease (P&D) monitoring: remote sensing, image processing, and artificial intelligence perspectives, Rem. Sens. Appl.: Soc. Environ. (2023) 100996.
[84] M.A. Ali, R.K. Dhanaraj, A. Nayyar, A high performance-oriented AI-enabled IoT-based pest detection system using sound analytics in large agricultural field, Microprocess. Microsyst. 103 (2023) 104946.
[85] G. Hasanaliyeva, et al., Innovations in disease detection and forecasting: a digital roadmap for sustainable management of fruit and foliar disease, Agronomy 12 (7) (2022) 1707.
[86] J. Su, et al., AI meets UAVs: a survey on AI empowered UAV perception systems for precision agriculture, Neurocomputing. 518 (2023) 242–270.
[87] Jiang, Y. and C. Li, Convolutional neural networks for image-based high-throughput plant phenotyping: a review. Plant phenomics, 2020.
[88] A. Kowalska, H. Ashraf, Advances in deep learning algorithms for agricultural monitoring and management, Appl. Res. Artif. Intell. Cloud Comput. 6 (1) (2023) 68–88.
[89] D. Olson, J. Anderson, Review on unmanned aerial vehicles, remote sensors, imagery processing, and their applications in agriculture, Agron. J. 113 (2) (2021) 971–992.
[90] V. Balaska, et al., Sustainable crop protection via robotics and artificial intelligence solutions, Machines 11 (8) (2023) 774.
[91] N. Bayomi, J.E. Fernandez, Eyes in the sky: drones applications in the built environment under climate change challenges, Drones 7 (10) (2023) 637.
[92] T. Pereira, et al., Sensor Integration in a Forestry Machine, Sensors 23 (24) (2023) 9853.
[93] A. Olsen, Improving the Accuracy of Weed Species Detection for Robotic Weed Control in Complex Real-Time Environments, James Cook University, 2020.
[94] S. Lockie, et al., The Future of Agricultural Technologies, Australian Council of Learned Academies (ACOLA), 2020.
[95] D. Elavarasan, et al., Forecasting yield by integrating agrarian factors and machine learning models: a survey, Comput. Electron. Agric. 155 (2018) 257–282.
[96] A. Feng, Quantifying the Effect of Environments on Crop Emergence, Development and Yield Using Sensing and Deep Learning Techniques, University of Missouri-Columbia, 2021.
[97] P. Feng, et al., Dynamic wheat yield forecasts are improved by a hybrid approach using a biophysical model and machine learning technique, Agric. For. Meteorol. 285 (2020) 107922.
[98] J. Chen, et al., CropQuant-Air: an AI-powered system to enable phenotypic analysis of yield-and performance-related traits using wheat canopy imagery collected by low-cost drones, Front. Plant Sci. 14 (2023) 1219983.
[99] F. Fuentes-Peñailillo, et al., Automating seedling counts in horticulture using computer vision and AI, Horticulturae 9 (10) (2023) 1134.
[100] R.K. Goel, et al., Smart agriculture–Urgent need of the day in developing countries, Sustain. Comput.: Informat. Syst. 30 (2021) 100512.
[101] D. Saha, et al., Development of an IOT based solenoid controlled pressure regulation system for precision sprayer, Int. J. Res. Appl. Sci. Eng. Technol. 11 (7) (2023) 2210–2216.
[102] I. Abbas, et al., Different sensor based intelligent spraying systems in agriculture, Sens. Actuat. A: Phys. 316 (2020) 112265.
[103] P.P. Pawase, et al., Comprehensive study of on-the-go sensing and variable rate application of liquid nitrogenous fertilizer, Comput. Electron. Agric. 216 (2024) 108482.
[104] P. Acharya, T. Burgers, K.-D. Nguyen, Ai-enabled droplet detection and tracking for agricultural spraying systems, Comput. Electron. Agric. 202 (2022) 107325.
[105] Dou, F., et al., Towards artificial general intelligence (agi) in the internet of things (iot): opportunities and challenges. arXiv preprint arXiv:2309.07438, 2023.
[106] S. Ghatrehsamani, et al., Artificial intelligence tools and techniques to combat herbicide resistant weeds—a review, Sustainability. 15 (3) (2023) 1843.
[107] D. Marković, et al., Prediction of pest insect appearance using sensors and machine learning, Sensors 21 (14) (2021) 4846.
[108] A. Corceiro, et al., Methods for detecting and classifying weeds, diseases and fruits using ai to improve the sustainability of agricultural crops: a review, Processes 11 (4) (2023) 1263.
[109] R.P. Sishodia, R.L. Ray, S.K. Singh, Applications of remote sensing in precision agriculture: a review, Remote Sens. (Basel) 12 (19) (2020) 3136.
[110] K. Berger, et al., Multi-sensor spectral synergies for crop stress detection and monitoring in the optical domain: a review, Remote Sens. Environ. 280 (2022) 113198.
[111] L. Heeb, E. Jenner, M.J. Cock, Climate-smart pest management: building resilience of farms and landscapes to changing pest threats, J. Pest. Sci. (2004) 92 (3) (2019) 951–969.
[112] M.U. Hassan, M. Ullah, J. Iqbal, Towards autonomy in agriculture: design and prototyping of a robotic vehicle with seed selector, in: 2016 2nd International Conference on Robotics and Artificial Intelligence (ICRAI), IEEE, 2016.
[113] S. Salcedo-Sanz, et al., Machine learning information fusion in Earth observation: a comprehensive review of methods, applications and data sources, Inf. Fus. 63 (2020) 256–272.
[114] V.R.R. Kolipaka, A. Namburu, An automatic crop yield prediction framework designed with two-stage classifiers: a meta-heuristic approach, Multimed. Tools. Appl. (2023) 1–24.
[115] R. Sharma, et al., A systematic literature review on machine learning applications for sustainable agriculture supply chain performance, Comput. Oper. Res. 119 (2020) 104926.
[116] Z. Zhai, et al., Decision support systems for agriculture 4.0: survey and challenges, Comput. Electron. Agric. 170 (2020) 105256.
[117] M. Perez-Ruiz, J. Martínez-Guanter, S.K. Upadhyaya, High-precision GNSS for agricultural operations. GPS and GNSS Technology in Geosciences, Elsevier, 2021, pp. 299–335.
[118] A. De Castro, et al., Mapping Cynodon dactylon in vineyards using UAV images for site-specific weed control, Adv. Anim. Biosci. 8 (2) (2017) 267–271.
[119] N. Stefas, H. Bayram, V. Isler, Vision-based monitoring of orchards with UAVs, Comput. Electron. Agric. 163 (2019) 104814.
[120] L. Cantelli, et al., A small versatile electrical robot for autonomous spraying in agriculture, Agric. Eng. 1 (3) (2019) 391–402.
[121] Avalekar, U., et al., Optimizing agricultural efficiency: a fusion of Iot, Ai, cloud computing, and wireless sensor network. Prof.(Dr.) Kesava, optimizing agricultural efficiency: a fusion of Iot, Ai, cloud computing, and wireless sensor network.

[122] M. Javaid, et al., Understanding the potential applications of artificial intelligence in agriculture sector, Adv. Agrochem. 2 (1) (2023) 15–30.
[123] Márquez, M.S.F.G., RGB and multispectral image analysis based on deep learning for real-time detection and control of weeds in cornfields. 2024.
[124] V. Partel, et al., Automated vision-based system for monitoring Asian citrus psyllid in orchards utilizing artificial intelligence, Comput. Electron. Agric. 162 (2019) 328–336.
[125] C. Maraveas, et al., Applications of IoT for optimized greenhouse environment and resources management, Comput. Electron. Agric. 198 (2022) 106993.
[126] A. Danton, et al., Development of a spraying robot for precision agriculture: an edge following approach, in: 2020 IEEE Conference on Control Technology and Applications (CCTA), IEEE, 2020.
[127] T.S. Tanaka, et al., Can machine learning models provide accurate fertilizer recommendations? Precis. Agric. (2024) 1–18.
[128] A. Singh, et al., Recent advancement in postharvest loss mitigation and quality management of fruits and vegetables using machine learning frameworks, J. Food Qual. 2022 (2022) 1–9.
[129] A. Kumari, M.N. Khan, A.K. Sinha, Harvesting Intelligence: AI and ML Revolutionizing Agriculture, in Data-Driven Farming, Auerbach Publications, 2024, pp. 126–141.
[130] P.L. Ramteke, U. Kshirsagar, The role of machine intelligence in agriculture: a case study, Res. Trends Artif. Intell.: Internet Things (2023) 54.
[131] M. Chibuye, J. Phiri, Current trends in machine-based predictive analysis in agriculture for better crop management- a systematic review, Zambia ICT J. 7 (1) (2023) 29–37.
[132] E.-C. Oerke, H.-W. Dehne, Safeguarding production—Losses in major crops and the role of crop protection, Crop Protect. 23 (4) (2004) 275–285.
[133] P. Tamasiga, et al., Forecasting disruptions in global food value chains to tackle food insecurity: the role of AI and big data analytics–A bibliometric and scientometric analysis, J. Agric. Food Res. 14 (2023) 100819.
[134] A. Yazdinejad, et al., A review on security of smart farming and precision agriculture: security aspects, attacks, threats and countermeasures, Appl. Sci. 11 (16) (2021) 7518.
[135] S. Sontowski, et al., Cyber attacks on smart farming infrastructure, in: 2020 IEEE 6th International Conference on Collaboration and Internet Computing (CIC), IEEE, 2020.
[136] R. Shawe, I.R. McAndrew, Increasing threats to United States of America infrastructure based on cyber-attacks, J. Softw. Eng. Appl. 16 (10) (2023) 530–547.
[137] D. Mozzato, et al., The role of factors affecting the adoption of environmentally friendly farming practices: can geographical context and time explain the differences emerging from literature? Sustainability. 10 (9) (2018) 3101.
[138] T.M. Habtewold, A. Heshmati, Impacts of improved agricultural technology adoption on welfare in Africa: a meta-analysis, Heliyon. 9 (7) (2023).
[139] A. Aborujilah, et al., IoT Integration in Agriculture: advantages, Challenges, and Future Perspectives: short survey, in: 2023 10th International Conference on Wireless Networks and Mobile Communications (WINCOM), IEEE, 2023.
[140] I. Sittón-Candanedo, et al., A review of edge computing reference architectures and a new global edge proposal, Fut. Gener. Comput. Syst. 99 (2019) 278–294.
[141] M.A. Zamora-Izquierdo, et al., Smart farming IoT platform based on edge and cloud computing, Biosyst. Eng. 177 (2019) 4–17.
[142] A. Chandan, M. John, V. Potdar, Achieving UN SDGs in food supply chain using blockchain technology, Sustainability. 15 (3) (2023) 2109.
[143] Y.K. Dwivedi, et al., Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy, Int. J. Inf. Manage 57 (2021) 101994.