Artificial Intelligence in Agriculture 8 (2023) 46–59

Contents lists available at ScienceDirect

Artificial Intelligence in Agriculture

journal homepage: http://www.keaipublishing.com/en/journals/artificial-intelligence-in-agriculture/

How artificial intelligence uses to achieve the agriculture sustainability: Systematic review

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ARTICLE INFO

Article history:
Received 3 February 2022
Received in revised form 20 April 2023
Accepted 25 April 2023
Available online 28 April 2023

Keywords:
AI
Agriculture
Sustainability
Review
Robotics
Deep learning

ABSTRACT

The generation of food production that meets the rising demand for food and ecosystem security is a big challenge. With the development of Artificial Intelligence (AI) models, there is a growing need to use them to achieve sustainable agriculture. The continuous enhancement of AI in agriculture, researchers have proposed many models in agriculture functions such as prediction,weed control, resource management, advance care of crops, and so on. This article evaluates on a systematic review of AI models in agriculture functions. It also reviews how AI models are used in identified sustainable objectives. Through this extensive review, this paper discusses considerations and limitations for building the next generation of sustainable agriculture using AI.

1. Introduction

The agricultural sector in any nation plays a key role to address the one of universal challenges, provide sufficient foods to survive people. As estimated (Alexandratos and Bruinsma, 2012), in 2050, there is a requirement to increase global food supply by 60% in order to feed nearly 9 billion people (Padilla and Hudson, 2019). Growing population leads continuous farming with limited arable land (Jayne et al., 2014). This issue is further aligning with the 17 Sustainable Development Goals (SDGs) which has been focused to eliminate poverty and eradicate hunger and malnutrition by 2030 and 2025 respectively. Growing population leads continuous farming with limited arable land (Padilla and Hudson, 2019). It has been argued that food production process creates a foremost universal environmental degradation created through fertilizer utilization, greenhouse gas emissions and biodiversity (Tilman et al., 2011). Though intensive agriculture (known as intensive farming) and industrial agriculture have led to an increase in food production and easing of food shortages, now bring disadvantages due to utilization of high input of fertilizers, pesticides and fresh water (Tian et al., 2021). In particular, climate changes such as global warming, aggravating flooding and drought will in turn influence the food security (Wheeler and Von Braun, 2013). Consequently, how to feed the increasing population while decreasing the negative consequences on the environment and mitigating atmospheric changes is the biggest global challenge in the 21st century (Di Vaio et al., 2020). The terms “sustainability” and “sustainable” has gained substantial attention applied in varies contextual aspects (Bolis et al., 2014). Sustainability is defined as a balanced combination of social, environmental and economic performance to benefit current and future generations (Geissdoerfer et al., 2017). To safeguard food and ecological security, the sustaining of performing more of the same thing is commonly indicated as sustainable agriculture (Gaffney et al., 2019). Thus, to achieve sustainable growth in the agriculture sector has received greatest attention (Castro and Swart, 2017), and there is an emerging consumer demand for sustainable quality food products (Mangla et al., 2019). Sustainability lays in three pillars economic, social and environmental performance. Social performance focuses on social troubles namely human rights, ethics in doing business, environmental activities, identical opportunities concerns on waste generation, greenhouse gas emission; economic performance quantifies operational efficiency, shareholder value and transaction costs (Ala-Harja and Helo, 2015; Panda, 2014). Subsequently, Sayer and Cassman Sayer and Cassman (2013) opined that agricultural firms/farms require to obtain four objectives, which are often to be competing each other, to be considered sustainable growth namely 1) Ensure production of an adequate food supply; 2) Alleviate poverty; 3) Achieve better health and nutrition for a growing population; and 4) Conserve natural resources. These objectives are highly relevant to the sustainable pillars, and they are aligned properly with the SDGs. To certify the sufficient food productions to the growing population, technologically advanced inputs, cultivation techniques and soil

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https://doi.org/10.1016/j.aiia.2023.04.002

management approaches become the vital sources (Gaffney et al., 2019). High-yielding cropping systems must be concerned to convert resources to economic yield. Increasing protein obtainability of food sources of food (beans, vegetables, wheat, rice), and of availability of vitamins and minerals through poise diet should require to ensure healthy and affluence over 9 billion people people to be fed by 2050. Soil degradation, low irrigation management, and a less productivity sludge farmers in poverty (Tittonell and Giller, 2013). To eradicate poverty, agricultural sector must be move forwarded the modernized and productive agricultural transition where farmers are equipped with highly resourceful and resilient. Conserving natural resources consists of wide range of soil nutrient, quality of water, green-house gas, confrontation of pest and weed and reduction of aquifer. Preserving biodiversity of natural settings, flora and fauna are conservation challenges. Further, when underpinning technologies are infantile or improperly used, agricultural expansion causes a serious environmental damage. This is why Mellor (Mellor, 2017) insisted that identifying and utilizing vigorous pattern of technology improvements and efforts should focus not on just one aspect of sustainability objective, but rather on activation of the whole system that representing the prevailing agricultural enterprises. Yet, many firms/farms in the agricultural sector are stressed with squat profit and low productivity (Barth et al., 2021), hinders efforts to sustainable agriculture (McGuire, 2017). Gaffney et al. (Gaffney et al., 2019) further stressed that growth in emerging and recently emerged markets (Asia and Africa) creates the definitive restraints to meet sustainability objectives. Regardless of the complexity to meet all four objectives simultaneously, agriculture sector is moving towards sustainable agriculture (Tian et al., 2021). Realizing and utilizing technological advancements, the commitment derive to agriculture sustainability must be accompanied with technological improvement (Mellor, 2017). Thus, to meet Sayer and Cassman's sustainable objectives and face the global food security challenges ahead, wider application of existing technologies and utilization of advanced technological tools and techniques soon would be the straightforward strategies (Franco, 2021). What we observed from present panorama is that that Covid-19 pandemic emerges as a great crisis, leading to widen global food security issue. Although the generation of food production that meet the rising demand for food and ecosystem security is a big challenge, rapid developments in technology are making it possible. Researchers applied artificial intelligence (AI) to make sustainable agriculture (Li et al. 2021b; Mohapatra and Lenka, 2016). The recent application of the technologies of AI support to provide solutions to problems in agricultural domain. These technologies are used to reduce the cost as well as increase the effectiveness and efficiency. There are surveys which conducted to find what people did to make sustainable agriculture using AI. However, investigations on how AI used to achieve sustainable objectives are still under research-able area. Specifically, this research aims to map and create an understanding of the various technologies implement in agriculture sector with a special focus on the sustainability growth objectives. Thus, the main purposes of this systematic review are are to; 1) develop a more complete understanding of the enabling AI technologies currently applied in agriculture sector, 2) explore a variety of AI technology initiatives to achieve sustainability growth objectives, and 3) analyse how agriculture firms/farms improve sustainable growth through technologies which are already underway and new technologies are being developed. This systematic review would contribute to enhance the understanding of the present view of the agriculture sustainability and agriculture technology.

2. Research methodology

Systematic Literature Review (SLR) permits identifying and obtaining relevant information on interesting subject area from the existing literature (Kitchenham and Charters, 2007). The SLR pursues to identify the firsthand experiences on currently applied AI technologies in agriculture sector and variety of AI technology initiatives to achieve sustainability growth objectives in agriculture sector. To carry out this SLR, we set up three stages namely, planning; implementing and reporting (Ferreras-Fernández et al., 2013).

In the planning stage, described the key terms that could be considered relate to the study namely, agriculture, farming, protected agriculture, smart farming, Artificial Intelligence (AI), Deep Learning (DL), Machine Learning (ML), agricultural robot and robotics. The Boolean operators AND and OR were used to do more thorough searches, for example, “AI” AND “agriculture” AND “crops” OR “farming” AND “Smart Agriculture” AND “smart farming”. The search was performed in the four well-known data sources that encompass multidisciplinary publications, google scholar, Scopus, Science Direct and Web of Science, following the process used by similar recent studies of AI and sustainable agriculture (Traldi, 2021; Navarro et al., 2020). The scope of the publications was limited to documents such as journal and conference articles, published in English. The past ten years considered as the time range to conform the objectives of the study.

In the implementing phase, 1421 articles were selected with the search tool. A database review of publications about the desired keywords in Web of Science found 347 records since 2012. In the case of Scopus and Science Direct, there have been 256 and 244 documents published respectively. The total number of articles published in Google scholar search engine was 574 from 2012 to 2021 December. The areas in which they have been published the most are agriculture, technology, computer and electronic, agronomy, agriengineering, computer sciences and sustainability. After getting the articles, they were manually reviewed through the title, keywords, abstract and text analysis adherent to the objectives proposed of the study. Number of record screened was 313. During this process, the list of documents was consequently sorted to eliminate the duplicate articles (Åstrand and Baerveldt, 2002). 131 articles were excluded due to irrelevant to agriculture industry. This analysis resulted in 115 articles deemed eligible which were incorporated as a sample for this study. Out of 115 articles, 45 identified through Web of Science, 37 Science Direct and 33 identified through other sources listed above. The article list was finalized in December 2021 (Refer Table 1 in Appendix 1).

In the reporting stage, each of the articles retrieved was analyzed according to the AI component such as DL, ML, neutral network and robotics and agriculture activities namely harvesting, plant eco-phenotyping, grading system, weed and crop classification, disease detection and monitoring and soil management. The searched articles were then listed on excel spreadsheet. The data sheet contained the details of article namely name of author/s, year of published, study title, key AI technology used, main agriculture area, benefits obtained and limitations. Once the database was completed, a content analysis was performed to examine the review summary in-depth and summarise the empirical experiences on currently applied AI technologies in agriculture sector and variety of AI technology initiatives to achieve sustainability growth objectives in agriculture sector. Fig. 1 illustrates the methodological chart applied in the SLR.

3. AI methods use in agriculture

AI is one of the emerging areas of research in recent generation. Today AI is used to solve the problems particularly to reduce the use of the labor force, to enhance efficient utilization of resources and to facilitate the development of sustainable business. With the rapid technological advancement,people are more intend to developed these applications (Bannerjee et al., 2018). With that, different AI approaches have been suggested to solve the existing problems in the agriculture to improve the productivity.

In our analysis we found that the main AI approaches used in agriculture are Neural Network (NN), DL, Fuzzy Logic, Support Vector

Table 1
Agriculture functions and sustainability growth objectives.

Reference	AI technology	Technology used in agriculture function	Agriculture function category	Sustainability objective
(Han et al., 2018)	NN	Prediction for agricultural output value	Prediction	1
(Almomani, 2020)	ANN	Prediction model for agriculture waste	Prediction	1
(Espejo-Garcia et al., 2020)	DNN	Weeds identification	Weed control	1
(Yamaç, 2021)	KNN, SVM, RF, AB	Estimate sugar beet Etc for efficient irrigation management	Prediction	1
(Mohapatra and Lenka, 2016)	NN	Crop monitoring	Advanced care of crops	3
(Buyrukoğlu et al., 2021)	ANN	Prediction of Generic *Escherichia coli* population based on Weather Station Measurements	Prediction	1
(Dargan et al., 2020)	Machine learning applications	Sustainable agriculture supply chain performance	Supply chain	2
(Nguyen et al., 2019)	ANN	Agricultural landscapes management	Resource management	4
(Liu et al., 2020)	ANN	Develop integrated agricultural drought index	Prediction	1
(Castro et al., 2017)	ANN	High-performance prediction of Macauba fruit biomass	Prediction	1
(Jung et al., 2021)	AI	Improve the resilience of agricultural systems Crop simulation models utilize input variables such as crop management information, weather, and soil data to estimate crop productivity	Prediction	1
(Camaréna, 2020)	AI	Food production system	Supply chain	2
(Zhang et al., 2021)	LSTM	Weather radar echo prediction method	Prediction	1
(Dey and Shekhawat, 2021)	AI	Blockchain for sustainable e-agriculture Data management	Supply chain	2
(Albalasmeh et al., 2020)	ANN	Predict the quality of the biochar based on operational conditions of biochar production (parent biomass type, particle size, pyrolysis temperature)	Prediction	1
(Khan et al., 2020)	Deep Learning	Fruit Prediction	Prediction	1
(Senocak and Goren, 2021)	AI	Forecasting the biomass-based energy potential	Prediction	1
(Emmi et al., 2014)	Robotics	Integration and assessment of a real fleet	Advanced care of crops	3
(Abdullahi et al., 2017)	CNN	Plant image recognition and classification	Weed control	3
(McGuire, 2017)	ANN	Crop yield prediction Climate change impact assessment	Prediction	1
(Guillén et al., 2021)	Deep Learning	Performance evaluation of edge-computing platforms for the prediction of low temperatures	Prediction	1
(Sharma et al., 2020)	Machine Learning	Applications for precision agriculture	Advanced care of crops	3
(Espejo-Garcia et al., 2020)	DNN	Improving weeds identification	Weed control	3
(Mohapatra and Lenka, 2016)	ANN, Fuzzy Logic	Pattern classification and weather dependent Fuzzy Logic Model for irrigation control	Resource management	4
(Buyrukoğlu et al., 2021)	ANN	Prediction of Generic *Escherichia coli* Population in Agricultural Ponds Based on Weather Station Measurements	Prediction	1
(Giannakis et al., 2019)	Cloud Environment	Data sharing on production, diseases and weather	Advanced care of crops	3
(Ellafi et al., 2021)	ANN	Prediction of saturated hydraulic conductivity (Ksat) in order to enhance the efficacy of drainage system design in data-poor areas utilizing existing and currently under-utilised datasets.	Prediction	1
(Monteiro et al., 2021)	ANN	Weed control	Weed control	3
(Santin et al., 2016)	ANN	Design of performance-oriented riparian buffer strips for the filtering of nitrogen in agricultural catchments	Advanced care of crops	3
(Taghavifar et al., 2015)	ANN and Genetic Algorithm	Prediction of the power provided by the agricultural tractors	Prediction	1
(Singh et al., 2012)	ANN	WPredicting sediment yield in the Nagwa agricultural watershed in Jharkhand, India	prediction	1
(Liu et al., 2021)	ANN	Predict rice growth rate	Prediction	1
(Grimstad and From, 2017)	Robotic	Using cameras sensitive to visual and near infrared parts of the electromagnetic spectrum to study plants	Advanced care of crops	3
(Roshanianfard et al., 2021)	Robotic arms and manipulation systems	Seeding, watering, fertilizing, weeding, and harvesting	Advanced care of crops	3
(Ireri et al., 2019)	Machine learning	Applied in real-time tomato post-harvesting procedures Low-cost tomato grading system based	Harvesting	1
(Birrell et al., 2020)	Robotics	Achieve a consistent harvesting cutting height, high-quality cuts	Harvesting	1
(Mehta and Burks, 2016)	Robotic	Harvesting fruit detection efficiency, picking efficiency and picking rate	Harvesting	1
(Navas et al., 2020)	Robotic	Suitability of the cutting tools for the plants to be harvested	Harvesting	1
(Navas et al., 2020)	Robotic	Suitability of the cutting tools for the plants to be harvested	Harvesting	1
(Booth et al., 2020)	Machine learning	3D estimate of the plant bulb's growth direction from a triplet of 2D x-ray images	Advanced care of crops	3
(Raja et al., 2020)	Robotic	Crop signaling system Weed and crop classification	Advanced care of crops, Weed control	3
(Kounalakis et al., 2019)	Deep learning	Weed visual recognition algorithms	Weed control	1
(Magalhães et al., 2021)	Deep learning, Harvesting robot	Accurately identifying and detecting the mature fruit or fruit bunches	Harvesting	1
(Khort et al., 2021)	Robotic	10 h of continuous operation in low-light conditions in various weather conditions.	Advanced care of crops	3
(Aguiar et al., 2021)	Deep Learning	Detect tree trunks is still an area quite underdeveloped	Advanced care of crops	3
(Vincent et al., 2019)	Neural networks and Multi-Layer Perceptron (MLP)	Agriculture land suitability analysis: Measurements of soil moisture content, granular fragments (percentage of sand particles in the soil), structure of the soil, compact and cementation, cnternal drainage, available water content, porousness, organic matter, cation exchange capacity, degree	Resource management	4

Table 1 (*continued*)

Reference	AI technology	Technology used in agriculture function	Agriculture function category	Sustainability objective
		saturation, pH value, salinity, and carbonates		
(Hespeler et al., 2021)	Robotic	Harvesting in the evening hours or low light situations	Harvesting	1
(Buzzy et al., 2020)	Robotic	Real-time leaf detection and counting	Advanced care of crops	3
(Schor and Attwood-Charles, 2017)	Robotic	Disease detection and monitoring	Advanced care of crops	3
(Navas et al., 2020)	Robotic	Weed treatment with a flaming and row crop cultivator implement. Weed treatment with a herbicide patch sprayer. Pest control with a canopy sprayer.	Weed control	3
(Zapotezny-Anderson and Lehnert, 2019)	Robotic	Harvesting	Harvesting	1
(Kwon et al., 2019)	Deep convolutional neural networks (DCNNs)	Fruit monitoring and grading systems	Advanced care of crops	3
(Zujevs et al., 2015)	Robotic	Fruit detection, localizing, gripping and picking Quality measurements before picking	Advanced care of crops	3
(Mendes et al., 2019)	Robotic path planning	AgRob Vineyard Detector	Advanced care of crops	3
(Paliwal et al., 2019)	Robotic	Soil data collection, disease detection, and field classification to provide the best solutions for mixed cropping.	Resource management	4
(Fue et al., 2020)	Robotic	Cotton harvesting	Harvesting	1
(Linaza et al., 2021)	Machine learning	Yield prediction	Prediction	1
(Bi et al., 2021)	Slam robot	Positioning system for agricultural environment	Advanced care of crops	3
(Väljaots et al., 2018)	Robotic	Soil sampling and storage apparatus	Resource management	3
(Jez et al., 2021)	ANN, SVM, CNN	Plant growth status, pest management, water and fertilizer management for plant breeders and plant physiologists	Advanced care of crops	3
(Porsch et al., 2019)	Robotic	Gantry pneumatic robotic manipulator for greenhouse automation	Advanced care of crops	3
(Zhang et al., 2021)	Robotic	Gripper developments to minimize the risk of damage to fruits, vegetables or food	Harvesting	1
(Jung et al., 2021)	AI, Deep learning	Irrigation management service Soil moisture monitoring system to control irrigation, fight mildew, and deal with drought Image recognition application to identify potential defects and nutrient deficiencies in soil	Resource management	4
(Kakani et al., 2020)	Machine Learning	Utilize the data collected from farms, irrigation, soil characteristics and meteorological data to formulate field level insights as recommendations for farmers to improve their overall yield	Resource management	4
(Sharma and Bisen, 2013)	Electric National Agriculture Market (e-NAM) Deep learning	e-NAM envisages spatial market integration, reduction in transaction costs and has direct implications on price signals and price discovery, farmer's income and market liberalization	Prediction	2
(Oliveira et al., 2021)	Robotic	Robotic applications for land preparation, sowing and planting, plant treatment, harvesting, yield estimation and phenotyping	Resource management Advanced care of crops, Harvesting	2
(Beloev et al., 2021)	Robotic	Map or inspect a specific farming area in accordance to the situation and the surrounding environment	Advanced care of crops	3
(Isachsen et al., 2021)	Robust robot-based automation in primary production and processing	Real-time speed and high registration accuracy and resolution enable the correct manipulation of food products without quality degradation	Prediction	1
(Song et al., 2021)	Robotic	Greenhouse control system	Advanced care of crops	3
(Thomopoulos et al., 2021)	Robotic	Kiwifruit harvesting robot	Harvesting	1
(Seo and Umeda, 2021)	Unmanned aerial vehicles (UAVs)	UAVs are comparable to boom sprayers, showing similar pest-control costs and management efficiency	Weed control	3
(Ishii et al., 2021)	Robotic	Store, transport and relocate the boxes of tomato to the assigned storage area	Supply chain	2
(Peteinatos et al., 2020)	CNN	Plant and weed classifications	Weed control	3
(Fahey et al., 2021)	AI-based data fusion technique	Identify and quantify disease and pest epidemics accurately and at the earliest possible stage	Advanced care of crops	3
(ÖZLÜOYMAK et al. Özlüoymak et al., 2019)	Robotic	Weed control system	Weed control	3
(Balafoutis et al., 2017)	Machine learning	Autonomous plant classification	Advanced care of crops	3
(Spanaki et al., 2021)	AI AgriTech drones	Collecting data from the fields, and support monitored human decision making for everyday tasks (e.g. disease inspection, crop monitoring) and AgriFood operations (e.g. irrigation, fertilization etc.) of the farm	Prediction	1
(Bi et al., 2020)	Deep Learning	Predict consumer Yogurt preferences based on sensory attributes	Prediction	2
(Kiourt et al., 2020)	Deep Learning	Automatic image-based food recognition	Advanced care of crops	3
(Dargan et al., 2020)	Deep Learning	Predict wine taste preference	Prediction	2
(Chukkapalli et al., 2020)	AI	Smart farming Cooperative ecosystem	Advanced care of crops	3
(Utstumo et al., 2018)	Robotic	Drop-on-Demand (DoD) weed control system	Weed control	3
(Lytridis et al., 2021)	Robotic	Land preparation	Resource management	4
(Hossain and Komatsuzaki, 2021)	Robotic	Weed management	Weed control	3

(continued on next page)

Table 1 (*continued*)

Reference	AI technology	Technology used in agriculture function	Agriculture function category	Sustainability objective
(Kultongkham et al., 2021)	Robotic	Tomato harvesting	Harvesting	1
(Ruigrok et al., 2020)	Robotic	Weed detection	Weed control	3
(Magomadov, 2019)	Deep Learning	Plant disease detection	Advanced care of crops	3
(Feng et al., 2018)	Robotic	robotic harvesting system for cherry tomato	Harvesting	1
(Grieve et al., 2019)	Robotic	Weed control	Weed control	3
(Midtiby et al., 2016)	Robotic	weeding application	Weed control	3
(Williams et al., 2019)	Machine Vision, Convolutional Neural Networks, and Robotic	Kiwifruit Harvesting	Harvesting	1
(Hespeler et al., 2021)	Deep learning	harvesting of chili peppers	Harvesting	1
(Gonzalez-de Santos et al., 2017)	Robotic	weed and pest control	Weed control	3
(Sudars et al., 2020)	Robotic computer	Annotated food crops and weed images	Weed control	3
(Ngugi et al., 2021)	Machine learning	leaf pest and disease recognition	Advanced care of crops	3
(Ghafar et al., 2021)	Robotic	Spraying fertilizers and pesticides	Weed control	3
(Azmi et al., 2021)	Robotic	Crop seeding	Harvesting	1
(Yorozu et al., 2021)	Robotic	Smooth and safe harvesting support in the field	Advanced care of crops	3
(Kim et al., 2021)	Robotic	Estimate crop height and detect the target crop region	Prediction	1
(Gai et al., 2021)	Robotic	Generating crop field maps as occupancy grids and providing inter-row vehicle positioning data	Prediction	1
(Panarin and Khvorova, 2021)	Robotic	Taking into account the physical environment conditions and build mathematical models	Prediction	1
(Rysz and Mehta, 2021)	Robotic	Fruit harvesting	Harvesting	1
(Zangina et al., 2021)	Robotic	Selective and variable spray of pesticides to the plants	Weed control	3
(Mohamed et al., 2020)	Machine learning	Spatial mapping analysis of soil characteristics	Resource management	4
(Gupta et al., 2020)	Deep learning	Soil parameters analysis	Resource management	4
(Mohammed and Jassim, 2021)	Robotic	Seeding, fertilization and initial irrigation process	Harvesting, Advanced care of crops	1,3
(Villa-Henriksen et al., 2021)	Robotic	Harvesting	Harvesting	1
(Ünal et al., 2021)	Robotic	Soil penetration resistance and electrical conductivity	Resource management	4
(Li et al. 2021a)	Deep learning	Weed detection	Weed control	3

Machine (SVM), Random Forest, K-nearest and Robotics. As in Fig. 2 from the selected papers the most of researchers are applied robotics which is 44%. Thereafter, NN and DL is 26% and 15%, respectively.

Robotics are used in agriculture to assist farmers. These robots are developed with many operations such as weeding application, visual detection and harvesting where they can be used to match the needs of various tasks (Zhang et al., 2020; Benos et al., 2020; Yorozu et al., 2021). Ghafar et al. (Ghafar et al., 2021) design a robot to spray pesticides and fertilizers in harvesting field at low operating cost and general crop monitoring. This model is used two-wheeled robot that included a a mobile base which is used a spewing mechanism with a controlling of wireless tool that is used to manage the movements of the robot. Thereafter, crop growth conditions and health factors are monitored using cameras. This process assists to detect the presence of pests in the crop field. This problem is solved using low-cost agricultural robot (Azmi et al., 2021). For agricultural cyber-physical systems, researchers proposes a suggest an intelligent management deign using robotic technique(Huang et al., 2021). The robots can use in labour intensive, repetitive and physical demanding tasks in agricultural field. The recent literature reveals that robots are being used to perform several specialized tasks which were performed by experience farmers (Marinoudi et al., 2019; Le et al., 2019; Zhang and Noguchi, 2017; Huang and Chang, 2019; Kim et al., 2021). As such, there are advantages using robotics in agriculture such as production increase, widening the profit and saving time for performing repetitive tasks. It is estimated that pesticides usage can be reduced by 80% if the farmers use robots to spray

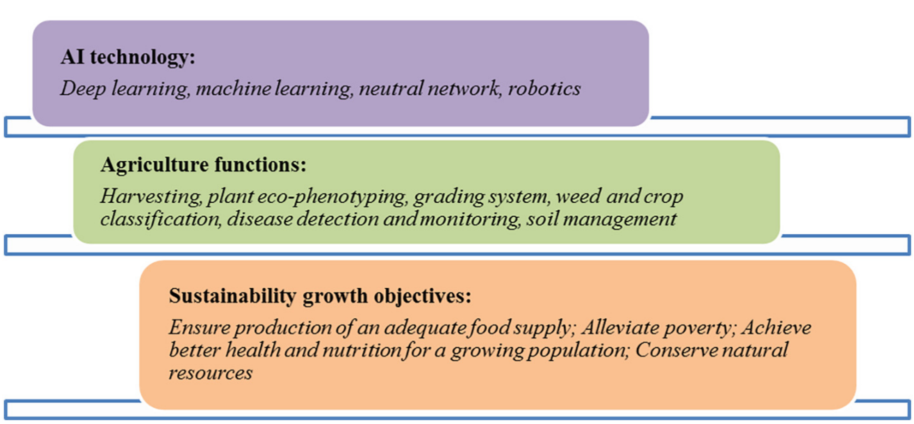

Fig. 1. Methodological chart.

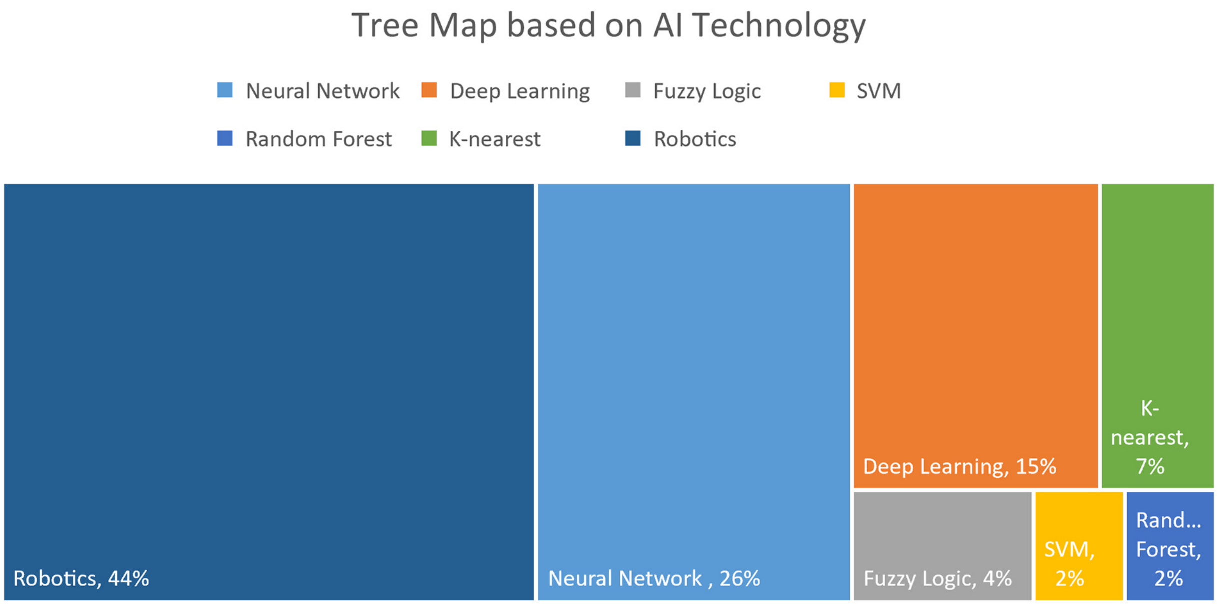

Fig. 2. AI approaches used in agriculture.

fertilizers. Moreover, since robots cab work around trees, rocks, lakes and other obstacle areas easily, crops can be cultivated more fields (Khare et al., 2021; Gai et al., 2021; Panarin and Khvorova, 2021; Rysz and Mehta, 2021).

Artificial neural networks (ANN) are one of the most important technique of AI. These models are developed using interconnected nodes which are performed functions as our human brain. The usage of NNs application is very wide, and it also includes in agriculture (Kujawa and Niedbala, 2021). (Almomani, 2020) was applied a NN to optimize the cumulative methane production. This NN model has showed significant results in prediction. In addition, NN has employed to pattern classification and soil moisture content prediction (Mohapatra and Lenka, 2016). Scaled Conjugate Gradient and BFGS Quasi-Newton based neural network algorithms used to take various soil and environmental parameters and predict hourly requirement of soil soil moisture content. The NN has become popular as a classification method in agricultural engineering. NNs are virtuous to formulate the model using non-linear data and data represents with images. Therefore, this approach is good for crop classification using image data (Boniecki et al., 2020). The prediction of growth rate of rice is important to obtain sustainability in agriculture. Researchers recommended rice growth rate modeling using NN which shows less errors compared to regression algorithm and gene expression programming (Liu et al., 2021).

With the training limitation of NN, researchers are used DL. DL deals with recent and modern technique to process images and analyse data, which guarantees the potential results. Application of DL into agricultural domain is emerged instead of various domain that DL has been successfully applied (Kamilaris and Prenafeta-Boldú, 2018; Zhu et al., 2018; Santos et al., 2019; Nguyen et al., 2020). Jiang et al. (Jiang et al., 2021) suggest a method to identify the disease in fruit like Apple and the method is useful to prevent the disease without harming the environment. In the method, capability of image processing and classification in DL were applied to classify the fruit image. Deep neural network with different convolution layers and different number of neurons are examined and evaluated. The results beat the performance of baseline models. DL stimulates multi-model approach to detect, disseminate and monitor the Active Fire Locations (AFL) in agricultural tasks and they are guaranteed the highly accurate results (Sharma et al., 2021). We found that DL has applied to identify seeds and pest, monitor nitrogen content in soil and leaf, detect irrigation and plants' water stress level, assess erosion of water, detect usage of herbicide, defects on food and damage of crop hail and monitor greenhouse (Bu and Wang, 2019; Li et al. 2021c; Zhou et al., 2021; Chen et al., 2020; Xue et al., 2019). However, DL models need comprehensive datasets as the input to serve at the training procedure. Other than the above methods, researcher were also applied Fuzzy Logic, SVM, Random Forest and K-nearest (Kurniasih et al., 2018; Center and Verma, 1998; Pujari et al., 2016; Jez et al., 2021; Yamaç, 2021). However, Robotic models and DL models have showed significant usage in the agriculture field.

To develop a more complete understanding of the enabling AI technologies currently applied in agriculture sector, Fig. 3 further illustrates main AI approaches used in agriculture functions.

Moreover, the study aligns the main agriculture functions with sustainability growth objective (Fig. 4) in order to provide contextual link with present view of the agricultural functions and sustainability. In here, the study focused on several functional areas highlighted in the selected studies. As such, the research hots-pots of AI and agriculture in the past decades comprise mainly prediction, harvesting, advanced care crops, weed control, resource management and supply chain.

4. Agriculture functions and AI

This section elaborates the inclusive review of the literature that applied automate functions in agriculture (e.g., prediction, harvesting, advanced care crops, weed control, resource management and supply chain) using AI techniques. Within the reviewed papers it was identified that the most common applications of AI are predicting, harvesting, advanced care of crop and so on Fig. 5.

4.1. Prediction

As shown in Fig. 5, of the total 115 studies, 36 (40%) articles reported that the most common applications of AI for agriculture is prediction model for total agricultural output value (Tian et al., 2021; Kim et al., 2021; Han et al., 2018; Khan et al., 2020; Crane-Droesch, 2018; Kumar and Joshi, 2015; Isachsen et al., 2021), waste minimization (Almomani, 2020), irrigation control (Mohapatra and Lenka, 2016), weather index (Buyrukoğlu et al., 2021; Liu et al., 2020; Zhang et al., 2021), energy

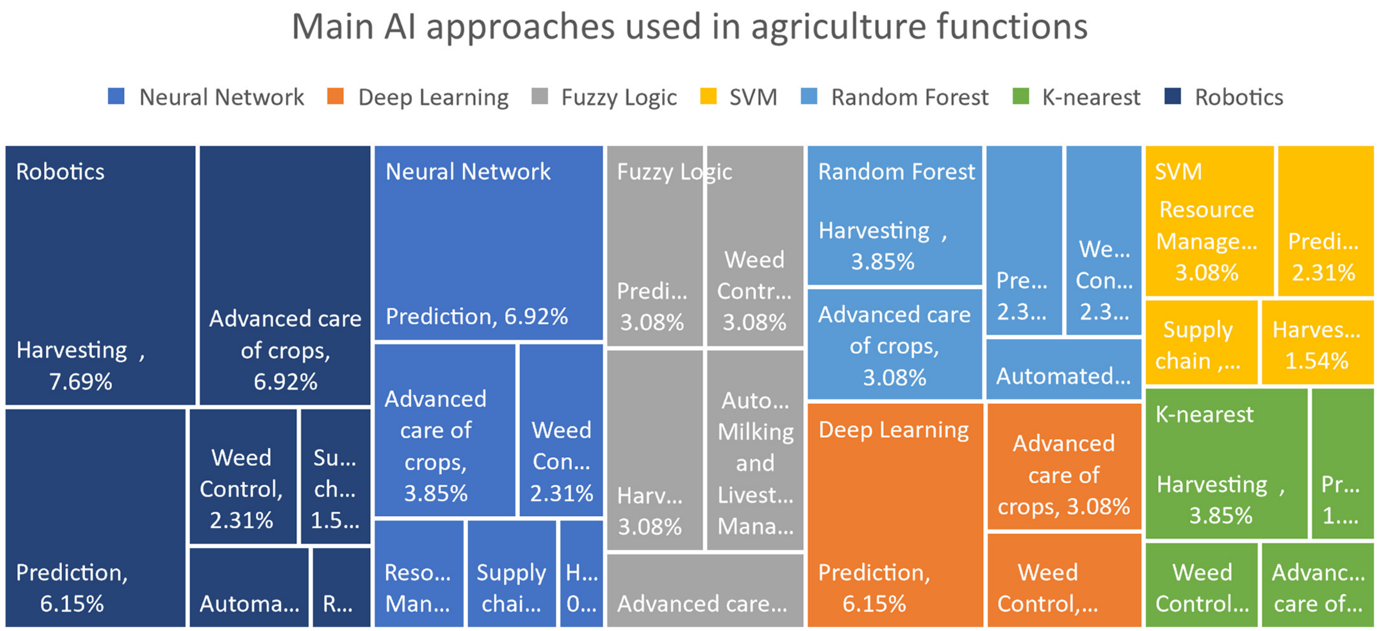

Fig. 3. Main AI approaches used in agriculture functions.

optimization (Senocak and Goren, 2021; Guillén et al., 2021) and demand and consumer preference (Sharma and Bisen, 2013; Giannakis et al., 2019; Dargan et al., 2020; Monteiro et al., 2021). To cover these scenarios, ANN and DL techniques are used by 95% of the reviewed papers. The ANN and DP are used to collect real-time data about multiple agricultural parameters, such as production quantity, waste, climate data, biomass, and land area to estimate yield, manage irrigation and land area and develop drought index. The fact that this AI application in prediction model in agriculture is so common can be justified by the complex and dynamic nature of the agricultural parameters, thus, it is perplexing to obtain accurate predictions. Thus, AI can be served as a method to face the complexities in the dynamic nature of agricultural

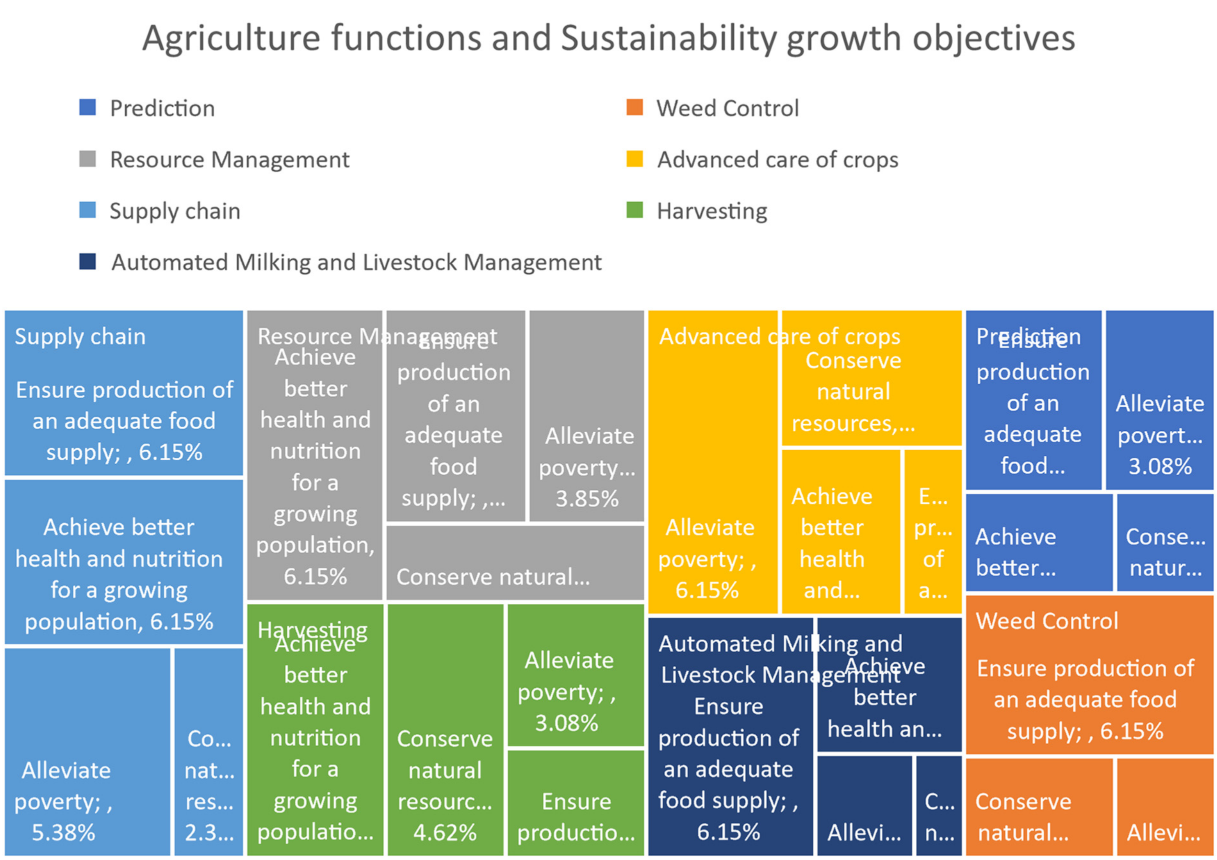

Fig. 4. Agriculture functions and Sustainability growth objectives.

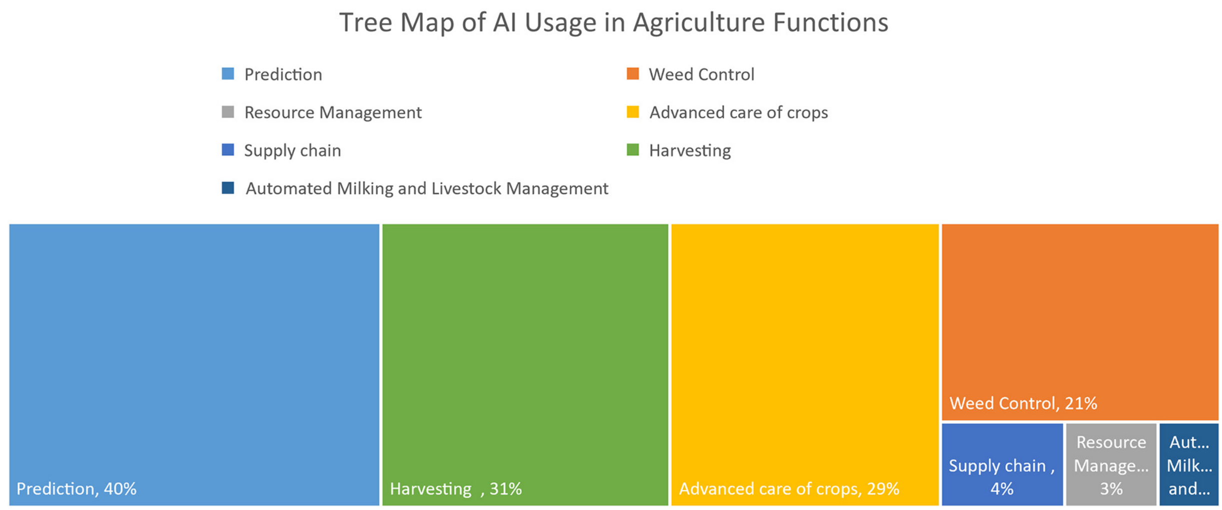

Fig. 5. AI usage in agriculture functions.

parameters. Interestedly, few papers (4) focused on predicting customer demand and preference and market integration for few agricultural products (e.g.: wine, yogurt). The studies focused on the the elements in sensory functions and reveal the associations among evaluators scoring and latent features. These preference predictions provide wider chances to develop food product designs in future. What we can conclude from these literature base is that agriculture sustainability is ensure production of an adequate food supply.

4.2. Harvesting

Harvesting is a challenging task in agriculture because harvesters strongly correlate to crop detection, quality cuts, damage, picking and packaging. The labour assets utilize for harvesting is one of the main cost components in agriculture production. To overcome the high labour cost component, the prior studies pay wider attention to exploit commercially doable AI applications for harvesting. As presented in Fig. 5, the next most common application of AI is harvesting (28 articles; 31%). Moreover, robotic technique (robot arm) has been identified as an effective tool for assistance in the agriculture industry to harvest the fruit/vegetable while not harming the plant (Hespeler et al., 2021). As a functional model, the robot could automatically move on the rail, identify, detect and locate the mature bunch, hold and separate the target and collect the crop harvested. Precisely identifying and detecting the mature crops encompass a key technique of harvesting robot. An efficient object detection and inspection algorithm are necessary for a robotic platform to be used in harvesting. Different types of sensor technologies use to detect and locate crop in the tree branches, determine the ripeness of the crop, determine the geometry of the tree canopy and locate the tree in orchard, and finally to pick the crop from the tree. Computer vision is used for crop ripeness estimation (Hespeler et al., 2021). In all cases, crops should be picked when they are ripe or mature without mechanical damage to the fruit. This action should take place as be as quick and as cost-effective as possible. Thus, research on harvesting robot mainly concentrations on five key areas; identifying targets under complex background; separating soft crop; level of consuming energy to harvest, harvesting tools suitability and conformation design to fit with unshaped work fields (Navas et al., 2020). Moreover, thermal imaging for real-time harvesting robot allow to harvest in the evening hours or low light situations (Hespeler et al., 2021). Finally, vision-based crop detection is a critical component for robotic harvesting and it includes crop detection with dimension, mass estimation, and localization prior to pick or slice (Lee et al., 2020; Zujevs et al., 2015; Villa-Henriksen et al., 2021). Using a robotic system would enable certain advantages such as minimum wastage, picking efficiency, high picking rate and flexible work force and nighttime operation. Development of timely, efficient, and careful robotic harvesting solutions lead to complete the harvesting process while generating high quality yields at minimum time consuming and at minimum unrecuperative damages in the harvesting process. Particularly, there have been significant developments of AI towards the sustainability agriculture objective of ensuring production of an adequate food supply. Besides research projects have been performed, very few have developed into the commercial world (Kiwi fruit; Tomato; Cotton; Apple; Rice).

4.3. Advanced care of crop

It is essential to repetitive detection and monitoring on the plant's life cycle in order to attain the yield with high quality and quantity. The plant growth and development could be detected with the number of leaves and that would be the key phenotype of plant growth and crop damage by attacks of bacteria, fungi, and other pests are threatening the long-term viability of plant phenotyping. Thus, advanced care of crops is another agricultural function where AI is mostly applied (26 articles; 29%). AI technologies, such as DL, ANN, robotic and ML, provide the means to automate disease detection, measure plants, monitoring plant growth status and applying fertilizer (Zargar et al., 2020; Emmi et al., 2014; Sharma et al., 2020; Santin et al., 2016; Grimstad and From, 2017; Raja et al., 2020; Magalhães et al., 2021; Buzzy et al., 2020; Schor and Attwood-Charles, 2017; Santos et al., 2020; Li et al. 2021b; Yorozu et al., 2021). Symptoms of diseases developed by attacks of bacteria, fungi, and other pests need to be identified in an initial stage according to the changes in the physiological condition of plant parts (leaves, stems, and flowers) to provide treatment at the right time.

Currently, labour intensive crop caring practices use vast amount of agricultural chemical inputs (fertilizers, herbicides, fungicides, and insecticides) cause to have high production cost and lead pollution matters as well. In general, it is estimated that more than 100 kg are applied per hectare in farm land. Unfortunately, majority of the nitrate applied were either washout or loss in the air. The robotic disease-detection systems were commonly designed in whole inclusive pattern to identify the results in infection and these results could be utilised to detect precise diseases and and apply fertilizes appropriately (Schor and Attwood-Charles, 2017; Grimstad and From, 2017). In addition, ML technique was used to measure plants with sensors (Sharma et al., 2020) to estimate plant growth direction (Booth et al., 2020) and plant classification (Libertn et al., 2018), ANN to design performance-oriented riparian buffer strips for the filtering of nitrogen

(Santin et al., 2016) and measure plant growth status (Li et al. 2021b), DL to detect underdeveloped plants (Aguiar et al., 2021) and to recognize the plant using image-based (Kiourt et al., 2020). Therefore, it is important to recognize the AI applications that favor both disease management and to provide sufficient, safe, and nutritious food to the global population. Particularly, there have been significant developments of AI towards the sustainability agriculture objective of achieving better health and nutrition for a growing population.

4.4. Weed control

It is necessary to control weed in the crop field to increase the production of agriculture. The review (26 articles; 29%) highlights that AANN, DNN, CNN and DL to identify and classify the plants as weed using image processing. These techniques include the crop signaling compound includes distinctive characteristics that assure the detection of crop diseases and ensure the classification of crop and weed (Zangina et al., 2021; Espejo-Garcia et al., 2020; Abdullahi et al., 2017; Monteiro et al., 2021; Raja et al., 2020; Kounalakis et al., 2019; Peteinatos et al., 2020). Next, the signal is transmitted to the robotic arm or Unmanned aerial vehicles (UAVs) to pluck the plant through serial communication or execute weed treatment with a flaming and row crop cultivator implement, weed treatment with a herbicide patch sprayer or canopy sprayer (Emmi et al., 2014; Seo and Umeda, 2021; Özlüoymak and Bolat, 2020; Kounalakis et al., 2019). Using AI in weed control enables to decrease unnecessary plants within fewer time frames and minimize fertilizers and herbicides utilization, which cause soil degradation and pollution.

4.5. Resource management

Agriculture is naturally bounded with the resource constraints (e.g., land, water and soil). Primarily,womb of agriculture is soil and soil management therefore serves as primal concern in agricultural resource management. Thus, assessing the suitability of agricultural land becomes the vital task in agriculture development. Moreover, in precision agriculture, irrigation management plays a crucial role. The review emphasized that AI driven agriculture is focusing on methods to optimize land (Nguyen et al., 2019; Oliveira et al., 2021), soil (Nguyen et al., 2019; Moya-Rico et al., 2019; Paliwal et al., 2019; Väljaots et al., 2018) and water/irrigation (Mohapatra and Lenka, 2016; Jung et al., 2021; Kakani et al., 2020) considering the benefit it brings to people linked with this profession. Moreover, the weather forecasts such as sunlight, rainfall, humidity, and moisture guide by using AI leads to the optimal use of water for scheduling and planning the crop. To cover these scenarios, ANN, DL, ML and robotic techniques are widely used by the reviewed papers. Ground robots and UAVs are more precisely used to collect soil and water sample and land preparation/sowing. Neural networks, deep and ML techniques used to computed the normalized soil moisture index to estimate the soil moisture content and develop a model to assess the agriculture land for cultivation in terms of four decision classes, namely more suitable, suitable, moderately suitable, and unsuitable. Since irrigation management plays a critical role in quantity and quality of the crops, estimating evapotranspiration, streamflows and real-time management of reservoir release by using ML algorithms are highlighted in the review (Sharma et al., 2020). ML helps to process all data samples to construct a heuristic model that can predict factors resulting high yields. While the use of UAVs and robots for sowing has advantages like large area coverage and speed. However, uncertainty in ground measurements and power requirements are restricting the number of task they can perform (Lytridis et al., 2021).

4.6. Supply chain

Supply chain (SC) in agriculture includes several tasks such as preproduction, production, storage, processing, distribution, retail, and reach final product the end consumers. In the process of SC also includes multiple stakeholders such as farmers, producers, processors, certification agencies, traders, government, retailers, distributors, and final consumers. Compared with other supply chains, agriculture SC is complex due to the nature of perishability and high supply-demand fluctuations of the products and high consumer awareness towards produce provenance, quality, and safety. All these notes, the review insists that AI applications, especially ML, in agriculture SC enable farmers and other relevant organizations to draw valuable insights on agriculture process, leading to increase agricultural productivity while taking decisions via data-driven platform (Sharma et al., 2020; Camaréna, 2020). Data pays a crucial role in supply chains thus improvisation in storage, collection, visualization, privacy, security, accuracy, and access of agriculture data can impact application of AI in agriculture supply chain. The common believe in agriculture is that farmer is classified under low income group and many firms/farms in the agricultural are worried with low-profitability. AI is widely used in SC to identify hidden patterns in the data, in this line, SC stakeholders consider to accelerating AI in SC, leads to achieve the expectations of farmers as well as customers. Contextual factors that have been identified as important influencers of AI in agriculture sustainability objective: alleviate poverty of farmers through formalize products sales to certified markets and global commodity price trends, visualize the farm income prior to the intervention and the formalize the existence market structure. As review highlights although SC using AI platforms leads to sustainable agriculture objective, questions related to the mechanism of reaction and selectivity of matrices for AIs in consumer aspect are still unanswered.

5. Considerations

Fig. 6 tabulates the contextual link of usage of AI techniques that are supposed to address sustainable agriculture.

The number of studies that address sustainable agriculture is increasing; however less attention has been devoted to investigating the sustainability aspect of agriculture with regard to AI technology. Obviously, the sustainable agricultural is not a typical research field for AI researchers to study; the field of AI research has a historical practice to focus on the industries that involving with new products and services. Furthermore, researches related to agricultural food tend to examine the way of increasing production rather that addressing sustainability issues. Moreover, most research within the agriculture food industry tends to examine production rather than sustainable issues. Due to the vast and increasingly expanding body of literature on agri-technology, this review has focused on how AI technology can improve the sustainability of agriculture industry. The aim of this review paper is therefore to analyse and create an understanding of the different types of AI applications in agriculture industry and how those applications align to achieve the agriculture sustainability objectives. A systematic and quantitative evaluation of different agricultural parameters is of vital importance to improve agriculture production and ensure sustainable food supply. Unsustainable agricultural production practices such as food wastage and production shocks due to climate changes can be minimized if the sector uses AI to get accurate predictions. Our review therefore underscores the importance of AI prediction driving the adoption of modern agricultural innovations to ensure adequate food production and supply. Within the context of the different concepts of sustainable agriculture objectives, AI applications in prediction specifically focus on the potential contribution towards satisfying human needs for food. However, the vast majority of agriculture products remain unaddressed, and almost no fully automated prediction models have been developed. Moreover, developing a specific prediction model for market demand and preference of agriculture products is insufficient. However, due to the low repeatability and difficulties in corresponding, AI implementation in agriculture sector become main challenge (Linaza et al., 2021) specifically in developing nations, which requires immediate solution/s.

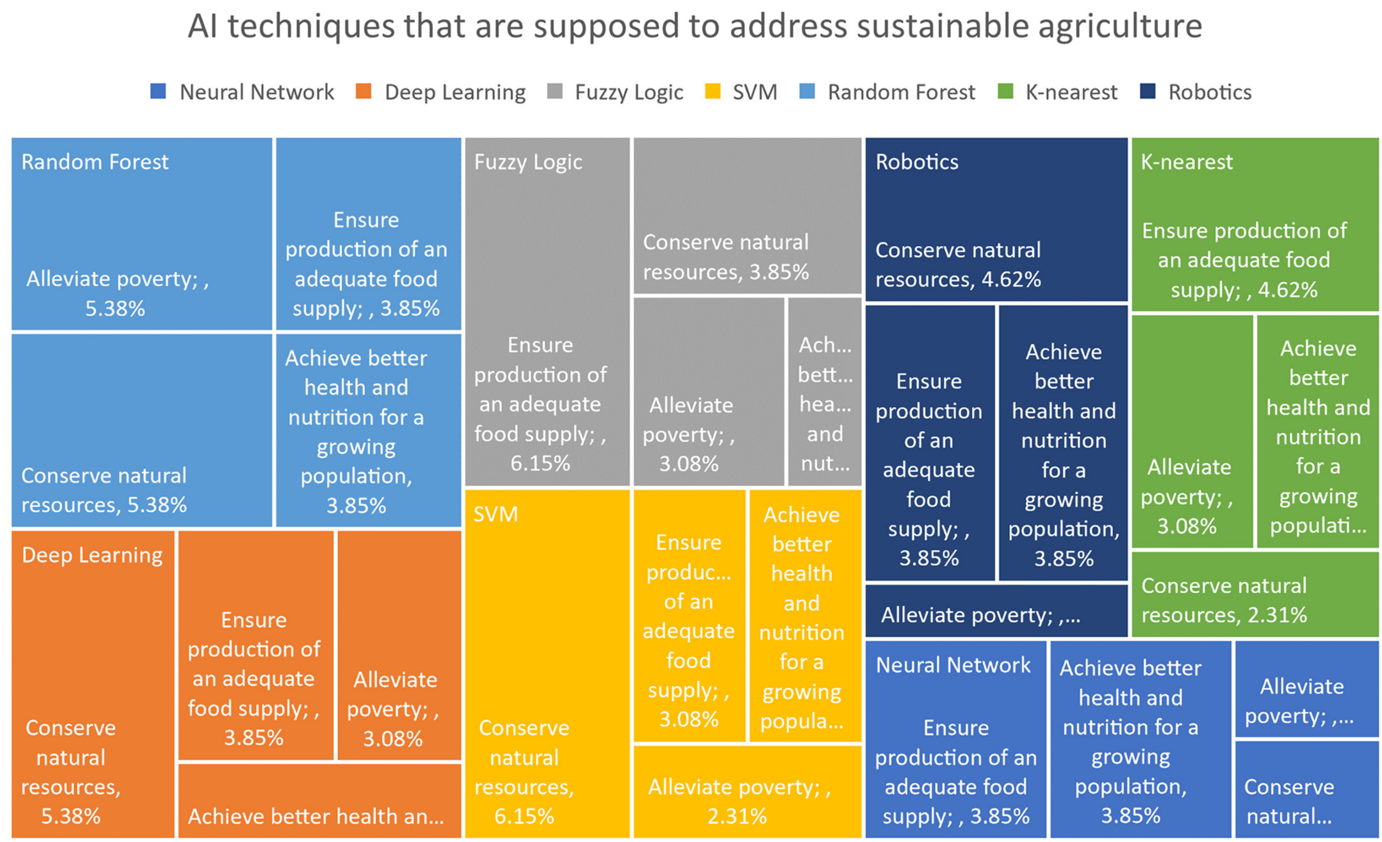

Fig. 6. AI techniques that are supposed to address sustainable agriculture.

Development of timely, efficient, and careful robotic harvesting solutions lead to obtain desired quality harvest at short-time period and more interestedly at minimum unrecoverable loss. Particularly, there have been significant developments of AI towards the sustainability agriculture objective of ensuring production of an adequate food supply. Besides research projects have been performed, very few have developed into the commercial world (Kiwi fruit; Tomato; Cotton; Apple; Rice). Moreover, the review revealed that disease detection systems are mostly concerned on leaves and the lower area of leaves is not properly sensed by the camera sensor. As said, besides leaves, AI techniques need to be expanded for a variety of plant parts. In line with that (Li et al. 2021b) insisted that AI technologies have been counted on a different sensors and imaging technologies to gather a variety of plant data, whereas analyzing different sensor data also relies on different hardware devices, software systems, and different platforms and different monitoring scales used to analyse date. Such complex operation process might slow down data acquisition and integration, leading to an information lag. This implies the need for international harmonization and standardization in phenotyping data. The phenotyping data collecting and analyzing then could lead to manage cultivating practices, plant breeding and overall management in agricultural functions.

Weeds destructively affect agricultural crop productions by contending with crop plants for resources, including soil moisture and nutrients. Providing sufficient and healthy foods for ever growing population heavily depends on the ways we control weeds and apply fertilizers in efficient manner. For future work, the review opines (Kounalakis et al., 2019) that more robust weed recognition approaches could be extended with additional data capturing conditions (like illumination, grass density) and sampling techniques could be synthetized with techniques like Synthetic Minority Over-sampling Technique (SMOTE) and Adaptive Synthetic Sampling (ADASYN).

Natural resources were jeopardized and different forms of environmental degradation became apparent, thus conservation practices of natural resources using AI technologies lead to increased global crop yields. Meeting the fourth objective - conserving natural resources, is a daunting challenge. As we identified, it includes protection of soil health and water quality and maintain biodiversity of flora, fauna, and natural landscapes. The review sheds a light that AI technological developments taking consideration on these challenges while improving agri-food productivity with minimum effects to the environment. Particularly, there have been significant developments of AI towards the sustainability agriculture objective of conserving natural resources. However, to improve overall crop water productivity, AI technology has to be advanced in irrigation technologies such as efficient low pressure center pivot irrigation and micro-irrigation and weather-based and soil moisture sensor-based irrigation scheduling. Moreover, improving decision support tools integrating weather, soil and crop information will ensure progress towards the sustainable objectives of agriculture.

Though AI helps to enhance the visibility of agriculture SC, more attention need to be focused on the food retailing phase for predicting consumer demand, perception and buying patterns. A precise prediction of food requirements or food consumption behavior of buyers helps to avoid overstocking, overproduction, resources overutilization and guarantee the fair income and price to farmers and buyers respectively. Dey et al. (Dey and Shekhawat, 2021) enhance the back and forward linkages in supply chain, reduce transportation cost and delivery time, enhance farmers' awareness on price, selling quotas, available stocks and online showcases and reduce the risks involved in contract arrangement. Subsequently, investments in AI applications in agriculture industry have exhibited the possibility of achieving four objectives in agriculture sustainability while enhancing the farmers' livelihood, minimizing food production cost, controlling food price fluctuation and ensuring food choices to consumers. It is observable that AI application in achieving the second sustainable objective – alleviate poverty of farming community, remains scantly addressed. On this note, there is a vital requirement to design comprehensive framework of AI that should be used in agriculture SC.

6. Conclusion and further research directions

As sum in the literature consulted, we observed that AI applications are extensively adopted nowadays to enhance operational automation and performance of agricultural industry. We found that the most common applications of AI for agriculture are prediction model for total agricultural output value, followed by harvesting applications. Though agriculture is naturally bounded with the resource constraints, AI applications in natural resources management (such as water, soil, land) are presently at unsatisfactory level. We were further able to identify that final consumer aspect in agriculture SC needs to be devouring extensive attention in order to achieve one of the key agriculture sustainability objective; alleviate poverty of farmers. Moreover, it was witnessed in this review that in recent work the use of AI and image processing techniques has become more common to improve the sustainable agriculture. When consider the DL models, these models are suffer from task dependent since all the models are using general word embedding vector. To overcome this problem attention-based DL models can be developed. In the future researchers can consider developing attention-based DL models. Likewise, the future studies should intend to address the gaps that identified in this systematic review such as under-utilised commercial crops appraisal, data capturing conditions, natural resource standards, functional areas and geographical locations.

This study has provided useful information to understand the implication of AI in agriculture sustainability. However, there can be limitations in this research. This work may extend by considering project costs, usability and regional challenges in AI applications. In addition, can explore how attention-based DL models are used in agriculture with the newest AI improvements. Due to the growing application of AI itself is not adequate to obtain sustainable objectives; it is required to assess the adaptability of AI together with other useful maneuvers like policy support for AI developers and programme intervention to implementations.

Credit authorship contribution statement

Vilani Sachithra: Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing –original draft, Writing – review & editing L.D.C.S. Subhashini: Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing – original draft, Writing – review & editing.

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.

Appendix 1. AI, Agriculture functions and Sustainability growth objectives

Sustainable objectives

1. Ensure production of an adequate food supply.
2. Alleviate poverty.
3. Achieve better health and nutrition for a growing population.
4. Conserve natural resources.

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