Artificial Intelligence in Agriculture

Jianlong Zhou and Fang Chen

Abstract Our world is experiencing rapidly increase of world population, urbanisation, and aging, which requires more food to produce more efficiently to feed the population. However, climate changes, droughts, floods, and crop diseases make the production of food more difficult in agriculture. Artificial Intelligence (AI) has powerful capabilities in prediction, automation, planning, targeting, and personalisation. This chapter presents contributions of AI to conquer those challenges in agriculture with a number of typical application areas in the lifecylce of agriculture. The chapter also discusses potential risks such as privacy and security as well as environmental consequences when AI is deployed in agriculture.

Key words: Artificial intelligence, agriculture, benefits, risks

Synonyms

Artificial Intelligence – AI
Food and Agriculture Organization – FAO
Machine Learning – ML
Internet of Things – IoT
Wireless Sensor Network – WSN

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1 Artificial Intelligence

Artificial Intelligence (AI), a computer system which performs tasks that are usually associated with human intelligence or expertise without being explicitly instructed, is progressing rapidly in recent years. It is typically defined as an autonomous and self-learning agency with the ability to perform cognitive functions in contrast to the natural intelligence displayed by humans, such as learning from experience and reasoning [18, 25, 6, 7]. AI works by dealing with large amounts of data, extracting and interpreting patterns in that data, and translating these interpretations into actions that should be often done by a human being. It has powerful capabilities in prediction, automation, planning, targeting, and personalisation (see Fig. 1), and is claimed to be the driving force of the next industrial revolution (Industry 4.0) compared with the steam engine in the first industrial revolution, the electricity in the second industrial revolution, and the electronics and information technology in the third industrial revolution.

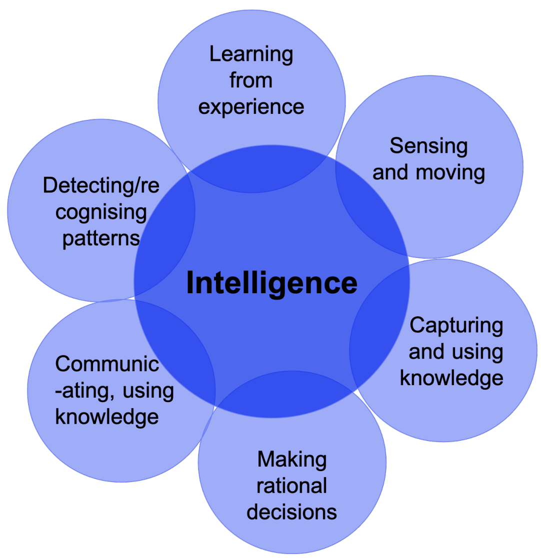

Fig. 1 AI can make things as smart as humans or even smarter.

The promise of AI is huge, and it is transforming our society and affects almost every aspect of our lives. In general, AI and machine learning techniques such as image processing, artificial neural network, deep learning, convolution neural network, fuzzy logic and computer vision with other techniques such as Wireless Sensor Network (WSN) technology, wireless communication, robotics, Internet of Things (IoT) together will transform the way we interact with the world. For example, AI enables the monitoring of climate change and natural disasters, enhances the management of public health and safety, helps doctors diagnose disease more accurately, assists judges make more consistent court decisions, enables employers hire more suitable job candidates, automates administration of government services, and promotes productivity for economic well-being of the country [25, 7]. This chapter specifically focuses on AI in agriculture.

1.1 AI pipeline

A typical AI and Machine Learning (ML) pipeline is the end-to-end construct that orchestrates the flow of data into AI algorithm for AI model training, an AI model, predictions, and decisions. It includes raw data input (training data and testing data), features, the AI model and model parameters, as well as prediction and decision outputs. In the AI pipeline as shown in Fig. 2, data is input to an AI algorithm to train an AI model. The AI model is then used to get predictions and further decisions by users based on predictions.

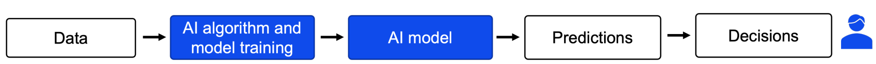

Fig. 2 A typical AI pipeline from data to decisions.

In the AI pipeline, data is the core of all AI steps. It could include different types of data that are related to prediction tasks. For example, in agriculture (see Fig. 3), typical data that can be used in AI include weather information, soil data, seed data, irrigation information, fertiliser usages, field management, historical yield information, as well as satellite images (remote sensing), and data from robot and drone used for the field management.

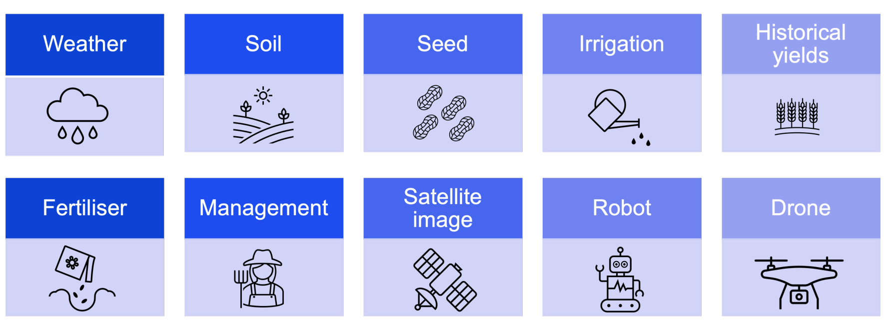

Fig. 3 Examples of data that could be obtained in agriculture.

1.2 AI lifecycle

A typical lifecycle for an AI application project development usually includes different stages from business and use-case development, data procurement, model building, system testing, deployment of the system to monitoring performance of the system (see Fig. 4). It provides a high-level perspective of how an AI application development should be organized for real values with the completion of every stages. The AI lifecycle delineates the role of every stage in order to make AI into practice with the consideration of business and engineering. For example, the first stage of the AI lifecycle is to identify a business and use case to tangibly improve operations, increase customer satisfaction, or otherwise create value. The next stage is to collect and prepare all of the relevant data such as training data and testing data for use in machine learning. After this, the machine learning model is trained and tested with the collected data. The major objective is to get high performed and easily generalised AI models. The model is then deployed in applications and monitored during the use to improve it iteratively if any problems are found.

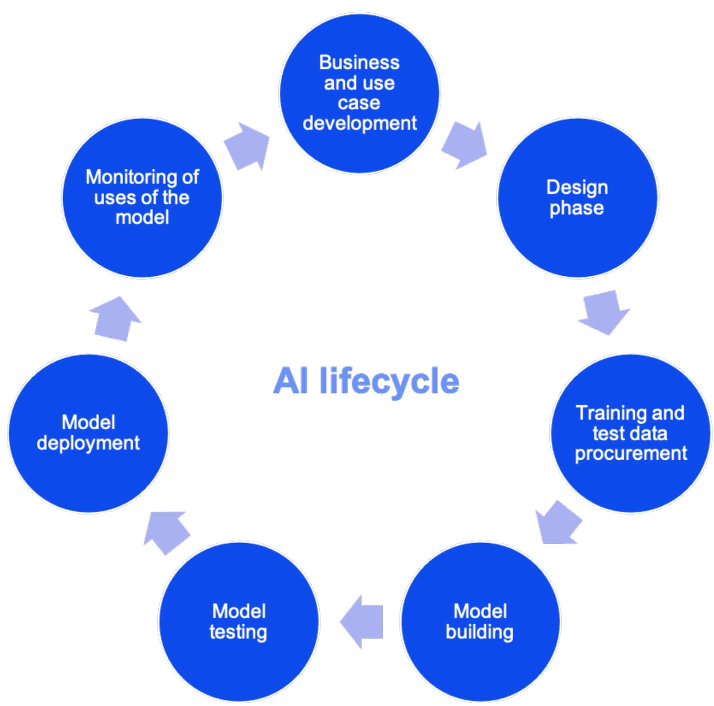

Fig. 4 Different stages of an AI lifecycle.

2 Lifecycle of agriculture

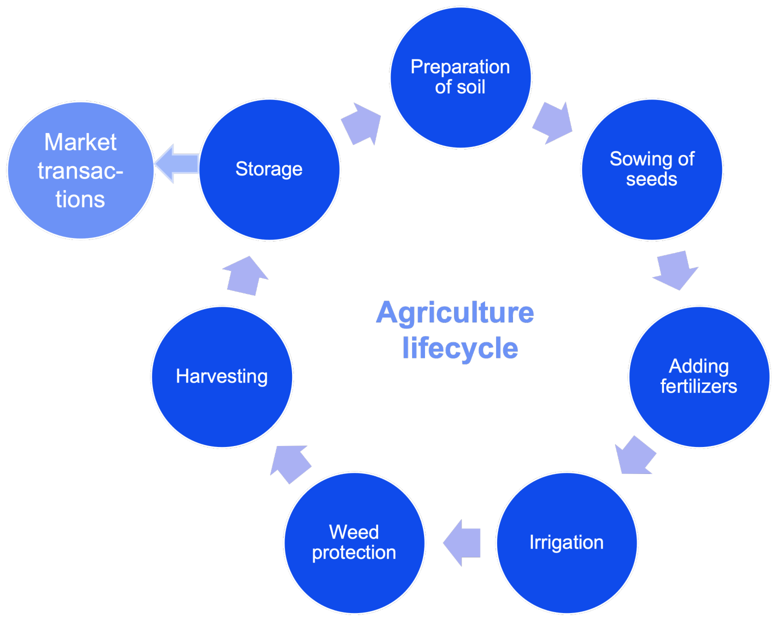

Fig. 5 Different stages of the agriculture lifecycle.

The lifecycle of agriculture can be divided into different stages as shown in Fig. 5: preparation of soil, sowing of seeds, adding fertilisers, irrigation, weed protection, harvesting, and storage. After storage, the yields can be delivered to market for transactions. In this lifecycle, the preparation of soil is the initial stage of farming preparing the soil for sowing seeds. It involves plowing soil to break large soil clumps and remove debris. After preparation of soil, seeds are sowed in the soil, which requires taking care of the distance between seeds, and depth for planting seeds. Fertilisers are important for the growing of crops and they are added when sowing seeds or other times. This stage also determines the quality of the crop. Besides, irrigation is important to help to keep the soil moist and maintain humidity. When crops grow, weeds growing near crops may decrease yields, increase production cost, interfere with harvest, and lower crop quality. They need to be removed. After crops are mature, they need to be harvested from the fields. This stage is a labor-intensive activity, and also includes post-harvest handling such as cleaning and packing. After harvesting, the products are stored in such a way as to guarantee food security. This stage also includes packing and transportation of crops as well as market transactions.

Similar to other sectors in our society, agriculture is also experiencing unprecedented changes with the advancement of AI, robotics, and Internet of Things as well as other emerging technologies. Characterised by these technologies,the agricultural revolution called “Agriculture 4.0” [17, 11, 8] has already begun. This is compared with the first agricultural revolution representing a transition from hunting and gathering to settled agriculture, the second one relating to the British agricultural revolution in the 18th century, and the third one of productivity increases associated with mechanization and the Green Revolution after the World War II [17, 8]. While AI is the key technology to Agriculture 4.0, it promises to mitigate different challenges faced in agriculture.

3 Challenges faced in agriculture

Our world is undergoing various critical changes that may shape the livelihood of millions of people in the coming years [5]. For example, the rapidly increasing world population, urbanisation, and aging will require more food to produce more efficiently to feed the population. Climate changes, droughts, floods, and crop diseases will make the production of food more difficult in agriculture. Transboundary pests and diseases will also affect the productivity significantly in agriculture.

The Food and Agriculture Organization (FAO) of the United Nations report entitled “The future of food and agriculture: trends and challenges” [10] has identified key challenges for the provision of adequate and affordable food supplies through sustainable agricultural services. The challenges are grouped into three clusters [10, 5]:

(a) Challenges related to food stability and availability

- Sustainably improve agricultural productivity to meet increasing demand.
- Ensure a sustainable natural resource base.
- Address climate change and intensification of natural hazards.
- Prevent transboundary and emerging agriculture and food system threats.

(b) Challenges related to food access and utilization

- Eradicate extreme poverty and reduce inequality.
- End hunger and all forms of malnutrition.
- Improve income-earning opportunities in rural areas and address the root causes of migration.
- Build resilience to protracted crises, disasters and conflicts.

(c) Systemic challenges

- Make food systems more efficient, inclusive and resilient.
- Address the needs for coherent and effective national and international governance.

While traditional farming techniques have difficulties to solve these challenges, this chapter gives examples that AI can contribute to fight the challenges.

4 AI for agriculture

Similar to the wide uses of AI in other domains, AI is also becoming one of solutions to different challenges in agriculture based on AI's powerful capabilities in prediction, automation, planning, targeting, and personalisation. For example (see Fig. 6), AI can be used to help yield more crops, control pests, monitor soil, growing conditions, help with the workload, determine the optimal time for sowing and harvesting, and improve a wide range of agriculture related tasks in the entire food supply chain. This section shows some key application examples of AI in solving agricultural challenges.

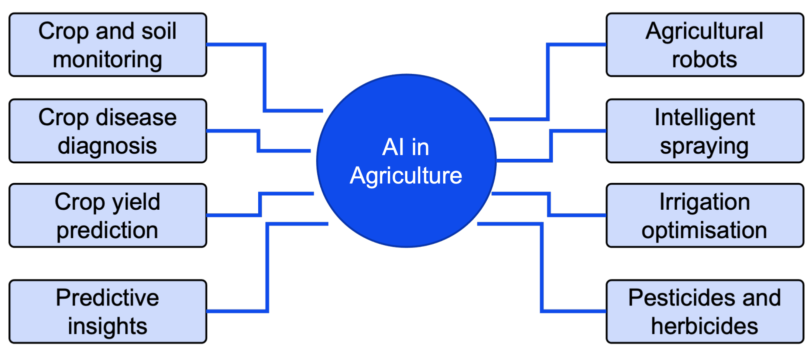

Fig. 6 Examples of AI in agricultural applications.

4.1 Agricultural robots

A key application of AI in agriculture is the use of intelligent and autonomous robots for various jobs in the agricultural production and management [13]. The original purpose of agricultural robots is to replace human labor and produce effective benefits on small as well as large scale productions [14]. The agricultural robots are not only better at agricultural jobs than humans, they also do jobs humans do not want and provide a workforce able to plant, weed, and harvest 24 hours a day, seven days a week. For example, there are machines like autonomous strawberry-picking machine [24]. VineRobot is a machine designed to roam the vine field autonomously, collecting data on the state of the vineyard, such as grape composition, water status, and other important data to monitor the grape growth [16]. These machines use different sensor technologies, machine vision and AI models to identify the location of the produces and perform corresponding actions.

4.2 Irrigation optimisation

Water is one of significant resources for agriculture. However, because of the limited resources of water in the planet, it is highly necessary to develop more efficient technologies to ensure proper use of water resources in irrigation. This is usually realised by replacing the manual irrigation which is based on soil water measurement with automatic irrigation scheduling techniques. The smart irrigation technology is developed to automatically control the irrigation by detecting the level of water, temperature of the soil, nutrient content and weather forecasting with the use of remote sensors and technology such as the Arduino and Raspberry pi3. AI technologies can be used to build evapotranspiration model based on different data such as the level of water, temperature of the soil, nutrient content and weather forecasting in order to provide optimal irrigation decision management [19, 1].

4.3 Intelligent spraying for pesticides and herbicides

Pests and weeds are the most impacting biotic and abiotic factors in agriculture, affecting the growth of crops by competing and destroying nutrients and water as well as others with crops, resulting in important yield loss. Therefore, the management of pests and weeds in agriculture plays deterministic roles in crop yields [19]. One of the traditional methods for the pest and weed control is to spray chemicals to the field massively without considering specific locations of pests and weeds. Such approach is not only unfriendly to the environment, but also cost usually ineffectively.

AI can be used to detect weeds, pests, and diseases in crops. AI techniques process the data received from different types of sensors that monitor climatic, environmental, and visual information from the surface, soil, and microclimate of crops. Such data is then used to train machine learning models such as convolutional neural networks for weed, pests, and diseases detection [15]. The detection results are then fed into autonomous precision spraying equipment for targeted application of the necessary treatment. Such

AI-driven pesticides and herbicides approach can dramatically reduce chemical inputs used in agriculture, which both reduces environmental impact and saves on production costs.

4.4 Soil and crop monitoring

Soil is the foundation of agriculture and food production. The nutrition of soil plays an important role in what type of crop to grow and what quality of the crop to obtain. Due to the increasing use of chemicals and industry fertilisers, the soil quality is degrading and it's hard to determine the quality of the soil for the crop productivity and environmental sustainability [2]. Furthermore, crop monitoring can help agricultural producers understand the health status of crops on time so that necessary actions can be taken in time.

Luckily, different types of data sources related to agriculture can be accessible now, such as satellite and unmanned aerial vehicles (UAV), humidity sensor readings, ground-based weather stations. Simultaneously, new monitoring and control systems are continually introduced. AI techniques such as computer vision and deep learning algorithms are then used to process these captured data to provide personalised, accurate analysis and predictions to monitor crop and soil health. For example, the weather data and rainfall data have been used to predict the volumetric water content of the soil through the use of deep learning models [3]. Images of crops taken by UAV or robot at different stages have been used to monitor the health and growing of crops using computer vision and deep learning techniques [20].

4.5 Crop yield prediction

Yield estimation is an essential pre-harvest practice to support business plans and decision making of large-scale farming companies. For example, accurate yield estimation can help companies to make selling contract with clients with more accurate pricing plans. An over-estimation leads to further costs to buy additional crops to meet contract that impacts profitability, while an under-estimation entails potential crop waste. Furthermore, yield prediction functions as the main basis for farming companies to make decisions on allocating essential logistics such as labor force, supplies, transportation means, as well as others. Yield prediction can also be used to optimise cultivation practices for different crops.

Manual yield estimation with the counting of products such as fruits or vegetables is very time-consuming, expensive, and even unpractical. With the availability of various data from drones, remote sensing images, and soil nitrogen levels, soil moisture, weather conditions, historical yield information, field management and more, AI techniques can use these data to train prediction models for the yield estimation [22]. For example, computer vision approaches can be used for the automatic counting of fruits or flowers. Historical yield information, images, weather conditions together with the field management can also be used to train AI models to predict yield of kiwifruit.

4.6 Predictive insights

Besides yield estimation and growth monitoring of crops as well as pest and weed management as discussed previously, AI can also provide other benefits in planting and management of crops in the agriculture lifecysle from preparation of soil and sowing of seeds to harvesting and storage.

For example, traditionally, the sowing dates of different crops are relied upon a fixed sowing time period or upon the estimation of current climate conditions. However, because of the effects of global warming, the shifts in the beginnings and endings of seasons makes the fixed sowing date unreasonable and disadvantageous in productivity [12]. An inaccurate sowing date may result in low productivity, financial and labor losses. AI techniques can help to determine the optimal sowing dates with the use of weather information, historical planting dates, crop yields each year and many more. Such data are used to train machine learning models to predict optimal sowing dates of crops. In another example, the prediction of harvest time of crops is crucial for crop production to perform planned activities, generating financial savings in handling, treatments, and management for agricultural producers. AI techniques can use different data related to crops such as weather data, soil information, crop management as well as historical harvest time to predict harvest time of crops [4]. Furthermore, because of weather dynamics such as wind speed and air humidity changes and growing stages of crops, it is important to determine an optimal time for spraying fertilisers or chemicals to maximise their effects. AI techniques can help to determine the optimal time for spraying with the use of weather data, crop management and others as well as machine learning algorithms.

4.7 Digital twins

A digital twin is a digital equivalent of a real-world object, and its behaviour and states are mirrored over its lifetime in a virtual space. Digital twins have been actively developed and deployed in different areas such as transport management and infrastructure management. In agriculture, digital twins as virtual counterparts of real-world plants can allow farmers to experiment and predict how plants will respond in different environments [23], such as when to apply fertilisers or how much irrigation water to use. As a result, digital twins can help agricultural producers to both increase crop efficiency and manage future growing conditions before they become a problem.

In digital twins, AI and machine learning models play the central role to simulate different conditions at scale by predicting plants responses under different conditions such as weather, fertiliser, irrigation, and management conditions. For example, field tests conducted in Australia won't predict which crop varieties have the potential to be the most resilient or produce the most yield in the northwest of China. Digital twins can help to solve such problem by simulating the weather, fertiliser, irrigation, and management as well as other conditions to maximise the yields of crops.

5 Risks of AI in agriculture

Despite the huge promise of AI for improving crop management and agricultural productivity, potential risks must be addressed responsibly to ensure they are safe, and secure against accidental failures, unintended consequences, and cyber-attacks [21]. Firstly, because of the use of large amount of data of both agriculture producer's private planting data and management data for model training, there are privacy issues in the use of AI. IoT sensors are often used to collect various conditions of plants and the environment, the low security of IoT such as limited computational resources and vulnerability in communication protocols also affect the AI security in agriculture [9]. For example, cyber-attacks and data leaks may cause agricultural producers serious problems such as shutting down sprayers, autonomous drones, and robotic harvesters. Secondly, the use of AI in agriculture is a lengthy technology adoption process. It requires a proper technology infrastructure such as internet access for it to work at the first step. AI is a new technology especially farmers may lack of experience with emerging technologies in most situations, it takes time for farmers to get used to it in planting and agriculture management with less complicated solutions. It will be reasonable to take step by step gradually to successfully adopt AI in agriculture by agricultural producers. Furthermore, AI can be expensive because of the infrastructure and maintaining. Agricultural producers might go into debt and will not be able to maintain the technology on their own. This may affect the implementation of AI in agriculture on a wide scale especially in developing countries. Last but not least, AI system is trained only to deliver the best performance such as best crop yield, and might ignore the environmental consequences of achieving this. This could lead to the overuse of fertilisers and over-application of pesticides in pursuit of high yields, resulting in the soil erosion and ecosystems poisoning in the long term. Therefore, the involvement of applied ecologists in the development of AI in agriculture could help to relieve such risks [21].

6 Conclusions

AI is transforming our society and affects almost every aspect of our lives. This chapter reviewed challenges faced in agriculture and presented the contributions of AI to mitigate those challenges. A number of typical application areas of AI in the lifecylce of agriculture were introduced, such as agricultural robots, irrigation optimisation, intelligent spraying, crop yield prediction and more. Furthermore, similar to the use of AI in other sectors, the application of AI in agriculture may also introduce risks. This chapter discussed potential risks that AI may introduce when it is used in agriculture. For example, AI might ignore the environmental consequences and only trying to deliver the best performance, and therefore the involvement of experts from other areas in the application of AI in agriculture is highly recommended.

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