

PAPER • OPEN ACCESS

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To cite this article: Jiali Zha 2020 *J. Phys.: Conf. Ser.* **1693** 012058

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Artificial Intelligence in Agriculture

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Abstract. The application of AI in agriculture has been widely considered as one of the most viable solutions to address food inadequacy and to adapt to the need of a growing population. This review provides an overview of AI's application in agronomic areas and progress in research labs. The review first presents two fields that AI can potentially play an important role in, which are soil management and weed management, and then Internet of Things (IoT) a technology that shows great potential in future usage is mentioned. Three challenges that need to be addressed in order for AI-based technology to be popularized in markets are uneven distribution of mechanization, the ability of algorithms to process large sets of data accurately and quickly, and the security and privacy of data, as well as the devices. Agricultural robots targeted at diverse aspects in agricultural industry have been developed and improved greatly in the past years, and although pointing out the hardship of applying machines and algorithms tested in experimental environment to real environments, the review highlights an already prosperous development and a promising prospect of application.

1. Introduction

The term “Artificial Intelligence” was first introduced in the 1955 Dartmouth Conference, in which John McCarthy proposed a study to be carried out grounded on the hypothesis that “every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it” [1]. Nowadays, AI, one of the essential areas in computer science, has penetrated a variety of domains, such as education, healthcare, finance and manufacturing, because of its nature to tackle problems that cannot be solved well by humans [2]. Humans continue to be shocked by AI's capacities. One example is IBM's Deep Blue's historical victory over world chess champion Garry Kasparov in 1997 and the triumph of AlphaGo over the world Go champion Lee Sedol in 2016, which proves that deep learning, the principle that AlphaGo is based on, enables AI to surpass the most human brainpower [3].

Agriculture, an essential consideration of any country, is still one of the major challenges currently. It is approximated that over 820 million people are in hunger today [4]. Furthermore, with the global expected to reach 9.1 billion in 2050, 70 percent more food needs to be produced. In addition to the projected investments in agriculture, further investment will be needed, otherwise about 370 million people would be in hunger in 2050 [5]. In addition, an expanding gap between a growing water demand and the available water supply is anticipated, and it is likely that over three billion people would experience water stress by 2025 [6].

Except for traditional measures, scientists and the government recognize the important role played by AI, despite its relatively short history of development. The application of AI in agriculture was first attempted by McKinion and Lemmon in 1985 to create GOSSYM, a cotton crop simulation model using Expert System to optimize cotton production under the influence of irrigation, fertilization, weed control-cultivation, climate and other factors [7]-[8].



This review aims to present the current situation of artificial intelligence in agriculture by highlighting three important considerations and achievements-soil management, weed management and the use of Internet of Things. It also evaluates the pressing challenges that are confronted in this field, like the predictable uneven distribution of mechanization in different areas, security and privacy issues, and the flexibility of algorithms in practical applications, when plants are physically heterogeneous and large data sets and additional factors need to be processed. Finally, this review emphasizes on the development of agricultural robots, providing the background of this specific field, giving particular examples and then pointing out major challenges. identifies the future prospects of application and also takes into considerations diverse circumstances in different countries.

2. Status of AI applications in agriculture

2.1 *The definition of Artificial Intelligence (AI)*

The definition of Artificial Intelligence changed over time because of its rapid development, and a unified definition does not exist even in current days. However, the definitions around can be generally classified into four categories: AI is a system that thinks like a human, acts like a human, thinks rationally or acts rationally [9]. Alan Turing wrote a paper in the 1950s, in which he proposed a game to answer the question “Can a machine think?” and the game is known as the Turing Test [10]. To pass the Turing test, a computer must possess four skills - natural language processing, knowledge representation, automated reasoning, and machine learning [9]. In this case, Turing gave the most widely spread definition of AI, but it had the problem of not distinguishing between the knowledge from the intellect, just like separating software from hardware when defining a computer [11]. AI was also defined as “such a program which in an arbitrary world will cope not worse than a human,” which means that AI is a set of programs, has inputs and outputs and also exists in an environment [11]. Some applications of AI include intelligent retrieval from databases, expert consulting systems, theorem proving, robotics, automatic programming and scheduling problems, perception problems, etc. [12].

2.2 *Current status of AI application in Agriculture*

2.2.1 *Soil Management*

Soil is one of the most important factors of successful agriculture, and as the original source of nutrition, soil stores water, nitrogen, phosphorus, potassium, and proteins that are crucial for proper crop growth and development [13]. Soil condition can be enhanced with compost and manure, which improves soil porosity and aggregation, and with an alternative tillage system to inhibit soil physical degradation. With soil management, for example, negative factors, such as soil-borne pathogens and pollutants, could be minimized [13]. Another example is that AI can be used to make soil maps, which helps to show soil-landscape relationships and various layers and proportions of soil underground [14].

2.2.2 *Weed Management*

Weed is one of the aspects that reduces a farmer’s expected profit most: for example, if weed invasion is not under control, a 50% loss in yield can occur for dried beans and corn crops, and weed competition can cause a 48% reduction in wheat yield. Weeds compete with crops for resources, like water, nutrients and sunlight, regardless of some being poisonous and even threatening public health [13]. While spray is often used to inhibit weeds, it has a potentially negative impact on public health and the excess use can pollute the environment. Therefore, artificial intelligence weed detection systems have been tested in laboratories to calculate the precise amount of spray to be used and to spray on the target location accurately, which also lower costs and the risk of damaging crops [15].

2.2.3 *The Use of Internet of Things Technology*

The Internet of Things (IoT) is a system consisted of computing devices, mechanical machines and various objects that are interrelated, and each is provided with a unique identifier and possesses the

capability of data transfer. Therefore, human-to-human or human-to-computer interactions can be avoided. IoT is an advancement built on several existing technology, such as wireless sensor networks (WSNs), cloud computing and RF identification. IoT can be applied in manifold fields, such as monitoring, precision agriculture, tracking and tracing, greenhouse production and agricultural machinery. For example, the tracking and tracing of agricultural product chain include information input (the complete life cycle of the product, the transportation process, etc.), the ability to store the information for a period of time, and to transfer, process and output the data. The tracking and tracing of the product chain can be used for commercial reasons, especially forming trust between the seller and buyer – by seeing the entire history of the product, the agricultural companies can make better decisions, find business partners wisely, and save time and money. The IoT applies data analysis in a variety of ways, and the data are in various forms, such as sensor data, audio, image and video. Areas that data analysis is vital to includes prediction, storage management, decision, farm management, precise application, insurance, etc. [14].

3. Challenges of practical application of AI-based techniques in agriculture

3.1 Possible uneven future distribution of mechanization

From the projection of robot shipments during the period 2011-2013, an average 9% increase each year in the U.S.s, a 12% increase in Asia-Australia countries and an 8% increase in Europe are anticipated. According to this trend, it is estimated that the penetration rate of robots by 2030 will be 15% and will be 75% by 2045. However, the distribution of mechanization can possibly be unevenly distributed with some areas lacking access to resources and having situations which can't not be changed with science discoveries and technological development [6]. For example, since most AI systems are based on the Internet, their utilization may be restricted in remote or rural areas with the absence of a web service and familiarity with handling AI operations [13]. Therefore, a slower and unequally distributed adoption process of AI in agriculture should be expected, and meanwhile, whether the adoption would increase food production beyond certain natural limits of land or not remains uncertain [6].

3.2 Discrepancies between control experiments and actual implementation

The fact that images taken when applied differ from the images used in control environments because of factors such as lighting variability, the complexities in the background, the angle when capturing, etc. In addition, grains cultivated in the field, even at the same location, are physically heterogeneous as a result of the impact of other elements, like insects, soil and inert matter. In that case, the physiological characteristics of individuals increases the complexity of variables to be considered when processing images, and therefore, a larger and more diverse set of control data was required to improve the current classification accuracy. Nevertheless, with the help of computer vision, algorithms like DBN (Deep Belief Networks) and CNN (Convolution Neural Network), regardless of the small number of case studies, indicate promising applications in the future for processing large sets of complicated data [16]. Moreover, in order to shorten the response time of a system, data processed should be the most relevant ones. A system's capability of executing tasks precisely in a short period of time is critical in deciding its commercial value, affecting users' selection greatly - what customers consider most is the minimized effort required for them and the maximized accuracy [13].

3.3 Security and privacy

Many physical devices, such as the IoT, are first vulnerable to attacks on the hardware because the device can be placed in an open space for long periods of time without supervision. Typical security counter measurements are data encryption, tag frequency modification, tag destruction policy, use of blocker tags, etc. Location-based services are also exposed to device capture attack, which means after capturing the device, the attacker can extract cryptographic implementations and therefore have unlimited access to data stored in the device. Data can also be attacked when transferring from the device to the gateway, where the data is then uploaded to other infrastructures, like the cloud. The cloud servers

are vulnerable to data tampering, which can unauthorizedly interfere the automated operations in the farm. Means such as session hijacking, logon abuse and denial of service (DoS) can also interfere cloud infrastructures. The corresponding security policies include cryptographic algorithms, data flow control policies, identity authentication mechanisms etc. Therefore, security issues are causing serious problems and should be addressed in different levels [14]+[17].

4. Development of Agricultural Robots

4.1 Background and Examples

One field of applications that AI plays an important role in is the robotics system, and to incorporate robotics into agriculture and to improve the efficiency, reliability and precision have been attempted for years, which would dramatically replace manual labor needed with automatic labor-intensive work. Automation are keys to pressing social phenomena such as aging population and decreasing population, but to be able to accomplish the accurate and complicated operations that were traditionally done by farmers to maintain the good quality always remains as a great challenge.

The study of robots for agricultural purposes began as early as in the 1980s, and Japan first developed a robot that can spray pesticide [18]. Acknowledging that to navigate in real agricultural environments is a hardship, a research team in 1996 designed an autonomous mobile robot called AURORA that was able to navigate autonomously or to be controlled remotely in greenhouses while performing specific task that conventionally required considerable manual labor. In fact, the initial motivation for designing robots specific to greenhouse environment was that human operators are vulnerable to pesticides, fungicides and other chemical products especially in the warm and poor ventilation greenhouse environment, which caused them skin diseases, chronic diseases and even mortality [19]. One early example of agricultural robot the tractors obtain an input, or more specifically, a program indicating the travelling path, from the global positioning system (GPS), and using machine vision, the device can operate along with crop line [20]. In an experiment to estimate apple fruit location for manipulation in 2000, robots designed for picking apples used a Cartesian coordinate system to determine the position of the apples. The non-linear least square method was used to store the distribution of the apples in the horizontal and vertical directions, which can be applied for designing the manipulator of the apple harvesting robot [21]. Regarding to the weed management problem discussed above, a 2003 design aimed to test a robotic platform for mapping weed populations and focused on the mobility and user friendliness of the four wheel system, of which its functionality is predominately carried out with embedded controllers and standard communication protocols [22]. To expand on the idea of weed management, another study conducted in 2003 emphasized on distinguishing between crops and weeds to locate precise spots for herbicide. Image recognition of species focusing on plant morphology is one of the most reliable methods: if characteristics such as leaf edge, border patterns and overall shape is determined, then the plant type should be interpreted. However, because of the variability of measurements, such as lighting conditions, distortion of the shape of the leaf and position, and the fact that young plants vary significantly due to different burgeon dates, growth rate and variation in growing environments, like temperature and moisture, to distinguish between weeds and crops remains challenging. It also shows that the device needs to learn important features for itself based on neural network (NN) approaches in order to attain desired functions. Furthermore, the selectivity of herbicides being used in fields reduces the total quantity used and therefore can reduce herbicide pollution in water [23].

An Autonomous Fruit Picking Machine (AFPM) for harvesting apples published in 2008 focused on designing a flexible gripper, which ensured the accuracy that was crucial for picking apple by apple instead of harvesting many in one go and therefore minimized economic loss due to damages of apples' qualities [24]. A fruit picking robot published in 2013 has an automatic extraction method applied to varying agricultural background for vision system, and the method is based on features in OHTA color space and an improving Otsu threshold algorithm. The OHTA color space has color features that transform color extraction in one-dimension rather than three-dimension. A new color feature in OHTH

color space is first defined, and then an Otsu threshold algorithm extracts the fruit objects based on properties in OHTA color space. The distinguish of colors serves the need to recognize ripe fruits, and the extract rate is more than 95%, indicating its accuracy and effectiveness [18].

4.2 Challenge of agricultural robots

Although the study of agricultural robots has made tremendous progress, robots that are applicable to work in complex agricultural environment are still not available in the market. The main reason was that algorithms that can cope with the uncontrolled and unpredictable real agricultural environment have not been developed yet, and other factors, such as the seasonality of agriculture, also marks the difference between real environment and experimental environment in laboratories. The dynamic and rapid changing in time and space of agricultural environment are almost unavoidable, no matter in unstructured environments, such as military and space environments, or in environment where atmospheric conditions have uncertainty inherently, like rugged terrain, visibility and illumination.

Nevertheless, partial autonomy will still benefit the production with technology. The Pareto principle applies to many tasks, and it basically means that automation can be applied in 80% of a task, leaving the remaining 20% very difficult. In another word, 80% of required manual work can be reduced with automation. Furthermore, the 80% automation can serve as a transition from traditional farming systems to completely autonomous farming systems and more experience will be learnt by experimenting with software and hardware elements [20].

5. Conclusion

This review presents an overview of the application of AI technology in agriculture. Corresponding to the current social situation of decreasing manual labor, limited usable agronomic land and a greater gap between total food produced and the world population, AI has been regarded as one of the most feasible solution to those problems and has been developed and improved for years by scientists worldwide. In this review, the definitions of AI are first introduced, in which the highlight is the Turing Test. Then two sub fields that AI has been playing an important role in are demonstrated, which are in soil management, weed management, and Internet of Things (IoT), a useful data analysis and storing technology that has wide application in agriculture, is introduced. This review also points out three major practical challenges of AI in agriculture: first, due to certain geographical, social or political reasons, the distribution of modern technology is uneven, which foreshadows that the application of AI will have its limitation in certain areas; secondly, despite significant improvements made in the past years, to transfer AI-based machines and algorithms from control experiments to real agricultural environment requires much more studies and research, and to be able to handle large sets of data and to interpret them accurately and quickly are two main challenges that need to be addressed in order to enable the application; finally, the security of devices used in open spaces of agricultural environment and the privacy of data collected are also problems to address. Then this review specifically introduces the development of agricultural robots. First, a couple of examples of robots designed to tackle different tasks in the agricultural industry are listed. There are autonomous mobile robots that can spray pesticides in greenhouses, tractors that use GPS and machine vision and have a travelling path pre-programmed, apple picking robots that use a Cartesian coordinate system to locate objects, two types of robots that manage weed problems and innovate in several directions, such as physical mobility and the ability to distinguish between crops and weeds, an apple harvesting machine that has an innovative flexible gripper, etc. Then the review indicates challenges of applying agricultural robots, basically circulating around the question of the unpredictability in real environments, but underscores the considerable development and a promising prospect in this field.

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