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Artificial Intelligence in Agriculture

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Abstract
A lot of people think that using AI in agriculture is one of the best ways to deal with food insecurity and meet the needs of a growing population. An overview of AI's use in agriculture and development in research labs is provided in this review. The Internet of Things (IoT), a technology with great potential for use in the future, is mentioned after the review first discusses soil management and weed management, two fields in which AI could potentially play a significant role. The uneven distribution of mechanization, the capacity of algorithms to process large sets of data accurately and quickly, and the security and privacy of data and devices are the three obstacles that must be overcome before AI-based technology can gain traction in markets. Despite highlighting the difficulty of transferring machines and algorithms tested in an experimental environment to real environments, the review highlights an already successful development and a promising application possibility for agricultural robots that target various aspects of the agricultural industry.

I. Introduction

At the Dartmouth Conference in 1955, John McCarthy proposed a study based 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." This was the first time the term "Artificial Intelligence" was used. Because it is designed to solve problems that humans cannot effectively solve, artificial intelligence (AI), one of the most important subfields of computer science today, has spread to a wide range of fields, including manufacturing, finance, healthcare, education, and healthcare. The capabilities of AI continue to astonish human beings. IBM's Deep Blue's historic 1997 victory over world chess champion Garry Kasparov and AlphaGo's 2016 victory over world Go champion Lee Sedol demonstrate that deep learning, the foundation of AlphaGo, enables AI to surpass human intelligence. Despite being an essential aspect of any nation, agriculture remains one of the major obstacles at the moment. Over 820 million people are estimated to be suffering from hunger today. Furthermore, 70 percent more food needs to be produced as the global population is projected to reach 9.1 billion in 2050. If additional investments are not made in addition to those that are anticipated to be made in agriculture, approximately 370 million people will suffer from hunger in 2050. Additionally, it is anticipated that the gap between the growing demand for water and the available supply will widen, and by 2025, it is likely that over three billion people will be experiencing water stress. Despite AI's relatively short development history, scientists and the government recognize the significant role it plays, with the exception of traditional measures. In 1985, McKinion and Lemmon made their first attempt at using AI in agriculture by developing GOSSYM, a cotton crop simulation model that utilized Expert System to optimize cotton production in response to a variety of factors, including irrigation, fertilization, weed control, climate, and others.

The goal of this review is to present the state of artificial intelligence in agriculture at the moment by focusing on soil management, weed management, and the use of the Internet of Things. It also looks at the pressing issues that have to be solved in this area, such as the predictable uneven distribution of mechanization across different areas, privacy and security concerns, and the adaptability of algorithms in real-world applications when plants are physically heterogeneous, large data sets need to be processed, and additional factors need to be taken into account. Last but not least, the development of agricultural robots is the focus of this review, which provides background information, specific examples, and major obstacles. identifies potential applications in the future and takes into account a variety of circumstances in various nations

II. Status of AI applications in agriculture

2.1 The definition of artificial intelligence (AI) Due to its rapid development, the definition of AI has changed over time, and even today, no unified definition exists. However, there are four general categories that can be applied to the definitions: An artificial intelligence (AI) is a system that behaves and thinks like a human. In the 1950s, Alan Turing published a paper in which he proposed a game to address the question, "Can a machine think?" The Turing Test is the name of the game. Natural language processing, knowledge representation, automated reasoning, and machine learning are the four skills that a computer needs to pass the Turing test . In this instance, Turing's definition of AI was the most widely used, but it was flawed because it did not distinguish between intelligence and knowledge, as he did when defining a computer. In addition, AI was defined as "such a program which in an arbitrary world will cope not worse than a human," indicating that AI is a collection of programs with inputs and outputs and an environment. Intelligent database retrieval, expert consulting systems, theorem proving, robotics, automatic programming and scheduling issues, perception issues, and other applications of AI include.

2.2 Current status of AI application in agriculture

2.2.1 Soil Management

As the primary source of nutrition, soil stores water, nitrogen, phosphorus, potassium, and proteins that are necessary for crop growth and development, making it one of the most important aspects of successful agriculture. Compost and manure, which increase soil porosity and aggregate, and a different tillage method, which prevents physical soil degradation, can both improve soil condition. Negative factors, for instance, soil-borne pathogens and pollutants, could be minimized through soil management. AI can also be used to create soil maps, which help to illustrate relationships between soil and landscape as well as the various layers and proportions of underground soil.

2.2.2 Weed Management

One of the factors that significantly lowers a farmer's expected profit is weeds: For instance, the yield of dried beans and corn crops can be reduced by 50% and the yield of wheat by 48% respectively if weed competition is not controlled. Despite the fact that some weeds are toxic and even pose a threat to public health, they compete with crops for water, nutrients, and sunlight. Spraying weeds can be effective, but it can be harmful to public health and pollute the environment if used excessively. As a result, artificial intelligence weed detection systems have been tested in labs to accurately calculate the amount of spray to use and spray on the intended location, both of which reduce costs and reduce the likelihood of crop damage.

2.2.3 How Technology from the Internet of Things

The Internet of Things (IoT) is a system made up of interconnected computing devices, mechanical machines, and other objects. Each one has a unique identifier and possesses the ability to transfer data. As a result, interactions between humans and computers can be avoided. The Internet of Things (IoT) is a development based on a number of established technologies, such as RF identification, cloud computing, and wireless sensor networks (WSNs). Monitoring, precision agriculture, tracking and tracing, greenhouse production, and agricultural machinery are just a few of the many applications for IoT. Information input (such as the product's entire life cycle and the transportation process) is one example of the tracking and tracing of agricultural product chains. the capacity to transfer, process, and output data in addition to storing it for some time. Agricultural businesses can use the tracking and tracing of the product chain for business purposes, particularly to build trust between the seller and the buyer. By seeing the product's entire history, they can make better decisions, choose wise business partners, and save time and money. The Internet of Things uses data analysis in a variety of ways, and the data come in a variety of formats, including audio, video, image, and sensor data. Prediction, management of storage, decision-making, farm management, precise application, insurance, and other areas all require data analysis.

III. Difficulties encountered when using AI-based farming techniques in practice

3.1 A potential uneven distribution of mechanization
According to projections for robot shipments from 2011 to 2013, the United States will see an annual increase of 9%, Asia-Australian countries will see a 12% increase, and Europe will see an 8% increase. By 2030, the penetration rate of robots is expected to be 15%, and by 2045, it is expected to be 75%. However, the distribution of mechanization may be uneven, with some areas lacking access to resources and circumstances that cannot be changed by technological advancements or scientific discoveries. For instance, due to the fact that the majority of AI systems are based on the Internet, their use may be limited in remote or rural areas due to a lack of a web service and a lack of familiarity with AI operations. As a result, it is reasonable to anticipate a more sluggish and unevenly distributed adoption of AI in agriculture. However, it is still unclear whether this adoption would result in an increase in food production beyond certain natural land limits.

3.2 Disparities between actual implementation and control experiments
The fact that applied images differ from control environments' images due to variables like lighting variability, background complexity, angle of capture, and so on. In addition, the influence of other elements like insects, soil, and inert matter makes field-cultivated grains, even in the same location, physically diverse. Because of the increased complexity of the variables to be considered when processing images caused by individuals' physiological characteristics, a larger and more diverse set of control data was required to enhance the current classification accuracy. Despite the limited number of case studies, computer vision-based algorithms like DBN (Deep Belief Network) and CNN (Convolution Neural Network) point to potential uses for processing large sets of complex data in the future. Furthermore, processed data ought to be the most pertinent in order to reduce a system's response time. In determining a system's commercial value, a system's ability to complete tasks precisely in a short amount of time has a significant impact on user preference—customers prioritize accuracy and minimal effort.

3.3 Safety and privacy
A lot of physical devices, like the Internet of Things, are first vulnerable to attacks on their hardware because they can be left in an open area for a long time without being watched. Data encryption, tag frequency modification, tag destruction policy, and the use of blocker tags are all common security counter measurements. Device capture attacks can also target location-based services. After capturing the device, the attacker can extract cryptographic implementations and gain unrestricted access to the device's data. When data is transferred from the device to the gateway, where it is uploaded to other infrastructures like the cloud, it can also be attacked. Cloud-based servers.

IV. Conclusion

An overview of how AI is being used in agriculture is presented in this review. AI has been considered one of the most feasible solutions to the current social situation of decreasing manual labor, limited usable agronomic land, and a wider gap between the total amount of food produced and the global population. It has been developed and improved for years by scientists all over the world. The Turing Test serves as the highlight of this review's introduction to AI definitions. The Internet of Things (IoT), a useful data analysis and storage technology with a wide range of applications in agriculture, is then introduced, demonstrating two subfields in which AI has been playing an important role: weed management and soil management. Additionally, this review highlights three major AI-related practical obstacles: First, the uneven distribution of modern technology is a sign that its application will be limited in some areas due to geographic, social, or political factors; Second, despite significant advancements over the past few years, transferring AI-based machines and algorithms from control experiments to the real agricultural environment necessitates a significant amount of additional research. Additionally, in order to make the application possible, it is necessary to overcome two primary obstacles: Lastly, issues to address include the privacy of collected data and the security of devices used in agricultural environments. Then, the development of agricultural robots is specifically discussed in this review. To begin, a few examples of robots created to perform various agricultural tasks are listed. 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. There are autonomous mobile robots that can spray pesticides in greenhouses, tractors that use GPS and machine vision and have a traveling path that is preprogrammed. The review then discusses the difficulties of implementing agricultural robots, primarily centered on the unpredictability of real-world environments, but also highlights significant progress and promising prospects in this area.

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