Available online www.jsaer.com

Journal of Scientific and Engineering Research, 2024, 11(5):1-6

Research Article

ISSN: 2394-2630
CODEN(USA): JSERBR

Application of Artificial Intelligence for Digital Agriculture and Water Resources

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Abstract The development of intelligent farm equipment, irrigation systems, weed and pest control, fertilizer application, greenhouse culture, storage structures, drones for plant protection, and crop health monitoring are just a few of the possible uses for Internet of Things (IoT) and Artificial Intelligence (AI) that have been well-established. The main promise of digital agriculture is its capacity to evaluate the system holistically at many scales (individual, local, regional, and global) and to produce tools that enable better decision-making in each sub-process. It is now possible to gather data from various sources in a so-called "smart farm" thanks to recent improvements in Internet of Things (IoT) technology and software. It is feasible to get data from a broad linked region at many time scales, including in near real-time (i.e., latency of a few tens of seconds), by connecting these IoT devices. In a wireless sensor network (WSN) environment, IoT devices can connect with one another and can sense various types of data. Data is produced from a variety of sources in row crop systems. Data is produced in vast quantities by field operations. Six operations of soil sampling, fertilizer application, planting, scouting, spraying, and harvesting produce the majority of the data in most systems. This will facilitate the introduction of AI- and IoT-based solutions on farms and aid in the understanding of how digital technology can be incorporated into agricultural processes.

Keywords Artificial Intelligence, Internet of Things, Agricultural processes, Smart farm, Field operation

1. Introduction

It is predicted that there will be 10 billion people on the planet due to the high population growth by 2050s. This places a huge burden on the agricultural industry to raise yield per hectare and crop production [1]. Agriculture is becoming less profitable due to a number of issues that farmers face, including small land holdings, workforce shortages, climate change, harsh weather conditions, decreased soil fertility, etc. Climate change and other environmental issues have been a constant struggle for agriculture over the past few years, making it extremely difficult to increase productivity. Increased land use and extensive farming are two potential solutions to the food shortfall, as are the adoption of best practices and technological assistance to boost productivity. In developing nations with dense populations, when expanding the geographical area is practically difficult, the only option is to become wiser with the aid of cutting-edge technologies like the internet of things (IoT) and related technologies like artificial intelligence (AI).

The issues related to the food, water, and energy nexus will worsen by 2050 when there will be 9 billion people on the planet. A growth in affluence and increased meat consumption among people, as well as an increase in the use of cropland for biofuels, will both increase demand. Precision farming, or site-specific farm management, has the potential to feed the globe while boosting farm output under times of limited resource availability. Despite improvements in GPS, grid soil sampling, and field sensors, farm operators have not adopted technology to the extent that was anticipated [2, 3, 4]. Furthermore, it is not yet apparent how portable the use of such technologies would be [5]. The decision to invest in site-specific management methods is influenced by operator demographics, operation size, and perceived benefits. Adoption rates vary greatly across technology kinds [6, 2]. For instance, the adoption of yield monitors and automated guiding systems has been slower than that of variable rate technology (VRT). Between farm technology and the agricultural information that supports the technology, a crucial contrast has been made [3].

A set of technologies collectively known as artificial intelligence (AI) enables computers and other machines (such as robots) to carry out activities that were previously assumed to need human expertise, creativity, and resourcefulness. It involves the capacity for computers to operate independently and "learn" from sizable input data sets without being specifically programmed for the necessary task. By (i) providing support services that were previously deemed too resource-intensive, expensive, or unavailable (for example, due to a lack of skills and expertise among local professionals), and (ii) reducing current operational costs by sparing time and labour performed by agriculture workers, AI's ability to perform intelligent tasks opens opportunities to improve current agricultural practices. AI is increasingly regarded as one of the most effective answers to the numerous problems that the agricultural sector in both high- and low-income countries faces. With applications across the entire food system, including production, distribution, consumption, and harvest yield uncertainty, AI has entered the agriculture domain, following the healthcare, automotive, industrial, and finance industries. AI-enabled technologies can assist farmers in increasing crop yields, addressing issues with soil health and herbicide resistance, and using resources more sustainably to cut greenhouse gas emissions from the agricultural industry.

1.1 Smart Agriculture Using Artificial Intelligence

It is possible to think of smart agriculture as a management idea that draws on information and understanding gleaned from both research and agri-food operations. The information can be organized in a variety of ways, leading to decisions that are sometimes automatically implemented into activities to protect or improve agricultural output and food security under fluctuating physical and chemical restrictions in a changing environment. Smart agriculture can use artificial intelligence to accomplish goals that are beyond the capacity of humans. One of the problems for the future is digesting a vast amount of data and turning it into useful information. Based on the investigation and use of data when available, improvements in several sectors of agriculture are anticipated or promised (Figure 10. Farmers also gain directly from cost savings, crop predictions, and enhanced decision-making and productivity.

Figure 1: Promised areas of improvement of agriculture in the exploitation of the data
Source: Mark, 2019

1.1.1 AI-Based Water Use Efficiency Improvement

A better forecast of the irrigation requirements in various field locations, based on a combination of local sensing of the crop and soil indicators, as well as water loss owing to evapotranspiration, can enhance the timing and amount of irrigation scheduling. It is possible to feed improved models for the dynamics of water consumption and water needs with data from a monitoring system that collects a number of plant, soil, and weather factors. These could be physics models that have been artificial intelligence (AI) improved by processing all the data that is now accessible and its temporal and spatial variability. For accurate forecasting, a system like this makes sure that the majority of local disruptions are taken into account. After a suitable field evaluation, a novel irrigation management technique based on a hybrid model of predictive control may lead to increased water productivity and use efficiency [8]. Depending on the growth season and these expectations, efficient precision irrigation technology distributes water to each field or a specific area within it. The adoption of digital twins will likely lead to advances in irrigation management in the following phase. Additionally, this creates possibilities for precise "fertigation".

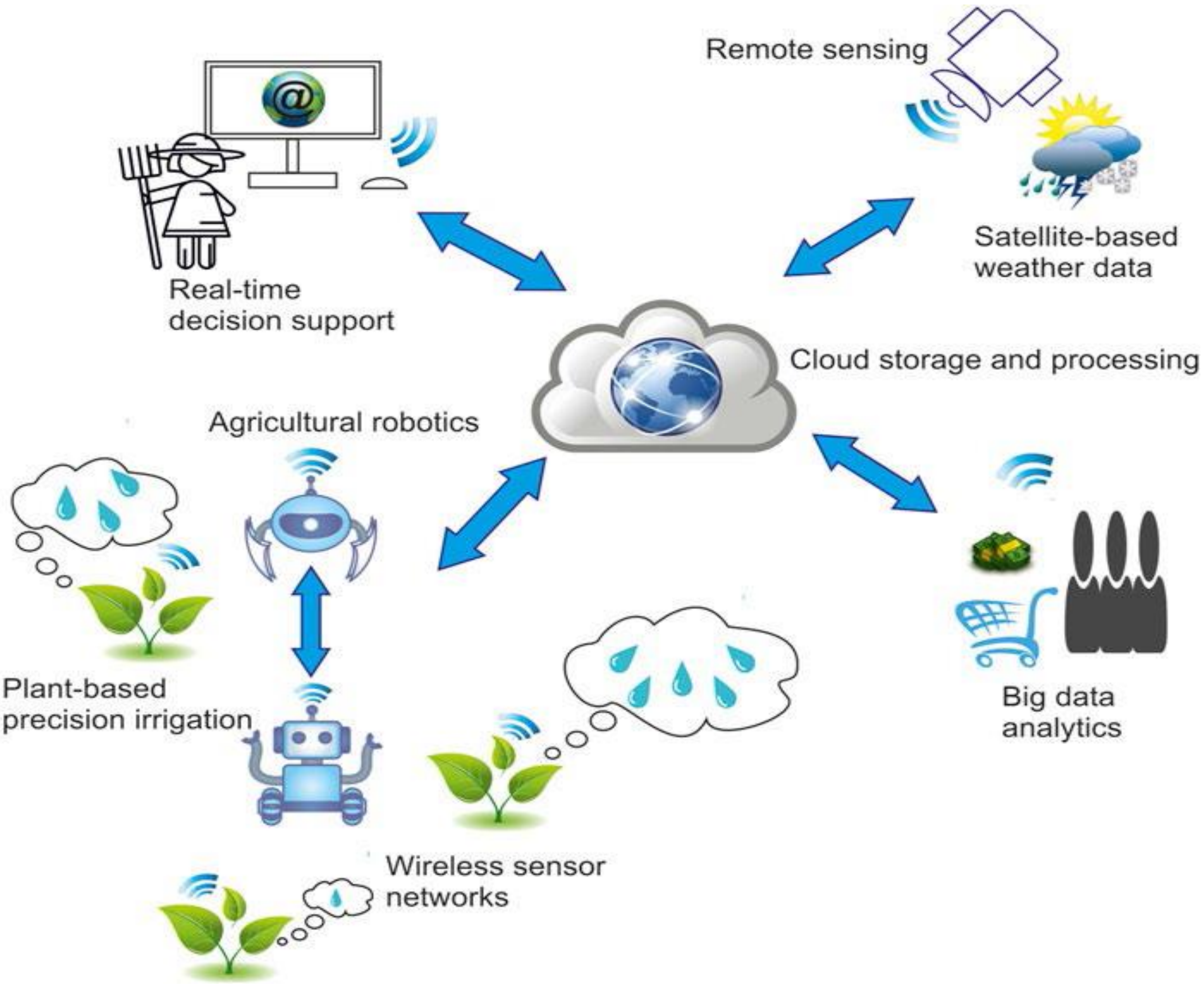

Figure 2: The future of precision irrigation control, with cloud-based data storage and processing, real-time communication between plant-based sensors, intelligent agents (including robots), supported by weather data and market analytics [8].

Although there have always been technological solutions for effective water management, the Internet of Things (IoT) revolution has raised the bar significantly. Using the Internet of Things, decision support systems equipped with artificial intelligence, and cloud computing, the entire work flow of an irrigation system can be intelligently automated (Fig. 3). The main data sources that are input into the system are the soil moisture, temperature, and humidity sensors. The data are kept in a database for further examination, and historical data can be used to train the model. The ready-to-use classification technique is an artificial neural network, which can be trained using data from the database to create the model. The model can then be used to categorize unclassified data after being trained. Transferring the data from the sensors via protocols like MQTT allows for real-time monitoring.

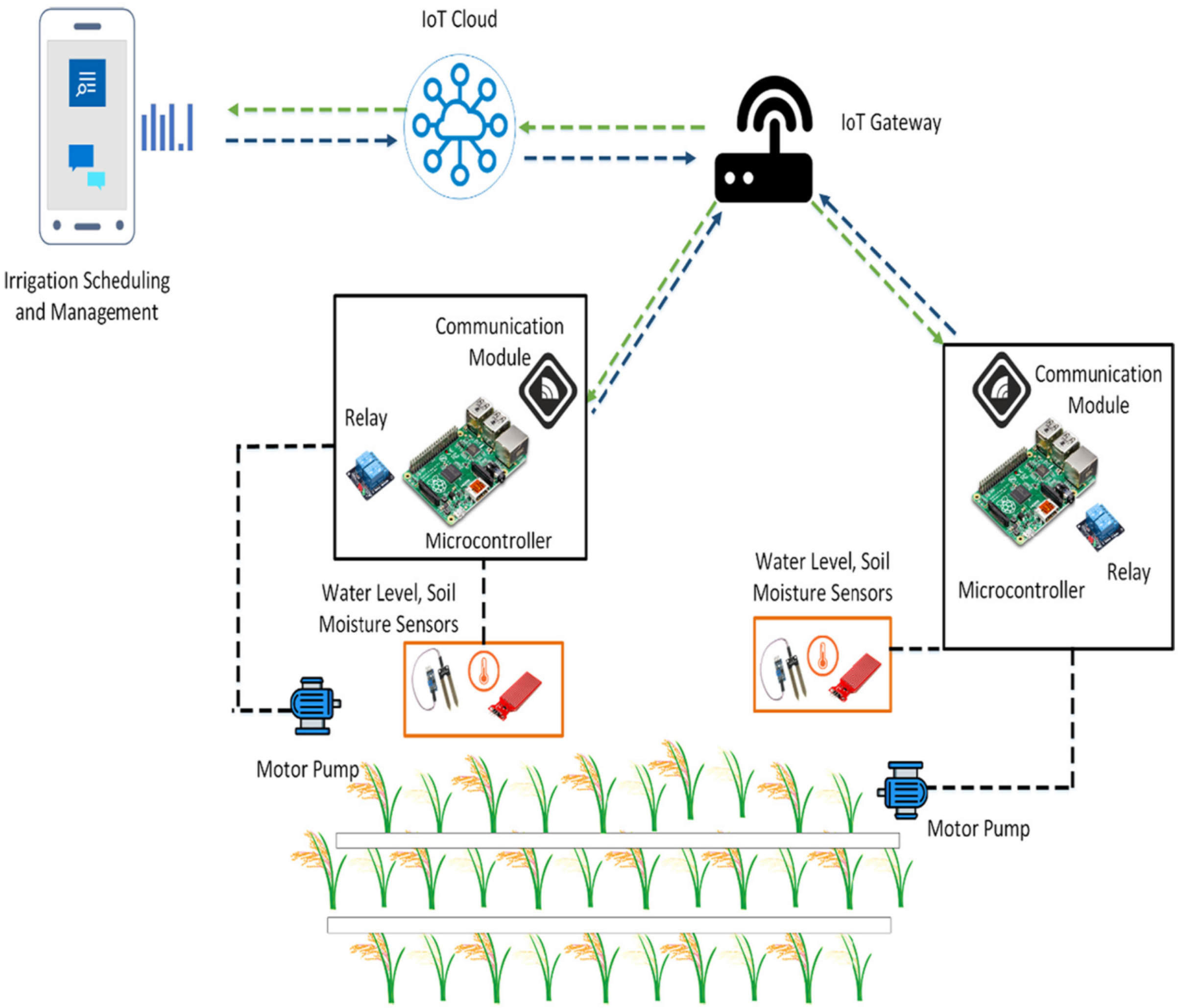

Figure 3: Automated irrigation systems using Internet of Things

1.2 Artificial Intelligence and Digitization for Crop Morphology

Plant morphology and shape are influenced by genetic makeup, environmental conditions (such as light, temperature, and irrigation), and variation. The term "digital plant phenotyping" describes the process of phenotyping plants using computers and digital sensors to measure various aspects of the plants. Image analysis is one of the most popular digital phenotyping methodologies, where cameras are used to record images and software is used to automatically extract measurements from the images in order to access plant morphology (the shape of a plant) in a repeatable and accurate manner [10]. The measurement of significant plant characteristics to determine plant morphology is already possible with a wide variety of cameras. The RGB color camera, which creates images in the visible range, mimics the human eye and is the most widely used type of camera. RGB camera-based 3D sensors were developed as a result of the frequent demand for 3D information to match the visuals to actual dimensions. An affordable RGB 3D sensor is the Intel Real-sense RGBD sensor, which is frequently used in horticultural phenotyping for tasks like tomato fruit counting and detection [11;12]. LiDAR sensors are yet another instance. Because of the advancement of consumer smart phone cameras, all of these could become inexpensive.

Some of the broad areas of AI application in agriculture include the following:

i. Crop, soil, and livestock monitoring. AI systems can assist farmers by keeping an eye on the health of their livestock, crops, and soil and making prompt recommendations on specific activities and decisions. For instance, AI systems can assist in determining the ideal time to sow seeds, gather fruits, distribute fertilizer, and/or give particular treatment to animals by examining inputs from field sensors or analysing photographs. Additionally, they can aid in identifying the specific plants or animals that need attention, enabling a more effective use of available resources.

ii. Detection of pests and diseases. Artificial intelligence (AI) systems can analyze digital photos captured by drones, farming robots, or farmers using a basic smartphone camera to detect pests and provide specific guidance to agricultural workers on how to stop their spread, treat injured plants, or lessen the harm they cause. AI is also able to examine data on cattle behavior to identify possibly ill animals and identify abnormalities, enabling prompt treatment.

iii. Weather and temperature forecasting. Using historical information and readings from nearby weather stations and field sensors, AI systems can help with local weather and temperature forecasting. Better weather and temperature predictions can assist farmers in planning when to plant seeds, use pesticides, and harvest their crops.

iv. Predictive analytics. AI can produce precise forecasts about yields and perhaps even the quality of the final product by evaluating various field data and/or looking at plant photos. Using this, farmers can forecast their income and decide how much to sell and how much to save for personal consumption. In order to forecast demand for a certain agricultural product, AI algorithms can also be employed to examine consumption patterns. To prevent any shortage or overstock, these predictions might be shared with the producers.

2. Conclusion

The creation of intelligent farm equipment, smart irrigation systems, weed and insect control, fertilizer application, greenhouse management, storage systems, etc. are some potential areas where digitization and automation in agriculture could be used. Artificial intelligence (AI) technologies rely on automated systems, the use of robots and drones, and expanded deployment of sensor and aerial picture data collection for crops and land use using deep learning technology. If certain obstacles to its widespread adoption are overcome, particularly among farmers in poor countries, the use of machine learning in diverse agricultural techniques is anticipated to increase significantly in the upcoming years. They consist of the prohibitive costs of the technologies, the lack of standards, farmers' ignorance of AI, and the scarcity of historical data. Although it is likely that AI will continue to be adopted in the agricultural sector, it is crucial that farmers have access to the most recent training to guarantee that the technology is used and gets better. As environmental factors that cannot be controlled have an impact on agriculture, unlike other industries where risk is easier to model and predict, extensive testing and validation of emerging AI applications will be crucial.

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